An Artificial Immune Approach for Optimizing Crowd Emergency Evacuation Route Planning Problem

Mohd Nor Akmal Khalid and Umi Kalsom Yusof
School of Computer Sciences, University Sains Malaysia, 11800 Georgetown, Pulau Pinang, Malaysia

Keywords: Emergency Evacuation, Emergency Route Planning, Immune Algorithm.

Abstract: Disastrous situations, either naturally (such as fires, earthquake, rising tides, hurricane) or man-made (such as terrorist bombings, chemical spills, and so on), have claimed the lives of thousands. As such, optimizing the evacuation operations during an emergency situation would require an effective crowd evacuation plan, which is acknowledged to be one of the vital studies of the societal research as well as emergency route planning (ERP) community. Several descriptions of prior developed approaches for emergency evacuation that encompassed the needs of a variety of public community as well as fulfilling the complexity of the situation, are summed up and discussed. This paper introduces an immune algorithm (IA) to optimize the evacuation plan for solving the ERP problems. The approach is first validated against previous work while further experimentation reveals the effectiveness of the proposed IA, with regard to certain parameter calibrations, in the context of ERP problems. The findings have been summarized and presented, whereas the potential for future work is identified.

1 INTRODUCTION

Extreme events or disasters, be it natural or man-made, often lead to emergency situations that requires immediate action. Examples of natural disasters include hurricanes, floods, landslides, and tsunamis. Examples of man-made disasters include terrorist attacks and hazard material releases. These critical events affect populated areas, inducing an immediate or life-threatening situation that triggers an emergency response. In many cases, evacuation is the common response to risk mitigation, requiring immediate mobilization and time-critical actions, primarily efficient coordination, space capacity utilization, and ensuring availability of emergency response resources (Alsnih and Stopher, 2004). Thus, an emergency evacuation can be deduced as the practical option for human survivability which is paramount in risk mitigation.

Emergency evacuation involves collective removal of residents/populations as quickly as possible and with utmost reliability from areas considered as dangerous zones to safe locations (Alsnih and Stopher, 2004). The most disastrous form of collective human behaviour are stampedes, which induced by panic that often leads to serious fatalities (Hajibabai et al., 2007). The ability to contribute towards an efficient movement of people in heavily populated enclosures or structures is vital to the daily operation of large and complex structures (Hajibabai et al., 2007). More importantly, it is an essential design feature in the event of emergency situations.

To support emergency evacuation operation, the crowd model is an essential tool in providing effective decision-making, enhancing the capability of response to disaster, and reducing any adverse impacts on both human beings and surroundings (Lv et al., 2012). However, comprehending such crowd activity and characteristics requires an appropriate crowd model to improve evacuation plan efficiency and crowd survivability (Wang et al., 2008).

There are four important factors that have pioneered the main foundation of the emergency route planning (ERP) problem (Alsnih and Stopher, 2004): (1) deciding where to evacuate people (goal); (2) deciding the best routes to take (routing); (3) determining the rate of evacuees egress (flow rate); and (4) determining how to regulate flow rates on these routes (schedule). These decisions are methodologically and computationally challenging due to the following reasons; decision interdependence, simultaneous decision making, and concurrency (Alsnih and Stopher, 2004). Therefore, effective ERP approaches are needed in order to address these challenging is-

Nor Akmal Khalid M. and Kalsom Yusof U..
An Artificial Immune Approach for Optimizing Crowd Emergency Evacuation Route Planning Problem.
DOI: 10.5220/0005275305030508
In *Proceedings of the International Conference on Agents and Artificial Intelligence* (ICAART-2015), pages 503-508
ISBN: 978-989-758-074-1

sues faced during emergency evacuation.

The paper organization is presented as follows: Section 2 will highlight the existing crowd evacuation approaches in the context of ERP problems. Discussion on the proposed IA approach and its features is given in Section 3. Section 4 validates and evaluates the proposed IA approach as well as analyzes the computational result. Finally, Section 5 summarizes the paper contribution and suggests the potential future works.

2 LITERATURE REVIEWS

The traditional crowd evacuation solution simply conveys warning and threat descriptions where the need for evacuation is issued via mass media communications to the affected population (Lu et al., 2003). The traditional crowd evacuation solution which conveys warning during an event of fire within a structure and allow evacuees to continue their occupancy and assist in finding a safe exit. However, this solution does not provide any information on how to escape and cannot give clear insights into the situation after the evacuation notice is elicited. Thus, lack of proper planning and management cause unanticipated effects on crowds such as massive congestion, confusion, and chaos. These include lacks of flexibility, insufficient information, less intelligence, dynamic and/or current information, and lack of means of providing interactivity (Lu et al., 2003). Since then, various ERP approaches had been introduced for an efficient evacuation plan during extreme events.

Some studies have proposed prominent mathematical-based approaches for solving the ERP problems. Wang *et al.* (Wang et al., 2008) had proposed a stochastic programming model for evacuating crowd in a building network. Hui *et al.* (Hui et al., 2010) had used a stochastic programming model to allocate rescue route, which is generated from particle swarm optimization algorithm. Lv *et al.* (Lv et al., 2012) had designed an integer programming model for supporting emergency management under uncertainties. Sayyady *et el.* (Sayyady and Eksioglu, 2010) had designed a model for transit-dependent residents during a no-notice disaster using a mixed-integer linear model incorporating Tabu search to simultaneously optimize the emergency response.

Heuristics are among the more popular and emerging ERP approaches, where most of them are well-known in the field of computational optimization. An examples of the ERP approach based on heuristics is the Capacity Constrained Route Planner (CCRP) (Lu et al., 2003; Kim et al., 2007). Lu *et al.* (Lu et al., 2003) had proposed CCRP approach to minimize evacuation time of evacuees while reducing computational cost. Kim *et al.* (Kim et al., 2007) had proposed CCRP approach which is focused on load reduction and scalability of the route plan.

Studies employing meta-heuristic algorithms had been proposed by several researchers. Cepolina (Cepolina, 2005) had proposed a simulated annealing approach for an evacuation plan. Li *et al.* (Li et al., 2010) had proposed genetic algorithm incorporating congestion as an important aspect for an effective evacuation plan. Xie *et al.* (Xie et al., 2010) had proposed a combination of Lagrangian relaxation and Tabu search algorithms for a bi-level network optimization model, where lane reversal (contraflow) and crossing elimination strategies are incorporated to optimize the network at the upper level and a cell transmission-based dynamic traffic assignment on the lower level.

Although several approaches have been introduced, there is no specific approach that encapsulates both crowd flow regulation and optimizes their designated route simultaneously, which is vital for an effective and time-critical evacuation plan. An artificial immune system (AIS) had offered a number of profound features, capable of encapsulating the complexity of the ERP problem. Among them are; the ability to detect changes, learning and memory, adaptation, self-organized, scalability, robust, and decentralization (Dasgupta et al., 2011). This algorithm was introduced to model and apply immunological principles of vertebrate into solving problems for a wide range of areas such as optimization, data mining, computer security, and robotics (Dasgupta et al., 2011). Therefore, these attractive and salient features of the AIS act as the primary motivation for adopting it as the proposed ERP approach for optimizing the evacuation plan.

3 THE PROPOSED IA FOR ERP OPTIMIZATION

This section will provide detailed description of the proposed immune algorithm approach for optimizing the ERP problem. The organization of this section are as follows: Section 3.1 highlights the proposed crowd and its correlation with the IA optimization approach. Section 3.2 describes the inspiration of the IA optimization approach from the natural immune system. Section 3.2.1 highlights the initialization scheme and population instance of IA. Lastly, Section 3.2.2 describes the IA's improvisation (mutation) mechanism, specific for the ERP problem.

3.1 The Proposed Crowd Model

The crowd model adopted is the mesoscopic model, where the relationship between local inter-individual interactions of the evacuees (micro) and collective patterns of the crowd (macro) are considered. One of the efforts conducted was the work in (Wang et al., 2008). Although the local inter-individual interactions of the evacuees are captured, the collective patterns of the crowd are vaguely defined and a clear boundary of the group is not raised. Therefore, the first aspect of this study will seek to get the apparent group characteristic, namely, group cohesion. Group cohesion can be defined as the tendency for a group to be in unity while working towards a goal or to fulfill the demands of its members (Carron and Brawley, 2000). The size of the group may affect and prolong the evacuation procedure, which potentially increases the evacuee's exposure to danger.

In this particular setting, the group size, with the assumption of a full compliance level, is initialized. The group is differentiated with an identification g which consists of evacuees k of different sizes d_g, where each of the groups are located at the starting or source location η_g similar or dissimilar from the other groups. From this formulation, the evacuee k is assumed to belong in a particular group g that strongly cooperate (100% compliance of individuals within the group) towards achieving their goal (i.e., escaping from danger). The evacuation network's capacity (C_{ij}) will be checked against the group sizes (d_g), where the allowance of passing through and possible delays are determined by two rules: (1) the travel time for the group remains the same, if group size $\leq$ capacity, or (2) the travel time for the group is equal to the (group size / capacity) * travel time, if group size $>$ capacity.

3.2 The Natural Immune System

Vertebrates (organisms having internal bones), have developed a highly complex and effective immune system composed of a vast array of cells, molecules, and organs that work together to maintain life. Together with other bodily systems, the immune system maintains a stable state of the organism's vital function, named homeostasis. The most exceptional roles of the system are the protection against the attack of disease-causing agents (*pathogen*), and the elimination of malfunctioning cells. Other roles of the system also include its capability of recognizing the cells (or molecules) within the organism as either harmful (*non-self*) or harmless (*self*) (Bagheri et al., 2010).

The clonal selection theory is used to elaborate the *adaptive immune system* which involves responding to recognized pathogens and enhance its capability of recognizing and eliminating future encounters (Bagheri et al., 2010). When a non-self antigen invades an organism, the immune system starts by reacting to pathogens that invade the organism in such a way that the immune cells recognize this antigen with different degrees of affinity. These immune cells then undergo affinity maturation, proliferation, and clonal selection.

3.2.1 Population Representation and Initialization

Information encoded in each population instance consists of arrays of antibody-antigen bindings, which represents the emergency route (antibody receptor) and the crowd model with their considered features (antigen). The antibody can vary in length and capture certain parts of the nodes and edges of the logical graph structure considered; a source-destination pair (a single evacuation path P). On the other hand, the antigen may be fixed to the crowd features which considers the size of the group d_g and the source location/node η_g. A single population consists of fixed size antibody-antigen bindings which make up the overall evacuation plan (the scheduling of the crowd egress). Thus, if the available group count is g and the available paths of the network are p, then the length of a single population would be $g \times p$.

The initialization scheme involves generating the antibody cells by the aggregation of all available paths or routes in the evacuation network considered. This collection is generated by performing a recursive depth first search algorithm where all the possible source-destination pairs are recorded regardless of the capacity and travel time involved. From this collection, the available antibody receptors are made. With the information of the crowd starting location, crowd size, and size of the crowd in a group, the antigen cells are generated and tagged with specific identification information. From these collections of antibodies binding to antigens, the entire available crowd's groups (antigen) and their randomly assigned source-destination path or route (antibody), form a population instance that represents the complete evacuation plan (schedule). When a population instance is generated, the evaluation process is conducted by simulating the evacuation plan. The NCT of the population instance, will form the affinity of the antibody-antigen bindings; higher affinity means lower NCT, and vice-versa. Thus, this population initialization process will be repeated to generate the collection of population instances based on user-defined population size (pop_{size}).

3.2.2 Proliferation, Clonal Selection, and Affinity Maturation

During this stage, every population instance is subjected to proliferation, but special condition is specified for populating instances to undergo affinity maturation. The proliferation involves cloning the original parent cell, where it will undergo further process (affinity maturation). Affinity maturation is where the cloned cell will undergo somatic hyper-mutation process based on the user-defined mutation steps ($mutate_{steps}$) where it will determine how many repetitions are needed based on the population instance's affinity value ($pop_{affinity}$). Two types of affinity maturation are adopted: Type-1 Ab-Mutate and Type-2 Ag-Mutate.

For Type-1 Ab-Mutate, all the population instances that have undergone previous proliferation, will be mutated by exchanging the allowable range of available antibody receptors with certain antigens. This means the source-destination pair (antibody receptor) for a specific crowd group (antigen) is changed into another similar source-destination pair (the same source but different destination, or the same source and destination). This mutation method is adopted to produce a variety of population instance's antibody-antigen binding. This process can be broadly related to the differentiation of an immune cell into an effector cell.

In contrast, for Type-2 Ag-Mutate, a clonal selection mechanism is first conducted based on the user-defined clonal selection rate ($select_{rate}$) (within the range of [0,1] and the value is very small). When the clonal selection condition is met, a mutation rate ($mutate_{rate}$) which is also a user-defined parameter, will determine how many population instances undergo Type-2 Ag-Mutate that are selected randomly. Next, the randomly selected population instances will proliferate (cloned) and undergo Type-2 Ag-Mutate where the antibody receptor will be tested with a different "closely-shaped" or similarly-signature antigen. This means a source-destination pair (antibody receptor) for a specific crowd group (antigen) will be exchanged into another crowd group of similar starting location or source. This mutation method is adopted to simulate a small tweak of the population instance's antibody-antigen binding. Since this mutation type is rarely happens, this process can be considered the event of immune cells differentiating into memory cells.

For the case of better affinity, the "mutated" antibody-antigen binding will replace the parent cell. These two types of somatic hyper-mutations will basically automate the ordering of the evacuation schedule (antibody-antigen binding) and ensure the diversity of the population instances. In addition, the somatic hyper-mutation performed based on the user-defined mutation steps ($mutate_{steps}$) will determine how many times the mutation process is repeated based on the population instance's affinity value ($pop_{affinity}$). Thus, the mutation process is repeated $pop_{affinity} \times mutation_{steps}$ times, which is in accordance with the term hyper-mutation (high rate mutation).

4 COMPUTATIONAL RESULT

This section involves evaluating the approach performance study and highlights the findings of the study. This section is divided into three sections: Section 4.1 describes the evaluation of the approach; Lastly, Section 4.2 describes the finding of group cohesion.

4.1 Evaluating the Proposed Approach

The main purpose for this experiment is to determine the optimal parameter calibrations and evaluate the performance of the proposed IA. The performance measure considered is the Network Clearance Time (NCT) which, in this study's context, refers to the last exit time of the evacuees. 9 options of the IA parameter settings are considered where 50 samples are collected from each options. The parameter settings of each options is given in Table 1. Exhaustive computation is conducted where the best NCT value out of the 50 samples is taken, as well as their average and standard deviation before and after optimization. From the options, the optimal parameter of the proposed IA is determined from the obtained results.

The results obtained is analyzed and depicted as in Figure 1. The percentage of the relative standard deviation (RSD) is computed for each option, where it is compared with the best and the average of NCT. As depicted in Figure 1, option 2 and option 4 have the lowest RSD for NCT value which means the solution had obtained the best value all the time (no variability). Option 3, option 5, and option 7 also obtained low RSD for NCT, which means the solution obtained contain a small amount of variation where small inconsistencies are present. This is caused by the different pop_{size}, gen_{size}, and $mutate_{steps}$ values, since all of them shared similar values of $mutate_{rate}$, $select_{rate}$, and d_g. The remaining options (option 1, option 6, option 8, and option 9) do not share any similarity in their parameter settings, all of them used the d_g value

Table 1: The IA parameter options.

Parameters	Options 1	2	3	4	5
pop_{size}	50	70	100	50	70
gen_{size}	300	300	300	500	500
$mutation_{steps}$	100	75	50	75	50
$mutation_{rate}$	0.05	0.01	0.03	0.01	0.03
$selection_{rate}$	0.3	0.5	0.7	0.5	0.7
d_g	1	5	3	5	3

Parameters	Options 6	7	8	9
pop_{size}	100	50	70	100
gen_{size}	500	700	700	700
$mutation_{steps}$	100	50	100	75
$mutation_{rate}$	0.05	0.03	0.05	0.01
$selection_{rate}$	0.3	0.7	0.3	0.5
d_g	1	3	1	1

of 1. This causes the RSD of NCT value to be high and variation of the solution becomes very inconsistent. Thus, option 2 and option 4 parameter settings are believed to be the best setting for the proposed IA algorithm.

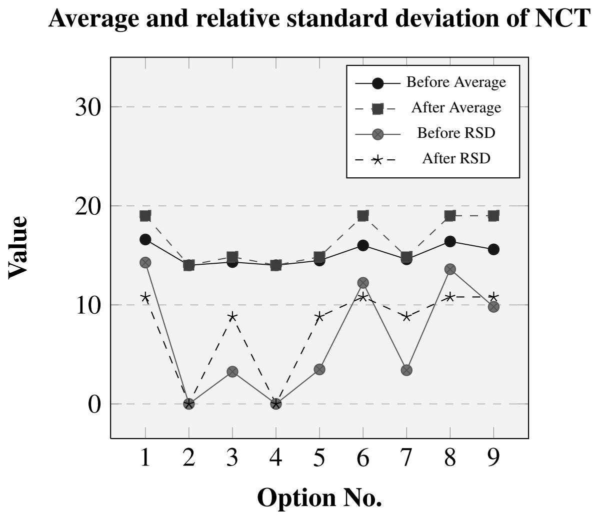

Figure 1: NCT analysis before and after optimization for every options.

The options also reveal that the smaller size of the pop_{size} (e.g. 50 or 70) and the gen_{size} (e.g. 300 or 500) are able to obtain optimum results for this public data set. The possible routes of the evacuation network itself are 15 in total, make the search space limited. Thus, using larger pop_{size} would not be feasible and will burden the search process with redundant routes. In addition, the crowd size of 30 in total (medium scale) which is further divided into smaller groups, had lesser need of greater gen_{size} due to a small amount of variation and limited search space (only 15 route options). From the two best options (option 2 and option 4), their pop_{size} is balanced with the gen_{size}. For example, in option 2, lower pop_{size} (e.g. 50) should have higher gen_{size} (e.g. 500) and vice-versa. This would cause optimum result to be achieved with acceptable convergence rate. The evacuation solution improves when $gen_{size} \leq 500$ and is believed to be affected by the group size (d_g) as well.

4.2 The Effect of Group Cohesion

An additional options of 2a and 2b, relative to option 2 with changes in the parameter setting of d_g (1 and 3, respectively) are conducted. The value of of best and average values of the solution is computed as well as the RSD for each additional options. Figure 2 depicts the best, average, and RSD of NCT for the additional options. Although there are not many indications present in the best values of NCT, the average and RSD had showed to inversely proportional relationship with d_g values when the d_g increases (see Figure 2). The steadily declining value of RSD had proven that increases in the value of d_g (within a certain size) results in lower variations of the solution, where better NCT value is obtained with low inconsistency.

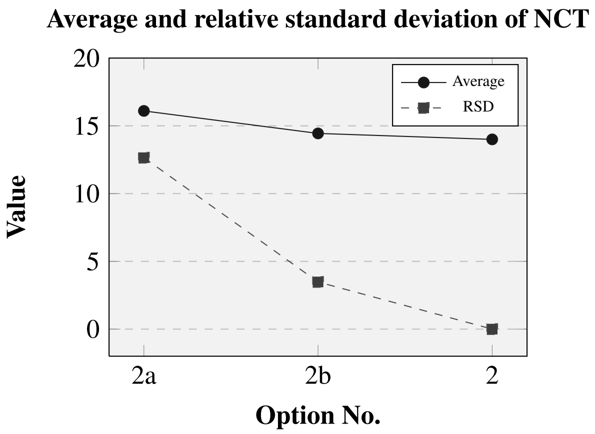

Figure 2: Analysis of NCT for option 2a, 2b, and 2.

The group size (d_g) affects the solution quality, where an increase in the flow rate happens when the d_g is increased. When evaluating the flow rate, $d_g \geq 3$ indirectly decrease the NCT value of a particular solution. This is possible due to the group cohesion assumption in the crowd model, where evacuees that move in larger groups tend to move better (better flow rate) while conforming to the network capacity. This particular situation simulates a strong bond between the evacuees within a group and cooperative behavior is elicited. Although the proposed crowd evacuation model does not considers the dynamic behavior(s) of groups, the general group behavior with certain degrees of assumptions (assuming 100% compliance of individual within group and 0% cooperation of inter-groups relation) during evacuation has been successfully demonstrated.

5 CONCLUDING REMARKS

This paper offers an immune algorithm (IA) approach, that incorporates new ideas in designing the solution representations and their respective operators in solving the ERP problems. A crowd model that considers group cohesion with a certain degree of assumptions is presented and evaluated, while IA approach is also evaluated by performing various experiments which constitute the parameter calibration in order to attain an optimal result. The insights and findings of the observed results from the experiments have been discussed and presented with respect to the main interest of the study.

The group cohesion is assumed on the basis that everyone within a group completely cooperates with each other without capturing individual compliance rate. In addition, the inter-group relation is also neglected (no social interaction between group) which is shown to exhibit discrete delays in the flow rate of the evacuation. In a real evacuation, group behavior tends to have varying compliances due to different needs and goals, as well as a certain amount of interaction between groups (causing greater delays and even blocking). Therefore, further enhancement of the proposed IA approach considering dynamics of group is expected while considering the effects of larger crowd sizes is recommended to further support the findings presented in this paper.

REFERENCES

Alsnih, R. and Stopher, P. R. (2004). Review of procedures associated with devising emergency evacuation plans. *Transportation Research Record: Journal of the Transportation Research Board*, 1865(1):89–97.

Bagheri, A., Zandieh, M., Mahdavi, I., and Yazdani, M. (2010). An artificial immune algorithm for the flexible job-shop scheduling problem. *Future Generation Computer Systems*, 26(4):533–541.

Carron, A. V. and Brawley, L. R. (2000). Cohesion conceptual and measurement issues. *Small Group Research*, 31(1):89–106.

Cepolina, E. M. (2005). A methodology for defining building evacuation routes. *Civil engineering and environmental systems*, 22(1):29–47.

Dasgupta, D., Yu, S., and Nino, F. (2011). Recent advances in artificial immune systems: models and applications. *Applied Soft Computing*, 11(2):1574–1587.

Hajibabai, L., Delavar, M., Malek, M., and Frank, A. (2007). Agent-based simulation of spatial cognition and wayfinding in building fire emergency evacuation. In *Geomatics Solutions for Disaster Management*, pages 255–270. Springer.

Hui, F., Zi, Z., and Gang, H. (2010). Developing a model for the emergency rescue routing problem using stochastic programming theory. In *Logistics engineering and intelligent transportation systems (LEITS), 2010 International Conference on*, pages 1–4. IEEE.

Kim, S., George, B., and Shekhar, S. (2007). Evacuation route planning: scalable heuristics. In *Proceedings of the 15th annual ACM international symposium on Advances in geographic information systems*, page 20. ACM.

Li, Q., Fang, Z., Li, Q., and Zong, X. (2010). Multiobjective evacuation route assignment model based on genetic algorithm. In *Geoinformatics, 2010 18th International Conference on*, pages 1–5. IEEE.

Lu, Q., Huang, Y., and Shekhar, S. (2003). Evacuation planning: a capacity constrained routing approach. In *Intelligence and Security Informatics*, pages 111–125. Springer.

Lv, Y., Huang, G., Sun, W., and Chao, D. (2012). A scenario-based modeling approach for emergency evacuation management and risk analysis under multiple uncertainties. *Journal of hazardous materials*.

Sayyady, F. and Eksioglu, S. D. (2010). Optimizing the use of public transit system during no-notice evacuation of urban areas. *Computers & Industrial Engineering*, 59(4):488–495.

Wang, P., Luh, P. B., Chang, S.-C., and Sun, J. (2008). Modeling and optimization of crowd guidance for building emergency evacuation. In *Automation Science and Engineering, 2008. CASE 2008. IEEE International Conference on*, pages 328–334. IEEE.

Xie, C., Lin, D.-Y., and Travis Waller, S. (2010). A dynamic evacuation network optimization problem with lane reversal and crossing elimination strategies. *Transportation research part E: logistics and transportation review*, 46(3):295–316.

Zeng, M. and Wang, C. (2009). Evacuation route planning algorithm: Longer route preferential. In *Advances in Neural Networks–ISNN 2009*, pages 1062–1071. Springer.