A multi-objective hybrid metaheuristic for zone definition procedure

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Abstract: Zone Definition Procedure (ZDP) is defined as the drawing of territory lines for geographical zones for space control. It is a spatial multiple criteria decision problem but there is limited research attempts in this aspect. Therefore, this paper presents a multi-objective hybrid metaheuristic for ZDP based on multi-objective definition. It is a more realistic solution to the real-world ZDP problem because it helps to consider the relationship among objectives with dominancy comparison among different objectives. The fusion of Tabu Search (TS), Scatter Search (SS) and Path Relinking (PR) was used in the ZDP search process. The exploration of the solution space is based on the strategic oscillation philosophy. An evaluation on the proposed one is done with a commonly used single objective hybrid metaheuristic. This study has conducted several testing and experiments to compare the quality of the results and computation effectiveness of the two approaches.

Keywords: soft-computing; metaheuristic; multiple criteria decision-making.

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1 Introduction

Zone Definition Procedure (ZDP) is a normative spatial model for dividing land into territories for schools, sales/services, voting and others for identifying sites or patterns of sites to provide service accessibility (Church and Sorensen, 1994). It serves two main purposes: to describe the choice of existing facility locations and to prescribe the selection of a new location in a general location model. ZDP is extremely significant because all human activities involve locational decision-making either explicitly or implicitly in their attempts to describe the occurrence of existing location patterns.

On the other hand, Teghem (2001) also mentioned that the multi-objective approach is often a realistic and efficient way to treat many real-world applications. The consideration of many objectives in the planning stages provides three major improvements to the procedure that directly supports the decision-making process (Savic, 2002):

1. a wider range of alternatives is usually identified when the multi-objective methodology is employed
2. consideration of multi-objective promotes more appropriate roles for the participants in the planning and decision-making processes, that is, 'analyst' or 'modeller' – who generates alternative solutions and 'decision-maker' – who uses the solutions generated by the analyst to make informed decisions and
3. models of a problem will be more realistic if many objectives are considered.

The 'No free lunch' theorem for optimisation clearly indicates that no method can outperform all the other methods on all problems (Bong and Wang, 2004). Each problem has its own specifics and a general multi-objective method cannot cope with all of these. In addition, the ZDP problem is an application specific location model that its structure forms the objectives, constraint and variables is determined by the particular location problem under study (Current et al., 2001).

Consequently, this paper presents a multi-objective hybrid metaheuristic for ZDP based on multi-objective definition. Firstly, the paper presents the single objective and multi-objective problem definition of ZDP in Section 2. Then, the proposed hybrid metaheuristic for multi-objective environment is presented in Section 3. An experiment to compare a multi-objective and single objective decision-making is conducted to demonstrate the significance of the multi-objective solution for ZDP. The result of the experiment is finally presented in Section 5.

2 ZDP problem definition

The political districting data definition from (Bozkaya et al., 2003) are adapted and used in the survey: I is the set of all Basic Units (BUs). For each unit, population data and geographical data are linked, J is the set of BUs used as 'seeds', m is the number of zones to be created which is given, p_i is the population capacity of unit i, $[a, b]$ is the interval of the population capacity of any zone.

The decision variables considered is to let x_{ij} be a binary variable equal to 1 if and only if unit i is assigned to seed j.

$$x_{ij} = 0 \quad \text{or} \quad 1 \; (i \in I, j \in J) \tag{1}$$

The constraints include:

1 Each BU is assigned to one district

$$\sum_{i \in I} x_{ij} = 1, \quad (i \in I) \tag{2}$$

2 The number of districts is equal to m

$$\sum_{j \in J} x_{ij} = m \tag{3}$$

3 No BU can be assigned to an unselected seed

$$x_{ij} \leq x_{ij}, \quad (i \in I, j \in J) \tag{4}$$

4 Resources capacity is taken into account

$$a \leq \sum_{i \in I} p_i x_{ij} \leq b, (j \in J) \tag{5}$$

Three to four criteria are considered in this survey. Each of the following functions corresponds to one of the criteria.

The objective function f_1 measures the average deviation of the population. Indeed, population equality, $P_j(x)$ is the population of district j, the average population of each district is $\overline{P} = \sum_{j \in J} P_j(x) / m.$ The population of each district lies within some interval $[a, b] = [(1-\beta)\overline{P}, (1+\beta)\overline{P}]$ where $0 \leq \beta < 1$. The objective is formulated in the following way:

$$f_1 = \frac{\sum_{j \in J} \max\left\{(1+\beta)\overline{P} - P_j(x), P_j(x) - (1-\beta)\overline{P}, 0\right\}}{\overline{P}} \tag{6}$$

The objective function f_2 measures shape compactness by measuring the total length of all boundary lengths between districts, excluding the outside boundary of the territory:

$$f_2 = \sum_{j \in J} 1 - \frac{\left(2\pi\sqrt{A_j(x)/\pi}\right) \Big/ R_j(x)}{m} \tag{7}$$

where $R_j(x)$ and $A_j(x)$ are the perimeter and area of j in the solution x.

The objective function f_3 measures a socio-economic homogeneity, S. This objective is to minimise the sum over all districts j, of the standard deviation $S_j(x)$ by the average income of each basic unit in the district.

$$f_3 = \frac{\sum_{j \in J} S_j(x)}{\overline{S}} \tag{8}$$

The objective function f_4 measures the similarity of a solution with the existing plan. It computes each district j of the existing plan for the largest overlay $O_j(x)$ with a district contained in a new solution x. The objective is to minimise the dissimilarity of the new solution with the existing solution. The similarity index is defined as

$$f_4 = 1 - \frac{\sum_{j \in J} O_j(x)}{A} \tag{9}$$

2.1 Single objective decision rules

A single objective method called minimisation of a Weighted Additive Multiple Criteria Function (WAMCF) is commonly used ZDP method. It was selected as the single objective method to compare with the proposed multi-objective. Thus, it is used as a representative of single objective methods for the comparison. The WAMCF is defined as follows:

$$F(x) = \sum_{r} \alpha_r f_r(x) \tag{10}$$

where α_r is a weight and $f_r(x)$ is the value of a function assigning a value of criterion r to any given solution x.

2.2 Multi-objective decision rules and measurement

Multi-objective ZDP problem solving in this study is called as Multi-objective Spatial ZDP Method (MoSReM). It includes a set of n parameters (decision variables), a set of k objective functions and a set of m constraints. The optimisation goal is as below:

$$\begin{aligned}&\min\ y = f(x) = \left(f_1(x), f_2(x), f_3(x)\right)\\ &\text{s.t. } e(x) = \left(e_1(x), e_2(x), \ldots, e_m(x)\right) \le 0\end{aligned}$$

where $x = (x_1, x_2, \ldots, x_n) \in X$ (x is the decision vector and X denotes the decision space) and $y = (y_1, y_2, y_3) \in Y$ (y is the objective vector and Y is called the objective space). The constraints $e(x) \le 0$ determine the set of feasible solutions.

For shorter notation, the study often refers to an objective function vector as a point z, where $z^x = [z_1^x \ldots, z_j^x] = f(x)$ such that j = 1,…,J. Throughout this paper, objective indices are written in superscript. The point z_1 dominates the point z_2 if and only if $z_1 > z_2$ (i.e. if $z_1^k \ge z_2^k$ for all objectives k and $z_1^k > z_2^k$ for at least one objective k). The point z_1 is dominated by the point z_2, if the point z_2 dominates the point z_1. If any other points do not dominate a point, it is called a non-dominated point.

The set of all non-inferior solutions is referred to as the Pareto-optima set or the efficient set. The set of all non-dominated points is referred to as the non-dominated set. An efficient solution for MoSReM should be Pareto-optima, and the solutions are uniformly sampled from the Pareto-optima set.

Also, a range of equalisation factors are used to equalise the ranges of the objectives, and calculated as

$$\pi_j = \frac{1}{R_j}, \quad j = 1, \ldots, J \tag{11}$$

where R_j is the (approximate) range of objective j given a set of points.

The neighbouring move will first ensure optimisation towards the non-dominated frontier. Therefore, each element in the weight vector is set according to the proximity of other points for that objective. This study only compares a point with the points of the current solution to which it is non-dominated. The closer the another point is, the more it should influence the weight vector. The closeness is measured by a distance function (d)

based on some metric in the objective function space and the range of equalisation weights. The influence is given by a decreasing, positive value of proximity function $g(d) = 1/d$ on the Manhattan distance norm as in Equation (12). The distance norm, π used on the objectives is scaled by the range of equalisation factors.

$$d\left(z_i^k, z_j^k, \pi\right) = \sum \pi^k \left|z_i^k - z_j^k\right| \tag{12}$$

The use of a multi-objective acceptance rule in a quality measurement is crucial in approximating the non-dominated solution for the multi-objective ZDP problem. This study concentrates on the quality counter with Achievement Tchebycheff Scalarising Function (ATSF), which takes into account the weight vector, the optimal solutions set and also each objective function scaling. The advantage of scalarising function is the possibility of forcing particular solutions to explore the desired regions of non-dominated set. The ATSF helps to qualify the generated solution with the reference point at the objective functions $f(x)$ or z where z^0 is a reference point is, $\Lambda = [\lambda_1, \ldots, \lambda_j]$ is weight vector, and ρ is a sufficiently small positive number. ATSF is defined as Equation (13) and the use of ATSF is good at locating non-supported non-dominated points (Hansen, 1997a,b).

$$S\left(z, z^0, \Lambda, \rho\right) = \max_j \left\{\lambda_j \left(z_j^0 - z_j\right)\right\} + \rho \sum_{j=1}^{j} \lambda_j \left(z_j^0 - z_j\right) \tag{13}$$

This study chooses to use interactive modes for guiding the search by using a reference point from Czyzak and Jaszkiewicz (1998). The preferences from decision-maker are aggregated with range of equalisation factors and a γ-parameter range from 0 to 1 to define the intensification of the search in the reference direction on behalf of the diversification of the current solution and therefore in the resulting approximation. The aggregation of a reference weight vector, r with range of equalisation factors and a γ-parameter is given as below.

$$\lambda^k = \gamma d^k + (1-\gamma)\lambda^k \tag{14}$$

where $d^k = \pi^k r^k$.

The solutions set obtained from the approximation process are handled in a Reference Set (RS) with the adapted method from Jaszkiewicz (2001). The method stores the constantly updated set of potential Pareto-optimal solutions in a RS. RS is empty at the beginning of the method. The scheme continuously updates it whenever a new solution is generated. Whenever a new solution is created, the zoning plan becomes the member of the RS memory.

3 The hybrid metaheuristic search process

The fusion of Tabu Search (TS), Scatter Search (SS) and Path Relinking (PR) was used in the ZDP search process. As the basic concept of TS as described by Glover (1998) is a meta-heuristic superimposed on another heuristic, its integration with SS and PR can support one another. In addition, the TS method still requires further extension and improvement in ZDP because it is in an early stage of development and application to ZDP problem.

The proposed Hybrid Metaheuristic (HMH) is divided into four sub-components. Each of the components has been enhanced to avoid exclusive problems or weaknesses faced in existing ZDP problem. This includes the problems of being trapped in the local optimal and a thorough search in the solution space. The sub-components of the proposed design are as following:

- Random Seed Generator (SEED): to generate a set of diversifiable seed solutions randomly to create an initial solution.
- Neighbouring Tabu Move (NAT): to generate a set of candidate moves on the BU that return to attractive regions of the solution space to search them more thoroughly.
- Generated Subset Combination (GSC): to create a district from the generated subset of the groups of BU from NAT or ITR in forming an individual district. In other words, when a subset of the BU has been selected, it would be combined to form a district zone. When a desired number of the districts have been created, a generating solution is successfully produced.
- Improved Territory Procedure (ITR): to produce an improved solution with PR concept.

SEED and ITR were the diversification tool whereas NAT was the intensification tool that provided a wide exploration of the solution space. On the other hand, GSC played an important role in avoiding the problem of trapping in the local optima. With the underlying idea of TS, SS and PR, the proposed search method was able to provide a supporting tool for the decision-making method.

3.1 Exploration of the solution space

The exploration of the solution space is based on the strategic oscillation philosophy of the SS and PR. It helps to provide the necessary mixture of intensification and diversification in the proposed HMH. A wide exploration of the solution space is important to effectively navigate the algorithm into various regions of the search domain. Thus, the exploration technique in the solution space requires the enhancement of an intelligent and a wide exploration in the spatial multi-objective solution space. The rest of this section describes the exploration of solution plan with the processes of intensification and diversification that create an oscillation wave that enables a thorough search of the solution space for the recombination process.

3.1.1 Diversification

Incorporating generic and problem specific knowledge of ZDP, the proposed HMH is the structure, which will have a wide exploration of the solution domain. Several diversification processes are described here to enable the solution from being betrayed in an intensified area so it will not be easily trapped in the local optima. Indeed, there are two diversification processes in the proposed framework. The first diversified move is during the random seed solution generator with SEED and the second one is during the activation of the ITR. The first step in the proposed approach is to create an initial solution with diversification purpose to encourage the search process to examine random regions of the solution space. Given a set I of BU and attributes in a layer form, the study will generate a set of initial solutions with a process of SEED with random diversification as shown in Figure 1. The algorithm of the SEED is demonstrated in Figure 2. Firstly, a seed unit is selected randomly to initialise a district. Then, this district is extended gradually to one of its adjacent units. The district is complete whenever no adjacent unit is available or when its capacity attains *P*. When there is left over BU or there is any basic unit that has not been assigned with a district number, they will be merged with the least populated district. If all districts in the final district plan are continuous, it becomes the initial seed solution. In other words, at the end of this process, the initial district plan will be made up of *m* continuous districts, some of which may be infeasible with respect to some of the objectives defined. When it comes to hard constraint, the gradual expansion conducted by the SEED is slightly different. In facing natural geography factors such as major bodies of water, the ZDP process is conducted to minimise the affected area. In the case of electoral ZDP, when there is a major body of water cutting over a district, some of the population will be affected in reaching the provided service for election purposes. Therefore, the ZDP process should be conducted to minimise the affected population in reaching the service area. In contrast, the proposed intelligent process above aims to ensure continuity of the district. Thus, if there is a sea in the middle of a district, the district is not continuous any more. The gradual expansion when facing hard constraint is demonstrated in Figure 3.

Figure 1 The gradual expansion of the SEED from a random selected basic unit to a completed district plans with three districts

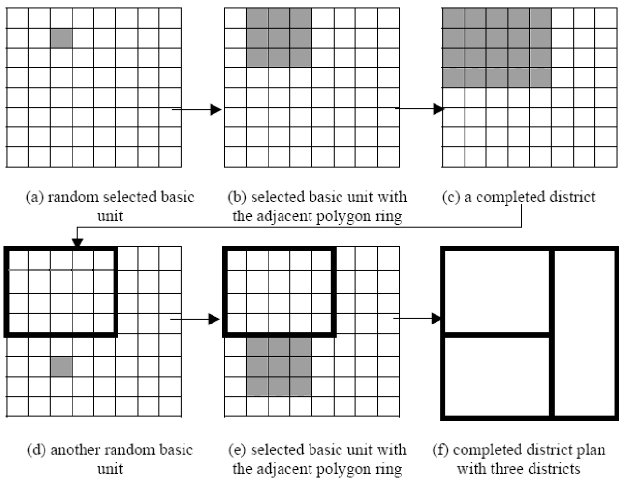
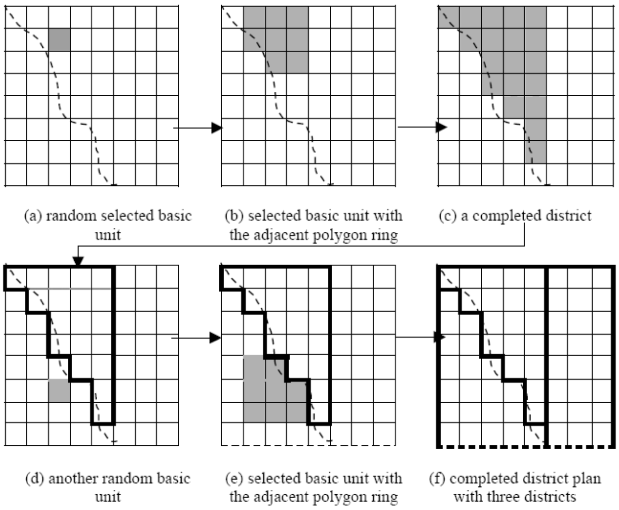


Figure 2 Algorithm for seed solution and random diversification generator

SEED ()
1. Start
2. Select a seed unit, x randomly
3. Select adjacent basic units for x
4. If number of districts is less than m
4.1 If total capacity size, P within interval [a, b]
4.1.1 Merge the basic units
4.2 Else
4.2.1 Reduce basic unit one by one until reach P
4.3 End if
4.4 Merge the left over basic unit with smallest district
5. End if
6. Check continuity
7. Obtain seed solution, s

Figure 3 The gradual expansion of the SEED when facing the hard constraint



On the other hand, PR has been suggested as an approach to integrate intensification and diversification strategies (Beausoleil, 2001). Therefore, ITR in this research acts to enhance the RS with diversification process with the concept of PR to combine reference points by generating paths between and beyond these solutions in neighbourhood space. It encourages the search process to examine unvisited regions of the solution space and to generate sequences that differ in various significant ways from those seen before. These strategies are used, respectively to focus the search in more promising regions. Starting from an initiating solution called parent *i*, PR selects moves that progressively introduce attributes contributed by a guiding solution called parent *j*. It is to reduce the distance between attributes of the initiating and guiding solutions. Figure 4 shows the algorithm of the ITR and the generation of improved boundary is shown in Figure 5. After two initial layers have been overlaid, the composite layer would contain many smaller and undesired *n* districts. Therefore, the framework first starts to sort area in size descending order. Then, for the biggest district found, it counts the adjacent polygon ring to form a balanced path for a new territory from the two old boundaries. This process continues to the second biggest district until all the BU are assigned to relative district number.

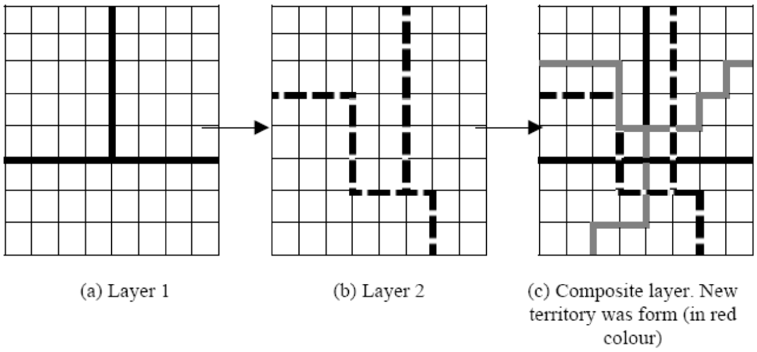
Figure 4 Algorithm for the PR generation method in the ITR: (1) layer 1 (2) layer 2 (3) composite layer. New territory was form (in grey colour)

ITR ()
1. *Start*
2. *Initial parent plans, s_1 and s_2*
3. *Overlay s_1 and s_2*
4. *Sort capacity size, P descending of all districts, $x_1, x_2, \ldots x_n$ in the overlaid plan*
5. *Select the max($x_1, x_2, \ldots x_n$)*
6. *Repeat*

6.1. *Select the adjacent basic units for max($x_1, x_2, \ldots x_n$)*
6.2. *If total capacity size, P within interval [a, b]*
6.2.1. *Update attribute*
6.3 *Else*
6.3.1 *Select the second biggest district*
6.4 *End if*

7. *Until all basic units are assigned to relative district number,* $\sum_{i \in I} x_{ij} = 1, (i \in I)$
8. *End*

Figure 5 Generating improved territory by using the ITR from the parent layer 1 and parent layer 2 to a composite layer



3.1.2 Intensification

As the SEED and ITR provides highly diversified solutions, there is a need to achieve varying degrees of intensification. The proposed algorithm conducts a NAT strategy to prepare for generating an intensified solution to return to attractive regions of the solution space to search them more thoroughly. The tabu move is conducted for each boundary to solve ZDP as a super-wipeout problem that is to separate the problem into smaller and easier sub-problems. Aspiration criteria in TS would be then defined by using the multi-objective decision rules as defined earlier. The tabu neighbouring move, or called candidate move can be activated twice in the proposed framework. It is activated for the seed solution and then for the *RS* members again. The intensification process is first activated in the seed solution to create a set of RS. Then, the process is repeated for the RS members again to encourage the move combinations and solution features, which are historically found to be good. It helps to return to attractive regions of the solution space to search them more thoroughly. The types of move strategies here include MOVE I (Figure 6a), MOVE II (Figure 6b) and the combination MOVE. This study adopts these move strategies from Bozkaya et al. (2003). MOVE I is made up of all solutions reachable from x by moving a basic unit i from its current districts j to a neighbour district l without creating a non-contiguous solution. Such a move is said to be of Type I and denoted by (i, j, l). The second neighbourhood MOVE II is made up of all solutions that can be reached from x by swapping two border units i and k between their respective districts j and l, again without creating discontinuities. Such a move is said to be of MOVE II and denoted by (i, k, j, l). The move strategy for MOVE I and MOVE II is sequential whereas the combination MOVE is random. Combination MOVE refers to the movement of MOVE I and MOVE II concurrently. For implementation purpose, the framework generated five sets of seed solutions. For each seed solution, the framework continues the tabu neighbouring move for each boundary. After a set of RS is built, the tabu neighbouring move will be conducted again for each boundary for all members in the RS.

Before conducting MOVE I and MOVE II, the initial solution from the seed solution is treated as current solution. Then, area size is used as the criteria for creating the territory because it is straightforward and easy to manipulate. In fact, the factor used to create the territory is not very important because the framework works with multi-objective environment. Generating a district plan based on any of the objectives may not grant an optimal district plan implicitly or explicitly because the multi-objective could be conflicting or complementing. On the other hand, generating the plan by considering multi-objective would complicate the process. After the diversification and intensification, the components of SEED, NAT and ITR provide a pool of BU for GSC to construct solutions by combining various elements with the aim that the solution based on the combined elements will exploit features not contained separately in the original elements. The neighbouring subsets contain dynamic number of BU depending on adjacent units and this helps to reduce the computation time in the procedure. Therefore, the GSC works with the underlying concept of SS and has intimate association with TS metaheuristic. SS (Glover, 1999; García et al., 2002) generates linear combinations of a set of reference points (parents) to create new points (children) inside as well as outside the convex region of the parents. Linear combinations of these in turn allow examination of new regions of the search space. Indeed, Corberán et al. (2002) have addressed the problem of routing school buses in a rural area with SS and their computational testing reveals the ability of our procedure to approximate the efficient frontier for each routing problem for bi-objective case. Besides, García et al. (2002) have applied it to a multi-objective *p*-facility location problem. Therefore, the solution combination method transforms the given subset of solutions produced by the dynamic neighbouring subset into a combined solution. The algorithm for the GSC is presented in Figure 7 and the combination of this module is capable of handling the spatial data features.

Figure 6 Sequential tabu neighbouring move for: (a) MOVE I and (b) MOVE II

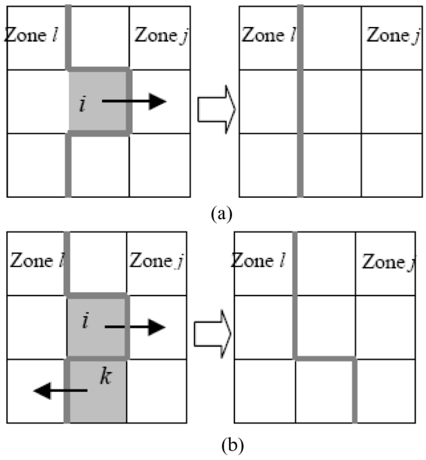


Figure 7 Algorithm for generated subset combination

GSC ()
1. *Start*
2. *Gather district plan from **SEED()** and **ITR()***
3. *Group the basic units with their updated district number, where* $x_{ij} \le x_{jj}, (i \in I, j \in J)$
4. *Dissolve the basic unit layer to create a new district plan,* s_t
5. *If* s_t *is not duplicate*

5.1 *Add* s_t *to the generating solution*

6. *Else*

6.1 *Reject* s_t

7. *End if*
8. *End*

3.2 The tabu list and the tabu daemon

An important feature of TS is the tabu list and called the short-term memory, which records those solutions' states that are not permitted at the current iteration. The short-term memory of the proposed multi-objective hybrid metaheuristic constitutes a form of aggressive exploration that seeks to make the best move possible, subject to satisfying certain constraint. These constraints embodies in the tabu restrictions are designed to prevent the reversal or sometimes repetition of certain moves by making selected attributes of these moves forbidden (tabu). The primary goal of the tabu restrictions permits the method to go beyond points of local optimality while still making high quality moves at each step. Without such restrictions, the method could take a 'best' move away from a local optimum or making a non-improved move and then conceivably at the next step falls back into the local optimum by taking the best move available at that point. In general, tabu restrictions are intended to prevent such cycling behaviour and move broadly to induce the search to follow a new trajectory. These restrictions are counterbalanced by the application of aspiring criteria in the dominancy comparison and quality measurement from earlier section. Restricting the next move to only non-tabu state solutions has the role of preventing cycling and overcoming the local optimal (Chen and Lin, 2000). Hence, to prevent cycling in the proposed redesign, whenever a move (i, j, l) or (i, k, j, l) is performed, any move that puts i back into j or unit k back into district l is declared as tabu for θ iteration where θ is randomly selected in some interval $[\theta_{min}, \theta_{max}]$. As opposed to fixed tabu tenure, the random tabu tenure virtually removes the probability of cycling provided θ_{min} and θ_{max} are sufficiently large. However, using too large values may impair the search, as most potential moves will soon become tabu. Therefore, the only circumstance where the algorithm will perform a tabu move is when this yields a better incumbent. Every move that puts the district back to the original district is a tabu and it may happen in MOVE II. When the combination MOVE is used, it is important to prevent the cycling of the search process. The algorithm using the tabu list and tabu daemon for NAT is given in Figure 8. The research makes use of geographical factors that the tabu is defined per boundary. The purpose is to maintain the smaller current solutions. Only the neighbouring districts adjacent to the boundary will be considered for each loop. The smaller size of the current solutions is important because too many current solutions in the multi-objective problem solving will lead to computational complexity. Each basic unit in the raw district plan carries a unique id because every basic unit carries a unique amount of attribute information and geographical information. Therefore, the unique number of the zone ID is stored in the tabu list to simplify the management of the tabu list. The unique ID for each individual district is an important characteristic to identify the move of the boundary definition. The problem size is used in the quality measurement as a penalty for the search process. The ρ value in the scalarising function in the multi-objective decision-making is a tabu daemon that helps enhance the proposed HMH. The tabu daemon overrides the tabu status of a move when it yields the best solution obtained up till then (Alves and Clímaco, 2000). Usually tabu daemon is also referred as 'aspiration criterion' (Gandibleux and Freville, 2000). In other words, it is satisfied if the function value reached after the move is better than the best found previously (Battiti and Tecchiolli, 1994). In that case, ρ is a sufficiently small positive number and is a penalty term related to problem size. Therefore, $t/1 = \rho$, where m is the size of the basic unit used. Choosing t rather than t for example is common for the idea to use a multiplier that reflects the problem size. It was observed empirically that t overemphasises problem size whereas t produces a smoother search (Bozkaya et al., 2003). Besides the problem size, another tabu daemon used is the number of desired district to be formed. When the number of districts to be built is increased, the adjacency effect becomes more complicated. Therefore, the two factors of problem size and the desired number of districts be formed will be part of the tabu daemon in the quality measurement penalty.

Figure 8 Algorithm for neighbouring tabu move with tabu list and tabu daemon

```
NAT( )
1.      Start
2.      Get x with max(x1, x2, ... xn)
3.      For MOVE I
3.1         Select border unit of the x
3.2         Update attribute
4.      End for
5.      For MOVE II
4.1         Swap two border units, xm and xn
4.2         Check tabu status
4.3         If not approve
4.3.1           Swap another two border units, xm+1 and xn-1
4.3.2           Store the border unit in tabu list
4.4         Else
4.4.1           Update attribute
4.5         End if
5.          End for
6.      End
```

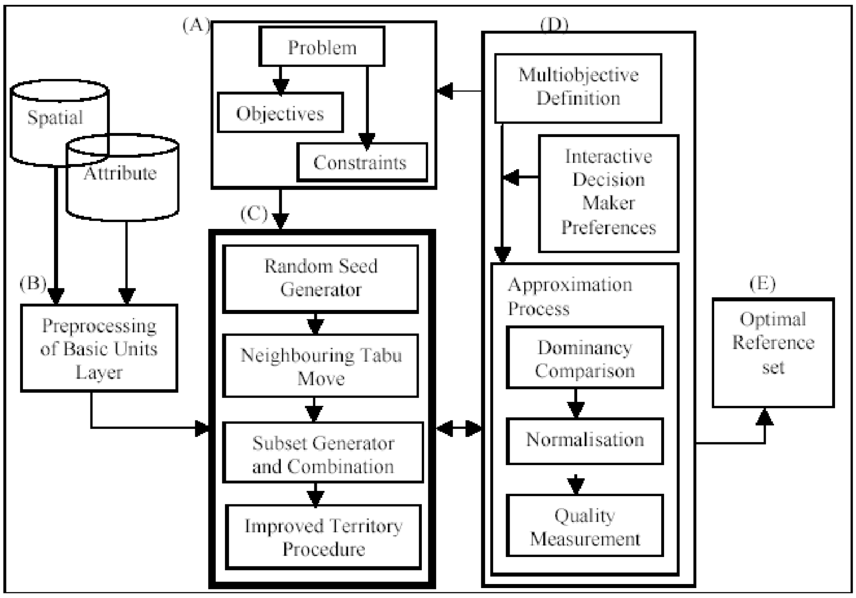
3.3 Stopping criteria

The stopping criterion is by the number of loops, which depends on the number of boundary. Intensification and diversification is conducted at the boundaries formed. For a three-zone district plan, there are three boundaries excluding the external boundaries. Therefore, the strategic oscillation will be conducted for each boundary. The more district zone being formed, the longer is the iteration process. In each of major iteration, diversification of the ITR and intensification of the NAT will be conducted to get the tabu status before the Pareto-optima solution is inserted into the RS. When all the boundaries have conducted the strategic oscillation, the process will be stopped. All the Pareto-optima solutions that filtered through the multi-objective decision-making engine will be stored in the RS. There are a dynamic number of solutions in the RS because it contains the Pareto-optima solutions that achieve the multi-objective incommensurate and conflicting objectives.

3.4 HMH in MoSReM

With HMH fitted into the MoSReM, the overall architectural design is presented in Figure 9. As shown in the architectural design, the Preprocessing of the BU Layers first prepare and link the spatial BU with relevant attributes, which are necessary in the redistricting process. After the spatial topology and relationship of the spatial and non-spatial data have been well prepared, the HMH search process would be activated. SEED will start to produce a set of seed solutions whereas NAT will be conducted to generate a set of candidate move to the next process. In the GSC, a set of solutions will be generated. Every time a generating solution is produced, the multi-objective decision rules will be conducted to compare the dominancy degree and measure the quality to approximate the non-dominated solutions. In approximating the non-dominated solutions, decision-makers' preferences are integrated with the multi-objective defined earlier. Then, a set of non-dominated solution plans will be generated for quality measurement with the achievement scalarising function so that a set of optimal solutions will be produced finally in the optimal RS.

Figure 9 The overall design of the multi-objective ZDP with hybrid metaheuristic based on the MoSReM



The components of the hybrid metaheuristic have a wide exploration in the solution space. Each of the current generated solutions in the objectives spaces deviates from the centre of its region. With the intensification and diversification to avoid the bad behaviour to approximate the whole non-dominated frontier because there is diversity. The TS concept applied in the NAT has the most powerful component to avoid trapping in local optima. Meanwhile, SS concept is applied in the GSC. SS generates linear combinations of a set of BU polygons (parents) to create new generating solution with a new district (children). The PR concept in ITR helps generating new territory between and beyond these solutions in neighbourhood space.

At the same time, intensification in SEED and the NAT encourage move combinations and solution features, which are historically found to be good. The intensification could return to attractive regions of the solution space to search them more thoroughly. Therefore, the HMH has carefully designed component to work together to produce a powerful search strategy to support the MoSReM. On the other hand, the diversification process enables the solution from being betrayed in an intensified area so it easily avoids trapping in the local optima. It is easy to implement because the hybrid metaheuristic component is similar to a plug-in concept where other plug-in can be used to the proposed framework if only if they are able to fulfil the requirement specification.

4 Experiment

An experiment was conducted in Visual Basic Application (VBA) embedded in ArcGIS and on a Pentium IV 2.4 GHz PC with 256 MB RAM. ArcGIS, a high-end GIS software, is flagship product of Environmental Software Research Institute (ESRI), which has the capabilities of automation, modification, management, analysis and display of geographical information. The input data to the ZDP problem was stored in the form of map layers in Shapefiles format, which were handled and visualised using the ArcGIS. As it was not possible to use the standard operations alone to generate the solutions, the multi-objective solution was specifically designed, coded and aggregated in the VBA code to tackle multi-objective ZDP decision problem.

The study considers three zones created for each zoning plan and uses 50–100 BU for the input of the model (refer Figure 10). Besides the weight vectors for each of the criteria for the WAMCF are given in Table 1.

Figure 10 Initial zoning plans and the BU used

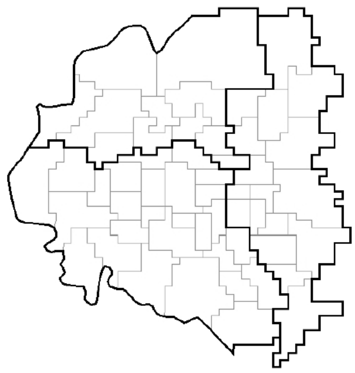


Table 1 Weight vectors for each of the criteria for the WAMCF

Three criteria		*Four criteria*	
Objective	*Weight vector*	*Objective*	*Weight vector*
f_1	0.6	f_1	0.5
f_2	0.3	f_2	0.3
f_3	0.1	f_3	0.1
		f_4	0.1

5 Results

Comparatively, the result for MoSReM is better than WAMCF according to Table 2 because most of the objective values achieved are lower than WAMCF. In both conditions where different problem sizes are used (50 and 100 BU, respectively) for a three-objective problem, the result produced by the MoSReM has better achievement. The mean values in Table 2 are the values that are lower and better than the mean values from WAMCF.

The individual solution generated by the MoSReM gives steadier solutions compared to the WAMCF. As shown in Figure 11, the results generated by the MoSReM are more consistent in that the gap between the maximum and minimum optimal values is not very big. In comparing with the WAMCF approach, the result generated each time is different because the average value has a big gap with the generated maximum and minimum best values.

Table 2 Result of WAMCF – MoSReM comparison for a three-objectives problem

No. seed solutions		*WAMCF*				*MoSReM*				
		CPU time (s)	f_1	f_2	f_3	*CPU time (s)*	f_1	f_2	f_3	*No. Pareto-optimal solution*
3 Objectives, 50 BU										
3	Mean	46	1.1086	0.4378	6.9875	126	0.9250	0.4246	6.5874	5
	Min		0.7159	0.3917	5.5866		0.9095	0.4116	6.4695	
	Max		1.5516	0.5001	10.7511		0.9870	0.4767	7.0588	
5	Mean	45	1.1746	0.3931	7.4107	165	1.1669	0.4382	7.0963	10
	Min		0.7334	0.3159	4.8621		0.9095	0.4140	6.5108	
	Max		1.5955	0.4330	12.6622		1.4243	0.4963	7.6133	
10	Mean	48	1.1267	0.3929	7.5999	330	1.1182	0.4331	6.6577	17
	Min		0.6837	0.3473	4.7290		0.9095	0.3802	5.9637	
	Max		1.5647	0.4653	11.7500		1.4243	0.4963	7.6133	
3 Objectives, 100 BU										
3	Mean	50.67	1.1423	0.3804	7.7449	272	1.0645	0.4351	7.5840	6
	Min		0.6368	0.3242	4.9652		1.0567	0.4186	7.1597	
	Max		1.4731	0.4198	12.8155		1.0800	0.4794	7.9408	
5	Mean	56.8	1.2477	0.4178	6.4043	348	1.2466	0.4088	6.5399	10
	Min		0.9763	0.3358	5.4982		1.2014	0.3714	6.0564	
	Max		1.3423	0.4734	8.6466		1.3012	0.4533	6.9531	
10	Mean	52.3	1.2477	0.4178	6.4043	702	1.2639	0.4171	6.0735	20
	Min		0.9763	0.3358	5.4982		1.1613	0.3408	5.2148	
	Max		1.3423	0.4734	8.6466		1.3423	0.4697	7.3991	

In another experiment with a four-objective 50 BU problem, the result produced by the MoSReM again proves its advantage over WAMCF. The experiment shows concrete evidence on two aspects: that the MoSReM can achieve better results for the problem with lower values in the objectives achieved and produces more consistent results for individual solutions. Table 3 presents the results of the experiments. The mean values in the MoSReM are the values that are lower and better than the mean values from WAMCF. Figure 12 shows its consistency in the individual result for two selected objectives.

Figure 11 Individual results for the first objective for the problem of three initial seeds, three objectives defined and 100 BU

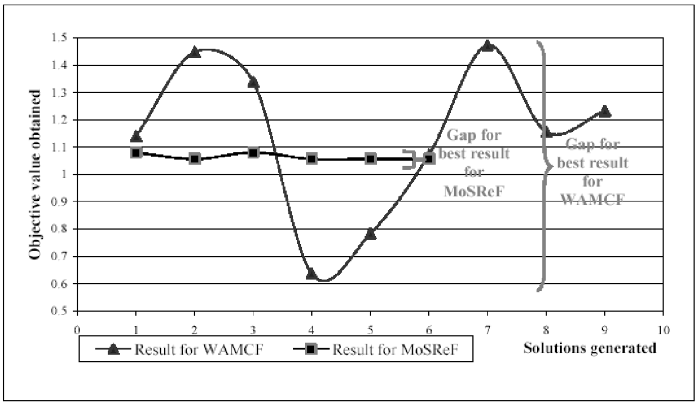
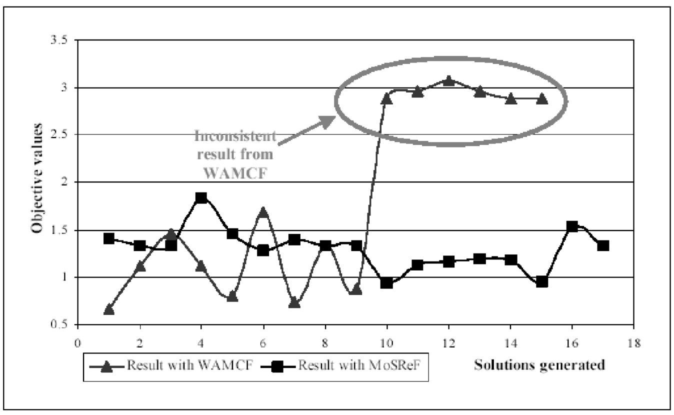


Table 3 Result of WAMCF – MoSReM comparison for a four-objectives and 50 BU problem.

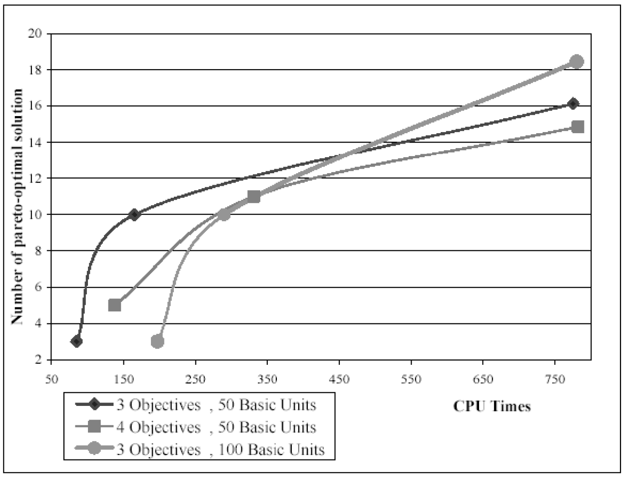
No. of seed solutions		*WAMCF*					*MoSReM*					
		CPU time (s)	f_1	f_2	f_3	f_4	*CPU time (s)*	f_1	f_2	f_3	f_4	*No. Pareto-optimal solution*
3	Mean	44	2.2864	0.4090	8.9641	0.9707	138	1.0483	0.3944	9.7739	0.9585	5
	Min		0.7373	0.3059	5.0242	0.9491		0.5244	0.3620	5.1452	0.9475	
	Max		3.0695	0.4697	18.4059	0.9867		1.6892	0.4165	14.100	0.9663	
5	Mean	42	1.8286	0.4027	8.8741	0.9669	282	1.3019	0.4163	6.0650	0.9595	17
	Min		0.6668	0.3059	5.0242	0.9475		0.9420	0.3449	4.7612	0.9513	
	Max		3.0695	0.4697	18.4059	0.9867		1.8329	0.5081	7.3904	0.9812	
10	Mean	46	1.4744	0.3980	8.6231	0.9652	432	1.3974	0.4134	5.9304	0.9614	32
	Min		0.6071	0.3059	5.0242	0.9462		0.9420	0.3270	4.0435	0.9450	
	Max		3.0695	0.4697	18.4059	0.9867		1.8329	0.5081	7.9698	0.9812	

Figure 12 Individual result for the first objective for the problem of five initial seeds, four objectives defined and 50 BU



Another aspect that this paper has surveyed is on the computation time for MoSReM. This aspect of the survey is to find out the computational effectiveness of MoSReM with respect to increment of problem size and additional objectives. Figure 13 shows the results of the CPU times corresponding to the number of Pareto-optimal solutions generated for problems with three-objectives 50 BU, three-objectives 100 BU and four-objectives 50 BU problems. As the proposed MoSReM consumes most of the CPU time, this study tends to measures the running time in seconds. When the problem size increased, the computational time for solutions generation is clearly increased because the framework needs more time to explore the search space more thoroughly. On the other hand, the computation time also increased when the number of objectives defined increased. Longer time is needed for the framework to evaluate additional objectives. Note that if the objectives defined are relevant with spatial aspect, the computational time increase is more noticeable.

Figure 13 Computational results of the three objectives and four objectives problems



Although the computation time in a single objective decision-making method is obviously shorter than the multi-objective framework, the multi-objective framework has a number of advantages over the single objective multiple attributes decision-making method. For instance, Macmillan and Pierce (1994) attempted to use their single objective approach for congressional ZDP in Louisiana but terminated the program after five days without a solution. Carmen et al. (2000) also have applied their methodology to Louisiana and have generated 20,000 plans within a day. Even when some researchers have successfully applied the single objective optimisation methods, they have generally employed large aggregation units such as counties and have often combined counties to reduce the complexity of the problem. In other words, the weakness in the single objective approach is that there is no theory to allow the decision-makers to further understand the alternatives. Different plans are resulted when different initial plans are given. Therefore, there will be many results, which need further assessment and evaluation.

Although computation time for the MoSReM is greater compared to the selected single objective approach, it is not the reason for not using this framework. By using the approach, the decision-makers obtained a set of solutions in a range of the alternatives that belong to the Pareto-optimal set. The result is computed based on the dominancy of the competing objective in a multi-objective environment. Thus, the relationship between the objectives in term of their dominancy is considered. Therefore, the MoSReM is able to show the practicality and effectiveness when multi-objective are considered.

6 Conclusion

A comparative study between the results of multi-objective decision-making and single objective decision-making is conducted for a proposed multi-objective method with a selected single objective method called WAMCF. Although the computation time in a single objective decision-making method is relatively lower than the multi-objective method, but it has a number of disadvantages. The experiment shows concrete evidence on two aspects that the MoSReM can produce better results for the problem with lower values in the objectives achieved for the minimisation problem. It also produces a more consistent result for the individual solution compared to the single objective approach because there is a big difference between the generated maximum and minimum best values. Besides the weakness in the single objective approach is that there is no theory for the decision-makers to further comprehend the alternatives. Different plans are resulted when different initial values are given. However, by using the multi-objective approach, the decision-makers obtained a set of solutions with a range of the alternatives that belong to the Pareto-optimal set. The result is produced by considering the dominancy measurement of the competing objective in a multi-objective environment. Thus, the relationship between the objectives in terms of their dominancy is described.

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