Multi-objective Evolutive Multi-thread Path-Planning Algorithm Considering Real-Time Extreme Weather Events

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Abstract. Public transportation systems (PTS) should not only guarantee the mobility of users in the city but also, it should guarantee users health during trips. For example, users with health problems such as: high blood pressure, migraine, fever, asthma, back pain, dizziness, among others could be affected in their health when using the system in extreme weather conditions. This paper proposes an algorithm that makes path recommendations maximizing protection to weather conditions and minimizing the total traveling time until reaching the final destination. This paper presents the execution of this algorithm for thousands of user requests running on a Quad-core Intel Xeon processor 8 GB RAM OSX 10.5.

Keywords: Smart-cities · Transportation · Path-planning · Health · Extreme weather

1 Introduction

In recent years, most cities have intense weather patterns; this trend seems to continue the next coming years. Some of these patterns are: torrential rains, heat waves, intense cold, strong winds, among others. These patterns are beginning to be a common phenomenon on several cities around the world. This tendency is so evident that international organizations such as the United Nations [1], UNESCO [2] and the European Union [3] contemplate this issue directly in their work plans.

In particular, the Mexican Federal Government analyzes climate change, and its effects, on Mexican inhabitants through the National Institute of Ecology and Climate Change [4]. This institute has several studies on the effects of climate change in

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different sectors in Mexico [5]. Government policies on this issue has been strengthened over time. These policies have been included in several free trade agreements between Mexico and other countries to prevent environment deterioration. Such is the case of the USMCA trade agreement with the United States of America and Canada [6]. All these international policies let us see that climate change and its impact on the population should be considered as a priority. That is why, the population in urban areas must adjust their daily lives to these extreme weather conditions.

Consider the case of people with health problems such as high blood pressure, fever, migraine, allergies, asthma, back problems, diabetes, etc. This sector of the population could be affected when they are exposed to extreme weather conditions. For example, people with respiratory problems should not be exposed to sudden changes in temperature; the same goes for people with diabetes, who should not spend a lot of time without checking their glucose levels. Even elderly people how could be affected when seated for long periods of time.

Public transportation users are vulnerable to weather when they are on board at buses, taxis, subway, etc., or when they walk between transfer stations. This is why, public transportation authorities should consider reducing the exposure of users to climatic events that put their health at risk.

This paper proposes a strategy to recommend the use of public transportation that reduces traveling time; but this strategy also reduces health risks when vulnerable people are using the public transportation units.

There are several studies about people mobility in public transportation. There are studies about static travel planning considering different construction techniques [7–13]. There are also studies about tracking routes in multimodal units [14]. Similarly, there are studies on dynamic planning [15–17] and analysis of multiple objectives [18–20]. Moreover, there are studies on user's mobility who use private transportation as the one presented in [21]. In addition, there are some studies that present software architectures based on ontologies that use multiple criteria for decision-making techniques to design a customized route planning system [22–24].

However, this paper presents a different approach because it is oriented to reduce health problems not provoked by transportation system but provoked by climatic events. Paper orientation gives another meaning to traveling time minimization, but it also introduces a proposal on how it is possible to prevent affectations to user's health by checking transfer stations.

This paper is organized as follows: in section two, the modeling of the system is presented. The third section presents how the user protection measurements are defined.

Section four present the design of the algorithm while section five presents a parallelization of the Algorithm. Finally, in section six, some conclusions of the utility of the algorithm as a tool for the protection of public transport users are presented.

2 System Modeling

In this section, we present a mathematical model of a public transportation system *(PTS)* that considers weather conditions in order to make path-recommendations. *PTS = G(S, P)* where S is a set of stations and P is a set of paths between stations. Some definitions are presented next:

2.1 Defining Stations

A station is where users can get on and get off from transportation units. A station is also a space where users wait until the transportation unit arrives to that location. Stations could be physical which means that there is a physical construction, or they could be virtual which means that there is a space used as a station but there is no construction or special designated space for that station. For this paper, there are two types of stations: simple stations and transfer stations.

2.1.1 Simple Stations

A simple station, the i-th station in the transportation system at time t, is represented as $s_i^t = \langle \alpha_i^t, \beta_i^t, e_i^t, \delta_i \rangle$. Variables described next:

α_i^t This function retrieves the next scheduled arrival of a transportation unit to the *i-th* station at time t. For instance, $\alpha_{17E}^{09:15}$ retrieves the next scheduled-time when a transportation unit would arrive to the station 17E. When current time is 09:15 h then the value of α would be $\alpha = 09{:}23\,\text{h}$; while $\alpha_{17E}^{15:35} = 15{:}57$. These values are statically assigned to each station.

β_i^t This function retrieves the number of users in the *i-th* station at time *t*. For instance, $\beta_{17E}^{16:24}$ retrieves the number of users already present at station 17E at 16:24 h; then, an answer would be $\beta = 28$ while $\beta_{17E}^{20:18} = 52$. These values come from statistical analysis done at each station in the *PTS*.

e_i^t This function retrieves all stations nearby the station s_i^t under some criteria of proximity. For example:

$$e_i^{08:46} = \{\langle s_{20F}^{08:46}, 65\rangle, \langle s_{11H}^{08:46}, 70\rangle, < s_{8C}^{08:46}, 120 >\}$$

These values are statically assigned to each station in the PTS.

δ_i This variable is the adaptation of the *i-th* station to extreme weather conditions. This value comes from a checklist applied to that particular station which contributes to rate how well adapted is that station to extreme weather. For instance, if the station has roof, walls, sits, or it is adapted to avoid floods, it is near to a safe place, etc. All features previously described make a station has a better protection rate $0 \leq \delta_i \leq 1$.

With these previous definitions, it is possible to define a set of stations in the entire transportation system. This set is defined as $S = \left\{ s_1^t, s_2^t, \ldots, s_\eta^t \right\}$ where $\eta = |S|$ is the number of stations in the PTS.

2.1.2 Transfer Stations

A transfer station is a tuple defined as: $\varphi^t_{xy} = < s^t_x, s^t_y, w_{xy}, \sigma_{xy}, \tau >$ and it is required when users need to change transportation units to continue their journey. The description of its elements is presented next.

$s^t_x \epsilon S$ This is a station where users get off from a transportation unit.

$s^t_y \epsilon S$ This is a station where users wait until they get on a transportation unit in order to continue their journey.

w_{xy} It is the time users spend when walking from station s^t_x to station s^t_y.

σ_{xy} It represents the level of protection of a transfer station to extreme weather conditions $0 \le \sigma_{xy} \le 1$. When considering a transfer station with station s^t_x and station s^t_y, then, $\sigma_{xy} = \left(\delta_x + \delta_y\right)/2$.

τ The status of a transfer station is represented as $\tau = \{0, 1\}$ where

$$\tau = \begin{cases} 0, & \textit{the transfer station is not} - \textit{available} \\ 1, & \textit{the transfer station is available} \end{cases}$$

After these definitions, the set of all transfer stations in the transportation system is defined as: $\Theta = \left\{\varphi^t_{ab}, \ldots, \varphi^t_{yz}\right\}$ where $\psi = |\Theta|$ is the total number of transfer stations.

2.2 Defining Path Recommendations

Public transportation system has two types of paths: simple paths and complex paths recommendations. The details of their definition are presented next.

2.2.1 Simple-Path Recommendation

A simple path in the transportation system is a sequence of stations needed to travel from one station to another. They are represented as: $p^t_{az} = \left(s^t_a, \ldots, s^t_z\right)$ where s^t_a is the beginning of the path and s^t_z is the final destination. The number of stations in the path is defined as: $\mu = \left|p^t_{az}\right|;\ 0 < \mu \le \eta$. If the station s^t_z is the next station from s^t_a then $\mu = 1$. If user requires two stations to travel from s^t_a to s^t_z then $\mu = 2$ and so on.

The set containing all paths in the transportation system is defined as: $P = \left\{p^t_{12}, \ldots, p^t_{wz}\right\}$. The number of paths in P is defined as $= |P|$.

2.2.2 Complex-Path Recommendation

A complex path is a sequence of two or more simple paths joined by transfer stations. They are represented as follows: $\phi^t_{az} = \left(s^t_a, \ldots, \varphi^t_{mn}, \ldots, s^t_z\right)$. The entire complex path could be disabled if at least one transfer station is disabled $(\tau = 0)$.

2.3 Flexible Path Recommendation

Under this public transportation model, it is possible that a transfer station could be disabled $(\tau = 0)$ when the number of users exceeds its capacity, or a transportation authority decides to disable it. So, in other to make the transportation system more flexible, the model finds additional paths starting or finishing in alternative stations.

These additional paths are added to the original set of paths and the system now has to find an optimal recommendation considering all possible paths.

To clarify this concept, let's present an example. Be p^t_{ij} the path needed to be more flexible. To make this happen, it is necessary to find all stations which are nearby the initial station (s^t_i). This set of stations could be $I = \{s^t_1, s^t_2, s^t_3\}$. Also, it is necessary to find all stations which are nearby the final station (s^t_j); this set of stations could be $\mathrm{F} = \{s^t_a, s^t_b\}$. Thus, a set of alternative paths to the original path p^t_{ij} could be defined as follows: $e^t_{ij} = \{p^t_{1a}, p^t_{1b}, p^t_{2a}, p^t_{2b}, p^t_{3a}, p^t_{3b}\}$. Therefore, $E = \left\{e^t_{ab}, \ldots, e^t_{yz}\right\}$ defines a set of alternative paths in the transportation system. From this perspective, if a path is disabled for some reason, then, the transportation system has some alternative paths still to consider.

3 Measuring User Protection

In this section, it is defined how the transportation system could protect users from extreme weather conditions. There are two variables to consider: total traveling time and user protection in transfer stations. The definition of them is presented next.

3.1 Total Traveling Time in Paths (T_{total})

The total traveling time is a variable that counts the amount of time that a user spends in the transportation system. This variable considers three values: time on-board (T_{board}), walking time (T_{walk}) and waiting time (T_{wait}).

$$T_{total} = T_{board} + T_{walk} + T_{wait} \tag{1}$$

- Time on-board (T_{board}). This value is the time that user spends on board of a transportation unit.
- The walking time (T_{walk}). This variable is the time needed to walk from the final station of the first path to the initial station of the next path.
- The waiting time (T_{wait}). It is the difference between the current time and the next scheduled time for a transportation unit to arrive to a transfer station.

The computation of T_{total} varies when a path is simple or complex, more information on these variations are shown next.

3.2 For Simple Paths

Let's define $t_{i(i+1)}$ as the time spent by users when traveling on transportation units from station s^t_i to the immediate next station s^{t+1}_{i+1}. Then, the time (β_{ij}) spent by users traveling in a path (p^t_{az}) could be defined as follows:

$$\beta_{ij} = \sum\nolimits_{i=1}^{n} t_{i(i+1)} \tag{2}$$

Then, for simple paths like $p_{az}^{t} = \left(s_a^t, \ldots, s_z^t\right)$, T_{board} is computed as the time spent in the path p_{ij}^{t} without leaving the transportation unit. Thus, $T_{board} = \beta_{ij}$, $T_{walk} = 0$ because the user does not need to walk during the travel.$T_{wait} = \alpha_a^t$; where α_a^t is the time spent by users waiting at the initial station s_a^t.

3.3 For Complex Paths

In case of a complex path, like the following: $\phi_{az}^{t} = \left(s_a^t, \ldots, \varphi_{mn}^t, \ldots, \varphi_{wy}^t, \ldots, s_z^t\right)$, the time on-board (T_{board}) is the summation of the time to ride the three paths: p_{am}^t, p_{nw}^t, p_{yz}^t.Then

$$T_{board} = \beta_{am} + \beta_{nw} + \beta_{yz} \tag{3}$$

The value of T_{walk} considers the walking time inside the transfer station φ_{mn}^t to go from station s_m^t to station s_n^t and inside the transfer station φ_{wy}^t from station s_w^t to station s_y^t. Then, this variable is computed as follows:

$$T_{walk} = w_{mn} + w_{wy} \tag{4}$$

Finally, the waiting time (T_{wait}) considering the transfer stations $\varphi_{mn}^t, \varphi_{wy}^t$ is defined as $T_{wait} = \alpha_a + \alpha_n + \alpha_y$ where α_a is the waiting time at station s_a^t, α_n is the waiting time at station s_n^t and, α_y is the waiting time at station s_y^t.

3.4 Defining the Total User Protection (Υ)

The value of the total user protection variable is computed considering the protection to extreme weather that each transfer station.

3.4.1 For Simple Paths

Considering the path $p_{az}^t = \left(s_a^t, \ldots, s_z^t\right)$ then $\Upsilon = \delta_a$ where δ_a is the protection of the initial station s_a^t.

3.4.2 For Complex Paths

Let's again consider the complex path : $p_{az}^t = \left(s_a^t, \ldots, \varphi_{mn}^t, \ldots, \varphi_{wy}^t, \ldots, s_z^t\right)$, this path has two transfer stations and each station has a value for adaptation to extreme weather defined as: σ_{mn} and σ_{wy}. Also, δ_a is the protection of the initial station s_a^t. Then, total user protection is defined as follows:

$$\Upsilon = \delta_a + \sigma_{mn} + \sigma_{wy} \tag{5}$$

4 Path Selection Algorithm

This section shows the algorithm to recommend a path in the transportation system that considers $ax\{\Upsilon\}, Min\{T_{total}\}$ (See Table 1).

Table 1. Algorithm to select a path recommendation using evolutive computing.

$P' = P \cup E$
For all $p_{ij}^{t} \in P'$ with initial station s_{a}^{t}, and final station s_{z}^{t}.
    For all φ_{xy}^{t} *in the path*
        If $\tau = 0$ then
            status=0
        end if
    end for
    if status $\neq$ 0
        Compute T_{total}
        Compute Υ
        Store path in vector χ
        Increment β_{i}^{t} in all transfer stations at time *t*.
    end if
end for
Select a path from χ that fulfills both objectives: $Max\{\Upsilon\}, Min\{T_{total}\}$.

Experimentation for this algorithm considers the city of Poza Rica's public transportation system (PR-PTS). This system has 45 routes, 1024 stations and a total of 1024 $\times$ 1024 paths where users can travel from a station to any other station in the PTS.

Using this PTS, the algorithm has to select a path that fulfils both objectives: $Max\{\Upsilon\}, Min\{T_{total}\}$. In order to explain how the algorithm works, a pair of stations from PR-PTS are selected.

Initial station: station [A-EB500] named "Civic Plaza" belonging to route [RB03-A] "Downtown – November 20th".

Final station: station [B-EB196] named "Gas station Lopez" belonging to the route [RTX05-B] "Technologic - Downtown".

This pair of stations have three paths in the PR-PTS to take users from initial station to final station. However, the initial station has thirteen nearby stations and the final station has four nearby stations. Thus, the algorithm considers 3 solutions for user-selected initial and final stations; but there are also (13 * 4) alternative solutions.

Each alternative path which consist of an alternative initial station and an alternative final station. In the case of the PR-PTS has 10 possible paths in average. Thus, the algorithm has to decide an optimal path that satisfies both objectives: $Max\{\Upsilon\}, Min\{T_{total}\}$ between 3 + [(13 * 4) * 10] = 523 possible solutions.

Figure 1 shows the evaluation of all 523 possible paths to travel from initial station to final station. X-axis considers the total time (T_{total}) spent by user in the PR-PTS and y-axis considers the protection value (Υ) of a path for user sensitive to extreme weather conditions.

Figure 2 shows the Pareto front of paths that fulfills both objectives: $Max\{\Upsilon\}$, $Min\{T_{total}\}$.

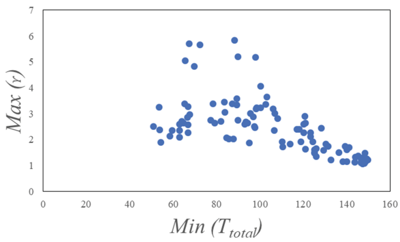

Fig. 1. Evaluation of all possible paths going from initial to destination stations.

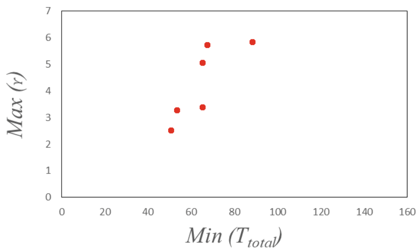

Fig. 2. Paths that fulfills both objectives: $Max\{\Upsilon\}, Min\{T_{total}\}$.

5 Algorithm Parallelization

This section presents the parallelization of the requests for path recommendations made by public transportation users. For example, Fig. 3 shows the time spent the computation of selecting a path recommendation for 2, 4, 8, 16 thousands of users. As can be seen, the algorithm is time consuming. However, Fig. 4 shows how processing time can be reduced when using concurrent programming. Distributing tasks between the processing elements is a well-known technique for reducing computation time.

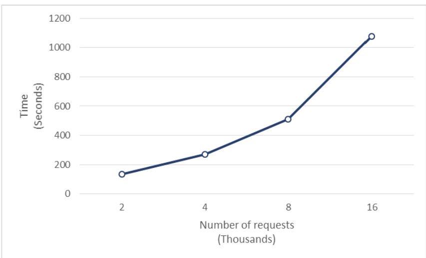

Fig. 3. Finding an optimal path for 2, 4, 8, 16 thousand PR-PTS concurrent users.

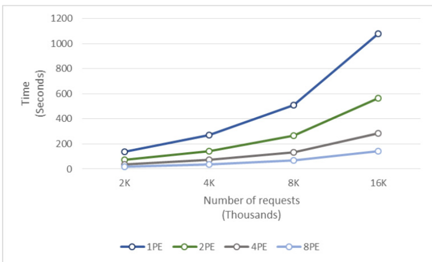

Fig. 4. Optimization of the algorithm using distributed computing.

6 Conclusions

This paper presents a research oriented to help people sensitive to extreme weather conditions such as: elders, pregnant women, children, etc. This research involves an algorithm that makes path recommendations considering the minimum time needed to travel from one station in the PTS to another one. At the same time, the algorithm considers maximizing the user protection against extreme climate conditions.

The algorithm considers all paths possible including alternative paths to departure from stations which are nearby the initial station or arrive to a station which is nearby the final station. Once all paths are defined, then, the algorithm uses a non-dominant function to decide which path better fulfills bi-objective criteria to maximize user protection and minimize the total time users spend in the transportation system.

This paper also shows how to improve the algorithm performance by distributing the requests for path recommendations between several processing units.

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