COMPUTER-AIDED CIVIL AND INFRASTRUCTURE ENGINEERING

Computer-Aided Civil and Infrastructure Engineering **29** (2014) 723–737

Ant Colony Optimization Model for Tsunamis Evacuation Routes

Eric Forcael*

Department of Civil and Environmental Engineering, Universidad del Bío-Bío, Concepción, Chile

Vicente González

Department of Civil and Environmental Engineering, The University of Auckland, Auckland, New Zealand

Francisco Orozco

School of Engineering, Universidad Panamericana, Guadalajara, México

Sergio Vargas, Alejandro Pantoja & Pablo Moscoso

Department of Civil and Environmental Engineering, Universidad del Bío-Bío, Concepción, Chile

Abstract: *Natural disasters such as earthquakes and tsunamis foster the creation of effective evacuation strategies to prevent the loss of human lives. This article proposes a simulation model to find out optimum evacuation routes, during a tsunami using Ant Colony Optimization (ACO) algorithms. ACO is a discrete optimization algorithm inspired by the ability of ants to establish the shortest path from their nest to a food source, and vice versa, using pheromones. The validation of the model was carried out through two drills, which were conducted in the coastal town of Penco, Chile. This town was strongly affected by an 8.8 Mw earthquake and tsunami over February 2010. The first drill was held with minimum information, leaving the population to act randomly and intuitively. The second drill was carried out with information provided by the model, inducing people to use the optimized routes generated by the ACO algorithm. The results showed that, in case of an emergency, conventional evacuation routes showed longer escape times compared to those produced by the model developed in this research.*

*To whom correspondence should be addressed. E-mail: *eforcael@ubiobio.cl*.

DOI: 10.1111/mice.12113

1 INTRODUCTION

Throughout history, humans have been interacting with natural disasters. Therefore, advanced planning is fundamental to properly face these natural events (Nejat and Damnjanovic, 2012). During the last decades, however, not much attention has been given to strategic thinking and foresight (Potangaroa, 2011; Rubin, 2012). Some disasters such as volcanic eruptions and earthquakes occur spontaneously and violently, causing loss of lives and economic losses. Worldwide, the impacts of these natural disasters amount to around 150,000 deaths a year, more than three million sufferers and costs estimated at US$48,000,000,000 annually (Montenegro and Peña, 2010). As a result, disaster response has been studied extensively over the past decades from different approaches (Chen and Peña-Mora, 2009; Mannakkara and Wilkinson, 2013).

Some of the major natural hazards are tsunamis, rare events characterized by a rapid onset. They are responsible for widespread destruction in coastal and port areas (Lagos, 2000). In case of a near-source-generated tsunami, the first wave may arrive within minutes, so travel time to a safety zone or an evacuation structure is vital (FEMA, 2009). To design an effective evacuation plan, it is necessary to systematically study the evacuation times for each safety zone, incorporating field measurements from simple to sophisticated simulation programs (Chu, 2009). These programs should incorporate the behavior of the population as a whole, and the effect of the actions/interactions of people as they organize when facing a natural disaster such as a quake.

By using biology-based systems or organisms, simulation models can mimic key aspects of the way in which they organize when facing critical events such as natural disasters. For instance, it has been observed that ants are social insects able to self-organize. Other species of insects (e.g., termites or bees) behave in the same manner. This self-organization is achieved by chemical modification of the environment called Stigmergy (Wilson, 1975). The collective behavior of social insects (Formicidae) has been studied in engineering to exploit their search ability. Their self-organizing capabilities can be mimicked by "simulated ants" on a graph to solve real human problems that take place under certain conditions. This is the basis for techniques of optimization and metaheuristic control called Ant Colony Optimization (ACO), Ant Program (AP), Ant System (AS), Ant Colony Routing (ACR), among others (Almiron et al., 1998).

Currently, the application of these models to design and optimize tsunami evacuation routes is not apparent. Therefore, this research seeks to develop an ACO algorithm to optimize the evacuation times when tsunamis occur, ensuring safe routes.

The city of Penco in Chile was chosen to apply and validate the simulation model developed. Penco is a coastal town which has been affected by earthquakes and tsunamis for centuries, and particularly by one of the most powerful telluric movements in human history on February 27, 2010 (8.8 Mw Richter scale).

2 LITERATURE REVIEW

2.1 Tsunami threat

A tsunami can be generated by various mechanisms with different consequences (Wiegel, 1970). However, "tsunamigenic" earthquakes are the most significant (Lagos, 2000). These tectonic processes occur in subduction zones such as the Pacific Ring of Fire comprising: South, Central, and North America, Alaska, the Aleutian Islands, the Kamchatka Peninsula, the Kuril Islands, Japan, and the South Pacific (SHOA, 2011).

In Chile, one of the most earthquake-prone places in the world, near-source-generated tsunamis are those which have caused major damage (Lagos, 2000). For example, the 1960 Valdivia earthquake in Chile, with a magnitude of 9.5 Mw (Seismological Service of Chile, 2010), generated a tsunami that struck not only the Chilean coasts, but also countries as far away as Japan and the Hawaiian Islands (Madariaga et al., 2010).

2.2 Institutional framework for prevention

In 1803, the Federal Emergency Management Agency (FEMA) was founded in the United States. FEMA is responsible for preparedness, protection, response, recovery, and mitigation, when catastrophes occur (FEMA, 2010). In addition, the United States Geological Survey was created in 1879 (USGS, 2014).

In Chile, the Hydrographic and Oceanographic Service of the Chilean Navy was established in 1834 (SHOA, 2011). After the 1960 Valdivia Earthquake, the National Emergency Office (ONEMI) was founded as a complement to the Chilean Navy Service. ONEMI is responsible for managing the information and deciding what actions should take place in case of an emergency affecting the population (ONEMI, 2011).

2.3 Evacuation plans

In recent years, an increased interest in emergency evacuation planning has been evidenced to effectively cope with natural disasters (Ng et al., 2010). After the mega-earthquake and tsunami of 2010 in Chile, various drills were conducted as part of its evacuation plans in Chilean cities such as Iquique, Mejillones, Antofagasta, and Taltal in 2010, and Puerto Aysén, Constitución, Atacama, and Arica in 2011. Others have been conducted in several cities in central southern Chile over 2013 (ONEMI, 2013).

Tsunamis are categorized into two types, depending on their location: near and distant, the former being the most dangerous due to its short arrival time, between 15 and 30 minutes (Figueras, 2005). Therefore, evacuation time becomes the main variable to direct people to buildings or safety areas located at levels higher than the wave train. This process is defined as "vertical" evacuation (FEMA, 2009). Vertical evacuation is particularly suitable for cities with a flat topography, and the present research considered evacuations to high topographic elevations only.

2.4 ACO algorithms

For years, humans have faced complex optimization problems such as finding the shortest path between various points, allocating the optimum amount of resources, determining the optimum sequence of the processes in a production line, among others (Herrera, 2009). Regarding evacuation simulations and optimization, diverse authors have conducted researches related to emergency evacuation (Du and Sun, 2011) emphasizing transportation route optimization and evacuation transportation planning under uncertainty (Yao et al., 2009).

In civil engineering, construction engineering and management, and natural disaster management, some problems have been solved by using sophisticated optimization and simulation techniques such as building asset management (Hegazy et al., 2012), optimization of large steel structures (Sarma and Adeli, 2002), and optimum assignment of shelters in emergency evacuation (Ng et al., 2010). One of the tools used to address these problems has been metaheuristic algorithms, which are capable of performing well in solving highly complex optimization problems through a set of heuristic procedures (Son and Skibniewski, 1999; Melián et al., 2003).

Some of those metaheuristic algorithms are: (1) Local Search: a method for solving optimization problems by moving within a space of candidate solutions and applying local changes until the optimum solution is found; (2) Swarm Intelligent Systems: a type of algorithm that solves problems inspired by the collective behavior of social insect colonies and other animal societies; and (3) Evolutionary Algorithms: a technique based on the selection mechanisms used by nature, where individuals best adapted to changes in their environment are those who survive and evolve (Herrera, 2009).

Several engineering applications have been developed based on Swarm Intelligent Systems such as Particle Swarm Optimization (PSO) to optimize structural design (Plevris and Papadrakakis, 2011) or applied to imagery (Tao et al., 2012; Hsu, 2013). In this context, some Swarm Intelligence methods use ant colony-based optimization algorithms. This approach is called ACO. The ACO algorithm is a heuristic discrete optimization technique, which uses the foraging behavior of ants (Dorigo, 1992). This algorithm has been highlighted for its ability to deliver highly effective solutions, along with its ease of implementation and speed of processing (Melián et al., 2003; Herrera, 2009) as described later.

The first ACO-based algorithm capable of simulating the behavior of an ant colony was called "The Ant System." This algorithm was used to solve complex NP-type problems (Nondeterministic Polynomial problems), that is, decision problems containing many optimization and search processes, where it is needed to know if there is a certain solution or if there is a best known solution, such as the traveling salesman problem (Dorigo et al., 1991; Colorni et al., 1992). Other ACO optimization problems are the asymmetric traveling salesman, the quadratic assignment, and the scheduling store (Dorigo et al., 1996).

Even though the first ant colony-based model proved to be a viable method, it turned out to have a lower performance compared to other more sophisticated algorithms. To improve the search procedure, "elite ants" that do not follow the first solution found were included in models, because they find the best solution arcs until they reach a global solution (Stützle and Hoos, 1996). Subsequently, the efficiency of these algorithms was increased by running parallel tests to solve the same problem (Stützle, 1998).

In recent years, ACO has proved to be efficient in finding optimum solutions with a low number of iterations (Kaveh and Shojaee, 2007). In the case of tsunamis, the optimum path (or route) is that which saves the largest number of human lives in the shortest time. Thus, the present research aims to accomplish this objective, considering two aspects: distance and safety, as shown later.

Several applications of these ACO algorithms have been carried out in many fields. For instance, they have been used in telecommunications to reduce congestion affecting network performance (Schoonderwoerd et al., 1997). ACO applications in technology and multimedia systems have been able to detect the edges or boundaries of objects in graphic images (Nezamabadi et al., 2006). Also, searching or image recognition systems have been created using ACO algorithms (Picard et al., 2010).

On the other side, the tasks performed by ants are not only limited to roaming and moving their food, but also to other chores that must be done to maintain the nest in optimal conditions (e.g., reparations, expansions, and clean up). In this regard, ACO algorithms have been applied to real engineering problems, such as the construction of underground mines (Parpinelli et al., 2002) or classification techniques (Martens et al., 2007).

In the field of civil engineering, there are interesting applications. For instance, the study of the relationship between Newton's second law and the ACO algorithms, where mass static parameters may be associated with the number of ants, and strength with the output of ants from the system (Hong-biao et al., 2010). Another example is found in transportation engineering, where ACO has shown significantly less variance between a set of random trials which use a large number of model evaluations, being a good alternative to solve very complicated networks (Putha et al., 2012).

In terms of emergency evacuation models, there are some ACO-based applications, which emphasize the importance of evacuating people properly from large public buildings under emergency conditions (Duan et al., 2012), whereas others propose route planning in complex multiexit evacuation environment (Zong et al., 2010).

Regarding the advantages of using ACO over other path algorithms, such as the Dijkstra's algorithm, which

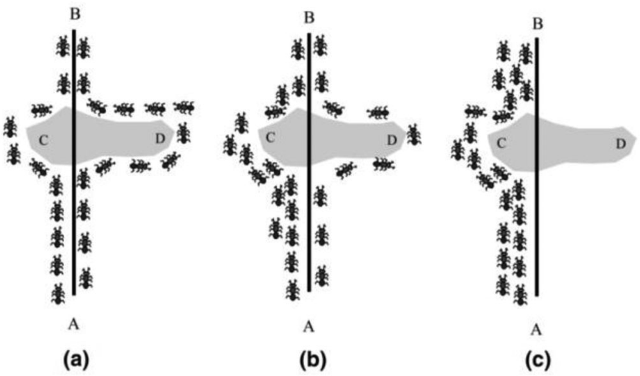

Fig. 1. Mechanism for selection of the optimal route (adapted from Abbaspour et al., 2001).

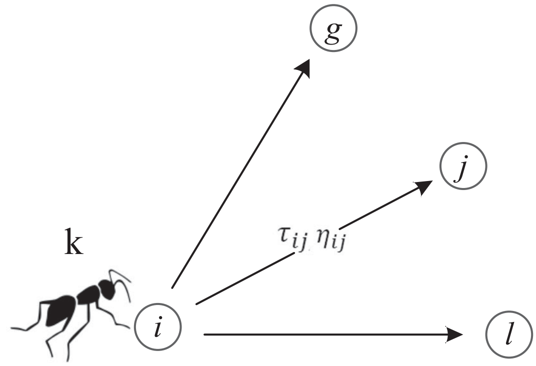

Fig. 2. Influence of pheromones and heuristic factors (adapted from Dorigo and Stützle, 2004).

focuses on always finding the shortest distance between two nodes, one of the main advantages of ACO is it considers aspects other than distance only. For example, for this study, the ACO algorithm takes into account safety, because the shortest path is not always the safest one. Another advantage of ACO is its quick convergence compared with other algorithms, such as the A-star algorithm, which needs a large number of iterations to find the optimum solution. Similarly, ACO is an algorithm inspired in living beings (ants), which would allow comparing their behavior with humans (in this case, facing a tsunami).

Regardless of the wide range of applications of ACO algorithms to engineering problems, the specific application of these algorithms to optimizing evacuation routes in case of tsunamis has not received much attention in the literature up to this date.

3 MODEL DESIGN

3.1 Steps to build the model

The steps to search for the optimal route between the nest (A) and the food source (B) are described in Figure 1 and explained below:

1. Initially, the ants choose either the ACB path or the ADB path with the same probability. This exploration phase is completely random and ends when the ants find the food source.
2. As time elapses, the probability of choosing the ACB path increases as the shorter distance of this path is associated with a lower travel time and, therefore, a shorter evaporation time of the pheromone trail.
3. Due to the fact that the ACB path has received more pheromones, it is more attractive for the following ants. The process ends when all the ants converge to the ACB path.
4. The mechanism discussed above can be summarized into two stages: exploration and operation. The movement in exploring is from the nest to the food source. In the operation stage the movement is bidirectional (Dorigo and Stützle, 2004).

3.1.1 Exploration phase. In this phase, ants seek food randomly by tracking all possible paths until reaching the food source. The goal of exploration is to establish, for each ant, an initial path between the nest and the food source.

The number of routes found depends on the number of ants forming the colony, and their complexity depends on the natural environment and the distance between the nest and the food source. Furthermore, the observation of real ant colonies has confirmed that, while prowling, they deposit pheromones that allow them to find their way back to the nest (J. Deneubourg, Université Libre de Bruxelles, Brussels, Belgium, 2002, personal communication).

3.1.2 Operational phase. When ants return to the nest, they inform the colony about the quantity and quality of food (Hölldobler, 2004). After that, the remaining ants have to select a route to exploit the food source. As explained in Figure 2, the selection of a route is controlled by two factors: the quantity of pheromones τ_{ij} and a heuristic factor η_{ij}. This decision pattern is called *random proportional* (Dorigo and Stützle, 2004).

Dorigo (1992) defines the probability of the k ant deciding to go from node i to node j, through the use of Equation (1):

$$p_{ij}^{k} = \frac{(\tau_{ij}^{\alpha})(\eta_{ij}^{\beta})}{\sum^{(}\tau_{ij}^{\alpha})(\eta_{ij}^{\beta})} \tag{1}$$

where p_{ij}^k is the probability of selection between nodes i and j for a k ant; τ_{ij} is the quantity of pheromones on the arc (i, j); η_{ij} is the heuristic factor for the selection of the arc, it is defined as the inverse of the distance between nodes i and j ($1/d_{ij}$); α is the controlling factor of the influence of τ_{ij}; and β is the controlling factor of the influence of η_{ij}.

To improve the understanding of Equation (1), it is necessary to extend the explanation of the parameters α and β.

If $\alpha = 0$, pheromones are not used and the algorithm is completely stochastic. In this case, only the nearby nodes are probable. By contrast, when $\alpha = 1$, evaporation is difficult, and therefore, it is not easy to establish the optimized route.

In the case of tsunamis, it is difficult to consider only safety over other variables (e.g., distance), because not taking into account the distance (evacuation time), may cause more people to be reached by the wave, and in consequence, be killed. This is why the algorithm does not decide between safety and distance, but it combines both variables to find the best path. To do this, factors α and β, take control over the solution pondering between the shortest path and the safest one.

The τ_{ij} factor is calculated by considering the evaporation coefficient ρ and the contribution from other ants as shown in Equation (2).

$$\tau_{ij}^k = (1-\rho)\,\tau_{ij}^k + \Delta\tau_{ij}^k \tag{2}$$

where ρ is the evaporation coefficient of pheromones. $\Delta\tau_{ij}^k$ is the variation of the amount of pheromones in an arc (i, j), reinforced by each k ant passing through. This variation of pheromones per iteration k provokes changes in τ. Here, the superscript k is a counter which changes with each iteration and takes different values of α and β per iteration.

Due to the ρ vaporation, the ants can choose the most attractive paths, as a shorter path has a higher concentration of pheromones (Marco and Krzysztof, 2006).

The variation in the quantity of pheromones $\Delta\tau_{ij}$ is explained because each k ant moving between a pair of nodes (i, j) releases an amount of pheromones Q along the length of the stretch L_k. This variation $\Delta\tau_{xy}^k$ of the stretch (i, j) is mathematically expressed by Equation (3).

$$\Delta\tau_{ij}^k = \begin{cases} Q/L_k & \text{if the } k \text{ ant uses the stretch } (i,j) \\ 0 & \text{if the } k \text{ ant does not use the stretch } (i,j) \end{cases} \tag{3}$$

where L_κ is the length of the stretch (i, j) and Q is the quantity of pheromones released by each ant.

3.1.3 Building the path. When ants build their path, they are conditioned by the natural environment (obstacles, slopes, etc.). To overcome natural barriers, ants break up the path into small sections to find the total solution.

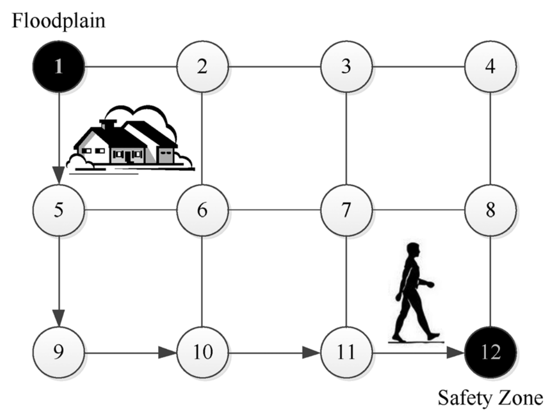

Fig. 3. Building the path for humans.

For humans, the stretches or arcs of solutions are equivalent to evacuation routes, and barriers are equivalent to buildings. As shown in Figure 3, when a human is evacuating, the start-point node corresponds to the starting point from the floodplain, and the destination node corresponds to the safety zone.

To implement an ACO algorithm on evacuation routes, it has been considered to design the routes through the exploration phase, that is, a fully random node-to-node way until getting the end node. Then, each route will be assessed through the operation phase, where α and β factors represent the field conditions. These modifications allow the number of possible solutions to be increased, including external elements in the search process.

3.2 Pseudocode

The ACO algorithm adapted to this research was compiled in Matlab. Due to space limitations, the algorithm is presented in the form of pseudocode, which in turn describes how the algorithm works. The pseudocode is outlined step by step in Figure 4.

First of all, values for each parameter are assigned: number of points, matrix α and β, quantity of pheromones τ_{ij}^k, and the evaporation coefficient ρ. Then, each k ant starts building a vector from the nest to the next node (randomly selected) until it reaches the source. Because this step represents the exploration phase of the algorithm, the *rand* function has been included to assign the node visited at random. To find the shortest distances in the matrix of routes and choose the optimal route, two criteria have been incorporated: the shortest distance and the amount of pheromones.

// Choice of the paths

// Counter Number of nodes

```
minimum←min(vect);
maximum←max(vect);
Write D_mejor;
//Short Distance
for m←1 To c2-1 with step by step make
        Best_path(m) ←selection(m);
End For
Write Best_Path

//Pheromones
For m←1 To c2-1 with step by step make
    Pacum←0;
    for i←2 to minimum
      p1←Best_path(m,i-1);
      p2←Best_Paths(m,i);
     D_path (m,i) ←D(p1,p2);
     eta←1/D(p1,p2);
     P(m,i) ← (txy^alfha(p1,p2))*(eta^beta(p1,p2));
     Pacum←Pacum+P(m,i);
     P_total(m,i) ←P(m,i)/Pacum;
    End for
End for
Prob_optimal←zeros(c2-1,1);
For m←1 Toc2-1 with step by step make
     Prob_optimal(m) ←prod(P_total(m,minimum));
End for
Write Best_probability←max(Prob_optima)
 c3←1;
      for m←1 to c2-1 with step by step make
      If Prob_optimal(m,1)=Best_probabilidad Else
              Best_Path(c3,:)=Best_Path(m,:);
              c3←c3+1;
      End If
      End for
Write Optimal_Path
Write Graphs
End routine
```

Fig. 4. Pseudocode of the ACO algorithm adapted to this research.

The existence of these two criteria allows solving cases where multiple paths match the shortest distance.

3.3 Variables

The variables used in the model proposed are explained below.

3.3.1 Factors ρ and τ. The values for the evaporation coefficient of pheromones, ρ, and the quantity of pheromones, τ, for the ACO model implemented were obtained from data existing in the literature. These values are shown in Table 1. Experimentally, these values have shown to obtain good results in various studies (Dorigo and Stützle, 2004).

Table 1
Values of ρ and τ

Parameter	*Value*
ρ	0.5
τ_{ij}^{k}	1

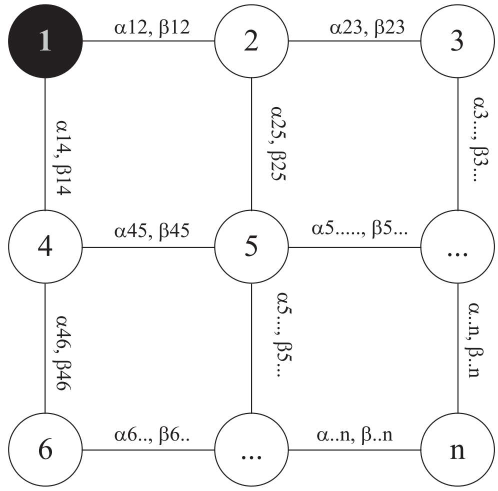

Fig. 5. Factors α and β throughout the matrix.

3.3.2 Factors α and β. The factors α and β can be used to provide useful local information to the model, including damage in pathways (Jiang et al., 2010). In this research, it was decided to incorporate field conditions using matrices of the factors α and β. Thus, α represents safety and serviceability conditions, whereas β considers topography requirements throughout the streets where the evacuation will take place. Figure 5 explains the use of factors α and β for n nodes. Matrices A and B are represented by Equations (4) and (5), respectively.

$$\mathrm{A} = \begin{pmatrix} \alpha 11 & \cdots & \alpha 1n \\ \vdots & \ddots & \vdots \\ \alpha n1 & \cdots & \alpha nn \end{pmatrix} \tag{4}$$

$$\mathrm{B} = \begin{pmatrix} \beta 11 & \cdots & \beta 1n \\ \vdots & \ddots & \vdots \\ \beta n1 & \cdots & \beta nn \end{pmatrix} \tag{5}$$

where $\alpha_{ij} = \alpha_{ji},$ and $\beta_{ij} = \beta_{ji}$.

The values of α to be incorporated into the above matrices are shown in Equation (6):

$$\alpha = \begin{cases} 0.3 & \text{Good} \\ 0.5 & \text{Regular} \\ 0.8 & \text{Poor} \end{cases} \tag{6}$$

1. Good: Wide roads that provide good security conditions and solid surrounding buildings.
2. Regular: Appropriate roads but with lower standard than those defined in the good category.
3. Poor: Roads that have facilities with potentially hazardous risk conditions, such as gas pipelines, power lines, bridges.

The values of β that are to be incorporated into the equations are shown in Equation (7):

$$\beta = \begin{cases} 0.3 & \text{Steep road in the direction of the evacuation} \\ 0.5 & \text{Moderate slope in the direction of the evacuation} \\ 0.8 & \text{Negative slope in the direction of the evacuation} \end{cases} \tag{7}$$

The influence of factors α and β was previously explained using values ranging between 0 and 1. According to Jiang et al. (2010), these parameters have to be set dynamically. Therefore, these values were established after multiple iterations that yielded stable solutions for different road conditions (good, $\alpha = 0.3$; regular, $\alpha = 0.5$; and bad, $\alpha = 0.8$) and slopes (steep, $\beta = 0.3$; moderate, $\beta = 0.5$; and negative, $\beta = 0.8$).

3.3.3 Distance matrix. Unlike Dorigo's (1992) model, where the distance matrix is calculated from the coordinates of each point, permitting free movement from one node to another, this research manually incorporates a matrix according to the actual distances between the nodes representing intersections. This was done to constrain the displacement between nodes which were only physically feasible, that is, to avoid travels between nodes, which would be impossible in reality (e.g., crossing a block using the diagonals). To achieve this, high values were assigned to these arcs, as shown in Figure 6. Thus, the matrix D for n nodes is mathematically represented by Equation (8).

$$D = \begin{pmatrix} d11 & \cdots & d1n \\ \vdots & \ddots & \vdots \\ dn1 & \cdots & dnn \end{pmatrix} \tag{8}$$

where $d_{ij} = d_{ji}$.

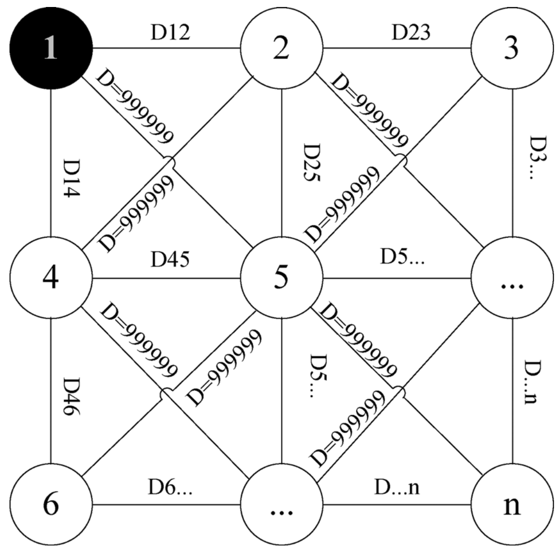

Fig. 6. Representation of the distances matrix.

3.4 Application of the model

3.4.1 Context. This research has been performed for tsunamis which occur in small cities, that is, less than 250,000 inhabitants for Europe and Latin America, and less than 500,000 for the rest of the world (United Nations, 2011). In this research, the small town of Penco was considered to verify and validate the proposed model. Penco has 50,000 habitants and is located 500 km to the south of Santiago, the capital of Chile. Penco is one of the most earthquake-prone cities in the world and is constantly affected by tsunamis. To verify the ACO algorithm, Penco was divided into a great matrix where the street intersections were modeled as nodes and the distances between intersections were taken as the distances between nodes. Figure 7 shows the nodes (numbered from 1 to 67), and the two safety zones considered to apply the ACO algorithm.

3.4.2 Convergence analysis. The number of iterations was estimated using the following convergence analysis. The simulation was performed in Matlab by considering a model for 2,500 ants (iterations), moving from the starting nodes (e.g., node 11, node 12) to the destination node (node 1 or node 67) as shown in Figure 7.

In this simulation experiment, the shortest distance between the starting node and destination node corresponded to 770 m, which was achieved before 50 iterations. This is explained by the low number of nodes needed to find the solution and shown with the dotted line in Figure 8.

On the other hand, the solid line plots how the model reaches a steady state as the size of the colony increases (iterations) for values over 100 ants (although

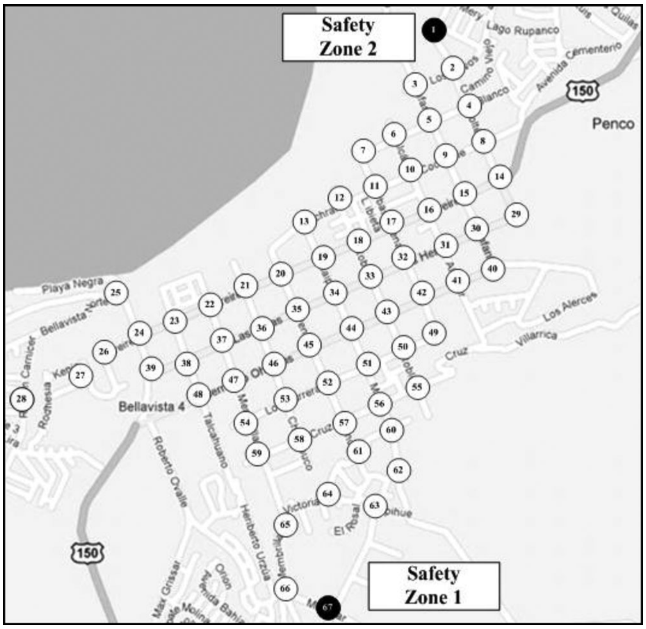

Fig. 7. Map of Penco with nodes and safety zones.

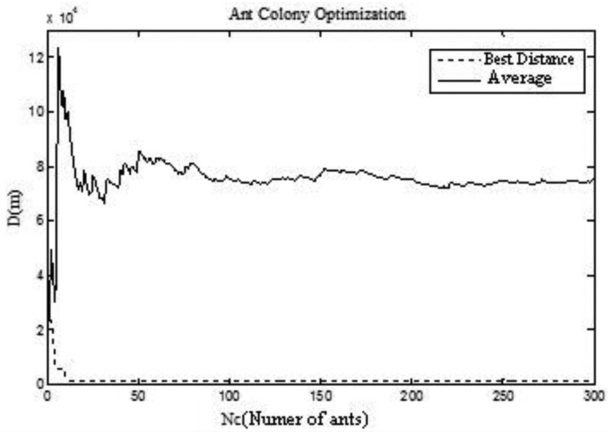

Fig. 8. Chart of distance versus number of ants.

the simulation was run up to 2,500 iterations, Figure 8 shows 300 iterations only because the steady state has already been reached and the solid line does not show significant variations beyond 100 iterations).

As a verification process, the number of iterations was increased up to 5,000 (under the overflow risk). However, no significant improvements in accuracy were evidenced (less than 0.5% per each thousand iterations).

Thus, with a number of 2,500 iterations and the origin-destination nodes, different factors were combined for the respective levels considered in the model through the experimental design presented in the following section.

Table 2
Combination of factors and levels

Exp	α	β
1	0.3	0.3
2	0.3	0.5
3	0.3	0.8
4	0.5	0.3
5	0.5	0.5
6	0.5	0.8
7	0.8	0.3
8	0.8	0.5
9	0.8	0.8

Table 3
Start-point nodes assessed

Zone 1	11	12	13	16	19	20	21	22	30	33
	34	35	37	40	43	44	46	47	49	
Zone 2	6	7	8	9	10	11	12	13	14	15
	16	17	18	20	21					

3.4.3 Experimental design. The factors and levels used to verify the model are shown in Table 2, according to Law and Kelton (1991). Thus, 300 iterations for each of the 67 nodes of the town were run. Each experiment was repeated for each combination of Table 2.

3.4.4 Design speed. In this research, an average evacuation speed of 1.76 (m/s) for healthy people was considered (FEMA, 2009). Subsequently, the time used as input for the model was calculated as the quotient between distance and velocity.

3.4.5 Outputs of the model. According to Figure 7, Table 3 shows the start-point nodes to be assessed and the two safety zones considered. They were chosen based on the potential reach of a tsunami taking into account a historical analysis, cartography, official information, and technical exploration visits. In other words, the start-point nodes had to fulfill the requirement of being located in zones prone to flooding. Also, the start-point nodes were chosen based on the average of distances between all pairs of nodes, for example, the average distance between nodes 1 and 2, between 1 and 3, between 1 and 67, between 3 and 51, between 14 and 47. This average distance between all pairs of nodes makes sense, because there is no reason to calculate an evacuation route between two consecutive nodes, and even worse if any pair of nodes is located on the coast line (the most dangerous location).

Table 4
Routes for Zones 1 and 2

Starting node	*Route*	*No. of nodes*	*Distance (m)*
Zone 1			
11	11 17 32 42 49 50 55 56 60 62 63 67	12	1,578
12	12 18 33 43 50 55 56 60 62 63 67	10	1,458
13	13 19 34 44 51 56 60 62 63 67	10	1,333
16	16 17 32 42 49 50 51 56 60 62 63 67	12	1,578
19	19 34 44 51 56 60 62 63 67	9	1,208
20	20 35 45 52 51 56 60 62 63 67	10	1,343
21	21 20 35 45 52 57 61 62 63 67	10	1,316
22	22 21 20 19 34 44 45 52 57 61 62 63 67	13	1,696
30	30 31 32 33 43 50 55 56 57 61 62 63 67	13	1,701
33	33 43 50 51 56 60 62 63 67	8	838
34	34 44 51 56 60 62 63 67	8	1,083
35	35 45 44 51 56 60 62 63 67	8	848
37	37 47 54 59 58 57 61 62 63 67	10	1,341
40	40 41 42 43 50 55 56 60 62 63 67	11	1,458
43	43 50 55 56 60 62 63 67	8	1,083
44	44 51 56 60 62 63 67	7	958
46	46 45 44 51 56 60 56 60 62 67	10	1,403
47	47 54 59 58 57 61 62 63 67	9	1,216
49	49 50 55 56 60 62 63 67	8	1,078
Zone 2			
6	6 5 3 2 1	5	528
7	7 6 5 3 2 1	6	653
8	8 4 2 1	4	395
9	9 5 3 2 1	5	528
10	10 9 5 3 2 1	6	653
11	11 7 6 5 3 2 1	7	774
12	12 11 7 6 5 3 2 1	8	899
13	13 12 11 10 6 5 4 2 1	9	1,022
14	14 8 4 2 1	6	518
15	15 9 5 3 2 1	6	653
16	16 15 9 8 4 2 1	7	770
17	17 16 15 9 5 3 2 1	8	904
18	18 12 11 10 9 8 4 2 1	9	1,020
20	20 13 12 11 7 6 5 3 2 1	10	1,246
21	21 20 19 18 17 11 10 6 5 4 2 1	12	1,402

Meanwhile, Table 4 shows the routes obtained for the nodes of Table 3. The first column shows the starting node. The second column shows the route obtained by the model or solution vector for consecutive nodes, until reaching the end node corresponding to a security zone. The third column shows the number of nodes required for achieving the security zone. Finally, the fourth column shows the distance in meters for each route.

3.4.6 Limitations of the model. Some researchers have conducted studies related to emergency evacuations, using various means of transportation such as buses or subways (Abdelgawad and Abdulhai, 2012), while others have focused on strategies that can reduce traffic congestion caused by a catastrophe (Deng et al., 2008). However, the present research considered only evacuation on foot. Despite this fact, FEMA considers studies that include evacuations by walk, as a valid tool to assess emergency evacuation responses in disasters (FEMA, 2009).

4 VALIDATION OF THE MODEL

4.1 Implementation of the model

Even though the tsunami considered in this study only reached near-shore sectors not beyond the public square (node 45), the proposed model included all urban sectors of the city. The reason is that during the 463 years of the city's history some tsunamis have reached higher areas of the city.

4.2 Study group

To simulate the reality in the best possible way, participants were chosen randomly from: people who live in the city under study, people who do not live in the city (simulating to be tourists), people of different ages and sex. Therefore, some of the participants knew the area whereas the others did not, as is usual in these cases. The study group was made up of a total of 34 young adults between 18 and 25 years. They were chosen randomly, considering the recommendations given by FEMA regarding tsunami evacuation drills (FEMA, 2009).

4.3 Planning and coordination of drills

The fast growth of the world population has resulted in more crowded cities. Thus, the effectiveness of crowd evacuation is an important public safety issue and, therefore, interest in developing new techniques to assist in crowd evacuation has grown (Kerrache et al., 2013). In this sense, some large-scale evacuation problems have been studied during the last years (Chiu et al., 2007; Abdelgawad and Abdulhai, 2012).

However, to carry out evacuation drills with large crowds takes a vast financial and personal effort. With this in mind, FEMA considers small drills with volunteers as useful products to prepare the population to face tsunamis (FEMA, 2009). Thus, this research has considered conducting small drills to validate the model proposed as described below.

Each participant of the drills had a stopwatch to measure the shift time between the start point and the designated security zone, along with an identification number, which allowed arrivals to be controlled at the respective safety area. To mitigate any distortion due to Hawthorne effect, volunteers were only instructed on how to measure the travel times required for the experiment, but without telling them about the research goals. Thus, both study groups had the same willingness to participate, because they both knew they were part of a study, but they had no information on who would be the control group (or placebo), and who would be the study group (Laporte, 2007).

In each safety zone, there was a person waiting to collect the measured times, which were recorded from the moment that volunteers began walking from the start point until arrival at any of the safety zones. Then, the data were tabulated and processed in Excel spreadsheets, verifying their consistency. At the end of the experiment, participants answered a survey to assess some qualitative characteristics of this research.

4.4 Evacuation drills

After developing the ACO-based model, the results obtained were evaluated through field activities to verify the performance of the algorithm developed. To do so, two drills were conducted to simulate the threat of a possible tsunami off the coast of the town of Penco. The first exercise was performed conventionally or without preestablished escape routes, and the second exercise was conducted by using the optimized routes given by the proposed model.

4.4.1 First evacuation drill or "No Route Drill". The first drill consisted of placing the participants randomly at different starting points (see Table 3). They were only instructed regarding the location of the start point and the safety zones, but without information on possible evacuation routes. This simulation exercise was called "*No Route Drill*" (NRD) and it was used as the control group (or placebo).

During this first evacuation, participants followed random routes based only on the perception they had of the area and the information provided by the city map given at the beginning of the drill.

4.4.2 Second evacuation drill or "With Route Drill". For this second drill, the same procedure was implemented; however, the participants were instructed to follow a specific route on the map (route generated by the ACO-based model). This evacuation exercise was called *"With Route Drill"* (WRD) and it corresponded to the study group.

4.5 Statistical tests

To statistically analyze the onsite measures and the times given by the model developed with ACO algorithms, it was needed to compare the times obtained from the model and the times obtained from the onsite measures by using the Wilcoxon test with a significance level of 5%. The statistical tests were based on two-tailed type considering the worst possible scenario (this scenario considers that evacuation times delivered by the ACO-based simulation model were at least equal in comparison with the onsite measurements).

Data were divided into two parts in accordance with each analyzed zone. For Zone 1, 19 samples were considered, and 15 samples for Zone 2.

It must be mentioned that evaluations at the disaggregate level were conducted by subgroups from each zone and by subgroups of participants. However, the results were not significantly different in comparison with the outputs shown below. Therefore, the authors did not add information that would be unnecessarily redundant.

4.5.1 Results of each zone. Table 5 shows the results of each zone, with times from the NRD experiment, times from the WRD experiment, and times from the Model (M).

4.6 Statistical analysis

Based on the results obtained, measured times are compared with each other (WRD and NRD), and then, times from the "NRD" experiment and times delivered by the model are compared, too. The following are the hypotheses considered to conduct the statistical analyses.

1 *Hypotheses for comparison between "WRD" and "NRD" evacuation times.*

H_0 = The evacuation times for people who participated in the drill, without any previously known route, are equal to the evacuation times of those participants in the drill who knew a route previously defined (generated by the ACO algorithm).
H_a = The evacuation times for people who participated in the drill, without any previously known route, are different to the evacuation times of those participants in the drill who knew a route previously defined (generated by the ACO algorithm).

2 *Hypotheses for comparison between times delivered by the model and "NRD" evacuation times.*

H_0 = The evacuation times delivered by the ACO-based simulation model are equal to the evaluation times for people who participated in the drill without any previously known route.
H_a = The evacuation times delivered by the ACO-based simulation model are different from the evaluation times for people who participated in the drill without any previously known route.

3 *Hypotheses for comparison between times delivered by the model and "WRD" evacuation times.*

H_0 = The evacuation times delivered by the ACO-based simulation model are equal to the evaluation times of those participants in the second drill, who knew a route previously defined (generated by the ACO algorithm).
H_a = The evacuation times delivered by the ACO-based simulation model are different from the evaluation times of those participants in the second drill, who knew a route previously defined (generated by the ACO algorithm).

The results delivered after running statistical analysis using Infostat software (2006), given a 5% of significance, are shown in Table 6.

By looking at the first two comparisons for both zones (NRD versus WRD and NRD versus Model), it is observed that the *p*-value is less than 5%, which means the null hypothesis was rejected for both comparisons and, therefore, there are statistically significant differences in both cases. Because the No Route evacuation times were higher than both the With Route evacuation times and the evacuation times delivered by the Model, it is concluded that there was a statistically significant improvement in the evacuation times when using routes provided by the model.

The previous findings are explained by the fact that the participants of the first study group did not have access to prior information about any evacuation routes, and they based their movement on their own perceptions of the environment in terms of safety (it is recalled that hypothetically this group could have been a group of tourists, or simply residents who could have used their own experience to follow their best evacuation route). However, the second study group had accurate information about the best route (route previously generated by the model). Therefore, the fact that they achieved the best times was due to the existence of a previously established route, which corresponded to the optimal path delivered by the model, eliminating unnecessary times associated with hesitations on which routes to follow (hesitations that naturally appear when there are no preestablished routes).

The third comparison conducted for Zones 1 and 2 (WRD versus Model), corresponded to the comparison between the times measured in the field for the group that used the route provided by the computational model and the times delivered by the computer for the same model. For both zones, Table 6 shows that the *p*-values were greater than 5%; thus, the null hypothesis is not rejected, concluding that there are no statistically significant differences between the two events (computational model applied and measured in the field versus the same computational model measured in the laboratory). Therefore, the absence of statistically significant differences between the onsite measurements and laboratory measurements make it possible to validate the computational model developed in this research as an effective tool to design evacuation routes.

Notwithstanding the abovementioned, there were a few specific points on which differences between the evacuation times of who evacuated without a route were slightly lower than those who evacuated with a route

Table 5
Results from drills and model

Zone 1																			
Node	*11*	*12*	*13*	*16*	*19*	*20*	*21*	*22*	*30*	*33*	*34*	*35*	*37*	*40*	*43*	*44*	*46*	*47*	*49*
t (seconds) NRD	922	856	815	859	941	776	800	950	1180	949	770	875	877	895	766	656	865	626	638
t (seconds) WRD	898	945	917	801	895	650	743	950	955	776	672	455	823	764	599	608	811	571	662
t (seconds) M	895	828	757	897	686	763	748	964	966	476	615	482	762	828	615	544	797	691	613
Zone 2																			
Node	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*20*	*21*				
t (seconds) NRD	395	497	245	357	504	451	467	647	316	317	418	519	733	948	811				
t (seconds) WRD	236	346	210	325	422	418	444	609	379	405	316	419	573	727	780				
t (seconds) M	300	371	224	300	371	440	511	581	294	371	438	514	580	708	797				

Table 6
Outputs from Wilcoxon test (Infostat, 2006)

Zone 1	*Obs (1)*	*Obs (2)*	*N*	*Mean differences*	*p-value*
	No route	With route	19	80.11	<0.0001
	No route	Model	19	109.84	<0.0001
	With route	Model	19	29.74	0.2076
Zone 2	*Obs (1)*	*Obs (2)*	*N*	*Mean differences*	*p-value*
	No route	With route	15	67.73	0.0044
	No route	Model	15	55.00	0.0084
	With route	Model	15	–12.73	0.6564

and the model. This is explained because in the first drill (without route) some participants preferred to avoid streets with a high slope, a behavior that contradicts one of the fundamental principles of this study: the higher the slope of the street, the more likely it will be to be chosen, as leading faster to a safe area. To measure this phenomenon, at the end of the evacuation drill the participants who obtained lower evacuation times without a route were asked their reasons for choosing a particular route over others. The results showed that over 90% of the participants preferred routes that allowed easy movement to get as far as possible from the sea. The last statement does not necessarily imply safety, because a person may walk tens of meters away from the sea, but if he/she failed to gain altitude, the probability of being reached by waves remains high.

Regarding the second evacuation drill (with route), some of the streets of the route given to the participants had steep slopes because the ACO algorithm (model) favors this terrain feature significantly (steep slopes lead to safe areas more quickly). However, there were some cases where the sustained increase in slope caused the travel speeds of some participants to decrease, which could also have affected a few cases where the evacuation times were slightly higher than those without route. This phenomenon calls to mind those people with disabilities or elderly people who could be tempted to take routes with lower slopes to facilitate their movement, even though this behavior increases the risk of being hit by a tsunami because the time to reach safety zones is longer.

5 CONCLUSIONS

Modern societies are vulnerable to natural disasters. In this sense, tsunamis are complex physical events, unpredictable and with a cyclical recurrence, whose impact can last for years and even decades in areas with little preparation.

To mitigate the effects that natural disasters cause in a population, emergency management or prevention culture has been developed. This preparation should be constant and should consider the study of these phenomena and the variables involved. From this perspective, this research is focused on developing optimized routes to minimize the evacuation times of people who are walking away from a tsunami.

According to the Wilcoxon statistical test, there were no statistically significant differences between the times delivered by the model and those measured in the experiment in the field where the optimized route was provided. This leads to the conclusion that modeling evacuation routes through ACO algorithms allows the reality to be effectively represented in terms of the routes proposed to walk away from a tsunami.

Moreover, after comparing the evacuation times given by the model and those measured onsite for participants who evacuated without using predefined routes, statistically significant differences were found in favor of the model. In other words, the evacuation times following the routes delivered by the model were lower than those times measured in the field for people who followed a route, which was not predefined. This was evidenced by a significant decrease in the evacuation times, whose values reached in some cases up to 7 minutes, that is, 48% less than the evacuation times measured for people evacuating without a defined route.

Nevertheless, there were a few cases where times of people evacuating without a route were slightly higher than those who followed the route delivered by the model. This phenomenon occurred because those few participants who obtained lower evacuation times opted for easier movement (e.g., streets without steep slopes) instead of favoring the early search for safety zones, which are easily found when using routes with steeper slopes (those routes given by the model). This phenomenon, although unusual, opens a new line of research related to people with disabilities or elderly people who do not hesitate to search for routes with lower slopes to facilitate their movements, even though this increases the risk of being reached by a tsunami due to the increase in evacuation times.

Finally, we concluded that having significantly reduced evacuation times for people who faced a tsunami by using a model developed under the theory of ACO algorithms, it is possible to replicate this type of model to develop more expeditious evacuation routes in all those small coastal cities around the world prone to natural disasters, particularly tsunamis.

ACKNOWLEDGMENTS

The authors would like to thank the Universidad del Bío-Bío, Chile; the University of Auckland, New Zealand; and the Universidad Panamericana, Mexico, for facilitating the realization of this research.

REFERENCES

Abbaspour, K. C., Schulin, R. & Van Genuchten, M. T. (2001), Estimating unsaturated soil hydraulic parameters using ant colony optimization, *Advances in Water Resources*, **24**(8), 827–41.

Abdelgawad, H. & Abdulhai, B. (2012), Large-scale evacuation using subway and bus transit: approach and application in city of Toronto, *ASCE Journal of Transportation Engineering*, **138**(10), 1215–32.

Almiron, M., Chaparro, E. & Barán, B. (1998), Optimización Basada en Sistemas de Hormigas con Heurística de Optimización, IX Panel de Informática, Expomática '98, Asunción, Paraguay.

Chen, A. & Peña-Mora, F. (2009), Collaborative GIS for request of construction equipment in disaster response, in *Proceedings of International Workshop on Computing in Civil Engineering*, Austin, TX, 146–55.

Chiu, Y. C., Zheng, H., Villalobos, J. & Gautam, B. (2007), Modeling no-notice mass evacuation using a dynamic traffic flow optimization model. *IIE Transactions*, **39**, 83–94.

Chu, C.-Y. (2009), A computer model for selecting facility evacuation design using cellular automata, *Computer-Aided Civil and Infrastructure Engineering*, **24**(8), 608–22.

Colorni, A., Dorigo, M. & Maniezzo, V. (1992), Distributed optimization by ant colony, in *Proceedings of the First European Conference on Artificial Life*, Paris, France, 134–42.

Deng, W., Jia, L., Cai, G., Qin, Y. & Zhou, X. (2008), Research the strategy of the highway transportation in the earthquake, in *Proceedings of 2008 IEEE International Conference on Service Operations and Logistics, and Informatics IEEE/SOLI'2008*, Beijing, China, **2**, 1582–86.

Dorigo, M. (1992), Optimization, learning and natural algorithms. Ph.D. thesis, Politecnico di Milano, Italia.

Dorigo, M., Maniezzo, V. & Colorni, A. (1991), *Positive Feedback as a Search Strategy*, Rapport technique 91–016, Dip. Elettronica, Politecnico di Milano, 1–20.

Dorigo, M., Maniezzo, V. & Colorni, A. (1996), The Ant System Optimization by a colony of cooperating agents, *IEEE Transactions on Systems, Man, and Cybernetics*, **26**(1), 29–41.

Dorigo, M. & Stützle, T. (2004), *Ant Colony Optimization*, The MIT Press, London, United Kingdom.

Du, X. & Sun, Q. (2011), Research on transportation route optimization among emergency evacuation, in *Proceedings-2011 International IEEE Conference on Mechatronic Science, Electric Engineering and Computer*, Jilin, China, 2139–42.

Duan, P., Xiong, S. & Jiang, H. (2012), Multi-objective optimization model based on heuristic ant colony algorithm for emergency evacuation, in *Proceedings-2012 15th International IEEE Conference on Intelligent Transportation Systems*, Anchorage, AK, 1258–62.

FEMA (2009), *Vertical Evacuation from Tsunamis: A Guide for Community Officials*, Federal Emergency Management Agency U.S. Department of Homeland Security, Washington DC. Available at: http://www.fema.gov/library/viewRecord.do?id3808, accessed October 2013.

FEMA (2010), *Federal Emergency Management Agency (History)*. Available at: http://www.fema.gov/about-agency, accessed March 2014.

Figueras, S. (2005), Networks for earthquake monitoring and tsunami warning (Redes de Vigilancia Sísmica y Vigilancia de Tsunamis), *Enseñanza de las Ciencias de la Tierra*, **15**(1), 46–51.

Hegazy, T., Elhakeem, A. Ahluwalia, S. S. & Attalla, M. (2012), MOST-FIT: support techniques for inspection and life cycle optimization in building asset management, *Computer-Aided Civil and Infrastructure Engineering*, **27**(2), 130–42.

Herrera, F. (2009), *Introduction to Metaheuristic Algorithms (Introducción a los Algoritmos Metaheurísticos)*, Soft Computing and Intelligent Information Systems of the Dept. of Computing Sciences, University of Granada, Spain.

Hölldobler, B. (2004), *Ants-Nature's Secret Power*, Documentary. Available at: http://topdocumentaryfilms.com/ants-natures-secret-power/, accessed July 2013.

Hong-biao, M., Lin-quan, X. & Chun-hong, Z. (2010), An ant colony algorithm with the 2nd Newton law, in *Proceedings of International Conference on Geoscience and Remote Sensing (IITA-GRS)*, Qingdao, China, **2**, 95–99.

Hsu, W. Y. (2013), Application of quantum-behaved particle swarm optimization to motor imagery EEG classification, *International Journal of Neural Systems*, **23**(6), 18–32.

Jiang, H., Yu, Q. & Huang, Y. (2010), An improved ant colony algorithm for urban transit network optimization, in *Proceedings of 2010 Sixth International Conference on Natural Computation*, Yantai, China, **5**, 2739–43.

Kaveh, A. & Shojaee, S. (2007), Optimal design of scissor-link foldable structures using ant colony optimization algorithm, *Computer-Aided Civil and Infrastructure Engineering*, **22**(1), 56–64.

Kerrache, S., Benhidour, H. & Al-Homaidhi, S. (2013), An optimal transport-based approach for crowd evacuation, in *Proceedings of 2013 Fifth International IEEE Conference on Computational Intelligence, Modelling and Simulation*, Seoul, South Korea, 142–47.

Lagos, M. (2000), Near-source-generated tsunamis at the coasts of Chile (Tsunamis de origen cercano a las costas de Chile), *Revista de Geografía Norte Grande*, **27**, 93–102.

Laporte, J.-R. (2007), *Basic Principles on Clinical Research (Principios Básicos de Investigación Clínica)*, Fundación Institut Català de Farmacologia, Barcelona, Spain.

Law, A. M. & Kelton, D. (1991), *Simulation Modeling and Analysis*, MacGraw Hill, NJ.

Madariaga, R., Métois, M., Vigny, C. & Campos, J. (2010), Central Chile finally breaks, *Science*, **328**, 181–82.

Mannakkara, S. & Wilkinson, S. (2013), Build back better principles for post-disaster structural improvements, *Structural Survey*, **31**(4), 314–27.

Marco, D. & Krzysztof, S. (2006), *An Introduction to Ant Colony Optimization*, Universite Libre de Bruxelles, Brussels, Belgium.

Martens, D., De Backe, M., Haesen, R., Vanthienen, J., Snoeck, M. & Baesens, B. (2007), Classification with ant colony optimization, *IEEE Transactions on Evolutionary Computation*, **11**(5), 651–65.

Melián, B., Moreno Pérez, J. & Moreno Vega, J. (2003), Artificial intelligence (Inteligencia artificial), *Revista Iberoamericana de Inteligencia Artificial*, **19**, 7–28.

Montenegro, T. & Peña, F. (2010), Emergency management for floods caused by tsunamis in Chile (Gestión de la Emergencia ante eventos de inundación por Tsunami en Chile), *Revista Geográfica del Norte*, **47**, 68–80.

Nejat, A. & Damnjanovic, I. (2012), Agent-based modeling of behavioral housing recovery following disasters, *Computer-Aided Civil and Infrastructure Engineering*, **27**(10), 748–63.

Nezamabadi, H., Saryazdi, S. & Rashedi, E. (2006), Edge detection using ant algorithms. Soft computing: a fusion of foundations, *Methodologies and Applications*, **10**(7), 623–28.

Ng, M. W., Park, J. & Walter, S. T. (2010), A hybrid bilevel model for the optimal shelter assignment in emergency evacuations, *Computer-Aided Civil and Infrastructure Engineering*, **25**(8), 547–56.

ONEMI (2011), Standards and Codes (Marco Normativo), Oficina Nacional de Emergencia del Ministerio del Interior y Seguridad Pública. Available at: http://www.onemi.cl/transparencia/marconormativo.html, accessed October 2012.

ONEMI (2013), News (Noticias), Oficina Nacional de Emergencia del Ministerio del Interior y Seguridad Pública. Available at: http://www.onemi.cl/noticia/onemi-maule-realiza-primer-simulacro-regional-de-terremoto-y-tsunami.html, accessed June 2013.

Parpinelli, R. S., Lopes, H. S. & Freitas, A. (2002), An ant colony algorithm for classification rule discovery, in H. A. Abbass, R. A. Sarker, and C. S. Newton (eds.), *Data Mining: A Heuristic Approach*, Idea Group Publishing, London, United Kingdom, pp. 191–209.

Picard, D., Revel, A. & Cord, M. (2010), An application of swarm intelligence to distributed image retrieval, *Information Sciences*, **192**, 71–81.

Plevris, V. & Papadrakakis, M. (2011), A hybrid particle swarm-gradient algorithm for global structural optimization, *Computer-Aided Civil and Infrastructure Engineering*, **26**(1), 48–68.

Potangaroa, R. (2011), Structural engineers and post disaster recovery: lessons learnt from Haiti, *Human Ecology Journal*, **24**, 35–39.

Putha, R., Quadrifoglio, L. & Zechman, E. (2012), Comparing ant colony optimization and genetic algorithm approaches for solving traffic signal coordination under oversaturation conditions, *Computer-Aided Civil and Infrastructure Engineering*, **27**(1), 14–28.

Rubin, C. B. (2012), ed. *Emergency Management: The American Experience, 1900–2010*, 2nd edn., Taylor & Francis Group, LLC, Boca Raton, FL.

Sarma, K. C. & Adeli, H. (2002), Life-cycle cost optimization of steel structures, *International Journal for Numerical Methods in Engineering*, **55**(12), 1451–62.

Schoonderwoerd, R., Holland, O., Bruten, J. & Rothkrantz, L. (1997), Ant-based load balancing in telecommunications networks, *Adaptive Behaviour*, **5**(2), 169–207.

SHOA (2011), *Chilean Navy's Hydrographic and Oceanographic Service (Servicio Hidrográfico y Oceanográfico de la Armada de Chile)*. Available at: http://www.shoa.cl/index.htm, accessed March 2014.

Son, J. & Skibniewski, M. (1999), Multi-heuristic approach for resource leveling problem in construction engineering: hybrid approach, *ASCE Journal of Construction Engineering and Management*, **125**(1), 23–31.

Stützle, T. (1998), Parallelization strategies for ant colony optimization, in *Proceedings of 5th International Conference of Parallel Problem Solving from Nature - PPSN V (Lecture Notes in Computer Science),* Amsterdam, The Netherlands, 722–31.

Stützle, T. & Hoos, H. H. (1996), Max-min ant system, *Future Generation Computer Systems*, **16**, 889–914.

Tao, H., Zain, J. M., Ahmed, M. M., Abdalla, A. N. & Jing, W. (2012), A wavelet-based particle swarm optimization algorithm for digital image watermarking, *Integrated Computer-Aided Engineering*, **19**(1), 81–91.

United Nations (2011), *World Urbanization Prospects: The 2011 Revision*, Department of Economic and Social Affairs, Washington DC. Available at: http://esa.un.org/unup/pdf/WUP2011_Highlights.pdf, accessed March 2014.

USGS (2014), *History of the USGS*, United States Geological Survey. Available at: http://www.usgs.gov/aboutusgs/who_we_are/history.asp, accessed March 2014.

Wiegel, R. (1970), ed. Earthquake engineering, in *Tsunamis*, Prentice-Hall, Englewood Cliffs, NJ, pp. 253–306.

Wilson, E. (1975), *Sociobiology: The New Synthesis*, Harvard University Press, Cambridge, MA.

Yao, T., Mandala, S. R. & Chung, B. D. (2009), Evacuation transportation planning under uncertainty: a robust optimization approach, *Networks and Spatial Economics*, **9**, 171–89.

Zong, X., Xiong, S., Fang, Z. & Lin, W. (2010), Multi-objective ant colony optimization model for emergency evacuation, in *Proceedings of 2010 6th International Conference on Natural Computation*, Yantai, China, ICNC 2010, **6**, 2774–2778.