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Tabu Search to Draw Evacuation Plans in Emergency Situations

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***Abstract*—**Disasters are quite experienced in our days. They are caused by floods, landslides, and building fires that is the main objective of this study. To cope with these unexpected events, precautions must be taken to protect human lives. The emphasis on disposal work focuses on the resolution of the evacuation problem in case of no-notice disaster. The problem of evacuation is listed as a dynamic network flow problem. Particularly, we model the evacuation problem as an earliest arrival flow problem with load dependent transit time. This problem is classified as NP-Hard. Our challenge here is to propose a metaheuristic solution for solving the evacuation problem. We define our objective as the maximization of evacuees during earliest periods of a time horizon *T*. The objective provides the evacuation of persons as soon as possible. We performed an experimental study on emergency evacuation from the tunisian children's hospital. This work prompts us to look for evacuation plans corresponding to several situations where the network dynamically changes.

***Keywords*—**Dynamic network flow, Load dependent transit time, Evacuation strategy, Earliest arrival flow problem.

I. Introduction

DUE to the increase of risks of some disasters such as flood, earthquakes, terrorist attacks, and fire, we may provide an efficient solution to save people from danger. However, this problem greatly depends on evacuation's space and disaster's type. Thus, it's not sufficient to try to evacuate people but also to produce a suitable plan adapted to the various emergency situations. Our main purpose is to produce a generic evacuation plan based on a set of variables. We treat the problem as a dynamic process that has to be planned in fire situation. Hence, we propose a specific framework to our evacuation resolution. In fact there are a set of parameters and constraints that reflect our resolution view.

These parameters are the incoming of the problem and they are illustrated in Fig. 1. Our evacuation process depends on some incoming parameters of Fig. 1 including *Env*, *T*, *Dis*, *Feat*, and *Tr*. The incoming parameter *Env* represents the environment which has to be evacuated. It can be a building, an open area, or a ship. We fix our evacuation space as a building. The time horizon *T* is the time devoted to complete the evacuation process. The distribution *Dis* of people corresponds to the initial location of evacuees in the building. The incoming parameter *Feat* represents the building capacity as the rooms' capacities, the doors' capacities, and the corridors' capacities. On the other hand, we assume transit times *Tr* to characterize the time needed to cross the doors.

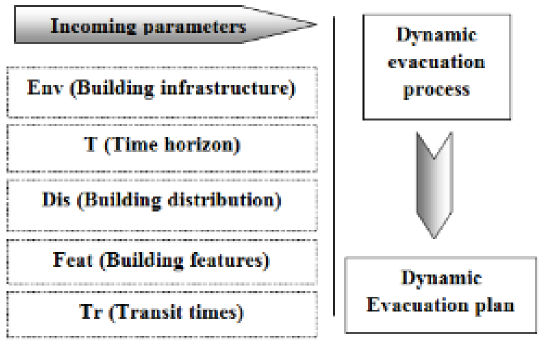

Fig. 1 Evacuation problem parameters

To solve the problem issue, we focus on the dynamic network flow models that are proposed for the macroscopic evacuation problem [13]. We choose the earliest arrival flow problem with load dependent transit time to simulate a real-life case study. The objective function of *EAFP* is to save people as fast as possible during the early units of time. This model has been shown to be NP-hard [2]. Thus, no exact method can be elaborated to solve this problem with a polynomial time. Our challenge is to propose tabu search (TS) metaheuristic as a simple local search technique for an NP-hard problem. The solution that we emphasize consists in finding a dynamic plan that saves people as fast as possible with discrete time horizon *T*. The main contribution of this work is to introduce an optimization technique on the dynamic plan that is based on a strategy of move which applies various network flow management. This strategy allows us to manage nodes that need more control and security. The proposed method is called *TS-EAFP* which is experimentally tested on a real-life case. We propose a dynamic evacuation plan for the second floor of the tunisian children's hospital.

II. Evacuation Problem: Modeling and Resolution

Evacuation problems can be treated from two general points of view macroscopic versus microscopic patterns and modeled as flow problems on dynamic networks versus static networks.

A. Macroscopic and Microscopic Patterns

Several approaches are proposed for the evacuation problem. The first one is the microscopic pattern which is based on the simulation of individual movements and the

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interaction between evacuees during this movement [7]. Therefore, every evacuee is modeled as a separate object. The second one is the macroscopic pattern which assumes that the individual movement follows the movement of group in panic situations as it is explained in [7]. In our case, we work on macroscopic pattern that reflects models of the operational research field and more precisely models based on the network flow.

B. Static and Dynamic Models

Two classes of network flow models are provided for macroscopic evacuation [13]. First, the static network flow model is used to deal with evacuation problems without considering the notion of time. For example, the shortest path model [17] uses the static network class to solve evacuation problems within the macroscopic approach. Second, the dynamic network model is another model to solve macroscopic evacuation problem. This class of models focuses on the time property to characterize the network features. For example, Quickest flow over time [5] is provided for evacuation problems [13] using a purely macroscopic point of view. It consists in sending a given amount of flow from a source to a sink in the shortest possible time.

1. Static Network Flow Model

Given a network $G = (N,A)$, where N corresponds to the set of nodes and A the set of arcs. A static flow is assigned to each arc (i,j) as a non-negative flow denoted by $x_{i,j}$. This flow must satisfy constraints (1) and (2).

$$x_{i,j} \leq C_{i,j} \ \ \forall (i,j) \in A \tag{1}$$

$$\sum_{i,j \in A} x_{i,j} = \sum_{j,k \in A} x_{j,k} \ \ \forall i,j,k \in N \tag{2}$$

This static model is used in [15] to solve an evacuation problem over the shortest path algorithm. It is a graph search algorithm that solves the single-source shortest path problem for a graph with non-negative edge path costs, producing a shortest path tree. This approach consists in handling the evacuation of a large population of individuals from a high-rise building where the notion of time is not considered. However, the use of time is more suitable to simulate a real-life building evacuation while the network can probably change. This dynamic property is due to the evacuee's movement and the change of network's features over time. In real-life evacuation and in a situation like a fire emergency, the building features change over time due to fire or smoke. To tackle this problem, Ford and Fulkerson [8] introduce a dynamic property to network problems called flow over time problems.

2. Dynamic Network Flow Model

The dynamic network flow class describes the evolution of the network flow over a time horizon T. We can formulate flow over time problems in two ways depending on the use of discrete or continuous time. In our case, we broke the time horizon T into a set of discrete time periods tin $\{0\ldots T\}$.

A dynamic network is defined by $G_T = (N,A,T)$ and it is presented with a time expanded network $G_T = (N_T,A_T)$ over the time horizon T. A time expanded network G_T with a time horizon T consists of T copies of the set of nodes N_T and the set of arcs A_T, one for each time unit t in$\{0\ldots T\}$. The expression $x_{i,j}(t)$ denotes the flow over time on an arc (i,j) at period t . All arcs in G_T may have a set of copies related to the dynamic aspect of the network flow. Each unit of time can be considered as an arrival time to any node in the network, then $t' = t + \lambda_{i,j}(t)$ while t in $\{0\ldots T\text{-}1\}$, t' in $\{1\ldots T\}$ and $\lambda_{i,j}(t)$ is the transit time on arc (i,j) at period t. Fig. 2 represents an example of static network that we transform into a time expanded network.

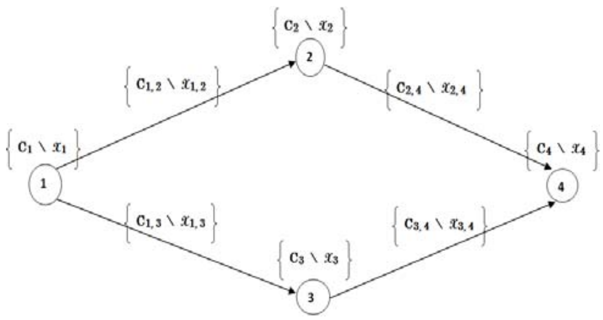

Fig. 2 Static graph example

In Fig. 2, we suppose that we have 4 nodes and each node I has maximal capacity C_i and a load x_i. On the other hand, arcs have capacities and loads respectively denoted by $C_{i,j}$ and $x_{i,j}$. As an example, arc (2,4) has a maximal capacity $C_{2,4}$ and a load $x_{2,4}$. Fig. 3 represents the transformation of the static network of Fig. 2 to a time expanded network.

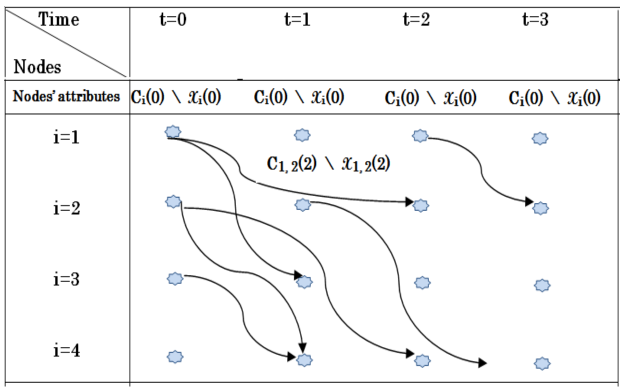

Fig. 3 Time expanded network

Fig. 3 shows a network evolution over a time horizon T that is supposed to be equal to 4 periods t in $\{0\ldots 3\}$ where $t = 0$ is the initial time of the horizon T. Each node i has two time dependent attributes that are the capacity $C_i(t)$ and the load $x_i(t)$ for all t in $\{0\ldots 3\}$. As well as, arcs (i,j) have time dependent attributes mentioned in Fig. 3 by the capacities $C_{i,j}(t)$ and the loads $x_{i,j}(t)$ for all t in $\{0..3\}$. As an example, the arc (1,2) in Fig. 3 has a capacity $C_{1,2}(2)$ at period $t = 2$ and a load $x_{1,2}(2)$ also at period t = 2. We present the capacity constraint on the arcs in (3). Equation (4) defines the dynamic capacity constraint on the nodes. The dynamic conservation constraint on nodes is expressed by (5).

$$x_{i,j}(t) \prec C_{i,j}(t) \;\; \forall (i,j) \in A, \quad \forall t \in \{0...T\} \tag{3}$$

$$x_{i,i}(t) \prec C_i(t) \;\; \forall\, i \in N, \quad \forall\, t \in \{0...T\} \tag{4}$$

$$\sum_{(j,i)\in A} \sum_{t'\in T} x_{j,i}(t') - \sum_{(i,k)\in A} \sum_{t\in T} x_{i,k}(t) = x_{ii}(t) - x_{ii}(t-1) \quad \forall\, i,j,k \in N, \quad \forall\, t,t' \in \{0...T\} \tag{5}$$

In dynamic network, each flow $x_{ii}(t)$ in node i at period t must not exceed its capacity at period t denoted by $C_i(t)$ as in (4). As well as, each flow $x_{i,j}(t)$ on arc (i,j) must not exceed its capacity $C_{i,j}(t)$ at period t mentioned in (3). On the other hand, the flow in nodes i in N must satisfy the dynamic conservation constraints (5) while the network is dynamically changing.

C. Mathematical Problem Formulations

Dynamic evacuation problem is treated from a macroscopic level using various mathematical formulations including Minimum Cost Dynamic Flow Problem (MCDFP) [6], Maximum Dynamic Flow Problem (MDFP) [8], and Earliest Arrival Flow Problem (EAFP) [3]. In real-life emergency situation like a fire, it is more suitable for saving people as fast as possible from danger. Hence, we seek not only to maximize the total number of evacuees at the time T but also maximizing the evacuees during the earliest time' units t in $\{0\dots T\}$.

This objective corresponds to the objective function of *EAFP* that is formulated in [20] by (6) under the same constraints formulated by (3), (4), and (5) with an additional constraint on travel times (7). This constraint explains that the sum of all transit times on a path from a source to a sink must not exceed the time horizon T. This formulation is related to one source i and one sink s and it is called *i-s-EAFP*. It consists in maximizing the arrival flows $x_{is}(t')$ at each time unit t' in $\{0\dots T\}$. Here the goal is to maximize the amount of flow reaching the sink up to any time according to Gale under constraint (7).

$$Max \;\; X(T) = \sum_{t=0}^{t=T} \sum_{(i,s)\in N} \sum_{t':t'+\lambda_{is}(t')=t} x_{is}(t') \;\; \forall (T' \prec T) \tag{6}$$

$$t + \lambda_{i,j}(t) \le T \qquad \forall (i,j) \in A, \;\; \forall t \in \{0...T\} \tag{7}$$

This constraint explains that the sum of all transit times $\lambda_{i,j}(t)$ on a path must not exceed the upper bound of horizon T. Gale showed in [10] that *i-s-EAFP* always exists in the case of constant and time dependent attributes. But for the case of load dependent transit time it is not obvious and it becomes NP-hard as in [2]. In our resolution, we use *EAFP* with load dependent transit time in a dynamic network with multiple sources i and one sink s.

III. Resolution of the Evacuation Problem as EAFP

Several resolution techniques are proposed for solving the evacuation problem using the earliest arrival flow model with different features.

A. Literature Review

Some polynomial algorithms are proposed for specific cases of evacuation problem without considering the load dependent transit time property. As a first example, Baumann and Skutella solve in [4] an evacuation problem according to earliest arrival flows with multiple sources and one sink. In matter of a fact, they suppose a network with capacities and transit times on arcs without relying on time expansion of Fig. 3. They give a polynomial algorithm by computing an earliest arrival flow based on the quickest transshipment algorithm of Hoppe and Tardos [12]. This technique consists in turning the earliest arrival pattern into earliest arrival transshipment by considering each arrival flow as a breakpoint (one sink to the quickest model) that provides a sink. Hence, authors obtain a new model with multiple sources and multiple sinks. The proposed algorithm is polynomial related to the number of sources and the number of breakpoints (flow that reaches the sink) of the earliest arrival pattern. As a second example, Stefan, Heike, and Mechtchild propose an exact algorithm in [21] to compute an earliest arrival flow on series-parallel graphs. This technique uses a greedy algorithm with a polynomial time to yield an earliest arrival flow. It is based on the algorithm of the Minimum Cost Flows for Series-Parallel Networks [22] to solve the *MDFP* using a temporally repeated flow. The authors add a specific condition to the cost on the paths. It consists in neglecting the path having a cost upper than the time horizon T.

Furthermore, there are some approximate algorithms proposed for solving the evacuation problem modeled as *EAFP* with load dependent transit time. Baumanm gives in [2] an approximate algorithm. He relaxes the problem by relaxing the amount of flow fixed as α then sent it into the sink. Then, he divides the time unit t by α to define the α-earliest arrival flow. The goal of this relaxation is to find the α-earliest arrival flow that reduces the time. Minieka is among the first who propose an algorithm in [14] for this problem by using the successive shortest paths technique on residual networks. This polynomial time algorithm is given only in the case of constant capacities.

B. Our Contribution

In this work, we attempt to introduce the load dependent transit time property on the dynamic network with time dependent attributes (nodes' capacities, nodes' loads, arcs' capacities, and arcs' loads). This assumption is to simulate a real-life evacuation. In fact, there is a high correlation between the rate of crowd on an arc (i,j) and the transit time $\lambda_{i,j}$. A more accurate model for describing this correlation is provided by the use of flow dependent transit time also called the load dependent transit time property. Indeed, in a dynamic network, the travel time of an arc depends on the congestion degree at each period t in $\{0\ldots T\}$. This travel time $\lambda_{i,j}(t)$ is expressed by (8) in [3].

$$\lambda_{i,j}(t) = \lambda_{i,j}(0) * (1 + \gamma * (x_{i,j}(t)/C_{i,j}(t))) \quad \forall (i,j) \in A, \quad \forall t \in \{0 \ldots T\} \tag{8}$$

Equation (8) is the travel time function which expresses the transmission time for traffic networks used in [19]. Whereas, $\lambda_{i,j}(0)$ is the initial transit time when the arcs are empty, □ is a constant parameter, $x_{i,j}(t)$ is the arc's load at period t and $C_{i,j}(t)$ is the maximal arc's capacity which is time dependent.

The emphasis of this equation is that the transit time not only depends on time t but also on arc's load that is time dependent. Since the *EAFP* with load dependent transit time is NP-hard [2], the scope of our study is to propose a metaheuristic for solving the evacuation problem using this model. Indeed, the effectiveness of the metaheuristics in solving combinatorial optimization [16] and NP-hard problems draw us to test this technique on the evacuation problem. We attempt to adapt tabu search on the problem. We want to exploit the local search technique and to propose a novel neighborhood strategy that promotes a rapid solution convergence. Our goal is to improve the evacuation strategy by introducing some network flow management that contributes in the dynamic evacuation plan optimization. Next section represents the adaptation details of this metaheuristic on the evacuation problem. Hence, we operate a novel approach called *TS-EAFP*.

IV. TS-EAFP FOR THE EVACUATION PROBLEM

Tabu search, created by Glover in [9] is a local search method that examines the space of all possible solutions that can be visited during the search. A trajectory sequence of the best solutions is provided while the stopping criterion is not yet. Indeed, the algorithm of *TS* starts from an initial solution chosen at random or by using a specific heuristic method and finishes when stopping criterion is verified. To diversify the search, *TS* uses a tabu list to avoid cycling by saving solutions that were recently examined.

A. Solution Representation

Several solutions can be found in the search space, but they have unique representation. Here, we propose that a solution shows the network's loads at each unit t in $\{0\ldots T\}$. Hence, we choose to represent a solution in the search space by a matrix $M(|N|,T)$ illustrated in Fig. 4. In this example, we suppose to have 6 nodes (rooms or corridors) and 5 periods. The first period $t = 0$ represents the initial persons distribution in the building at the beginning of fire whereas the last period $t = 5$ is devoted as the end of the dynamic evacuation process. On the other hand, the last node $i = 6$ is supposed to be the safety area s and it is used to show the number of evacuees leaving the building at every period t in $\{0\ldots 5\}$. The goal of this representation is to show the dynamic evacuation plan by observing several building states according to each time unit t in $\{0\ldots T\}$. The building state is described by the matrix M using nodes' loads over time.

$x_i(t)$	t=0	t=1	t=2	t=3	t=4	t=5
i=1	6	0	0	0	0	1
i=2	3	2	1	1	5	7
i=3	2	0	0	0	0	0
i=4	8	8	7	0	0	0
i=5	10	0	7	0	9	2
i=6	0	0	8	4	8	2

Fig. 4 The matrix of the solution

These loads correspond to the evacuees who still exist in node i at each unit t in $\{0\ldots T\}$. Hence, cell (i,t) in M corresponds to the load $x_i(t)$ on node i at period t denoted by $M(i,t)$. As in the example of Fig. 4, the load in node $i = 1$at the initial period $t = 0$ is equal to 6 whereas the load of this node at the end of the time horizon $T = 5$ is equal to 1 denoted by $M(1,5) = 1$.

B. The Initial Solution of TS-EAFP

Several problems were treated by *TS* using specific heuristics for the generation of the initial solution. However, these heuristics can be optimal or not optimal as well as feasible or not feasible. Concerning the performance of these heuristics, it does not imply to the obtaining of an optimal solution at the end of the research in the neighborhood. Authors in [11] propose a flexible algorithm starting from any initial solution (feasible or not) and leads to the best known solutions. In addition, a good feasible (yet not-optimal) solution to a problem in [18] can be found quickly using a greedy approach and provide an efficient solution. As well as, a greedy algorithm is used to create a completely random initial solution in [1]. This heuristic does not give very good results in the initial solution. Although the algorithm does not start from an efficient solution, it achieves better performance in execution time.

In this study, we focus on the development of a rapid and simple heuristic to provide a feasible initial solution for *TS-EAFP*. The initial solution is defined as an initial feasible evacuation plan such that dynamic constraints (3), (4), (5), and (7) are satisfied. This initial plan is constructed by initially setting at random a feasible flow on the nodes at period $t = 0$. The initial loads $M(i,0)$ represent the initial distribution of persons at $t = 0$. This period corresponds to the alarm detection's moment. In addition, we suppose that no person is in the safety node $i = N$ given it is the final destination s. However, the flow of next units t in $\{1\ldots T\}$ is generated by executing a specific heuristic named *TS-EAFP-initial solution*. Hence, the generation of the dynamic flow consists in iteratively evacuating each node i in $\{1\ldots N\}$ if it contains persons $M(i,t) > 0$ for all t in $\{0\ldots T\}$. This operation consists in distributing feasible flows on successors j in $\{1\ldots N\}$ according to the capacities of arcs (i,j) at period t and the capacities of nodes j at period t' such as $t' = t + \lambda_{i,j}(t)$. The node's evacuation follows steps mentioned in the algorithm of Fig. 5. It reflects the greedy construction of an initial solution to the problem.

```
Input: matrix M with initial random distribution of
loads M(i,0), initial capacities C_i(0) of nodes and
C_{i,j}(0) of arcs, initial arcs' loads x_{i,j}(0), and initial
transit times λ_{i,j}(0)
Output: feasible flows over time on matrix M
for all periods t ∈ {0...T − 1} do
  for all nodes i ∈ {1...N − 1} do
    if M(i,t) > 0 then
      for all successors j of node i do
        if C_{i,j}(t) > 0 then
          Compute flow satisfying (3) such as:
          flow ≤ C_{i,j}(t) and flow ≤ M(i,t)
          t' ← t + λ_{i,j}(t); using equation (6)
          if C_j(t') − M(j,t') > 0 then
            Update flow satisfying (4)
            Update loads in M to ensure (5)
            M(i,t) ← M(i,t) − flow;
            M(j,t') ← M(j,t') + flow;
```

Fig. 5 TS-EAFP-initial solution

The output of the heuristic in Fig. 5 focuses on the horizon $\{0\ldots T\}$ satisfying the dynamic travel time constraint in (7). The complexity of this heuristic is on $\Theta(N * T)$ depending on the number of nodes N and the number of periods in the horizon T.

C. The Objective Function of TS-EAFP

Referring to the *EAFP*, the objective consists in maximizing evacuees at earliest periods in the time horizon T. To deal with this objective, we propose an objective function that attributes a higher coefficient for the earliest periods of the evacuation. Let $f(S)$ is the objective function of a solution S that we attempt to maximize.

$$f(S) = \sum_{t \in 0 \ldots T} x_s(t) * (T - t + 1) \tag{9}$$

The value of the objective function $f(S)$ is computed by the sum of the number of the evacuees in the sink s at each period t denoted by $x_s(t)$ that is multiplied by the coefficient $T - t + 1$. Equation (9) reflects the earliest model since flow is evacuated as soon as it is weighted by a high coefficient.

D. The Neighborhood Strategy of TS-EAFP

The number of neighboring solutions is equal to the neighborhood's size. Each neighboring solution is obtained by applying a move operation on the current solution. In fact, each move alters one part of a current dynamic evacuation plan. Firstly, our move's technique consists in randomly choosing a cell $M(i,t)$ from a current solution's matrix. This random cell is called the move's cell. Secondly, we increase $M(i,t)$ using the predecessors' loads of the chosen node i while its capacity constraint (4) is not violated. This move strategy is illustrated by the example of Figs. 6 and 7. In this example, we suppose having 5 periods and 6 nodes. Consequently, the time horizon T corresponds to the interval $\{0...5\}$ and the safety node s corresponds to $i = 6$. On the other hand, we suppose that $M(4,2)$ is the move's cell. Fig. 6 represents a current solution in the search space. In this example, we assume that node $i = 4$ has only one predecessor which is node $i = 1$ having the load $M(1,1) = 6$ in the current solution of Fig. 6.

$x_i(t)$	t=0	t=1	t=2	t=3	t=4	t=5
i=1	6	6	5	4	3	3
i=2	3	2	2	1	1	1
i=3	2	2	1	1	1	1
i=4	8	8	8	5	5	5
i=5	2	2	2	1	0	0
i=6	0	0	0	7	0	7

Fig. 6 Current solution

In addition, we suppose that this predecessor has other successors that are different from $i = 4$. Then, node $i = 4$ is directly connected to the safety node s. The application of a move on the current solution provides a new solution that is a neighbor as in Fig. 7.

$x_i(t)$	t=0	t=1	t=2	t=3	t=4	t=5
i=1	6	6 -5	1	0	0	0
i=2	3	2	2	1	1	1
i=3	2	2 +5	1	1	1	1
i=4	8	8	13	9	6	6
i=5	2	2	2	1	0	0
i=6	0	0	0	9	0	7

Fig. 7 Neighbor solution

As we see, the move's cell having value $M(4, 2) = 8$ in the current solution Fig. 6 is updated by value $M(4, 2) = 13$ in the neighboring solution. This new value is obtained by adding its predecessors' loads while maintaining its residual capacity $C_4(2)$- $x_4(2)$ at the same period $t = 2$. As a result, the predecessor obtains a new load $M(1, 2) = 1$ in the neighbor's solution after applying this move operation. Consequently, it acts on the evacuation results $x_s(t)$. As in the example of Fig. 7, the evacuees number reaching the sink s at period $t = 3$ increases. Furthermore, one move is defined as promising while it improves a current solution of *TS-EAFP*. The neighborhood strategy allows *TS-EAFP* visiting several regions on the dynamic plan and executing promising moves that contribute in the evacuation plan's optimization. Indeed, the move's technique focuses on the use of the load dependent transit time property of (8). As a result, good network flows manage leads to the decrease of some transit times $\lambda_{i,j}(t)$ as well as the travel times' decrease.

E. The Tabu List of TS-EAFP

The tabu list is represented by a matrix such as the initial solution matrix of Fig. 4. Each cell in the tabu list matrix reflects the node and the period that is chosen for applying a move related to a random cell in Fig. 6. We initially suppose that the tabu list matrix contains cells with values setting at zero. Hence, to prohibit one promising move to be applied again, *TS-EAFP* sets the tabu list's size as a new value in the accorded cell. Then, in next iterations, this cell is decreased until reaching zero. In this case, the flipping of this cell is allowed to apply again the move into this cell. Our goal is to diversify the regions of the network flow management in order to capture nodes that need more security and control.

F. The Algorithm of TS-EAFP

The main aim of the tabu search technique is to seek a good plan while browsing several neighborhoods. Fig. 8 represents the algorithm of *TS-EAFP*.

```
Input: Initial solution (S0)
Output: Last solution (Last)
S ← S0; n1 ← 0; Last ← S;
Repeat
    Generate a neighborhood of S;
    S1 ← the best solution in the neighborhood;
    if S1 is not tabu then
        if f(S) < f(S1) then
            S ← S1;
            Update the tabu list;

    /* aspiration criterion
    if f(S) > f(Last) then
        Last ← S;
    n1 ← n1+1;
Until n1=nbmax;
```

Fig. 8 TS-EAFP

The variable *S0* in Fig. 8 is the initial solution generated by the heuristic in Fig. 5; *S* is the current solution in the search space and *Last* is the last solution found when the stopping criterion is met. Here, the stopping criterion is the maximal number of iterations called *nbmax* in Fig. 8. This trajectory starts from an initial plan and is guided by the move from a current solution to another while it can improve it. The algorithm of Fig. 8 applies a local search in each neighborhood allowing the appearance of the local optima *S1* that improves the objective function *f*(*S*) of the current solution *S*. This local optimum must not be in the tabu list. The use of the tabu list allows *TS-EAFP* to diversify the plan as well as to visit several regions in the building while it is dynamically changing.

V. Experimental Results of TS-EAFP

According to the framework in Fig. 1, we have to define the set of the incoming parameters. Hence, we initially describe the first incoming parameter that is the environment *Env* to be evacuated. Particularly, we consider the second floor of the Tunisian children's hospital as our case study illustrated in Fig. 9. We transform Fig. 9 into a directed graph as illustrated in Fig. 10.

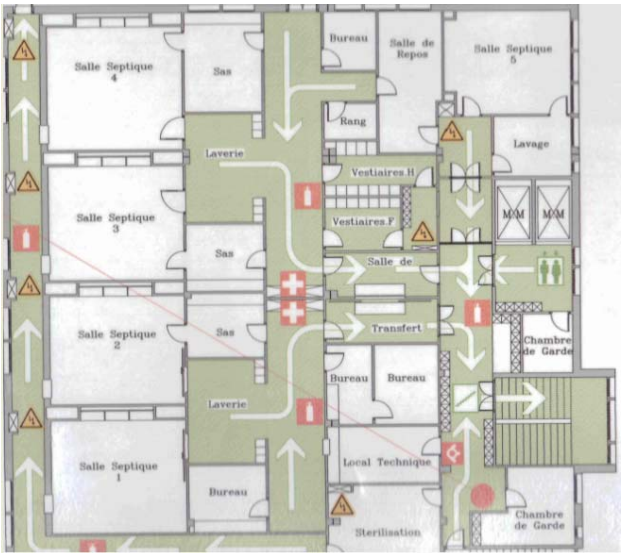

Fig. 9 The second floor of the children's hospital

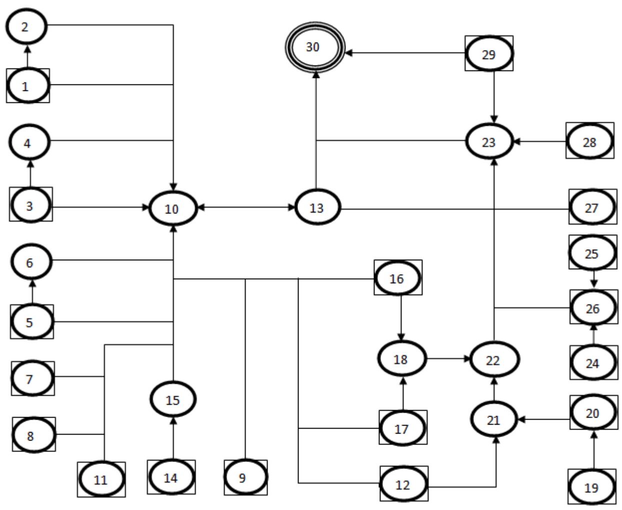

Fig. 10 Graph model of the floor

The nodes correspond to rooms and corridors, whereas the arcs correspond to doors. We add an artificial node i = 30 that represents the safety area s and it is connected to the three hospital' exits that are i = 13, i = 23, and i= 29. All nodes in graph of Fig. 10 represent the sources to be evacuated except node 30. The second incoming parameter of the framework is related to the time horizon T. It is supposed to be equal to 20 periods. The period is supposed to be equal to 1 minute. The third incoming parameter of our framework in Fig. 1 is the initial distribution *Dis* of persons in the floor of Fig. 10. Hence, we suppose that the total number of evacuees is equal to 100 and it is randomly distributed on the nodes at $t = 0$. Whereas, the arcs which represent the doors, are supposed to be empty at $t = 0$.

The incoming parameter *Feat* of Fig. 1 describes the nodes' capacities and the arcs' capacities at the initial time $t = 0$. For that, we suppose that the initial nodes' capacities are between 15 and 30 and the initial arcs' capacities are between 2 and 5. However, due to the time dependent attribute property, many changes may be done on the nodes' capacities and the arcs' capacities. Indeed, the fire progress can damage rooms, corridors and doors by falling objects, smoke and destruction. Then, many nodes and arcs may be partially or totally blocked. This phenomenon is represented by the capacities' decrease over time. Finally, we assume that the transit time *Tr* is initially equal to 5 seconds $\lambda_{i,j}(0) = 5$ for all arcs (i,j) in A while they are empty. This transmission time is changed according to the load dependent transit time property in (8).

A. Solution Found Using TS-EAFP

Starting from an initial solution, *TS-EAFP* constructs the first neighborhood by following the move strategy explained in Figs. 6 and 7. Then, the process is performed by choosing better solutions found during the trajectory sequence. This procedure is experimentally tested on the evacuation problem related to the case study of Fig. 9. We found out an improvement of the objective function $f(S)$ according to the initial solution. Fig. 11 shows the number of evacuees reaching the sink s at each unit of time t in $\{0\ldots20\}$ related to the initial solution (*TS-init*) and the last solution (*TS-last*).

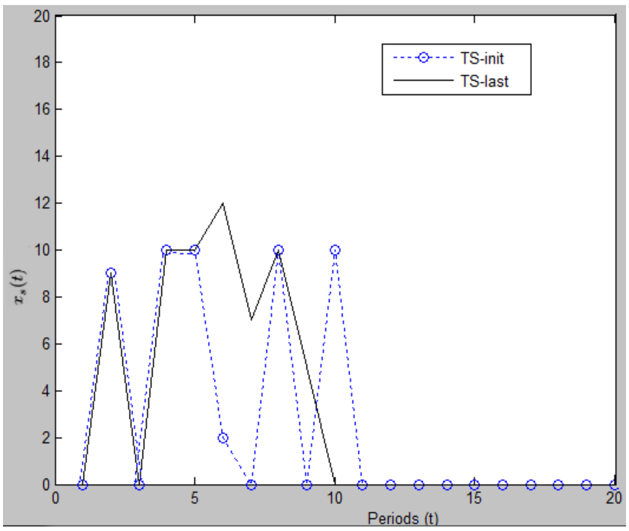

Fig. 11 The initial solution improvement

On the report of the objective function in (9) that consists in getting a higher evacuees number during the earliest periods t in $\{0\ldots T\}$, we respectively obtain $f(S) = 771$ and $f(S) = 969$ for *TS-init* and *TS-last*. Firstly, we deduct that the evacuation starts at period $t = 2$ with a value $x_s(2) = 9$ for the two solutions. As it was stated by the initial distribution *Dis* of Fig. 1, this travel time concerns evacuees initially nearest to the safety area s at $t = 0$. Secondly, the objective function improvement seen in Fig. 11 is mainly justified by the upper peaks corresponding to $x_s(6) = 12$ and $x_s(7) = 7$ in *TS-last*. This is explained by the introduction of some network flow management in the initial dynamic evacuation plan of *TS-init*. Indeed, thanks to the move's strategy, the evacuees are more organized during the evacuation. This action manages their arrival at the floor's exits and their output to the floor. Figs. 12 and 13 show two dynamic plans successively related to *TS-init* and *TS-last*. They show the number of evacuees in the nodes at each period t in $\{1\ldots20\}$.

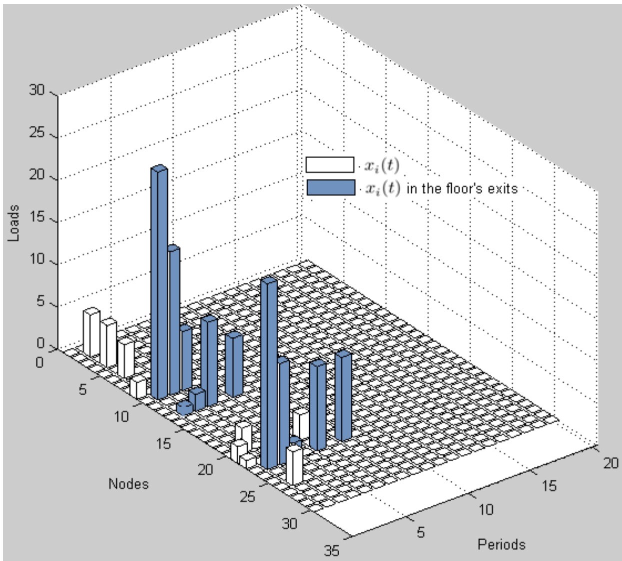

Fig. 12 The initial dynamic evacuation plan

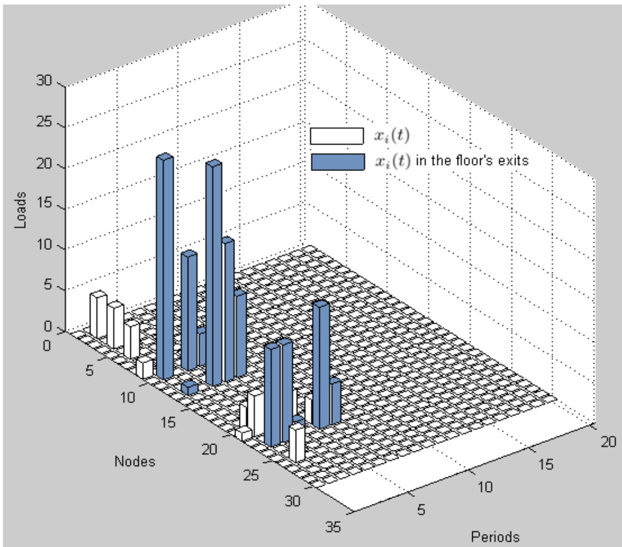

Fig. 13 The improved dynamic evacuation plan

We notice that the uppermost nodes receiving more movements than others are nodes 10, 13, and 23 in the two dynamic plans. Obviously, they are the floor' exits and they are the three points of evacuee reception. Hence, the evacuees' arrival at these regions allows their quickly exit according to the floor' infrastructure shown in Fig. 10. The improvements so obtained in Fig. 11 can be particularly noticed by periods in the floor's exits. As it is stated in Fig. 13, there are less evacuees in node 23 at $t = 2$ than in Fig. 12. In addition, Fig. 13 shows an evacuees' leave at $t = 3$ respectively from nodes 10 and 13. Consequently, they are exited from the building according to their transmission time (8) on the arcs connecting the destination node. This loads' decrease explains the improvement seen at period $t = 6$ and $t = 7$ in Fig. 11. As a deduction, *TS-EAFP* acts on the evacuees' movement by varying the dynamic network flow. Hence, the approach is able to provide better evacuation plan due to the move strategy proposed in Figs. 6 and 7.

Our objective is to focus on the evacuees' movement by organizing the flow transit on nodes in order to reduce their arrival time. Hence, the dynamic evacuation process can be guided by a specific order avoiding blocked situations. We can install camera, and indicators on the rooms to state the number of people at a current time then ability to reception. These equipments must be located in the appropriate places. These locations can be connected to the exits to be at strategic locations on the floor. In addition, they check the operation and the scope of the alarm system and the system telephone, including internal systems to ensure effective communications. All these techniques allow better evacuation plan adaptation on the floor as well as executing management techniques; where they can identify immediate actions to be taken at the onset of the alarm.

B. Sensitive Analysis of TS-EAFP on Transit Time

The examination of the impact of the input data on the output results is crucial. As it is stated in the framework of Fig. 1, the approach depends on the incoming parameters. The purpose of this sensitive study is to test the performance of *TS-EAFP* while the incoming parameters are changing and to highlight the relevance of our approach. The interest of this study is to measure the impact of the incoming parameters on *TS-EAFP* and especially on the objective function value. We are interested in the parameter *Tr* of Fig. 1 that describes the transit times. Hence, we propose to increase the initial transit time that is initially supposed to be equal to 5 seconds. However, we maintain the same values for the other parameters as in the former results. Fig. 14 shows the objective function $f(S)$ values of the last solutions related to each initial transit time $\lambda_{i,j}(0)$in {5, 10, 15, 20, 25, 30}.

As we see in Fig. 14, the initial transit time's growth negatively acting on the objective function. In fact, the increase of the initial transit time $\lambda_{i,j}(0)$ also increases the transmission times $\lambda_{i,j}(t)$ for all arcs (i,j) in A so obtained by (8) as well as the travel time. Indeed, the travel time from a source i in N to the destination s is equal to the sum of all transit times $\lambda_{i,j}(t)$ for all arcs (i,j) in A on this path.

Consequently, there are fewer evacuees reaching the sink s during the earliest periods of the time horizon T. Hence, an objective function's decline is proved in Fig. 14 for all initial transit times satisfying $\lambda_{i,j}(0)>5$.

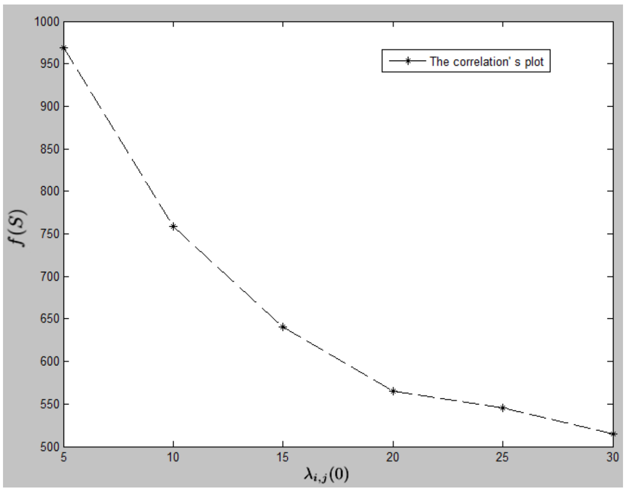

Fig. 14 The correlation between $\lambda_{i,j}(0)$ and f(S)

This sensitive study shows the capability of *TS-EAFP* to realistically simulate an emergency evacuation while varying the incoming parameters. In addition, the model is sensitive if a proposed change to another incoming parameter causes a change to the optimum objective function value.

VI. Conclusion

We study the evacuation problem from the macroscopic level to simulate a dynamic network flow in a building floor. The problem is modeled as an *EAFP* with load dependent transit time. A novel approach called *TS-EAFP* is implemented in a specific evacuation framework. The experimental results show that *TS-EAFP* relatively produces a good evacuation plan that maximizes the evacuees' output during the earliest periods. The optimization of the dynamic evacuation plan is successful due to the strategy of move. Our approach leads to the objective function improvement. In addition, the approach is able to support various incoming parameters and simulate different real-life evacuation scenarios. Furthermore, we are more attracted by testing *TS-EAFP* on other buildings. On the other hand, we propose using different move strategies and varying the objective function. This study motivates us to apply other metaheuristics to deal with the evacuation problem modeled as *EAFP* and more generally with flow over time problems such as the routing field.

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