

# Improving Customer Satisfaction using the Artificial Immune System

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**Abstract— This paper deals with the optimization of customer satisfaction in service systems using the Artificial Immune System (AIS). The objective function defined as the average residence time of the customers in the system provides a direct measure of customer satisfaction. The operational constraints include the number of servers, the service time and the local service satisfaction at some strategic service spots in the system. We illustrate the simulation optimization method by means of a practical clinic service system. The operation of the service system is simulated by means of a discrete event simulator and optimized by means of the Artificial Immune System, subject to the service constraints. AIS is a new paradigm in Evolutionary Computation, based on the principles of the human immune system. Compared to the other Evolutionary Computational algorithms like the Genetic Algorithm, it is found to be simpler in implementation and better in performance in our application.**

**Index Terms— Artificial Immune System (AIS), customer satisfaction, simulation, optimization**

## I. INTRODUCTION

The goal of practical service systems like banks, hospitals, restaurants, theme parks, post offices, reservation counters, etc. is to provide cost-efficient service, while taking into consideration the satisfaction of the customers who seek service from the service system. In recent years, customer satisfaction has become a major issue in marketing research and a number of customer satisfaction measurement techniques have been proposed [17]. Increasing efforts have been made to analyze the causes of customer dissatisfaction and to suggest remedies [16], [22]. In queuing systems, nothing can be as detrimental to customer satisfaction as the experience of waiting for service. Waiting has a negative impact on service quality evaluations [26]. For customers, waiting is frustrating, demoralizing, agonizing, aggravating, annoying, time-consuming, and incredibly expensive [23].

In this study, we present the application of the Artificial Immune System (AIS) for the optimization of the customer satisfaction in service systems. The objective function is the average residence time (waiting time + service time) of the

customers in the system, while the operational constraints include the number of servers, the service time and the local service satisfaction at some strategic service spots in the system. We illustrate the simulation optimization method by means of a practical clinic service system.

The service system model is descriptive in nature, and has static as well as dynamic aspects. The former portrays a detailed map of the workflow in the service system, while the latter produces the operational characteristics by means of a discrete event simulation. The queuing statistics obtained from the discrete event simulation [2], [15] are used to compute the weighted average of the residence time of the customers in the system. The objective function is minimized using the AIS Clonal Selection Algorithm.

The AIS is a recently developed intelligent approach inspired by the biological immune system [5], [13], [14]. It emerged in the 1990s as a new branch in Evolutionary Computation [7], [14]. Research in AIS has been applied to solve complex problems such as scheduling [4], pattern recognition [3], anomaly detection [6], computer security [21], data mining and machine learning [11], [13], [27] and optimization [14].

The biological immune system is made up of primarily two types of cells - B cells which are produced in the bone marrow and T cells which are produced in the thymus.

The pathogens like bacteria and viruses invading the body are called antigens. Both the antigen and the receptors on the surface of the B cells have three-dimensional structures. The affinity between the structure of the receptors and that of the antigen is a measure of the complementarities between the two. When an antigen invades the body, the immune system generates antibodies to diminish the antigen. Initially, the invaded antigen is recognized by a few of the B cells with high affinity for the antigen. Stimulated by the helper T cells, these high affinity B cells proliferate by cloning. This process is called clonal selection principle [1]. The new cloned cells undergo a high rate of somatic mutations called hyper-mutation. The mutations undergone by the clones are inversely proportional to their affinity to the antigen. The highest affinity antibodies experience the lowest mutation rates, whereas the lowest affinity antibodies have the highest mutation rates. The high affinity B cells and their clones proliferate and differentiate into plasma cells. Finally, the plasma cells generate a large number of antibodies to neutralize and eliminate the antigens.

After the cloning and hyper-mutation stage, the immune system must return to its normal condition, eliminating the extra cells. However, some cells remain circulating throughout the body as memory cells. When the immune system is later attacked by the same type of antigen (or a similar one), these memory cells are activated, presenting a better and more efficient secondary response.

Among the various mechanisms in the biological immune system that are explored as AISs, negative selection [19], immune network model [11] and clonal selection [18] are the most discussed models. The CLONALG algorithm is based

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on the above clonal selection principle [8], [13]. De Castro's work [14] describes the use of CLONALG in optimization.

Our algorithm closely follows the CLONALG with modifications to fit the objective function in service systems. In our application, the antigens refer to the objective function of the problem and the antibodies to the candidate solution of the problem. For the minimization problem, affinity is defined as the reciprocal of the objective function. CLONALG searches for the optimal solution through a series of iterative operations such as selection, cloning and mutation. After the stipulated number of iterations, the antibody with the highest affinity (minimum value) is selected as the optimal solution.

This paper is organized as follows: Section 2 presents the static and the dynamic simulation model of the service systems. Section 3 presents the optimization problem formulation. Section 4 deals with the simulation optimization results using the AIS clonal algorithm. Section 5 gives a brief conclusion and indications for further research.

## II. SIMULATION MODEL OF SERVICE SYSTEMS

The clinic service system is modeled as a Multi-Context Map (MCM). It is made up of seven different "contexts" represented by rectangles in the diagram. Reception, Diagnosis 1, Diagnosis 2, Prescription, Medical tests, Physiotherapy and Accounts are the respective contexts. These contexts are essentially the places of work, or the "service stations" in which service is provided to the customers. The servers or the service-providing personnel at the contexts are known as "Perspectives". These include physicians, nurses, medical technicians, physiotherapists, pharmacists, etc. The Perspectives are labeled above, while the rest of the resources are labeled below the contexts. There are also junctions such as branch (Br), join or serialize (Se), etc., which control the workflow in the system. These are represented by smaller rectangles. The MCM modeling details of collaborative service systems are found in [20].

## III. OPTIMIZATION PROBLEM FORMULATION

### A. Objective function

Let  $QT_i$  be the average time spent by the customer (patient) in the  $i^{\text{th}}$  queue in the network. Let  $QN_i$  be the average number of customers in that queue. The weighted average of the time spent by the customers in  $n$  number of queues is given by:

$$\overline{QT} = \frac{\sum_{i=1}^n QT_i QN_i}{\sum_{i=1}^n QN_i} \quad (1)$$

Let  $ST_i$  be the average service time of the  $i^{\text{th}}$  server. Let  $SN_i$  be the average number of customers served by the  $i^{\text{th}}$  server. The weighted average of the time spent by the customer in receiving service at the  $i^{\text{th}}$  server is given by:

$$\overline{ST} = \frac{\sum_{i=1}^n ST_i SN_i}{\sum_{i=1}^n SN_i} \quad (2)$$

The objective function is given by:

$$Z = \overline{QT} + \overline{ST} \quad (3)$$

### Service Constraints

The capacity of the server represents the number of servers allotted to a given context. If  $N_p$  is the capacity of a server serving at a context, then the constraints are:

$$N_{p<} \leq N_p \leq N_{p>} \quad (4)$$

where  $N_{p<}$  and  $N_{p>}$  are the lower and the upper bounds, respectively.

Further, each context has an appropriate service time that is usually drawn from an exponential distribution. The service time limits can be expressed as:

$$t_{<} \leq t \leq t_{>} \quad (5)$$

where  $t_{<}$  and  $t_{>}$  are the lower and the upper bounds, respectively.

### B. Service Satisfaction Constraints

A model of customer satisfaction with regard to ordering a product is found in [24]. We extend this model of customer satisfaction (CS) towards services. In general, the shorter the service time, the greater is the customer satisfaction. However, in a medical setup, if the time spent by the doctors in treating patients is made very short, the patients feel they have not been listened to, that they have been rushed. On the

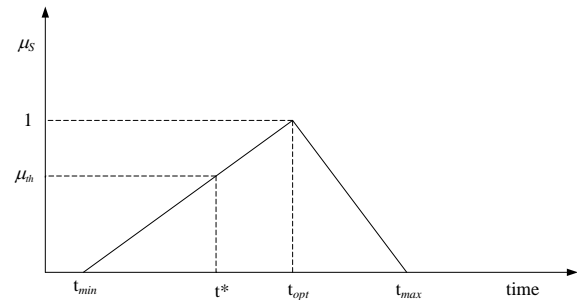


Fig. 1. Fuzzy membership function representing CS in medical diagnosis

other hand, if the doctor takes too long in examining the patient, the latter may feel bored. There exists an optimal service time ( $t_{min} \leq t_{opt} \leq t_{max}$ ) for which the patient is fully satisfied with the medical service ( $\mu_s(t) = 1$ ). The same service constraints apply at the physiotherapy context. If  $\mu_{th}$  is the threshold of the service satisfaction decided upon by the clinic's management policy, then the crisp value of the appropriate service time  $t^*$  would be the time corresponding to  $\mu_{th}$  value of the fuzzy membership function, as shown in Fig. 1. However, if the diagnosis and the physiotherapy contexts fail to deliver the required level of customer satisfaction, then the total residence time at these contexts is imposed as a penalty on the objective function (Equation 5).

$$p_{cs} = \sum_{i=1}^n QT_i \delta_i + \sum_{i=1}^n ST_i \delta_i \quad (6)$$

where,

$$\delta_i = 1, \text{ if the } i^{\text{th}} \text{ constraint is violated, and}$$

$$\delta_i = 0, \text{ if the } i^{\text{th}} \text{ constraint is satisfied.}$$

Imposing penalties for violating the service satisfaction constraint ( $p_{cs}$ ), the objective function with penalties [25],  $f_p$  effectively becomes:

$$f_p = f + p_{cs} \tag{7}$$

#### IV. AIS AND SERVICE SYSTEMS OPTIMIZATION

##### A. AIS Algorithm

The AIS clonal algorithm consists of the following steps:

##### Generation of antibody population

A population consisting of N antibodies (Abs) is randomly generated. Each antibody represents a feasible solution to the optimization problem. The Abs in our application are shown in Table 1. The service time at each of the service contexts, the number of Perspectives in each of Type I, Type II and Type III are the decision variables of the optimization problem. The current variable values (cur) are bounded by the minimum (min) and the maximum (max) values. Initially, these values are generated randomly.

Traditional GA as well as AIS follows the bit string representation. However, we represent the decision variables as real numbers in our application. The real-number representation scheme saves computational overhead, since no bit string to real number conversion is required to evaluate the objective function.

##### Simulation of system operation

The MCM model of the system is simulated by using a discrete event simulator. The simulation is based on the Extend package (<http://www.extendsim.com>). The clinic system operation for a day is simulated. The output of the simulation provides statistics like the average waiting time, the average queue-length, server utilization, etc. These are used to compute the objective function and the constraints.

##### Affinity Calculation

The affinity of each individual antibody is evaluated by computing the objective function given in equation 3. Appropriate penalties (equation 6) are imposed when the server utilization constraints and service satisfaction constraints are violated.

##### Clone Selection

A certain percentage of the antibodies with greater affinities are selected from the population. These are then cloned to produce additional antibodies.

##### Affinity Proportional Mutation

The clones produced in the above step are subjected to mutations in proportion to their affinities.

##### Memory Renewal

The antibodies with relatively lower affinities (i.e., with higher values of the objective function) are eliminated. The selected clones are introduced into the antibody population as the immune memory cells.

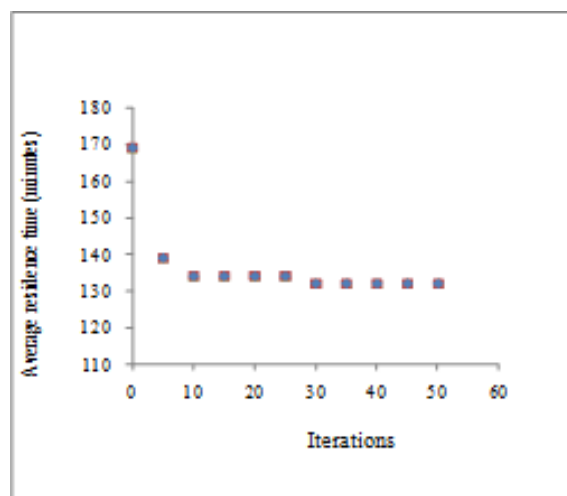
The above steps are iterated for M number of cycles. The Ab with the highest affinity (minimum values) found in all the iterations is the optimal solution.

##### A. Optimization Results

The operational parameters of the small clinic service system are listed in Table 1. In general, three groups of personnel, Type I (eg. doctors), Type II (eg. senior nurses) and Type III (eg. junior nurses) are assigned to the clinic contexts. The number in each type is bounded by a minimum and a maximum (hard constraints). Similarly, the service time with its upper and lower bounds for each of the contexts is also shown. The current values of the number of personnel (cur) and of the service time that minimize  $f_p$  are obtained by the AIS algorithm. The simulation output parameters are also shown. These include the server utilization ( $\rho$ ), the average queue length ( $QN$ ) and the average queue time ( $QT$ ). In the optimized scenario, the service satisfaction constraints ( $\mu_{th} = 0.6$ ) are not violated. For an average inter-arrival time of 5 minutes, the minimum cost of system operation for a day (10 hours) is found to be 132.76 minutes. The rapid convergence of the AIS algorithm for 30 antibodies is shown in Fig. 3.

**Table 1.** Simulation Optimization input (personnel)

Contexts	Perspective I			Perspective II			Perspective III			Service Time			Util. (r)	Queues		CS	
	Number			Number			Number			Min	Cur	Max		QN (Num)	QT (Min)		
	Min	Cur	Max	Min	Cur	Max	Min	Cur	Max								
Reception	1	3	3	1	2	2	0	0	0	8	10	12	0.63	30.00	150.00	----	
Diagnosis1	1	1	3	1	1	3	1	2	2	15	20	30	0.60	0.15	5.00	1.00	
Diagnosis2	1	2	4	1	3	3	1	1	2	16	25	35	0.53	2.41	62.65	0.77	
Med.Tests	1	1	3	1	2	2	0	0	0	15	25	25	0.57	0.12	5.00	----	
Prescription	1	3	3	1	1	2	1	2	2	15	15	35	0.62	3.45	53.68	----	
Physiotherapy	1	2	2	1	2	2	1	1	2	20	40	55	0.41	0.36	26.88	0.60	
Accounts	1	1	2	1	2	2	0	0	0	8	12	15	0.47	0.03	0.33	----	
														f	132.76		



**Fig. 2.** Convergence of AIS for 30 antibodies

## V. CONCLUSION

In this paper, we have presented the application of the Artificial Immune System (AIS) clonal algorithm for the optimization of the customer satisfaction in a practical business system. The cost function is expressed as the sum of the weighted averages of the service time and waiting time at the service contexts. It represents the average residence time in the system, providing a direct measure of customer satisfaction. The AIS simulation optimization strategy finds the optimal residence time in the system under the given operational constraints. The clonal algorithm is found to converge rapidly even for a very large search space. Further, AIS is found to converge faster than GA in our application problem. The higher performance of AIS can be attributed to the affinity-proportional cloning and hyper-mutation characteristics. There are several promising directions for future research including the development of AIS to handle multi-objective optimization problems (MOPs), and, comparing its performance to the well-known MOPs like SPEA, MOPSO and NSGA-II.

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