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## Optimisation of Infrastructure Location

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# Optimisation of Infrastructure Location \*

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## Abstract

This paper presents a model aimed at finding an efficient allocation of infrastructure investments in a region. The problem's complexity is due, not only to its combinatorial nature, but also due to the intrinsic multidimensional spatio-temporal relationships of its variables. Furthermore, there is no explicit solution for such NP-complete combinatorial optimisation problem; thus a heuristic optimisation technique such as Simulated Annealing is used to search for “good” solutions in a finite but huge solution space. In this paper, the approach applied in the “Xuzhou Integrated Settlement and Transportation Planning Project”, carried out in the People's Republic of China as a joint venture between the Jiangsu Development Planning Commission (JDPC) and the Institute of Regional Development Planning of the University of Stuttgart (IREUS), is to be presented. This study considered projects in 18 realms of infrastructure, in 115 locations of an administrative unit with about 9 million inhabitants. The results of the study suggest a significant gain in allocation efficiency due to the applied method of optimisation.

**Keywords:** Infrastructure location, combinatorial optimisation, Simulated Annealing.

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# 1 Introduction

The investment in key infrastructure projects is of crucial importance to create favourable conditions for the future development in a region. In general, it will boost its economic growth, improve its efficiency, and raise the living standards of its inhabitants. Decision makers often assume that the higher the investment in infrastructure, the better the prospects for development of their region will be. Budgets for investments and land availability, in contrast, are in most cases constrained within a time horizon.

In this context the following dilemma will eventually emerge. On the one hand, a simplistic solution that is the result of a series of ad hoc decisions and/or uncoordinated sectoral planning approaches will certainly not lead planners and/or decision makers to the most efficient use of the available resources simply because of the complexity of the system<sup>1</sup>, although it might appear politically interesting for some individuals. On the other hand, a holistic approach that takes into account simultaneously all relevant elements and objectives set for a given planning situation will very likely lead to a much better solution because it exploits the synergy effects among the components of the system. This approach, nonetheless, will be more difficult to implement because it leads to a huge combinatorial problem, whose solution exists but is probabilistically quite difficult to find. The ratio of benefits over costs associated with the application of such a method, however, may become so big that it is worth trying it.

This implies that planners aiming for a holistic allocation of funds should also pursue quantitative methods that provide insights on likely consequences of their infrastructure location decisions with regard - at least - to their area of jurisdiction.

In this paper, a holistic investment decision approach as well as the results of its application to a Study Area will be briefly presented and discussed.

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<sup>1</sup>In this case the system comprises a large number of microelements or actors (e.g. people, firms, or government) and a number of tightly coupled subsystems (e.g. anthropogenic activities, transportation systems; urban and suburban biotopes; water supply, waste collection and waste water systems) interacting in both space and time. The domains of interaction in space and time are called the region and the time horizon respectively.

## 2 Methodological Foundations

### 2.1 The Basic Question

One of the fundamental questions to be answered in the context of infrastructure location is:

Which of the proposed infrastructure projects assumed to require more funds than available should be built in order to get the highest benefits from them at the end of a predefined time horizon under given budgetary and environmental restrictions, and when?

Analytically, answering this question implies finding an optimal solution to one of the most difficult problems in the context of location theory. The problem's complexity is due, not only to its combinatorial nature, but also due to the intrinsic multi-dimensional spatio-temporal relationships of its variables. This, in turn, requires the formulation of a dynamic evaluation model that should be able to estimate the main effects of a given set of infrastructure investments in a given planning period.

An extensive description of such a model is out of the scope of the present paper, however, for the sake of completeness, a brief description of the main characteristics and variables involved in the model used in the present study is presented next. For more details, please refer to [13].

### 2.2 Brief Description of the Model

#### 2.2.1 Purpose, Scope, and Notation

The purpose of the evaluation model presented below is to interlink a number of interdependent dynamical sub-models (which have been previously calibrated and validated) in such a way that they together can resemble the most relevant development aspects of a given region and then to use this ensemble to evaluate the costs and benefits of a given infrastructure investment decision.

Let  $\Omega$  denote the spatial domain of a region or an administrative unit where the evaluation model is to be applied.  $\Omega$  can in turn be subdivided into  $N$  spatial units whose space is denoted by  $\Omega_i$  so that  $\Omega = \bigcup_i \Omega_i, \forall i = 1, \dots, N$ . For practical and

analytical reasons these spatial units may be grouped into  $U$  spatial unit classes so that a given class  $u$  is  $\mathcal{C}_u = \{i \mid C_u(i) = 0\}$ , where  $C_u(\cdot)$  is a set of predefined characteristics defining the class  $u$ . By definition, spatial unit classes are disjoint sets.

Let  $t = 1, \dots, T$  denote a time point within the time horizon  $T$  predefined for the evaluation process. The time horizon, due to planning reasons, is also subdivided into  $R$  planning periods (e.g. 5-year interval).

Furthermore, let each spatial unit  $i$  have its economy subdivided into  $S$  economic sectors, where a given sector is denoted by  $s = 1, \dots, S$ ; and the infrastructure equipment levels in  $i$  be composed of  $G$  infrastructure categories, where a given category is denoted by  $g = 1, \dots, G$ . Finally, let its population  $P_i$  be subdivided by gender and one year age groups; and its land use  $L_i$  be characterised by  $l$  land use types.

Based on the previous definitions, the most important variables of the model are (based on [8]).

- $I$  Investment in infrastructure in €.
- $X$  Indicator vector (e.g. statistical information) related to an infrastructure category. It has various additive dimensions denoted by the index  $p$ . Dimension  $q$  denotes the implementation cost in €.
- $\Delta X$  Increment in the indicator  $X$  due to investment  $I$ .
- $Z$  Evaluation of the infrastructure situation on the basis of indicators (defined in the interval  $[0, 1]$ , dimensionless).
- $\gamma$  Evaluation parameters (various dimensions according to each indicator  $X_q$ ).
- $\mathcal{T}$  Accessibility (e.g. average travel time in minutes).
- $E$  Employment (people).
- $K$  Economic investment in €.
- $\Delta E$  Change in employment (people).
- $\beta$  Economic model parameters.
- $Y$  GDP of the region  $\Omega$  in €.
- $A$  Infrastructure attractiveness for in-migration (dimensionless).
- $\hat{A}$  Attractiveness for economic investment (dimensionless).
- $U$  Environmental function.

$\Delta P$	Natural population growth (people).
$M$	Migration component of population growth (people).
$\eta$	Natural population change parameters (various dimensions).
$B$	Total available budget in €.
$\alpha$	Fraction of the GDP invested in infrastructure (dimensionless).

### 2.2.2 Basic Equations of the Model

In general the model contains six main components, namely: 1) the population sub-model that includes natural change and migration; 2) the infrastructure evaluation sub-models; 3) the environmental evaluation sub-models; 4) the land use sub-model; 5) the economic forecasting sub-model; and 6) the transportation sub-model.

The system of equations described below evaluate the change in GDP of the region given a set of infrastructure investments  $\mathcal{I}^t = \{I_{igp}^t\}$ . Where  $I_{igp}^t$  denotes an identification index of a given project  $p$  of the infrastructure category  $g$ , whereas  $I_{igpq}^t$  represents statistical information associated with project  $p$ , e.g. its implementation cost in spatial unit  $i$  and time point  $t$ . The main equations are:

$$Y_{is}^t = Y_{is}^{t-1} + \Delta Y_{is}^t \quad (1)$$

$$\Delta Y_{is}^t \equiv \Delta Y_{is}^t(K_{is}^t, \Delta E_{is}^t, \hat{A}_{is}^t, \beta_{us}) \quad (2)$$

$$K_{is}^t \equiv K_{is}^t(Y_{is}^{t-1}, \hat{A}_{is}^{t-1}) \quad (3)$$

$$E_i^t = E_i^{t-1} + \Delta E_i^t + E(I_{igp}^t) \quad (4)$$

$$\Delta E_{is}^t \equiv \Delta E_{is}^t(E_{is}^{t-1}, K_{is}^t) \quad (5)$$

$$P_i^t = P_i^{t-1} + \Delta P_i^t + M_i^t \quad (6)$$

$$\Delta P_i^t \equiv \Delta P_i^t(P_i^t, \eta_i^{t-1}) \quad (7)$$

$$M_{ji}^t \equiv M_{ji}^t(A_j^{t-1}, A_i^{t-1}, P_i^t, \Delta E_j^t, \Delta E_i^t, L_i^t, U_i^t) \quad (8)$$

$$\hat{A}_{is}^t \equiv \hat{A}_{is}^t(Z_{ig}^t, L_i^t, U_{ig}^t) \quad (9)$$

$$A_i^t \equiv A_i^t(Z_{ig}^t) \quad (10)$$

$$Z_{ig}^t \equiv Z_{ig}^t(X_{ijgp}^t, \gamma_{igp}^t, \mathcal{T}_{ijg\hat{g}}^t, P_i^{t-1}, E_i^{t-1}, Y_i^{t-1}) \quad (11)$$

$$X_{igp}^t = X_{igp}^{t-1} + \Delta X_{igp}^t(I_{igp}^t) \quad (12)$$

$$\mathcal{T}_{ij}^t \equiv \mathcal{T}_{ij}^t(I_{igp}^t) \quad (13)$$

Additionally, these variables should satisfy the following consistency equations:

$$E_i^t = \sum_s E_{is}^t \quad (14)$$

$$M_i^t = \sum_j M_{ji}^t \quad (15)$$

The GDP of the region at the end of the planning horizon  $T$  is therefore:

$$Y_\Omega = \sum_i \sum_s Y_{is}^T \quad (16)$$

Because of the nature of the economic sub-model—which interrelates investment, employment, and production—the system of equations has to be solved iteratively for a given planing period until convergence is reached. The parameters  $\beta_{us}^t$  are to be calibrated with observed past information for the region  $\Omega$ .

Ceteris paribus, the estimation of the travelling time from every spatial unit  $i$  to every  $j$ ,  $\mathcal{T}_{ij}^t$ , given a road network  $\mathcal{N}^t$  and a transport mode, is obtained by the shortest path algorithm developed by Dijkstra [5]—because of its extraordinary efficiency [18]—and assuming average speeds which depend on link type only.

The evaluation of the infrastructure category  $g$  in spatial unit  $i$  in time point  $t$ ,  $Z_{ig}^t$ , is based on indicators for this spatial unit with dependence on population, employment and/or economic level. It may also include time accessibility  $\mathcal{T}_{ij}^t$  of the same and - if necessary - other infrastructure  $\hat{g}$  in other spatial units  $j$  [8].

### 3 Problem Definition

The question stated in section (2.1) can be formalised as:

Find

$$\mathcal{I}^*$$

so that

$$\Phi(\mathcal{I}^*) = \max \Phi(\mathcal{I}) \quad (17)$$

subject to

$$\sum_{t \in r} \sum_{i \in \mathcal{C}_u} \sum_g \sum_p I_{igpq}^t \geq \tau_u Y^r \quad \forall r, u \quad (18)$$

$$\sum_{t \in r} \sum_i \sum_p I_{igp}^t \geq \tau_g Y^r \quad \forall r, g \quad (19)$$

$$\sum_{t \in r} \sum_i \sum_g \sum_p I_{igp}^t \leq B^r \quad \forall r \quad (20)$$

$$\sum_t \sum_i \sum_g \sum_p I_{igp}^t \leq \alpha Y_\Omega \quad (21)$$

$$Z_{ig}^t \leq \xi_{ug} \quad \forall r, u, i \in \mathcal{C}_u, t \in r \quad (22)$$

$$L_i^t(\mathcal{I}^*) = 0 \quad \forall r, u, i \in \mathcal{C}_u, t \in r \quad (23)$$

$$\mathcal{I}^*, \mathcal{I} \subset \Upsilon(\mathcal{P}), \quad (24)$$

and

$$Y^r = \sum_{t \in r} \sum_i \sum_s \Delta Y_{is}^t \quad \forall r \quad (25)$$

$$B^r = \alpha Y^r \quad \forall r \quad (26)$$

where  $\Phi(\cdot)$  is an economic objective function;  $\mathcal{P}$  is the pool of infrastructure projects proposed for  $\Omega$ .  $\tau_u$  and  $\tau_g$  are fractions associated with the minimum investment for each spatial unit class and investment category respectively.  $\xi_{ig}$  is an exogenous threshold value to be satisfied by the overall evaluation indicator in order to accept a given project. This threshold is  $i$  and  $g$  specific to avoid overspending in a given infrastructure category and/or a spatial unit class when a given level has been attained. Finally,  $\Upsilon(\mathcal{P})$  is the set of all possible combinations—*with repetition*—of projects in the pool  $\mathcal{P}$  that fulfil all constraints of the problem stated above.

The objective function  $\Phi(\cdot)$  may be set either as a scalar, i.e. it deals with only one objective, or as a vector composed by many sub-objectives dealing with many areas of interest separately. In this study, just for the sake of simplicity, the former approach was adopted only for the formulation of the problem. Here the explicit objective is



an “economic objective function” (17) dealing with the effects of the infrastructure allocation on the region’s economy, whereas the indirect objectives —internalised as constraints of the system—are taking into account the budget availability, environmental protection issues, the improvement of “quality of life” and the “attractiveness” due to infrastructure investment.

The simplest *long-term* economic-orientated objective function<sup>2</sup> among other possibilities (please refer to [12] for more details) to be considered for this study—given a random allocation of infrastructure investments  $\mathcal{I}$  and assuming that a given society is willing to sacrifice its short term effects for those at the end of a time horizon—is the region’s cumulative GDP gains over the time horizon. Formally it can be written as follows:

$$\Phi = Y_{\Omega}(\mathcal{I}) \tag{27}$$

Moreover, the set of constraints given by (18) and (19) were included to ensure both an appropriate distribution of the available investment funds among every infrastructure category and an appropriate distribution of the available investment funds among every spatial unit class [17]. The constraints denoted by (20) and (21) were set to define the available investment funds as a percentage of the GDP of the region, and those given by (22) were introduced to avoid overspending when a given evaluation threshold was satisfied in the infrastructure category  $g$  in the spatial unit  $i$ . Put differently, they are effectively restricting the level of supply of infrastructure to satisfactory levels. Consequently, it is assumed that the higher the value of  $\xi_{ig}$  is, the better the attractiveness and the quality of life in spatial unit  $i$ . Finally, all solutions have to fulfill land use consistency equations denoted by (23).

## 4 Optimisation Method

Analytically the problem stated in (17) is termed a NP-complete<sup>3</sup> combinatorial optimisation problem, which is the most difficult problem to be solved in the context of

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<sup>2</sup>Proposed by Wang et al. [7, 19].

<sup>3</sup>A combinatorial problem that is solvable in Non-Polynomial time, i.e. *a problem that cannot be solved to optimality because the search for an optimum requires prohibitive amounts of time* [14].

combinatorial optimisation theory and for which there is no explicit mathematical solution. In the present case, for example, if the cardinality of the set of possible projects  $\mathcal{P}$  is 845 (as the case study presented in section 5), then the number of feasible combinations *with repetition* of  $n \approx 500$  investment projects is greater than  $10^{100}$ ! Finding the global optimum or optima for such an intractable NP-complete combinatorial problem would demand eons of computing time. Therefore, one can only aim to find a “good” solution that is close enough to the global minima (or maximum) of the objective function under given constraints. Because of this, the only alternative that can effectively be utilised to find “good” solutions are heuristic optimisation techniques such as the Monte Carlo Search, Genetic Algorithms (GA), Tabu Search, and Simulated Annealing (SA), among others.

In the present study some technical considerations were analysed in order to choose the most appropriate heuristic optimisation method for the present problem. As a result of them, for instance, it was found that GA is not appropriate because the cardinality of the solution of the problem,  $\#\{\mathcal{I}\}$ , varies from realisation to realisation, which in turn, makes an implementation of GA more complicated than that of other methods. Furthermore, there is no criteria available to guide regarding the size of the representative population to be used for this huge combinatorial problem in an implementation of GA. , the main issue regarding other optimisation methods was their expected efficiency. Finally, SA was found to be the most advantageous for the problem defined before. Hereafter, its main concept and then its implementation to solve this problem will be described.

SA is a heuristic optimisation technique based on the Metropolis algorithm [10] that simulates the evolution of a melted solid in a heat bath towards thermodynamic equilibrium, which is noting but reaching the ground state of this solid where a crystalline structure is attained. When a solid reaches the ground state, its atoms have self organised in a spatial lattice with the lowest internal energy and thus entropy (i.e. a measure of disorder in thermodynamics); put differently, the most stable configuration of its atoms has been achieved, one having the best mechanical properties [1].

In metallurgy, the process to obtain the ground state of a melted alloy is called annealing. It basically consists of heating up a solid until it melts, decrease its temper-

Table 1: Analogy between a physical many-particle system and a combinatorial optimisation problem.

Physical Many-Particle System	Combinatorial Optimisation Problem	Variable
State	Solution	$\mathcal{I}_k$
Temperature	Control parameter	$v_\ell$
Energy of a state	Cost of a solution	$\Phi'(\mathcal{I}_k)$
Perturbation	Generation	$\mathcal{I}_{k+1} = \mathcal{G}(\mathcal{I}_k)$
Metropolis criterion <sup>a</sup>	Acceptance criteria	
Cooling schedule	Decrement of the control parameter	$v_{\ell+1} = d(v_\ell, \delta)$

<sup>a</sup> The Metropolis criterion states that the acceptance probability is estimated according to the Boltzmann distribution, which specifies that the probability to find a system in a new state  $\mathcal{I}_{k+1}$  is proportional to  $\exp\left(\frac{-\Delta\Phi'(\mathcal{I}_{k+1})}{v_\ell}\right)$ .

ature carefully a very small amount and then let its particles to reorganise themselves into a stable state - at this temperature -. Continue this procedure until ambient temperature is reached. If the cooling is done too fast (i.e. quenching) a polycrystalline structure—i.e. a non-desirable meta-stable state—will be obtained.

A relevant question at this point may be — Is there a relationship between this metallurgical process and a combinatorial optimisation akin to that mentioned above? The answer to this fundamental question was provided by Kirkpatrick et al. [9]. They found out that there exists a strong analogy between these apparently disparate realms as is summarised in table 1.

Mathematically this optimisation technique can be seen as a Markov chain [14] of finite length  $\Lambda = \ell(\iota^+ + \iota^-)$  in which a starting solution  $\mathcal{I}_0$  is set to evolve by introducing small systematic changes aimed at improving the value of the objective function  $\Phi(\mathcal{I}_k)$ . Here,  $\ell$  is the number of consecutive transitions at a given value of the control parameter denoted by  $v_\ell$ .  $\iota^+$  and  $\iota^-$  are the number of accepted transitions that either decrease or increase, respectively, the cost of the solution as can be seen in algorithm (1).

After the introduction of SA by Kirkpatrick et al. this general stochastic optimisation technique has been very successfully applied in a large variety of problems belonging to different disciplines such as engineering, physics, operations research, biology, and economics. Few remarkable examples are the design of integrated circuits [9], a heuristic solution to the famous Travelling Salesman Problem by Lawler et al. (1988) [1], Scheduling problems by Dige and Lund (1992) [15], telecommunication networks by Chardaire (1993) [15], the afforestation problem by Valqui-Vidal (1993) [15], and classification of remotely sensed imagery by Bárdossy and Samaniego (2002) [2] among many others. The success of SA in these applications comes from the following facts: 1) it can deal efficiently with cost or objective functions possessing quite arbitrary degrees of nonlinearities, discontinuities, and stochasticity; 2) it can process quite arbitrary boundary conditions and constraints imposed on these cost functions; 3) it can be implemented quite easily with a degree of coding quite minimal as to other nonlinear optimisation algorithms; and finally 4) the algorithm converges to the minimum global solution if  $\Lambda \rightarrow \infty$  and  $v_\ell \downarrow 0$ , thus, finding a “near optimum” solution is mathematically guaranteed [14] if  $\Lambda$  is large enough.

A disadvantage of this method is that there is no general procedure for its application apart from its general four components shown in table 1: 1) generation of a feasible solution or transition mechanism, 2) evaluation of the objective function and the acceptance criterion, 3) the so-called cooling schedule, and 4) the stopping criteria. The algorithm used in this study to optimise the problem given in (17) is presented below.

**Algorithm 1** *Minimisation Algorithm using Simulated Annealing*

1. Set  $k = \ell = 0$  and initialise the control parameter  $v_\ell$
2. Find a random initial solution  $\mathcal{I}_k$  and calculate its cost function  $f_o = \Phi'(\mathcal{I}_k)$ , set  $\mathcal{I}^* \equiv \mathcal{I}_k$  and  $f^* = f_o$
3. Repeat
  - a. Initialise  $\iota^+ = \iota^- = 0$
  - b. Repeat  $\zeta$  times

*Generate a perturbation of the previous solution so that  $\mathcal{I}_{k+1} = \mathcal{G}(\mathcal{I}_k)$*

*Evaluate the cost of the new solution  $f_n = \Phi'(\mathcal{I}_{k+1})$*

*If  $f_n \leq f_o$  then*

$$\iota^+ \leftarrow \iota^+ + 1$$

$$f_o \leftarrow f_n$$

$$\text{If } f_o < f^* \text{ then } f^* \leftarrow f_o \text{ and } \mathcal{I}^* \leftarrow \mathcal{I}_{k+1}$$

$$k \leftarrow k + 1$$

*Else*

*Generate a random number  $\pi \in \text{unif}[0, 1)$*

*Estimate the transition probability  $\rho = \exp\left(\frac{f_o - f_n}{v_\ell}\right)$*

*If  $\rho > \pi$  then*

$$\iota^- \leftarrow \iota^- + 1$$

$$f_o \leftarrow f_n$$

$$k \leftarrow k + 1$$

*Else reject the perturbation  $\mathcal{I}_{k+1}$*

*c. Estimate the acceptance ratio  $\chi_\ell = \frac{\iota^+ + \iota^-}{\zeta}$*

*d. Update the control parameter  $v_{\ell+1} = d(v_\ell, \delta)$*

*e. Evaluate the stopping criteria  $\mathcal{S}_\ell(f_o, f^*, \chi_\ell, \zeta, \varepsilon, \epsilon, \kappa)$*

*f.  $\ell \leftarrow \ell + 1$*

*4. Until  $\mathcal{S}_\ell \equiv 1$*

*5. End*

It should be noted that this algorithm is conceived for a minimisation problem. A maximisation problem such as that shown in (17) can be converted into a minimisation problem by reversing the sign of the scalar objective function, i.e.  $-\Phi'$ .

In order to apply the algorithm (1) to maximise the combinatorial problem proposed in (17), some issues still have to be discussed.

## 4.1 Initialisation of the Control Parameter

The appropriate selection of the initial value of the control parameter  $v_0$ , given a particular problem is normally very tricky unless some additional information is employed. The additional information used in this case is the acceptance ratio<sup>4</sup>,  $\chi_\ell$ , which is estimated for each  $\zeta$  – proposed random transitions. As a rule of thumb,  $v_0$  is chosen large enough so that  $\chi_0 = \chi(v_0)$  is close to 1, say between the interval 0.90 to 0.98 [1]. The physical analogy of this situation corresponds to the random arrangement of particles in the liquid phase of a melted alloy, or in other words, a state of very high entropy.

## 4.2 Decrement of the Control Parameter

The second issue to be discussed is the so-called cooling schedule or decrement of the control parameter. Based on many proposals found in the cited literature [15, 1, 2] many experiments were carried out for this study to find out which strategy renders the best results for the present problem. As a result of them, a two-phase decrement of the control parameters was implemented. It is given by

$$v_{\ell+1} = \begin{cases} \delta_f v_\ell & \text{if } \chi_\ell < \chi_f \\ \delta v_\ell & \text{otherwise} \end{cases} \quad (28)$$

Where  $\delta$  and  $\delta_f$  are rates of decrement in the first and second phase, respectively. The latter is also called the “freezing” phase. Additionally, a reheating schedule may be implemented as a way to escape from local minima when the system is in the freezing phase.

The elapsed “time” at a constant control parameter  $v_\ell$  was modelled as a Markov chain of length  $\zeta$ . Its value is a function of the neighbourhood size but it is not advisable to have values less than 100.

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<sup>4</sup>This indicator is calculated as the quotient between the number of all accepted transitions and all proposed ones. It ranges from 0 to 1. A value greater than 0.90 means that the system is in a state of very high disorder or entropy, whilst a value close to 0 represents a state quite close to the ground state.

### 4.3 Generator of Feasible Solutions

The purpose of the function  $\mathcal{G}$  introduced in algorithm (17) is to find a random perturbation in the neighbourhood of  $\mathcal{I}_k$  that fulfils the problem's constraints (18), (19), (20), (22), and (23) simultaneously. The new state or solution of the system is therefore  $\mathcal{I}_{k+1} = \mathcal{G}(\mathcal{I}_k)$ . Finding, however, a new state that satisfies these conditions is computationally too expensive given the myriad of constraints of the problem at hand. This implies that, in order to solve (17) using SA, some constraints have to be initially relaxed but, later, penalise the objective function if a violation of a given constraint happens. This procedure has been successfully applied in many problems reported in the literature, e.g. in [4, 2]. Consequently,  $\mathcal{G}$  will only retain the budget [(20), (21)], level of supply (22), and land use (23) constraints, since the former ones will ensure the convergence of the economic model and the remaining ones can easily be checked. Those constraints not observed by the generator will be internalised as penalty functions  $\psi$  that will be discussed afterwards.

Some definitions are necessary to define the generator. Let  $\mathcal{P}_k^r \in \Upsilon(\mathcal{P})$  be a set composed of indices of those investment projects to be carried out in the planning period  $r$  in a given solution  $k$ , so that  $\mathcal{I}_k = \cup_r \mathcal{P}_k^r$ . Furthermore, it is necessary to define three transition modes termed  $\mathbf{M}_m$ ,  $m = 1, 2, 3$ , each of them occurring at a predetermined probabilities  $\pi_m$ , so that  $\sum_m \pi_m = 1$ . These modes are designed to meet specific purpose related with the nature of the optimisation problem at hand. Now, this function can be written in an algorithmic way as follows

**Algorithm 2** *Generator function  $\mathcal{G}$*

1. *Given  $\mathcal{I}_k$  and  $\pi_m$*
2. *Generate a random number  $\varrho \in \text{unif}[0, 1)$*
3. *Select the transition mode  $m$  so that  $\min(\sum_m \pi_m - \varrho) > 0$*
4. *Select randomly two indices  $r, r' \in [1, R]$ , and  $r \neq r'$*
5. *Define the sets  $\mathcal{L}^r$  and  $\mathcal{L}^{r'}$  as follows*

$$\mathcal{L}^r = \begin{cases} \mathcal{P}_k^r & \text{if } m = 1, 2 \\ \mathcal{P} & \text{otherwise} \end{cases} \quad (29)$$

$$\mathcal{L}^{r'} = \begin{cases} \mathcal{P}_k^{r'} & \text{if } m = 1, 3 \\ \mathcal{P} & \text{otherwise} \end{cases} \quad (30)$$

6. Select randomly a project from the set  $\mathcal{L}^r$ , say  $\hat{p}$ , whose total cost is  $\theta_r$  and call this subset  $\Delta\mathcal{L}^r$
7. Chose randomly a set of projects from the set  $\mathcal{L}^{r'}$  whose total cost  $\theta_{r'}$  satisfy both the condition  $|\theta_r - \theta_{r'}| \leq \varpi$  and the supply levels<sup>5</sup>. Call this new subset  $\Delta\mathcal{L}^{r'}$
8. Swap these two sets so that the new state becomes

$$\mathcal{I}_{k+1} = \begin{cases} \cup\{\mathcal{P}_k^1, \dots, \mathcal{P}_k^r - \Delta\mathcal{L}^r + \Delta\mathcal{L}^{r'}, \dots, \mathcal{P}_k^{r'} - \Delta\mathcal{L}^{r'} + \Delta\mathcal{L}^r, \dots, \mathcal{P}_k^R\} & \text{if } m = 1 \\ \cup\{\mathcal{P}_k^1, \dots, \mathcal{P}_k^r - \Delta\mathcal{L}^r + \Delta\mathcal{L}^{r'}, \dots, \mathcal{P}_k^R\} & \text{if } m = 2 \\ \cup\{\mathcal{P}_k^1, \dots, \mathcal{P}_k^{r'} + \Delta\mathcal{L}^r - \Delta\mathcal{L}^{r'}, \dots, \mathcal{P}_k^R\} & \text{if } m = 3 \end{cases} \quad (31)$$

Where the cost of a project  $\hat{p}$  that belongs to region  $i$  and category  $g$  is  $\theta_r = \sum_{t \in r} I_{ig\hat{p}q}^t$ ;  $\varpi$  is a threshold tolerance in €.

The purpose of mode  $M_1$  is shifting projects along time, hence it helps to determine *when* the best moment to implement an investment project  $\hat{p}$  is. This sort of operator is called inversion in many applications of GA [11].

Modes  $M_2$  and  $M_3$  are called mutations<sup>6</sup> because they swap a set of projects from a randomly selected planning period  $r$  with those belonging to another planing period  $r'$  or those from the pool of investment projects provided that the budget constraint, as well as the constraint associated with the level of infrastructure supply are fulfilled. These transition mechanisms have something in common, namely: To find *which* investment project  $\hat{p}$  should be implemented in a given planning period (the question of where is inherent to the project itself). This goal will be achieved by introducing projects from the pool to the original list while removing others from it. These operators have a fundamental difference though.  $M_2$  tends to increase the number of investment projects in a given planning period whereas  $M_3$  does the contrary.

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<sup>5</sup>These ensure the fulfilment of constraints (20), (21), and (22).

<sup>6</sup>This type of operator is also borrowed from GA [11].



## 4.4 Evaluation of the Objective Function

The next point to be discussed in this section is the evaluation of the *overall* objective function  $\Phi'$ . As it was explained before, all transition modes have a downside, i.e. they may alter the solution  $\mathcal{I}_k$  in such a way that at least one of the remaining constraints [(18) and/or (19)] with the new solution  $\mathcal{I}_{k+1}$  are no longer satisfied. This implies that in order to achieve a near-optimum solution employing the algorithm 1, the objective function should not only maximise the economic objective function but should also internalise remaining constraints as objectives as well. One way of doing so is the following.

Let  $\vartheta$  be the degree of fulfilment (DOF) of a given constraint to be equal to the ratio between the proposed investment over the minimum guaranteed investment, then (18) and (19) can be rewritten as

$$\vartheta_u^r = \frac{\sum_{t \in r} \sum_{i \in \mathcal{C}_u} \sum_g \sum_p I_{igpq}^t}{\tau_u Y^r} \geq 1 \quad \forall r, u \quad (32)$$

$$\vartheta_g^r = \frac{\sum_{t \in r} \sum_i \sum_p I_{igp}^t}{\tau_g Y^r} \geq 1 \quad \forall r, g \quad (33)$$

These new variables can be seen as “social objectives” because they ensure an equitable distribution of funds among spatial unit classes and infrastructure categories in all planning periods. Hence, the higher the DOFs, the more equitable the distribution of funds. Creating, however, a newly composed objective function that internalises these constraints still requires some additional considerations.

First, since the order of magnitude of the various objectives differs considerably, it is necessary to transform them into the common interval  $[0, 1]$ , where 1 would mean the best and 0 the worst case respectively. Second, the pure maximisation of the DOFs will also have a drawback, namely: it will tend to favour those regions with high productivity, which are nothing but those that already have good accessibility and supply of infrastructure. Therefore, it will be convenient to penalise the overspending either in a given infrastructure category or in a given spatial unit class if this occurs. By doing so, the situation in lagging regions will tend to improve. Third, if this multi-objective optimisation problem is transformed into a scalar one<sup>7</sup>, then the issue of the partial substitution of one objective by others at lower values of these indicators should

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<sup>7</sup>For example by an additive weighted aggregation [4, 3].

be dealt with thoroughly in order to avoid misleading results. The procedure adopted in this study in this respect is a technique called compromise programming [6, 3]. This method reduces these non-desirable substitution effects among different objectives by powering each objective to an exponent  $\varsigma$  before they are aggregated. If  $\varsigma$  is big enough, say 6 or more, the substitution effect is practically negligible. Additionally, each objective is weighted so that its relative importance is reflected by the magnitude of its corresponding weight. Finally, since the algorithm (1) is conceived to minimise a given objective function, the transformed scalar objective to be maximised should be transformed into a minimisation problem. In the present study this can be easily be done by minimising the degree of discordance with respect to the ideal objective vector  $\mathbf{1}$ .

Mathematically these considerations can be written as

$$\psi_0 = \begin{cases} 0 & \text{if } \Phi \leq a_1 \\ \frac{\Phi - a_1}{a_2 - a_1} & \text{if } a_1 < \Phi \leq a_2 \\ 1 & \text{otherwise} \end{cases} \quad (34)$$

and

$$\psi_c = \begin{cases} 0 & \text{if } \Phi \leq b_1 \\ \frac{\vartheta_c^r - b_1}{b_2 - b_1} & \text{if } b_1 < \Phi \leq b_2 \\ 1 & \text{if } b_2 < \Phi \leq b_3 \\ \frac{b_4 - \vartheta_c^r}{b_4 - b_3} & \text{otherwise} \end{cases} \quad (35)$$

where  $c \in \{1, \dots, u, \dots, U, U+1, \dots, U+g, \dots, U+G\}, \forall r$ . The transformed overall objective is

$$\Phi' = \left[ \sum_{c=0}^{U+G} \omega_c (1 - \psi_c)^\varsigma \right]^{\frac{1}{\varsigma}} \quad \sum_c \omega_c = 1, \omega_c > 0, \forall c \quad (36)$$

Summarising, minimising  $\Phi'$  is equivalent to finding one Pareto-optimum of the multi-objective function  $\vec{\Phi} = \{\psi_0, \dots, \psi_{G+U}\}$ , in which the relative importance of the objectives is given [4].

Additional constraints, if necessary, can be modelled as multiplicative penalty functions applied to  $\vartheta_c^r$ . These functions are equal to one only if a given constraint is fulfilled

and less than one if it is not. Its value is proportional to the degree of mismatch with respect to its target value [4].

## 4.5 Stopping Criteria

The purpose of the stopping criteria  $\mathcal{S}_\ell(f_o, f^*, \chi_\ell, \zeta, \varepsilon, \epsilon, \kappa)$  is to ensure the convergence of the proposed algorithm to a solution close to the “global minimum”. Since the size of the solution space of the proposed problem is enormous, two hard-to-fulfill conditions were set in the previous function to indicate when a quasi-optimal state has been reached. In this study  $\mathcal{S}_\ell \equiv 1$  —i.e. convergence was reached— only if the following conditions are satisfied simultaneously: 1) the “best” value ( $f^*$ ) found has not been further reduced by a given percentage  $\epsilon$  during  $\kappa$  successive Markov chains of length  $\zeta$  and 2) the acceptance ratio  $\chi_\ell$  is less than a threshold value  $\varepsilon$ .

# 5 Application

## 5.1 The Study Area

The model reported in this paper was applied in the “Xuzhou Integrated Settlement and Transportation Planning Project” which was carried out in the People’s Republic of China as a joint venture between the Jiangsu Development Planning Commission (JDPC) and the Institute of Regional Development Planning of the University of Stuttgart (IREUS). The region chosen for its implementation was the so-called Xuzhou City<sup>8</sup>.

This administrative area is located in the north-west corner of Jiangsu Province (see figure 1) and is almost surrounded by the territories of the Anhui, Henan, and Shandong provinces. Xuzhou City is a typical case of an important regional centre, which, because of both its particularly favourable situation on the transportation axis from Beijing to Nanjing and Shanghai and its hinterland population of about 50 million inhabitants, promises excellent perspectives for its future development. At the moment, this region is already participating in the economic boom occurring in East China [13]. Its GDP in 2000 was 6.4 billion € with an average growth rate of 12.2%.

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<sup>8</sup>In Chinese the whole administrative area is designated — in translation — “Xuzhou City” [13].

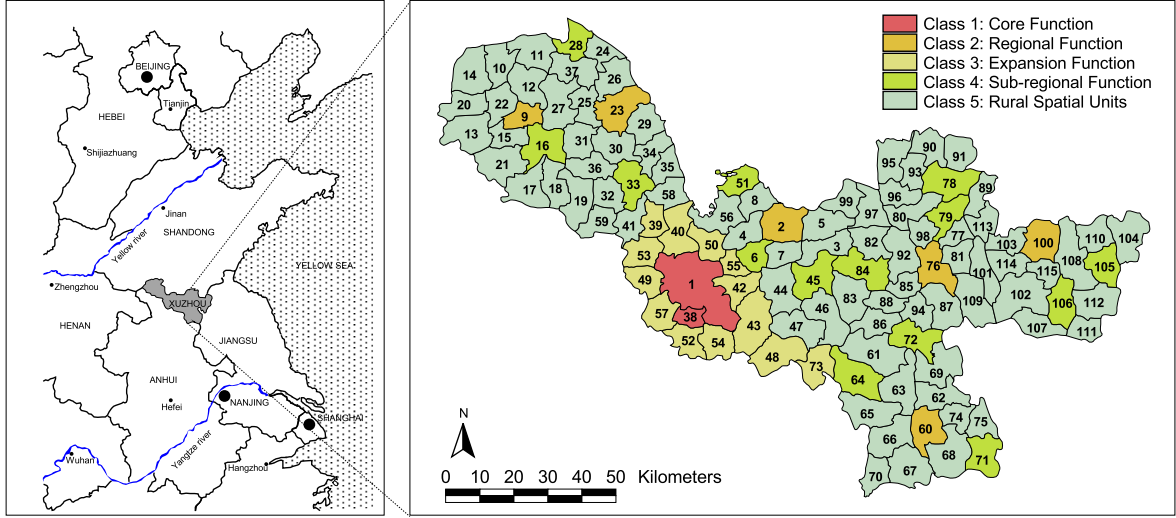


Figure 1: Left: Location of the Study Area in Eastern China. Right: Spatial disaggregation of the area of the Xuzhou City into spatial units and spatial unit classes.

In the year 2000 Xuzhou’s population was 8.91 million inhabitants and the settlement population density was generally above  $600 \text{ inh/km}^2$ . This fact together with the continuing increase of per capita income and the need to improve the population’s living conditions will certainly induce land use changes, specially from agriculture to settlement or industrial areas. If the population development continues as indicated in the last census, Xuzhou’s population is expected to reach a maximum of 9.28 million people by the year 2017, and then decrease to 9.26 million by 2020 [13].

## 5.2 Data Requirements

The data employed in the proposed model was surveyed in the last national population census held on November 2000. The spatial information was disaggregated into 115 ( $N$ ) spatial units (see figure 1), which were, in turn, classified into 5 ( $U$ ) spatial unit classes because of technical and planning reasons. The characteristics of each class are explained hereafter.

**Spatial Unit Class 1** is composed of the central urban core districts that provide supra-regional infrastructure functions [13].

**Spatial Unit Class 2** is composed of district and county towns that are already firmly established as regional centres, hence, provide regional infrastructure functions [13].

**Spatial Unit Class 3** is composed mainly of the ring of spatial units surrounding the core area and other spatial units along a possible southeast development axis up to the airport located in spatial unit No. 73. These are the potential locations with an expansion role for the core area either with residential, commercial or manufacturing functions [13].

**Spatial Unit Class 4** is composed of all key towns that potentially could strengthen the development of a northwest axis. These spatial units are potential sub-regional centres and from their presently low level of development will need to be equipped with infrastructure for their intended future residential and manufacturing functions [13].

**Spatial Unit Class 5** is composed of the remaining rural spatial units presently having, and intended to retain it in the future, a principal function of agricultural production. These areas must, of course, not be neglected by investment measures [13].

The data concerning the economy of each of spatial unit was obtained for 15 (*S*) sectors and branches, namely: Agriculture; mining; food processing; textiles; chemicals; machinery; construction materials; other manufacturing; water, electricity, and gas; construction; real estate; banking, insurance, and stock market; transportation and communications; commerce; and other services including government. The infrastructure investments, on the other hand, were subdivided into 6 (*G*) categories, which were further disaggregated into 18 subcategories: road transportation; education (high schools, senior secondary schools, universities and colleges); medical care (comprehensive medicine, Chinese medicine, specialised hospitals, and university clinics); recreation (culture- and sport-facilities, parks); residential supply (water and piped gas supply), and environmental protection (sewage treatment plants; solid waste disposal and open urban areas). In total, 849 economically feasible infrastructure projects were analysed.

Additionally, for each spatial unit, environmental and land use transfer conditions were established. Finally, it is worth mentioning that the information used in this study, with regard to time, was disaggregated at one-year intervals. In the case of population information, further disaggregation into gender and one year age groups was still needed. The time horizon for the present study was set to start in 2005 and end by 2020 because the present five-year plan ends by the end of 2005, thus giving enough time for the implementations of the recommendations of this study. Hence, the parameters  $T = 15$  and  $R = 3$  were adopted.

### 5.3 Model Calibration

Each sub-module of the proposed model was calibrated and verified with past information. The economic model, for example, was calibrated by regression analysis with data available for the region from 1991 to 2000. The Pearson's correlation coefficient obtained for the various economic sectors ranged from 0.80 to 0.95 [16]. Similar approaches were used for the calibration of the parameters of the remaining equations of the model (see section 2.2.2).

The optimisation method also required some fine-tuning of its various parameters. This was done by a series of experiments aimed at finding the sensitivity of the parameters with regard to the convergence of the algorithm. The parameters adopted were:  $\zeta = 500$ ,  $\kappa = 50$ ,  $\delta_f = 0.995$ ,  $\delta = 0.95$  and  $\chi_f = 0.40$  for the cooling scheduled; the tolerances  $\varepsilon = 0.01$  and  $\epsilon = 0.0001$  for the stopping criteria; and  $\pi_1 = 0.90$  and  $\pi_2 = \pi_3 = 0.05$  for the generator. With regard to the overall objective function, the relative weights between the first component and the sum of the rest were set to identical values because both are equally important in the present optimisation problem, i.e.  $\omega_0 = 0.5$   $\omega_c = \frac{0.5}{(U+G)R} \forall c$ . The scaling factors for the objective functions were:  $a_1 = 3.70 \times 10^{12} \text{ €}$ ,  $a_2 = 3.95 \times 10^{12} \text{ €}$  and  $b_1 = 0.9$ ,  $b_2 = 1.0$ ,  $b_3 = 1.5$ ,  $b_4 = 2.0$ .

In order to run the model, additional exogenous parameters were set according to socio-economic recommendations ([17, 13]), thus no calibration was required. For example, the ratio between the investment budget and the government revenue,  $\alpha$ , was set to 0.6%; the vectors of minimum fractions of GDP for allocation of funds for spatial units classes and infrastructure categories were set to  $\tau_u = \{9.0 \ 9.0 \ 9.0 \ 6.0 \ 9.0\} \times 10^{-4}$

and  $\tau_g = \{9.6 \ 12.0 \ 4.8 \ 1.8 \ 6.0 \ 7.8\} \times 10^{-4}$  respectively. The vector of relative importance of the infrastructure categories was set to  $\lambda_g = \{0.13 \ 0.18 \ 0.17 \ 0.14 \ 0.25 \ 0.13\}$ .

## 5.4 Results

As shown in the previous paragraph, the stopping criteria and the so-called cooling parameters were adjusted so that the optimisation algorithm conducts intensive searches within the solution space of the present problem. The cardinality of this set is unknown, but raw estimates indicated that it is larger than  $10^{100}$ , taking into account that projects can be repeated if necessary, but always satisfying the myriad of restrictions imposed on the problem. As a result of these parameters, about  $1.5 \times 10^6$  realisations were needed to find a “very good” solution for  $(\Phi^*)$  that lies about 8 standard deviations to the right of the mean value of the economic objective function, which was obtained from a large sample of size  $(n = 4.0 \times 10^5)$  taken from  $5.5 \times 10^6$  Monte Carlo realisations carried out for the same problem (see figure 2). It is worth mentioning that  $(\Phi^*)$  is also higher than the maximum value obtained during the Monte Carlo search, despite the fact that the computational effort of the SA algorithm was about a quarter of the latter. This demonstrates clearly the efficiency of the proposed algorithm.

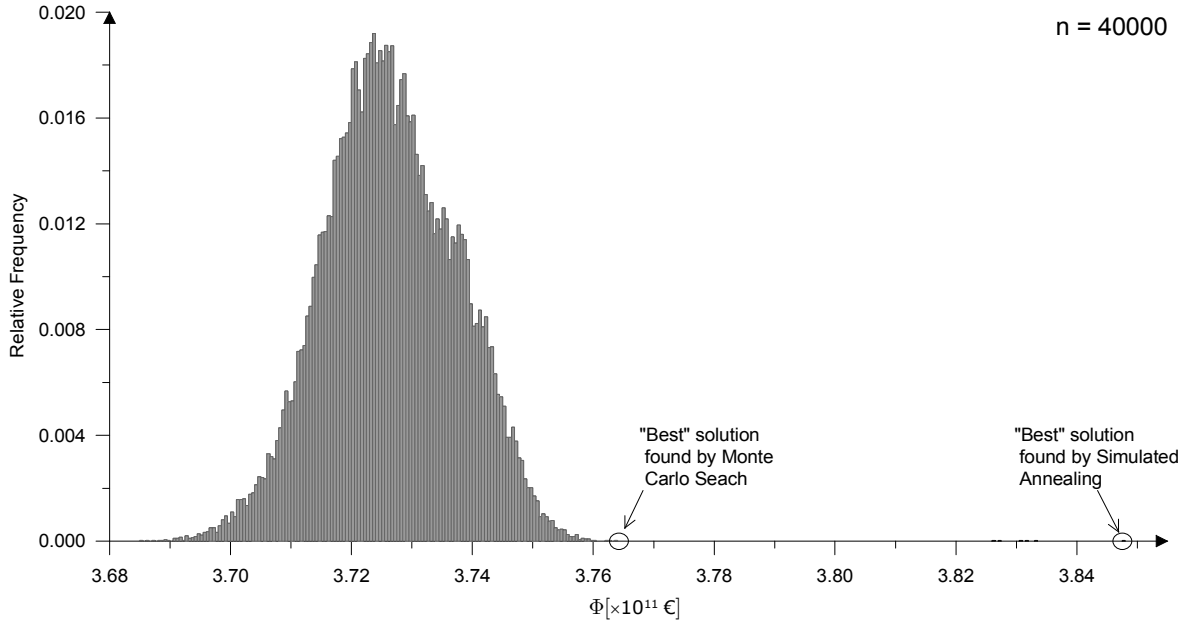


Figure 2: Distribution of the economic objective function  $\Phi$  and location of the best solution found by the proposed algorithm.

The solution related with  $(\Phi^*)$  is certainly not the global optimum, but it is good enough for planning purposes. In fact, the probability that a well-intentioned but traditional planner would not have chosen such a solution —without the aid of modelling an optimisation techniques— is about  $1 - 2 \times 10^{-7}$ , i.e. very unlikely!

The *modus operandi* of the algorithm—depicted in figure 3—systematically prevents the generation mechanism from getting stuck in local minima by accepting deteriorations in the objective function at given acceptance probabilities given by Metropolis criterion. This characteristic oscillating behaviour of SA is clearly shown in figure 3. The range of these oscillations, however, tends to zero when the control parameter approaches the value of zero. By doing so, the algorithm is compelled to search for the optimal solution in new “valleys” of the overall objective function which eventually leads to finding a solution probabilistically close to the “global minimum or “optima”. Therefore, the Metropolis criterion is what makes SA a robust stochastic optimisation technique, and definitely what characterises it from other heuristic approaches such as the so-called hill-climbing method or the Monte Carlo search.

For any NP-complete combinatorial problem -in general- and for the present problem -in particular- there is no 100% certainty that a heuristic optimisation technique would be able to find the “global minimum”. This shortcoming, however, can be overcome in a pragmatic way. For instance, one can plot the results obtained for some key variables during many optimisation runs and then analyse how consistent these solutions are. If the sub-set of the  $n'$ —best solutions exhibit small ranges of variation with respect to the mean of these variables, then one can conclude that any of these solutions can be regarded as the final solution, i.e. the quasi-global minimum. Otherwise, some parameters of the the optimisation algorithm have to be strengthened and then this procedure has to be repeated again.

In this study the algorithm was run 20 times, from which the best five solutions were selected for further analysis. Figures 4 and 5 depict the mean fraction of investment for each planning period —according to infrastructure categories and spatial unit classes— with respect to the mean GDP obtained in the best five solutions. As expected, each solution differs from each other, however, these figures show that the structure of investments is highly consistent among the best-five solutions. In this case, for example,



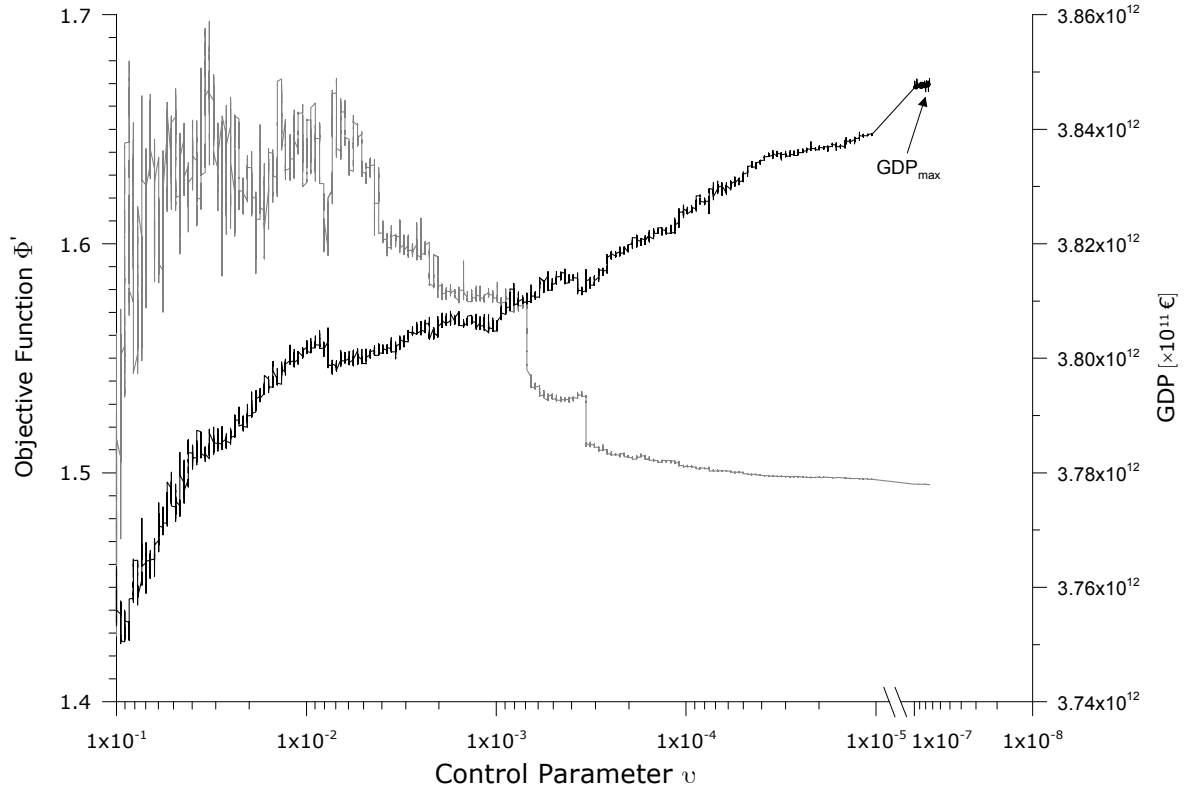


Figure 3: Evolution of the overall objective function  $\Phi'$  and one of its components  $\Phi$  (i.e. The GDP of the region over the planning period).

these results clearly indicate that a policy guideline for this region should state that the education sector should be a priority for the policy makers if they want to raise as much as possible the GDP of the region by the end of 2020. These results also point out that the distribution of funds is uneven—specially in the first planning period—if this objective is to be realised by 2020. In particular, spatial unit classes one and two (i.e. the urban core area and the regional centres) appear to be the most favourable places where to invest in order to achieve the previously stated objective.

Finally, figure 6 is presented as a complement to the previous results and to depict the spatio-temporal distribution of the fraction of total investment in each spatial unit and planning period within the region. This figure clearly shows that the most favourable places for investment are both those along the main transportation axes that pass through the region and those around the main urban core. Rural areas receive investment funds but only the minimum stipulated by the guarantees. This effect is mainly a result of the high migration flows originated in rural areas toward

main settlements. These results also point out the well known effect of the accessibility into the spatial unit's productivity.

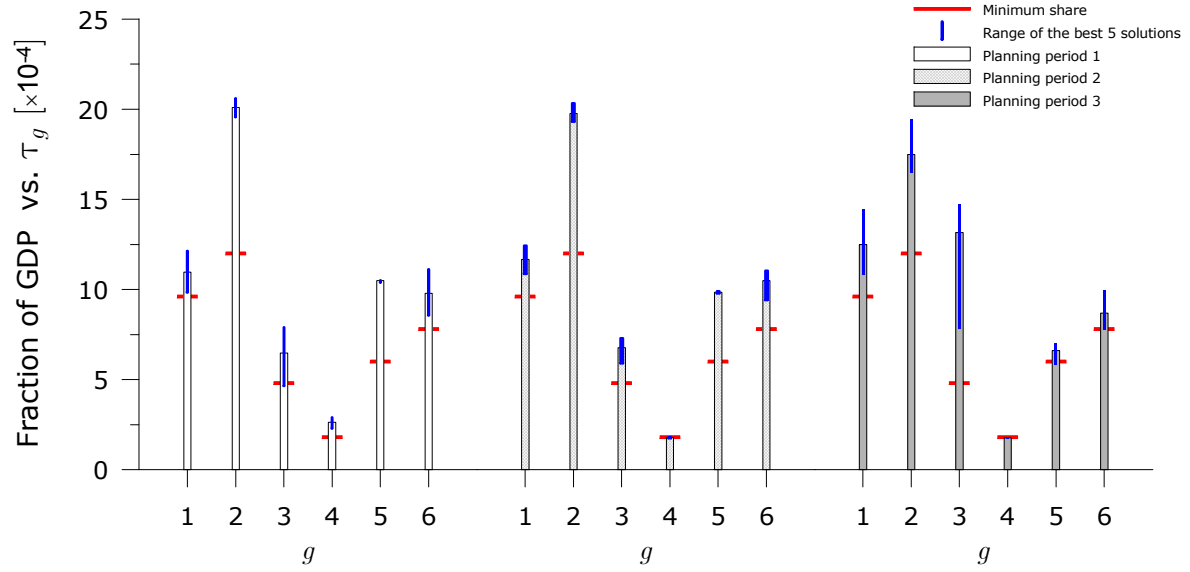


Figure 4: Average distribution of investments per infrastructure category in every planning period (mean of the the best five solutions).

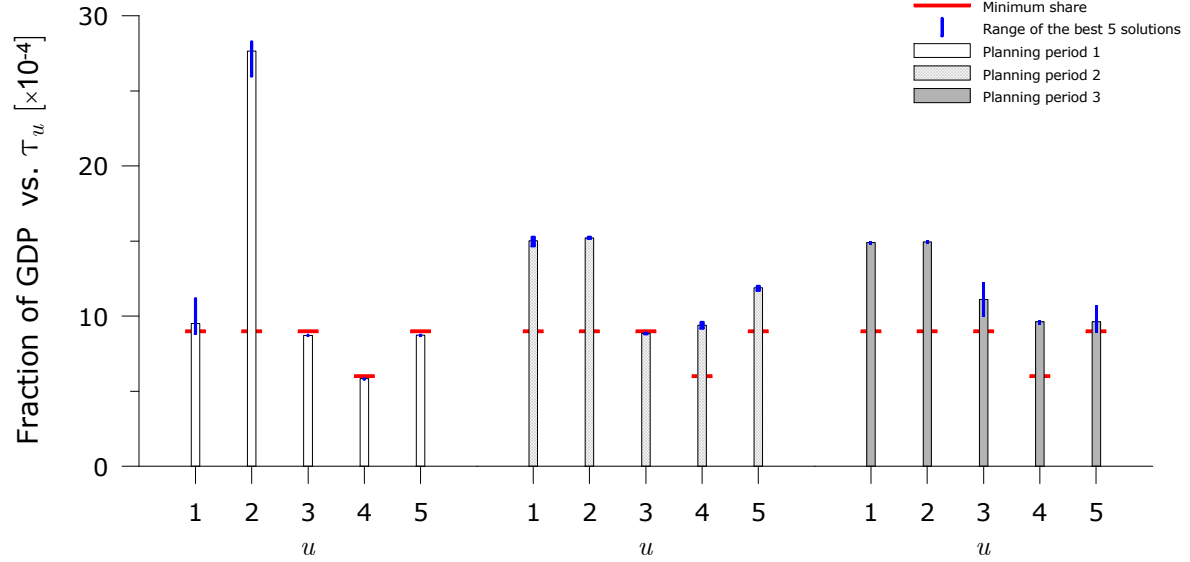


Figure 5: Average distribution of investments per spatial unit class in every planning period (mean of the the best five solutions).

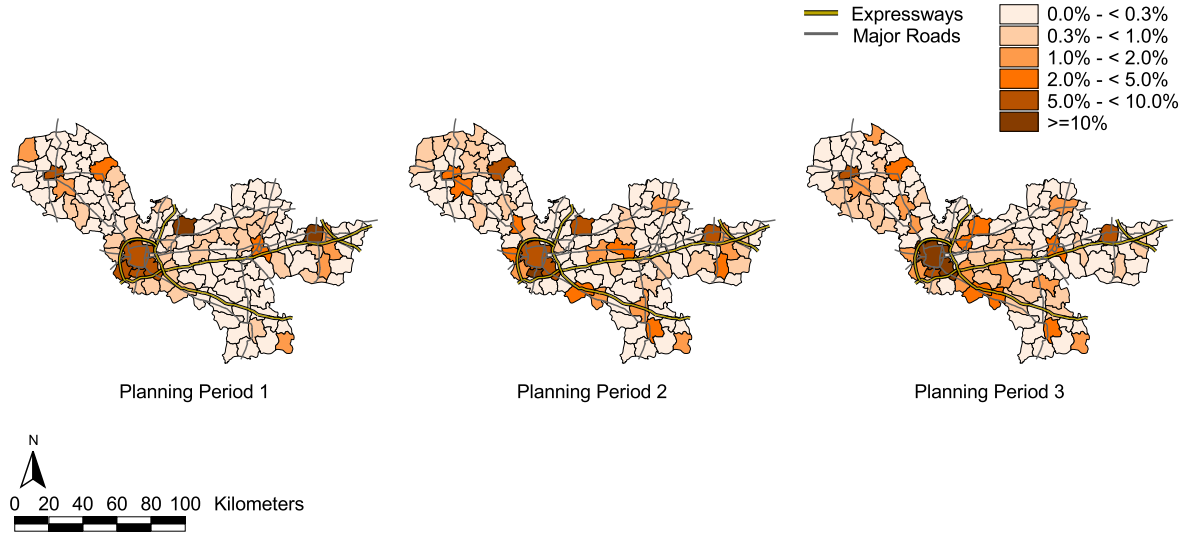


Figure 6: Spatio-temporal distribution of infrastructure investments for each planning period (plotted values represent the fraction of investment with respect to the regions’s GDP in each planning period).

## 6 Final Discussion and Conclusions

In a real planning situation, such as that presented before, finding the “optimum distribution” of funds fulfilling some predefined objectives and constraints is a non-trivial and cumbersome task. Thus, based on previous experiences including this one, it can be stated that if a well-intentioned regional development planner does not have a systematic planing tool to guide his or her investment decisions, the probability that a “very good” solution is found by ad-hoc procedures is very small. Finally, as a result of the development and application of this method, some relevant conclusions can be presented here.

- The results of the study suggest a significant gain in allocation efficiency due to the applied method of optimisation. Consequently, policy recommendations based on these results will have higher probabilities of success than other possible solutions.
- This method can be applied everywhere if the appropriate parameters and data are available. However, much is still to be done regarding the modelling techniques, sensitivity analyses, and the quality of the available data in general.

- This method may deal with additional objective functions and /or constraints if a given situation required it.
- Results of this method can easily be linked with a GIS system for further visualisation and analysis.
- Insightful recommendations can be draw by combining the proposed modelling technique and some plausible future development scenarios of the region.
- The costs for development and application of this kind of formal model and optimisation technique in real planning situations is minimal compared with its potential benefits.

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