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Research Article

A Spatial Optimization Model of Social Housing

Sosyal Konut için Mekânsal Optimizasyon Modeli

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Abstract

This study explains the price interactions in the housing market using a spatial framework. Introduced spatial model connects the average Euclidean distance between social and luxury houses to house pricing. When a cheaper alternative exists, even if it's not perfect, there will be pressure on the prices of expensive goods or services. In addition to this, the cost, and hence the price of houses, depends on the price of lots. Lots closer to highly priced house clusters tend to be more expensive. Concerning social justice, the social planner aims to produce as many social houses as possible. Also, in line with macroeconomic stability aim, government tries to keep the house price index low. These goals, however, presents a dual optimization problem. The planner must allocate the social houses far away from luxury houses to maximize their number. On the other hand, in order to keep the housing price index low, social houses must be built near to luxury houses in order to create a serious price pressure. The model introduced in this paper provides a method for balancing social fairness with economic viability. Introducing models with dynamic factors such as population growth and migration could be considered for further research. Also, testing the models in different urban areas could be a good option. By connecting spatial planning with economic and social goals, this study adds an analytical aspect to sustainable urban design and fair housing policy.

Keywords: *Spatial optimization, Euclidian distance, house pricing, social housing*

Jel Codes: *R31, R38, H41, J18, C21, C61*

Öz

Bu çalışmada, konut piyasasındaki fiyat etkileşimlerinin mekânsal bir çerçeve içinde açıklanması amaçlanmaktadır. Sunulan mekânsal model, sosyal konutlar ile lüks konutlar arasındaki ortalama Öklidyen mesafeyi konut fiyatlarıyla ilişkilendirmektedir. Mükemmel olmasa da, görece daha ucuz bir alternatif mevcut olduğunda, pahalı mal veya hizmetler üzerinde fiyat baskısı oluşur. Ayrıca konutların maliyeti ve dolayısıyla fiyatı, arsa fiyatına bağlıdır. Lüks konut kümelerine yakın arsalar genellikle daha pahalıdır. Bu nedenle, amacı hem mümkün olduğunca fazla sayıda sosyal konut üretmek hem de konut fiyat endeksini düşük tutmak olan bir sosyal planlayıcı, ikili bir optimizasyon problemiyle karşı karşıyadır. Başka bir deyişle, planlayıcı sosyal konutları öyle bir şekilde yerleştirmelidir ki, sosyal konut sayısı maksimuma ulaşırken konut fiyat endeksi mümkün olan en düşük seviyede tutulabilsin. Bu model, sosyal adalet ile ekonomik sürdürülebilirlik arasında denge kurmaya yönelik sistematik bir yaklaşım sunmaktadır. Gelecek araştırmalar, nüfus artışı ve göç gibi dinamik faktörlerin modele dâhil edilmesini ve modelin farklı kentsel bağlamlarda uygulanarak uyarlanabilirliğinin test edilmesini içermelidir. Mekânsal planlamayı ekonomik ve sosyal hedeflerle uyumlu hâle getirerek, bu araştırma sürdürülebilir kentsel kalkınma ve adil konut politikası için veriye dayalı bir bakış açısı sunmaktadır.

Anahtar Kelimeler: *Mekânsal optimizasyon, Öklidyen mesafe, konut fiyatlandırması, sosyal konut*

Jel Kodları: *R31, R38, H41, J18, C21, C61*

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1. Introduction

The fundamental intention of housing production is to satisfy the basic human need of shelter. Yet, demand for housing and instability of its prices are driven by far more than the mere fact of need of accommodation. Prices of houses are affected by many determinants such as economic conditions, demographic change, cultural forces, technological advances and monetary and fiscal policies. Therefore, there is very strong correlation and interaction between housing market and financial system and therefore the overall economy. Housing cost, whether in rent payment or mortgage payment, takes significant share of household expenses. Therefore, housing cost directly or indirectly impacts total demand and therefore the rate of economic growth. Moreover, housing market contributes importantly towards keeping the financial health. These said crucial functions and contributions of housing markets, in a sense, provide bases for government intervention in the housing market. These tools for intervention are: rent control, regulation of housing loans, tax incentives, subsidies and, lastly, supply of low-cost housing.

The mutual and complicated interaction between urban planning and housing market brings us challenges related to social equality, fairness and urban growth. That is why this study is interested in the connection between spatial distribution of houses and price interactions. The idea relies on the sensitivity of price threat to spatial distance. When there is a cheaper alternative, such as social houses, the price of luxury houses will tend to decrease. This effect will be higher when the distance is getting less.

In addition, cost and hence price of both social and luxury houses depend on the lot cost and material costs, besides many other factors. So, when the distance to luxury houses gets smaller, although the price threat on luxury houses increases indirectly causing a smaller housing price index, the lot price and cost of social houses tend to increase, which in turn causes a less social house production. Thus, there is a trade-off between the goals of social planner. On one hand, the social planner wants to achieve a smaller housing price index, which favors less distance to luxury houses. On the other hand, social planner wants to produce as much social houses as possible which favors greater distances to luxury houses (due to favorable lot prices). Thus, there could exist an optimal spatial distribution of social houses providing both a maximum amount of social house production and a minimum level of housing price index.

Drawing from interdisciplinary insights, including hedonic price theories and macroeconomic influences, this paper contributes a nuanced perspective to the discourse on sustainable urban planning and housing affordability. This paper is organized as follows: The following section provide a brief review of literature on house pricing. In this section literature on mostly hedonic house pricing models is analyzed. The third section introduces a summary of selected research on spatial optimization. The spatial distribution optimization model of social housing is introduced in the fourth section. And the final section is conclusion.

2. Literature on House Pricing

The analytical framework of this paper is based on the relationship between housing prices and distance. The closer a property is to highly sought-after, expensive areas, the higher its price tends to be. Consequently, when social housing is built near desirable districts, its cost increases, reducing the overall quantity of social housing that can be provided within a fixed budget. Conversely, when social housing is located near luxury properties, it tends to lower the rental prices and, by extension, the prices of the luxury homes themselves. This creates downward pressure on the housing price index, which ultimately contributes to lower inflation. Therefore, a trade-off exists between the number of social housing units and the housing price index. This relationship transforms the housing issue into an optimization problem, given its non-linear nature. To sum up, house pricing and spatial optimization are the two trivets of the analytical framework of this paper. Therefore, firstly a brief summary of the literature on house pricing will be introduced in this section and it will be followed by the literature on spatial optimization.

A comprehensive review of the literature on housing market price formation highlights a diverse array of focal points. Certain studies emphasize the dynamics of housing prices, others delve into rental prices, while some approach housing as an investment asset, analyzing the interplay between rental prices and house prices. Empirical investigations into the rental price-to-house price ratio frequently draw parallels with the standard rate of return observed in financial investments. In studies that conceptualize housing purchases from an investment perspective, the analysis is often grounded in an investment rate framework (Duca, Muellbauer, & Murphy, May 2011).

A seminal study by Poterba et al. (1991) analyzing housing price dynamics across various U.S. regions from 1963 to 1989 identified several critical factors influencing housing prices. These included inflation rates, income tax rates, nominal interest rates, expectations of future housing price appreciation, housing depreciation rates, and land prices. Among these, land prices emerged as the primary determinant of intercity housing price disparities, while demographic variables exhibited no statistically significant impact.

Similarly, an investigation into housing price trends in selected Canadian cities from 1985 to 2005 revealed the absence of a unified housing market or consistent pricing trends across cities. Notably, while long-term interest rates showed minimal influence on housing prices, city-specific factors—particularly wage levels influenced by union negotiations—proved to be significant drivers (Allen, Amano, & Gregory, 2009).

A parallel observation arose from a study of housing prices in various Chinese cities, employing a general equilibrium model based on the movement of capital and labor. The findings highlighted that greater distances from metropolitan hubs—characterized by high productivity and wages—and elevated levels of air pollution exerted downward pressure on housing prices. Conversely, factors such as a higher number of doctors per capita, improved student-to-teacher ratios, favorable air temperatures, and proximity to ports positively influenced housing prices (Gong, de Haan, & Boelhouwer, 2016).

Interest rates, inflation, property taxes, and regulations on long-term housing loans, alongside broader monetary policy adjustments, exert significant influence on price formation within the housing market. A study employing the rent-to-house price ratio to analyze the U.S. housing market highlighted that housing loan regulations markedly affect demand and pricing, particularly among first-time buyers (Duca, Muellbauer, & Murphy, May 2011).

The relaxation of criteria for long-term housing loans and the extension of credit to high-risk borrowers can perpetuate housing price growth, fostering expectations of continued appreciation. This phenomenon was evident during the early 2000s U.S. real estate bubble, which ended in a sharp decline in property values as high-risk borrowers defaulted on repayments. Since the 1980s, the U.S. housing market has transitioned from a risk-averse to a risk-seeking orientation, leading to increased market fragility and culminating in the severe financial crisis of 2008 (Immergluck, 2011).

When housing prices rise significantly above average inflation rates, rational economic agents may deem these prices unsustainable, anticipating a market correction. Classical asset pricing models, which exclude the influence of investor sentiment, often fail to capture this dynamic. Behavioral finance models, on the other hand, focus on the essential function of investors' emotions in determination of prices, regardless of basic financial parameters (Ling, Ooi, & Le, 2015). Investor sentiment is often shaped by past price movements, with rising prices fostering confidence and falling prices leading to caution. These emotional reactions can push prices far beyond what economic fundamentals—like interest rates, inflation, GDP growth, unemployment rates, and resource utilization—would logically suggest. Although such price fluctuations may stray significantly from short-term expectations, they usually return to align with underlying economic realities over time. (Li & Bao, 2017).

In the housing market, demand originates from buyers, while supply encompasses construction companies and loan providers. When all three parties anticipate rising prices based on historical trends, this expectation often materializes, further driving prices upward. Loan providers, confident that mortgage values will remain below market prices, persist in taking risks. This dynamic creates autocorrelation in housing prices, whereby rising prices fuel expectations of further increases, and falling prices amplify expectations of continued declines (Ling, Ooi, & Le, 2015).

This sequential dependency in housing prices suggests that econometric models such as autoregressive (AR) and vector autoregressive (VAR) frameworks are particularly effective for analysis. For instance, an AR model study examining housing prices across 20 U.S. metropolitan cities from 1985 to 2004 found statistically significant results in all cities except Los Angeles (Nagaraja, Brown, & Zhao, 2011).

Given the housing market's sensitivity to macroeconomic variables, some studies have analyzed it within the context of the business cycle model. During periods of rising demand, asset prices, including housing, increase, and inflation enhances net wealth by reducing the real value of fixed nominal debts. Since borrowers typically have a higher marginal propensity to consume than lenders, this creates an expansionary effect on demand. Simultaneously, rising consumer price indices negatively correlate with product supply, creating a contractionary force that counterbalances demand-driven expansion (Iacoviello, 2005).

Another area of inquiry explores whether housing markets exhibit global coordination or correlated movements. International trade and financial flows are believed to drive interconnected housing price trends. For example, Case, Goetzmann, and Rouwenhorst (2000) found evidence of coordinated movements through an output link mechanism in their analysis of international commercial real estate dynamics from 1987 to 1997. Similarly, using an FVAR model, Terrones and Otrok (September, 2004) demonstrated synchronization between housing prices and global income across 14 developed countries from 1970 to 2004. De Bandt, Barhoumi, and Bruneau (2010), employing the FAVAR model, found that U.S. housing prices lead movements in other OECD countries. Furthermore, Beltratti and Morana (2010), utilizing an FVAR model across G7 nations, established that house prices, stock prices, and market movements are interconnected, with supply shocks playing a particularly critical role.

In the housing market, price formation is influenced by demand, land prices, housing supply, and construction costs. A study used a simultaneous equations model to show that house prices are affected by land prices and construction costs, as well as other demand factors. It analyzed housing price data from both rural and urban areas in Georgia, USA, from 1970 to 2012. This research looked at the relationship between land and house prices. It found some coordination but also a growing gap between the house price index and land price index after 1980 in both settings. The study also revealed lagged effects. It showed that increases in house prices explained 52% of later land price rises, while the reverse effect accounted for only 6% (Zhang & Hou, 2015). These results highlight that rising house prices have a much stronger impact on land prices than the other way around.

Hedonic housing demand models further explain what drives housing demand. They focus on factors like interest rates, inflation, taxes, income, and expected price increases, along with individual preferences and the physical features of properties. These models come from hedonic pricing theories developed in the 1930s. They describe housing prices based on various characteristics, such as property size, distance to amenities like shopping centers, public transit, places of worship, and schools, as well as neighborhood traits like residents' socioeconomic status, ethnic makeup, and the house's age, view, and materials (Sirmans, Macpherson, & Zietz, 2005).

A key aspect of hedonic models is how the significance of explanatory variables can change based on personal preferences. For example, older adults might prefer homes that are farther from schools to avoid noise, while families with children look for nearby educational facilities. Likewise, preferences for quiet neighborhoods versus central locations can differ among buyers, affecting the importance and direction of variables in the model.

Since housing purchases are often financed through long-term loans, some hedonic models adopt a dynamic life cycle framework. These models compare the lifetime utility of homeownership against renting, positing that rational individuals will choose the option offering greater lifetime benefits. Simulation models examining choices between investing in financial assets or purchasing a home with a long-term mortgage to hedge against retirement income loss analyze variables such as age, income, interest rates, family size, and the rent-to-mortgage payment ratio. They also assess how shocks to factors like interest rates, income, and house prices influence purchasing decisions. For instance, Bajari et al. (2013) used household survey data to calibrate a model and found that sudden declines in interest rates or house prices positively impacted the decision to buy, whereas drops in income or rental prices had the opposite effect.

Regional heterogeneity is another critical consideration in hedonic housing studies (Sirmans, Macpherson, & Zietz, 2005). For example, a study of 1,691 detached houses sold across Norwegian cities (1997–2002) demonstrated that variables like building age, room and bathroom count, garage presence, and distance to city centers or workplaces exerted different impacts on prices depending on the region (Osland, July 2010). Similarly, a geographically weighted regression analysis of 3,887 detached houses sold in Austria (1998–2009) revealed significant geographic variations, underscoring the importance of location-specific considerations for policymakers and financial institutions (Helbich, Brunauer, Vaz, & Nijkamp, 2014). In Turkey, an analysis of rural and urban housing rents using the 2004 Household Budget Survey found that coefficients for key variables like house type, size, room count, and access to utilities differed significantly between these areas (Selim, 2008).

Beyond physical characteristics, socioeconomic attributes of neighborhoods also influence housing prices. Factors such as the proportion of Black residents, education levels, unemployment rates, and poverty levels play a role. A study on housing prices in socioeconomically diverse neighborhoods found that property-specific attributes largely drove price variations, while in homogeneous neighborhoods, variations were attributed to measurement errors or omitted variables (Goodman, 1977). This suggests that in economically homogeneous areas, physical characteristics have a minimal impact on price differences, making it economically irrational to construct luxury homes in predominantly low-income neighborhoods.

The following section summarizes some of the research on spatial optimization, since it forms the second trivet of the basic framework introduced in this paper. As mentioned at the introduction of this section, the aim of this study is to provide an analytical framework for social planning via the connection between house pricing and distance.

3. Literature on Spatial Optimization

As shown below, the existing literature on spatial optimization generally focuses on broader urban planning issues. Therefore, this study is likely the first to apply spatial optimization to the dual problem faced by a social planner dealing with social housing problem. On the one hand, the social planner aims to maximize the production of social housing. On the other hand, the planner must work to reduce the housing price index as part of the effort to combat inflation.

In spatial optimization, distance can function as a constraint or variable when facility locations are unknown, as in the Weber problem with Euclidean metrics. It may also serve as a predefined model parameter. Regardless of its role—constraint, function, or parameter—distance is integral to model design and structure. Geographic studies frequently employ proximity measures to optimize service facility locations (Goodchild & Massam, 1969; ReVelle & Swain., 1970; Hillsman, 1984; Densham & Rushton, 1988; Church, 1990). Sensitivity analyses using different distance metrics, such as those by Peeters and Thomas (2000), further illustrate the significance of this concept in spatial optimization.

The concept of proximity, whether defined by physical distance or travel time, is a common focus in geographic studies. Nystuen (1968) emphasized that distance is a core spatial principle. Depending on the situation, one might examine the average distance individuals travel in a region, the farthest distance someone must go to access a service, the shortest route between two locations, or the quickest connection among multiple points. Distance essentially represents the separation between two geographic points and can be quantified differently depending on the study's purpose. Various methods, including Euclidean, rectilinear and network distances, have been employed in two-dimensional spatial optimization applications (Church & Murray, 2009). Since the Earth is three-dimensional, its curvature must be accounted for, leading to metrics like geodesic or great-circle distances, based on the Earth's assumed shape. Reviews of these measures are available in Church and Murray (2009), Miller and Wentz (2003), and de Smith et al. (2011). Tools like GIS software facilitate the calculation and application of these measures.

Lark (2016) investigates the optimization of spatial sampling using multi-objective optimization algorithms, such as simulated annealing and Pareto fronts. The study concentrates on balancing conflicting objectives such as sampling efficiency and cost, demonstrated through a case study of regional soil sampling. The research also seeks applications in wireless sensor networks and unmanned aerial vehicles, presenting insights into logistical and statistical trade-offs. The study highlights the heterogeneity of these methods for various domains and makes suggestions for future research.

Wang et al. (2018) provide an overview of the allocation of heterogeneous spatial crowdsourcing tasks based on multi-objective optimization techniques like enhanced particle swarm optimization. The study tries to maximize task coverage and reduce incentive spending given worker mobility and deadline for tasks. The study introduces methods to determine Pareto-optimal solutions, and such solutions are evaluated using real and synthetic data and hence enhance efficiency and stability in spatial crowdsourcing systems

Chen et al. (2023) form a multi-objective spatial model for optimizing fire station locations using the combination of traffic dynamics and real demand areas. A case study of Nanjing, China, validates the model's effectiveness in reducing response times, eliminating duplications of resources, and optimizing urban safety. Combining urban functional areas with traffic data enhances the shortcomings of existing models and has real-world implications for fire service policies.

Li et al. (2024) explore regional spatial structures using a simulation optimization framework to promote balanced development. The study models regional dynamics via spatial networks, focusing on resource flow and equilibrium matching. It introduces a quantitative framework integrating network modeling and optimization strategies, applied to the Guangdong-Hong Kong-Macao Greater Bay Area. The key outcomes are to determine spatial imbalances, to define stages of optimization, and to achieve improved equilibrium and resource utilization. The authors emphasize incorporating policy networks to enhance macro-governance and spatial planning. Li et al. (2024) introduces data-informed regional policymaking, ensuring balanced development and disparities.

Wang and Mu (2024) propose a spatial optimization method to demarcating metropolitan areas, overcoming the challenges of polycentric urban systems and geographical coherence. The method optimizes industry and everyday life intercounty relations, guarantees geographical contiguity, and prevents boundary anomalies. The research proves, with the case of Nanjing and Lhasa metropolitan areas, how the method can be employed to demarcate rational metropolitan boundaries. This research stresses the importance of taking into account different intercounty interactions, and it demands stronger urban planning and development policies.

Xu et al. (2019) investigate the spatial optimization of Chinese rural settlements based on quality-of-life (QoL) theory. According to the research, there is an implied "road-oriented" model of spatial organization that optimizes spatial functions, structures, and scales. It weighs balancing settlement size and distances to achieve maximum economic and social benefits and address ecological challenges. The approach integrates rural development with QoL improvement, lending insights into sustainable rural planning and integration.

4. A Spatial Distribution Model of Social Housing for Effective Price Control

The idea behind the model for social housing is the link between price and distance. When there is a cheaper option for any good or service nearby, suppliers must lower their prices. This principle applies to the housing market as well. If there is a social housing option close by those costs less, the rental or selling price of more expensive houses should decrease somewhat due to the competition. Consequently, having more affordable social housing choices puts downward pressure on rental prices throughout the entire property market.

Consider a region containing "*m*" luxury properties, represented as points in a Euclidean space. A social planner seeks to construct "*n*" social housing units to minimize the overall housing price index, effectively maximizing the price-reducing impact of social housing while accounting for the spatial distribution of existing properties and adhering to budgetary constraints. The extent to which social housing exerts price pressure is determined by its average Euclidean distance from other properties: the closer the social housing is situated to existing properties, the stronger its price-pressure effect. For simplicity, assume the housing market comprises only two categories: luxury properties and social housing.

Thus; the basic assumptions of the model can be summarized as:

-There are only two types of houses: luxury and social, denoted with "L" and "S" respectively.

-The number of the luxury houses, “m”, is given and social planner has no control over it, and hence the planner takes this as a parameter.

-The budget of the social planner, “B” is fixed and it is the monetary constraint of the optimization problem.

-The cost of each and every social house depends on its plot cost and building costs.

-Plot (land) costs depend on the Euclidian distance to luxury houses: lower the distance to luxury houses, higher the plot cost

-Building costs are independent of Euclidian distance and are uniform among social houses

-The number of the social houses, “n”, depends on the average cost of social houses

-Social planner has two aims: increasing the provision of social housing (maximizing “n”) and minimizing the house pricing index which are non-linearly connected.

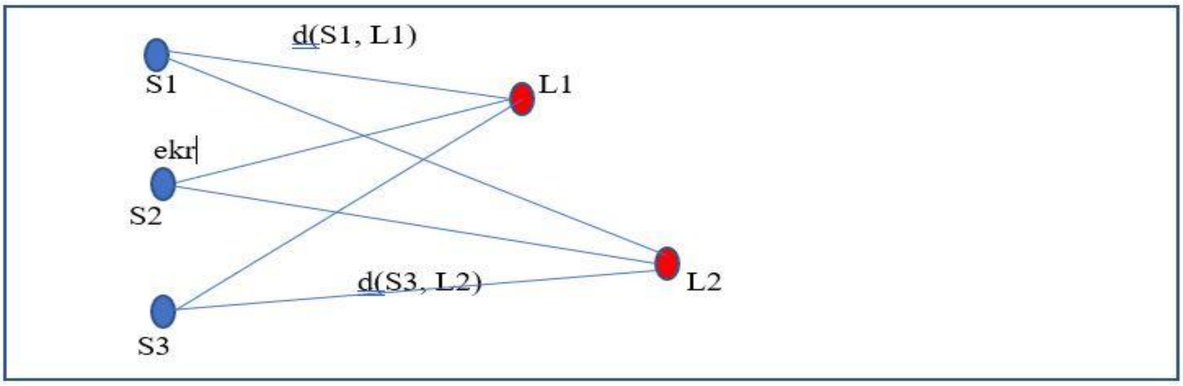
For simplicity, consider a scenario with three social houses and two luxury houses, as depicted in Figure 1. It is noteworthy to state that when there are n social houses and m luxury houses, we can define n x m Euclidian distances. For instance, in the simple case defined in Figure 1 there are 2x3=6 Euclidian distances. The Euclidean distance between a social house and a luxury house is defined as the shortest straight-line path connecting them. For example, the Euclidean distance between social house 1 (S1) and luxury house 1 (L1), represented as d(S1,L1) in the figure is defined as:

$$\mathrm{d}(\mathrm{S1}, \mathrm{L1}) = \sqrt{(x_{S1} - x_{L1})^2 + (y_{S1} - y_{L1})^2} \tag{1}$$

where “x_{S1}” and “x_{L1}” represent the x-coordinates of social house 1 and luxury house1 respectively, and y’s represent same for y-coordinates of them.

To evaluate the impact of social housing on luxury house prices, the Euclidean distances between each social house and every luxury house are calculated to determine the average distance. A smaller average distance correlates with greater downward price pressure on luxury properties. In the simplified case shown in Figure 1, the price pressure on L1 is greater than that on L2 because the average distance between L1 and the social houses is shorter than the corresponding average distance for L2. Consequently, all else being equal, the price of L1 would be expected to be lower than that of L2.

Figure 1: Illustration of Euclidian Distance between social and luxury houses



Thus, if d(Si, Lj) denotes the distance between social house “i” and luxury house “j” the price of luxury house “j”, PL_j, will be defined as:

$$PL_j = \vartheta_L X_j + \beta \left(\frac{1}{n} \sum_{i=1}^{n} d(Si, Lj) \right) \tag{2}$$

where ϑ_L denotes the coefficient vector of all other variables determining the price of luxury house j and X_j denotes all other variables vector. β>0 since the price of luxury house will increase as the average distance of it from social houses increases by our assumption on price pressure and distance relationship.

The cost, and consequently the price, of each social house is primarily determined by the expenses associated with land and building materials. For simplicity, we assume that building material costs are uniform across all social houses, while land costs vary based on location. Generally, plots situated closer to luxury houses tend to command higher prices. As a result, the price of a social house increases as its average proximity to luxury houses decreases, and conversely, it decreases as the average distance increases. Accordingly, the price of social house "i", denoted as "PS_i", is defined as:

$$PS_i = \vartheta_S X_i + \alpha\left(\frac{1}{m}\sum_{j=1}^{m} d(Si, Lj)\right) \tag{3}$$

where ϑ_S denotes the coefficient vector of all other variables determining the price of social house "i" and X_i denotes all other variables vector. $\alpha<0$ since the price of social house will decrease as the average distance of it from luxury houses increases by our assumption about lot price. Therefore, reducing the average Euclidean distance to luxury properties results in both higher social housing costs and greater price pressure effects.

We posit that the social planner operates with two primary objectives. First, the planner seeks to maximize the provision of social housing to address societal needs. Constrained by a fixed budget, the planner endeavors to produce the greatest possible number of social housing units. As the average distance between social and luxury housing increases, the reduced cost of land plots enables the production of a larger quantity of social housing units.

Second, the social planner aims to minimize the housing price index. A decrease in the average distance between social and luxury housing exerts upward pressure on luxury housing prices, thereby reducing the overall housing price index. However, this comes at the expense of a reduced output of social housing units. Conversely, increasing the distance between social and luxury housing mitigates price pressure on luxury homes, leading to a higher housing price index. This trade-off allows the planner to allocate resources toward greater social housing production.

This mechanism can be formally modeled by correlating the average Euclidean distance with both the social planner's budgetary constraints and the housing price index.

Let's first show how the social planner's budget is related to average Euclidean distance between social and luxury houses. Assume that social planner has a fixed budget(B) for production of social houses defined as:

$$B = \sum_{i=1}^{n} PS_i = \sum_{i=1}^{n}\left\{\vartheta_S X_i + \alpha\left(\frac{1}{m}\sum_{j=1}^{m} d(Si, Lj)\right)\right\} = \sum_{i=1}^{n}\vartheta_S X_i + \frac{\alpha}{m}\sum_{i=1}^{n}\sum_{j=1}^{m} d(Si, Lj) \tag{4}$$

The second part of right-side expression ($\sum_{i=1}^{n}\sum_{j=1}^{m} d(Si, Lj)$) is in fact the sum of all Euclidian distances of all social houses to all social houses. Since there are "m x n" distances between m luxury and n social houses, we can write:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} d(Si, Lj) = mn\bar{d} \tag{5}$$

where $\bar{d}$ stands for the average distance of all social houses to all luxury houses.

Therefore, we can rewrite the budget equation as:

$$B = \left(\sum_{i=1}^{n}\vartheta_S X_i\right) + \frac{\alpha}{m} mn\bar{d} = \left(\sum_{i=1}^{n}\vartheta_S X_i\right) + \alpha n\bar{d} \tag{6}$$

Now we can write the number of social houses that could be built as:

$$n = \frac{1}{\alpha\bar{d}}\left\{B - \left(\sum_{i=1}^{n} \vartheta_S X_i\right)\right\} \tag{7}$$

Thus, higher the fixed budget B, higher the average distance $\bar{d}$ and/or lower the lot cost excluding costs ($\sum_{i=1}^{n} \vartheta_S X_i$), higher the n. Therefore, the social planner must choose the locations and hence spatial distribution of social houses so that the average distance $\bar{d}$ allows maximum possible quantity of social houses, *n*. Namely, in a sense, $\bar{d}$ is the indirect decision variable and *n* is the target value, which means Equation (7) is one of the object functions.

Now we can show how the average Euclidian distance affects the price index. We can define the housing price index as a weighted average of luxury house prices and social house prices. Therefore, housing price index, HPI is defined as:

$$HPI = \frac{1}{(m+n)}\left(\sum_{i=1}^{n} PS_i + \sum_{j=1}^{m} PL_j\right) \tag{8}$$

By substituting Equation (2) and Equation (3) we can rewrite the HPI as following:

$$HPI = \frac{1}{(m+n)}\left\{\sum_{i=1}^{n}\left\{\vartheta_S X_i + \alpha\left(\frac{1}{m}\sum_{j=1}^{m} d(Si, Lj)\right)\right\} + \sum_{j=1}^{m}\left\{\vartheta_L X_j + \beta\left(\frac{1}{n}\sum_{i=1}^{n} d(Si, Lj)\right)\right\}\right\} \tag{9}$$

Adding the definition we obtained in equation (5) we can rewrite the housing price index as:

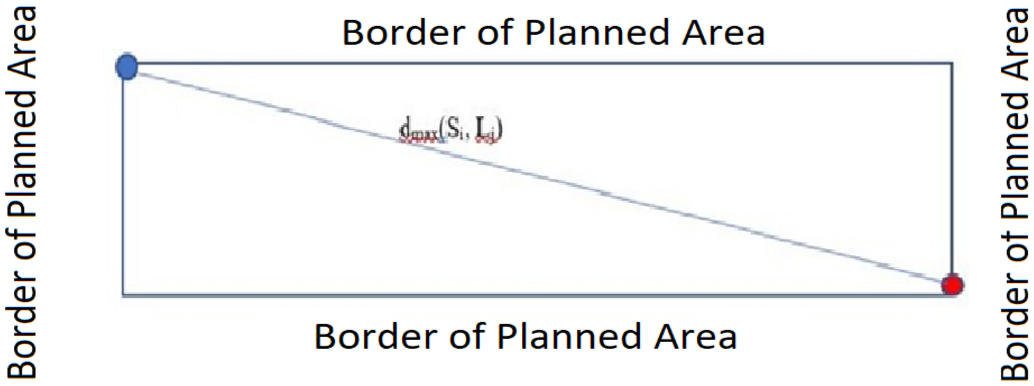
$$HPI = \frac{1}{(m+n)}\left\{\sum_{i=1}^{n} \vartheta_S X_i + \sum_{j=1}^{m} \vartheta_L X_j\right\} + \frac{\alpha}{(m+n)}\, n\bar{d} + \frac{\beta}{(m+n)}\, m\bar{d} \tag{10}$$

Now our optimization problem is complete. In one hand, in Equation (7), we show that the average distance between all social and luxury houses, $\bar{d}$, is one of the paramaters in determination of the number of the social houses, "n". On the other hand, we have shown in Equation (10) that average distance also affects the housing price index. By the help of first order conditions, we can find the optimum level of average distance which provides the maximum quantity of social houses and optimum level of average distance which provides the minimum possible housing price index. Partial differential of Equation 7 is:

$$\frac{\partial n}{\partial \bar{d}} = \frac{-1}{\alpha\bar{d}^2}\left\{B - \left(\sum_{i=1}^{n} \vartheta_S X_i\right)\right\} \tag{11}$$

This partial derivative is equal to zero if either $\bar{d}$ is infinite or $B = (\sum_{i=1}^{n} \vartheta_S X_i)$. However, by definition of budget in Equation 6, we know that the latter is impossible. Thus, this fact brings us to the fact that this is a constrained optimization problem, since the maximum of distance will be equal to the maximum possible Euclidian distance available in the region as illustrated in Figure 2. If the region is modelled as a rectangle, then the maximum possible distance between any social house and any luxury house will be equal to the diagonal of the rectangle.

Figure 2: Maximum distance between any social house and luxury house



Thus, the optimization problem for social house production will be:

Maximize
$n = \frac{1}{\alpha\bar{d}}\{B - (\sum_{i=1}^{n} \vartheta_S X_i)\}$ subject to $\bar{d} \leq d_{max}(S_i, L_j)$

We can also formulate the optimization problem for housing price index as:

Minimize

$$HPI = \frac{1}{(m+n)}\left\{\sum_{i=1}^{n} \vartheta_S X_i + \sum_{j=1}^{m} \vartheta_L X_j\right\} + \frac{\alpha}{(m+n)}\, n\bar{d} + \frac{\beta}{(m+n)}\, m\bar{d}$$

subject to $\boldsymbol{\bar{d} \leq d_{max}(S_i, L_j)}$ and $\boldsymbol{n = \frac{1}{\alpha\bar{d}}\{B - (\sum_{i=1}^{n} \vartheta_S X_i)\}}$

Thus, the social planner has a dual optimization problem involving maximization of social housing production and minimizing the housing price index. As shown in Equation (10) HPI is not a linear function of the average distance between social houses and luxury houses, since the partial derivative can be either zero, negative or positive depending on the value of the average distance. Therefore, this optimization problem could be solved by several iteration methods and algorithms, once the model is calibrated.

5. Algorithms for Solving Nonlinear Spatial Optimization Problems

Depending on the nature of the problem and the characteristics of the decision variables, a number of algorithmic approaches may be adopted to solve nonlinear spatial optimization problems. Gradient-based algorithms, such as Sequential Quadratic Programming (SQP) and Interior-Point Methods, are suitable when the objective function is differentiable and the problem space is smooth. However, heuristic and metaheuristic methods, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), by their nature offer a flexible means of exploring the solution space when the problem is intricate, non-convex, or involves discrete variables. These methods are particularly effective at solving highly nonlinear, multimodal, high-dimensional problems, which abound in the realm of spatial optimization (Boyd & Vandenberghe, 2004).

In situations where the spatial relationships between variables are significant, spatially explicit optimization techniques such as Spatial Simulated Annealing (SSA) or Cellular Automata Optimization can be adopted. These techniques take into consideration spatial dependencies in terms of adjacency or contiguity, which is often very important when dealing with urban planning and land-use allocation problems. For models containing both continuous and discrete variables, the Mixed-Integer Nonlinear Programming (MINLP) solvers-Branch-and-Bound or Outer Approximation-can help analyze complex spatial configurations under a fixed budget or other constraints. For multi-objective optimization tasks, for example, balancing the production of social housing against minimizing the housing price index, NSGA-II or MOEA/D can be used to provide a set of Pareto-optimal solutions, giving a range of trade-offs between competing objectives (Bazaraa, Sherali, & Shetty, 2013).

Overall, the choice of an algorithm will depend upon the specific features of the spatial optimization problem. For highly complex and nonlinear problems, the use of evolutionary algorithms, spatially explicit optimization methods, and multi-objective optimization techniques is generally most appropriate (Hillier & Lieberman, 2014).

6. Conclusion and Recommendations

This research addresses the potential use of spatial optimization as a tool for the complicated challenges of housing market and urban development. The offered dual-objective framework in this study balances two critical priorities: efficient use of budget devoted to social housing provision and minimizing the house pricing index. Using Euclidian distance as a decision variable in explaining the relationship between two distinct types (luxury and social) of housing prices highlights the essential role of spatial distribution of buildings in determining price trends and market stability.

The spatial optimization model in this paper tells that building social houses fairly close to luxury houses results in more affordable prices in housing market for a significant range of people. On the other hand, this must be done considering a balance with the effect of proximity on increasing prices of lots that social houses would be built on. Namely, while trying to create a higher pressure on high-end housing prices, the social planner must face the higher costs of social housing provision. This fact in turn, requires an effective and rational resource allocation in order to provide balance between social fairness and economic stability.

Although the proposed spatial optimization model provides a good starting point, it is open to further extensions. For instance; population dynamics such as migration, population growth rate could be added as parameters to model. Also, instead of, or in addition to Euclidian distance, the travel time can be used as a decision variable. Further, distance to hospitals, schools and malls can be used in price formation equations for different type of houses. Last but not least, the type of houses could be extended to social-moderate-luxury in order to provide further and detailed price relationships and elasticities.

After extensions to model, once spatial data is available, the extended version of this model could be tested in order to determine whether the spatial distribution of social housing is optimal or not, by assigning a normalized index, for instance. With such indexing, comparison of cities or districts can be possible. Thus, the offered model can be a useful tool for urban planning and economy governance.

Spatial distribution lies at the heart of social justice, as the geographic configuration of resources, services, and opportunities determines who is included or excluded in a society. As social policy literature reminds us, unequal spatial distribution-whether of housing, transport networks, healthcare, or education-can entrench structural inequalities by rendering vital resources inaccessible to marginalized groups. When low-income or minority groups are concentrated in peripheral or poorly serviced areas, they suffer several disadvantages: longer travel times, less job availability, insufficient public services, and lower political visibility. These disadvantages in space and place are not an accident, but more often reflect historical processes of segregation, discriminatory zoning, and market-driven urban development-all of which produce varied landscapes of inequality that transcend generations.

On the other hand, more equitable spatial planning and distribution of public goods serve as a strong mechanism for reducing exclusion and promoting social justice. Policies that enhance accessibility-for example, integrated public transit, mixed-income housing strategies, decentralized social services, or investments in underserved neighborhoods-can counteract entrenched disparities. According to social policy scholars, spatial justice requires not only the redistribution of resources but also participatory processes that allow the perspectives of marginalized groups to shape decisions about their environments. By reshaping the built environment to ensure that all communities enjoy proximity to opportunity, safety, and civic participation, spatially aware social policies can foster greater social inclusion and contribute to more resilient and cohesive societies.

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Araştırma Makalesi

A Spatial Optimization Model of Social Housing

Sosyal Konut için Mekânsal Optimizasyon Modeli

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Genişletilmiş Özet

Giriş

Konut üretiminin temel amacı, bireylerin barınma gereksinimini karşılamaktır. Ancak konut piyasası yalnızca fiziksel bir ihtiyaç çerçevesinde şekillenmez; aynı zamanda ekonomik, sosyal, kültürel ve politik dinamiklerin kesiştiği bir alanı temsil eder. Konut fiyatları, ekonomik büyüme oranları, faiz politikaları, enflasyon, gelir dağılımı, demografik yapı ve teknolojik yenilikler gibi çok sayıda faktörden etkilenir. Dolayısıyla; konut piyasası, hem finansal sistem hem de genel ekonomik istikrar açısından belirleyici bir role sahiptir.

Konut harcamaları hane bütçelerinin önemli bir kısmını oluşturur ve toplam talep ile ekonomik büyüme oranını doğrudan etkiler. Bu nedenle devletlerin konut piyasasına müdahalesi, ekonomik rasyonalite kadar sosyal adalet ilkeleriyle de ilişkilidir. Devletin kullandığı başlıca araçlar arasında kira kontrolleri, konut kredisi düzenlemeleri, vergi indirimleri, sübvansiyonlar ve en önemlisi sosyal konut üretimi yer alır.

Bu çalışmanın çıkış noktası, sosyal konut politikalarının yalnızca miktar veya finansman açısından değil, mekânsal dağılım açısından da değerlendirilmesi gerektiği varsayımıdır. Sosyal konutların şehir içinde nerelere yerleştirileceği, hem arsa maliyetini hem de lüks konut fiyatlarını etkileyen önemli bir değişkendir. Çalışma, sosyal ve lüks konutlar arasındaki ortalama Öklidyen mesafeyi bir karar değişkeni olarak ele alarak, fiyat endeksi ile sosyal konut üretimi arasındaki dengeyi matematiksel biçimde analiz etmektedir.

Literatür Taraması

Konut Fiyatlarının Belirleyicileri

Konut fiyat oluşumu üzerine yapılan araştırmalar çok çeşitli yönleriyle bu karmaşık piyasayı açıklamaya çalışmıştır. Poterba, Weil ve Shiller (1991), ABD'de 1963–1989 döneminde konut fiyatlarının temel belirleyicileri arasında enflasyon, faiz, vergi politikaları ve özellikle arsa fiyatını öne çıkarmıştır. Benzer biçimde Allen, Amano ve Gregory (2009), Kanada şehirlerinde ücret düzeyleri ve yerel faktörlerin fiyatlar üzerinde belirleyici olduğunu göstermiştir.

Çin örneğinde ise Gong, de Haan ve Boelhouwer (2016), şehir merkezlerinden uzaklık, hava kirliliği ve sosyal hizmetlere erişim gibi değişkenlerin konut değerlerini doğrudan etkilediğini bulmuştur. Türkiye için Selim (2008), kırsal ve kentsel bölgelerde konut fiyatlarını etkileyen faktörlerin anlamlı biçimde farklılaştığını göstermiştir.

Faiz oranları, kredi koşulları ve para politikaları da fiyat oluşumunda belirleyicidir. Duca, Muellbauer ve Murphy (2011), kredi genişlemesinin konut fiyatlarını yukarı yönlü baskıladığını; 2008 krizinde olduğu gibi riskli kredi politikalarının balon etkisi yarattığını vurgulamıştır (Immergluck, 2011).

Buna ek olarak davranışsal finans literatürü, yatırımcı duygularının fiyat dinamiklerinde önemli rol oynadığını ortaya koyar (Ling, Ooi & Le, 2015). Fiyatlar, beklenti ve duyarlılığa bağlı olarak ekonomik temellerden sapabilir; bu da konut piyasasında otokorelasyon yaratır.

Mekânsal Optimizasyon Yaklaşımları

Mekânsal optimizasyon, coğrafi konumların veya tesislerin en uygun biçimde belirlenmesini amaçlayan bir matematiksel planlama alanıdır. Bu yaklaşımda mesafe, ulaşım süresi veya maliyet temel değişkenlerdir. Klasik Weber problemi, Öklidyen mesafeye dayalı tesis konumlandırma problemlerinin öncüsüdür (Goodchild & Massam, 1969; ReVelle & Swain, 1970).

Son yıllarda, çok amaçlı optimizasyon ve yapay zekâ algoritmaları mekânsal karar problemlerine entegre edilmiştir. Chen vd. (2023), trafik koşulları ve kent fonksiyonlarını dikkate alarak yangın istasyonu yerlerini optimize etmiş; Xu vd. (2019) ise kırsal yerleşimlerin yaşam kalitesini artıracak mekânsal düzen modelleri geliştirmiştir. Bu literatür, mekânsal verilerin sadece coğrafi değil, ekonomik ve sosyal çıktılar üzerinde de etkili olduğunu göstermektedir.

Yöntem ve Modelin Kurulumu

Bu çalışmada sosyal konutların mekânsal dağılımı ile konut fiyat endeksi arasındaki ilişki Öklidyen mesafe aracılığıyla açıklamaktadır. Temel varsayım şudur:

Bir bölgede lüks konutlara yakın sosyal konutlar bulunuyorsa, bu yakınlık lüks konutlar üzerinde fiyat baskısı oluşturur.

Model iki tür konutu dikkate alır: “lüks konutlar (L)” ve “sosyal konutlar (S)”. Her bir sosyal konut ile lüks konut arasındaki mesafe d(Si, Lj) ile ifade edilir. Bu mesafelerin ortalaması azaldıkça, lüks konut fiyatları düşer; ancak bu durum, sosyal konutların arsa maliyetini yükselterek üretim maliyetini artırır.

Bu nedenle sosyal planlayıcı iki hedef arasında denge arar:

Konut fiyat endeksini (HPI) mümkün olduğunca düşük tutmak,

Üretilebilecek sosyal konut sayısını (n) mümkün olduğunca artırmak.

Planlayıcının bütçesi, B, sabittir ve sosyal konut birim maliyeti PSi ortalama mesafeye bağlıdır. Ortalama mesafe arttıkça arsa maliyeti azalır, üretim artar; ancak fiyat baskısı azalır ve genel fiyat endeksi yükselir.

Konut fiyat endeksi (HPI), lüks ve sosyal konut fiyatlarının ağırlıklı ortalamasıyla tanımlanır. Her iki fiyat da ortalama mesafeyle ilişkilidir. Bu iki fonksiyon birlikte ele alındığında, sosyal planlayıcının çözmesi gereken çift amaçlı optimizasyon problemi ortaya çıkar:

$$HPI = \frac{1}{(m+n)}\left\{\sum_{i=1}^{n} \vartheta_S X_i + \sum_{j=1}^{m} \vartheta_L X_j\right\} + \frac{\alpha}{(m+n)}\, n\bar{d} + \frac{\beta}{(m+n)}\, m\bar{d}$$

$\bar{d} \le d_{max}(S_i, L_j)$ ve $n = \frac{1}{\alpha\bar{d}}\{B - (\sum_{i=1}^{n} \vartheta_S X_i)\}$ olmak üzere.

Bu optimizasyon problemi doğrusal değildir; çünkü ortalama mesafe parametresi her iki hedefi de zıt yönlerde etkiler. Dolayısıyla çözüm, sayısal iterasyon yöntemleri veya simülasyon teknikleri ile gerçekleştirilebilir.

Model aynı zamanda bölgesel sınırları da dikkate alır. Örneğin çalışma alanı dikdörtgen olarak kabul edilirse, sosyal ve lüks konutlar arasındaki en büyük mesafe bu dikdörtgenin köşegen uzunluğu ile sınırlıdır. Böylece optimizasyon, fiziksel mekânın geometrisiyle doğrudan bağlantılı hale gelir.

Bulgular ve Yorum

Model, sosyal konutların lüks konutlara yakın konumlandırılmasının konut fiyat endeksini düşürmede etkili olduğunu göstermektedir. Bu durumda piyasadaki lüks konutların fiyatları üzerinde "fiyat tehdidi" oluşur ve genel fiyat seviyesi daha dengeli hale gelir. Ancak bu strateji, arsa maliyetlerini artırdığı için aynı bütçeyle üretilebilecek sosyal konut sayısını azaltır.

Tersine, sosyal konutlar lüks konutlardan çok uzak yerleştirildiğinde arsa maliyetleri düşer, dolayısıyla üretim sayısı artar; ancak bu kez sosyal konutların piyasa üzerindeki fiyat baskısı zayıflar ve toplam konut fiyat endeksi yükselir.

Bu karşıt etkiler, "optimal mesafe" kavramını ortaya çıkarır. Optimal mesafe, hem lüks konut fiyatlarını makul düzeyde düşüren hem de sosyal konut üretimini ekonomik kılan mesafedir. Bu mesafenin belirlenmesi, şehir planlamasında sosyal adalet (düşük fiyatlar, erişilebilir konutlar) ile ekonomik sürdürülebilirlik (bütçe etkinliği) arasında bir denge noktası sağlar.

Modelin öngörülerine göre, sosyal konutların lüks konut bölgelerine tam entegre edilmesi değil, kontrollü bir yakınlıkta inşa edilmesi en verimli çözümdür. Bu yaklaşım, konut piyasasında fiyat istikrarını desteklerken sosyal dışlanmayı da azaltır.

Sonuç ve Öneriler

Bu çalışma, sosyal konut politikalarına mekânsal optimizasyon perspektifini kazandırmaktadır. Model, şehir planlamasında mekânsal faktörlerin ekonomik göstergelerle nasıl bütünleştirilebileceğini gösteren yenilikçi bir çerçeve sunar.

Başlıca sonuçlar şunlardır:

Sosyal konutların lüks konutlara yakın konumlandırılması genel konut fiyatlarını aşağı çeker.

Ancak bu strateji arsa maliyetini artırarak üretim miktarını kısıtlar.

Dolayısıyla sosyal planlayıcı, bu iki hedef arasında rasyonel bir denge kurmak zorundadır.

Model, sosyal adalet ile ekonomik verimlilik arasındaki bu ikili ilişkiyi sayısal biçimde somutlaştırmaktadır.

Modelin Genişletilmesi İçin Öneriler

Yazar, gelecekte modelin aşağıdaki yönlerde genişletilebileceğini öne sürmektedir:

Nüfus dinamikleri (göç, nüfus artışı) modele parametre olarak eklenebilir.

Öklidyen mesafe yerine veya yanında seyahat süresi değişkeni kullanılabilir.

Hastane, okul, ulaşım merkezleri gibi kentsel hizmetlere erişim değişkenleri modele dâhil edilebilir.

Konut türleri sosyal–orta–lüks şeklinde çeşitlendirilerek fiyat esneklikleri daha detaylı analiz edilebilir.

Model sonuçları mekânsal veriyle test edilip şehirler arası optimumluk endeksi geliştirilebilir.

Bu öneriler doğrultusunda, model gelecekte şehir planlamacıları ve kamu politikası yapıcıları için pratik bir araç hâline gelebilir. Özellikle büyük şehirlerdeki konut krizi, gelir adaletsizliği ve kentsel ayrışma sorunlarına karşı, bu model veri temelli karar mekanizmaları oluşturulmasına katkı sunabilir.

Sonuç olarak, çalışma sosyal konutların mekânsal dağılımının yalnızca fiziksel bir tasarım değil, aynı zamanda ekonomik bir optimizasyon problemi olduğunu göstermektedir. Mekânın matematiksel analiziyle sosyal adalet ilkelerinin bütünleştirilmesi, sürdürülebilir kentleşme için yeni bir yol haritası sunmaktadır.