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Tradeoff Between Economic Development and Environment in Yangtze River Basin: Optimized Solutions

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Abstract

This research used multiple objectives method with two-dimensional genetic algorithm to find out feasible optimal solutions via Pareto frontier. They reveal trade-off and optimization between objectives of Non-Point Source (NPS) load and changing cost index, GDP value, and land use incomatibility index objectives. The results indicate although these objectives have conflicting with each other, but between them exists still optimal solutions, which create the tradeoff of objectives. Particular, there are four optimal solutions in the first generation and six optimal solutions in the last generation in minimization of non-point source load and minimization of changing cost index objectives; 5 the best solutions in the first generation and 12 optimal solutions in the last generation in minimization of non-point source load and maximization of GDP value objectives; 4 optimal solutions in the first generation and 6 the best solutions in the last generation in minimization of land use incompatibility index and minimization of non-point source load objectives. They are laid on Pareto frontier and reveal as perfect Pareto sets. Therefore, this research presented optimal solutions, which satisfy conditions of objectives as well as to be achieved the tradeoff between objectives.

Keywords: Non-point source loads; Cellular automata; Yangtze River basin; Genetic Algorithm; Multi-objective optimization

Introduction

Pollutants are regarded as a harmful substance when it is discharged into the environment. The pollutants may be distributed into water through direct industrial discharge, domestic pollution, precipitation and the application of agrochemicals [12]. Pollution in environment include water pollution, soil pollution, and air pollution however NPS pollution is related to water pollution. Water plays an essential role in the ecological balance of the Earth and water quality degradation threatens socioeconomic development and human health [27]. As the point source pollution has been monitored and treated, the current water pollution is mainly caused by non-point source (NPS) pollution [7]. Non-Point Source (NPS) pollution comes from many diffuse sources [18]. These nutrients input pathways as irrigation, fertilization, seeding, atmospheric deposition and biological nitrogen fixation, while the output pathways consist of plant uptake, surface runoff, leaching and other direct discharges of agricultural/rural wastes into the environment [5]. The transport and transformation of NPS pollutants relate strong from the human activities and natural factors [8,11,23]. NPS inputs have resulted in large amounts of nitrogen (N) and phosphorous (P) [4,6]. According to the EPA estimates that non-point source pollution is from the agriculture activities accounting for 60 percent of all the impaired or threatened surface waters and overgrazed pastures, fertilizers, pesticides, nutrients from agricultural lands, animal wastes from feedlots. Subsequently, it can drive property values come down [18,20] because runoffs pick pollutant substances up and carry away in a natural way, and deposited into groundwater, inland, coastal waters, and streaming system. NPS pollution can affect to community and human health, such as affects the beauty and health of surface water [6], or leading aquatic organisms is killed due to impairment of oxygen concentration in the water. Thus, affective level of non-point source pollution can cause more seriously to human health, environment from water quality impairment due to eutrophication and its is more difficult to be controlled/treated by its non-identified release sources. Urban growth is accompanied by industrialization and economic development [21]. Urban growth usually implies higher economic production, opportunities for the underemployed and unemployed. However, in parallel with those positive impacts, uncontrolled urban growth can also lead to some negative effects [9] including depletion of local resources, destruction of open spaces, and pollution. Many researches on urban growth prediction have been more popular than in urban growth optimization such as the SLEUTH model [10,16,19] or the Cellular Automata (CA) model. CA can be represented in the spatial complexity and dynamics of urban growth by selecting various configurations of the basic elements. However, it has not been resolved optimizing problems, especially in multiple

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objectives optimization. Therefore, this research focus on optimization multi-objectives including non-point source load, changing cost index, GDP value, and land use incomatibility index objectives to find out the trade-off between objectives via Pareto optimal solutions.

Methodology

Study area: China is one of the largest producer and consumer of chemical fertilizers in the world, and the excessive nutrient loading from agricultural watersheds is considered the principal source of NPS pollution [15]. The Yangtze River in southern China, is the largest river in China and the third largest river in the world [14]. It is about 6380 km long and originates from the Tibetan Plateau at an elevation higher than 5000 m, flowing from its source in Qinghai Province eastwards into the east China Sea in Shanghai [3]. The Yangtze River basin, with an area of about 1.8 million km^2 , lies between 24.50°N-35.75°N and 92.43°E-122.45°E [18]. Most parts of the basin have a subtropical monsoon climate [3,25,26] and the annual mean temperature in the basin is between 15°C and 19°C [26] with its average annual precipitation of 1067 mm [26].

In order to manage non-point source pollution in basin environment and water quality, a multi-objective optimization of genetic algorithm is researched basing on GDP objective, changing cost objective, compatibility objective between land use, and NPS pollution load objective to find out optimized solutions of the urban growth and environmental pollution. In which, multi-objectives optimization of two-dimensional genetic algorithm is applied in this research including objectives:

1. Maximization of GDP value
2. Minimization of NPS pollutant load
3. Minimization of the cost of changing from the status quo

Minimization of incompatibility between the land uses and constraints:

1. Urban construction land > a certain level
2. Agricultural land > a certain level
3. Water bodies unchanged

The land use data were retrieved from the Earth System Scientific Data Sharing Network, which covered the whole China, and then the land coverage of the Yangtze River basin was clipped by its boundary. In addition, the elevation, which was employed to calculate the terrain impact factor in the ECM, was retrieved from the internet (http://www.csdb.cn/). The precipitation data, which were used in the ECM as the precipitation impact factor to calculate the NPS pollutant load, were retrieved by interpolating the site monitoring data. The GDP value of each administration was obtained from provincial statistical yearbooks.

Objective Evaluation

Maximization of GDP value

Maximization of economic benefit is calculated as:

$$MAX(Z_1) = \sum_{i=1}^{n} Unit\_GDP_{InbasinAd\_i} * A_i$$

Where: Z_1: Total GDP value in the basin;

$Unit\_GDP_{InbasinAd\_i}$: GDP unit for the *i*-n land-use (RMB/m^2);

A_i: Total area on the *i*-th land-use (m^2);

In order to calculate GDP value for each land-use type (agricultural land, wetland, desert land, urban construction land. grassland, water area, forest land, and barren land), the research used weighted method. Firstly, the research used GDP value of urban fields from statistical yearbook for the Yangtze River basin. Then, rate of area as administrative scope and it belongs to the basin via equation:

$$GDP_{InbasinAd\_j} = GDP_{Ad_j} * \frac{AreaInbasinAd_j}{AreaAd_j} \quad (2)$$

In which: $AreaInbasinAd_j$ is administrative scope;

$Area\ Ad_j$: GDP value is extracted for the basin,

Next, $GDP_{InbasinAd\_i}$ and land-use area extracted from raster data; GDP value is made on each i-th land-use kind in the j-th administrative scope. From that, $Unit\_GDP_{InbasinAd\_i,j}$, can be calculated by following equation as:

$$Unit\_GDP_{InbasinAd\_i,j} = GDP_{InbasinAd\_i,j} / AreaInbasinAd_{i,j} \quad (3)$$

Weighting method is used and $Unit\_GDP_{InbasinAd\_i}$ is calculated as:

$$Unit\_GDP_{InBasinAd\_i} = \sum_{j=1}^{19} Unit\_GDP_{InBasinAd\_i,j} * \frac{AreaInBasinAd_j}{AreaBasin} \quad (4)$$

Where: $Unit\_GDP_{InbasinAd\_i}$ is the GDP value for each i-th land-use kind and number of 19 is province number on the Yangtze River Bain.

Minimization of NPS pollutant load

To estimate NPS pollutant load, a relationship between land-use types and NPS pollutant load is established, the Export Coefficient Model (ECM) is used again in the optimization of urban growth. Therefore, the diminishing to minimum level of NPS pollution is the desire of natural environment protection:

$$MIN(Z_2) = \sum_{i=1}^{n} \alpha\beta E_i A_i \quad (5)$$

Where: Z_2: is pollutant load in the basin;

E_i *(ton/km^2)* is the export coefficient for *i*-th land use;

A_i: Area of each land-use type (km^2);

α: precipitation impact factor

β: terrain impact factor

With export coefficient E_i for *i*-th land-use type is extracted in different patterns (8 types of land-use) the Yangtze River Basin from many studies on NPS pollution by ECM [6,14]; Precipitation impact factor and the terrain impact factor are identified via rate of precipitation and slope at location (*i,j*). They are calculated as:

$$\alpha_{x,y} = \frac{\text{Precipation}_{x,y}}{\text{averagePre}} \quad (6)$$

$$\beta_{x,y} = \frac{Slope_{x,y}}{averageSlo} \qquad (7)$$

Where: *(x,y)* is the location of the cell; $Precipation_{x,y}$ and $Slope_{x,y}$ are the precipitation and slope at location *(x,y)*, respectively; Average Pre and average Slo are average precipitation and average slope.

Minimization of changing cost index

Changing cost index is calculated via dimensionless value from *i*-th land use to j-th land-use because dimensionless cost can be presented the relationship of different land-use changing and approaching nearly to real cost (Zhang et al. 2010). It presents as:

$$MIN(Z_3) = \sum_{(x,y)\in U} change\_index_{(x,y)} \quad (8)$$

Where: Z_3: Cost value in land-use changing;

U: Basin area;

(x,y): Land-use cell in the basin;

In which, $change\_index_{(x,y)}$ is the changing cost index for land-use cell *(x,y)*, and $change\_index_{(x,y)}$ is identified via current land-use situation and the optimized land-use for land use cell *(x,y)*. it ranges from 0-1, and with higher value will get higher cost in land-use changing. This changing cost index is referenced from existing researches [1].

Minimization of Incompatibility Index

Incomatibility is presents via total incompability index of centre land-use cell and neighboring cells including 9 cells as well as is identified by review materials [2,13]. This index range from 0-1, it reveals that with more higher value and more happening big conflict between land-use types. Calculation is showed as:

$$MIN(Z_4) = \sum_{(x,y)\in U} \sum_{(ii,jj)\in N_{x,y}} IncompleteIndex\,(Landuse(x,y), Landuse(ii,jj)) \quad (9)$$

Where: Z_4: incompatibility value;

U: Basin area;

$N_{x,y}$: 8 neighboring cells of center cell *(x,y)*;

Landuse*(x,y)* : Land-use type for cell *(x,y)*,

and Land-use (*ii,jj*) is represented for land-use type of cell (*ii,jj*);

Incomplete Index (Land-use (*x,y*) and Land-use (*ii,jj*)): incompatibility index between Landuse (*x,y*) and Landuse (*ii,jj*).

Constraints

Constraint 1: Urban Construction Land

Based on population in 2010 and area value of per capita urban construction land to make a statistical population data in the basin. From that finding annual growth rate and using this statistical population data to prove urban construction land in the basin, which is no less than a certain value.

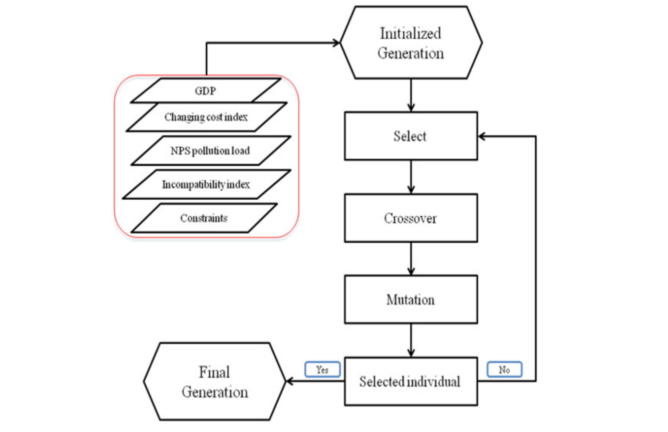

Figure 1: Two-dimensional genetic algorithm optimization process.

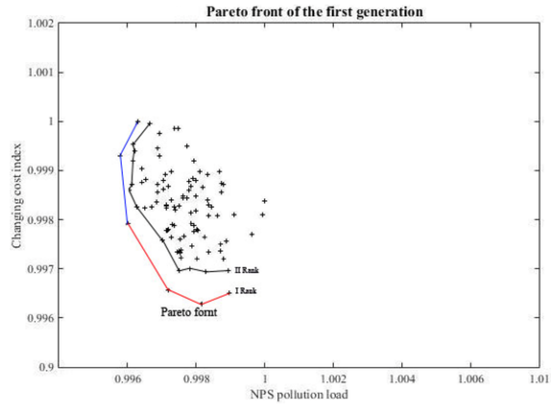

Figure 2: Pareto fronts of the first generation for NPS pollution load and changing cost index.

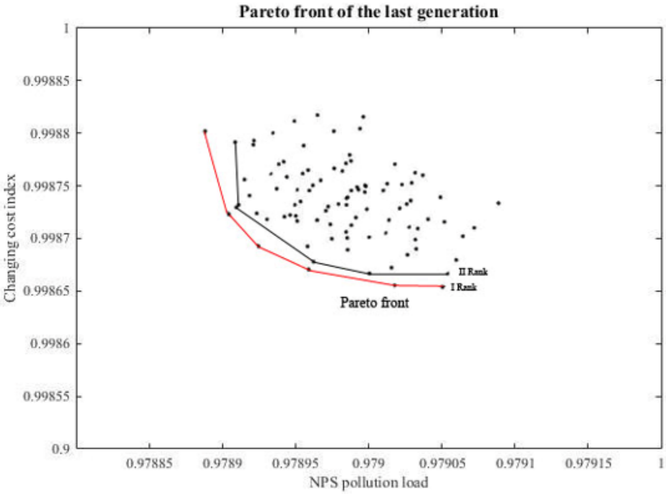

Figure 3: Pareto fronts of the last generation for NPS pollution load and changing cost index.

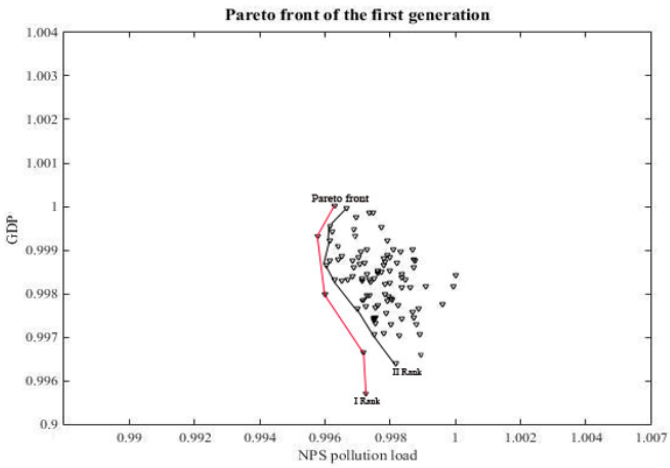

Figure 4: Pareto fronts of the first generation for NPS pollution load and GDP objectives.

Constraint 2: Agricultural land

Based on total area of agricultural land in 2010 of basin and according to Regulations on the Basic Farmland Protection, the basic farmland is more than 80% of current farmland in order to increase population. Therefore, total agricultural land is no less than a certain value as well.

Constraint 3: Water bodies

In the basin, except for main streaming, but many branches and lakes locate/enter into Yangtze River Basin. It is very important to water ecological system and in ordeer to conduct this research, which is supposed water space is not occupied by urban development process.

Genetic Algorithm Process

Multiple objectives can be combine with one-dimensional Genetic Algorithm (GA) or two-dimension GA. Normally, GA for one-dimensional is applied in land-use when it is divided similar as traffic lines. This significant is easy to identify and assess non-spatial objectives. However, with spacial objectives, it is difficult to apply one-dimension GA because it can be found the gap between two land-use type and neighbor cells. Therefore, applying of two-dimension GA will be resolved this problems and it becomes easier for optimizing of urban growth, in which land-use grid in a raster map is denoted by genes, each gene is set up as an integer and is ranged from 1 to th-land-use number. A Genetic algorithm is started by 100 randomly land-use patterns and is presented as a generation, in which constraints and satisfying are ranked by fitness. Next generation is second 100 land-use patterns and it is gained via selection; crossover; mutation; and elitism process. Such process is taken place to the last generation. Processes of two-dimensional genetic algorithm is revealed as:

Selection: from the set of solutions, a number of fitter individuals are selected and their name is called as mother and father.

Crossover: from more than one parent is selected, then one or more off-springs are produced via crossover and they use the genetic material of the parents.

Mutation: the mutation is happened in natural genetic when the children have featured non the same their parents and this process is conducted to avoid a local optimum.

Elitism: To be gained the best solution in each generation, the first solutions have highest fitness value will be exited to next generation without any operation.

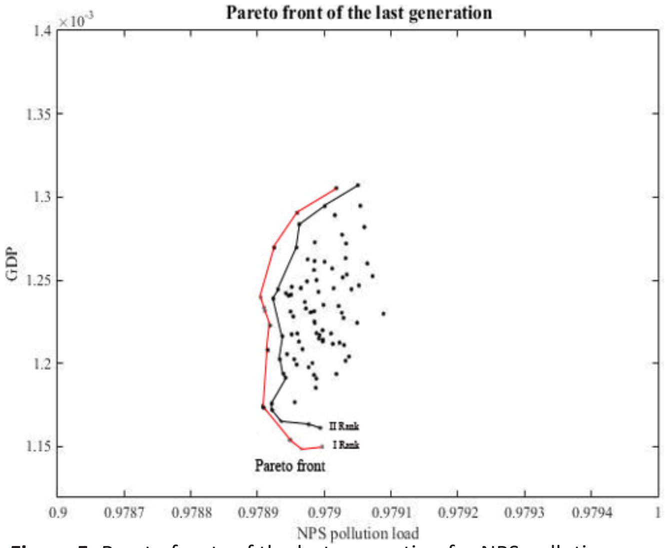

Figure 5: Pareto fronts of the last generation for NPS pollution load and GDP objectives.

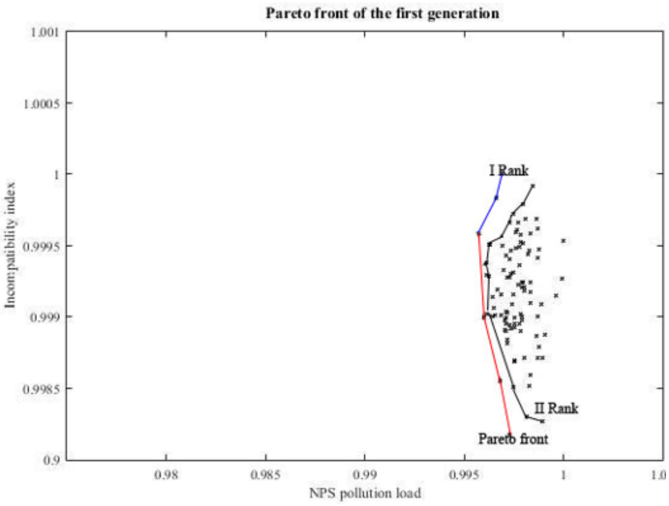

Figure 6: Pareto fronts of the first generation for NPS pollution load and incompatibility index.

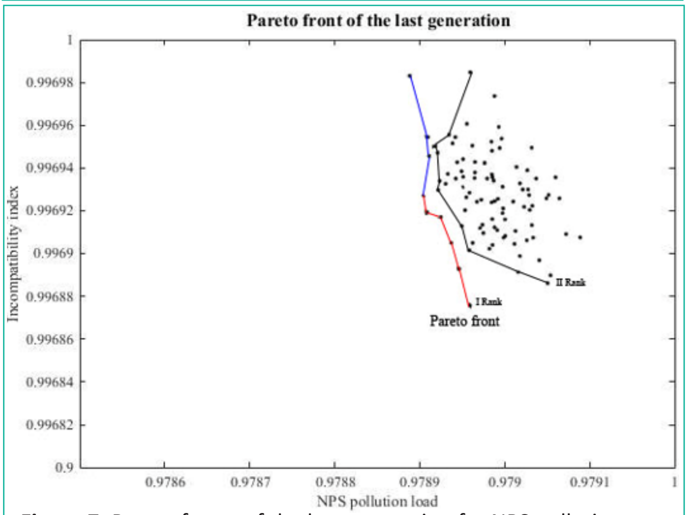

Figure 7: Pareto fronts of the last generation for NPS pollution load and incompatibility index.

Results and Discussion

Optimization of the Objectives

Optimization of non-point source load and changing cost index: From two-dimensional GA for optimizing, the research proposes optimal solutions of non-point source load and other objectives, in which these optimal solutions are satisfied objective functions although between objectives occur conflicting.

Below figure presents optimal solutions between non-point source load and changing cost index objectives with condition of objectives is minimization of NPS pollution load and minimization of changing cost index objectives. In fact, it is very difficult to exist the relationship between two these objectives because in order to be gained NPS pollution in minimum value, it has to pay a high cost for treatment and controlling it. Nevertheless, via optimal process of two-dimensional genetic algorithm, the research is indicated out existence of two feasible solution sets for the first generation and the last generation between non-point source load and changing cost index objectives.

In the first generation, the research finds out four optimal solutions and two weakly feasible points belonging to criterion space. They are laid on Pareto frontier. However, they only have four optimal solutions and are regarded as a set of optimal solution with the best value as red Pareto front line, which are satisfied conditions on minimization of non-point source load and minimization of changing cost index objectives.

Thus, this optimal solution set is gained the tradeoff of objectives when minimum changing cost index and it still ensures without pollution from non-point source. In optimization of this first generation indicates also out two weak optimal solutions. They are not regarded as the best solutions belonging to the set of optimal solution because they only satisfy about minimization of non-point source load when changing cost index is high. It presents only satisfies one objective while optimal condition is satisfied on two objectives. Moreover, the research shows also Pareto frontier in the second rank including 12 optimal solutions, which are non-dominated individuals in the population than the first rank. However, in the second rank has more optimal point than the first rank and the individuals lie below space are more optimal than above space of the second rank frontier. The individuals locate further Pareto frontier, which have diminishing about optimization between non-point source load and changing cost index objectives in the criterion space (Figure 2).

On the figure 3 is a population in the last generation including individuals are achieved after two-dimension genetic algorithm optimizing process. In the last generation of optimal process for non-point source load and changing cost index objectives indicates that the best solutions in this generation is more than the first generation as 2 optimal solutions. These six optimal solutions make a set of optimal points with the best value that they satisfy objective conditions as minimization of non-point source load and minimization of changing cost index. Especially, in the last generation does not appear weakly optimal solution.

Thus, in the last generation exists a perfect Pareto set with six optimal points lie on red Pareto frontier, and is gained the tradeoff between objectives. Furthermore, the research finds also out six optimal points in the second rank with optimal value less than of the first rank Pareto frontier. Therefore, in multi-objective optimization of non-point source load and changing cost index presents four optimal solutions in the first generation and six optimal solutions in the last generation as Pareto frontiers that they are satisfied the tradeoff between objectives.

Optimization of non-point source load and GDP: When considering objectives in maximization of GDP and minimization of non-point source load reveals confliction with each other. These objectives have high conflicting because in a country, when a higher GDP reveals better people life level; more consumption; increase polluted emission; needing more urban construction area to develop and create productions as well as showing the country is more and more developed. This development leads to increase pollution in the environment, especially in emission of non-point source. Generally, they are difficult to exist in the fact. However, nowadays, people are directing to use fresh energy in national development in order to mitigate the environment pollution but still ensuring economic development. Thus, with conflicting of these objectives, optimal solutions can be still occurred and it is demonstrated by two-dimension genetic algorithm optimization process in this research via minimization of NPS pollution load and maximization of GDP objectives.

Figure 4 is optimal map of two these objectives in the first generation and the last generation, where individuals make a population and locate at criterion space. It indicated that in the first generation, a set of optimal points includes five the best solutions lie on red Pareto frontier and to be located on the left of criterion space. These optimal solutions have the best value and satisfy both maximization of GDP and minimization of non-point source load as well as to be achieved the tradeoff between objectives. This is a perfect Pareto set. Furthermore, the research proposes eight optimal points in the second rank that they are non-dominated than optimal solutions in the first rank. However, optimal solutions in the first rank are less than the second rank in the criterion space. After selecting process, crossover, mutation, and elitism of individuals in two-dimension genetic algorithm optimization, the last generation of two these objectives reveal a set of feasible decision space, in which includes twelve optimal solutions locate on the left of criterion space as red Pareto frontier. On the figure 5 shows that amount of Pareto optimal solutions in the last generation is more than the first generation as seven best solutions and of course they satisfy conditions on maximization of GDP with minimization of non-point source load at all, as well as to be achieved the tradeoff of objectives. Moreover, in the second rank of optimal solutions, the research indicates there are 15 optimal points, which are non-dominated individuals than the first rank. Thus, 12 optimal points is the best solutions of Pareto optimization set in the last generation for GDP and non-point source load objectives. Therefore, with multi-objective optimization of non-point source load minimization and maximization of GDP objectives indicates 5 the best solutions in the first generation and 12 optimal solutions in the last generation, they lie on red Pareto frontier at all and to be gained the tradeoff between objectives.

Optimization of NPS load and land use incompatibility index: Land use compatibility is understood as attaining the highest and best in land-use. The land-use compatibility can reduce the most conflicting between neighbor land-uses and less changing around land use areas. Moreover, land use compatibility is also regarded as an index to assess conflicting land uses about economy and society in community. Especially it becomes more important in urban development, and with minimization of land use incompatibility means that maximum diminishing of conflicting in land use. If comparison to non-point source load, this mean is not right in fact because urban development makes increasing and expanding of land uses leading to rise conflicting in land uses and emit more pollution. Thus, minimization of land use incompatibility and minimization of non-point source load are difficult to happen in fact that they really conflict each other. Nevertheless, from selecting individuals and genetic algorithm optimal process proposes two sets of optimal solutions for the first generation and the last generation for non-point source load and land use incompatibility index objectives. Below figure indicates out those optimal solution sets.

In the first generation, a set of Pareto optimal points locates on the left of criterion space including four optimal points with the best solutions. They are laid on red Pareto frontier and satisfied optimal conditions on minimization of land use incompatibility and minimization of non-point source load objectives.

Moreover, via optimal process find also out two weak optimal points lying on red Pareto front line that they only satisfy minimization of non-point source load but not satisfying minimization of land use incompatibility index. Except for the best optimal solutions, the research also indicates out the existence of non-dominated individuals in the second rank including 11 optimal points that theirs values less optimal than the first rank, which is black Pareto frontier. Thus, in the first generation of above objectives proposes four optimal solutions as a set of Pareto optimization.

In the last generation of multiple objectives optimization with minimization of land use incompatibility index and minimization of non-point source load objectives, the research indicates a set of feasible solutions concluding six optimal points that they satisfy conditions of objectives as minimization of land use incompatibility index and minimization of non-point source load and form a red Pareto front line. Moreover, on the figure also shows there are three weak optimal solutions lying on blue Pareto frontier too of the first rank. They are not regarded as the best solutions because they only satisfy condition of one objective as minimization of non-point source load but they have high land use incompatibility index as well as they gain the tradeoff of objectives.

Furthermore, the research presents also optimal points in the second rank with 10 feasible solutions, which include non-dominated individuals than ones in the first rank. In ten these individuals, there are 5 individuals satisfy secondary optimization solution, left individuals can be regarded as very weak optimal points because they only satisfy minimization of non-point source load objective (5 optimal points) or minimization of land use incompatibility index objective. Thus, in the last generation of these objectives exists six optimal solutions with the best value and shows on black Pareto frontier. From optimizing process on minimization of land use incompatibility index and minimization of non-point source load objectives denote 4 optimal solutions in the first generation and 6 the best solutions in the last generation. They are presented by Pareto frontier and reveal as perfect Pareto set.

Conclusion

Via multi-objective optimization of two-dimension genetic, this research is found out some points as: the objectives of minimization of NPS pollution load, minimization of changing cost index, maximization of GDP value, and minimization of incompatibility index objectives have conflicting at all. However, they exist still optimal solutions, which create the tradeoff of objectives. Particular, there are four optimal solutions in the first generation and six optimal solutions in the last generation in minimization of non-point source load and minimization of changing cost index objectives; 5 the best solutions in the first generation and 12 optimal solutions in the last generation in minimization of non-point source load and maximization of GDP value objectives; 4 optimal solutions in the first generation and 6 the best solutions in the last generation in minimization of land use incompatibility index and minimization of non-point source load objectives. They are laid on Pareto frontier and reveal as perfect Pareto sets.

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