TRANSPORT MODELING: AN ARTIFICIAL IMMUNE SYSTEM APPROACH

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Abstract: This paper describes an artificial immune system approach (AIS) to modelling time-dependent (dynamic, real time) transportation phenomenon characterized by uncertainty. The basic idea behind this research is to develop the Artificial Immune System, which generates a set of antibodies (decisions, control actions) that altogether can successfully cover a wide range of potential situations. The proposed artificial immune system develops antibodies (the best control strategies) for different antigens (different traffic "scenarios"). This task is performed using some of the optimization or heuristics techniques. Then a set of antibodies is combined to create Artificial Immune System. The developed Artificial Immune transportation systems are able to generalize, adapt, and learn based on new knowledge and new information. Applications of the systems are considered for airline yield management, the stochastic vehicle routing, and real-time traffic control at the isolated intersection. The preliminary research results are very promising.

Keywords: Uncertainty modelling, fuzzy sets, artificial immune system, transportation, traffic.

1. INTRODUCTION

Foreign substances or cells constantly attack our body. The attackers are different microbes (Bacteria, Viruses, Fungi and other parasites). Bacteria are unicellular organisms, while Viruses are nucleic acids surrounded by a protein coat. Our body constantly destroys and/or neutralizes foreign matter through different physiological

responses. The body immune system is composed of the cells that carry out immune responses. These cells (Leukocytes (Neutrophils, Basophils, Eosinophils, Monocytes, Lymphocytes (B cells, T cells, NK cells)), Plasma cells, Macrophages, Mast cells) can be found in our blood, organs and tissues. An *antigen* represents any foreign molecule that causes a specific immune response. Antigen must be encountered and recognized by a lymphocyte. This means that the lymphocytes have the *ability to distinguish* one antigen from another. Some lymphocyte types are activated and an attack is launched against all antigens that cause the immune response. *Antibodies* that are secreted travel all over the body to reach antigens, and direct an attack that eliminates antigens and/or cells bearing antigens. The number of different antigens is practically limitless. Our body is capable of fighting with the antigens it has encountered in the past, as well as with the unknown antigens that attack our body for the first time (Vander et al. (1990)).

The following analogy between an immune system and many transportation systems is obvious. Most complex traffic and transportation engineering, management and control problems are characterized by many different *known* transportation supply, demand, and/or cost patterns or by *uncertainty*. This means that there are limitless number of potential situations in traffic and transportation that request adequate control and action. A wide range of different traffic and transportation parameters (travel time, travel cost, transportation supply, transportation demand) are characterized by uncertainty, subjectivity, imprecision and ambiguity. The potential *situation* that can happen in the transportation system represents an *antigen*. An *antibody* represents adequate *decision* and *action*. Some of these decisions (antibodies) involve human decision-makers (i.e., air traffic controllers, pilots, drivers, passengers, operators, dispatchers, etc.) whereas others involve automatic control mechanisms triggered by computer hardware. Passengers, drivers, air traffic controllers, and dispatchers make decisions about path choice, mode of transportation, most suitable take-off time, dispatching vehicles, or allocating resources.

The initial assumption in this paper is that it is possible to develop a new type of intelligent control system that makes on-line decisions of a high quality. These systems are inspired and based on the body immune systems. In other words, this paper assumes that it is possible to develop the systems that will recognize different situations and make the appropriate decision without knowing the functional relationships between individual variables. Artificial Immune traffic and transportation control systems should be able to generalize, adapt, and learn based on new knowledge and new information.

The proposed concept is general and it can be applied to a broad class of engineering, and management real time problems that are characterized by uncertainty. The paper is organized as follows: the analogy between an immune system and many transportation systems is elaborated in more details in section 2. Creating the antigen database in transportation system is presented in Section 3, and creating the antibodies for known antigens is presented in Section 4. Detailed description of the creation of the artificial immune system is given in Section 5. Section 6 describes creation of the antibodies for unknown antigens. Successful examples of the Artificial Immune System concept in solving complex traffic and transportation problems are described in Section 7. Section 8 presents the concluding remarks and further research orientations.

2. THE ANALOGY BETWEEN AN IMMUNE SYSTEM AND TRAFFIC AND TRANSPORTATION SYSTEMS

Considered transportation system can be treated as human's body. Different bacteria penetrate body's lining with the external environment. Clients requesting cabs call cab's dispatchers. They request certain transportation service. Clients are bacteria that want to penetrate into the transportation system. Let us consider a signalized intersection as a body. Cars, trucks, buses, motorcycles, bicycles, emergency vehicles and pedestrians coming from different approaches attempt to pass through an intersection at the same time. In other words, all users try to simultaneously occupy the same space. In this case cars and other vehicles are bacteria that want to penetrate into the body (intersection). This leads the analyst to focus on the performance of intersections in terms of their operational characteristics such as congestion, stopped delay and safety among others that are paramount to the users of the intersection. Designing safe intersections and providing efficient intersection control are some of the most important tasks of the transportation engineering profession. Providing efficient intersection control means the development of the antibodies (control strategies) that will be applied for different antigens (different traffic situations). Set of vehicle arrival times at the intersection define traffic situation at the intersection during considered time interval.

Table 1: Antigens and antibodies in different transportation problems

Antigen	Antibody
Airline schedule disturbance	The new airline schedule
Highway incident	Adequate incident detection and response to the incident
Bunched-Up-Buses	Dispatcher's response (new buses headways)
Bus requesting priority at the intersection	Decision about the priority
Unexpected air traffic congestion	Decisions about aircraft ground holding times, and new air routes
Congestion along planned route	Driver's choice of the new route
Passengers requests for a cabs	Cab assignment to passengers requests
Clients requests for courier service	Vehicle assignment to clients requests
Citizens requests for police patrols	Police patrol assignment to citizens requests
Set of vehicle arrival times at the intersection	Real time traffic control at the intersection
Cumulative numbers of passengers reservations for the flight	Decision about the number of seats allocated to different passenger tariff classes
New policy regarding aircraft landing fees	New airline business plans

The potential *situation* that can happen in the transportation system represents an *antigen*. Every Antigen that enters our body must be encountered and recognized. Specific immune responses depend on this recognition. This means that every potential situation in the considered transportation system must be recognized. Consequently, triggering the specific action (green light extension at the intersection, flight cancellation in the case of

serious airline schedule disturbance, assignment of particular cab to specific request, etc) depends on the recognized "traffic scenario"(antigen). Antibodies direct an attack that eliminates antigens and/or cells bearing antigens. Elimination of antigens by antibodies can be interpreted as the successful application of specific control strategy in specific traffic situation.

3. CREATING THE ANTIGEN DATABASE IN TRANSPORTATION SYSTEM

Our body is capable to fight with the antigens it has encountered in the past, as well as with the unknown antigens that attack our body for the first time. In the same way, we can be familiar with some traffic situations that have encountered in the past and be prepared for them with adequate response. On the other hand, we must be able to find adequate response for the traffic situations that we are facing for the first time. Let us first consider "known antigens (known "traffic situations"). We can create the antigen database of the considered transportation system by simulation. Depending on the context of the problem, this means that we are able to "predict" moments of time in which different events will happen. In context of airline seat inventory control problem, this means that we are able to exactly predict moments of time in which different classes of passengers are making their reservations, the moments of time in which passengers are making their cancellations, the numbers of passengers from different tariff classes who will not show up at the departure, the number of "go-show" passengers, etc. In context of isolated intersection on-line control problem, this means that we are able to predict exact time of the arrival of each vehicle on each approach during certain time period. Let us consider, for example, an isolated "T" intersection consisting of two one-way streets as shown in Figure 1.
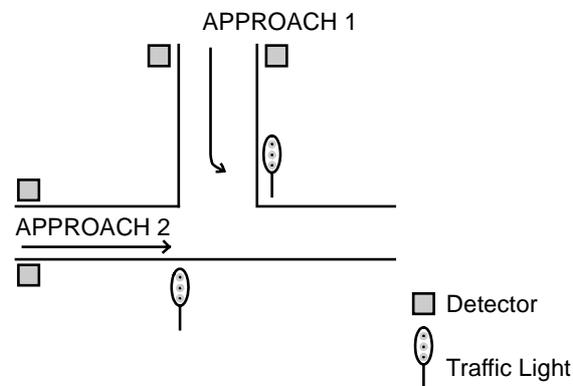

Figure 1: "T" intersection of two one-way streets

We will assume that our "T" intersection is isolated and relatively "busy" with significant demand variations during certain time periods. In this paper we will not take into consideration the whole set of engineering details like detector placement,

calculation of the minimum and maximum green times, yellow and all-red times, and pedestrian requirements. The detectors provide real time information on the exact time of the arrival of each vehicle on each approach during time T. Let us assume that time interval T equals 10 minutes (600 seconds). By simulation we can create different traffic patterns during considered 10 minutes. Every created traffic pattern will represents specific antigen. Two created antigens are given in Table 1.

Table 1: Two created antigens

Antigen 1

Approach 1	Approach 2
5	3
15	12
22	16
36	26
50	33
55	49
63	58
68	66
81	72
…	…
…	…
592	595

Antigen 2

Approach 1	Approach 2
8	4
25	9
28	13
33	26
39	43
44	59
47	70
50	85
54	101
…	…
…	…
566	597

We observed our intersection during 600 seconds. From the first antigen created by simulation we can "read", for example, that the first vehicle appeared from the first approach in the fifth second, that the second vehicle appeared from the first approach in fifteenth second, etc. By simulation we can create large antigen database. The greater the database, the stronger will be our artificial immune system.

4. CREATING THE ANTIBODIES FOR KNOWN ANTIGENS

Let us first try to develop the antibodies for known antigens. Known antigens (generated by simulation) give us full information about future events. In the case of perfect prediction we must be able to make optimal decisions. For known antigens we must have on our disposal antibodies that will attack antigens and kill them. In other words, if we know the random moments of time in which events happen (antigen), we will find the best control strategy during considered time interval (corresponding antibody).

Let us denote by (P_1) **t**he problem of discovering antibody$_1$ for given antigen$_1$. For known antigen$_1$, depending on the studied transportation phenomenon, the problem (P_1) could be solved by using linear programming, nonlinear programming, dynamic programming, multi-objective programming, or by using some metaheuristic algorithms (genetic algorithms, simulated annealing technique, taboo search). The problem of

discovering antibody$_2$ for given antigen$_2$ is denoted by (P_2). In this way, for given set of m antigens:

$$AntigenSet = \{antigen_1, antigen_2, ..., antigen_n\}$$

the set of antibodies:

$$AntibodySet = \{antibody_1, antibody_2, ..., antibody_n\}$$

is produced after solving the corresponding problems $P_1, P_2, ..., P_n$.

We can get the optimal solution (or "good" solution) for every generated antigen (simulated traffic "scenario").

Let us consider again, for example, an isolated "T" intersection consisting of two one-way streets as shown in Figure 1. Let us introduce the following notation:

g_{min} - minimum allowed duration of green time for any approach,

g_{max} - maximum allowed duration of green time for any approach

Let g_{max} be an integer multiple of g_{min}, and k be the ratio between g_{max} and g_{min}.

i.e. $g_{max} = k \cdot g_{min}$.

Let us divide time period T into m small time periods (stages), each having width g_{min} ($mg_{min} = T$). We will assume that the signal phase can change only at any multiple of g_{min}. Consider just one of the approaches of Figure 1. Let 1 denote the situation when the signal phase on the approach in question is green, and, 0 the situation when the approach in question is red. Then over the period (T), each small time interval may be designated either 0 or 1, and the chain of the numbers such as the following indicates the pattern of signal phase change over T:

101011100001111100…..........................……....…..11000101011000111

|◄—————————— a string of m elements —————————►|
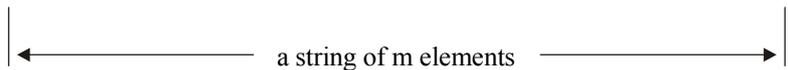
This sequence represents how the signal phase changes during time T. When developing the 1-0 sequence, more than *k* consecutive 1's or *k* consecutive 0's should not be allowed because of the limit of the maximum length of green time for the approach. Because the vehicle arrival pattern is known (antigen), the total number of vehicles that have passed the intersection, the total vehicle delays and the total number of vehicles stopped during time period T can be calculated. We are interested in identifying the corresponding antibody that represents the sequence that minimizes the value of the objective function (usually objective function represents linear combination of the total delay and the number of stops). Teodorovic et al. (2001) used genetic algorithms (Holland (1975), Goldberg (1989)) to develop the optimum sequence of signal phases (antibody) assuming that the future traffic conditions at the intersection (antigen) are known. Many different hypothetical antigens (traffic scenarios) are generated, and for

each scenario, the corresponding antibody (best solution consisting of a string of 1's and 0's) is developed using Genetic Algorithm. This set of solutions constitutes the Antigen - Antibody Database (AAD) for the considered transportation system. The developed Antigen - Antibody Database is the starting point for creating the antibodies for unknown antigens.

5. CREATING THE ARTIFICIAL IMMUNE SYSTEM

The basic characteristic of intelligent systems is their adaptive estimation of continuous functions based on data without mathematically specifying the manner in which the output results depend on the input data. Unlike statistical methods, artificial neural networks and fuzzy systems estimate the functions without specifying the mathematical model that describes the manner in which output results depend on input data (artificial neural networks and fuzzy systems are "models without a model"). The system behaves "intelligently" if it "emits" similar output results for similar input variables. Artificial neural networks and fuzzy systems are "intelligent" systems since they have the ability to "learn from experience". Recognition without definition is a characteristic of intelligent behavior.

When creating the Artificial Immune System we can use artificial neural networks, or fuzzy logic techniques. In this paper, we create Artificial Immune System using fuzzy logic techniques. Theoretical results reached during the past several years (Wang and Mendel (1992(a), 1992(b), 1992(c)), Mendel (1995), Mendel (2001)) have indicated that fuzzy logic systems are universal approximators and this explains why fuzzy logic systems are so successful in engineering applications. Feedforward neural networks also approximate unknown functions, that is, they can be considered as universal approximators. The theorem proved by Hornik et al. (1989) and Cybenko (1989) states that a multilayered feed forward neural network with one hidden layer can approximate any continuous function up to a desired degree of accuracy provided it contains a sufficient number of nodes in the hidden layer.

The proposed system that makes on-line decisions of a high quality is able to recognize different situations, generalize, adapt, learn and make the appropriate decision without knowing the functional relationships between individual variables.

The proposed approach for creating the Artificial Immune System could be formulated through the following steps:

Step 1: Using simulation, generate many different antigens.

Step 2: Formulate considered problem and find the antibody (optimal solution or sub-optimal solution) for each generated antigen using optimization techniques or heuristic algorithms. Create the Antigen - Antibody Database.

Step 3: Based on the Antigen - Antibody Database resulted from Steps 1 and 2, create the Artificial Immune System.

In this paper, we create Artificial Immune System using fuzzy logic techniques. The fuzzy rule base is generated from numerical examples (Antigen - Antibody Database). There are few different methods for generating fuzzy rule base from numerical data (Wang and Mendel (1992(a)), Mendel (2001)). In this paper, we used the

procedure proposed by Wang and Mendel (1992(a)). They proposed to establish fuzzy sets for all the antecedents and the consequence. We will do it in such a way that, at the very beginning, we will establish the domain intervals for all input and output variables (Figure 2).
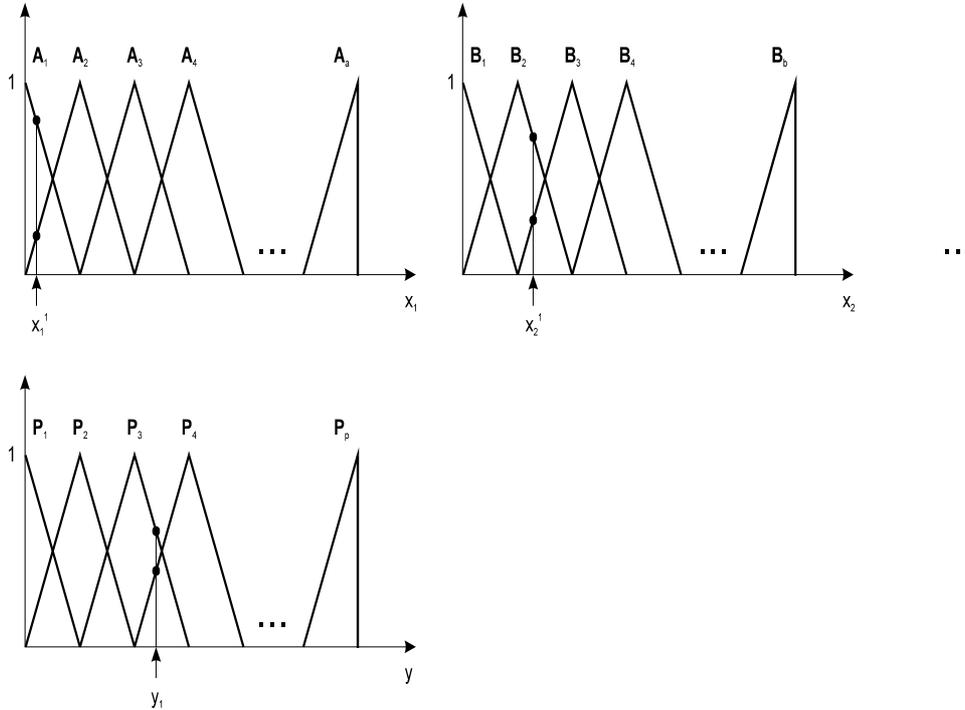

Figure 2: Division of the domain interval into a prespecified number of overlapping regions

As it was suggested by Wang and Mendel (1992), we can divide each domain interval into a pre-specified number of overlapping regions (Figure 2). We can mention that the number of overlapping regions is not equal for each variable. The lengths of these overlapping regions are usually equal, but not necessarily so. In the next step each overlapping region is labeled and one membership function is assigned to it. We can also use different types of membership functions for different variables. In our case we used triangular membership functions for all variables. Let us assume that we have the following set of the input-output data pairs:

$$\left(x_1^1, x_2^1, ..., x_n^1; y^1 \right), \left(x_1^2, x_2^2, ..., x_n^2; y^2 \right), ...$$

where $x_1, x_2, ..., x_n$ are inputs and y is output.

Wang and Mendel (1992) proposed to generate the fuzzy rule base from this set of input-output data pairs. The values $x_1, x_2, ..., x_n$ and y belong to the domain intervals

$(x_{1\min}, x_{1\max}), (x_{2\min}, x_{2\max}), ..., (x_{n\min}, x_{n\max}), (y_{\min}, y_{\max})$ respectively. From every input-output data pair we can eventually generate one fuzzy rule. Let us explain how we can generate fuzzy rule from the first input-output data pair $(x_1^1, x_2^1, ..., x_n^1; y^1)$

We have to determine the membership function values of the elements. From Figure 1 we see that x_1^1 has degree 0.2 in A_2, and 0.8 in A_1, x_2^1 has degree 0.3 in B_3, and 0.7 in B_2,... and y^1 has degree 0.4 in P_4, and 0.6 in P_3. In the next step we will assign each variable to the region with maximum degree. This means that x_1^1 is considered to be A_1, x_2^1 is considered to be B_2, ... and y^1 is considered to be P_3. The rule, which we are obtaining from the first pair of the input-output data, is:

If x_1 is A_1 and x_2 is B_2.... and x_n

Then y^1 is P_3

This is the way in which we generate rules from the antigen-antibody data pairs. Since we have many antigen-antibody data pairs it can happen that we produce some conflicting rules. The conflicting rules are the rules with the same antecedents but different consequents. Wang and Mendel (1992) resolved this " by assigning a degree to each rule and accept only the rule from a conflict group that has maximum degree ". Degree of a rule 1 which we got from the first input-output data pair equals:

$$D(Rule\,1) = \mu_{A_1}\left(x_1^1\right) \cdot \mu_{B_2}\left(x_2^1\right) \cdot ... \mu_{P_3}\left(y^1\right) = 0.8 \cdot 0.7 ... \cdot 0.6 \cdot$$

6. CREATING THE ANTIBODIES FOR UNKNOWN ANTIGENS

Let us create by simulation one unknown antigen. This antigen was not used to develop the Artificial Immune System (Fuzzy Rule Base). The following question is very logical: Is the developed Artificial Immune System able to produce new antibody that will eventually kill unknown antigen? In other words, is the developed "Intelligent" system competent to find "good" solution for the unknown traffic "scenario? To properly answer this question we have to pose ourselves the following question: What is the *ideal antibody* for *unknown antigen*? How can we create the *ideal antibody* that will kill unknown antigen? The answer is very simple. We use the same techniques (optimization techniques, and/or heuristic algorithms) that we used to create Antigen-Antibody Database. In this way, we know what is the ideal antibody for unknown antigen. The created Artificial Immune System does not contain this ideal antibody. Let us now allow an unknown antigen to attack the body. Created Artificial Immune System responds to this attack by producing certain antibody. We consider our Artificial Immune System as "good enough" if it is able to produce antibodies "similar" to ideal antibodies in the case of unknown antigens attacks (In some cases it can happen that Artificial Immune System produces the ideal antibody). Since the produced antibodies are similar to the ideal antibodies, we assume that produced antibodies will kill unknown antigens.

We assume that we need significant amount of time to produce ideal antibody in our "laboratory". On the other hand, we assume that Artificial Immune System can

produce antibody similar to the ideal antibody practically immediately in the case of unknown antigen attack. This means that the Artificial Immune System, which is "good enough", can be used for solving complex real-time traffic and transportation problems.

7. SUCCESSFUL EXAMPLES OF THE ARTIFICIAL IMMUNE SYSTEM CONCEPT IN SOLVING COMPLEX TRAFFIC AND TRANSPORTATION PROBLEMS

We have tested the proposed approach trying to solve different traffic and transportation engineering problems. In this paper we will show the results obtained when we applied this approach to the airline seat inventory control problem (Teodorovic et al. (1998), Teodorovic et al. (2002a)), isolated intersection on-line control problem (Teodorovic et al. (2001), Teodorovic er al. (2002b)) and stochastic vehicle routing problem (Teodorovic and Lucic (2000). Stochastic vehicle routing problem is one of the very important logistics problems. On line control at the isolated intersection belongs to the class of traffic engineering and control problems. Airline seat control problem is one of the most important problems in the area of airline planning and operations. Airline planning and operations, traffic engineering and control, and logistics and distribution systems are different areas of transportation science. On the other hand, the problems considered have two basic characteristics in common: (1) uncertainty; (2) need for on-line control.

These problems were solved by using the proposed approach, without formally introducing the concept of Artificial Immune System. In this paper we try to articulate previous ideas and formally introduce Artificial Immune System that is capable of solving real-time traffic and transportation problems characterized by uncertainty.

7.1. Airline Seat Inventory Control Problem

Passengers make their requests at random moments of time. A certain number of passengers cancel their reservations at random moments of time before flight departure. Also, a certain number of passengers do not appear for flights for which they have a confirmed reservation and purchased ticket. These "no-show" passengers can considerably decrease the air carrier's profits. Some passengers appear right before departure looking for an empty seat on the flight, even though they do not have a confirmed reservation ("go-show" passengers). The liberalization of airline tariffs has also resulted in a large number of different tariffs existing on the same flight. Passengers paying lower tariffs (as a rule, when making private trips) often reserve seats before the passengers who pay higher tariffs (business passengers who decide to travel several days or hours before the flight), which is why a certain number of passengers prepared to pay a higher tariff cannot sometimes find a vacant seat on the flight they want. This causes an additional decrease in the air carrier's profits. Daily flights are made both nonstop and with one or more stopovers. The greatest number of large airlines developed hub-and-spoke route networks. At the same time, large airlines make more than 1,500 flights per day and they usually serve few thousands origin-destination markets. As a result, the number of possible fare class / origin-destination combinations could be large for every seat on each flight leg. Each combination has different contribution to the airline's

revenue. In the past thirty years a relatively large number of papers have been devoted to different aspects of the airline seat inventory control problem. (Littlewood (1972), Belobaba (1987, 1989), Brumelle and McGill (1993), Brumelle et. al (1990), Weatherford and Bodily (1992), Weatherford et. al (1993), Teodorovic et. al (1993), Bodily and Weatherford (1995), Weatherford (1997), Popovic and Teodorovic (1997), Teodorovic (1998), Subramanian et. al. (1999), Lautenbacher and Stidham (1999), van Ryzin and McGill (2000), Secomandi et. al. (2002), Gosavi et. al (2002), Swan (2002)).

Teodorovic et al. (2001) made an attempt to make reservation decisions on the "request-by-request" basis. They considered the airline seat inventory control problem for nonstop flights (Figure 3a) and for flights with one stopover (Figure 3b) when there were more than two types of tariffs.
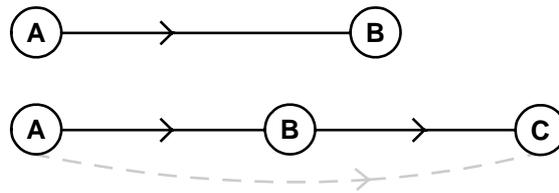

Figure 3: A direct flight (a) and a flight with one stopover (b)

Let us assume that passengers are offered n tariff classes on each itinerary. We denote the flight tariffs respectively by $R_1, R_2, ..., R_k$, where $R_1 > R_2 > ... > R_k$. We introduce the assumption that we have statistical information available regarding passengers' requests on previous flights. Let us denote by $D_i(t)$ the stochastic process representing cumulative number of requests in the i-th passenger tariff class t days before planned departure. Teodorovic et al. (2001) treated the cumulative number of passenger requests in the i-th passenger tariff class t days before planned departure $D_i(t)$ as the number finally arrived at considering the "original" desires for flight in question, certain number of passengers who abandoned some other airlines, as well as certain number of passengers who chose flight in question as their subsequent selection. Every passenger tariff class is defined by the origin and destination of the trip, and the tariff the passenger pays. The considered airline seat inventory control problem can be defined as follows:

For known passenger tariffs $R_1, R_2, ..., R_k$, based on a large number of realizations of stochastic processes $D_i(t)$ in different passenger tariff classes, develop a seat inventory control model that will maximize air carrier revenues, while constantly making "on-line" decisions regarding the acceptance or rejection of passenger requests.

7.1.1. Creating the antibodies for known antigens in the case of Airline Seat Inventory Control Problem

We assume that we are able to predict the exact cumulative number of requests in the i-th passenger tariff class t days before planned departure $D_i(t)$, $(i = 1,2,...,n)$. In the case of perfect prediction we must be able to make optimal decisions. Let us show

how we will reach the maximum revenue in the case of a flight with two legs for which we know in advance the dynamics of passengers reservations, cancellations, etc. Let us also introduce the following notation:

n - the number of passenger tariff classes on each leg

C - aircraft capacity (the number of seats in the aircraft)

C_{AB}^i - i-th tariff on leg AB

C_{AC}^i - i-th tariff on leg AC

C_{BC}^i - i-th tariff on leg BC

D_{AB}^i - the cumulative number of requests in the i-th passenger tariff class on leg AB in the departure moment

D_{AC}^i - the cumulative number of requests in the i-th passenger tariff class on leg AC in the departure moment

D_{BC}^i - the cumulative number of requests in the i-th passenger tariff class on leg BC in the departure moment

x_{AB}^i - the total number of sold seats in the i-th passenger tariff class on leg AB

x_{AC}^i - the total number of sold seats in the i-th passenger tariff class on leg AC

x_{BC}^i - the total number of sold seats in the i-th passenger tariff class on leg BC

We assume that we have four tariff classes on each leg. We also assume that we know the values of the cumulative numbers of requests in particular tariff classes on all legs in the moments of departures. In other words, we will assume that we know the values of D_{AB}^i, D_{AC}^i and D_{BC}^i. We have to determine the total numbers of sold seats x_{AB}^i, x_{AC}^i and x_{BC}^i in order to reach the maximum revenue. Our problem is:

(P):
Maximize

$$F = \sum_{i=1}^{n} c_{AB}^i x_{AB}^i + \sum_{i=1}^{n} c_{AC}^i x_{AC}^i + \sum_{i=1}^{n} c_{BC}^i x_{BC}^i \tag{1}$$

subject to:

$$\sum_{i=1}^{n} \left(x_{AB}^i + x_{AC}^i \right) \le C \tag{2}$$

$$\sum_{i=1}^{n} \left(x_{AB}^i + x_{AC}^i \right) \le C \tag{3}$$

$$x_{AB}^i \le D_{AB}^i \qquad i = 1, 2, ..., n \tag{4}$$

$$x_{AC}^i \le D_{AC}^i \qquad i = 1, 2, ..., n \tag{5}$$

$$x_{BC}^i \le D_{BC}^i \qquad i = 1, 2, ..., n \tag{6}$$

$$x_{AB}^i \geq 0 \qquad i = 1, 2, ..., n \tag{7}$$

$$x_{AC}^i \geq 0 \qquad i = 1, 2, ..., n \tag{8}$$

$$x_{BC}^i \geq 0 \qquad i = 1, 2, ..., n \tag{9}$$

$$x_{AB}^i, x_{AC}^i, x_{BC}^i - \text{integer} \qquad i = 1, 2, ..., n \tag{10}$$

The first generated (by simulation) values of D_{AB}^i, D_{AC}^i and D_{BC}^i represent *antigen*₁. The obtained total numbers of sold seats x_{AB}^i, x_{AC}^i and x_{BC}^i that generate the maximum airline's revenue represent *antibody*₁. The *antibody₁* is the *ideal antibody* for the *antigen₁*, since it represents optimal solution of the problem (P).

The second generated (by simulation) values of D_{AB}^i, D_{AC}^i and D_{BC}^i represent *antigen*₂. The obtained total numbers of sold seats x_{AB}^i, x_{AC}^i and x_{BC}^i that generate the maximum airline's revenue represent *antibody*₂. The *antibody₂* is the *ideal antibody* for the *antigen₂* , etc. since it represents optimal solution of the problem (P).

The problem (P) could be easily solved by using any of the commercially available computer packages. The problem (P) was solved many times for different scenarios. Many different hypothetical antigens (many different $D_i(t)$, ($i = 1,2,…,n$)) are generated, and for each scenario, the corresponding antibody (best solution that represents total number of sold sets) is obtained using commercially available computer package. This set of solutions constitutes the Antigen - Antibody Database (AAD) for the Airline Seat Inventory Control Problem. The developed Antigen - Antibody Database is the starting point for creating the antibodies for unknown antigens.

7.1.2. Creating the Artificial Immune System :"On line" Decisions About Rejecting or Accepting Passenger Request

After analyzing optimal solution, as well as the cumulative numbers of requests in the particular passenger tariff classes, it is easy to determine for every passenger tariff class the time moment t^* after which there are no longer vacant seats for passengers requesting that tariff class. In other words, at any time moment t we know the remaining time period $t - t^*$ for selling the seats for every passenger tariff class. In the table 1 we showed this in the case of leg *AB*.

Table 1: Remaining time until departure t, the cumulative numbers of passengers requests and the remaining time period $t - t^*$ for selling the seats

Remaining time until departure	The cumulative numbers of passengers requests	Remaining time period for selling the seats
T	$D_{AB}^1(t)$ $D_{AB}^2(t)$ $D_{AB}^3(t)$ $D_{AB}^4(t)$	$t - t^*$ Tariff classes 1 2 3 4
-	-	-
-	-	-

As a result of integer programming we get optimal solution in which, for example, all passenger requests for the first tariff class are accepted, the part of passenger requests for the second tariff class is not accepted and no request from the third and fourth tariff class is accepted. In some other examples all passenger requests from the first and second tariff classes are accepted, the part of the passengers from the third tariff class is accepted and no passenger from the fourth tariff class is accepted, etc. In other words, if only a part of the passengers from some tariff class is accepted, no passenger from the lower tariff classes is accepted. In the moment when $t - t^*$ becomes less than zero for some tariff class this means that we must stop selling the seats in that tariff class and all lower tariff classes.

For every itinerary (*AB*, *ABC* or *BC*) we make a separate fuzzy rule base for making decision about rejecting or accepting certain passenger who shows up. Let us consider for example the itinerary *AB*. On this leg we have four tariff classes. It is clear that $t - t^*$ depends on the cumulative numbers of passengers requests $D_{AB}^i(t)$, ($i = 1, 2, 3,$ 4). The cumulative numbers of passengers requests are antecedents, while remaining time period for selling the seats $t - t^*$ the consequence. We can establish fuzzy sets for all the antecedents and the consequence. Typical fuzzy rule in the fuzzy rule base for leg *AB* could be, for the example, the following one:

If D_{AB}^1 is A_2 and D_{AB}^2 is B_4 and D_{AB}^3 is C_7 and D_{AB}^4 is D_{11}

Then $t - t^*$ is E_3

where:

A_i, B_i, C_i, D_i and E_i, $(i = 1, 2, 3, ...)$ are the established fuzzy sets for the antecedents

All three fuzzy rule bases are generated from numerical examples using Wang-Mendel's method (1992). All pairs antigen - antibody were used to produce a fuzzy rule base. The available numbers of seats at the airports *A* and *B* must be updated every time when some passenger is accepted for a flight. For passenger request in time moment *t* we will apply the appropriate fuzzy rule base according to the itinerary in question. In the case when $t - t^*$ is positive, the passenger will be accepted conditionally, as we will check the appropriate number of vacant seats. If we have at least one vacant seat we will accept the passenger. In the opposite case, we will reject the passenger. We will also reject the passenger when $t - t^*$ is negative.

7.1.3. Creating the antibodies for unknown antigens: Results Obtained Using The Intelligent Airline Seat Inventory Control System

During last four decades different approaches were developed for solving airline seat inventory control problem. The most important and widely used model is Expected Marginal Seat Revenue Model (EMSR). The model was originally proposed by Littlewood (1972) and further extended by Belobaba (1987, 1989).

We tested the model developed on a large number of different numerical examples. The results are shown in Tables 1 and 2. The results referring to direct, nonstop flights are given in Table 1 and flights with one stopover are given in Table 2.

Table 1: Comparison of revenues for nonstop flights
a) Demand is 95% of aircraft capacity with 107 seats

	EMSR	Artificial Immune System	Optimal
Training set (50 flights)	348,746	352,168	361,994
Test set (100 flights)	702,299	708,032	730,424
Test set (200 flights)	1,401,372	1,413,170	1,459,778
Test set (300 flights)	2,130,594	2,144,750	2,201,801

b) Demand is 120% of aircraft capacity with 107 seats

	EMSR	Artificial Immune System	Optimal
Training set (50 flights)	353,126	391,047	418,606
Test set (100 flights)	706,206	775,605	829,882
Test set (200 flights)	1,411,740	1,562,448	1,668,986

Table 2: Comparison of revenues for flights with one stopover
a) Demand is 75% of aircraft with capacity of 300 seats

	Artificial Immune System	Optimal	Ratio (%)
Training set (100 flights)	21,770,890	21,772,690	99.99
Test set (100 flights)	22,161,370	22,169,170	99.96

b) Demand is 85% of aircraft with capacity of 300 seats

	Artificial Immune System	Optimal	Ratio (%)
Training set (100 flights)	24,468,550	24,548,620	99.67
Test set (100 flights)	24,751,750	24,865,680	99.54

c) Demand is 95% of aircraft with capacity of 300 seats

	Artificial Immune System	Optimal	Ratio (%)
Training set (100 flights)	26,374,720	26,820,260	98.34
Test set (100 flights)	26,223,740	26,662,900	98.35
Test set (100 flights)	26,519,680	26,805,520	98.93

d) Demand is 105% of aircraft with capacity of 300 seats

	Artificial Immune System	Optimal	Ratio (%)
Training set (100 flights)	27,302,590	28,409,930	96.10
Test set (100 flights)	27,456,840	28,552,560	96.16
Test set (100 flights)	27,551,550	28,689,440	96.03

In most tested examples the Artificial Immune System developed gave considerably better results than the EMSR model. We would note that the EMSR model is used by a large number of world air carriers. For flights with one stopover the comparison was made between the results produced by the Artificial Immune System (produced antibody for unknown antigen) and those obtained using integer programming (ideal antibody). The integer programming results are the maximum revenue values attainable *when the future is ideally predicted*. Bearing this fact in mind, as well as the fact that the Artificial Immune System operates in an *on-line regime in conditions of uncertainty*, it can be concluded that exceptionally good results would be achieved using the Artificial Immune System.

7.2. Intelligent Isolated Intersection

Fuzzy control has been studied for different traffic control problems (Pappis and Mamdani (1977), Nakatsuyama et al (1983), Sayers and Bell (1996), Chang and Shyu (1993), Chen et al (1990), Niittymaki and Kikuchi (1998), Teodorovic (1994), Teodorovic and Vukadinovic (1998), Kim et. al. (1998), Lee and Lee-Kwang (1999), Niittymaki and Pursula (2000), Sayers (2001), Niittymaki (2001), Bingham (2001)).

Teodorovic et al. (2001) tried to continue and expand the applications of fuzzy control at isolated intersections. They explored new approaches in fuzzy control at isolated intersections, and also at similar facilities or situations (Freeway Entrance-Ramp Control for example). Their research aims to test the proposed concept in a simple model of the isolated intersection, making it a "benchmark model", rather than to attempt to solve traffic control in real situations.

Consider an isolated "*T*" intersection consisting of two one-way streets as shown in Figure 1. We assume that the "*T*" intersection is isolated and relatively "busy" with significant demand variations during certain time periods. In this paper we will not take into consideration the whole set of engineering details like detector placement, calculation of the minimum and maximum green times, yellow and all-red times, and pedestrian requirements. The detectors provide real time information on the numbers of incoming vehicles, stopped vehicles, and the total vehicle waiting time (delay) on each approach. This information is updated in short time intervals. Based on this information, a set of rules is applied to control the signal phase for the next time interval. The decision is either to continue or to terminate the current signal phase. The question is how to build the rules so that they sat the following objectives of signal control: (1) to minimize the total number of stopped vehicles S, and (2) to minimize the total delay *D* over a given time period (0, *T*). In other words, our performance index ("cost" or "penalty function") should represent some weighted combination of stops and delays. In certain cases some other factors could be also included in the performance index. For example, the performance function could read as follows:

$$F = w_1 S + w_2 D \tag{11}$$

where: w_1 - the weight (the importance) given to the total number of stopped vehicles;
w_2 - the weight (the importance) given to the total delay; $w_1 + w_2 = 1$

The terms S and D are added with weights of w_1 and w_2. This enables multi-criteria sensitivity analysis and generation of a great number of different control strategies depending on chosen criteria weights (importance). The better the control strategy, the smaller the average delay and the total number of stopped vehicles. In other words, we are interested in identifying the corresponding antibody that represents the sequence that minimizes the value of the objective function. We use genetic algorithms to develop the optimum sequence of signal phases (antibody) assuming that the future traffic conditions at the intersection (antigen) are known. Many different hypothetical antigens (traffic scenarios) are generated, and for each scenario, the corresponding antibody (best solution consisting of a string of 1's and 0's) is developed using Genetic Algorithm. This set of solutions constitutes the Antigen - Antibody Database (AAD) for the intersection. The developed Antigen - Antibody Database is the starting point for creating the Artificial Immune System. The Artificial Immune System (Fuzzy Rule Base) is generated using Wang-Mendel's (1992) method. Typical fuzzy rule in the fuzzy rule base is, for the example, the following one:

> **If** the total number of approaching vehicles is SMALL, and if the total number of vehicles waiting in the other approach is LARGE, and if time elapsed since the last phase change is VERY LONG
>
> **Then** the time length until the next phase change is VERY SHORT

7.2.1. Testing results of the proposed Isolated Intersection Artificial Immune System Creating the antibodies for unknown antigens

In this section, we compare the results obtained by the Artificial Immune System with the "best" solution (ideal antibody) obtained by the genetic algorithm. Because the Genetic Algorithm result was the retrospectively derived best solution for a given traffic pattern, the performance associated with it is considered as the target or reference for evaluation. The criterion used to compare the two cases (Artificial Immune System result vs. Ideal antibody (Genetic Algorithm result) is the performance index defined in relation (11) (weighted combination of two objectives: the minimum number of stopped vehicles and the minimum total delay).

The vehicle arrivals are assumed to follow the Poisson process. Thirty-two patterns are generated with each pattern lasting for 10 minutes (600 seconds). The headway between two successive vehicles is not less than 1.5 seconds. The size of the small time interval at which control decisions are made is 6 seconds. The best decision at each small time interval is developed using the genetic algorithm. The specific values of weights between the minimum total delay (w_1) and minimum total number of stopped vehicles (w_2) are as follows: ($w_1 = 0$; $w_2 = 1$), ($w_1 = 0.2$; $w_2 = 0.8$), ($w_1 = 0.4$; $w_2 = 0.6$), ($w_1 = 0.6$; $w_2 = 0.4$), ($w_1 = 0.8$; $w_2 = 0.2$), ($w_1 = 1$; $w_2 = 0$). Thus, for a given traffic pattern, six best solutions, corresponding to each weight combination, are developed. Figure 4 show the number of stopped vehicles for the traffic arrival patterns that *are not previously used*. In this figure (as in the case of the total delay), most points line up along the 45-degree line. This indicates that Artificial Immune System result and Genetic Algorithm results (ideal antibodies) are very similar and that the rules from the proposed method can yield solutions close to the best solution.
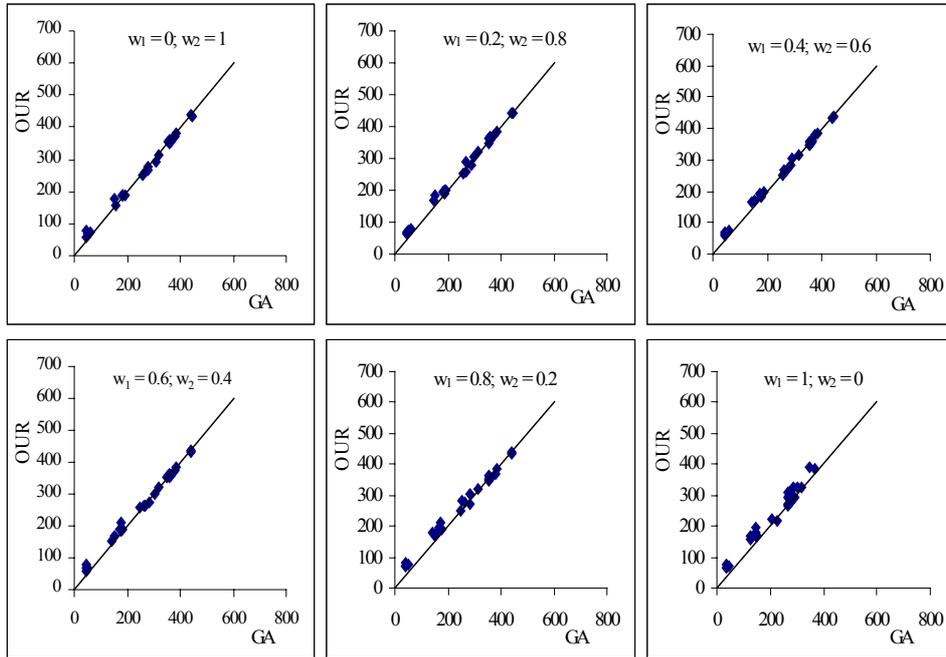
Figure 4: Total Number of Stopped Vehicles: Comparison between the ideal antibodies and antibodies produced by the developed Artificial Immune System

7.3. Intelligent Vehicle Routing System

Vehicle routing problems appear in various transportation activities (Larson and Odoni (1981), Bodin et al. (1983), Solomon and Desrosiers (1988), and Golden and Assad (1988), and Laporte (1992)). Vehicles leave the depot, serve nodes in the network and on completion of their routes, and return to the depot. Every node is described by a certain *demand* (the amount to be delivered to the node or the amount to be picked up from the node). Other known values include the *co-ordinates* of the depot and nodes, the *distance* between all pairs of nodes, and the *capacity* of the vehicles providing service. The classical vehicle routing problem consists of finding the set of routes that minimizes transport costs. During last two decades, papers have started to appear (Dror and Trudeau (1986), Dror et al., (1989), Teodorović and Pavković (1992), Lambert et al (1993), Dror (1993), Dror et al (1993), Bertsimas et al (1995), Popovic (1995), Potvin et al (1996), Gendreau et al (1996), Teodorovic and Pavkovic (1996), Yang et al (2000), Teodorovic and Lucic (2000), Secomandi (2000), Van Breedam (2001)) in which demand at nodes is treated as a random variable and actual demand value is known only after the visit to the node. The problem of routing vehicles in the case of stochastic demand at nodes is known in the literature as the *stochastic vehicle routing problem* Stochastic vehicle routing problem appears in delivery of home heating, trash collection, beer and soft drinks distribution, provision of the bank automates with cash and collection of cash from bank branches. The basic characteristic of the stochastic vehicle routing problem is that the

real value of demand at a node is only known when the vehicle reaches the node. Due to the uncertainty of demand at the nodes, a vehicle might not be able to service a node once it arrives there due to an insufficient capacity. Such situation is known as a "route failure". In the case of "route failure" different actions need to be applied. Teodorovic and Lucic (2000) developed an "intelligent" system which can make "on line" decisions regarding route shapes for the situations in which locations of the depot, nodes to be served and vehicle capacity are known, and demand at the nodes only approximated (represented by probability density functions), so as to produce a set of "high quality routes" for the vehicles in service. The developed "intelligent" system is Based on the Artificial Immune Sysstem principles.

Let us assume that there are *n* nodes in the network to be served. We also assume that service is provided by vehicles of the same size. We will denote vehicle capacity by *C*. Vehicles set out from depot D, serve a number of nodes and on completion of their service, return to the depot. Let us note depot D and n nodes shown in Figure 5. We also assume that the demand at each node is only approximately known. Such demand can be represented by a probability density function or in the case of subjective estimate by the appropriate fuzzy number.
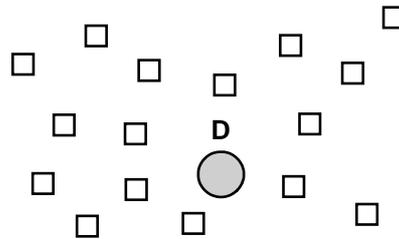

Figure 5: Depot D and nodes requiring service

Let us assume that demand D_i at any node *i* can be represented by the Normal distribution with mean μ_i and standard deviation σ_i, i.e.:

$$D_i \sim N(\mu_i, \sigma_i) \qquad i = 1, 2, ..., n. \tag{12}$$

In the past four decades, a large number of different heuristic algorithms have been developed to route vehicles. One of the simplest is the sweep algorithm proposed by Gillett and Miller (1974). This algorithm is applied to polar co-ordinates, and the depot is considered to be the origin of the co-ordinate system. The depot is joined with an arbitrarily chosen point that is called the *seed point*. All other points are joined to the depot and then aligned by increasing angles that are formed by the segments that connect the points to the depot and the segment that connects the depot to the seed point. The route starts with the seed point, and then the points aligned by increasing angles are included, all the while respecting given constraints. When a point cannot be included in the route since that would violate a certain constraint, the point becomes the seed point of a new route, and so on. The process is completed when all points are included in the route (Figure 6).

Increasing the number of nodes served along a route decreases the available (remaining) capacity of the vehicle. When demand at the nodes is deterministic, after completing service at one node it is easy to calculate whether the vehicle is able to serve the next node. On the other hand, when demand at the nodes is characterized by probability density functions, or fuzzy numbers, it is not a simple task to decide whether the vehicle should serve the next node or return to the depot.
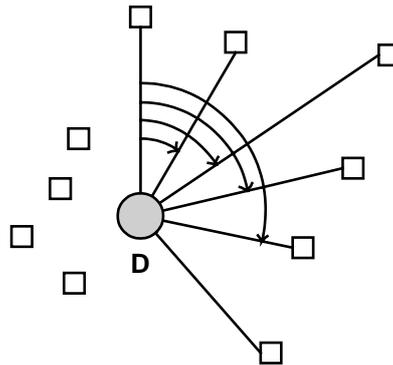

Figure 6: Sweep algorithm

It is clear that the greater the vehicle's remaining capacity and the lesser the demand at the next node, the greater the vehicle's "chances" of being able to serve the next node. In other words, the greater the difference between the remaining capacity and demand at the next node, the greater our preference to send the vehicle to serve that next node and the greater the number of nodes in the route. Teodorović and Lucic (2000) assumed in such situations that the vehicle returns to the depot, empties what it has picked up thus far, returns to the node where it had a "failure," and continues service along the rest of the planned route (Figure 7). When evaluating the planned route, the additional distance that the vehicle makes due to "failure" arising in some nodes along the route must be taken into consideration. Our desire to use vehicle capacity in the best possible way we can will produce planned routes with shorter total distances. On the other hand, this will increase the number of cases in which vehicles arrive at a node and are unable to service it. In other words, the total distance due to the route "failure" will be increased. Smaller utilization of vehicle capacity along the planned routes will produce longer planned routes and less additional distance to cover due to failures. The problem (P) logically arises when designing such a set of routes, which will result in the least total sum of planned route lengths and additional distance covered by vehicles due to failure.
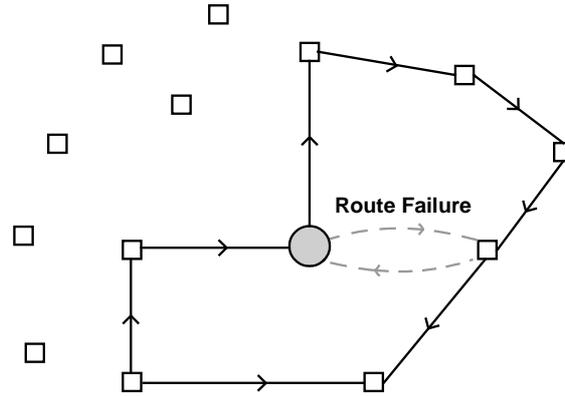
Figure 7: "Failure" at a node of the planned route

The problem (P) is solved many times for different scenarios (known the random demand values at all nodes). Using Sweep algorithm, we got "good" solution (antibody) for every simulated "scenario" (antigen). This "statistical material" enables the generation of a fuzzy rule base from numerical examples (Artificial Immune System).

After serving the first k nodes, the available capacity of vehicle B_k will equal

$$B_k = C - \sum_{i=1}^{k} D_i \qquad (13)$$

It is clear that the "strength" of our preference for the vehicle to serve the next node after it has served k nodes depends on the available capacity B_k, as well as on expected demand in the next node. In other words, the bigger the available capacity and the smaller the expected demand in the next node, the higher our expectation that the route will contain more nodes. We can expect that at a certain time point the route will have "small," "medium," or "big" number of nodes. We will denote by n_k the expected number of new nodes in the route after vehicle already has served k nodes. The linguistic expressions "small number of new nodes," "medium number of new nodes," and "big number of new nodes" can be represented by corresponding fuzzy sets. Available capacity can also be subjectively estimated, for example, as "small," "medium, and "large." Let us denote respectively by X_1, X_2 and X_3 the following variables:

$$X_{1k} = \frac{B_k}{C} ; \quad X_{2k} = \frac{\mu_{k+1}}{C} ; \quad X_{3k} = \frac{o_{k+1}}{C} \qquad (14)$$

The first variable represents relative available capacity after serving the first k nodes. The second variable represents relative expected demand in the next node, while the third one describes relative variability of the demand in the next node. The typical rule in the approximate reasoning algorithm (Artificial Immune System) to determine the expected number of the new nodes in the route can be the following one:

If   Relative available capacity is **Large** and Relative expected demand in the next node is **Small** and Relative variability of the demand in the next node is **Small**

Then   Expected number of the new nodes in the route is **Big.**

We can see that the antecedent of the rules contains remaining vehicle capacity and the expected demand in the next node. The consequence contains the expected number of new nodes in the route. For known available capacity B_k that remains after serving k nodes, and for known characteristics of the demand in the next node it is possible to use the approximate reasoning rules to determine the expected number of new nodes in the route. We are now able to answer the following question: should we send the vehicle to the next node or return it to the depot after completing service to *k* nodes? Let the expected number of the new nodes in the route equal n_k^*. Based on this value, a decision must be made whether to send the vehicle to the next node or return it to the depot.

The vehicle should be sent to the next node if the following relation is fulfilled:

$$n_k^* > 1 \tag{15}$$

When:

$$n_k^* < 1 \tag{16}$$

the vehicle should be returned to the depot.

7.3.1. Results Obtained Using 'Intelligent" Vehicle Routing System

The developed model was tested by Teodorovic and Lucic (2000) on a large number of different numerical examples. In the first step the location of the depot and 1000 nodes are generated randomly. The characteristics of the node demand (mean and standard deviation) are also randomly generated for every created node. When randomly generating mean and standard deviation of the demand in every node the following relations are fulfilled:

$$0 \le \mu_i \le C ; \quad \sigma_i \le \frac{\mu_i}{3} ; \quad i = 1,, 2, ..., 1000. \tag{17}$$

The "real" demand in every node (antigen) was also generated randomly. The routes were generated using the Sweep algorithm (antibodies). Generated routes enabled us to "walk" along the routes and to "read" the available capacity in every node, as well as demand characteristics of the next node on the route. In this way, we obtained statistical material for generating fuzzy rule base.

We have compared the results obtained by the proposed Artificial Immune System with the "best" solution (ideal antibody) obtained by the Sweep algorithm.

The criterion used to compare the two cases (Artificial Immune System result versus Sweep Algorithm result) is the total distance traveled by all vehicles. Demand at each node is a deterministic amount that is obtained by simulation. By moving along the route designed by the approximate reasoning algorithm and accumulating the amounts picked up at each node, it was easy to determine the nodes where failures occurred and to calculate the additional distance that the vehicles had to make.

For a different set of demand pattern, the best set of routes was developed by the Sweep Algorithm, and the performance was measured. This performance was then compared with the one obtained using the previously developed Artificial Immune System.

Practically negligible CPU times were achieved, and were thus absolutely acceptable for the "real time" application of the developed algorithm.

Table 3: Total distance traveled by all vehicles: Comparison between the ideal antibodies and antibodies produced by the developed Artificial Immune System

| Number of Nodes	"Ideal antibody" (Solution obtained by the Sweep Algorithm) (SA)	Artificial Immune System solution (AIS)	$\dfrac{\lvert AIS - SA\rvert}{SA}$ [%]
30	21495.2	21495.2	0
50	20486.4	20486.4	0
100	31272.03	34399.23	9.9
150	76714.3	76707.1	0.009
200	73354.8	76688.5	4.5
250	94540.6	97800.6	3.4
300	98806.4	101894.1	3.1
350	156966.02	160990.1	2.5
400	176117.5	184290.1	4.6
450	199049.3	207173.7	4.1
500	154281.02	157192	1.9
550	219866.8	222605.2	1.2
600	215407.3	218575.1	1.5
650	267579.1	257322.2	3.8
700	257326.4	264098.1	2.6
750	342801.4	351162.4	2.4
800	246516.1	252315.8	2.3
850	314369.6	319440.4	1.6
900	521581.74	537881.2	3.1
950	187791.9	195456.9	4.1
1000	285147.4	295807.1	3.7
1500	576617.1	570738.2	1
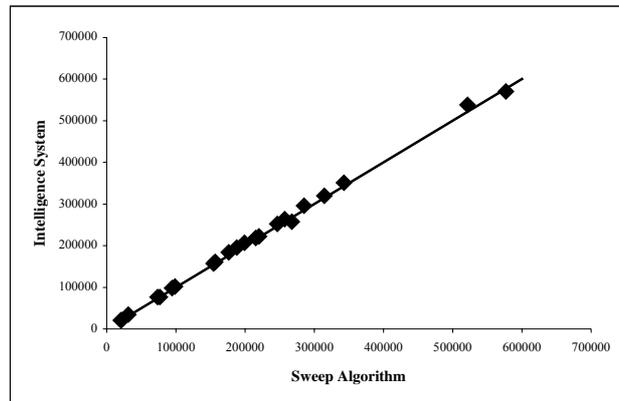
Figure 8: Comparing Artificial Immune System result with ideal antigen result for unknown antigen (for demand pattern not used previously)

Table 3 and Figure 8 illustrate "the effectiveness of vaccination in providing protection". It can be seen in Figure 8 that Artificial Immune System result and the ideal antigen result are very close. In other words, the obtained results indicate that the Artificial Immune System can match the result of the "best" solution closely.

8. CONCLUSIONS

Lymphocytes have the ability to distinguish one antigen from another. The number of different antigens is practically limitless. Usually, our body is able to fight with the antigens it has encountered in the past. Even our body does not have one specific receptor for each possible antigen. It is usually able to fight with the unknown antigens that the immune system can be exposed to.

The Artificial Immune Systems is biologically motivated approach to problem solving. Proposed Artificial Immune System has the following main components: (a) Antigen set generation; (b) Antibody set generation; (c) Artificial Immune System creation; (d) Testing Artificial Immune System response.

Antigen set is composed of many different antigens. Every antigen is generated by simulation. In this way uncertain traffic conditions in a transportation system are decomposed in many different possible realizations. Every Antigen represents different "traffic scenario" than can happen in considered transportation system. Different optimization or heuristics techniques can be used to derive the optimal or "good" solution (ideal antibody) for a generated traffic patterns. In this way, Antibody set is generated. Antigen set generation, as well as Antibody set generation is time consuming procedure. All antigen-antibody pairs ("demand scenario – appropriate airline seat inventory control strategy"; "demand scenario – appropriate isolated intersection control strategy", "demand scenario- appropriate set of vehicle routes") were used to create Artificial Immune System. The Artificial Immune System learns from the solutions obtained assuming that the future traffic situations are known.

Evaluating the performance of the Artificial Immune System is also noble. Because the optimal or "good" solution (ideal antibody) is known for a particular traffic scenario (antigen), the performance of the proposed Artificial Immune System can easily be checked against the result of the optimal or "good" solution (ideal antibody). Many tests show that the response (outcome) of the proposed Artificial Immune System is nearly equal to the optimal or "good" solution (ideal antibody).

On the one hand Antigen set generation, as well as Antibody set generation is time consuming procedures while on the other, the time for the Artificial Immune System response is practically negligible. In other words, we need a lot of time to create the tool called Artificial Immune System. Once, when tool is created, it can be used for solving real-time problems.

The basic goal of this research is an attempt to develop new approaches for solving a class of complex real-time problems that are characterized by uncertainty. The proposed Artificial Immune Systems could be treated as "intelligent" systems, because of their ability to recognize different situations, as well as their ability to make the appropriate decision without knowing the functional relationships in effect between individual variables. The developed Artificial Immune transportation systems are able to generalize, adapt, and learn based on new knowledge and new information.

The proposed idea is to create Artificial Immune System using numerical training data of the highest quality (obtained by some optimization technique, or by some sophisticated heuristic algorithm). In this paper, we create Artificial Immune System using fuzzy logic techniques. The fuzzy rule base is generated from numerical examples (Antigen - Antibody Database).

Artificial Immune System could be also created using neural networks approach Recently, when considering real time traffic control at the four-way intersection, Teodorovic et al. (2002b) used numerical training data obtained by dynamic programming to train the neural network. Any Optimization Technique (or good Heuristic Algorithm) could be used together with Fuzzy Logic System (or Artificial Neural Network) to create an Artificial Immune System.

It can be ascertained that the proposed Artificial Immune System is "model-free," which means it is not necessary to have a mathematical model for the problem considered.

The human immune system represents complex adaptive system The proposed Artificial Immune System has the possibility to learn from examples, which means that it is adaptable. With new examples, from time to time, changes appear in the rules and/or new fuzzy rules are added. There are numerous transportation and logistic problems where this research could apply. The proposed concept is especially important for research activities whose unified themes are uncertainty (randomness, stochasticity, fuzziness...) and time-dependence (dynamic, real-time).

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