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Application of Artificial Intelligence for Planning of Transportation System

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Abstract

A transport network is a regional network of linkages connecting groups of people that have grown as a result of the interaction of economic, social, and environmental variables. The regional area's long-term growth, which began with the first settlements, led to the current configuration of the transportation network. When a modernization or extension was carried out throughout history, it was to satisfy the new transport requirements, and the work was based on the transportation network's present structure. These short-term needs were primarily caused by sporadic circumstances that subsided over time. As a result, the structure is typically not ideal. We currently see a sharp increase in communication demands brought on by the acceleration of economic expansion, increased societal wealth, and urbanization of new regions. The issue of the transport network's expansion in response to the rising demands is discussed in the article. The goal is to reduce overall network impedance while taking into consideration the financial limitations of the investment. The transport network was represented as a bi-level model using several kinds of road connectors. The utilization cost indicated by the total trip time is the objective function at the higher level. At the lowest level, the ideal traffic distribution is looked for at each stage of the process. The major goal was to highlight the most beneficial and appropriate directions.

Keywords: artificial immune system; genetic algorithm; simulated annealing; transportation network

1.Introduction

The Network Design Problem (NDP) is the term used to describe the quest for the transportation network's ideal structure. The network's chosen performance metric can be improved either continuously (Continuous NDP), discretely (Discrete NDP), or mixed (Mixed NDP) by increasing the capacity of already-existing links. NDP is an NP-hard class, hence the solution techniques are quite computationally demanding. So, among many others, Poorzahedy and Rouhani (2007) and Chiou (2007) offered various heuristic methods.

Authors like Nie et al. (2007), Pinninghoff et al. (2008), and a few others have employed genetic algorithm-based techniques. Simulated annealing was employed by Kim et al. (2008), Xu et al. (2009), and Tianze (2009), while Sun et al. (2009) incorporated certain concepts from immune systems. (2008) Zhang, Lu, and Xiang demonstrated a streamlined method using a set grid of network vertices. Paramet et al. (2011), Changmin et al. (2012), and Shuaian et al. (2013) expanded on this concept by introducing certain deterministic algorithms and using them for test tasks of modest scale.

2.Model description

The network's overall journey time was used in this case as a performance indicator. As a result, the NDP goal is described as reducing overall travel time while taking financial considerations into account.

The topic examined in this article may be viewed as a variant of the Mixed Network Design topic, where attempts are made to change the capabilities of already-existing linkages or to add new links in order to improve the current transportation network structure. In rare instances, limiting the capacity of a specific connection might paradoxically lead to a decrease in the overall network impedance.

2.1.Transportation network representation

A graph is used to model the structure of a transportation network. The road linkages and crossroads are represented by the edges, respectively. Cities are indicated for certain vertices. This difference enables the inclusion of the model's transportation requirements. The origin-destination matrix identifies the necessary transportation. The number of cars that go between two cities in a certain amount of time is specified by each matrix member.

Even though every road section's capacity may fluctuate continually during the optimization process, each connection has an extra characteristic defining its class for the best visualization. For each class, the capacity and the unit construction cost are stated.

2.2.The network impedance determination

The topology of the transport network is changed to achieve lowest impedance as the main goal of optimisation is sought at the higher level. At the lowest level, the user balance traffic assignment with specified transport demands is carried out for the real network structure at each stage. All drivers are presumed to be fully aware of the state of the traffic and to make logical judgements. According to Wardrop (1952), each driver independently determines the quickest path based on his or her knowledge of the present state of the network. The formula developed by the US Bureau of Public Roads (1973) may be used to calculate how long it takes one motorist to go along a link

For each connection class, the average value of the unit duration of free driving traffic has been calculated (vehicles of various classes are not differentiated).

The desirability of a specific route is strongly dependent on the present network demand because of significant nonlinearity. The entire volume of traffic is separated into tens (or more) sections based on the needed precision. Dijkstra's technique is used to find the current quickest routes for each pair of cities for each percentage of traffic volume starting from zero. Then, this portion loads the links that are a part of the chosen routes.

This process allows for the division of the overall vehicle flow between each pair of cities into a number of alternative routes. The model taken into account in this study focuses mostly on long excursions that take place on interurban routes and extend for many hours. Roads are not overcrowded in big cities when rush hour and strict neighborhoods are excluded, therefore even with a relatively low number of iterations, an estimate does not significantly create distortions.

2.3.The network impedance determination

The connection class affects the unit construction cost. The cost sensitivity to the neighborhood's natural environment or infrastructure might be considered by the model that is being provided. However, given the size of the region being studied, it is presumed that building prices are uniform everywhere.

The total cost of the network alteration is just the sum of the individual component expenses. Here, the following premises are made. If a connection's capacity needs be extended, the cost of the expansion will depend on the link class's building costs.

When a connection's capacity has to be increased, the cost is considered to be zero (increasing capacity may be accomplished administratively, which is essentially free), but when a link needs to be added, the cost is equal to the whole cost of construction.

3.The optimization methods

Because of the computational complexity of the presented problem, which was already indicated, it is impossible to use the exact optimization procedures. In these situations, heuristic techniques should be utilized to find a solution that is close to the ideal one in a reasonable amount of time. The transportation network's fundamental concept is generally the same throughout the work that has been presented, however several artificial intelligence techniques have been created. The strategy incorporating artificial intelligence has the essential benefit that it is not necessary to completely comprehend or even be aware of all of the internal dependencies of the model. There is only one requirement: the model must enable calculation of the objective function's value. The objective function, which is established in the solution domain, establishes the level of quality of the solution. It is not necessary for any of the gradients of the objective function to be known or for the objective function to be differentiable.

Here, three widely utilizedoptimization techniques—genetic algorithms (GA), simulated annealing (SA), and artificial immune system (AIS)—were used and then contrasted. These methodologies' fundamental ideas are very dissimilar, and the terminology used to explain them is likewise very different. The solutions from a set are evaluated, and the offspring set is then generated while taking into account the computed value of the goal function, notwithstanding the disparities among these procedures. Additionally, the current is held in each step and contrasted with the best solution found so far. In reality, all of these techniques enable one to identify a solution that is as near to the ideal as desired by just perusing a small portion of the solution space. A single solution illustrates one possible evolution of the transportation network: the goal function's value is the overall reduction in journey time for all drivers. Additionally, the price of the implemented improvements is known and may be contrasted with the budgetary constraints.

The items in the solution set are exposed to several operations during the optimization process, some of which might alter the structure of a single item or swap structural components between a number of items. Exploration of the solution space is carried out in this manner. All of these operations are carried out in the same way here, but each method's interpretation and outcomes are different. Each technique has a distinct approach to handling the expenses associated with expanding the transport network.

There are several ways to change an item's structure (Figure 1):the capacity of a randomly chosen link is changed by a random factor,a new vertex can be inserted by splitting the randomly chosen link, a new link between a pair of randomly chosen vertices is added, its class is also random.

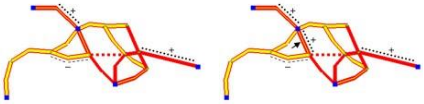

Fig. 1. An example of an item structure changes. Capacities to be increased or decreased are marked by "•" or "-" lines, links to be added are marked by dashed fill.

The exchange operation between two items applies to the randomly selected subset of links – the capacities for these links are copied to each other as shown at Figure 2.

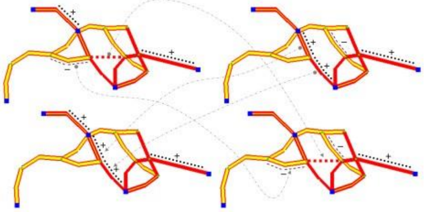

Fig. 2. The exchange operation.

3.1.Artificial immune system

De Castro et al. (2000, 2003) claim that the optimization approach is founded on certain concepts drawn from the examination of the adaptive immune system. The strength of the immune response may be modified by an adaptive immune system as it learns and memorises the pathogens. Lymphocytes are the most crucial elements. Each cell is filled with many antibodies, which are essential to its function. B-lymphocytes and T-lymphocytes are the two main types of lymphocytes, which greatly differ in their functions yet closely collaborate. It is unnecessary to differentiate between the two kinds in this case, and another simplification involves equating an antibody with a lymphocyte.

Due to the structural differences between individual antibodies, a function known as affinity—which characterises how well an antibody fits a pathogen—takes on distinct values for each of them. The therapy given to antibodies varies depending on the affinity value and a few other characteristics. The antibodies that indicate the greater chances of network formation are encouraged during the fit-increasing procedure. Two types of transformations, crossover and mutation, are what drive the evolution of the antibody population. The chance of applying both transformations is predetermined.

Certain conditions (explained below) call for the application of hypermutation transformation. This indicates that an antibody undergoes highly rapid, repetitive mutations. Age is another characteristic of any antibody. The antibody is unaltered, but the number of generations is stored. The age is reset by any mutation or crossover.

The gain of the aggregate trip time of all the cars is the definition of affinity. Following guidelines can be used to define how the population of all antibodies in each generation is treated. Most antibodies are subject to positive selection ("positive" means here "due to a desired feature"): those with the smallest (less than the mean minus the standard deviation) affinity are removed, leaving only the best and average ones in the population. Antibodies with the highest (greater than the mean) costs of modification, regardless of the value of the affinity, are removed from the population. After being multiplied and undergoing hyper mutation and crossover transformations, antibodies with the highest affinity (greater than the mean plus the standard deviation) are subjected to clonal selection, while the average antibodies (corresponding to the total travel time gain) are aged: thosepeople there,

A certain number of vacancies emerge from the selections mentioned above. Simply cloning the antibodies with the highest affinity fills the gaps. But not every one of these antibodies is cloned. The progeny people would be remarkably similar to one another if the initial antibodies were merely picked based on the affinity value. This is because the best antibody frequently has a large number of near neighbours with slightly altered structures. Finding the greatest people who are genuinely different is the challenge. Król (2014) presented similarity as a new feature to address the issue. A pair of antibodies' similarity is measured and used to identify their relatives. It enables the selection of a group of the finest but diverse antibodies: if an antibody with a high affinity value is too identical to all those already chosen, it will not be considered. Such care guarantees that the population is diverse.

3.2.Genetic algorithm

The following characteristics of genetic algorithms closely resemble the processes of evolution in living things: different solution versions compete with one another (individuals), the structure of each individual is determined by a sequence of genes - genotype,the genotype is subject to random changes (mutations), randomly chosen individuals may exchange parts of their genotypes (crossover), and the fit function, which is a measure of adaptation, determines the probability of passing to the next generation (selection probability).

This decreases the likelihood that such a person will be passed on to the following generation. The penalty factor p should be changed empirically and remains constant during the optimisation process. The roulette wheel rule is used to produce the next generation; the likelihood of being approved is inversely correlated with the value of the fit function. The fit function value might be increased to a power to change the distribution of chances such that it is either sharper or blurrier. Any positive real integer can serve as the exponent; in this case, it was presumed to be one. The next change is referred to as elite selection, in which a certain number of the best people (the elite) are passed unconditionally to the following generation.

3.3.Simulated annealing

The concept of "simulated annealing," which Kirkpatrick, Gelatt, and Vecchi first proposed in 1983, is based on an analogy to the actual events that take place as solids slowly cool and solidify. The process is distinguished by a change from a highly energetic state (hot fluid) to a structured state with less energy (crystal). With its extra energy, a molecule may move to any location at high temperatures, but when the temperature drops, transitions to lower energies are favoured.

Every step compares the present solution to a neighbouring solution that was produced at random (there is only one modification made). The new answer becomes the current one if the goal function value is increased.

In-depth study of the solution space is made possible by the high temperature at first, which subsequently drops with time. As a result, there is very little chance that you will select a poorer option once all is said and done. Additionally, the budgetary limitation checks followed a similar rule. Following iterations, the temperature is frequently decreased geometricaly

Based on the assumed number of steps, the empirical formula may be used to get the factor q. When dealing with issues of this nature, when the "effective diameter" of the solutions space is modest, simulated annealing can be an effective optimisation technique. This means that in a reasonable number of steps, the operator creating the neighbouring solution should be able to scan the whole domain of each variable. The situation at hand appears to be this way because there are so few different classifications of prospective route connections.

Here, the common simulated annealing procedure was changed by adding a parallel mode; several almost independent processes are operating concurrently. Information can be shared between two processes that were chosen at random.

4.Obtained results

4.1.Description of the examined example

The simplified model of Poland's transport system was used to test the suggested methodologies. The model includes all national and international highways, as well as several significant voivodeship routes. Many small-town roads were left out when building the model. The model covers significant route junctions and major towns from Poland. Some large, nearby towns were amalgamated. Due to the model's exclusion of several smaller towns and villages, it does not accurately reflect reality. Therefore, a sizable portion of the population's travels are beyond the parameters of the model. The primary goal of the work that has been given is instead to demonstrate the viability of using artificial intelligence technologies to such a large-scale challenge.

There isn't any consistent, comprehensive information available about transportation requirements that can be utilised to establish an origin-to-destination matrix. However, it is feasible to approximate the required values owing to data made available by the Polish General Directorate of National Roads and Motorways (GDDKiA). General Traffic Measurement is carried out on Polish roads every five years, and the data is then available on the GDDKiA website. The number of cars is tallied at the designated time at certain road segments, and the outcome is the average daily traffic (split into several vehicle groups). Fortunately, the General Traffic Measurement has coverage for all of the roadways in the analysed model. This made it possible to compare the theoretical and observed traffic flows to identify the components of the origin-destination matrix. The geographic potential technique was applied in the initial phase, and the population of the cities was taken into consideration. The addition of the outer flows for the cities near state borders and border crossings made it possible to incorporate transit traffic. The starting values of the OD matrix could be computed since the entire traffic volume for each town is known owing to General Traffic Measurement data. To further tweak these values to as closely match measured flows as feasible, a simulated annealing approach was used. The analysis area's actual map is shown in Figure 3 along with a visualisation of the estimated daily transportation requirements. The nonlinear scale was employed since the transportation requirements for certain cities vary significantly from one another; the diameter of the circle corresponds to the square root of the total number of cars entering and leaving the city. According to statistics already given by GDDKiA, the average unit cost of building a road was assumed.

Fig. 3. The model of polish road network and the transportation needs.

For certain road classifications, the capacity and unit periods of free driving were calculated using the numbers that were widely accepted. The budget is estimated to be 10 billion PLN (approximately 2.5 billion EUR). Table 1 displays the overall statistics of the input data for a single day.

Table 1. The overall statistics of the input data.

Item	Value	Item	Value
Number of trips	677520	Average trip length [km]	234.2
Total length of trips [km]	158702523	Average trip duration [min]	185
Initial total travel time [min]	125322857	Average speed [km/h]	76

4.2.Results

The effectiveness of the presented approaches is affected by a variety of crucial factors, including the population size, the number of iterations, the likelihood of mutation and crossover, etc. These numbers, which were in part previously corrected as a result of recent works, are compiled in Table 2. The optimisation procedure for all three techniques involves the same amount of people (30 000).

Table 2. The controlling parameters.

Method	Parameter	Value	Method	Parameter	Value
GA	Number of individuals	100	AIS	Number of lymphocytes	100
	Number of steps	300		Number of steps	300
	Probability of mutation	0.1		Probability of mutation	0.7
	Probability of crossover	0.7		Probability of crossover	0.8
	Elite	5	SA	Number of processes	20
	Fit function exponent	1		Number of steps	1500
	Penalty factor	3		Probability of crossover	0.05
				Initial temperature	1000

All the algorithms were then again performed while using the optimal parameter setting. The findings collected have demonstrated that all approaches respond differently even if the applied operators are comparable. Due to the nondeterministic nature of these procedures, each generated solution was slightly unique. The goal function's results had various values as well. The target function, which was discussed previously, expressed the gain in total trip time for all drivers and is given in minutes. The results are summarised in Table 3.

Table 3. Summary of the results (the gain of the total travel time).

Method	Average [min]	Standard deviation [min]	Standard deviation [%]	Min [min]	Max [min]
AIS	11.54e6	6.34e5	5.5	10.38e6	12.45e6
GA	9.67e6	2.94e5	3.0	9.14e6	10.05e6
SA	4.61e6	1.71e6	37.0	2.75e6	7.75e6

As can be seen, the simulated annealing algorithm's output is noticeably inferior to that of the others. Whereas the standard deviation is substantially higher, the average of the objective function is more than twice as tiny. This indicates that the simulated annealing technique is entirely unsuitable as a solution for this category of issues. It is a little surprising because using this strategy for smaller projects did not seem to provide as dismal outcomes. Finally, only the AIS and GA-derived solutions were taken into account. The development of the optimisation process for both techniques is shown in Figure 4.

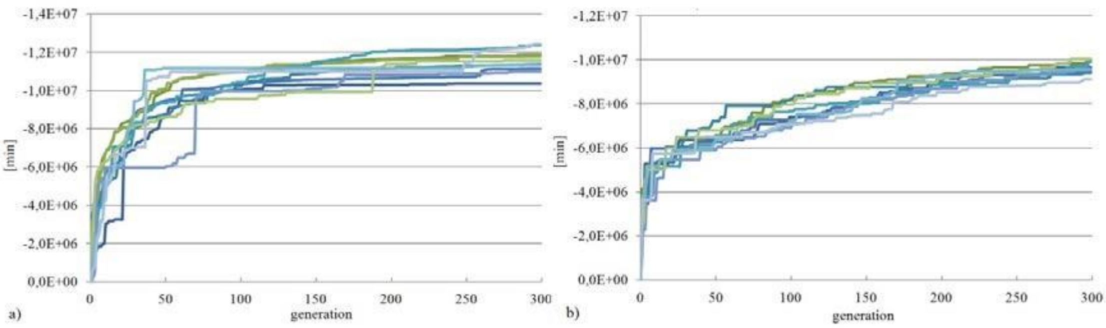

Fig. 4. The progress of the optimization process for several runs of AIS (a) and GA (b).

As can be observed, both algorithms quickly enhance the quality of the solutions at the beginning of the optimisation; but, after the 50th generation, the development becomes more sluggish. Up to the optimization's conclusion, only slight advancements take place. While GA significantly improves the solution at this stage, AIS approaches the plateau more quickly. Additionally, it is clear that GA has substantially higher convergence (the standard deviation of the objective function is almost half as small).

Additionally, AIS and GA have distinct optimisation details. When the best current option materialises, the AIS would prefer that it stay in place. In the meanwhile, optimisation for GA proceeds in a different manner: the best current solution is more likely to be lost, after which the algorithm errs and a generation or two must elapse before finding a new, better current solution can be found. Figure 5 provides an illustration of this, displaying the best and most recent solutions with almost overlapping AIS curves. The solutions produced by GA are noticeably more convergent despite this behaviour. It might be explained by the supposition that just going out on a tangent makes the approach more adaptable and enables the discovery of a superior but somewhat different answer.

Although the restrictions are stringent and all modifications are done using just the picked item, the complex selection process used in AIS ensures the excellent quality of the solution achieved. Once chosen, the direction tends to hold. This indicates that the flexibility is less than it is for GA.

Even if the results from several runs varied from one another in just tiny ways, all of the outputs indicated the same improvements. 10% more overall trip time was gained with the best approach (12.5e6 minutes multiplied by 208 000 hours or 8646 days). The typical journey time was cut by about 20 minutes.

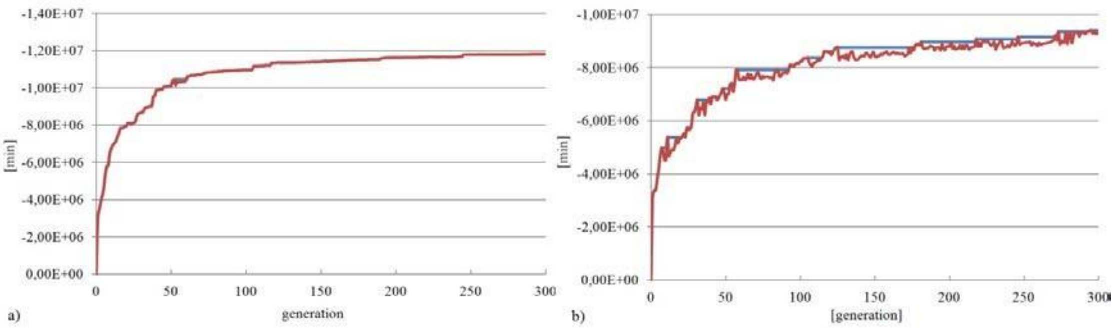

Fig. 5. An example of the best (blue) and current (red) solution for AIS (a) and GA (b). The curves for AIS are near the same.

It is challenging to compare the realised value to the presumptive budget clearly. However, certain very approximate calculations may be made. For example, if the stated Polish GDP per capita (about PLN 56 000) and the number of work hours in a year (48 weeks * 40 hours) are taken into consideration, the value of PLN 30/h can be calculated. Last but not least, the expected benefit, represented in money, is around 6 million PLN every day, thus the investment will be returned in approximately 3 years.

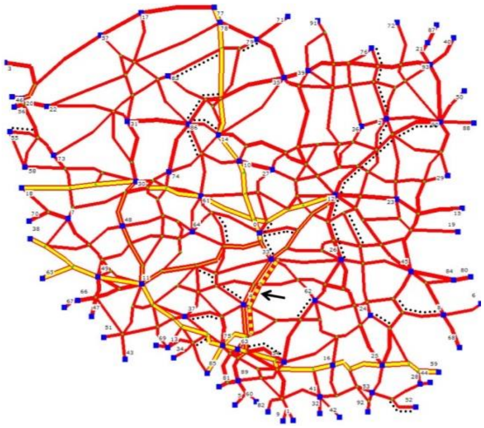

Fig. 6. The solution with most advantageous modifications of transportation network structure.

A example solution produced using the AIS method is shown in Figure 6. Due to readability issues, certain minor road modifications on local roads were deleted. The new segment of the A1 motorway from PiotrkówTrybunalski to Zawiercie (shown by the arrow) is the most significant idea. One proposal involved significantly increasing the capacity (by more than 80%) of the adjacent stretch of the E75 road. It is important to note that this is the component of the official plans for expanding the Polish highway network that must be completed by the year 2018. The next crucial suggestion is to expand the route's capacity from Radom and farther to the north and east towards Warsaw.

5.Conclusion

In this article, the most significant artificial intelligence techniques were briefly presented and contrasted. The assignment was to identify the most viable changes to the predetermined transport network structure. Budgetary restrictions should also be considered. The results show that AIS (Artificial Immune System) and GA (Genetic Algorithm) are effective in tackling this class of issues. The SA (Simulated Annealing) technique, however, has not worked well in this situation. Unstable and clearly poorer results were obtained.

There are some distinctions between AIS and GA. Although GA seemed to be more stable, the answers provided by AIS were often a little bit better. To combine the two approaches in some way to benefit from all of their advantages might be the starting point for additional research. Even though AIS and GA are non-deterministic processes, the results of consecutive runs are very similar. Such behaviour demonstrates the stability of the ideas put forward. A few hours should be deemed an acceptable amount of time for such a complicated data collection for computing the required results.Despite the model's numerous simplifications, the findings produced fit the actual goals for the expansion of Poland's transport network.

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