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Sustainable Multi-objective Optimisation in Land-use Planning based on Non-dominated Sorting Genetic Algorithm (NSGA-II): a Case Study in Alexandria, Egypt

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1 ABSTRACT

Due to urban sprawling, the world's land-use patterns have rapidly changed, leading to conflict and competition among urban land-uses. This conflict resulted in a range of inefficient land-use patterns. The negative impacts of such patterns suggest the need to improve the efficiency of land-use planning strategies to support better sustainable development. To attain such efficiency, many researchers have adopted algorithmic approaches perceiving land-use planning as a multi-objective optimization problem. These approaches allow encompassment of the numerous variables and constraints that are introduced in the planning process by decision makers and stakeholders. In this regard, a meta-heuristic method; the Non-dominated Sorting Genetic Algorithm (NSGA-II), could provide an efficient decision support tool for land-use planning through offering pareto optimal land-use allocation alternatives.

This paper aims at adopting NSGA-II to enhance sustainable land-use planning strategies at a neighborhood scale in the city of Alexandria, Egypt. The research suggests the adaptation of the Constrained Multi-objective Optimization of Land-use Allocation model (CoMOLA) for three main objectives: (i) maximizing the value of economic benefit, (ii) spatial compactness, and (iii) land-use compatibility. Several land-use allocation scenarios are investigated through an iterative process which includes the variables of spatial units' number, population sizes and significance of allocation objectives. The scenarios are then compared to the existing condition of land-use distribution. The results show that the proposed approach using CoMOLA tool exhibits good potential to support interactive land-use planning processes by searching over multiple plans for optimal sets of non-dominated solutions. The optimized results could provide the scientific basis for defining suitable interventions for improving sustainability measures and spatial optimization of land-uses at the neighborhood scale.

Keywords: Land-use allocation, Non-dominated Sorting Genetic Algorithm (NSGA-II), Multi-objective optimization, Constrained Multi-objective Optimization of Land-use Allocation model (CoMOLA), Land use planning

2 INTRODUCTION

Land-use allocation is a complex process that involves efficient arrangement of land-uses across a region. Its main purpose is providing the best land-use layout scenario while satisfying the demands of various activities (Huang & Zhang, 2014; Li & Parrott, 2016; Ligmann-Zielinska, Church, & Jankowski, 2005; Stewart, Janssen, & van Herwijnen, 2004; Yao, Murray, Wang, & Zhang, 2019). Land-use resources are identified in the sustainable development definition by World Commission on Environment and Development (WCED) in 1987. Thus, the configuration of land resources is critical to promote sustainable utilization of these resources, efficient land-uses, and plausible spatial distribution of activities (Ma, He, Liu, & Yu, 2011; Mohammadi, Nastaran, & Sahebgharani, 2015). In this regard, when considering macro-scale objectives of strengthening social, economic, and environmental characteristics of the city, sustainable land-use allocation is considered a primary policy of sustainable development (Li & Parrott, 2016; Lubida, Veysipanah, Pilesjo, & Mansourian, 2019; Ma et al., 2011; Yao et al., 2019). On the other hand, sustainable land-use planning is indispensable for addressing the current population trends and urban growth that lead to conflicting land-uses and excessive demand on services and activities (Yao et al., 2019). On this account, inefficient management of land-use change, and unbalanced land-use allocation, are the main drivers of environmental deterioration, ethnic and economic segregation, loss of heritage, and corrosion of land and habitat (Li & Parrott, 2016; Ligmann-Zielinska et al., 2005; Mohammadi et al., 2015). The negative impacts of such occurrences are demonstrated by the inefficient patterns of land-uses in the current urban form such as low densities, leapfrog fragmentation, edge development surpassing redevelopment of the inner cities and patches of single land-uses (Leccese & McCormick, 2000; Ligmann-Zielinska et al., 2005). Thus, sustainable land-use planning is essential to mitigate such patterns and maintain long term balanced development (Yao et al., 2019).

The involvement of various conflicting factors, as well as multiple stakeholders, defines sustainable land-use allocation as a multi-objective spatial optimization problem, which requires rational manipulation of land-uses locations and quantities by urban planners (Balling, Taber, Brown, & Day, 1999; Huang & Zhang, 2014; Li & Parrott, 2016; Lubida et al., 2019; Yang, Zhu, Shao, & Chi, 2018). In this regard, an urgent need exists for tools that utilizes such optimization approaches to assist planners with decision making. Computer-based techniques offer a potential tool, that can support handling unstructured, nonlinear multiple objectives, countless solutions, and spatial considerations of the problem (Huang & Zhang, 2014; Li & Parrott, 2016; Porta et al., 2013; Sharmin, Haque, & Islam, 2019). Nevertheless, conventional mathematical models cannot be relied upon to generate optimal solutions in a reasonable timeframe. Hence, intelligent algorithms have been developed for multi-objective land-use allocation MOLUA optimization (Yaolin Liu et al., 2015).

In correspondence to the problem of inefficient and unsustainable land-use patterns, and the necessity of competent tools that deals with MOLUA complex procedures, much research has attempted to examine the possibilities of quantitative assessment and comparison of sustainability measures for different land-use scenarios. However, the majority of existing literature disregards current land-use patterns in models' initializations and proposes a hypothetical framework instead (Ligmann-Zielinska et al., 2005). Furthermore, it mostly tackles land cover scale, whereas only a few research considered neighbourhood land-uses scale such as Cao et al. (2011), Cao et al. (2020), Huang and Zhang (2014), Lubida et al. (2019), Mohammadi et al. (2015) and Sharmin et al. (2019). Lastly, the abundant research works on developing MOLUA models that serve specific objectives rather than offering a generic decision support tool that comprehensively addresses urban sustainability and could be implemented by practitioners (Rahman & Szabó, 2021).

Within this context, this paper addresses the degree of reliability of MOLUA models to generate spatially plausible solutions, when dealing with real planning and development constraints at the neighbourhood scale.

Thereby, the objectives of this research are formulated as follows:

- To explore the possibilities of integrating spatial-related objectives into MOLUA models.
- To evaluate the efficiency and applicability of utilizing NSGA-II oriented models as a decision support tool for the local context of Egypt.
- To propose an extension to the generic CoMOLA model that promotes spatial and economic objectives along with ecological ones.

Therefore, this paper is organized into the following sections. Firstly, a literature review of related studies on multi-objective optimization problems and algorithms is demonstrated. Secondly, the paper investigates several methods to quantitatively evaluate spatial objectives and how to incorporate them in land-use optimization models. Thereafter, it adopts a generic tool for Constrained Multi-objective Optimization of Land-use Allocation (CoMOLA) to apply NSGA-II algorithm to a case study area in Alexandria, Egypt, such that three main objectives are considered: (i) maximizing spatial compactness, (ii) maximizing compatibility, and (iii) maximizing economic benefits. Consequently, the results of optimization are analyzed and evaluated according to various tests. Finally, concluded remarks and recommendations for future research are discussed.

3 LITERATURE REVIEW

3.1 Multi-objective Optimization problem

Land-use allocation constitutes an optimization problem where predefined objectives are represented as a fitness function, to be minimized or maximized. This enables quantitative assessment of alternative solutions, while conferring to constraints that determines the feasible solution set (Porta et al., 2013). Multiple variables of the problem arise from the diversity of land-use categories along with numerate spatial units (Li & Parrott, 2016; Porta et al., 2013).

Research has conducted two main approaches to multi-objective land-use allocation problems: scalarization and pareto-optimum (Li & Parrott, 2016; Mohammadi et al., 2015; Yang et al., 2018). Scalarization converts multiple objectives into a single-objective problem through techniques as weighted sum and goal programming (Yang et al., 2018). Some research has applied the weighted sum approach as Aerts, Van Herwijnen, Janssen, and Stewart (2005); Yaolin Liu et al. (2015); Yang et al. (2018). However, such approach relies much upon experts' opinions and requires prior knowledge besides its inefficiency in a non-convex solution space(Lubida et al., 2019; Yang et al., 2018; Yao et al., 2019). As for goal programming, it was adopted by Li and Ma (2018); Li and Parrott (2016); Sahebgharani (2016). It is argued that such approach is more convenient when different stakeholders can identify their demands as a preset reference goal although it may result in poor sub-objective values (Aerts et al., 2005; Li & Parrott, 2016; Yao et al., 2019). On the other hand, pareto-optimum approach resolves this issue, as it supports the evaluation of all trade-offs of multiple objectives seeking the pareto optimal set of solutions (Lubida et al., 2019; Yang et al., 2018). Gao et al. (2020) applied pareto-optimum methods as well as Cao et al. (2011); Cao, Zhang, and Wang (2019); Huang and Zhang (2014); Karakostas (2016); Lubida et al. (2019); Song and Chen (2018a). A solution is identified as a pareto optimal provided that no other solution is better or equivalently good regarding all the objective functions, besides being the best solution in at least one objective (Lubida et al., 2019; Yang et al., 2018). Although the pareto approach holds an advantage of manageable computation with respect to the attained results, some research doubts the efficiency of the pareto approach with an increased number of objectives (Li & Parrott, 2016; Mohammadi et al., 2015; Yang et al., 2018). Nonetheless, a compromise among a set of acceptable solutions is necessary because the concept of one best solution likely doesn't exist in the nation of land-use planning (Yao et al., 2019).

3.2 Multi-objective Optimization Algorithms

Researchers have run against several limitations when applying exact optimization models in MOLUA including: the inability to handle spatial interactions due to their nonlinear characteristics, the limited spatial area handled by the models, and the necessity of identifying a single objective (Aerts, Heuvelink, & Stewart, 2018; Aerts et al., 2005; Huang & Zhang, 2014; Li & Parrott, 2016). To overcome these limitations, research has suggested several non-deterministic approaches that rely on iterative heuristics for examining the search spaces in search for near optimal solutions (Porta et al., 2013). The meta-heuristic algorithms are mainly Swarm Intelligence (SI), Simulated Annealing (SA), and Evolutionary Algorithms (EA) (Aerts et al., 2005; Yaolin Liu et al., 2015; Lubida et al., 2019; Yang et al., 2018). Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) are argued as the most successful among SI, however, Genetic Algorithms is considered the most common evolutionary algorithm (Lubida et al., 2019; Mohammadi et al., 2015; Yao et al., 2019).

Since the 1970s, numerous studies have applied Genetic Algorithms in the urban field (Huang & Zhang, 2014). The algorithm relies on the theories of natural evolution and genetics to solve large complex computational problems. It is a global optimization algorithm that undergoes an iterative process of an operational sequence in order to produce high fitness child solutions from the parent individuals (Aerts et al., 2005; Porta et al., 2013; Yao et al., 2019). It is debated whether the evolutionary mechanism of the GA provides better convergence[1], or in fact affects genetic diversity leading to local optimal solutions (Li & Parrott, 2016; Yang et al., 2018). Among the several techniques developed from the GA is the elitist Non-dominated Sorting Genetic Algorithm (NSGAII) which will be adopted in this research and further explained in section 4.2. (Lubida et al., 2019; Yao et al., 2019).

4 METHODS AND TOOLS

4.1 Objective Functions

Objectives of land-use allocation can be divided into two main categories: additive objectives and spatial objectives (Li & Parrott, 2016). According to Stewart, Janssen, & Van Herwingen, additive objectives can be calculated through the attribute values of each cell (land parcel), while spatial objectives attend to the spatial characteristics of land-use patterns e.g., connectivity, contiguity, … etc. (Li & Parrott, 2016; Rahman & Szabó, 2021). With respect to sustainable land-use planning, the spatial arrangements and interrelations among land parcels are of primary significance, along with socioeconomic and environmental objectives

[1] Convergence refers to the stable point found at the end of a sequence of solutions via an iterative optimization algorithm. Premature convergence refers to a stable point found too soon, perhaps close to the starting point of the search, and with a worse evaluation than expected.

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(Yao et al., 2019). Within this context, two spatial objectives have been selected for this paper: maximizing spatial compactness and maximizing compatibility. In addition to one additive objective which is maximizing economic benefits.

4.1.1 Spatial Compactness

Spatial compactness is an expression of the degree of fragmentation or connectedness of land-uses. It encourages allocation of the same land-uses into clusters and in the vicinity of each other to maximize the assets of land-uses (Aerts et al., 2005; Li & Parrott, 2016; Rahman & Szabó, 2021; Yao et al., 2019). Compact forms are sought in sustainable land-use planning as they contribute to environmental quality, energy efficiency, and social equity (Aerts et al., 2005; Ligmann-Zielinska et al., 2005; X. Liu, Li, Shi, Huang, & Liu, 2012; Rahman & Szabó, 2021; Yao et al., 2019). Indicators of spatial compactness would involve cluster shape indices as: perimeter, area, and area to perimeter ratio. Therefore, when quantitatively evaluating compactness, four main strategies have been commonly used:

(i) Maximizing the number of land parcels in each land-use cluster,

(ii) Minimizing the land-use cluster perimeter,

(iii) Minimization of the number of clusters of each land-use type, and

(iv) Maximizing the area of the largest cluster (Aerts et al., 2005; Yao et al., 2019).

X. Liu et al. (2012); Porta et al. (2013); Yang et al. (2018) adopted the second strategy through the concept of circularity (Yao, Murray, Wang, & Zhang, 2019). Moreover, Ma et al. (2011) applied the third strategy through calculating the length of the public edge of adjacent similar cells. Meanwhile, the first strategy is the most common one among researchers, either through applying a summation equation for all land parcels with the exact land-use, or through the eight-neighbour method (Gharaibeh, Ali, Abo-Hammour, & Al Saaideh, 2021; Li & Ma, 2018; Masoumi, Coello Coello, & Mansourian, 2019; Sahebgharani, 2016; Song & Chen, 2018b; Yang, Sun, Peng, Shao, & Chi, 2015). Therefore, in this paper the eight-neighbour method is adopted and formulated as expressed in Eq. (1), where xijk is the land use of the core cell. If the land-use of the core cell and the neighbouring cell (m,n) is equal then neig(m,n) =1, if not neig(m,n)=0 (Li & Parrott, 2016; Song & Chen, 2018b).

$$\boldsymbol{Max} \sum_{K=1}^{K}\sum_{i=1}^{R}\sum_{j=1}^{C}\left(\sum_{m=i-1}^{i+1}\sum_{n=j-1}^{j+1}\frac{\boldsymbol{neig(m,n)}}{\boldsymbol{8}}\right) \qquad (1)$$

$$neig(m,n) = \begin{cases} 1 & x_{ijk} = x_{mnk} \\ 0 & otherwise \end{cases}$$

4.1.2 Compatibility

Compatibility indicates the coexistence among various land-use types of an area without inducing adverse and undesirable impacts on one another (Cao et al., 2020; Lubida et al., 2019; Masoumi et al., 2019; Mohammadi et al., 2015; Rahman & Szabó, 2021; Yao et al., 2019). The majority of published research follows the same approach for quantitatively evaluating compatibility, which is the sum of the conflict degrees for each pair of adjacent land unit, where the higher the sum, the more compatible the land-use scenario is (Cao et al., 2020; Cao et al., 2019; Karakostas, 2016; Ligmann-Zielinska et al., 2005; Lubida et al., 2019; Sahebgharani, 2016; Sharmin et al., 2019). Compatibility indices are demonstrated in a compatibility matrix, which is developed through gathering the opinions of experts, stakeholders, and urban practitioners using the Delphi method or Analytic Hierarchy Process (AHP) method (Cao et al., 2011; Masoumi et al., 2019; Mohammadi et al., 2015; Sharmin et al., 2019; Yao et al., 2019).In this regard, the compatibility indices in this paper are adopted from Mohammadi et al. (2015) and illustrated in Table 1. Compatibility is addressed in sustainable urban planning as it promotes accessibility, enhanced social interactions, liveability and overall, a healthier environment (Cao et al., 2019; Lubida et al., 2019). Furthermore, higher compatibility rates indicate competent use of land and reduces the social and economic burdens of conflict, which reflects economic prosperity and stable communities (Y. Liu, Wang, Ji, Liu, & Zhao, 2012; Rahman & Szabó, 2021). For each land parcel (i,j), it has neighbours (m,n) . Kij, Kmn represent the land-uses of cells (i,j) and (m,n) respectively. $Co_{K_{ij}K_{mn}}$ is the compatibility value between Kij, Kmn (Mohammadi et al., 2015). Hence the compatibility objective is formulated as follows:

$$\max \sum_{i=1}^{R} \sum_{j=1}^{C} \sum_{m=i-1}^{i+1} \sum_{n=j-1}^{j+1} Co_{K_{ij}K_{mn}} \tag{2}$$

	Arid [1]	*Recreational* [2]	*Mixed Residential -Commercial* [3]	*Medical* [4]	*Religious* [5]	*Educational* [6]	*Commercial* [7]	*Public Amenities* [8]	*High density Residential* [9]	*Offices* [10]
Arid	1	0.8	0.4	0.8	0.6	0.8	0.8	0.6	0.4	0.6
Recreational	0.8	1	0.8	0.6	0.8	0.8	1	0.8	1	0.8
Mixed Residential -Commercial	0.4	0.8	1	0.6	0.8	0.6	1	0.6	1	0.6
Medical	0.8	0.6	0.6	1	0.6	0.8	0.4	0.6	0.6	0.8
Religious	0.6	0.8	0.8	0.6	1	1	1	0.8	0.6	0.6
Educational	0.8	0.8	0.6	0.8	1.0	1	1	0.8	0.8	0.8
Commercial	0.8	1.0	1.0	0.4	1.0	1.0	1	1	1	0.8
Public Amenities	0.6	0.8	0.6	0.6	0.8	0.8	1.0	1	0.4	0.8
High density Residential	0.4	1.0	1.0	0.6	0.6	0.8	1.0	0.4	1	1
Offices	0.6	0.8	0.6	0.8	0.6	0.8	0.8	0.8	1	1

Table 1: Land-uses Compatibility Matrix (source: Authors adopted from Mohammadi et al. (2015))

4.1.3 Maximizing Economic Benefits

Researchers followed multiple approaches to evaluate economic benefits for land-use scenarios, being one of the three dimensions of sustainability. Some relied on comparing development costs for each land-use (Aerts et al., 2005). Others used conversion costs, whether as an independent objective or a sub-objective of land-use

suitability (Aerts et al., 2005; Li & Parrott, 2016). Another common strategy is evaluating the economic benefit of each land-use category and how they contribute to the Gross Domestic Product GDP. In this regard, some land-uses provide to GDP in a direct way such as commercial and industrial land-uses, while others support in an indirect way as hotels, businesses, … etc. (Cao et al., 2019; Li & Parrott, 2016; Mohammadi et al., 2015). On another account, Sharmin et al. (2019) has computed the economic factor through the values of employment capacity per land-use type. Based on the previous attempts, the available data sources, and the analogy that industrial land-uses are incompatible for neighbourhood scale, this paper considers maximizing the area of commercial land-uses for better economic benefits. Hence, the third objective equation is formulated as follows:

$$\max \sum_{i=1}^{R} \beta_{ij} x_{ij}^{commercial} \tag{3}$$

Where βij is the area of land parcel (i,j) and xij commercial is a binary variable equals 1 if (i,j) unit is assigned a commercial land-use and ‘zero’ otherwise (Mohammadi et al., 2015).

4.2 Constraints

For land-use allocation, constraints control the randomity of the attained scenarios and qualify more rational ones by including regulatory knowledge to the optimization process (Cao et al., 2019; Yaolin Liu et al., 2015). According to Yaolin Liu et al. (2015), constraints of land-use allocation may be divided into two types: (i) area constraints, and (ii) spatial constraints. The area constraints are of the most frequently applied constraints, which are accounted for managing a reasonable land-use structure in a given area without exploiting land resources or violating land-use policies (Yaolin Liu et al., 2015; Rahman & Szabó, 2021). Moreover, these constraints coincide with sustainability concerns of urbanization and urban expansion as it limits the built-up land growth (Cao et al., 2019; Rahman & Szabó, 2021). On the other hand, spatial constraints reflect the regional perspective of land-use planning into the equation (Li & Parrott, 2016). Meanwhile, some additional constraints may be derived due to computational complexities. In this regard, most authors disregarded mixed uses for the same land parcel despite being an impractical assumption (Aerts et al., 2005; Li & Parrott, 2016; Ligmann-Zielinska et al., 2005; Rahman & Szabó, 2021). Accordingly, this paper considers minimum and maximum land-use areas as an area constraint, where the Per capita demand for land-use types should be acquired. Eq. (5) and (6) illustrate that the area of land-use type k (Ak) should be within an upper and lower limit expressed as Uk and Lk respectively, where aij is the area of cell (i,j). In addition, transition rules that guide land-use change of different categories are applied as a spatial constraint. As per the optimization algorithm, one and only one use is allowed to be located in each cell in order to

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alleviate the computational complexity, as illustrated in Eq. (4), where the binary variable xijk must be 0 or 1 (Aerts et al., 2005).

$$\sum_{K=1}^{K} x_{ijk} \tag{4}$$

$\forall\, i = 1, \ldots\ldots R, j = 1, \ldots\ldots C, x_{ijk} \in \{0,1\}$

$$L_k \leq A_k \leq U_k \tag{5}$$

where,

$$\sum_{i=1}^{R}\sum_{i=j}^{C} x_{ijk}a_{ij} = A_k \;\forall\, K = 1,,,,,K \tag{6}$$

4.3 NSGA-II

NSGA-II is a variant of Genetic Algorithms that aims at providing a set of equally distributed non-dominated solutions to a multi-objective optimization problem (Masoumi et al., 2019; Song & Chen, 2018b). According to the basic concept of genetic algorithms, NSGA-II undergoes a sequential iterative process, which is illustrated in Fig. 1. It initiates with creating an initial population of solutions Pt, also called candidates or individuals. Secondly, parents selection takes place, based on fitness function evaluation, to create the offspring population Qt through the primary GA operators: crossover and mutation. Thereafter, the GA loop is repeated until the termination criteria is satisfied (Gao et al., 2020; Mohammadi et al., 2015). According to GA, parents are selected randomly by means of selection strategies as tournament selection or roulette wheel selection. As per NSGA-II, an elitist approach is applied to maintain diversity and pareto optimality of generated solutions. This approach consists of non-dominated sorting method followed by crowding distance method, that are used to rank population Rt, so that the fittest are selected (Cao et al., 2011; Gao et al., 2020; Lubida et al., 2019; Masoumi et al., 2019; Song & Chen, 2018b). Furthermore, the crowding distance method generates a well distributed diverse set of solutions through calculations of the density of solutions around a specific solution i in the population (Deb, Pratap, Agarwal, & Meyarivan, 2002; Masoumi et al., 2019).

4.3.1 Elements of NSGA-II

With respect to the land-use optimization problem, each land-use arrangement scenario is regarded as a solution or an individual which is encoded into NSGA-II in the form of a chromosome (Mohammadi et al., 2015). The definition of a chromosome within the optimization model has varied in literature, depending on whether spatial data are expressed in a raster (grid) or vector format. It is argued that vector format adds to the algorithm complexity (Cao et al., 2011). Hence, the prominent one relies on a grid representation that constitutes the chromosome of genes or cells, which represent different land units, each with an assigned value that represents the land-use type in this cell (Masoumi et al., 2019; Mohammadi et al., 2015). This paper adopts a generic tool for Constrained Multi-objective Optimization of Land use Allocation (CoMOLA), that applies NSGA-II to optimize raster maps proceeding from python “inspyred” library (Strauch et al., 2019). In the following section, operators of NSGA-II according to CoMOLA procedures are illustrated.

4.3.2 Initialization

The selection of initial feasible population influences how fast the algorithm would attain the pareto front (Cao et al., 2011; Mohammadi et al., 2015; Strauch et al., 2019). Therefore, CoMOLA adheres to Problem-Based Initialization Operators, which include the status quo of land-use arrangement into the iterative process (Cao et al., 2011; Masoumi et al., 2019). To further guarantee the feasibility of the initial individuals, constraint-controlled genome generation CG is applied (i.e., the genome expresses the chromosome of the initial individual). CG generates a genome gene-by-gene, where at each point the generated sequence of genes is tested for satisfying the algorithm constraints, so that it proceeds to the next gene, or it is regarded as an infeasible solution (Strauch et al., 2019).

4.3.3 Constraint Handling Methods

Integrating real world constraints into optimization models has commonly followed three strategies. The first is feasibility operators which allow only generation of solutions satisfying all constraints. The second strategy is to convert the constrained problem to an unconstrained one using Penalty Functions or Lagrange Multipliers (Mohammadi et al., 2015). The third strategy, and the one adopted by CoMOLA, is repair mechanisms. In this regard, constrained-controlled repair mutation is developed to repair infeasible individuals into feasible ones provided that the repaired ones are as close as possible to the originally suggested individuals by NSGA-II (Strauch et al., 2019).

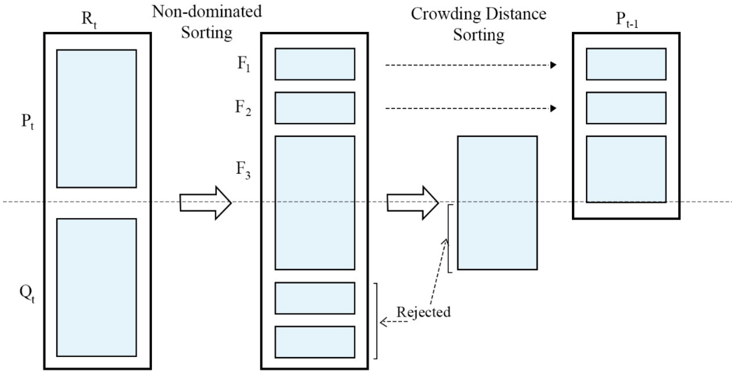

Fig. 1: Illustration of NSGA-II Algorithm procedure (source: Deb et al., 2002).

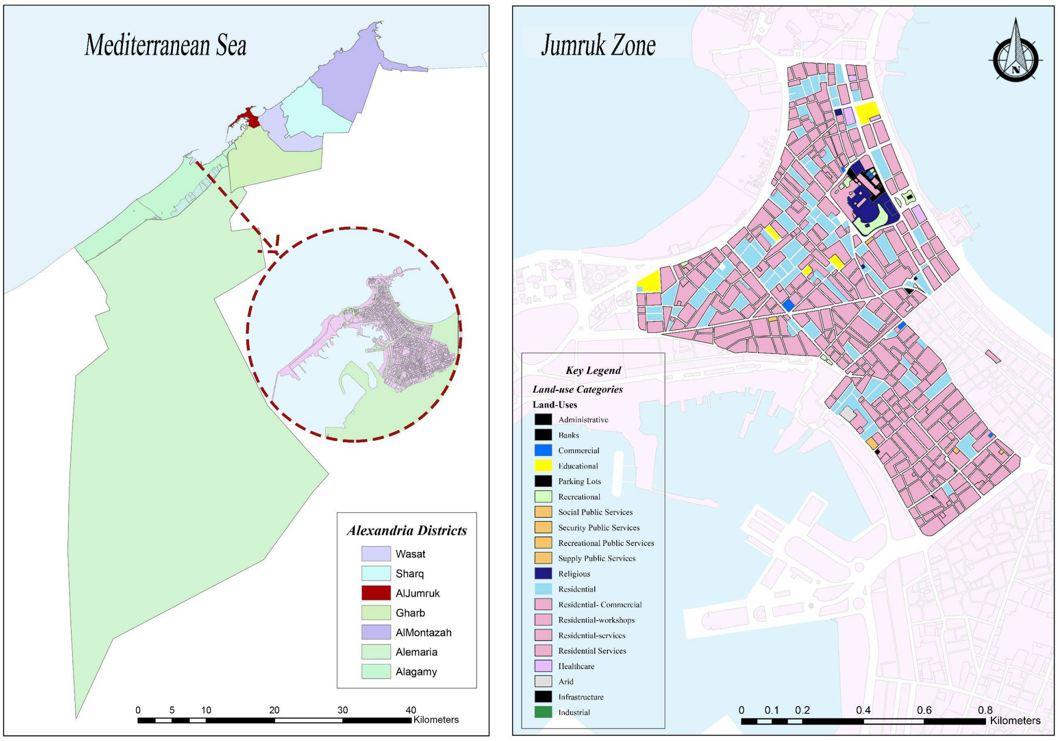

Fig.2: Location of the Study Area of Jumruk District (source: Authors)

4.4 Study Area

Al-Jumruk district is located in the centre of Alexandria city, Egypt as illustrated in Fig. 2. It covers an area of 4.7 Km2 and has 6083 plots of 409,329 population according to 2017 statistics by Central Agency for Public Mobilization and Statistics CAPMAS. It covers four main zones: Al-Jumruk, Al-Mansheyya, Al-Labban and

Alexandria's port. It accommodates a variety of activities and land-uses including administrative, cultural, educational, workshops, religious, public services, touristic, healthcare, residential, mixed-uses, warehouses, and industrial services. Since this district is considered the oldest district of the city, in addition to its unique history, multiple stakeholders are concerned with its development plans. Moreover, several revitalization and rehabilitation projects have been suggested for the area by researchers, urban practitioners, and governmental planning sectors (GOPP,2022). However, the district suffers from some challenges concerning its land-use

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urban structure, unsustainable conditions, and overcrowding. Hence, this paper recommends supporting urban planners with a design tool as illustrated in section 4.3., that could promote plausible interventions for managing the area in the future.

4.4.1 Data Collection and Preparation

Data required for land-use allocation optimization such as governmental guidelines, maps and statistical data were obtained from the General Organization for Physical Planning of Egypt (GOPP) and the National Organization for Urban Harmony. In addition, GIS data of the district including layers of land-uses, services, roads, infrastructure, transport, … etc. was gathered and adapted for the current research. Following the predominant course of sustainable development, land-use optimization for the study area aims at promoting sustainable land-use arrangements whilst preserving heritage and maintaining proper mix of land-uses.

4.4.2 Model Implementation

A study area of Al-Jumruk zone of an area 1 Km by 1.2 Km is selected for optimization, where the input variables are arranged as follows. CoMOLA model collects three categories of input variables: (1) Model Variables, (2) Map variables, and (3) Algorithm Variables. The model variables are expressed in the range of land-use classes to be optimized and the external models of objective functions. Concerning the land-use classes, the existing land-uses were re-categorized into the fundamental uses at a district level while maintaining an adequate percentage of mixed-uses (Mohammadi et al., 2015). Thus, ten classes of land-uses are considered in the model as shown in Table 2. As per objective functions models, the three objectives illustrated in section 4.1. are formulated into a python code and integrated into CoMOLA. Concerning the third objective, both commercial and mixed residential-commercial land-uses are promoted.

	Arid	*Recreational*	*Mixed Residential -Commercial*	*Medical*	*Religious*	*Educational*	*Commercial*	*Public Amenities*	*High density Residential*	*Offices*
Minimum Area	0	116,446	704,118	2,183	86,715	36,681	472	1997	133300	7312
Maximum Area	625	241,626	977,668	15,720	151,380	641,911	1348	2439	152100	8938

Table 2: Minimum and Maximum Areas Required for Land-use Classes (source: Authors, adapted from GOPP,2022)

The map variables deal with the land-use map and the constraint-related input data. For land-use optimization problems, the study area is defined as a two-dimensional array of R rows and C columns, where K land-use categories need to be assigned (Li & Parrott, 2016; Porta et al., 2013; Yang et al., 2018). Thus, using GIS, a raster map with resolution (cell size) of 25 m was created from the available database of the study area. The resolution is identified experimentally to best reflect the land-use categories of the area, besides following the recommended number of spatial units advised by Strauch et al. (2019). The raster map is thereafter introduced

into the model in ASCII format, where land-use classes are assigned consecutive integers starting with 1. As discussed by Porta et al. (2013), it is advised to adhere to the existing legal boundaries of land parcels when dealing with spatial allocation. Therefore, a patch ID map is generated for the study area, that groups the neighbouring raster cells of the same land plot into a patch or a cluster (Porta et al., 2013; Strauch et al., 2019). The patch ID doesn’t only serve planning purposes, but also alleviates the computational load through reducing the number of spatial units, where 252 patches are computed instead of 470 plots. Furthermore, patch ID map is supplied by the indices of static cells (i.e., cells that aren’t allowed to change during the optimization process). This serves the conservation of important touristic and heritage sites such as Abu-Al abbas Complex, that is located in the far east of the study area. As for the constraint-related input data, conversions between all land-use classes are permitted in the transition matrix aside from the static elements defined in the patch ID map. Additionally, the minimum and maximum demanded area for the ten land-use classes is deduced and presented in Table 2. In this regard, economic activities, represented in offices category, as well as public amenities are kept within the limits of the current areas. On the other hand, according to the analogy that already developed land isn’t converted to undeveloped ones, arid category is prohibited from growth. Furthermore, the ratio of mixed-use plots is preserved and expressed into the area calculations. Since the CoMOLA model perceives the area limits as an absolute constraint, a variation of the current land-use distribution is developed to qualify as the first individual of the first generation. Contextual constraints of allocating land-use categories are applied to this variation using GIS buffer tools.

Finally, the algorithm variables represent the parameters of the different iterations and directly impact the computation time and efficiency (Strauch et al., 2019). Required parameters of the algorithm include maximum number of generations, population size, crossover rate and mutation rate. Based on the rule of thumb crossover rate is set to 0.9, while mutation rate is set to 0.01. Multiple runs of the algorithm are executed to reach the optimum number of generations and population size.

5 RESULTS AND DISCUSSION

In this section, results from CoMOLA model implementation are discussed in detail. As a result of several trials, the model was executed for a population size of 20 and 400 iterations. Execution of the model for such parameters for the three identified objectives in the study area takes 17 hours on a laptop with an Intel(R) Core(TM) i7-7700HQ CPU @ 2.80GHz and 16 GB RAM. Fig. 3 (Right) illustrates the values of objective functions throughout the different iterations. The results show how the solutions gradually enhanced as the iterations proceeded during optimization, which advocates the abundant literature assertions.

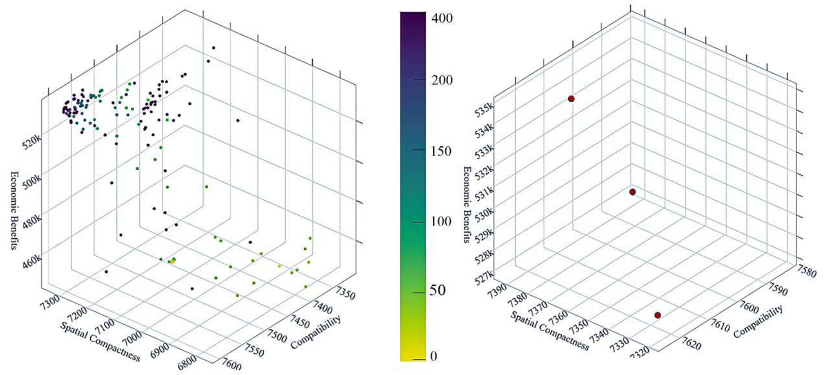

Fig. 5: (Left) The Evolutionary Process of Searching the Solution Space of Objectives and (Right) The Resulting Pareto Front Solutions generated by NSGA-II. The colour bar refers to the order of iterations (source: Authors)

Objectives	*Status Quo*	*Pareto 1*	*% of Improvement*	*Pareto 2*	*% of Improvement*	*Pareto 3*	*% of Improvement*
Spatial Compactness	7242	7394	2.10	7376	1.85	7318	1.05
Compatibility	7599	7581	-0.24	7615	0.21	7626	0.36
Economic Benefits	528125	526875	-0.24	535000	1.30	528125	0.00

Table 3: Comparison of Objective Functions Values of Pareto Solutions with Status quo (source: Authors)

The spatial compactness value ranges from 6760 to 7394. The compatibility objective ranges from 7335 to 7626, while the economic benefits objective increases from 450000 to 535000. However, it is noticed that the speed of generating solutions significantly decreases with each new generation. Different trade-offs among the objectives have been tested. Fig. 3 (Left) demonstrates the compared objective values in three different scenarios. Firstly, when spatial objectives are coupled together, secondly, when the additive objective is coupled with one spatial objective and lastly, when all objectives are pursued simultaneously. The results show that the spatial compactness objective values are enhanced when coupled with the objective of maximizing economic benefits. On the other hand, premature convergence is noticed when only spatial objectives are selected for optimization. In addition, the finest economic objective values are obtained when coupled with spatial compactness objective, whereas its mean values significantly deteriorate when coupled with compatibility. Finally, the results obviously depict that the least values are achieved when all three objectives are combined. The solution space for the algorithm run, along with the resulting pareto solutions, are plotted in Fig.5.

The model suggests three different scenarios as optimum ones for the study area. Each scenario offers a possible intervention that would improve a certain objective value. Table 3 shows the values of the objective functions of the pareto solutions compared to the current state. The comparison reveals slight degrees of improvement for both spatial compactness and economic objectives. However, the compatibility objective values are minimally improved as a trade-off to achieve better comprehensive values.

Fig.6 shows the three pareto land-use maps suggested by the algorithm. The three maps present different objectives preferences, such that the first pareto solution offers the highest spatial compactness value while

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the third one best supports maximizing compatibility. In addition, the second pareto solution displays a balanced improvement of all three objectives with maximum economic values.

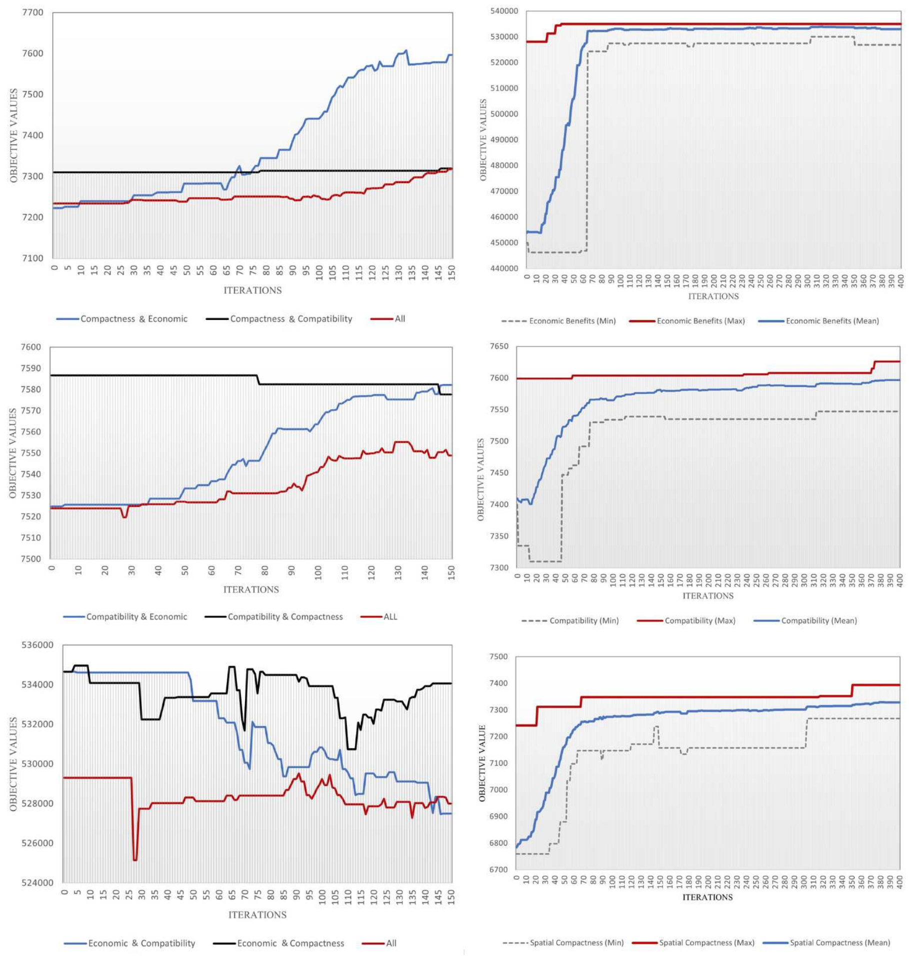

Fig. 3: (Left) Result Values for Trade-offs among Objective Functions and (Right) Maximum, Mean and Minimum Values for the Objective Functions at Each Iteration (source: Authors)

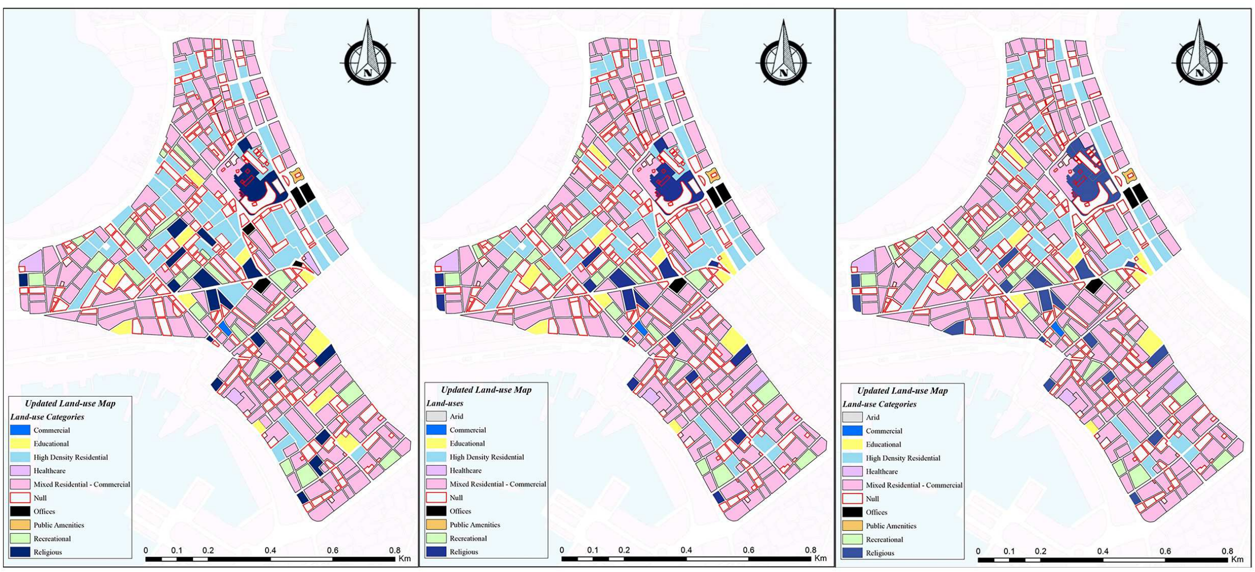

Fig.6: Optimized arrangements of land-uses under different objective preferences as suggested by NSGA-II (source: Authors)

It is noticed in pareto 1 that high density residential lots are promoted into clusters, also religious and healthcare land-uses are distributed in close proximity. With respect to pareto 2, it is observed that the percentage of mixed-use parcels is enlarged. Lastly, the third pareto proposes minimal adjustment to the second one concerning the educational land-uses arrangement, in order to promote better compatibility. The proposed land-use structures are generally more rational than status quo land-uses regarding the distribution of different land-use categories. The proposed intervention implies an increase in the areas of medical, recreational and religious land-uses by 12%,482% and 200% respectively. These rates can be justified due to the low per-capita demand for such uses in the area. The illustrated solution can be regarded as a preliminary step to support decision makers with general guidelines on how to pursue with the study area future plans.

Nevertheless, a number of plots can be observed missing from the pareto solutions due to raster representation of the study area map. Due to limitations in transferring maps into raster format, some plots might be ignored for their size or orientation. In this regard, different cell sizes might present better inclusion of plots, however, it may cost the optimization process additional running time and complexity. The analysis of results reveals the extensive time needed by the model to run a couple of hundred iterations which can be traced back to the constraint handling logic of the algorithm. In this respect, the area constraints are applied in an absolute manner, where all individuals that don't satisfy the minimum and maximum boundaries are completely neglected by the algorithm. This process consumes a large amount of time and imposes greater challenges for each generation to generate feasible solutions. Incorporation of such constraints into the selection procedures as penalty functions might lead to more diverse solutions in a better time frame. This would enable the algorithm execution with higher iteration values to attain better improvement results. Additionally, this approach is more rational when dealing with optimizing current land-use distribution, where it is expected to work on several scenarios of area constraints violations. On the other hand, the study area is regarded as a very dense residential region which limits the flexibility of land-use changes without compromising the per-capita demand of the region. Therefore, considering a less dense area with more vacant lots might result in better intervention scenarios. Finally, the spatial compactness approach adopted in this paper, can be observed in the results that it promotes adjacency of similar uses even for service land-uses.This might contradict the general urban planning guidelines for land-uses distribution where services as educational, medical, religious, etc. should be allocated within a maximum distance of served residential units. Hence, additional contextual constraints could be incorporated when developing objective functions.

6 CONCLUSION

Land-use allocation is one of the practices of land-use planning that involves arrangement of land-uses into different spatial units of land. It is a complex process as it is constrained by, as well as influencing on, the economic, social, and environmental conditions of the city. Hence, it is an important policy for sustainable development. Due to the numerity of the variables, objectives and constraints involved in the process, land-use allocation is considered a multi-objective spatial optimization problem. This paper addresses the use of land-use optimization models in real contexts through employing an NSGA-II optimization model to the local neighborhood of Aljumruk in Alexandria. It also provides an approach of integrating spatial and economic objectives into a generic CoMOLA model, where they are interpreted into a set of quantitative evaluation operations. GIS software was used to visualize the exports of the algorithm and compare them to the status quo land-uses. The application of the model depicted its potential to interactively support decision making processes through generating numerous alternatives and offering a multitude of near optimal solutions for land-use distributions. It also demonstrated the capacity of models to accommodate spatial objectives through mathematical expression. Nevertheless, the paper highlights a set of limitations that could be the scope of future work including the need for a framework that employs vector representation of land-use maps without adding further complexities. This could provide improved optimization for real contexts scenarios. Moreover, it is recommended to apply further tests to investigate the interrelation between constraint handling techniques and the algorithm running time. Finally, only three objectives were the scope of this research. Thus, incorporating more objectives in the future could give better insights for comprehensive sustainable land-use planning.

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