

Optimal Computing Budget Allocation for Urban Regeneration: An Unprecedented Match Between Economic/Extra-Economic Evaluations and Urban Planning

Giovanna Acampa(✉) and Alessio Pino

University of Enna "Kore", Enna Cittadella Universitaria, 94100 Enna, Italy
giovanna.acampa@unikore.it, alessio.pino@unikorestudent.it

Abstract. The path to creating livable cities passes through the transformation of underexploited urban areas and the revivification of neglected bits of urban fabrics within the contemporary and relevant theme of urban regeneration. However, this process is characterized by an operational misalignment between the urban administrative scale and the small scale of single neighborhoods. Due to their limited budget, public administrations refrain from attempting to perform capillary punctual regeneration interventions, as it would require higher economic investments. For this reason, local-scale actions often arise as bottom-up initiatives. These are sometimes effective, but their target context is hardly chosen by considering all the available possibilities through a higher-scale analysis.

A solution to this issue can be obtained by selecting the most suitable actions to implement according to a criterion of effectiveness and impact: this offers the ground for original contamination of OCBA (Optimal Computing Budget Allocation) methods and tools by using them in the field of urban planning. These methodologies are most frequently used in business management to determine the best use of limited resources: transferring them to urban planning involves finding criteria and parameters to quantify the impact of urban actions and compare alternatives. This paper describes the early reflections and articulations of this research work through a literature review of OCBA methods and their parameters and a tentative outline of suitable criteria for urban planning.

Keywords: urban regeneration · Optimal Computing Budget Allocation · livability · economic evaluation · green areas

1 Introduction

Most people reside in cities, which are the hub of global technical and economic progress [1]. Despite being temporary, the recent pandemic crises highlighted the urban environment's severe susceptibility [2]. Because of their rapid urbanization, fast population increase, and extensive use of transportation resources, cities have been to blame for the greatest COVID-19 transmission rate [3]. This temporary event has pushed urban

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planners, designers, and the scientific community to perform a more careful examination of urban structures and their capability to fulfill health needs, both in emergency scenarios and in the daily improvement of their population's well-being, and especially concerning the importance of green areas [4, 5]. Indeed, it has revealed the need for a diffuse distribution of urban services, spaces for leisure, meeting, and a detailed design of interstitial areas as a response to a spontaneous human tendency [7].

In order to create new urban management models that are resilient to the current and upcoming pandemic occurrences, the scientific community has continuously worked to examine the social and environmental effects of COVID-19. Both consolidated and in-development cities should be predicated on resilient and smart planning and design [8].

Several urban models have been introduced – and had been introduced in previous years – to systematize the design of this transformation aimed at urban regeneration [9]. They are now gathered under the broad and popular concept of the "15-min city", a city where, in any neighborhood, essential human functions (living, working, commerce, healthcare, education, and entertainment) are available within 15 min by walking or riding a bicycle [10].

This concept has already been warmly welcomed in several European cities, among which Paris [11]; in Italy, as well, several towns have accepted the challenge to realize this model, among which Rome [12] and Milan [13]. This positive and encouraging reception is motivated by the multiple benefits in this perspective: on the one hand, the achievement of a softer-paced life [14]; on the other hand, higher environmental sustainability thanks to the decrease in transport-based emissions [15].

However, implementing urban regeneration according to this model is not an easy task. The size of the involved cities requires a significant budget for a capillary regeneration to achieve the 15-min city model, which is not entirely in the Municipalities' availability. A frequent solution is a partnership with private stakeholders for private/public cooperation; however, the benefit for private stakeholders lies in the economic benefit deriving from improving the areas' conditions, which increases their economic attractiveness. For this reason, these cooperations are more often carried out in areas with higher economic potential, possibly creating inequality between the various areas of the city: this contradicts the model's foundation. It has also been highlighted that the difficulty of simultaneously considering the whole urban fabric when establishing the intervention targets ends up overlooking various social groups' needs [16]. Some attempts have been made in this direction, especially with the Italian experimentations in Parma and Milan, where intervention planning has been preceded by a consistent mapping of the urban and social fabric [17]; however, this has been fully implemented only in the latter and mainly consisted of the realization of residential neighborhoods outside the central areas.

This paper proposes an alternative solution for intervening in urban areas to perform urban regeneration along the "15-min city" model principles through Optimal Computing Budget Allocation (OCBA) methods. These methods originate in computer science and are employed for optimization purposes to establish the best use of given resources among some available alternatives. In addition, they are commonly utilized in finance and business management as a tool for selecting items of economic expenditure.

The scenario of large-scale urban regeneration outlined above may be assumed as a set of investment alternatives with different outcomes and effectiveness. Hence, OCBA methodologies, if correctly fine-tuned to fit this context, could be a valid support to.

The following section presents an outline of OCBA methodologies, briefly illustrating their framework, typologies of application, and alternative possibilities following a literature review. Then, the third section proposes an example of OCBA structure for applying the methods to urban regeneration cases, with an indication of the parameters to consider and their assessment modalities.

2 Materials and Methods

2.1 Literature Review

This section analyzes the investigation of OCBA in the scientific literature since its introduction in 1997. It focuses on the evolution of the popularity of these methods in scientific research and on the main items of interest within this theme.

The literature review was conducted through the Scopus platform, and the results related to the time distribution of the scientific articles are reported in Fig. 1.

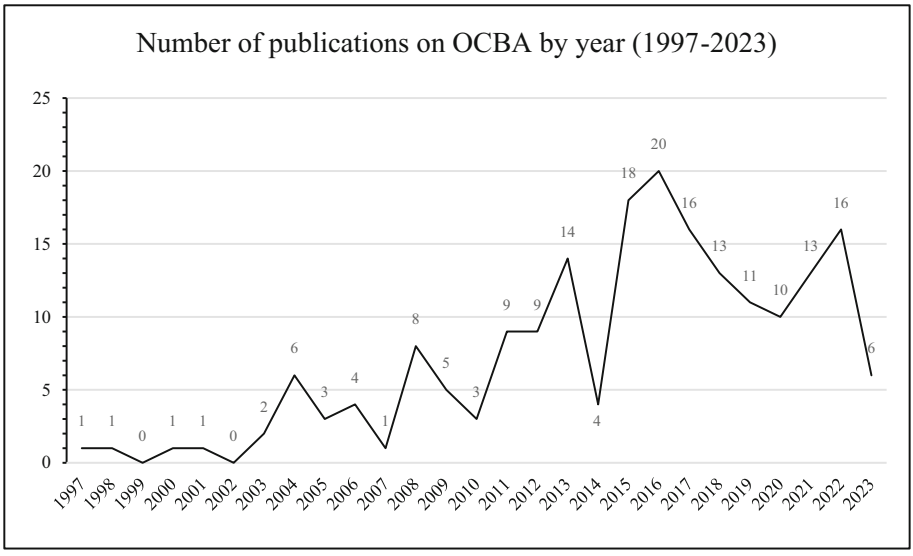

Fig. 1. Diagram reporting the number of scientific publications on OCBA methods found in the scientific literature from 1997 to 2023 (2023 data until April have been considered).

The review was only conducted using the Scopus platform, so it must be pointed out that it is not comprehensive of all the articles published on this theme; however, it allows inferring some trends concerning this topic. The diagram reports that these methods have received increasing interest from the scientific community in the last few years, with a

peak in 2016. The total number of individuated articles is 195; 141 out of 195 have been published in the last 10 years (from 2013 to 2023), resulting in over 70% of the total.

One reason for this drastic increase is the expansion of the range of fields these methods encompass. While the pioneering articles by H.C. Chen focused on the field of manufacturing, hence proposing applications for industrial purposes [18], more recent articles expand the scope to broader aspects, such as infrastructural themes, with a proposal for a time-of-day pricing system for toll roads [19], and healthcare, with a study on the management of hospital inpatient beds by using OCBA techniques [20] and one on the resolution of health examination scheduling problems [21]. These and other applications also show their adaptability for public uses, where several parameters are involved, besides their native private-sector applications. Some examples are represented by experimentation with OCBA methods for joint car-sharing relocation based on modular simulations [22] and a stochastic simulation optimization for route selection according to flight delay [23].

2.2 Outline of Optimal Computing Budget Allocation Techniques

Single-Parameter OCBA. The Optimal Computing Budget Allocation (OCBA) was introduced by H.C. Chen [18, 24] as a technique for the maximization of an approximation of the probability of correct selection P{CS}, where correct selection (CS) indicates choosing the alternative with minimum mean, leading to an efficient allocation algorithm that includes both means and variances. Extensions of the OCBA approach include correlated sampling [25]; non-normal distributions [26, 27]; multiple objective functions [28]; using expected opportunity cost instead of the probability of correct selection [29]; minimizing variance instead of maximizing the probability of correct selection [30]; selecting an optimal subset of top-m solutions rather than the single best solution (Chen et al. 2008).

OCBA methods are simulation techniques that evaluate the performance of multiple alternatives to achieve a given objective to minimize or maximize. The preliminary phase of OCBA utilization is to set the problem: establishing an objective and its sub-objectives and then defining the objective function. Drawing an example from the scientific literature [31], considering the objective of minimizing the makespan of a vehicle in a car factory, the following terms can be adopted:

- *Pij* is the processing time for the j-th operation of the i-th job;
- *Tij* is the travel time for the j-th operation of the i-th job;
- *Oij* is the operation completion time for the j-th operation of the i-th job.

The following relation results:

$$O_{ij} = T_{ij} + P_{ij} \tag{1}$$

Then, the summation of the completion time of the *j* operations for each i-th job can be considered:

$$C_i = \sum_{j=i}^{n} O_{ij} \tag{2}$$

The objective function is hence defined as:

$$Min\, makespan = E[Max(C_1, C_2, C_3, \ldots, C_n), \omega] \tag{3}$$

where ω represents randomness in this system.

Another aspect to consider in OCBA is noise; when it is too high, re-evaluation is needed to obtain a more precise function value. Its assessment is performed by assessing the means and variances of action performances. In the algorithmic structure of most OCBA methodologies, this is achieved through the allocation of an equal quantity of initial samples B_0 to each action. The following step is the allocation of an additional budget B_Δ that is sequentially based on the means and variances. Both are updated once after the reception of a response. The final step is the asymptotical maximization of the approximate probability of correct selection when the budget is used up according to the following equations:

$$\frac{N_i(t)}{N_j(t)} = \left(\frac{\frac{\sigma_i(t)}{(\delta_{i,m}(t))}}{\frac{\sigma_j(t)}{(\delta_{j,m}(t))}} \right)^2, \forall i, j \in IN_r \; and \; i \neq j \neq m \tag{4}$$

$$N_m(t) = \sigma_m(t) \sqrt{\sum_{i=1, i \neq m}^{r} \frac{N_i^2(t)}{(\sigma_i(t))^2}} \tag{5}$$

where $N_i(t)$ refers to the total number of evaluations arranged to action i at allocation time t, $d_i(t)$ and $\sigma_i(t)$ store its sample mean and variance, respectively, and m stands for the best action with the lowest mean, $\delta_{i,m}(t) = d_i(t) - d_m(t)$.

Multiparametric Optimization. The traditional formulation of OCBA is based on the individuation of a single objective to optimize, which stands as the reference parameter of the objective function [32]. However, this does not often comply with decision-making situations: the presence of heterogeneous items involved in the effects of the alternatives can hardly be entirely neglected [33]. For this reason, OCBA can be integrated with multiparametric optimization techniques [34] to consider various needs and effects of the choices.

The formulation of a multi-parametric optimization problem must include the multi-objective function (minimization or maximization), constraints for each involved parameter, and coefficients to determine the weight of the characteristics in the overall evaluation. The following are some multi-parametric optimization methods that can be integrated into OCBA's formulation:

- Branch and Bound [35];
- Tabu Search [36];
- Multi-Parametric Programming [37];
- Benders decomposition [38];
- Penalty Function [39];
- Chvatal-Gomory cuts (cutting plane) [40];
- Evolutionary Algorithm [41];

- Multi-Parametric Quadratic Programming [42].

The latter will be used for the exemplification of an optimization problem, structured as follows [43]:

$$\begin{aligned} x(t+1) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) \end{aligned} \tag{6}$$

where *x(t)* is the state variable, *u(t)* is the input, and *(A,B)* is a controllable pair. For the current *x(t)*, the optimization problem can be solved by applying the Karush-Kuhn-Tucker (KKT) conditions, resulting in:

$$V_z(x(t)) = min_z \frac{1}{2} z^T Hz \tag{7}$$

$$s.t.\ Gz \leq W + Sx(t) \tag{8}$$

where $z = U + H^{-1}F^T x(t)$, $U = \left[u_t^T, \ldots, u_{t+M-1}^T\right]$ and *x(t)* is the current state, which can be treated as a vector of parameters.

Finally, the constraints are expressed as follows:

$$\begin{gathered} y_{min} \leq y_{t+k|t} \leq y_{max}, k = 1, \ldots, N \\ u_{min} \leq u_{t+k} \leq u_{max}, k = 0, \ldots, M-1 \\ u_{t+k} = Kx_{t+k|t}, M \leq k \leq N-1 \\ x_{t|t} = x(t) \\ x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k}, k \geq 0 \\ y_{t+k|t} = Cx_{t+k|t}, k \geq 0 \end{gathered} \tag{9}$$

3 Elaborations on the Application for Urban Regeneration

As described above, OCBA single-parameter and multi-parameter methodologies require setting a problem by defining one or more objectives to be minimized or maximized by increasing the dependent variable to a given extent, determined by the budget.

Hence, exploring the possibilities for the application of these techniques to urban regeneration, it is first necessary to define the urban regeneration problem as a choice between discreet actions. For this reason, it is best to consider a case of punctual urban regeneration intervention (*RI*) occurring through:

- the redevelopment of a regeneration action on a public area to increase the quality of a neighborhood-scale public space;
- the reuse of an abandoned private location to realize a neighborhood-scale proximal service.

An intervention in one of these two categories produces a benefit for the neighborhood where it is performed, which can be associated with a Livability Benefit function in

the form *LB(RI)*. It must be considered that, due to the form of the OCBA, *RI* represents a generic intervention; in this way, the *LB* can be used to determine the maximum benefit that can be attained through any intervention of the two typologies outlined above.

The following step is to hypothesize the independent variables associated with the *LB(RI)* function: a significant suggestion can be drawn from the 15-min city model, which solidly relates urban livability with the distance from a service belonging to one of the six macro-categories (living, working, commerce, healthcare, education, and entertainment). These can be used as a parameter to estimate the benefit deriving from the insertion of a service in the 15-min walking range, which can be calculated as:

$$LB(RI) = P_i \cdot f_U(d_{15+} - d_{RI}) \tag{10}$$

where P_i is the population involved in the action (depending on the size of the neighborhood where it is carried out), f_U is the frequency of use of the service realized (in terms of a number of expected weekly visits for the average population), d_{15+} is the distance from the closest location where the given service is provided (outside the 15-min walking range), and d_{RI} is the distance from the place where the regeneration intervention would be carried out.

Homogeneous neighborhood population groups must perform the analysis and quantification of the values of these parameters. This mainly affects the determination of the frequency of use, which closely depends on the demographic characteristics of the involved population, as the use of education facilities is more frequent for younger individuals and families with children. In contrast, the use of healthcare can be considered more relevant for the elderly population. In this sense, the frequency of use is adopted as a parameter to determine the relevance of a service for a given part of the population. Then, distance is not a homogeneous value in both d_{15+} and d_{RI}, as it changes for each building block, each with a different involved population. Hence, since a whole neighborhood is considered as the scope of the realization of an intervention, the expression (10) can be further elaborated into:

$$LB(RI) = \sum_{j=1}^{n} P_{i,j} \cdot f_{U,j}(d_{15+,j} - d_{RI,j}) \tag{11}$$

That is, the neighborhood is broken down into *j* areas, whose demographic and spatial features determine the specific assignment of the values of $P_{i,j}$, $f_{U,j}$, $d_{15+,j}$, and $d_{RI,j}$, and the single products are summated to obtain the estimate of total *LB*. *Pi,j* serves as a ponderation coefficient, which allows relating the intrinsic goodness of the intervention to the real share of the population that will benefit from it.

Then, the objective function results to be:

$$\max LB = f(f_U, P_i, d_{15+} - d_{RI}) \tag{12}$$

By constructing a continuous function for the determination of the Livability Benefit, it is possible to run OCBA analyses on the whole urban fabric, subjecting the individuated opportunities to a segmentation of the involved residents. This application is intended as an exemplification of the possibilities to model the features of urban interventions for preliminary strategic planning. At the same time, it does not consider the detailed

aspects related to the architectural, typological, and morphological characteristics of the interventions. If they were also evaluated through an OCBA-based methodology, their analysis should be more detailed and focused on multiple factors affecting urban livability. The results of this subsequent analysis could overturn the initial suggestions deriving from this preliminary application of the OCBA methodology, leading to a new full routine of the process.

4 Conclusions and Future Developments

In such a complex and interdisciplinary field as urban planning, the most successful and updated design approaches encourage thorough and direct knowledge acquisition on the involved urban fabric, up to the modern operations that actively include participatory design, and co-design labs [44]. In this typology of contexts, active discussion and understanding of territorial and local criticalities and needs are an essential pre-requirement to conceive and define urban interventions. This positive evolution of urban planning must be preserved and continued.

However, it must also be considered that the issues of urban congestion and high distance from the services for the fulfillment of basic human needs mostly affect large metropolises. There, it is difficult to ensure an overall knowledge of the whole urban space, and some valid opportunities for redevelopment might be neglected. This instance has been the starting point for the presented research work: algorithmic optimization processes, such as OCBA methods, can be used to perform a general mapping of the locations characterized by higher strategic convenience in the introduction of a new service in a specific underused area or in the requalification of a specific abandoned place.

Further developments in using this method could include the extension of OCBA to other phenomena that involve the whole urban fabric, considering the maximization of the economic benefits deriving from the regeneration interventions and the redevelopment of the areas where they are performed. In detail, while this exemplification of the methodology focuses on determining the point where the maximum walkability benefit can be achieved, it will also be interesting to outline critical factors for the increase of environmental sustainability in cities concerning various typologies and locations of areal regenerations involving the introduction of green spaces. However, in this case, the economic objective function would have to be paired with other objectives in a multi-parametric structure, such as the other components of sustainability, in addition to the benefits provided by reducing vehicular transport thanks to the enhancement of 15-min walking mobility.

Finally, using computational methods for urban strategic planning should not overshadow the reflection on the symbolic and natural values of the urban fabric: interventions on the urban form shape a broader common imagery beyond strategic convenience. This embodies complex characters of abstraction, genericity, and sociality, which require deeper comprehension before an intervention is finalized.

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