A GAME THEORY-BASED DECISION-MAKING FRAMEWORK FOR SUSTAINABLE URBAN PLANNING: OPTIMIZING RESIDENTIAL DENSITY WITH THE AID OF MACHINE LEARNING TECHNIQUES

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Abstract: Residential density planning is crucial for urban growth, impacting resource use, sustainability, and quality of life. The urban fabric is significantly influenced by the decisions made by planners and stakeholders regarding building footprints. Aligned with the conference's focus on sustainable solutions, this research introduces a Game-Theoretic Interactive Decision-Making (GTIDM) tool that combines game theory (GT) and machine learning (ML). This framework model's stakeholder behavior in residential density planning enhances decision-making and promotes sustainable urban development. In complex, competitive, and conflicting decision-making contexts, a game-theoretic framework is used to achieve optimal results by considering all possible scenarios. Three diverse density character zones were selected, including two within and one outside the Colombo Municipal Council (CMC), and subjected to the model's application. Expert validation indicated that while both simultaneous and sequential models replicate realistic data, the simultaneous model is more suitable for determining ideal building density. This study demonstrates the integration of GT and ML as a powerful strategy for individual and group decision-making in urban planning. Accurately calculated payoffs using the GTIDM model, which align with the study's goals and strategies, are crucial. Rationalizing residential density decisions encourages better stakeholder judgments, thereby promoting sustainable solutions and advancing sustainable urban density practices.

Keywords: *Game theory, Competitive decision-making, Strategic form game, Machine-learning, Residential land use*

1. Introduction

Building density is a crucial component of urban planning, significantly shaping spatial configurations and filling neighborhoods with unique identities. Within urban environments, it profoundly influences both social justice and sustainability (Dempsey et al., 2012; Fleury-Bahi et al., 2016). Effective urban structure relies on well-considered decisions regarding building density, with both the public and private sectors involved in real estate choices to create practical solutions (Lehmann, 2016). Decisions about residential building density are crucial, as residential areas significantly impact people's quality of life and overall well-being (Fleury-Bahi et al., 2016). Building density plays a vital role in sustainable urban growth as it is accurately managed to maximize the efficient use of available land resources. By optimizing land use, building density ensures that urban expansion is both effective and sustainable (Acioli & Davidson, 1996). Optimal construction density is essential for urban economic viability, as it bolsters the economy and enhances urban resilience and sustainability. By supporting economic activity, it contributes significantly to the overall health and stability of urban areas (Yang et al., 2018; Narvaez et al., 2013).

Suitable residential density reflects the diverse character of the city instead of adhering to a uniform formula (Jacobs, 2016). However, affordable housing plays a pivotal role in shaping decision-making processes (Narvaez et al., 2013). Decision-making in building density is a vital area that demands comprehensive research. This is because it impacts social justice, sustainability, and other significant issues, involving numerous stakeholders in the process (Lehmann, 2016). Overcoming challenges and arriving at comprehensive, rational conclusions are essential for a good quality of life and social justice (Fleury-Bahi et al., 2016). Building density is a pivotal concern in urban planning and development, influencing both the social and physical fabric of cities (Yang et al., 2018).

Balancing privacy and sociability is challenging due to the need for adequate spacing between buildings for ventilation, high urban densities, and expensive housing that often leads to smaller living spaces, impairing issues like loneliness and depression (Tan, 1999; Sim, 2019). In terms of building density, there is a noticeable absence of comprehensive tools or models that aid decision-making at the micro level, focusing on individual land parcels rather than entire regions (Abolhasani et al., 2022).

Because of the vibrancy of urban areas, developers often acquire property before deciding on density, requiring them to negotiate with various stakeholders and navigate multiple constraints (Sivam et al., 2012; Chamberlain, 1972). As the

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authority on construction density in Sri Lanka, the Urban Development Authority (UDA) officials (2023) strictly enforce regulations, allowing changes only in exceptional cases that comply with existing rules.

This work addresses a key research gap and provides urban planners, developers, and decision-makers with a practical tool for sustainable residential density planning. The Game-Theoretic Interactive Decision Making (GTIDM) framework, integrated with machine learning, models the interdependent actions of stakeholders with incomplete information in complex and conflicted residential density situations. This research is crucial as it integrates game theory and machine learning into urban planning, offering a groundbreaking approach to addressing challenges and strategies involving developers and the government. (Abolhasani et al., 2023), (Zhou et al., 2018). In addition to the economic benefits, it also contributes to creating a sustainable urban setting that considers the context (Liao et al., 2023).

Beyond technological innovations, this research introduces an interactive decision-making framework that promotes inclusion, transparency, and stakeholder engagement in urban planning. It represents a novel contribution by integrating rational decision-making methods with technological advancements.

2. Literature review

This phase combines game theory and machine learning for interactive urban planning decisions. It reviews literature on machine learning techniques, game theory, and decision-making tools. It also covers site selection, real estate theories, and residential density options. By integrating diverse stakeholder opinions and variables, it emphasizes rational decision-making in residential density planning.

Residential density in urban planning is influenced by various factors, including site selection, the requirement for affordable housing, and the growing demand for housing (Wang et al., 2014). Developers focus on building height to increase floors and maximize earnings. They select building parameters based on site size, floor area ratio (FAR), and plot coverage. Construction density is also influenced by location, environment, and infrastructure. (Ye et al., 2016). Property development involves developers and the government in two steps: selecting land based on preferences and collaborating to align with the developer's strategy. Government policies influence zoning and urban design, requiring developers to comply with regulations for constructing affordable housing (Krisnaputri et al., 2016). Programming computer models and decision-making frameworks enhances technological advancements, improving accuracy and productivity in complex decision-making. (Evans, 2019). While rational and multicriteria decision-making models can be used interactively, these methods become difficult in complex processes (Montibeller & Franco, 2010).

Urban planning benefits from rational decisions using advanced techniques like game theory, conventional multi-criteria decision-making (CMCDM) frameworks, and multi-agent systems (MAS). Game theory is especially suited for stakeholder decision-making, as it evaluates interconnected behaviours, focuses on interactive situations, and handles complex scenarios by considering stakeholder actions (Abolhasani et al., 2023). Machine learning excels in initial suitability assessments by analysing large data sets and detecting patterns. Its algorithms predict unlabelled samples, train on labelled data, and understand target concepts (Zhou et al., 2018). Game theory is ideal for interactive decision-making with stakeholders as it handles diverse behaviours and covers strategic interactions, such as cooperative and non-cooperative games, one-shot and repeated games, simultaneous and sequential games, and zero-sum and non-zero-sum scenarios (Owen, 2013). In decisions regarding residential land use density, where developers and the government interact, players may act both simultaneously and sequentially (Abolhasani et al., 2023). Simultaneous games involve players making decisions without knowledge of the choices made by others (Owen, 2013). A sequential game is one in which players make decisions in a specific sequence, with each player observing the choices made by those who acted before them (Orsini et al., 2005). In strategic form games, rational players prioritize their outcomes by choosing the optimal strategy over those of their opponents (Wang et al., 2021). In a Nash equilibrium, each player selects the best possible strategy, such that no player can improve their outcome by changing their strategy unilaterally (Agrawal & Jaiswal, 2012).

There is a notable research gap in developing a game-theoretic model for interactive decision-making in residential density. Current frameworks struggle with simultaneous interactions among multiple stakeholders. The combined use of game theory and machine learning remains under-explored. This phase highlights the need for a game-theoretic model by examining theoretical components of rational decision-making frameworks. Residential density results from two stages: initial suitability assessment and subsequent rational interactions between developers and government policies.

3. Methodology

This study used a mixed-method approach with a stakeholder narrative-driven methodology. The model, developed from stakeholder feedback and in-depth interviews, incorporates Machine Learning (ML) and Game Theory (GT). It was designed for the CMC and Dehiwala Municipal Council. Two main stakeholder groups were involved: the government (represented by UDA) and developers. UDA experts provided information, while major developers were selected: John Keels Properties, Prime Lands, and Blue Ocean for large-scale; Bhoomi for medium-scale; and Mode Engineering for small-scale. These companies, with extensive experience, have completed over 1000 apartment projects in CMC and suburb areas.

3.1. CONCEPTUAL FRAMEWORK

		Developer	
		Develop	Not Develop
Government	Can Approve	UG(g1d1) , UD(g1d1)	UG(g1d2) , UD(g1d2)
	Deny	UG(g2d1) , UD(g2d1)	UG(g2d2) , UD(g2d2)

Figure 1: Game matrix of strategic interaction between government and developer (Source: Compiled by Author)

This research uses the rational decision-making framework as its conceptual foundation, guiding each step in the methodology. The GTIDM framework combines ML and GT based decision-making techniques developed to support systematic analysis; each component is explained step by step in the analysis phase. Table 1 illustrates how decision-making elements are integrated into the GTIDM framework's development.

Table 1: Detailed conceptual framework Source: Prepared by author

Decision-making Components	Used in developed framework
Decision identification	Optimum residential density
Problem identification	Argument with policies; The government controls the allowable developable (Stakeholder Interaction)
Stakeholder identification	Government and developer
Eliminate infeasible alternatives and judgment	Developed algorithm (explained in upcoming steps)
Synthesize, examine, verify, and document the decision	Outputs of the model & validating the outputs

3.2. ANALYTICAL FRAMEWORK

In-depth interviews with stakeholders reveal that developers make decisions in two stages. First, land is selected based on physical characteristics without interactive decisions. In the second stage, a desired density for development is proposed, and the government evaluates whether it meets area-specific limits before granting approval. This interaction can occur either sequentially, where stakeholders consider previous decisions, or simultaneously, without knowledge of others' choices. Criteria for both land selection and density decisions are detailed in the analysis phase, with Table 2 presenting the analytical framework.

Table 2: Analytical framework Source: Prepared by author

Decision-making stage	Selected criteria	Selected model
Initial suitability	Accessibility	Machine learning model
	Mobility	
	Environmental Condition	
	Infrastructure availability	
Interactive decision-making	Strategic plan of the developer	Game theoretic model
	Site	

3.3. DETAILED RESEARCH DESIGN

The research methodology involves two decision-making steps with distinct models. In the initial suitability phase, developers select land based on mobility, environmental conditions, disaster risk, accessibility, and infrastructure, using GIS and the random forest model.

In the interactive decision-making stage, developers use game theory to determine land density for maximum profit. Simultaneous and sequential games illustrate different patterns, with the Nash equilibrium identifying optimal decisions. Developers choose to "develop" or "not develop," while the government decides to "approve" or "deny" based on regulations. Payoff *(Figure 1)* and utility calculations identify the most profitable choice, with the government focusing on compliance. This entire process is detailed in the research design *(Figure 3).*

The model was developed for the Dehiwala Mount-Lavinia Municipal Council and CMC *(figure 2),* selected based on expert recommendations from UDA, Sri Lanka, and interviews. These areas were chosen for their significance in residential density, zone factors, and physical conditions.

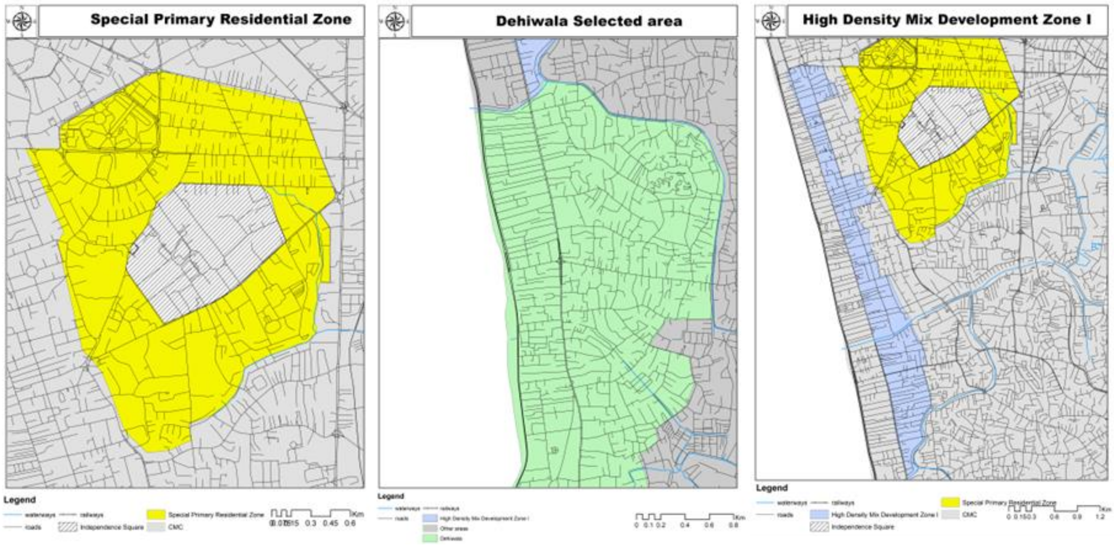


Figure 2: Applied Areas Source: Prepared by author

4. Analysis and results

The model for determining optimal residential density uses space-matrix classification, representing vertical density according to 2022 regulations and horizontal density categorization. Zoning regulations for CMC and Dehiwala MC in 2022 were used to prepare the model. Factors affecting residential density were identified from interview summaries. UDA officials, responsible for urban development regulations, noted that developers prioritize density for financial benefits, creating conflicts in finding rational solutions. The main stakeholders—government and developers—drive residential development decisions. Zoning regulations reflect regional carrying capacity. The decision-making framework calculates optimal density based on regulations and maximum profit, benefiting both parties. This model eliminates infeasible solutions and provides the best outcomes for both stakeholders. Two models were used: one for initial site suitability *()* and another for game-theoretic analysis of optimal residential density.

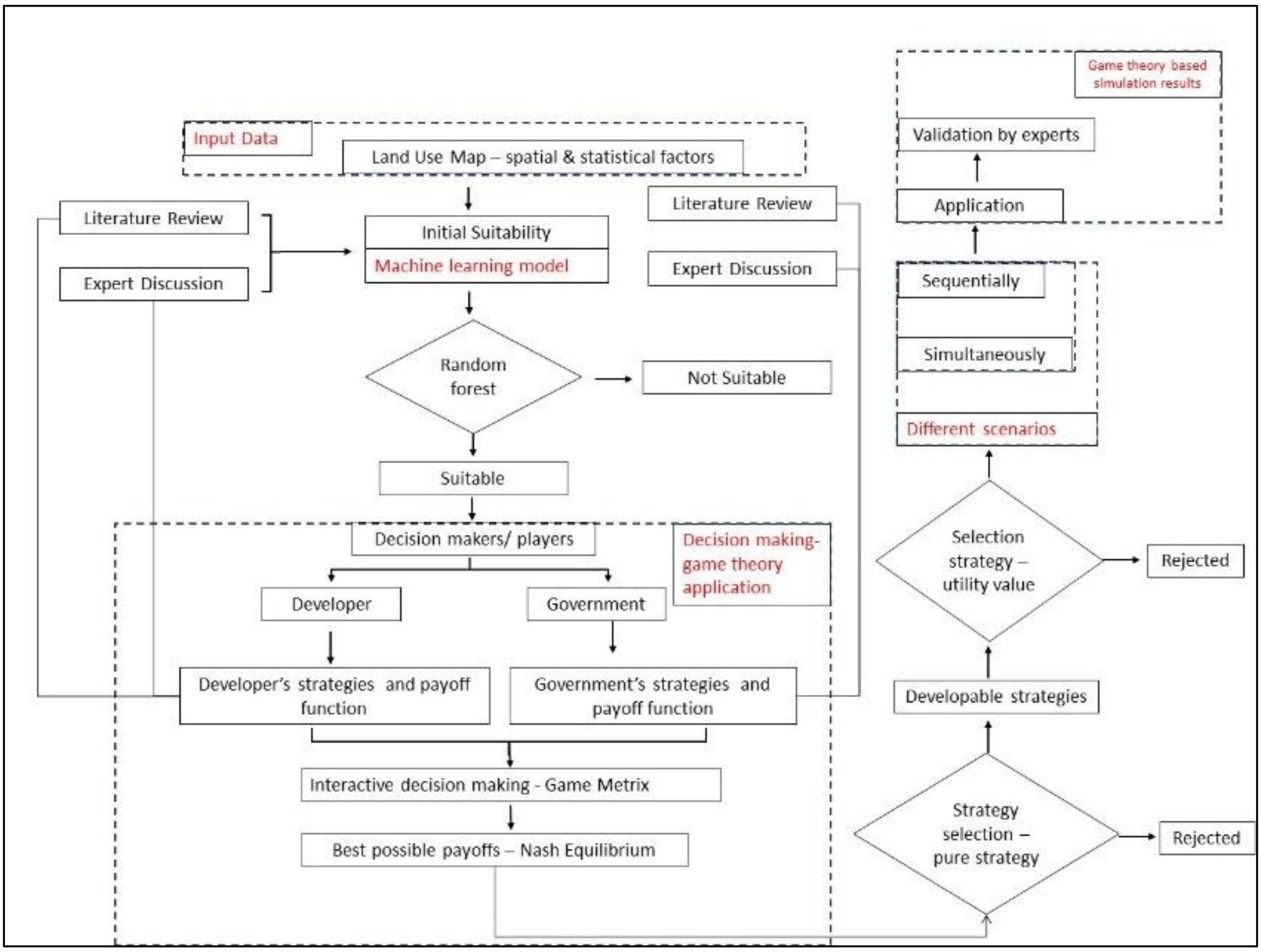


Figure 3: Detailed research design Source: Prepared by author

Table 3: Initial Suitability attributes Source: Prepared by author

Main criteria	Attributes
Accessibility	Accessibility of the connected road network.
Mobility	Access to the amenities nearby
Environmental Condition	Disaster risk
Infrastructure availability	Electricity, water and sewerage

4.1. MACHINE LEARNING MODEL

Based on selected time frames, the training data for apartment locations is limited but effectively predicts land plots suitable for residential use. The dataset covers market categories from ultra-luxury to low-mid-level, incorporating financial considerations into both training and test sets. Although not exhaustive, the data aligns with developers' perspectives on existing apartments in Colombo and its suburbs. The approach assumes that land surveys adhere to standard regulations and that land legality has been verified for over 30 years. The random forest model used for predicting initial suitability achieved an accuracy of 90.506% through cross-validation, reflecting robust performance.

4.2 GAME-THEORETIC MODEL

A game-theoretic model calculates optimal residential density for urban areas. Sequential and simultaneous decision-making models are used to simulate scenarios where players are unaware of other players' decisions in simultaneous models and aware in sequential models. Both models compare player decisions and results. Initial assumptions include a land slope not exceeding 10^0, with each floor 3 meters in height. Single residences are for land below 40 perches, and apartments for land above 40 perches, with at least 4 units per apartment. Minimum sizes are 645 square feet for single houses and 5145 square feet for apartments. The models use space-syntax categorization to classify building densities both vertically and horizontally, based on building regulations and corresponding categories (Figure 4).

For each player government and developer's optimum payoff of each player has taken differently. As the developers seek higher profits that developer would increase either vertically or horizontally and even when the position of decision has to be taken developer will seek vertical density.

Density category	Plot coverage	Number of floors
Low-rise Point	0.1 - 0.19	1-4
Low-rise strip	0.2 - 0.4	1-4
Low-rise block	0.4 – 0.65	1-4
Intermediate-rise Point	0.1 - 0.19	5-9
Intermediate-rise strip	0.2 - 0.4	5-9
Intermediate-rise block	0.4 – 0.65	5-9
Middle-rise Point	0.1 - 0.19	10-16
Middle-rise strip	0.2 - 0.4	10-16
Middle-rise block	0.4 – 0.65	10-16
High-rise Point	0.1 - 0.19	17-34
High-rise strip	0.2 - 0.4	17-34
High-rise block	0.4 – 0.65	17-34

Figure 4: range Source: Prepared by author

Open area regulations were considered through a logical approach: assuming both maximum building footprint and minimum land plot are block-shaped. This simplifies calculations by setting a constant maximum plot coverage, as non-rectangular shapes typically have lower coverage. The model maximizes horizontal density using a hypothetical block-shaped land plot with the largest possible area, ensuring actual plots meet the same density criteria. It adjusts both vertical and horizontal densities using two equilibria, considering key features of open space and density. Game theory is applied with two models to compute payoffs for each scenario, determining development decisions based on zoning regulations and open area requirements.

If the government approves the development and the land is viable, the developer earns a net profit or loss. If the government approves but the developer rejects, the developer incurs a loss. If the government denies approval while the land is feasible, it is considered a negative irrational decision, as described in the game matrix (figure 5). In figure 6, (4000+a) reflects the fee that the developer has to pay to the government. 134000 is the net profit from 1 m^2. Two models were created to assess simultaneous and sequential scenarios, with Nash equilibrium used to determine the optimal outcomes and highest utility for the developer. Sequential games focus on maximizing vertical density. Outcomes from both models are generated, observed, and compared, followed by validation of the study.

If developable floor area > 0

		Developer	
		Develop	Not Develop
Government	Can approve	4000 + a , Developer payoff 1	0, 0
	Deny	-1, -(4000+a)	-1, -(4000+a)

Developable area = d

Developer payoff 1 – 1st scenario

= (d* 134000) - (land value * land area)

If developable floor area = 0

		Developer	
		Develop	Not Develop
Government	Can approve	-1 , Developer payoff 1	-1, 1
	Deny	1, -(4000+a)	1, 0

Land area >= 400

a = (land area - 400) * 15

Else:
a = 0

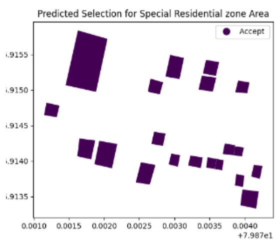
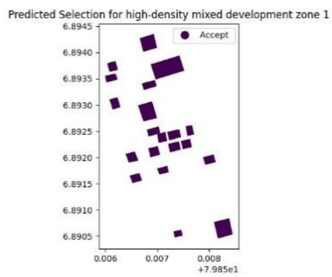
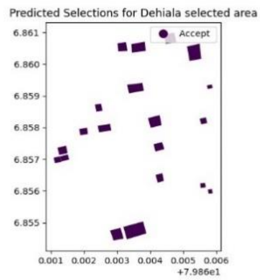
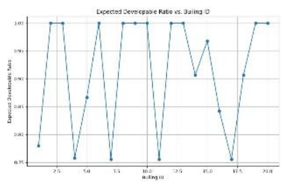
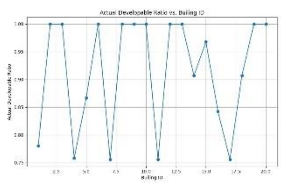
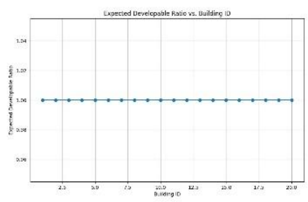
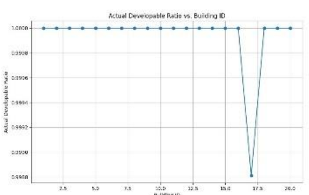
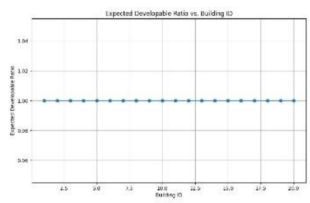
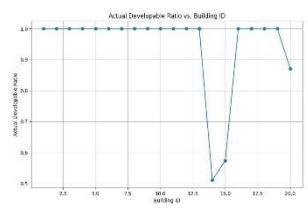
Developer payoff 1 = (maximum floors * plot coverage * land area * 134000) - (land value * land area)

Figure 5: game-Matrix Source: Prepared by author

The model was applied to two zones of CMC: the high-density mixed development zone 1, the controlled zone, and Dehiwala CMC area. The analysis provides two ratios: expected and actual developable FAR. The expected ratio doesn't consider land shape, while the actual ratio considers land shape and regulations, providing the final FAR. Figures describe FAR ratio calculations, aiming to understand developable potential.

4.2.1 Application

Table 4: Model application summary Source: Prepared by author

Stage	**Special primary residential zone**	**High-density mixed development zone 1**	**Dehiwala Selected area**
Initial suitability			
Analysis	The selected lands are initially suitable for residential development, as shown by the ML model.		
Simultaneous model	 	 	 

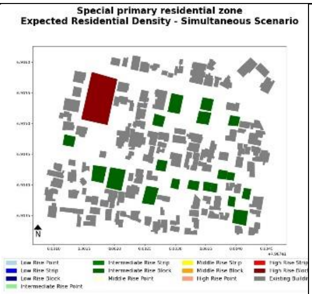
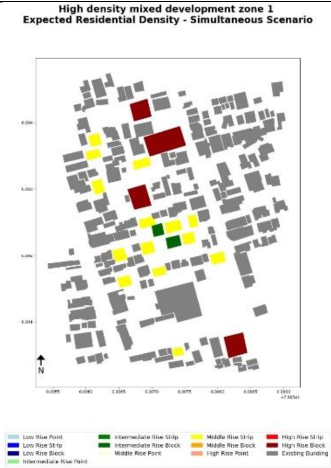
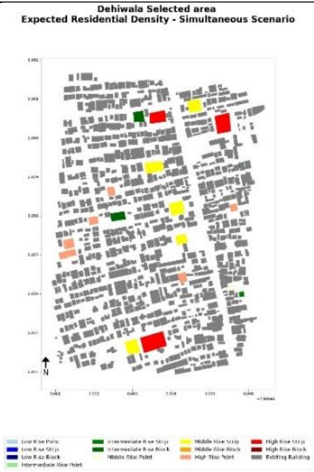
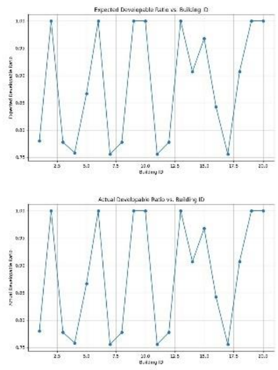
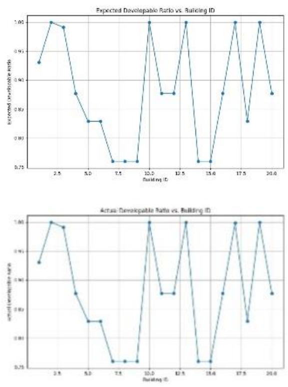
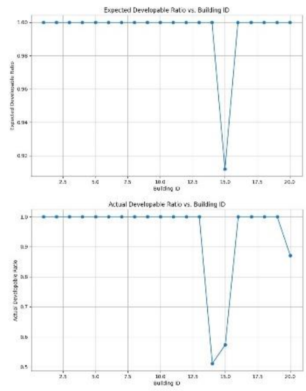
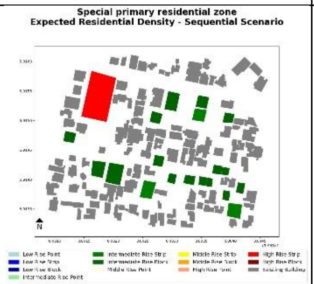
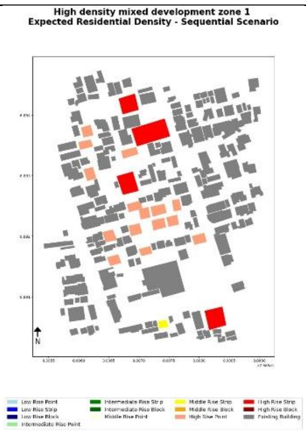
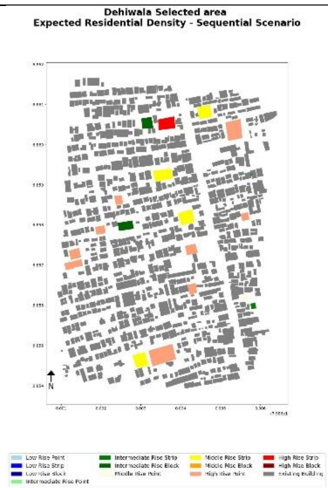
			
Analysis	The decision was not influenced by land shape, and the output densities are higher in intermediate-rise areas.	The decision for one land was affected by its shape, resulting in output densities that varied from intermediate to high-rise.	The shape of the land affected three properties, with output densities varying from intermediate to high-rise.
Sequential game			
			
Analysis	Densities varied most in intermediate-rise areas.	The graph shows no significant impact on land shape. Outcome densities varied from middle-rise to high-rise."	Densities ranged from intermediate-rise to high-rise.

Table 5: Model application summary-2 Source: Prepared by author

Selected zone	Common compression

Special primary residential zone

	Simultaneous game				Sequential game				Common
OBJECTID	Selected Game	Plot Coverage	Number of Floors	Actual Developable Ratio	Selected Game	Plot Coverage	Number of Floors	Actual Developable Ratio	FAR Ratio
1	Intermediate Rise Block	0.65	6	0.78	Intermediate Rise Block	0.65	6	0.78	1
2	Intermediate Rise Block	0.566667	6	1	Intermediate Rise Block	0.566667	6	1	1
3	Intermediate Rise Block	0.6	6	1	Intermediate Rise Strip	0.4	7	0.777778	0.777778
4	Intermediate Rise Block	0.65	7	0.758333	Intermediate Rise Block	0.65	7	0.758333	1
5	Intermediate Rise Block	0.65	6	0.866667	Intermediate Rise Block	0.65	6	0.866667	1
6	Intermediate Rise Block	0.64	5	1	Intermediate Rise Block	0.64	5	1	1
7	Intermediate Rise Block	0.65	5	0.755814	Intermediate Rise Block	0.65	5	0.755814	1
8	Intermediate Rise Block	0.6	6	1	Intermediate Rise Strip	0.4	7	0.777778	0.777778
9	Intermediate Rise Block	0.64	5	1	Intermediate Rise Block	0.64	5	1	1
10	Intermediate Rise Block	0.64	5	1	Intermediate Rise Block	0.64	5	1	1
11	Intermediate Rise Block	0.65	5	0.755814	Intermediate Rise Block	0.65	5	0.755814	1
12	Intermediate Rise Block	0.6	6	1	Intermediate Rise Strip	0.4	7	0.777778	0.777778
13	High Rise Block	0.413043	23	1	High Rise Strip	0.395833	24	1	1
14	Intermediate Rise Block	0.65	6	0.906977	Intermediate Rise Block	0.65	6	0.906977	1
15	Intermediate Rise Block	0.65	7	0.968085	Intermediate Rise Block	0.65	7	0.968085	1
16	Intermediate Rise Block	0.65	7	0.842593	Intermediate Rise Block	0.65	7	0.842593	1
17	Intermediate Rise Block	0.65	5	0.755814	Intermediate Rise Block	0.65	5	0.755814	1
18	Intermediate Rise Block	0.65	6	0.906977	Intermediate Rise Block	0.65	6	0.906977	1
19	Intermediate Rise Block	0.583333	6	1	Intermediate Rise Block	0.583333	6	1	1
20	Intermediate Rise Block	0.64	5	1	Intermediate Rise Block	0.64	5	1	1

Analysis: Both models identify the maximum developable area, predominantly in low-density zones.

High-density mixed development zone 1

	Simultaneous game				Sequential game				Common
OBJECTID	Selected Game	Plot Coverage	Number of Floors	Actual Developable Ratio	Selected Game	Plot Coverage	Number of Floors	Actual Developable Ratio	FAR Ratio
1	Middle Rise Strip	0.376923	13	1	High Rise Point	0.19	24	0.930612	0.930612
2	High Rise Block	0.421053	19	1	High Rise Strip	0.333333	24	1	1
3	Middle Rise Strip	0.383333	12	1	High Rise Point	0.19	24	0.991304	0.991304
4	Middle Rise Strip	0.4	13	1	High Rise Point	0.19	24	0.876923	0.876923
5	Middle Rise Strip	0.392857	14	1	High Rise Point	0.19	24	0.829091	0.829091
6	Intermediate Rise Block	0.611111	9	1	High Rise Point	0.19	24	0.829091	0.829091
7	Middle Rise Strip	0.4	15	1	High Rise Point	0.19	24	0.76	0.76
8	Middle Rise Strip	0.4	15	1	High Rise Point	0.19	24	0.76	0.76
9	Middle Rise Strip	0.4	15	1	High Rise Point	0.19	24	0.76	0.76
10	High Rise Block	0.421053	19	1	High Rise Strip	0.333333	24	1	1
11	Middle Rise Strip	0.4	13	1	High Rise Point	0.19	24	0.876923	0.876923
12	Middle Rise Strip	0.4	13	1	High Rise Point	0.19	24	0.876923	0.876923
13	High Rise Block	0.421053	19	1	High Rise Strip	0.363636	22	1	1
14	Middle Rise Strip	0.4	15	1	High Rise Point	0.19	24	0.76	0.76
15	Middle Rise Strip	0.4	15	1	High Rise Point	0.19	24	0.76	0.76
16	Middle Rise Strip	0.4	13	1	High Rise Point	0.19	24	0.876923	0.876923
17	Middle Rise Strip	0.384159	13	0.998812	Middle Rise Strip	0.384159	13	0.998812	1
18	Middle Rise Strip	0.392857	14	1	High Rise Point	0.19	24	0.829091	0.829091
19	High Rise Block	0.421053	19	1	High Rise Strip	0.363636	22	1	1
20	Intermediate Rise Block	0.65	8	1	High Rise Point	0.19	24	0.876923	0.876923

Analysis: Comparing the models, the sequential one yields more floors, while the simultaneous model provides fewer floors but better plot coverage. The simultaneous model achieves higher developable areas, with higher plot coverage and FAR ratios not equal to 1.

Dehiwala Selected area

	Simultaneous game				Sequential game				Common
OBJECTID	Selected Game	Plot Coverage	Number of Floors	Actual Developable Ratio	Selected Game	Plot Coverage	Number of Floors	Actual Developable Ratio	FAR Ratio
1	High Rise Strip	0.289474	19	1	High Rise Strip	0.289474	19	1	1
2	Middle Rise Strip	0.266667	15	1	Middle Rise Strip	0.266667	15	1	1
3	High Rise Strip	0.2	20	1	High Rise Point	0.166667	24	1	1
4	Middle Rise Strip	0.307692	13	1	Middle Rise Strip	0.307692	13	1	1
5	High Rise Point	0.185	20	1	High Rise Point	0.185	20	1	1
6	High Rise Point	0.185	20	1	High Rise Point	0.185	20	1	1
7	High Rise Point	0.19	20	1	High Rise Point	0.19	20	1	1
8	High Rise Point	0.185	20	1	High Rise Point	0.185	20	1	1
9	High Rise Point	0.185	20	1	High Rise Point	0.185	20	1	1
10	Intermediate Rise Block	0.433333	9	1	Intermediate Rise Block	0.433333	9	1	1
11	High Rise Point	0.185	20	1	High Rise Point	0.185	20	1	1
12	Middle Rise Strip	0.285714	14	1	Middle Rise Strip	0.285714	14	1	1
13	Middle Rise Strip	0.38	10	1	High Rise Point	0.19	20	1	1
14	Intermediate Rise Strip	0.283902	9	0.511024	Intermediate Rise Strip	0.283902	9	0.511024	1
15	Middle Rise Point	0.179323	16	0.573834	Middle Rise Point	0.179323	16	0.573834	1
16	High Rise Point	0.185	20	1	High Rise Point	0.185	20	1	1
17	Intermediate Rise Strip	0.375	8	1	Intermediate Rise Strip	0.375	8	1	1
18	High Rise Strip	0.2	20	1	High Rise Point	0.181818	22	1	1
19	Middle Rise Strip	0.325	12	1	Middle Rise Strip	0.325	12	1	1
20	Intermediate Rise Block	0.522666	9	0.87111	Intermediate Rise Block	0.522666	9	0.87111	1

Analysis: Due to its greater number of floors, the sequential model results in a higher density category and a larger developable area. On the other hand, the simultaneous model achieves the highest developable area, while the sequential model opts for taller floors because of height restrictions.

4.2.2 Validation

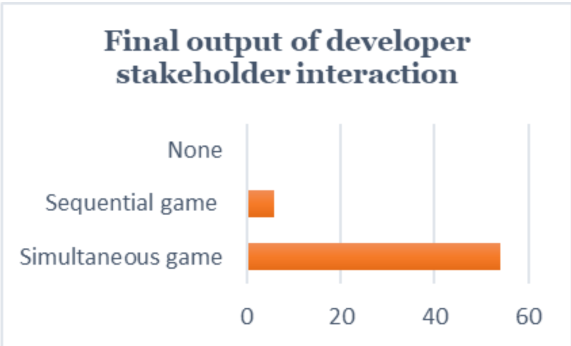
Government Stakeholder

	input data							Simultaneous game			Sequential game		
Building ID	Land area	Restricted due to Building line	Perpendicular length	Perpendicular width	Road width	zone factor	Site frontage	Plot Coverage	Number of Floors	Government chose	Plot Coverage	Number of Floors	Government chose
Special zone - 6	229.4	0	26.45	35.74	12	1.75	32.74	0.64	5	accept	0.64	5	accept
Special zone - 9	181	7.6	31.87	21.46	14.75	1.75	18.46	0.64	5	accept	0.64	5	accept
Special zone - 13	4181.25	11.89	168.28	97.16	30	1.75	94.16	0.413043	23	accept	0.395833	24	accept
Special zone - 15	687	7.6	54.81	44.63	14.75	1.75	41.67	0.65	7	accept	0.65	7	accept
High density zone - 5	567.4	0	28.3	20	12	3.25	30	0.392857	14	accept	0.19	24	accept
High density zone - 9	497.13	7.6	20	45	18	3.25	20	0.4	15	accept	0.19	24	accept
High density zone - 14	428.9	0	19	21	18	3.25	19	0.4	15	accept	0.19	24	accept
High density zone - 20	422.34	0	11.18	17	12	3.25	17	0.65	8	accept	0.19	24	accept
Dehiwala - 5	738.13	0	21.5	24.6	8	2.5	21.5	0.185	20	accept	0.185	20	accept
Dehiwala - 10	1148.74	0	41.8	21	7.5	2.5	41.8	0.433333	9	accept	0.433333	9	accept
Dehiwala - 18	2590	0.25	40.5	52.5	6.5	2.75	40.52	0.2	20	accept	0.181818	22	accept
Dehiwala - 20	1072.67	2	23.5	41.56	10	2.5	25.5	0.522666	9	accept	0.522666	9	accept

Figure 6: Government stakeholder validation Source: Prepared by author

According to the outputs of government stakeholder *(figure 6),* all the input lands have been accepted as the model is making rational decisions within the used regulations of schedule 6 from A-E.

This analysis showed that the given answers were close to the answer of the model or gave the same answer and after collaborating on the answer given by the stakeholder and model every developer accepted the answer which suggests that the stakeholder ideas vary and decisions will be unique to each other *(table-5).* Also, the model will help the developer to make rational decisions in complex and conflicting situations by collaborating on the answer mainly because developers' choices would vary.



Charts 1 - Final-output of developer interaction

Developer Stakeholders

Primary Residential zone

	Special zone - 6				Special zone - 9				Special zone - 13				Special zone - 15			
	Plot Coverage	Number of Floors	Model close to the answer	Accepted model	Plot Coverage	Number of Floors	Model close to the answer	Accepted model	Plot Coverage	Number of Floors	Model close to the answer	Accepted model	Plot Coverage	Number of Floors	Model close to the answer	Accepted model
Developer 1	0.65	4	none	1,2	0.65	4	none	1,2	0.39	24	2	1,2	0.65	7	1,2	1,2
Developer 2	0.64	5	1,2	1,2	0.64	5	1,2	1,2	0.4	23	1	1,2	0.65	7	1,2	1,2
Developer 3	0.64	5	1,2	1,2	0.64	5	1,2	1,2	0.39	24	2	1,2	0.65	7	1,2	1,2
Developer 4	0.64	5	1,2	1,2	0.64	5	1,2	1,2	0.39	24	2	1,2	0.65	7	1,2	1,2
Developer 5	0.64	5	1,2	1,2	0.64	5	1,2	1,2	0.4	23	1	1,2	0.65	7	1,2	1,2

High-density mixed development zone 1

	High density zone - 5				High density zone - 9				High density zone - 14				High density zone - 20			
	Plot Coverage	Number of Floors	Model close to the answer	Accepted model	Plot Coverage	Number of Floors	Model close to the answer	Accepted model	Plot Coverage	Number of Floors	Model close to the answer	Accepted model	Plot Coverage	Number of Floors	Model close to the answer	Accepted model
Developer 1	0.39	14	1	1,2	0.4	9	1	1	0.4	15	1	1	0.65	8	1	1,2
Developer 2	0.19	24	2	1,2	0.4	9	1	1	0.19	24	1,2	1,2	0.19	24	2	1,2
Developer 3	0.39	14	1	1,2	0.19	24	2	1,2	0.4	15	1	1,2	0.65	8	1	1,2
Developer 4	0.39	14	1	1,2	0.4	9	1	1	0.4	15	1	1,2	0.19	24	2	1,2
Developer 5	0.19	24	2	1,2	0.37	16	none	1,2	0.19	24	1,2	1,2	0.65	8	1	1,2

Dehiwala Selected area

	Dehiwala - 5				Dehiwala - 10				Dehiwala - 18				Dehiwala - 20			
	Plot Coverage	Number of Floors	Model close to the answer	Accepted model	Plot Coverage	Number of Floors	Model close to the answer	Accepted model	Plot Coverage	Number of Floors	Model close to the answer	Accepted model	Plot Coverage	Number of Floors	Model close to the answer	Accepted model
Developer 1	0.18	20	1,2	1,2	0.43	9	1,2	1,2	0.2	20	1	1	0.5	9	1,2	1,2
Developer 2	0.185	20	1,2	1,2	0.44	8	1,2	1,2	0.2	20	1	1,2	0.5	9	1,2	1,2
Developer 3	0.24	15	none	1,2	0.4	9	1,2	1,2	0.18	22	2	2	0.52	9	1,2	1,2
Developer 4	0.18	20	1,2	1,2	0.43	9	1,2	1,2	0.2	20	1	1	0.5	9	1,2	1,2
Developer 5	0.23	16	none	1,2	0.43	9	1,2	1,2	0.2	20	1	1,2	0.5	9	1,2	1,2

1 – Simultaneous model
2 – sequential model

Figure 7: Developer stakeholder validation Source: Prepared by author

The stakeholder interaction revealed that most developers preferred the simultaneous model after grasping its strategy *(charts - 1).* Initially, developers aimed to maximize developable area, but some opted for a maximum floor strategy to reduce horizontal density in complex scenarios. Despite the developers' final rational decisions amid stakeholder conflicts, initial choices sometimes led to irrational outcomes. Overall, engaging with the model facilitated more rational decisions and minimized conflicts.

5. Conclusion and recommendation

This research presents a game-theoretic model that leverages machine learning and handles imperfect information to facilitate interactive decision-making. The model identifies the optimal sequence of action based on a predefined strategy, effectively replicating stakeholder prospects in real-life residential density scenarios. Although both sequential and simultaneous game theory models can be employed according to the chosen strategy, the simultaneous model is particularly effective for determining the ideal residential density. Developers can apply this model individually to determine the maximum achievable density both horizontally and vertically, as well as the optimal developable area. Additionally, town planners, acting as government agents, can utilize this model to understand residential density patterns within selected zones based on existing regulations, which can be refined through observations derived from the model. For a detailed understanding of land and structural layouts, the use of accurate data, such as floor plans and survey plans, is recommended. The study's limitations include its reliance on an inaccurate financial model, its approach to market fields, and its integration of land character data. Nevertheless, the developed framework can be adapted for residential development planning and other land uses, accommodating market segments, the time value of money, and a robust financial framework. Overall, the field of urban planning can benefit from creating interactive decision-making models to facilitate more rational decisions among stakeholders.

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