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An interactive dynamic multi-objective programming model to support better land use planning

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Abstract

This study develops a dynamic multi-objective programming (DMOP) approach to handle problems of optimization under conditions of uncertainty typified by multiple goals and dynamic subsystems. The proposed approach seamlessly integrates multi-objective programming, fuzzy set theory, and system dynamics tools to conduct optimal land use planning in dynamic and complex environmental systems. Based on the DMOP approach, this study constructs an interactive dynamic multi-objective programming model, investigates the connection between land use and future urban development, and incorporates the preferences of decision makers using a compromise index. A case study from Taiwan shows that the proposed modeling framework can accommodate more complete information, allowing improvements to be made in strategic planning for land use.

Keywords: Land use ~~p~~planning; Multi-objective programming; Fuzzy set theory; System dynamics

Introduction

Land use planning requires the consideration of multiple objectives, including environmental, ecological, economic, social, and other factors. Climate change, rapid economic development, changing social needs, and land use diversity have led to rapid changes in land use patterns and space requirements. Objective trade-offs are inevitable in appropriately allocating land resources, and stakeholders' participation in the planning process is important. Traditional multi-objective programming (MOP) effectively solves the issues of objective trade-offs and the preferences of decision makers in land use planning. For example, previous land resource planning studies, including those of ~~G~~Gibert et al. (1985), Diamond and Wright (1989), Chang et al. (1995), Seppelt and Voinov (2003), and Stewart et al. (2004), used mathematical programming to analyze the connection between objectives and find the optimal solution based on the given conditions as well as decision makers' requirements. However, without conducting simulations, decision makers cannot evaluate the dynamic effects of their plans, which is important in the land use planning process because zoning decisions are neither entirely reversible nor cheap to adjust yearly. Meanwhile, if model parameters are not adjusted based on environmental changes, the system may generate an inappropriate solution that does not maximize the value of the land usage. The traditional system dynamics (SD) approach, which analyzes system structure and developmental patterns based on system simulations, is gradually being implemented in urban development studies, such as those of Costanza et al. (1990), Francisco et al. (1993), Matthias and Frederick (1994), de Kok and Wind (1996), Gulen and Lale (1996), Cavallaro and Ciraolo (2002), Elrefaie and Herrmann (2003), Chen et al. (2005), Bald et al. (2006), and Chang et al. (2008). However, decision makers can usually only select from among a predefined set of scenarios that have been developed either based on the experience of the system builder or through trial and error. In addition, high-leverage solutions, which represent small, well-focused actions in the right place, can produce significant, enduring improvements in a system dynamics model (Senge, 1990). However, these may not be optimal solutions. Although both types of traditional tools have some drawbacks, a hybrid optimization/simulation model maximizes the advantages of both approaches and avoids their deficiencies. Compared to the MOP model, the proposed dynamic multi-objective programming (DMOP) approach provides optimal solutions that incorporate the development of the urban system over time. This modeling approach also improves the efficiency of policy analysis and design for the SD model.

In this paper, we address the shortcomings of traditional urban planning methods, including optimization and simulation. To satisfy the requirements for decision-makers in urban spatial planning, we propose a new approach that handles problems of optimization under conditions of uncertainty. The proposed DMOP approach is capable of dealing with the increased complexity of spatial planning for dynamic urban environments and provides decision support tools for participants. Specifically, an interactive dynamic multi-objective programming (IDMOP) model is developed to derive compromised land use scenarios that balance the conflicting objectives of various stakeholders while reflecting the dynamic changes in the system produced by spatial planning solutions. The case study from the Cijin Island in Taiwan is also included to illustrate the implementation of the dynamic-optimized methodology in a general way. The remainder of this paper is organized as follows. ~~S~~Methodology section describes the methodology and the evolution of the new approach to decision support for dynamic optimization problems. The verification of the approach and an empirical case study are discussed in ~~S~~model application and land use scenarios analysis section. Finally, results section describes the implications of this case study and is followed by overall conclusions in ~~S~~conclusions section.

Methodology

Dynamic multi-objective programming approach

Strategic assessment refers to proposed planning performed to achieve a future development. The projected system states of the planning period form the initial basis for the model parameters of the assessment methods. In dynamic systems, however, a strategic plan changes system states. These variations influence the assessment model parameters, which, in turn, generate different strategic plans. Therefore, it is only when system states and model parameters reach stability in a dynamic environment that an optimal strategic assessment can be obtained. Fig~~F~~. 1 illustrates this dynamic strategic assessment process.

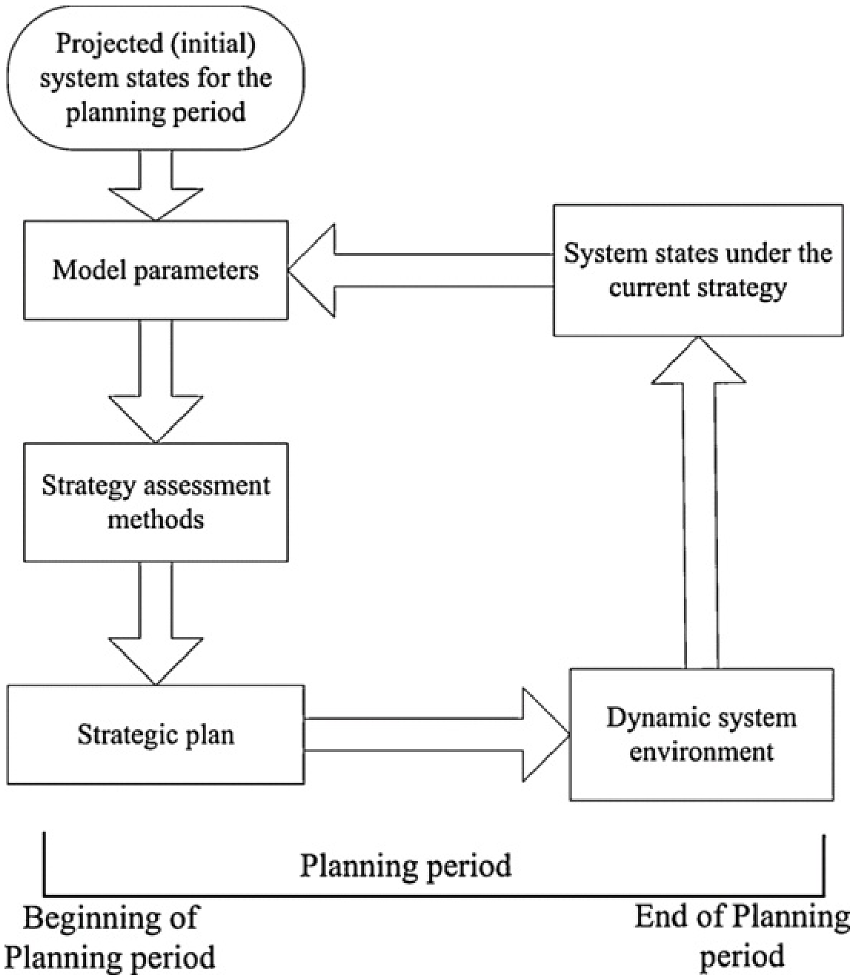


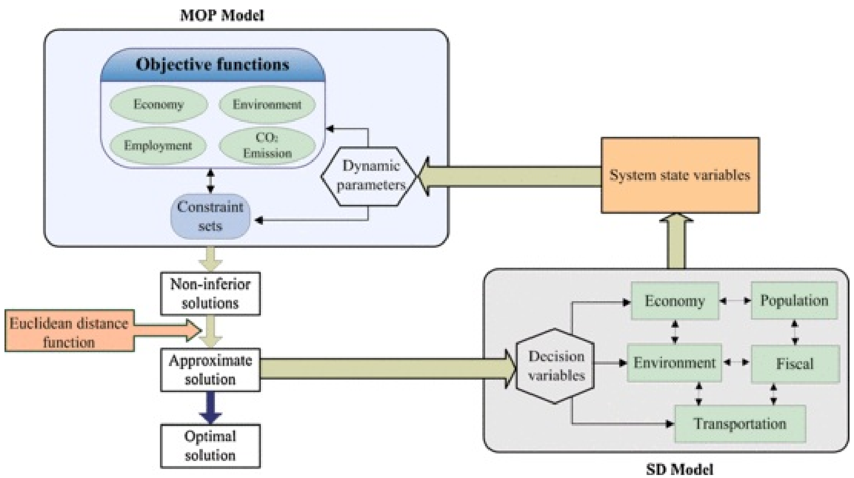
Fig. 1 Optimal dynamic strategic assessment process.

At a fixed time point, traditional optimization problems with multiple objectives derive optimal plans for multi-objective decision making and problem evaluation. In real life, however, many optimization problems are connected to time factors. Objective functions are influenced by dynamic changes within the system. As a result, the optimal solution changes dynamically with time. Such problems are called dynamic optimization problems (DOPs). DOPs include both dynamic single-objective and multi-objective optimization problems. The key to solving DOPs is the automatic updating of objective functions, constraints, and related parameters in the search for an optimal solution based on environmental changes.

Many parameters in an objective function are dynamically uncertain in real life. Variability is intricately connected to time and previous solutions adopted by decision makers. In other words, the choice of different plans at an earlier stage changes the factors within the system over time, which inevitably influences the model parameters. When model parameters change over time, the optimal solution derived from past parameters may no longer be the optimal solution and a new optimal solution must be generated using parameters that have been adjusted to reflect such changes.

The DMOP approach is a hybrid optimization/simulation approach and addresses dynamic multi-objective optimization problems, which are dynamically uncertain by nature, by formulating an integrated modeling framework that consists of the system dynamics model (SD model) and the multi-objective programming model (MOP model). The land use planning MOP model was formulated according to the principle of sustainability, which strives to balance the issues of environmental protection, economic development, and social justice. The SD model simulates dynamic changes in urban development by synthesizing the interaction of key factors, such as population variation, environmental pollution, economic development, transportation, and the government's financial position.

The proposed land use MOP model can derive several non-inferior solution sets for the system dynamic model. Based on the derived land use scenario, the SD model for urban development was used to simulate the interaction between critical factors in the urban system (e.g., land use area, population, number of industries). The results of the SD simulation provide insight into the effectiveness and drawbacks of the designated land use planning from the MOP model. At the end of the SD simulation, the predicted values of the system state variables are derived by simulating dynamic changes in the environment. After converting the simulated system state variables into the dynamic parameters, which are used to modify the corresponding parameters in the MOP model, updated non-inferior solutions are derived. Among the set of updated solutions, the solution with the shortest Euclidean distance from the previous scenario is selected as an approximate solution. The SD model based on the new decision variables is applied again to acquire revised system state variables. In comparing the revised system state variables with the previous set, if the variations in the simulated system state variables are acceptable to decision makers, the most appropriate solutions in this dynamic environment can be obtained. The integration of SD and MOP models in the proposed DMOP framework articulates the connections between static land use planning and dynamic urban development. As a result, the DMOP approach achieves the optimal urban land use planning strategy for a dynamic environment. Fig~~F~~. 2 shows a schematic diagram of the DMOP framework and describes the process of finding an optimal solution.

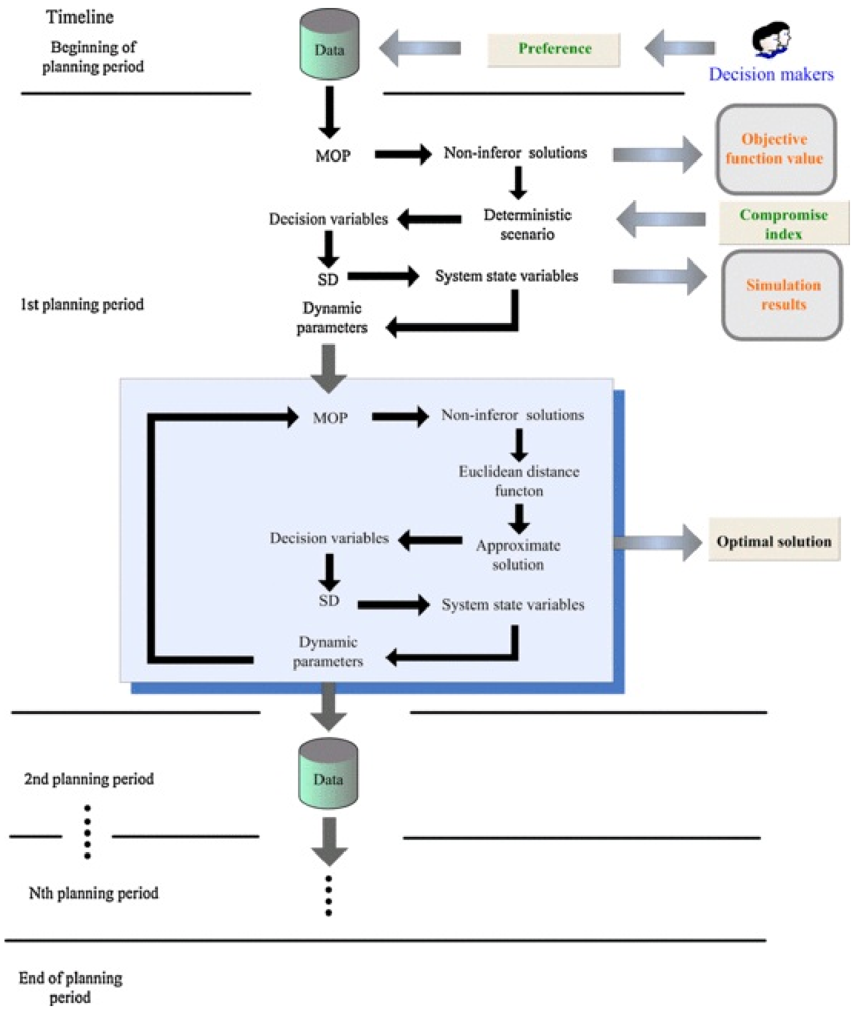


Fig~~F~~. 2 Schematic diagram of dynamic multi-objective programming (DMOP) approach.

Interactive ~~D~~dynamic multi-objective programming model

To establish an interactive channel between analysts and decision makers, the IDMOP model integrates the two using an interactive computer-aided system, which allows decision makers to input their preferences as well as receive simulation results. A unique feature of the IDMOP model is that it does not generate multi-objective solutions from the viewpoint of the analyst. Instead, the IDMOP model incorporates fuzzy set theory and compromise indices to establish a multi-objective compromise model that enables decision makers to choose a deterministic scenario based on desirable trade-offs between multiple objectives.

Fig~~F~~. 3 illustrates the operational flow of the IDMOP model for land use planning. In each period, the SD model takes the output (decision variables) of the MOP model as its parameters, and the output (dynamic parameters) from the SD simulation are used to modify the MOP model. This process incorporates decision makers' preferences by allowing decision makers to assign a compromise index α' to find a compromise policy for land use that satisfies their preferences for each objective. Once the IDMOP model in one period is terminated, an optimal land use strategy based on the decision makers' preferences can therefore be obtained and the simulated results of the optimal solution can be used as the initial conditions for the upcoming period. The number of periods required for long-term planning depends on the characteristics of the planning scheme. The interactive system can therefore apply to either short-term or long-term land use planning when considering multiple objectives and the dynamic nature of the system.



FigF. 3 Operational flow of the interactive dynamic multi-objective programming (IDMOP) model.

Formulation of land use MOP model

To achieve the goal of sustainable urban development, a city planner should strike a balance among the key factors of sustainable development and conduct reasonable and effective urban planning through scientific methods. The four objective functions of the proposed land use MOP model are to maximize economic development, minimize environmental pollution, maximize employment opportunities, and minimize carbon dioxide (CO_2) emissions.

(1) Maximizing economic development The output values generated through industrial activities are a region's main source of economic development. The land use pattern associated with an industry type and its land use area determine the output values of an industry, and summing up the output values of a region's land use patterns yields its total industrial output value. Higher levels of total industrial output value indicate better economic development in a region. The objective function is described as

$$MinZ_1 = -\sum_{j=1}^{n}(V_j \times X_j) \quad \text{or} \quad MaxZ_1 = \sum_{j=1}^{n}(V_j \times X_j)$$

where Z_1 is the total annual output value (TWD/year~~)~~). V_j is the annual industrial output value per hectare (TWD/year-ha) for the jth land use pattern ~~;~~and X_j is the land use area (ha) of the jth land use pattern, j = 1, 2, ..., n~~;~~.

(2) Minimizing environmental pollution Maintaining good environmental quality is the primary goal of environmental protection. Pollution in aquatic environments is a good indicator of the integrity of environmental quality. In particular, the BOD_5 (~~(~~biochemical oxygen demand, five days) is a water quality index commonly used to assess the pollution levels of organic matter in water. Higher BOD_5 indicates more organic matter in an aquatic environment and, therefore, more severe environmental pollution. This study simplifies the scale of the model by designating BOD_5 as an urban environmental pollution indicator. The point and non-point source pollution combined determine a region's total BOD_5 pollution output. The objective function is described as

$$MinZ_2 = \sum_{j=1}^{n}(P_j \times X_j) + \sum_{i=1}^{m}(Q_i \times W_i)$$

where Z_2 is the total BOD_5 pollution output (kg/year~~)~~). P_j is the annual non-point source BOD_5 pollution output per hectare (kg/~~y~~year ha) for the jth land use pattern~~;~~. Q_i is the annual point source BOD_5 pollution output (kg/year) for the ith point source, i = 1, 2, ..., m ~~m~~and W_i is the amount of the ith point source (e.g., population, companies, and factories), i = 1, 2, ..., m~~m~~.

(3) Maximizing employment opportunities Unemployment directly affects the welfare of a family and causes social problems that affect the entire community. Therefore, it is crucial to provide sufficient jobs to sustain welfare and social security. Stronger industrial activities usually bring more job opportunities to a region. Thus, the land use pattern associated with an industry type and its land use area determine the number of employees. The total number of employees represents the employees of all industries. A higher total number of employees indicate ~~t~~better employment opportunities. The objective function is described as

$$MinZ_3 = -\sum_{j=1}^{n}(O_j \times X_j) \quad \text{or} \quad MaxZ_3 = \sum_{j=1}^{n}(O_j \times X_j)$$

where Z_3 is the total number of employees (people) ~~;~~and O_j is the number of employees per hectare (people/ha) for the jth land use pattern~~;~~.

(4) Minimizing carbon dioxide emissions The heavy use of coal, petroleum, and other fossil fuels in human economic development has significantly increased the greenhouse effect and led to global warming and climate change. For example, a rise in the sea level poses a critical threat to daily life, economic production, and ecology in coastal zones. Reducing greenhouse gas emissions has become an international goal and an important issue in sustainable urban development. Carbon dioxide is currently the most pervasive greenhouse gas and an important internationally target for significant reduction. The amount of carbon dioxide emissions is decided by a land use pattern and its land use area. The objective function is described as

$$MinZ_4 = \sum_{j=1}^{n}(E_j \times X_j)$$

where Z_4 is the total CO_2 emissions ~~(~~(10,000 tons) and E_j is the CO_2 emissions per hectare ~~(~~(10,000 tons/ha) for the jth land use pattern~~;~~.

The other part of MOP modeling formulates a constraint set to fulfill certain basic requirements. In real life situations, urban land use planning must conform to relevant regulations and consider practical restrictions. For simplicity, the MOP model in this study only considers two restrictions: the total area of the urban region, and various limitations in terms of land use patterns.

(1) ~~-~~Total area of the urban region The summation of the areas for all land use patterns in the study region should be equal to the total urban area:

$$\sum_{j=1}^{n} X_j = T$$

where ~~T~~T is the total urban area (ha~~)~~).

(2) Upper and lower bounds on the areas of the various land use patterns Upper and lower bounds on the areas of the various land use patterns were stipulated based on urban development needs and related land use regulations.

$$X_j \le U_j$$
$$X_j \ge L_j$$

where ~~U~~U_j is the upper bound on the area (ha) for the jth land use pattern, j = 1, 2, ..., n ~~n~~and L_j is the lower bound on the area (ha) for the jth land use pattern, j = 1, 2, ..., n~~n~~.

Following Wu and Guu (2001), this study adopts the following procedures to accommodate the compromise indices in the MOP model. The transformation of the multiple objective functions into compromise indices involves fuzzy set theory and decision makers' preferences can be easily adjusted using these indices. The following points describe this process (Chiou ~~&~~and Wu, 2006):

(1) Establish linear membership functions Multi-objective functions encounter conflicts and do not use standardized measurement units. To address this issue, this study employs the membership functions in fuzzy set theory, which need to calculate the possible range [Z_i^l, Z_i^u] of each objective function ~~Z~~$Z_i(x)$ in advance. Using Werners' (1987) method, the lower bound Z_i^l ~~Z~~and the upper bound Z_i^u of the objective function are obtained as follows:

$$\begin{cases} Z_i^l = \min Z_i(x) \\ s.t.\ \boldsymbol{Ax} \le \boldsymbol{b} \\ x \ge 0 \end{cases} \qquad \begin{cases} Z_i^u = \max Z_i(x) \\ s.t.\ \boldsymbol{Ax} \le \boldsymbol{b} \\ x \ge 0 \end{cases}$$

where $\boldsymbol{A}$ is the coefficient matrix in the constraint set ~~s~~and $\boldsymbol{b}$ is the right-hand vector in the constraint sets~~s~~. The objective functions Z_2 and Z_4 minimize pollutant discharge and CO_2 emissions. Therefore, the satisfaction levels of these two objective functions, in terms of fuzzy membership function, should be expressed as decreasing linear functions. The membership functions of Z_2 and Z_4 are defined as follows:

$$\mu_i = \frac{Z_i^u - Z_i(\boldsymbol{x})}{Z_i^u - Z_i^l}$$

The objective functions Z_1 and Z_3 maximize economic development and employment opportunities. Therefore, the satisfaction levels of these two objective functions, in terms of fuzzy membership function, should be expressed as increasing linear functions. The membership functions of Z_1 and Z_3 are defined as follows:

$$\mu_i = \frac{Z_i(x) - Z_i^l}{Z_i^u - Z_i^l}$$

(2) ~~(~~Using the min operator method After deriving the membership functions, the min operator method converts the original MOP model into a single objective linear programming model, as Program (1) shows~~:~~.

$$\begin{aligned} &Max\ \alpha \\ &\text{s.t. } \alpha \le \mu_i \forall i \\ &\boldsymbol{Ax} \le \boldsymbol{b} \\ &\alpha \in [0, 1], \quad \boldsymbol{x} \ge 0 \end{aligned} \tag{1}$$

Solving Model (1) derives the optimal solution x^* and the optimal objective function value α^*. The term α^* refers to the maximum least satisfaction level for all objective functions in the original MOP because it simultaneously satisfies all membership functions.

(3) ~~-~~Using the average operator method If the objective functions are equally important, the original MOP model should be converted into an average operator model, as Program (2) shows~~:~~.

$$\begin{aligned} &Max\alpha^{\#} = \frac{1}{n}\sum_{i=1}^{n}\alpha_i \\ &\text{s.t. } \alpha_i \le \mu_i \forall i \\ &\boldsymbol{Ax} \le \boldsymbol{b} \\ &\alpha_i \in [0, 1], \boldsymbol{x} \ge 0 \end{aligned} \tag{2}$$

Model (2) derives the optimal objective function value ~~α~~$\alpha^{\#}$, which refers to the average satisfaction level of the membership functions.

(4) ~~-~~Two-phase approach The two-phase approach combines the min operator and the average operator models. The min operator in Program 1 obtains the optimal objective function value α^* in the phase I. Phase II model is then formulated, as Program (3) shows, using the average operator model associated with the α^*. The optimal solution acquired by the two-phase approach is fuzzy-efficient (Werners, 1987, 1988). The optimal objective function value $\tilde{\alpha}$ ~~α~~is certainly not less than the satisfaction level ~~α~~α^*.

1 n

$$
\begin{aligned}
&Max\tilde{\alpha} = \frac{1}{n}\sum_{i=1}\alpha_i \\
&\text{s.t. } \alpha_i \leq \mu_i \forall i \\
&\alpha^* \leq \alpha_i \forall i \\
&Ax \leq b \\
&\alpha_i \in [0, 1], x \geq 0
\end{aligned} \tag{3}
$$

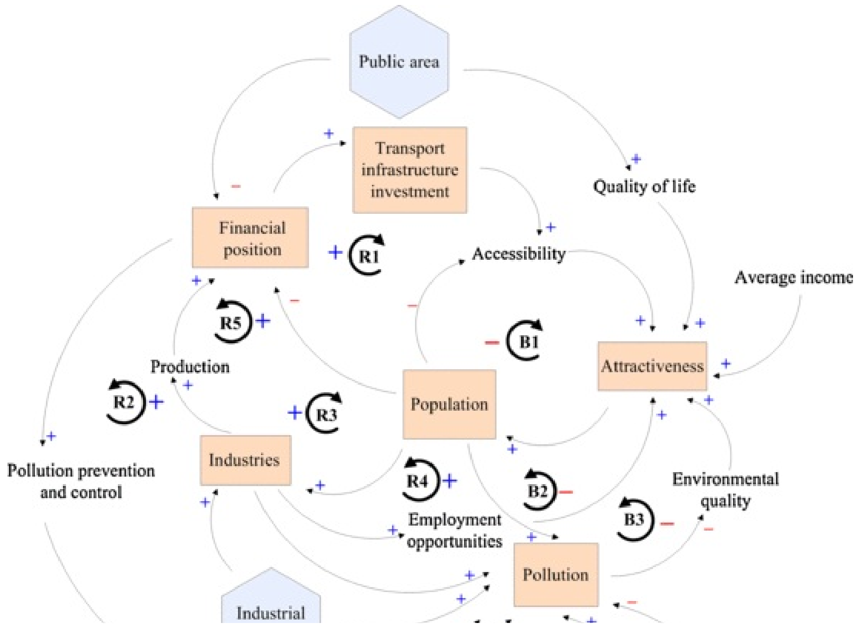
(5) Multi-objective programming compromise model The multi-objective programming compromise model is similar to the two-phase approach, as Program (4) shows, except that decision makers can assign their own satisfaction preference α'.

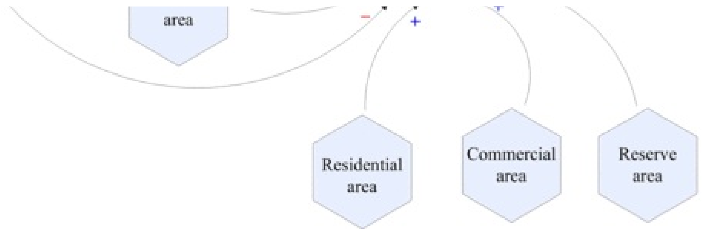
$$
\begin{aligned}
&Max\tilde{\alpha} = \frac{1}{n}\sum_{i=1}^{n}\alpha_i \\
&\text{s.t. } \alpha_i \leq \mu_i \forall i \\
&\alpha' \leq \alpha_i \forall i \\
&\boldsymbol{Ax} \leq \boldsymbol{b} \\
&\alpha_i \in [0, 1], x \geq 0
\end{aligned} \tag{4}
$$

The value of α' ranges between α^*, which was derived through the min operator, and the minimum membership function μ_i, which was derived through the average operator. Decision makers can adjust the value of α' within the designated range to obtain the corresponding compromise solution.

Urban development system dynamic model

The system dynamic model for urban development proposed in this study simulates the interaction between urban development and land use planning. There are five major aspects in the system: population, economy, environment, government finance, and transportation in an urban region. Fig. 4 shows a schematic diagram of the causal relationships between the key factors, including five positive feedback loops and three negative feedback loops.





Fig~~F~~. 4 Schematic causal loop diagram of the urban development SD model.

A dynamic system generally comprises several positive and negative feedback loop structures whose interactions have a profound effect on the system's behavior. A positive feedback loop represents a self-reinforced process over time if one ends up with the same result as the initial assumption after going around the loop. For example, one of the positive feedback loops in Fig. 4 involves the factors of urban attractiveness, population, government's financial position, investment on public transportation, accessibility, and then back to urban attractiveness. As urban attractiveness increases, the population in a city can be expected to increase. An increase in population leads to higher tax income for the public sector, and thus improves the government's financial position. With better a financial situation, the government can make greater investments in infrastructure, such as public transportation, and higher accessibility can be expected in the future. As a result of better accessibility, urban attractiveness increases accordingly. On the contrary, a negative feedback loop depicts a self-regulating process if the result contradicts the initial assumption. For instance, a negative feedback loop in Fig. 4 involves the factors of urban attractiveness, population, pollution, and environmental quality. When higher urban attractiveness brings increases the population of the city, the pollution discharges inevitably increase, degrading environmental quality. Eventually, the inferior environment will decrease urban attractiveness.

Whereas the SD model has been constructed, model validation is a prerequisite step before modeling real systems. The model validation process uses historic data to test the degree of authenticity of the model-generated behavior to the original behavior of the real system. After model validation, the dynamic simulation results could be used as parameters in the MOP model.

Modeling software

The next step, after formulating both MOP and SD models, is to implement the models using the designated software and integrate the software based on the proposed IDMOP framework. The MOP model in this study employs GAMS® optimization software to derive the solution of the model. GAMS® was developed by Brook et al. (1992), and stands for General Algebraic Modeling System. It incorporates Murtagh and Saunders' (1983) ~~M~~modular in-core non-linear optimization system (MINOS) algorithm to process linear and nonlinear planning problems and is an advanced modeling system that performs mathematical programming. GAMS® allows users to modularize problems using simple tools, solve complex problems in the shortest time possible, and present the results as Microsoft Excel® or text file outputs.

The simulation of the SD model was performed using Stella® system dynamics software. Stella® is a systems thinking software developed by ISEE Systems that is designed for modeling the dynamics of highly interdependent systems. This software has a friendly graphical interface that aids in constructing, laying out, and using a model to provide a practical approach, to dynamically visualize and communicate how sophisticated systems really work. The simulation results of the complex system can be expressed in the form of figures, tables, and numerical readouts. The input/output of Stella® can also be connected to Microsoft Excel®, which enhances convenience for linking with other software.

Model ~~A~~application and land use scenarios analysis

Using the MOP model and the SD model developed in the previous section, this study applies the IDMOP model to investigate land use planning in the Cijin District of Kaohsiung, Taiwan. The Cijin District is located on a slender island on the western side of Kaohsiung that serves as a natural breakwater for the Kaohsiung Harbor (Fig. 5). With an area of 1.46 ~~1~~km^2, Cijin has five fishing harbors and had nearly 30,000 residents in 2010. The current spatial plan includes five land use types, including residential areas (48.64 ha), industrial areas (13.11 ha), commercial areas (6.64 ha), public areas (113.09 ha), and reserve areas (0.65 ha). Cijin is a traditional fishing village community, and most of its residents are employed by the maritime industry. However, the Kaohsiung City Government is planning to transform Cijin into a sustainable island. This case study is expected to provide useful decision support for policymakers. There are three planning periods in the whole project starting from 2011, and each period spans five years. According to Taiwanese law, several restrictions are listed as follows:

$$X_1 + X_3 \geq L_1$$

$$X_i \geq L_i, \quad i = 2, 3, 4, 5$$

$$X_3 \leq U_3$$

$$L_1 = \frac{W_1}{D}$$

$U_4 = W_1 \times A_4$

$U_3 = W_1 \times A_3$

where X_1 is residential area, X_2 industrial area, X_3 commercial area, X_4 public area, X_5 reserve area, L_1 lower bound of required residential area, which is based on the regulations, L_2 lower bound of industrial area, which is based on the real use situation, L_3 lower bound of commercial area, which is based on the real use situation, L_4 lower bound of public area, which is based on the real use situation, L_5 lower bound of reserve area, which is based on the real use situation, U_3 upper bound of commercial area, which is based on regulations, W_1 total population, D population density, which is regulated by the local government, A_3 commercial area for people, which is regulated by law, and A_4 is public area for people, which is regulated by the local government.

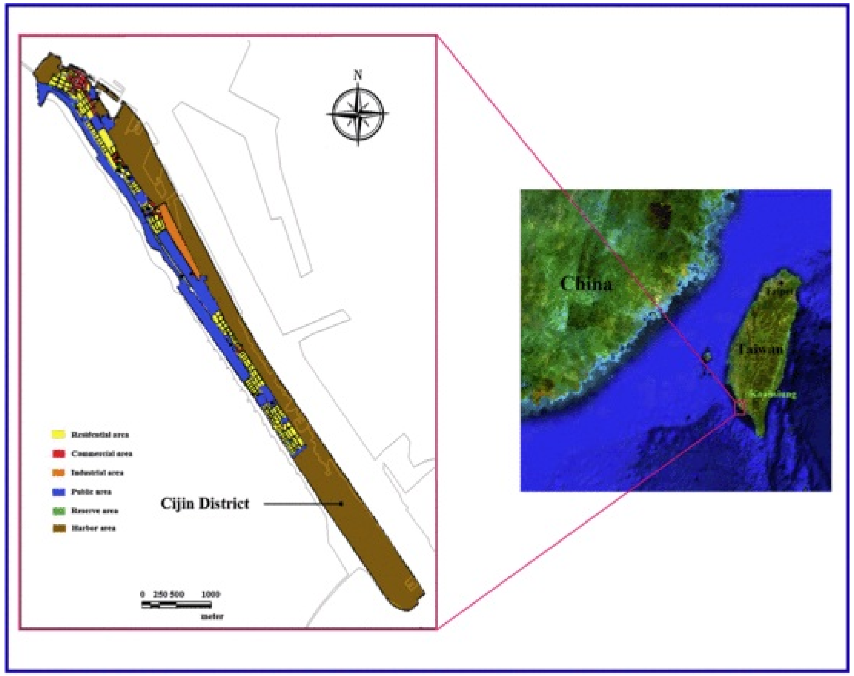


Fig. 5 Geographic location of Cijin District.

Population dynamics is the core element of land use planning and sufficiently serves the purpose of behavioral validation. Population statistics from the Cijin District between 1996 and 2010 were used to evaluate the historical fit of the SD model. Starting SD simulation in 1996 provided fifteen years of simulated-data to compare to the actual behavior of the population of the Cijin District. As indicated by Fig. 6, the results of the simulation show a similar trend of real experience in the Cijin District regarding population dynamics.

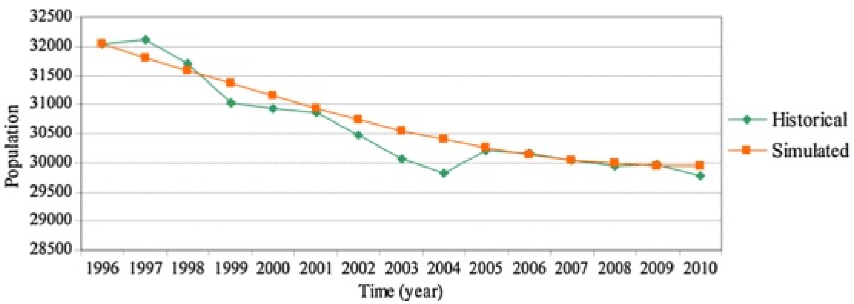


Fig. 6 Behavior validation of the SD model.

Fig~~.~~. 6 Behavior validation of the SD model.

Table 1 shows the initial set of non-inferior solutions in the first planning period ~~(~~(2011–2015) obtained through the compromise modeling. By adjusting the compromise index α', which ranges from 0.46 to 0.5, decision makers can acquire the corresponding compromise solution. The corresponding objective function values and satisfaction levels of the compromise solutions can be seen in Table 2. The "Current Plan" reveals the land use scheme adopted by the public sector. Table 2 shows that the total satisfaction level of the current land use plan in the Cijin District is less than that of the compromise solutions. Meanwhile, compromise modeling allows decision makers to select their favorite plans from the non-inferior solutions. The decision preference can be based on the satisfaction level of one single objective or the composite satisfaction level of various objectives. For example, if decision makers are looking for better economic development in Cijin, they should choose the plan with α equal to 0.5 because the objective function value Z_1 and the satisfaction level μ_1 of this type of plan are the highest. Alternately, they may prefer higher employment opportunity, in which case the plan with α equal to 0.46 is preferable to others because the objective function value Z_3 and the satisfaction level μ_3 of this type of plan are the highest. If the overall satisfaction of all objectives are the major concern, then decision makers should choose the land use plan with α equal to 0.46.

Table 1 Initial ~~N~~non-inferior solutions within the compromise index range in 1st planning period.

Compromise Index	Residential area (ha)	Industrial area (ha)	Commercial area (ha)	Public area (ha)	Reserve area (ha)
$\alpha' = 0.50$	42.86	18.00	8.16	97.63	15.48
$\alpha' = 0.49$	41.57	15.94	9.45	97.63	17.53
$\alpha' = 0.48$	40.28	13.89	10.74	97.63	19.58
$\alpha' = 0.47$	38.99	11.84	12.03	97.63	21.63
$\alpha' = 0.46$	37.70	9.79	13.32	97.63	23.69

Table 2 Initial ~~O~~objective function values and satisfaction levels of the compromise solutions and current plan in 1st planning period.

Scenarios	Objective function values				Satisfaction levels				
	Z_1 (TWD)	Z_2 (kg/year)	Z_3 (people)	Z_4 (tons)	μ_1	μ_2	μ_3	μ_4	Total
~~α~~α ~~3~~= ~~1~~0~~1~~.~~2~~5	12,958,664	444,704	4100	651,365	0.500	0.500	0.503	0.504	2.007
$\alpha = 0.49$	12,756,428	444,706	4242	589,117	0.490	0.490	0.526	0.574	2.080
$\alpha = 0.48$	12,558,780	444,709	4384	527,171	0.480	0.480	0.550	0.646	2.154
$\alpha = 0.47$	12,361,132	444,712	4527	465,224	0.470	0.470	0.574	0.713	2.227
$\alpha = 0.46$	12,163,484	444,715	4669	403,277	0.460	0.460	0.598	0.783	2.300
Current Plan	~~9~~9,838,389	444,683	3177	513,605	0.342	0.573	0.349	0.659	1.923

Results

Once the initial MOP land use plan is selected, the IDMOP model can proceed to SD simulation. Given the scenario that the maximum industrial output value is preferable (α equal to 0.5), the SD model took the land use plan, which is the decision variables acquired from the MOP, as its initial conditions and simulated the urban development from 2011 to 2015. The scenario of maximum industrial output value is hereafter called "Plan A." Table 3 shows the yearly system state variables obtained by the simulation. To summarize the system state variables during one planning period, which spans five years, this study calculated the average annual system state variables. These average values were then converted into the MOP model's dynamic parameters, e.g., coefficients of objective functions and constraints, so that the MOP model was modified to generate updated non-inferior solutions. An updated land use scenario was derived by computing the shortest Euclidean distance between the original vectors and the set of new non-inferior solutions to find the solution with the highest similarity to the original scenario. The updated scenario was applied to the next SD simulation run. The DMOP process continued several rounds until the variation in the system state variables of SD model were acceptable and the optimal solution was obtained. Table 4 shows that the updated scenario more closely approximate the previous one while the shortest Euclidean distance of each round (i.e. $\overline{R_0S_1}$, $\overline{R_1S_6}$) decreased after two rounds of DMOP. Meanwhile, the system state variables reached stable after two rounds of the DMOP process during the first planning period as shown in Table 5.

Table 3 System ~~S~~state variables of Plan A from 2011 to 2015.

System state variables	Year				
	2011	2012	2013	2014	2015
Population	~~2~~29,992	29,992	29,952	29,872	29,755
Number of industries	864	871	124	888	896
Industrial output value (~~(~~thousand TWD)	9,895,125	9,949,927	10,002,142	10,051,085	10,095,9944
Employees	3201	3223	3245	3266	3287

Table 4 Approximation of ~~L~~land use scenarios from 2011 to 2015.

Land use scenario (R_i)	Non-inferior solutions (S_j)	Euclidean distance ($\overline{R_i S_j}$)
R_0(42.86, 18, 8.16, 97.63, 15.48)	S_1(42.89, 18.18, 8.07, 97.52, 15.47)	$\overline{R_0 S_1}$ = 0.231516738
	$S_{\cancel{6}2}$(41.13, 15.2, 9.83, 97.52, 18.46)	$\overline{R_0 S_2}$ = 4.744923603
	$S_{\cancel{6}3}$(39.36, 12.21, 11.6, 97.52, 21.45)	$\overline{R_0 S_3}$ = 9.657157967
	$S_{\cancel{6}4}$(37.6, 9.22, 13.36, 97.52, 24.43)	$\overline{R_0 S_4}$ = 14.55714945
	S_5(37.5, 8.63, 13.46, 97.52, 5.03)	$\overline{R_0 S_5}$ = 15.35679329
R_1(42.89, 18.18, 8.07, 97.52, 15.47)	S_6(42.91, 18.2, 8.05, 97.51, 15.47)	$\overline{R_1 S_6}$ = 0.032954514
	$S_{\cancel{6}7}$(41.11, 15.12, 9.85, 97.51, 18.54)	$\overline{R_1 S_7}$ = 5.014704976
	S_8(39.23, 11.91, 11.72, 97.51, 21.75)	$\overline{R_1 S_8}$ = 10.27201859
	S_9(37.5, 8.91, 13.46, 97.51, 24.76)	$\overline{R_1 S_9}$ = 15.17918463
	S_{10}(37.5, 8.45, 13.46, 97.51, 25.21)	$\overline{R_1 S_{10}}$ = 15.73892963
R_2(42.91, 18.2, 8.05, 97.51, 15.47)		

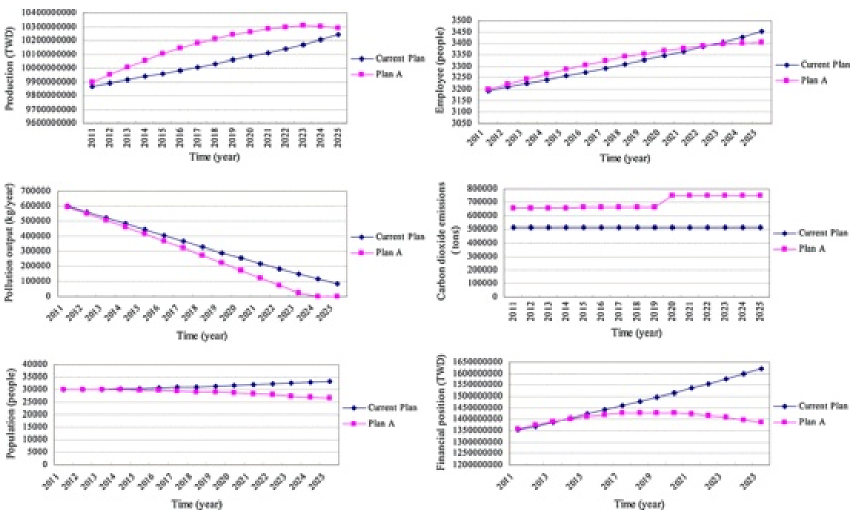
Table 5 Stability of ~~S~~system state variables from 2011 to 2015.

System state variables	Rounds of the DMOP		
	Round 0	Round 1	Round 2
Population	~~2~~29,913	29,911	29,911
Number of industries	880	880	880
Industrial output value (~~(~~thousand TWD)	9,998,855	10,001,200	10,001,353
Employees	3244	3245	3245

As mentioned earlier, there are three planning periods in the whole project. Once the first period DMOP process was finished, the results were transferred to the second planning period as the initial situations. Following the same procedure, the dynamic optimal land use planning in each period was acquired, as shown in Table 6. The land use scenario, which will be adjusted every five years, can further be simulated in the IDMOP model to provide decision makers with time series figures of urban development trends between various land use plans. Fig~~F~~. 7 shows the temporal variations of several variables through the ~~1~~15-year simulations of urban development under “Current Plan” and “Plan A.” Because “Plan A” is to pursue the best economic development, the SD simulation shows that “Plan A” would generate larger industrial output and more CO_2 emissions than “Current Plan.” The simulations also indicate “Plan A” gradually increases the industrial and commercial areas at the cost of the public area, which unavoidably diminishes the quality of life and causes some residents to relocate elsewhere. Consequently, the decreasing population retards economic growth and negatively affects the government's financial position. Urban planning results in a complex and dynamic environment that can be anticipated using the SD simulation. The simulation function provided by the IDMOP model will be a useful decision support tool for the public sector to finalize the Cijin land use scheme by evaluating the future urban development trends of all alternatives. In addition, the proposed IDMOP model can improve the performance of land use planning by updating model parameters through dynamic systems. To prove the above, the initial “Plan A” based on traditional MOP modeling with model parameters that are constant throughout the planning periods is simulated and named “Plan A~~A~~′” hereafter. Fig. 8 shows that “Plan A” can yield greater industrial output value than “Plan ~~P~~A′,” and the difference would increase with time. Therefore, the IDMOP model can locate a better land use plan to achieve the objective of maximum economic development.

Table 6 Decision variables in the various periods from 2011 to 2025.

Decision variables	Periods		
	1st period ~~2~~2011–2015	2nd period 2016–2020	3rd period 2021–2025
Residential area (ha)	42.91	40.78	37.78
Industrial area (ha)	18.20	18.56	21.55
Commercial area (ha)	8.05	8.83	8.98
Public area (ha)	97.51	94.93	89.47
Reserve area (ha)	15.47	19.03	24.35



Fig~~F~~. 7 Comparisons of urban development trends for the land use plans. Note: Plan A ~~A~~– the scenario generated by the IDMOP model; Current Plan ~~P~~– the scheme adopted by the public sector.

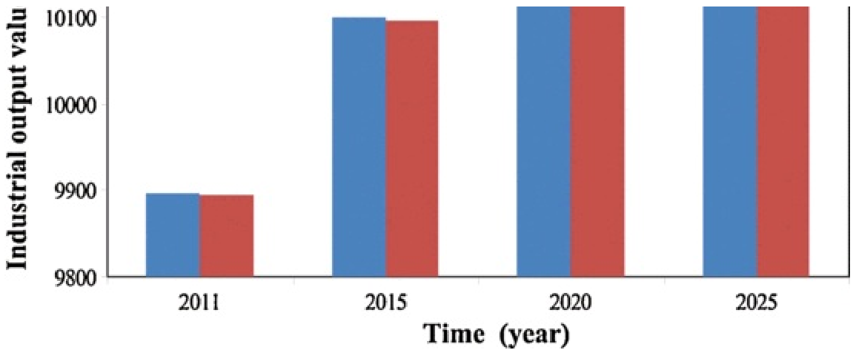


Fig. 8 Industrial output value changes. Note: Plan A – the IDMOP model with updating parameters; Plan A' – the IDMOP model without updating parameters.

Conclusions

With increasing competition for various human activities, multi-objective optimal planning of land resources, which helps find balanced solutions to meet economic, environmental and social needs, has become an important and indispensable part of sustainable urban development. The developed IDMOP model considers the holistic planning and spatial-temporal changes in a dynamic and complex urban environment to improve on the drawbacks of traditional land use planning methods. The IDMOP model offers an interactive human–computer interface so that decision makers can adjust the compromise index to generate scenarios that fit their preferences and gain insight into the potential development of different scenarios. This study provides a strategic planning tool for land resources management based on the anticipation of future development and decision makers' preferences. Other spatial allocation techniques (e.g., geographic information systems and land suitability analysis) should be combined with the proposed spatial planning model for land use allocation in further research.

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