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Land Use Spatial Optimization Using Accessibility Maps to Integrate Land Use and Transport in Urban Areas

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Abstract

The scarcity of urban land resources requires a well-organized spatial layout of land use to better accommodate human activities, however, as a widely accepted concept, the integration of land use and transport is not given due consideration in land use spatial optimization (LUSO). This paper aims to integrate land use and transport in LUSO to support urban land use planning. Maximizing accessibility fitness, which follows the underlying logic between land use types and transport characteristics, is introduced into multi-objective land use spatial optimization (MOLUSO) modelling to address transport considerations, together with widely-used objectives such as maximizing compactness, compatibility, and suitability. The transport characteristics, in this study, are identified by driving accessibility, cycling accessibility, and walking accessibility. Accessibility maps, which quantify and visualize the spatial variances in accessibility fitness for different land use types, are developed based on the empirical results of the relationship between land use types and transport characteristics for LUSO and addressing policy issues. The 4-objective LUSO model and a corresponding non-dominated sorting genetic algorithm (NSGA-II) based optimization method constitute a prototype decision support system (DSS) for urban land use planning. Decision-makers (e.g., planning departments) can choose an ideal solution to accommodate urban development needs from a set of Pareto-optimal alternatives generated by the DSS. The approaches to creating accessibility maps and MOLUSO modelling are demonstrated by the case study of Eindhoven, the Netherlands. This study advocates limited changes to the current land use pattern in urban planning, and the LUSO emphasizes urban renewal and upgrading rather than new town planning.

Keywords Land use planning · Spatial optimization · Land use and transport integration · Accessibility

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Introduction

Land use patterns result from the interaction between humans and the environment. As an intuitive expression of complex urban systems, land use patterns reflect the spatial structure of longstanding human activities and open up a window to observe and probe into cities. A well-organized land use pattern is an efficient and effective configuration of physical components to make our cities function. Given the land scarcity, land use spatial optimization (LUSO), as a resource allocation problem as well as a spatial optimization problem in geography, has drummed up considerable attention. The formation of a land use pattern is driven by multiple socio-economics, socio-political and biophysical forces (Verburg et al., 2004). Beyond the discussion on the mechanism of land use change, several issues of common concern for land use patterns have been drawn from urban planning practice, such as compactness, compatibility, and suitability, which are usually used as the objectives of LUSO. With the global trends of urbanization, integrating land use and transport is regarded as a response to problems caused by urban sprawl and extensive automobile use (Moeckel et al., 2018), and the concept has been placed at the heart of establishing more sustainable urban environments (Te Brömmelstroet & Bertolini, 2010). However, the consideration of land use and transport integration is lacking in LUSO modelling.

This paper aims at developing a multi-objective land use spatial optimization (MOLUSO) model to assist in urban land use planning, which addresses transport considerations as well as common concerns of LUSO modelling. Though some research (Cao et al., 2011, 2012; Li & Parrott, 2016, Ligmann-Zielinska et al. 2008 and Liu et al., 2013) takes into account the distance to roads or specific destinations, transport is not given due weight. To achieve the integration of land use and transport in LUSO, we first developed an indicator, accessibility fitness, to measure the degree of match between land use types and transport characteristics. Transport characteristics in this study are quantified by driving accessibility, cycling accessibility, and walking accessibility to compensate the lack of discussing the differences of road types in the literature.

The spatial distribution of accessibility fitness for a specific land use type is illustrated by the accessibility map. With accessibility maps, the concept of integrating land use and transport is embodied in maximizing accessibility fitness, which composes the objectives of the MOLUSO model combined with widely-used maximizing compactness, compatibility, and suitability. A non-dominated sorting genetic algorithm (NSGA-II) based optimization method was used to find the solutions of the model. The 4-objective LUSO model and the corresponding NSGA-II algorithm constitute a prototype decision support system (DSS). The DSS can provide urban planners and decision-makers with a set of alternative land use patterns approximating the Pareto front, which plays a vital role in the proposition of advisory and technical upstream services. The DSS reconciles the traditional point of view on LUSO modelling and the transport perspective, and the resulting land use patterns strengthen the ties between land use and transport compared to previous studies. The DSS was applied to a case study of a Dutch city, Eindhoven.

Furthermore, as a critical component of the MOLUSO model, the collection of accessibility maps not only leads transport considerations into LUSO but also facilitates the discussion on policy options for urban development (e.g., the debate on compact or extensive development) from an integrated land use and transport perspective. The accessibility fitness and the accessibility maps could be more straightforward decision support tools for formulating location policy, based on which this study proposes HML policy referring to the well-known Dutch ABC policy.

The remainder of this paper is organized as follows. In Sect. Literature Review, related work is reviewed, including the objectives of LUSO, the approaches to LUSO modelling, and the link between land use and transport. Section Methods presents the modules of the DSS, including the accessibility maps, the MOLUSO model, and the NSGA-II based method. Section Results reports the accessibility maps of Eindhoven and the application of the proposed DSS in Eindhoven. Conclusions and discussion are followed in Sect. Conclusions and Discussion.

Literature Review

In LUSO modelling, the selection of optimization objectives gives expression to researchers' understanding and concerns of land use planning. The scope of LUSO objectives is far-ranging, represented by compactness (see e.g., Cao et al., 2012; Stewart et al., 2004), compatibility (see e.g., Ligmann-Zielinska et al. 2008; Mohammadi et al., 2016) and suitability (see e.g., Liu et al., 2013; Huang et al., 2013). In LUSO studies, a compact land use pattern is characterized by concentrations of areas with the same land use type (Stewart et al., 2004); compatibility refers to the degree to which two or more land use types coexist without a significant negative impact (Taleai et al., 2007); suitability means the fitness of a land unit for a given land use type (Liu et al., 2013). Integrating land use and transport, as a widely-accepted concept in urban planning, has not been given adequate attention in LUSO. Transport considerations are barely presented as the distance to specific destinations or roads in the existing literature. For example, both Ligmann-Zielinska et al. (2008) and Liu et al. (2013) used an objective that minimizes the distance of new development to already developed areas. Li and Parrott (2016) incorporated the distance to key features into the measurement of suitability. Cao et al., (2011, 2012) created the function decreasing maps based on the distance to roads to evaluate accessibility. Feng and Lin (1999) proposed development efficiency, which contains distance-based accessibility, to identify the aspiration of the public on their living circumstances. However, distance measures, especially Euclidean distance, are too simplistic to adequately capture the role of road networks in the formation of land use patterns. Furthermore, the impact of road networks on land use planning varies in different types (e.g., driving, cycling, and walking), but the differences have yet to be discussed in LUSO. For example, for a pedestrian-friendly area, the allocation of commercial use is supposed to have priority over industrial use.

The link between land use and transport provides the logic to integrate transport considerations in land use planning and policy-making. The link between land use and transport is underpinned by numerous empirical studies (Kasraian et al., 2016). The studies on the relationship between land use and transport, according to the transport infrastructure, can be divided into following categories: pedestrian and bicycle infrastructure and land use (e.g., Cervero & Duncan, 2003), motorized infrastructure and land use (e.g., Stanilov, 2003), and urban rail systems and land use (e.g., Ratner & Goetz, 2013), all of which corroborate that land use and transport are interrelated. With the growing understanding of the relationship, more in-depth work keeps going forward. Since the pioneering work of Hansen (1959), land use transport interaction (LUTI) model, as a long-term focus in the field of urban planning, has cast its spell over urban planners, managers and researchers (Acheampong & Silva, 2015; Waddell, 2011). In the existing integrated land use and transport planning models (e.g., Li et al., 2016; Lin & Feng, 2003; Xu et al., 2016), the interaction between land use component (residential-job location choice) and transport component (travel demand management) is typically formulated by the bi-level programming approach. However, the mechanism of the interaction is still beyond empirical measurement, which can be attributed to the complex nature of land use and transport systems (Acheampong & Silva, 2015). In addition, some studies gear efforts towards policy integration concerning transport and land use issues (Geerlings & Stead, 2003). The concept of accessibility serves as the bridge between land use and transport policies, and integrated policies are developed based on accessibility analysis (e.g., Halden, 2002). While land use can be linked with transport in a variety of ways, the analysis of the relationship between land use types and transport characteristics, which is the theoretical basis for manipulating land use patterns with transport considerations, lacks depth.

The LUSO models, according to modelling techniques, can be grouped into linear models and non-linear models. The research on LUSO started with linear optimization methods, which is initiated by a wave of urban modelling applications in the 1960s (e.g., Schlager, 1965), and then linear programming has long been a popular approach to LUSO modelling (e.g., Aerts et al., 2003; Barber, 1976; Sadeghi et al., 2009). With computer performance improvement, a growing number of studies resort to non-linear programming to handle the increasing factors considered in urban planning. The application of non-linear programming brought in a large body of literature on metaheuristic optimization methods for LUSO, which includes genetic algorithm (GA)-based methods (e.g., Cao et al., 2011, 2012; Ertunç et al., 2018; Li & Parrott, 2016; Stewart et al., 2004) and particle swarm optimization (PSO)-based methods (e.g., Liu et al., 2013; Zhang et al., 2016), along with simulated annealing (Aerts & Heuvelink, 2002), ant colony optimization (Liu et al., 2012) and artificial immune systems (Huang et al., 2013), etc. GA has comparatively broader application because of its unique strengths for MOLUSO. The evolution process of GA provides an efficient convergence method, and GA can generate a non-dominated set for further analysis to reveal ideal solutions (Li & Parrott, 2016).

Methods

Study area and data

Eindhoven is the high-tech industrial heartland as well as the fifth-largest city of the Netherlands, with over 226,000 residents (April 2017) living in 88.84 km^2. Eindhoven is a monocentric city with a clear spatial structure and has complete non-motorized and motorized road networks. A case study in Eindhoven could help to unveil the relationship between land use types and transport characteristics using readily available data. The data of this study includes land use data and road network data. The spatial database BBG2012, which is published by Statistics Netherlands, provides the digital geometry of the boundaries of land use in 2012. A parcel (i.e., a digital geometry) in BBG2012 is a continuous area of single land use. Eindhoven contains 970 parcels belonging to 21 subclasses of 7 types (i.e., built, semi-built, transport, recreation, agricultural, forest and open natural, inland water). In this study, these 970 parcels are reclassified into commercial, residential, transport, industrial, open space, and natural area, and the land use pattern of 2012 is referred to as the base land use pattern (see Fig. 1). As shown in Fig. 1, the residential and commercial uses are mainly located along the north–south axis, and the industrial uses are distributed in the outskirts. The road network data of Eindhoven, obtained from Open Street Map (OSM), is composed of line geometries with attributes such as length and speed limit. The OSM data can construct a directed routable graph for

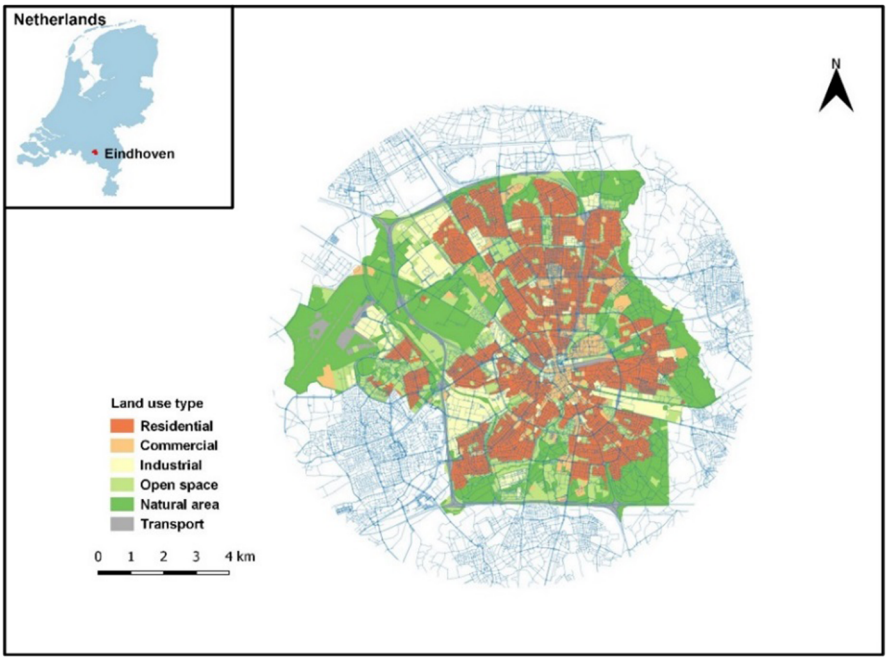

Fig. 1 Base land use pattern of Eindhoven and road networks

the implementation of route search algorithms (Graser et al., 2015). In the absence of OSM data for 2012, the available database for 2013 is used for this study (see Fig. 1).

Accessibility measures and data analysis

Accessibility measures

Accessibility, which measures what and how can be reached from a given point in space, is a flexible conceptual framework to integrate land use and transport (Bertolini et al., 2005). The accessibility of this study is the ease with which anyplace of a certain area can be reached by individuals at a particular location using the mobility service of given transport systems. For most cities without intra-city rail transit, bus-based transit is operated on road networks of motor vehicles. In terms of transport infrastructure, the transport characteristics of location i can be characterized by walking accessibility A_i^W (for the pedestrian network), cycling accessibility A_i^C (for the bicycle network) and driving accessibility A_i^D AD i(for the motorized network), which have the following equations:

$$A_i^W = e^{-f^W(i)} \tag{1}$$

$$A_i^C = e^{-f^C(i)} \tag{2}$$

$$A_i^D = e^{-f^D(i)} \tag{3}$$

where walking time function $f^W(i)$, cycling time function $f^C(i)$ and driving time function $f^D(i)$ can be given as Eq. (4), Eq. (5) and Eq. (6), respectively:

$$f^W(i) = \sum_{j \in Z_i^W} t_{ij}^W / N_i^W \tag{4}$$

$$f^C(i) = \sum_{j \in Z_i^C} t_{ij}^C / N_i^C \tag{5}$$

$$f^D(i) = \beta_{peak} \bullet \sum_{j \epsilon Z_i^D} t_{ij}^D \left(1 + \alpha_k\right) / N_i^D + \beta_{off-peak} \bullet \sum_{j \epsilon Z_i^D} t_{ij}^D / N_i^D \tag{6}$$

where t_{ij} is the minimum traveling time from origin i to destination j, Z_i is the trip area of origin i, N_i is the number of destinations in Z_i. The parameters of accessibility measures are consistent with Wang et al. (2019). In this study, the traffic zone is the spatial unit for defining the relationship between land use types and accessibility. The irregular-shaped parcels in BBG2012 can be divided into smaller pieces (i.e., traffic zones) with a single land use type in QGIS 2.18. By Brent's method (Brent,

1971), the traffic zones can be squarish with approximately the same size. This study refers to the division scheme of 5,218 6-digit postcode districts of Eindhoven, and the size of a traffic zone is 16,900m^2 (130 m × 130 m), which results in 5,355 traffic zones. The geometric centroids of traffic zones, as origins and destinations, construct 28,676,025 origin–destination (OD) pairs for travel time calculation. As the movement capacity varies in transport mode, there are incremental trip areas of a given location for walking, cycling, and driving. For each origin i, the walking trip area Z_i^W is a circular region of radius 800 m centered at i, the radius of its cycling trip area Z_i^C is 3 km, and the driving trip area Z_i^D is the whole study area.

In Eq. (6), α_k measures the driving time increase for roads of type k during peak hours. As the travel time increases 11% in highways and 25% in non-highways during peak hours (TomTom, 2016), α_1 for highways is 0.11 and α_2 for non-highways is 0.25. The operation performances of road networks in peak hours and off-peak hours are given equal ($\beta_{peak}=\beta_{off\text{-}peak}=0.5$) weight in the driving accessibility measure. The walking speed and cycling speed are set to 5 km/h and 15 km/h respectively, and the driving speed follows road speed limits. The minimum travel time paths were searched by Dijkstra's algorithm.

Classifications of traffic zones

As discussed in Sect. Accessibility measures, a traffic zone has both land use and transport attributes. Traffic zones can therefore serve as the media for investigating the relationship between land use types and transport characteristics. On the one hand, traffic zones can be classified by land use types as commercial traffic zone (CTZ), residential traffic zone (RTZ), industrial traffic zone (ITZ), open space traffic zone (OSTZ), natural area traffic zone (NATZ) and transport traffic zone (TTZ). Driving accessibility, cycling accessibility, and walking accessibility, on the other hand, can divide traffic zones into groups with similar transport characteristics by a clustering method.

The agglomerative hierarchical clustering (AHC) was used to synthesize accessibility indicators. AHC works in a bottom-up manner, which starts with each traffic zone as a single-element cluster and then successively agglomerates the two clusters that are the most similar in accessibility unitl all traffic zones are member of just one single cluster. The distance between two clusters is defined as the sum of the squared distance to the mean of the combined clusters, also known as Ward's method. Each resultant cluster represents specific transport characteristics, which is called transport characteristics cluster in this study. Transport characteristics clusters and land use types, as categorical variables, can be compiled in a contingency table, which consists of cells that count numbers and frequency distribution of variables. The cornerstone of integrating land use and transport in LUSO is that land use types are associated with transport characteristics. The independence of categorical variables can be tested by the Chi-square statistic on the contingency table.

MOLUSO model based on Non-dominated Sorting Genetic Algorithm II (NSGA-II)

MOLUSO modelling

Compared to vector-based optimization, the high maneuverability of grid-based optimization better serves the modification of land use patterns (Li & Parrott, 2016). Eindhoven can be represented by 5,451 grid cells in a grid with 83 rows and 102 columns when the grid cell is 130 m × 130 m. The larger number of grid cells than traffic zones are due to the grid cells on the edge to match the shape of the study area. LUSO is a multi-criteria decision-making problem, which deals with how to allocate K different land uses to grid cells. We assume that, under given road networks, the transport characteristics (i.e., driving, cycling, and walking accessibility) of grid cells vary spatially, and for a given grid cell, the degree of match between its transport characteristics and different land use types are different. Accordingly, the first and highlighted objective of this study is maximizing accessibility fitness (i.e., maximizing the degree of match between transport characteristics and land use types), which is given as follows:

$$Maxf_{Accessibility} = \sum_{k=1}^{K} \sum_{i=1}^{R} \sum_{j=1}^{C} a_{ijk} x_{ijk} \tag{7}$$

where a_{ijk} is the accessibility fitness of cell (i, j) for the kth land use. The accessibility fitness can be retrieved from accessibility maps, which will be introduced in Sect. Accessibility maps. x_{ijk} is a binary-state variable that is 1 if the cell (i, j) is allocated to the kth land use; otherwise, the value is 0. In addition to maximizing accessibility, the following three widely-used objectives: maximizing compactness, compatibility, and suitability are included in the MOLUSO model, which are formulated as follows:

$$Maxf_{Compactness} = \sum_{k=1}^{K} \sum_{i=1}^{R} \sum_{j=1}^{C} e_{ijk} x_{ijk} \tag{8}$$

$$Maxf_{Compatibility} = \sum_{k=1}^{K} \sum_{i=1}^{R} \sum_{j=1}^{C} b_{ijk} x_{ijk} \tag{9}$$

$$Maxf_{Suitability} = \sum_{k=1}^{K} \sum_{i=1}^{R} \sum_{j=1}^{C} s_{ijk} x_{ijk} \tag{10}$$

Subject to:

$$\sum_{k=1}^{K} x_{ijk} = 1 \quad \forall i = 1, \ \ldots, \ R, \ j = 1, \ \ldots, \ C, \ x_{ijk} \in \{0, \ 1\} \tag{11}$$

$$\sum_{i=1}^{R}\sum_{j=1}^{C} x_{ijk} = Q_k \quad \forall k = 1, \ldots, K \tag{12}$$

where e_{ijk} is the compactness of cell (i, j) to the kth land use, b_{ijk} is the compatibility of cell (i, j) to the kth land use, and s_{ijk} is the suitability of cell (i, j) to the kth land use. Equation (11) ensures that only one land use type can be allocated to a grid cell. Equation (12) specifies the quantity of different land use types, which is generally determined by a city's master plan, and Q_k is the number of grid cells that are allocated to the kth land use.

The compactness of urban space, which can contain urban sprawl, reduce energy consumption and transport-related pollution, is a significant feature of sustainable urban form (Jabareen, 2006). It may be easier to manage a compact area (e.g., a square or circular region) for a land use type than a thread-like area (Stewart et al., 2004). In this study, we used the basic Eight-neighbor (Moore neighborhood) method to measure compactness (see Cao et al., 2011; Li & Parrott, 2016), so the compactness parameter e_{ijk} has the following expression:

$$e_{ijk} = \sum_{m=i-1}^{i+1}\sum_{n=j-1}^{j+1} x_{mnk} - 1 \tag{13}$$

where cell (i, j) is the core cell; if the land use type of cell (m, n) is the same as the core cell's, x_{mnk} equals 1; otherwise, x_{mnk} equals 0.

LUSO should mitigate negative externalities between adjacent land uses by grouping compatible land uses and separating incompatible land uses (Taleai et al., 2007). The land use compatibility matrix defines the spatial harmony, i.e., compatibility between grid cells with different land use types. The compatibility matrix used in this study is drawn from the already developed compatibility matrices in the literature (see e.g., Ligmann-Zielinska et al., 2008; Liu et al., 2013; Mohammadi et al., 2016), and it has been adapted to the situation of Eindhoven, e.g., increasing the compatibility between residential use and commercial use, and decreasing the compatibility between industrial use and commercial use. The range of compatibility values is [0.0, 1.0] (see Table 1). Eindhoven is a monocentric small-sized city, which measures about 14 km from North to South, 11 km from East to West. The mixed land use in Eindhoven emphasizes commercial-residential mix-use, which is reflected in the full compatibility between

Table 1 Compatibility of land uses

Land use	Residential	Commercial	Industrial	Open space	Natural area
Residential	1	1	0	0.5	1
Commercial	1	1	0.2	0.3	0.4
Industrial	0	0.2	1	0.9	0.6
Open space	0.5	0.3	0.9	1	0.8
Natural area	1	0.4	0.6	0.8	1

residential use and commercial use. The relatively higher compatibility between industrial use and open space (or natural area) promotes the separation between industrial use and residential use, which would improve the living environment. The compatibility objective is calculated in a similar way to compactness' Eight-neighbor method (cf. Mohammadi et al., 2016; Zhang et al., 2016). A core cell (i, j)'s compatibility is the sum of compatibility values between the core cell and its neighbor cells, and thus the compatibility parameter b_{ijk} is given as follows:

$$b_{ijk} = \sum_{m=i-1}^{i+1} \sum_{n=j-1}^{j+1} \sum_{k'=1}^{K} u_{kk'} x_{mnk'} - 1 \tag{14}$$

where $u_{kk'}$ is the compatibility between land use types k and k'; $x_{mnk'}$ is 1 if the land use type of cell (m, n) is k'; otherwise $x_{mnk'}$ is 0.

Suitability is a multi-faceted objective, which typically involves geographical, ecological, social, and economic (i.e., conversion cost) factors in urban planning. Eindhoven can be argued that future development would not be subject to geographical constraints. The ecological, social, and economic elements in the suitability of this study are simplified as maintaining the natural area and keeping conversion between natural area and other uses within bounds. As given in Table 2, the suitability for conversion between land uses (base land use and planned land use) is 0 (easy to be converted) or -1 (difficult to be converted), the negative value of which signals the negative effects caused by the shrinkage of natural area and the expense of returning other uses to natural area. The suitability of this study can protect natural areas and limit the adjustments of land use within the other four types. The suitability parameter s_{ijk} is given as follows.

$$s_{ijk} = \sum_{k'=1}^{K} p_{kk'} x_{ijk'} \tag{15}$$

where $p_{kk'}$ is the suitability of cell (i, j) if the base land use type k is converted to land use type k'; $x_{ijk'}$ is 1 if the planned land use type of cell (i, j) is k'; otherwise $x_{ijk'}$ is 0.

Table 2 Suitability for conversion between land uses

Land use	Residential	Commercial	Industrial	Open space	Natural area
Residential	0	0	0	0	-1
Commercial	0	0	0	0	-1
Industrial	0	0	0	0	-1
Open space	0	0	0	0	-1
Natural area	-1	-1	-1	-1	0

NSGA-II for MOLUSO

LUSO, in mathematics, is a discrete combinatorial optimization problem. If there are K land use types to be allocated in a grid with R rows and C columns, the number of alternatives will be $K^{R\times C}$. The large solution space, the dependence of coefficients (e.g., the compactness parameter and the compatibility parameter), and the nonlinearity of objectives make LUSO an NP-hard (non-deterministic polynomial-time hard) problem. The techniques for multi-objective optimization mainly include global criterion method, weighted sum method, ε-constraint method and metaheuristics, the implementation of which can be divided into two stages: optimization of objective functions and trade-off decision making (Chiandussi et al., 2012). The application of the global criterion method and the weighted sum method needs preference information, and the ε-constraint method requires user-specific constraints settings (i.e., weights/ε-vector of objectives), which could turn into a non-objective exercise. Metaheuristics based methods, however, can search Pareto-optimal solutions by avoiding the discussion on preference information (or weights/ε-vector of objectives). The Pareto front, which captures the trade-offs between objectives, would provide a scientific basis for further analysis. As metaheuristics are efficient for both NP-hard problems and multi-objective optimization problems (Gogna & Tayal, 2013), the NSGA-II was used for computing the Pareto front of the MOLUSO problem in this study. The NSGA-II was developed by Deb et al. (2002), and it has already been a benchmark for multi-objective optimization methods. The NSGA-II features Pareto dominance-based multi-objective fitness evaluation, diversity maintenance, and elitism by keeping non-dominated solutions (Ishibuchi et al., 2008). As an algorithm under the framework of GAs, the basic operators of NSGA-II are also selection, crossover, and mutation.

The chromosome structure of GAs, which can be composed of either discrete or continuous variables, facilitates the representation of LUSO alternatives. For this study, a chromosome is a two-dimensional grid, and each gene denotes a grid cell. Random initialization and problem-based initialization were designed to initialize NSGA-II populations. The population generated by the problem-based initialization contains 95% random solutions and 5% solutions corresponding to the base land use pattern, and the population generated by random initialization is composed of 100% random solutions. The amount of a land use type in a random solution is constrained by Eq. (12). During the convergence to the Pareto front, according to the rank and the crowding distance, the NSGA-II selects individuals from the population through tournament selection. If solutions have different non-dominance ranks, the solution on the lower front is preferred; otherwise, if solutions are from the same front, the solution with the highest crowding distance is preferred.

Unlike the single-point or the multi-point crossover in conventional GAs, since the chromosome for MOLUSO problems is two-dimensional, the crossover used in this study operates on grid-cell patches. The crossover operation on a single grid cell, without the consideration of neighbor cells, will result in fragmented land use patterns. We herein proposed a crossover operator acting upon 3×3 cell windows. A simple example with 5×5 grid is used to illustrate the crossover operation (see Fig. 2a, the solid line with an arrow illustrates the crossover is successfully operated, while the dashed line

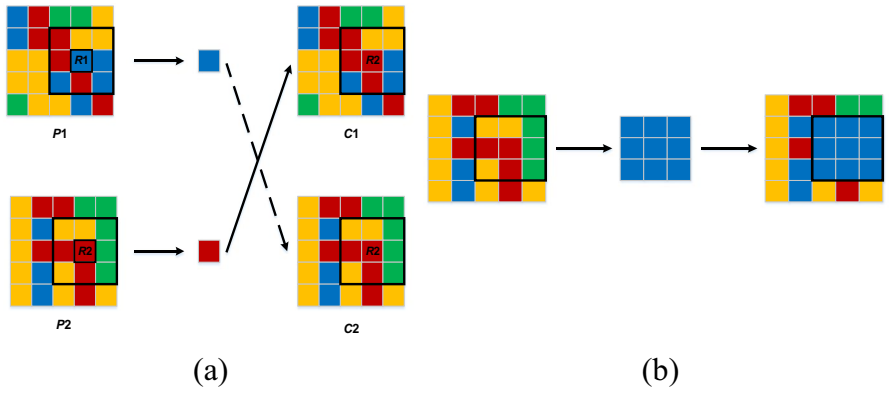

Fig. 2 NSGA-II operators: (**a**) crossover strategy for MOLUSO; (**b**) mutation strategy for MOLUSO

with an arrow means failed crossover). $P1$ and $P2$ are parent individuals selected from the population. A pair of cells from parents at the same location, e.g., $R1$ and $R2$, are chosen randomly, along with their eight neighbor cells. Among $R1$'s neighbor cells, if there is at least one cell of which the land use type is the same as $R2$'s, then $R1$ is replaced by $R2$ to generate a new offspring $C1$. Otherwise, $C1$ inherits all cells from $P1$. The operation is conducted on $P2$ as well. In one iteration of the NSGA-II, the crossover operation is executed $N_{\text{crossover}}$ (a predefined parameter) times on each pair of parent individuals.

The operation unit of mutation is also a 3×3 cell window. As illustrated in Fig. 2b, the location of a cell window is chosen at random, and the grid cells are all converted to the same land use type. After the crossover operation, the mutation operation is conducted N_{mutation} (a predefined parameter) times on each offspring individual. Given the constraints on the number of grid cells in different land use types (Eq. (12)), a second constraint-based mutation operator is designed for this NSGA-II to modify the offsprings which have been processed by crossover and mutation operations. The land use type of which the grid cells exceed the constraint is designated as excessive land use type, and the land use type of which the grid cells are less than the constraint is designated as inadequate land use type. For a chromosome, the grid cells in excessive land use types are randomly selected to be converted to inadequate land use types. For a converted cell, the new land use type is randomly selected from the set of inadequate land use types, and if the amount of a given inadequate land use type meets the quantity constraint, it will be removed from the set.

Results

Accessibility maps

The accessibility measurements with the cluster analysis and the contingency table analysis mentioned in Sect. Classifications of traffic zones followed the work of Wang

et al. (2019), which has confirmed the land use types are significantly associated with the transport characteristics clusters. Dividing the traffic zones of Eindhoven into seven clusters is adopted as the optimal clustering scheme (see Fig. 3a), informed by the *F*-statistics in Table 3. Each cluster represents specific transport characteristics, which are featured by the cluster center. The cluster center is specified by the means of driving, cycling, and walking accessibility of affiliated traffic zones (see Table 3). As mentioned in Sect. Classifications of traffic zones, another attribute of traffic zones is land use type (i.e., CTZ, RTZ, ITZ, NATZ, OSTZ, and TTZ). It can be drawn from the link between land use types and transport characteristics clusters that the allocation of a land use type favors grid cells in specific transport characteristics clusters. The proportions of a land use type in seven clusters, therefore, can be the attractiveness (i.e., accessibility fitness) of these clusters for the given land use type. In the example of residential use, 85% of RTZs are concentrated in Cluster 6 (50.7%) and cluster 7 (34.3%). Among the seven clusters, cluster 6 has the highest driving and walking accessibility, and the second-highest cycling accessibility; cluster 7 has the highest cycling accessibility, the second-highest walking accessibility, and the third-highest driving accessibility. Only 0.4% of RTZs are in cluster 1, and there is no RTZ in clusters 2 and 3, which are less accessible according to the cluster centers in Table 3. The remaining 14.6% of RTZs are in clusters 4 and 5, which are medium accessible compared to the other five clusters. Accordingly, the accessibility fitness of the seven clusters for residential use is ranked as follows: cluster 6 (0.507), cluster 7 (0.343), cluster 4 (0.085), cluster 5 (0.061), cluster 1 (0.004), cluster 2 (0.0) and cluster 3 (0.0). The accessibility maps for commercial, residential, industrial, open space, and natural area are shown in Figs. 3b, c, d, e, and f, respectively. The road networks hold constant in this study, and the accessibility fitness of transport land has no significance.

The accessibility maps quantify and visualize the variances in accessibility fitness across Eindhoven. The map legend displays the colours followed by the proportions of a land use type in seven clusters, i.e., the accessibility fitness of the clusters in parentheses for a given land use type. By performing spatial joins in QGIS, when a land use type is assigned to a grid cell, the accessibility fitness of this grid cell can be retrieved from the corresponding accessibility map. In addition to LUSO modelling, the accessibility maps can serve policy-making as a decision support tool. Land use policy strategies, as compared to the heavy investment required in transport infrastructure construction, can bring larger accessibility benefits (Geurs et al., 2010). The discussion on which scenario, e.g., either compact or extensive development, should be adopted with existing road networks provides an example of the potential of accessibility maps for land use policy issues. With existing road networks, the compact development strategy is better when areas with high accessibility fitness for residential, commercial, and industrial uses are spatially concentrated, while a scattered spread of highly accessible areas can better support the implementation of extensive development strategy. Furthermore, the accessibility fitness and the accessibility maps enable the proposal of location policies, which are similar to the Dutch ABC policy. The ABC policy specifies the location of premises for businesses and services. The philosophy of the ABC policy is "the right business at the right place" (Dieperink & Driessen, 2000). We referred to the ABC policy and formulated an inspiring location policy correspondingly, called the HML policy, which

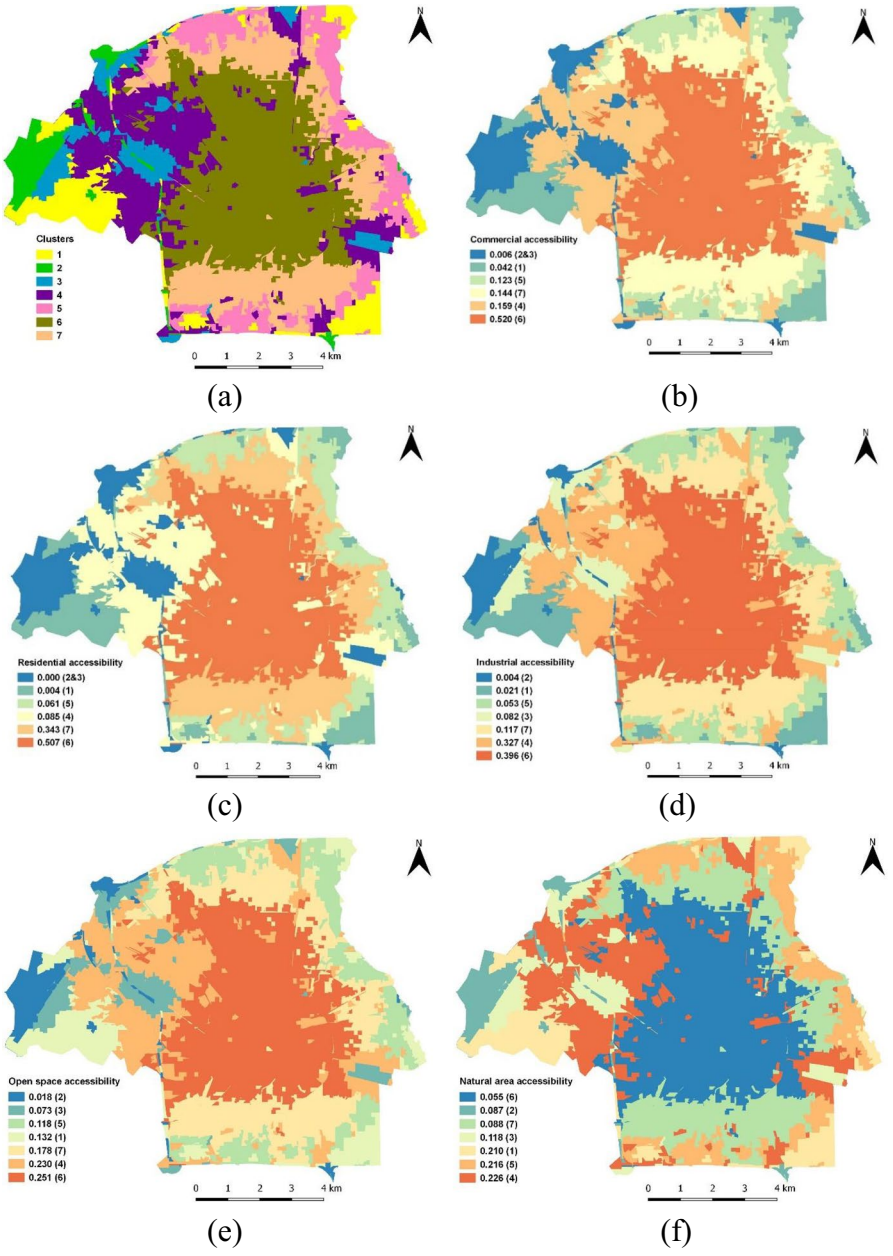

Fig. 3 Transport characteristics clusters and accessibility maps: (**a**) seven transport characteristics clusters; (**b**) commercial accessibility map; (**c**) residential accessibility map; (**d**) industrial accessibility map; (**e**) open space accessibility map; (**f**) natural area accessibility map

Table 3 Cluster centers

Variable	Cluster center							
	1	2	3	4	5	6	7	*F*-statistics
Walking accessibility*	0.3107	-0.5036	-2.0213	0.0518	0.6778	0.7448	0.7398	1780.757
Cycling accessibility*	-0.0760	-1.7384	-0.8900	0.1805	0.7406	0.8254	0.9579	2714.913
Driving accessibility*	-0.8932	-1.6307	0.1395	0.7024	-0.1799	1.2945	0.5674	2164.691

*The accessibility values have been normalized to zero mean and unit variance

aims at having the right land use type at the right place. In the case of Eindhoven, locations can be distinguished by transport characteristics clusters. In the HML policy, the less accessible clusters 1, 2 and 3 are categorized as type L; the medium accessible clusters 4 and 5 are categorized as type M; the highly accessible clusters 6 and 7 are categorized as type H. The goal of the proposed HML location policy is to co-ordinate transport characteristics and land use types. A city-level system of fines and subsidies, e.g., an earmarked fund, can be introduced to facilitate the allocation of commercial and residential uses to type H, the allocation of industrial use and open space to type M, and the allocation of natural area to type L.

Impact of accessibility on land use patterns

A control experiment, the results of which were analyzed with backward reasoning, was conducted to prove the role of road networks in the formation of the base land use pattern and justify the accessibility fitness being factored into MOLUSO. The MOLUSO of Group A (control group) aims at maximizing compactness (Eq. (8)), compatibility (Eq. (9)), and suitability (Eq. (10)). In Group B (experimental group), in addition to the three objectives of Group A, maximizing accessibility fitness (Eq. (7)) is added as the fourth objective. As mentioned in Sect. MOLUSO modelling, Eindhoven consists of 5,451 130 m × 130 m grid cells. The attribute of land use type, provided by BBG2012, can be joined to grid cells through the "Join Attributes by Location" tool of QGIS. 886 grid cells which contain transport land in the base land use pattern are handled as restricted areas. Excluding restricted area, similar to the classification of traffic zones by land use types, grid cells can be divided into residential grid cell (RGC), commercial grid cell (CGC), industrial grid cell (IGC), open space grid cell (OSGC) and natural area grid cell (NAGC). The number of RGCs, CGCs, IGCs, OSGCs, and NAGCs in the base land use pattern is 1588, 307, 464, 785, and 1421, which corresponds to the Q_k in Eq. (12), respectively.

The NSGA-II introduced in Sect. NSGA-II for MOLUSO is applicable to both Group A and Group B, and it was implemented in programming language Python on the Windows platform. The size of the initial population is 300, which balances computation cost and convergence ability. The NSGA-II for Group A and Group B was executed for 800 generations, respectively. Through extensive attempts, the execution number of crossover was set to 2000, and the execution number of mutation was set to 30. The difference between a non-dominated solution and the base land use pattern is measured by difference index (DI). DI is the number of grid cells whose land use type in the non-dominated solution is different from the base land use pattern. In the solution space of the four-objective optimization model, there are several convergence points where the performances of solutions are similar, but the spatial patterns are quite different. An initial population containing the base land use pattern can lead the convergence process to the solution space surrounding the base land use pattern. To avoid the impact of the base land use pattern on the optimization, Group A and Group B were initialized randomly (random initialization) to highlight the role of accessibility fitness, which may generate large DI within limited generations. The average DIs of Group A and Group B (see Table 4)

indicate that the solutions of Group B are closer to the base land use pattern than the solutions of Group A, from which it can be inferred that MOLUSO considering the accessibility fitness is more closely aligned with the urban development processes of Eindhoven. The transport logic in the long processes of urban development is embodied in accessibility maps. The role of transport-related knowledge in LUSO can be strengthened as the accessibility fitness objective.

Land use plan 2022

To demonstrate how the MOLUSO model and the NSGA-II based solution method can be used as a powerful tool for planning decision support, a land use plan for 2022 is designed. The population and the growth rate of Eindhoven from 2007 to 2017 are listed in Table 5. The population trend from 2017 to 2022 was estimated by time series analysis. It is predicted that the population of Eindhoven will increase by 8.27% from 2012 to 2022. The areas of residential, commercial, and industrial land are assumed to increase by 8% in plan 2022 accordingly, i.e., the number of RGCs, CGCs and IGCs will increase by 127, 25, and 37, respectively, as compared to 2012. Among the 189 newly developed grid cells, it is assumed that 70% of them are transformed from OSGCs, and the other 30% of them are transformed from NAGCs. The quantity constraints of plan 2022 are 1715, 332, 501, 653, 1364 for RGC, CGC, IGC, OSGC, and NAGC, respectively.

The initialization of the optimization method has a significant impact on the final solutions. The base land use pattern rises in the long-term urban development processes, which could be explained by a combination of urban development history, physical geography constraints, and land use zoning regulations. The initial population with the base land use pattern would make the optimization converge to the solution space surrounding the base land use pattern. To maintain population diversity while following the urban development trajectory, the initial population of plan 2022 (generated by the problem-based initialization) is composed of two parts: 95% individuals are randomly-generated land use patterns and 5% of them are the base land use pattern. The setting of the other parameters of NSGA-II is the same as Sect. Impact of accessibility on land use patterns. The achieved first front contains 316 alternatives (the filled circles in Fig. 4). The average compactness, compatibility, suitability, and accessibility fitness of Pareto optimal solutions are 24,670.04, 29,813.16, -335.28 and 1,448.94 (see the triangle in Fig. 4), respectively. Compared to the base land use pattern of which the compactness, the compatibility, and the accessibility fitness are 23,060.00, 28,726.40 and 1,320.83 (see the square in Fig. 4), the three objectives of the achieved alternatives in the first front

Table 4 Comparison of DIs of Group A and Group B

	Average DI	Number of solutions
Group A	2527.66	122
Group B	2290.40	324

Table 5 Population and growth rates of Eindhoven from 2007 to 2017

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Population	209,699	210,333	212,269	213,809	216,036	217,225	218,433	220,920	223,209	224,755	226,868
Growth rate (%)	–	0.30	0.92	0.73	1.04	0.55	0.56	1.14	1.04	0.69	0.94

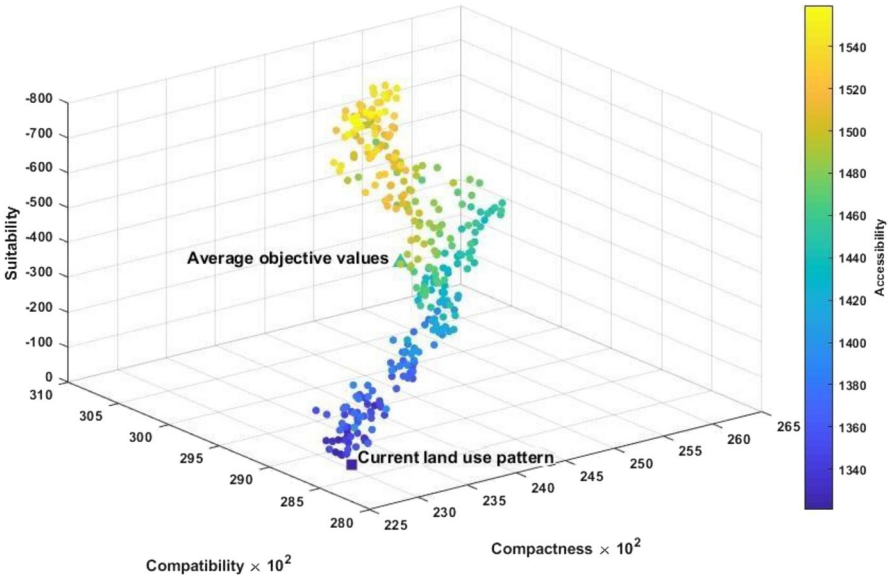

Fig. 4 Alternatives in the first front of plan 2022

have all improved. With the definition of suitability in this study, negative suitability indicates the conversion between NAGCs and other grid cells (i.e., RGCs, CGCs, IGCs, and OSGCs). For the case of Eindhoven, compactness, compatibility, and accessibility fitness are positively correlated with each other, while suitability has negative correlations with the other three objectives (as shown in Fig. 5), which suggests the improvements of compactness, compatibility, and accessibility fitness are at the expense of suitability. We mapped four representative alternatives: A1 with the maximum compactness (Fig. 6a), A2 with the maximum compatibility (Fig. 6b), A3 with the maximum suitability (Fig. 6c) and A4 with the maximum accessibility fitness (Fig. 6d). It is clear from the comparison between Fig. 6 and Fig. 1 that these alternatives are modifications of the base land use pattern. The compactness of A1, the compatibility of A2, and the accessibility fitness of A4 increase by 13.41%, 7.02%, and 18.07%, respectively, as compared to the base land use pattern. A3 is the alternative with the minimal alternation (the suitability is -57).

In the maximum accessibility fitness alternative (Fig. 6d), District 1 (D1) and District 2 (D2) give an illustration of the possible land use conversion. From the perspective of maximizing accessibility fitness, the CGCs with substandard accessibility in the base land use pattern in District 1 (the corresponding area in Fig. 3a is in Cluster 1) are relocated, and this district is reset to open space and natural area (see Fig. 6d), which are less demanding on transport. The OSGCs with high accessibility in the base land use pattern in District 2 (the corresponding area in Fig. 3a is in cluster 6) are developed as residential uses (see Fig. 6d) to meet the needs of 2022.

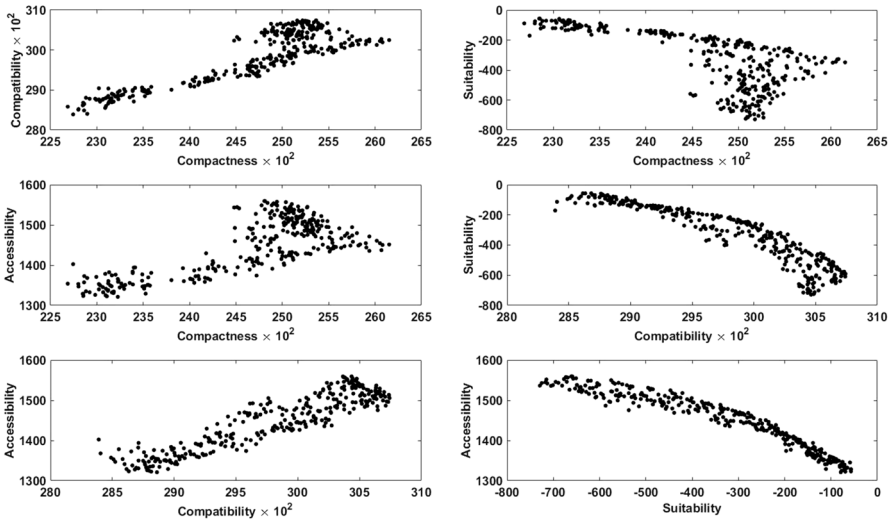

Fig. 5 Relationships among the four objectives

Conclusions and Discussion

This study developed a prototype DSS, the core modules of which are a MOLUSO model, an NSGA-II based solution algorithm, and accessibility maps. The MOLUSO model, besides the well-established maximizing compactness, compatibility, and suitability, incorporates maximizing accessibility fitness as an objective, which fills the gap in transport considerations of LUSO studies. The multiplicity of concerns involved in land use planning necessitates multi-objective optimization modelling, which can offer decision-makers (e.g., urban planners or managers) a set of alternatives for further analysis. The NSGA-II based solution algorithm, which can generate solutions to approximate the Pareto front, brings additional flexibility to the DSS. Any objective deserving to be managed in land use planning can be expediently added to the MOLUSO model, without worrying about the preferences of decision-makers and the weights of objectives. The Pareto optimal solutions provide decision-makers with a panorama of the trade-offs among objectives and therefore leave ample space for them to make the decision.

This study used driving accessibility, cycling accessibility, and walking accessibility to identify and quantify the transport characteristics of a location. The relationship between land use types and accessibility bridges land use and transport systems, based on which accessibility maps are developed and maximizing accessibility fitness is proposed. With the knowledge that a higher proportion of a land use type in a cluster means that the transport characteristics of the cluster better satisfy the requirements of the given land use type, the accessibility maps presented in Sect. Accessibility maps reflect and crystallize the transport logic underlying urban development processes. In addition to the role in MOLUSO modelling, accessibility fitness and accessibility maps can address policy issues, e.g., the discussion on

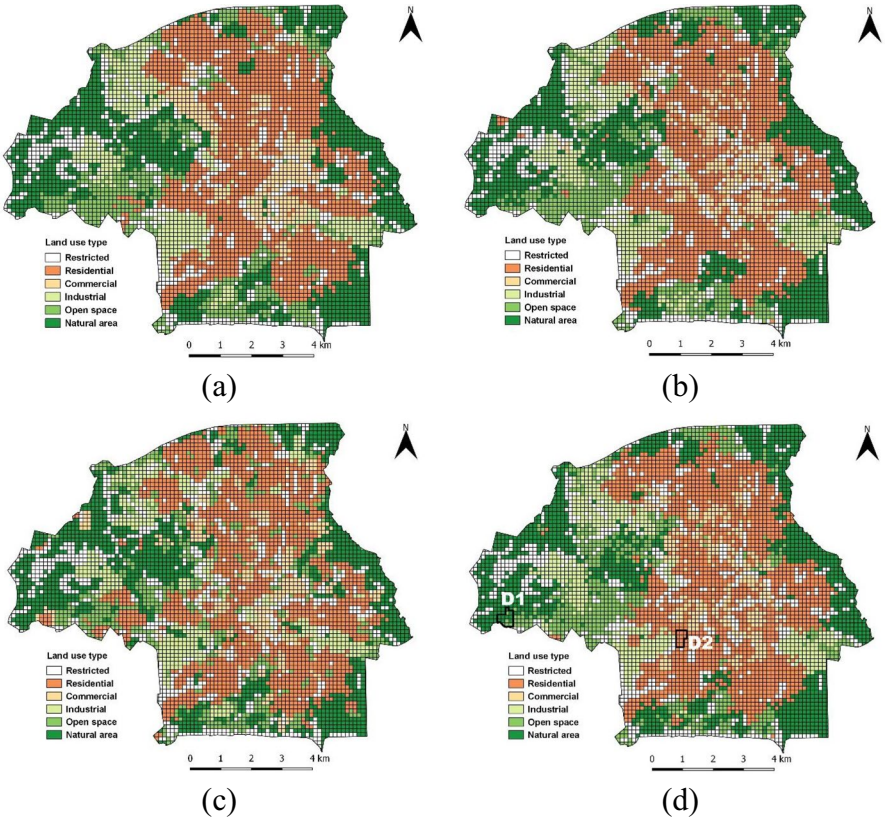

Fig. 6 Optimization results: (**a**) maximum compactness alternative; (**b**) maximum compatibility alternative; (**c**) maximum suitability alternative; (**d**) maximum accessibility fitness alternative

compact or extensive development and the HML policy. The appropriate accessibility values for different land use types are not measured in absolute terms but vary in cities and spatial scales. However, the procedure of creating accessibility maps, together with the established MOLUSO model and the NSGA-II based solution method, can be extended to other cities.

The accessibility maps, as the substratum to the integration of land use and transport in MOLUSO, are obtained from empirical analysis. As the planning profession lacks a normative answer to what the appropriate criteria for determining "good plans" are (Baer, 1997), it merits consideration whether lessons gained from previous stages of urban development can serve optimization with a view to the future. There is a paradox of modern planning thinking – the tensions between top-down plan-making and bottom-up organic development (Batty & Marshall, 2017). No matter whose disciple you are, the interaction between land use and transport does exist. However, land use change and transport infrastructure construction are slow and long-lasting in today's highly developed economies (Simmonds et al., 2013), which allows for the quasi-equilibrium representation of road networks and land use patterns. The LUSO approach of

this study builds on empirical results and thus applies to urban renewal and upgrading rather than new town planning. Significant changes to the land use pattern, such as centralized substantial residential development in a natural area, which is bound to have ripple effects on transport systems, are beyond the scope of this study. The optimization schemes of this study (as presented in Sect. Land use plan 2022) follow Patrick Geddes' notion of "conservative surgery", which advocates minimal demolition and widespread rehabilitation of existing structures (Bromley, 2017). "Conservative surgery" is particularly necessary for cities with a rich cultural heritage. In the context of "conservative surgery", the findings from the cross-sectional analysis of the relationship between land use types and transport characteristics are applicable to limited adjustments of land use status quo.

As mentioned in Sect. MOLUSO modelling, given the features of the study area (Eindhoven), we made some simplifications to the suitability evaluation. However, land use suitability analysis is an important fundamental and also a labor-intensive work for land use planning, which needs to consider a wide range of criteria, including physical, geological, ecological and socio-economic factors. When the MOLUSO model is applied to other cities, the land use suitability analysis is supposed to be conducted, in accordance with the features of the study area and the assessment needs for planning. Because of the small-scale geography of the study area, Eindhoven, this study does not address the issue of jobs-housing balance, and mixed land use is not regarded as an objective for LUSO modelling, which could be considered in further research. Furthermore, in order to improve the applicability of the proposed MOLUSO approach, more efficient solution methods with faster speed require continued attention. An increase in problem size often leads to an exponential growth in the Pareto front of a multi-objective optimization problem (Horoba & Neumann, 2010). Smart evolution strategy design is necessary for powerful global and local search abilities in evolutionary multi-objective optimization.

Declarations of interest None.

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