# EMERGENCY PREDICTION IN ELECTRIC UTILITIES: A CASE STUDY FROM SOUTH BRAZIL

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## KEYWORDS

Emergency orders, forecasting, dynamic vehicle routing.

## ABSTRACT

This work proposes a methodology to predict emergency requests on electric distribution utilities, based on the historical data in order to promote a further pro-active routing by reducing a dynamic vehicle routing in its static form. The proposed methodology aims to minimize the average service time for emergency services, from the consideration of typical aspects that exert influence on the service time required: the day of the week, time of the day and the geographical location where services are requested. A case study from actual data is presented to show how the methodology can be applied.

## INTRODUCTION

In the electric power utilities sector, there is a set of orders to be attended by a set of teams. The set of orders includes two subsets: the subset of commercial orders and the subset of emergency services. The former is known in advance and the latter is only known when vehicles are proceeding with theirs routes (Garcia et al. 2014).

The attendance of emergency services in electric utilities corresponds to a major and a high impact task related to the Network Operation Center. Not only by assuring security procedures but also by promoting efficiency and effectiveness on the services provided, accomplishing these random requests is a challenge especially with the occurrence of extreme climate changings, as in the South Brazil.

Since the Network Operation Center also manages service requests of non-emergency character, a general concern involves how to plan maintenance crew routes from the assumption that there will be unknown requests that will have to be attended immediately. The optimization problem involved in the routing planning corresponds to the vehicle routing problem (Toth and Vigo 2001), a well-studied problem with a large range of contributions (Eksioglu et al. 2009).

When assuming a scenario to handle emergency requests, the vehicle routing problem takes its dynamic form (Psaraftis 1995; Pillac et al. 2013). By knowing gradually these emergency requests in such a way that vehicles are following their pre-established routes, the question that arises from this context is how much time to wait in order to reprogramming their paths: (Larsen et al. 2002) suggest that the "degree of dynamism" may be considered. Another approach may be to predict these stochastic requests in order to obtain a static vehicle routing problem, which is the proposal of this paper.

This work presents a methodology to predict emergency services in an attempt to answer the following questions when a pro-active routing is assumed:

1. Which is the period of time over the time horizon considered that will be emergency requests?
2. Which are the locations where the random requests will occur?
3. How much time each emergency request predicted will involve as service time?

By answering the first question, the proposed methodology furnishes a time window to be considered in the static vehicle routing. The answer to the second question corresponds to the geographic consideration of dummy nodes in the vehicle routing problem. And finally, answering the last question one defines the service time to the dummy nodes previously created.

It is worth noting that the contribution of this work is only part of a more sophisticated dispatch system, as pointed out by (Weintraub et al. 1999). The following sections detail the proposed methodology, the case study developed from actual data and finally the final remarks.

## METHODOLOGY

Planning routes to maintenance crews is part of a dispatching process in electric distribution utilities, from the consideration of two main kinds of orders, which can be described as (Garcia et al. 2014):

a) The commercial orders: known in advance and are typically created from customer requests;
b) The emergency orders: these orders are not known a priori and can occur at any moment.

The dispatch of commercial orders is performed by the method proposed by (Garcia et al. 2014), comprising the well-know vehicle routing problem in its static form. From the business processes usually employed by the

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electric distribution utilities, the same maintenance crew that serves commercial orders should also attend emergency requests, thus qualifying a multitasking character and involving a partially dynamic vehicle routing problem as described by (Larsen et al. 2002).

Figure 1 illustrates a hypothetical routing solution to commercial orders: route 1, starting at node 1 and visiting nodes 3, 5 and 7; route 2, starting at node 2 and visiting nodes 8, 6 and 4. Since this routing problem involves on site service time due to the nature of the problem of attending service orders (Garcia et al. 2014), the arrival time at each node should be calculated. For this example, they are presented on Table 1 in minutes in the last column, as well as the service time also presented in minutes.

When considering partially dynamic scenarios, a certain number of emergency orders come up, two as the example of Figure 2 (emergency orders 9 and 10). The question that may arise is the moment when this perturbation occurs: if we consider the occurrence of both orders at instant t=0, a possible solution may be that one presented in Figure 3. However, if this occurrence is on instant of time t=27, only after completing services 3 and 8 that both 9 and 10 come up, making the most preemptive behavior as that presented in the solution of Figure 4.

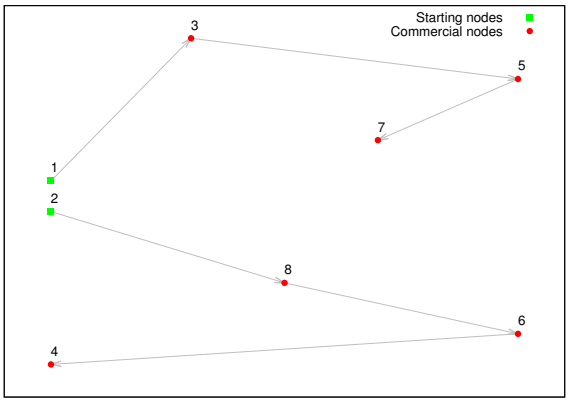


Figure 1: A hypothetical routing solution to commercial orders.

Table 1: Arrival times for the example of Figure 1.

| Route | Node | Service time | Arrival time |
|---|---|---|---|
| **1** | 1 | 0 | 0 |
| **1** | 3 | 10 | 15.23 |
| **1** | 5 | 3 | 39.79 |
| **1** | 7 | 55 | 60.27 |
| **2** | 2 | 0 | 0 |
| **2** | 8 | 6 | 12.20 |
| **2** | 6 | 3 | 29.38 |
| **2** | 4 | 30 | 55.61 |

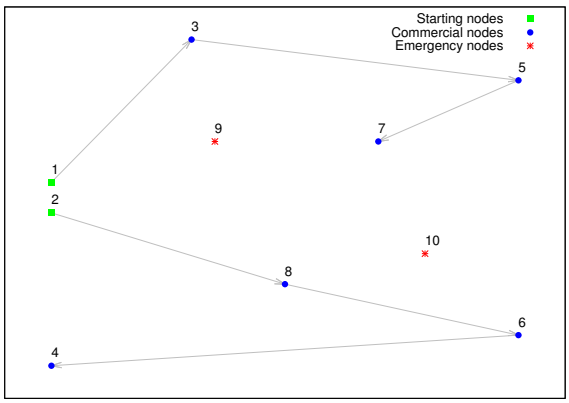


Figure 2: Hypothetical instance of emergency dispatch problem.

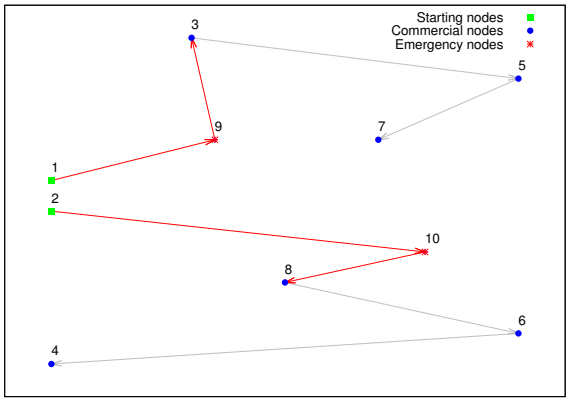


Figure 3: Solution for instance of Figure 2 (t=0).

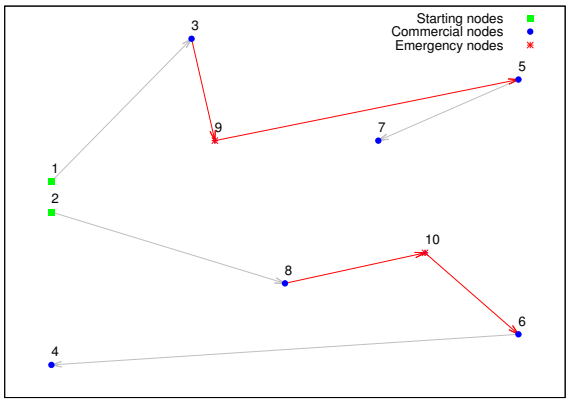


Figure 4: Solution for instance of Figure 2 (t=27).

The main inspiration for the proposed approach to handle this partially dynamic vehicle routing problem comes from the recent work of (Ferrucci et al. 2013), which describes a pro-active real-time control approach for dynamic vehicle routing problems. Following the same approach of Ferrucci et al. that considers historical request information, future emergency requests are predicted without assuming any prescribed probability distributions.

This work presents the following attributes as those fundamental to be considered in carrying out the emergency requests: (i) the location of the service, i.e. where is the customer order demand; (ii) time of occurrence; and (iii) service time. At the same time, it is assumed that the management of services to handle the assignment and routing decisions related to the maintenance crews involves observance of route time, since these crews have strict workload which may not be violated.

The definition of which variables significantly influence the occurrence of an emergency service order has been performed from the correlation analysis between the following variables: (1) Cause of the emergency event; (2) Latitude; (3) Longitude; (4) Year; (5) Month; (6) Day of the month; (7) Weekday; (8) Time of day; and (9) Service time. Afterwards, random variables and their domains (continuous or discrete) are defined. It is known that each random variable is quantified by a probability density function, so to identify the distribution of each variable the following steps were followed as (Taha 2007):

1. Summary of the raw data in the form of a suitable frequency histogram function to determine the empirical probability density associated with the random variable (day, time and geographical location);
2. Analysis of the dispersion of the number of service time hours by each geographical area considered;
3. From the definition of empirical Probability Density Function that every random variable (X) belongs, are calculated the expected value E(x) and standard deviation (σ);
4. Calculation of probabilities from frequency distribution ranges for service time considering day of week, time of day and the discretization of the geographical area assumed.

This method of prediction added the service time for every day of the week and every hour of day, with an estimated probability of occurrence in a particular geographic area.

Following these steps, one can obtain the dummy nodes, with their corresponding geographic locations and service time.

From a broader perspective, one can be easily situated on how to use this procedure in a more sophisticated dispatch system following the flowchart of Figure 5. At the beginning, all the information about teams is available, called "Team data", like workday hours, average speed and location. At the same time, all the information about the orders is also available from the database system, depicted as "node data", which means to capture location, service time and priority of those orders assumed as commercial ones. From the historical data, the procedure namely "dummy node prediction" corresponds to the methodology described by steps 1-4, in such a way that these nodes can be assumed a-priori by the dispatch system, thus performing a static vehicle routing. By executing "vehicle routing algorithm", one obtains the planned routes to all teams considered and including not only the commercial orders but also an "estimation" of possible occurrence of "emergency nodes", namely "dummy nodes", as previously depicted in Figure 1-Figure 4.

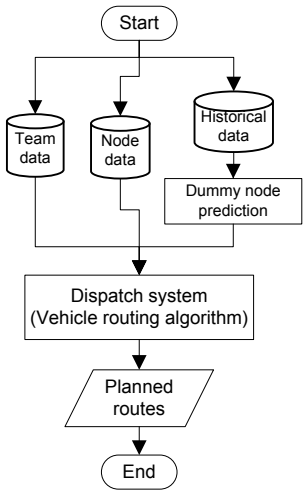


Figure 5: The proposed methodology in the whole dispatch system.

The next section presents the case study developed to show how to apply these four steps.

## CASE STUDY

The case study developed for testing and validating the proposed methodology is based on the observation 27989 occurrences of emergency services in an electric distribution utility, comprising a horizon of 392 days.

After accumulating these 27989 occurrences in each of 24 hours of day, the sample size is equal to 9408 units. Figure 6 depicted the service time in hours for each one of these 9408 units. After reducing the relative standard deviation from 102% to 79%, by removing approximately 3.6% of the sample, one obtains a reduced sample as shown in Figure 7.

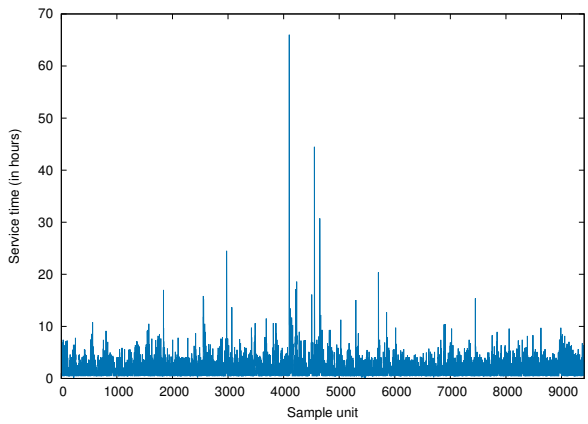


Figure 6: Service time for raw data.

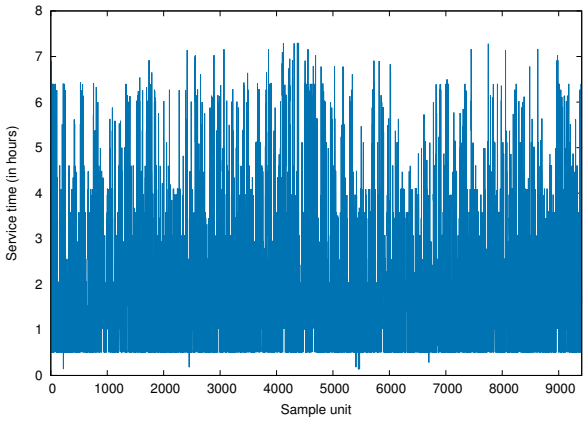


Figure 7: Service time for the reduced sample.

Next, it is necessary to carefully observe how data behave as the random variables assumed on the day of the week, the time of day and the geographical distribution. Figure 8, Figure 9 and Figure 10 analyze the reduced sample for the day of the week, the time of day and the geographical distribution, respectively. The latitude and longitude axis of Figure 10 are discretized according to the number of each box defined by following a pre-established size 16 km$^2$. This size is justified from the moment that routing for planning purposes, displacements within each box are disregarded.

From the analysis of Figure 8-Figure 10, one can conclude the following:

- Business days have similar behavior; Sundays and Saturdays require an individual analysis;
- In fact the time of day must be assumed in particular for every day of the week considered;
- Discretization of the geographical area in boxes of 16 km$^2$ (4 km x 4 km) allows the consideration about high demand regions.

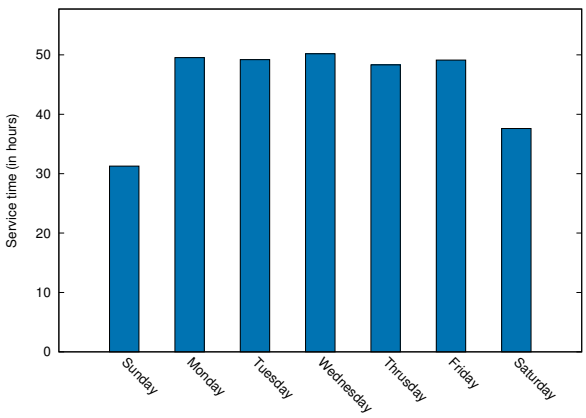


Figure 8: Analysis for the variation on "day of the week" variable.

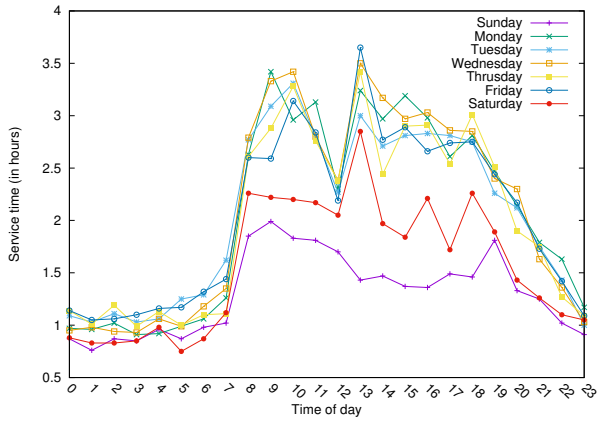


Figure 9: Analysis for the variation on "time of day" variable.

The next step corresponds to an attempt to answer the questions pointed out in the first section of this work: (1) Which is the period of time over the time horizon considered that will be emergency requests? According to Figure 9, the period between 7 and 20 hours of any business day is the most relevant to be considered; (2) Which are the locations where the random requests will occur? According to Figure 10, only a small subset of the potential locations are the most relevant with regard to the service time required; (3) How much time each emergency request predicted will involve as service time? The service time of each box of Figure 10 may help to evaluate how many working hours will be needed.

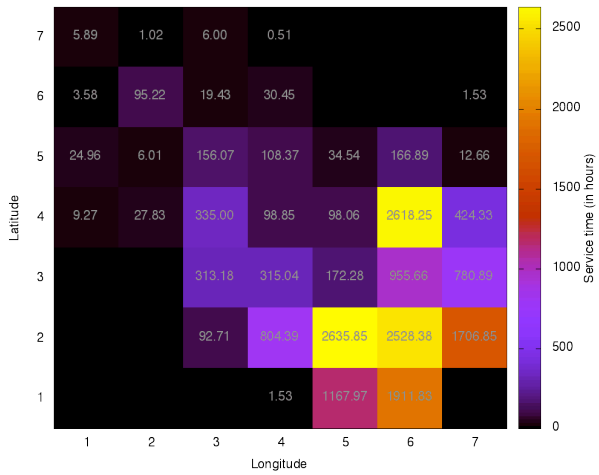


Figure 10: Analysis for the variation on "geographical distribution" variable.

The next step refers to the measurement of these quantities and the sample separation strategies in defined quantities. Considering that we are trying to predict the level of service time required to a period of a certain Tuesday, between 8 am and 12 pm, one must find the historical data for all occurrences of a Tuesday, between 8:12 in the morning, as Figure 11 summarizes. After that, occurrences need to be stratified in the geographical area according to the set division: since time of day is very important, Figure 12-Figure 16

includes the service time of each hour between 8 and 12 in the morning over the discretization of Figure 10.

With this result, each hour (8:12) has the its service time demand stratified within 49 boxes, and one may conclude that the area with the highest demand is not the same when comparing the hours.

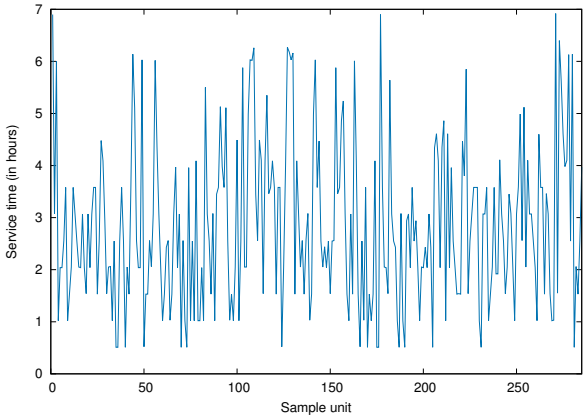


Figure 11: Service time for the Tuesday, between 8 am and 12 pm.

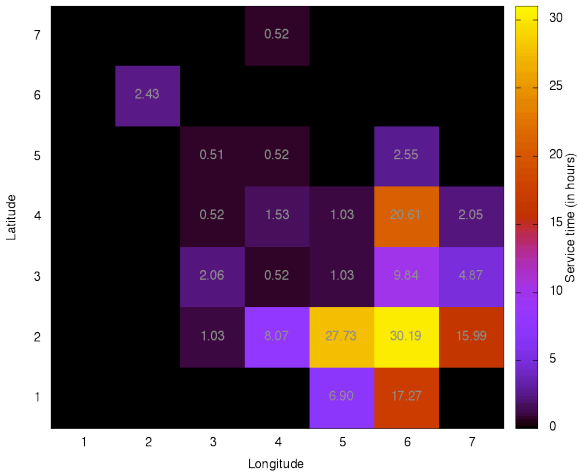


Figure 12: Historical service time on Tuesday, 8 am.

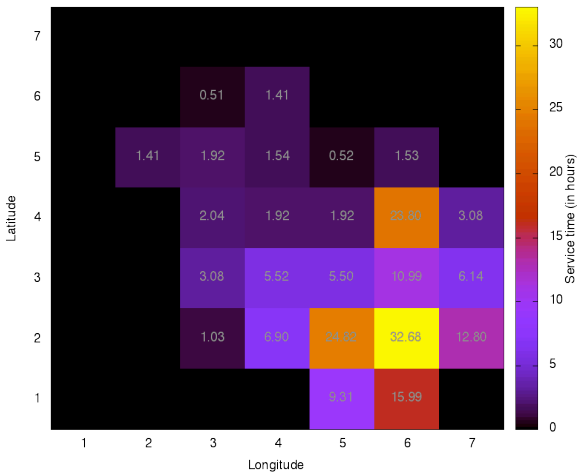


Figure 13: Historical service time on Tuesday, 9 am.

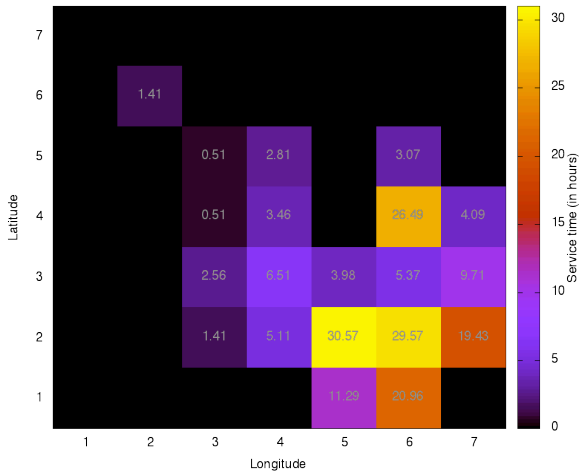


Figure 14: Historical service time on Tuesday, 10 am.

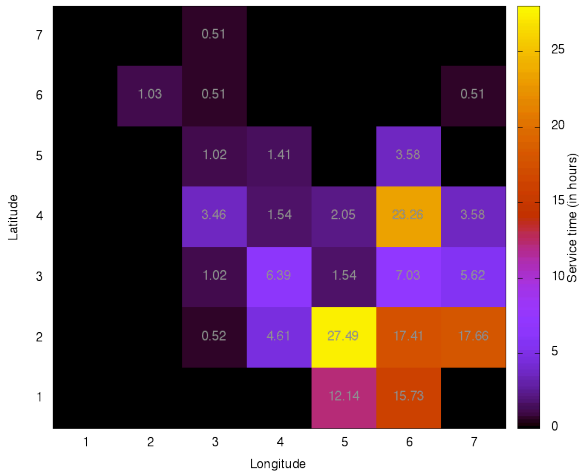


Figure 15: Historical service time on Tuesday, 11 am.

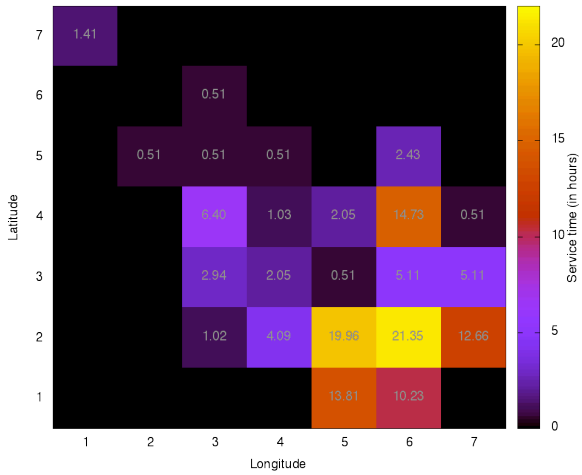


Figure 16: Historical service time on Tuesday, 12 pm.

Now it is time to define the level of service time in each area selected, for every hour considered: 8 am – 12 pm. According to (Taha 2007), this calculation may be done by assuming a random variable with empirical distribution and obtaining the expected value of each one of these variables: each variable corresponds to a box previously selected. First it is defined the histogram

information of each box for each hour, for instance, box (2;6) of Tueady, 8 am, Figure 12. Table 2 summarizes these results, resulting in a expected value of 0.56253 hours of service time.

Table 2: Histogram information about the service time for box (2;6) of Tuesday, 8 am.

| # Interval | Range | Observed frequency | Relative frequency | Cumulative frequency |
|---|---|---|---|---|
| 1 | [0-0.51090] | 48 | 0.92308 | 0.92308 |
| 2 | (0.51090-0.73465] | 0 | 0 | 0.92308 |
| 3 | (0.73465-0.95840] | 0 | 0 | 0.92308 |
| 4 | (0.95840-1.18215] | 4 | 0.07692 | 1.00000 |

These calculations are proceed for all boxes in each hour, thus resulting a new map, this turn showing the expected value of service time for each box, as pointed out in Figure 17 for Tuesday, 8 am.

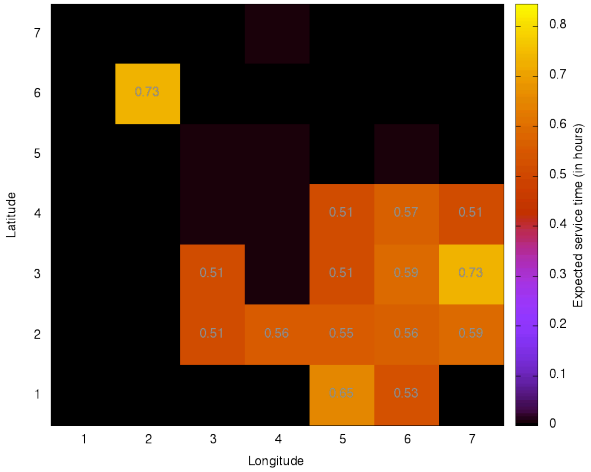


Figure 17: Expected service time for Tuesday, 8 am.

## FINAL REMARKS

This paper has presented a methodology to predict emergency requests in electric distribution utilities, based on historical data in order to allow a further pro-active routing, which is understood as a way of reducing a dynamic vehicle routing in its static form.

Even considering that this approach has a large number of open questions about the effectiveness, the simplicity involved turn easy its consideration on actual scenarios at least to obtain a estimation about lower bounds on route efficiency over a certain planning horizon.

Another favorable point refers to the low response time and the effort required to be self-adaptive over the time.

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