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Where will the next emergency event occur? Predicting ambulance demand in emergency medical services using artificial intelligence

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ABSTRACT

Predicting demand in emergency medical services is crucial for saving people's lives. Most studies aggregate demand prediction within a zone, failing to offer insights at a more detailed level. This study aspires to fill this gap by introducing a novel, three-level, spatial-based approach that identifies the geographical location of expected emergency events. First, the proposed methodology introduces new concepts and notions to model emergency events, as sets of interconnected points in space, that create paths over time. Second, based on these paths, an artificial neural network, optimized using a new evolutionary algorithm, predicts the location of future demand (emergencies). Third, based on the predicted demand, a location-allocation model is applied to site ambulances prior to actual emergencies occurrence, enhancing thus location planning and decision making. This method is applied to a dataset comprising 2851 emergency events in Athens, Greece, and the outcomes are evaluated based on the actual emergency events occurred. Results show that the mean distance, between an actual emergency event and the nearest ambulance, located based on the expected demand as estimated by our approach, deviates by 110 m relative to the optimal solution. This deviation, adds only a few seconds of delay to the response time of an ambulance relative to the theoretically optimal solution (post hoc location). In addition, it improves the current solution (in which ambulances are waiting in a set of fixed location throughout the year), by > 1 km, decreasing significantly response time. From a policy perspective, these results indicate that assessing expected emergency events through the proposed method, would allow medical services to optimally locate ambulances in advance, reducing response time and thus increasing survival rates and public safety.

1. Introduction

Decisions regarding vehicle location and dispatching are both crucial and challenging for every emergency medical service (EMS) (Goldberg, 2004). As the volume and the location of emergency events highly vary, difficulties in the positioning of ambulances and their crews, while waiting for the next call, arise (Ingolfsson, 2013). Location-allocation models have been extensively used to determine where to place ambulances in cities in order to cover demand in an optimal or near optimal way (Grekousis & Photis 2013, Henderson & Mason, 2005), and detailed reviews have been conducted by Bélanger, Ruiz, and Soriano (2019), Aringhieri, Bruni, Khodaparasti, and Van Essen (2017), Li, Zhao, Zhu, and Wyatt (2011), Erkut, Ingolfsson, Sim, and Erdogan (2009), and Daskin (2013).

Location-allocation problems can be formulated for EMS requirements as problems regarding the optimal location of p centers (ambulance locations) in a region and the corresponding allocation of demand, d (emergency events), to these centers, by minimizing some sort of cost/criterion (the objective function).

In fact, one of the most important parameters in solving location problems is the selection of a suitable criterion to be minimized, so that demand is optimally allocated to the centers (Rahman & Smith, 2000). Location problems can be classified, based on the perspective that the objective function is formulated, into three broad categories: the covering problem, the center problem, and the median problem (Daskin, 2013). The covering problems can be approached mainly by the set covering problem, and the maximum covering problem (a review of these models can be found in [ReVelle, Williams, & Boland, 2002]), which have been widely applied in the EMS context (Daskin, 2013). In the set covering problem, the objective is to minimize the number of ambulances that cover all demand within a specified a distance (or time). The maximum covering model provides an alternative objective, to maximize the demand that can be covered given a number of ambulances. This model assesses the tradeoff between additional

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ambulances and coverage, offering thus valuable information for planners and policy makers. A different perspective is offered through the *p*-center problem which minimizes the maximum distance between demands nodes (emergencies) and their closest facility (see Section 2.3 for model formulation and review). When applying this model, we are interested in covering the entire demand since we minimize the maximum distance that an emergency lies from the nearest ambulance. While coverage and center problems deal with extreme values (e.g. minimize maximum distance, or maximize coverage) the *p*-median problem minimizes the averaged (or total distance) between demand and a given number of ambulances (Daskin, 2013; Hakimi, 1964; ReVelle, Eiset, & Daskin, 2008). Many variants of the above models have been developed to address additional restrictions, factors and parameters such as probabilistic, maximal survival, equity, multiperiod, dynamic relocation, and real-time models (for a thorough review, see Bélanger et al. (2019)).

The mathematical formulation of the minimization criterion through an objective function reflects other social and philosophical issues such as the public or private nature of the facilities, and equity or fairness related to how people are homogeneously satisfied/covered from the provided services (Bélanger et al., 2019). For instance, in case of EMS a common criterion is to minimize the average distance between ambulances and the emergency events (which can be solved through the *p*-median problem). Still, such criterion tends to favor people residing in high densely populated areas in comparison to people living in less densely populated areas that are also further away from the prospective centers (Calik, Labbé, & Yaman, 2015). An alternative criterion would be to minimize the maximum distance that an ambulance should travel to an emergency (which can be solved through the *p*-center model) offering thus equity in facility location analysis (Marsh & Schilling, 1994). Still this approach tends to increase the average response times.

How location models will maximize public welfare is controversial and there is a large debate on the topic lately (Bélanger et al., 2019). In the context of EMS, classic coverage models tend to produce inequitable solutions as they offer better coverage to densely populated areas in comparison to low populated areas (Bélanger et al., 2019). On the other hand, considering equity issues may lead to inflated response times and as such to lower survival rates. Balancing between equity and effectiveness is not trivial but efforts have been made to provide formulations that guarantee both sufficient and fair response to all demand points (Calik et al., 2015; Chanta, Mayorga, Kurz, & McLay, 2011; Chanta, Mayorga, & McLay, 2014).

Although median and covering location allocation models are popular in public facility location problems (Bélanger et al., 2019; Daskin, 2013; Rahman & Smith, 2000), in this paper we are considering a criterion that focuses on the poorest served emergencies and as such we apply the *p*-center model. In a wider context, it is quite common that the efficiency of services that are beyond some critical distance declines (Rahman & Smith, 2000). Therefore, it's rational to consider maximum distance in formulating EMS problems and the *p*-center model which offers a fairer solution. For this reason, the *p*-center problem is not only widely used for determining optimal locations in EMS (i.e., fire stations, or police stations), but it can be applied whenever human life is at stake (i.e., natural or human-caused disasters, terrorist actions, or other criminal activities), by minimizing the worst-case offered service for evacuation and rescue (Calik et al., 2015). Still, we have to point out, that our research is not about location models in general, but on how demand can be modeled. For this reason, we apply a simple - from the mathematical formulation perspective - location-allocation model (*p*-center model), and we focus mostly our research on demand prediction. Additional location models along with related restrictions should be tested, something planned for future research.

Regardless of the restrictions, parameters and objective function involved, demand is one of the most critical parameters in a location-allocation model (Photis & Grekousis, 2012, Redondo, Fernández, García, & Ortigos, 2009). No matter which location-allocation model is selected, inaccurate demand estimation leads to incorrect positioning of the corresponding centers (ambulances) and low overall model performance, which may have fatal consequences (Li & Yeh, 2005). In this sense, predicting emergency demand is key to a successful and effective EMS, as it allows for enhanced spatial planning through better vehicle dispatching before event occurrence, which can significantly improve response times, pre-hospital care, and survival rates (Aringhieri, Carello, & Morale, 2016; Goldberg, 2004; Setzler, 2007).

Although crucial to EMS performance, demand forecasting has received limited research attention in the EMS context (Aringhieri et al., 2017). Regression models and statistical analysis are among the most widely used methods for demand prediction (Mabert, 1985, McConnell & Wilson, 1998, Brown, Lerner, Larmon, Gassick, & Taigman, 2007, Matteson, McLean, Woodard, & Henderson, 2011). For instance, Jasso et al. (2007) used a multiple regression linear model to predict the emergency calls received by San Francisco Bay area EMS. The model was calibrated using 730 days of data and was proven effective for detecting anomalously high numbers of calls. Channouf, Ecuyer, Ingolfsson, and Avramidis (2007) studied variations in daily and hourly call volumes through autoregressive models for the city of Calgary, Canada. Artificial neural networks (ANNs) were used by Setzler, Saydam, and Park (2009) to predict emergency call volume for the county of Mecklenburg, North Carolina. They investigated how the use of ANNs might improve forecasting at various temporal and spatial granularities. They embedded spatial analysis in their method by creating rectangular grids that were overlaid on the study area, and the ANN predicted the demand volume within each grid cell.

Sasaki, Comber, Suzuki, and Brundson (2010) used a genetic algorithm to locate ambulances in Niigata, Japan. They predicted emergency events based on five-year intervals from 2020 to 2050 by correlating current emergency cases with demographic factors at the census-area level. They estimated future emergency cases in relation to predicted population changes. In another study, singular spectrum analysis was used to predict daily ambulance demand in Wales (Vile, Gillard, Harper, & Knight, 2012). Finally, Grekousis, Manetos & Photis 2013 combined ANNs, GIS, and Kernel density estimation to generate maps of areas at high risk of future emergencies. More detailed reviews of studies dealing with demand prediction can be found in Setzler et al. (2009), Budge, Ingolfsson, and Zerom (2010), and Aringhieri et al. (2017).

Still, most of the studies described above focus on the volumes of expected emergencies within zones rather than on their geographic locations. Aringhieri et al. (2017) suggested that future studies should include spatial analysis methods combined with data mining techniques to identify the most likely locations of future emergency events.

This study's approach attempts to fill this gap. Our primary research assumption is that the display of similar spatiotemporal co-location patterns among emergency events indicates a spatial trend that, if captured, might enable the identification of similar future patterns (i.e., emergency events prediction). In other words, co-location patterns expressed as emergencies clustered in certain regions could hide a classification rule that can be used to predict future emergencies (Aringhieri et al., 2017; Mohan et al., 2011; Shang, Yuan, Deng, Xie, & Zhou, 2011). As EMS data is a typical example of spatio-temporal data, the hypothesized spatial trend can be captured by defining paths, as sequences of the emergencies served (Aringhieri et al., 2017). The analysis of such paths offers valuable findings providing evidence for inadequate coverage and thus a need to redeploy ambulances (Zhou, Shekhar, Mohan, Liess, & Snyder, 2011).

The approach is novel in three key ways. First, it develops a spatial-based method of handling temporal emergency events in order to formulate spatiotemporal paths of events, which we call “polyevents” (see Section 2 for definitions). To do so, we apply the improved Hungarian assignment algorithm in a progressive way (Jonker & Volgenant, 1986). The algorithm matches events among sequential timestamps on a one-to-one basis, to minimize the total distance cost among the assigned events. Second, examining these spatiotemporal paths of events enables us to predict the expected locations of future emergencies by identifying the next step in the sequence. To this end, the study utilizes ANNs to predict future expected emergency events locations (demand), whereas most current approaches aggregate predictions within certain geographical zones. Third, this study develops an evolutionary algorithm for ANNs' hyper-parameter optimization to a) avoid overfitting, and b) select the most appropriate neural network. ANNs hyper-parameter optimization is not trivial and using evolutionary algorithms has not been reported in a geographical EMS context. Results of the overall approach, are compared with the actual emergency events occurred as well as the with existing vehicle-locating practices (e.g., by using a location-allocation model).

Regarding the assignment problem (taking place in the first level of analysis), various applications can be found in the operational research, such as assigning people to jobs (Bhunia, Biswas, & Samanta, 2017), facilities to locations (Chmiel & Szwed, 2016), optimizing wireless sensor networks (Vinoba & Indhumathi, 2015), the traveling salesman problem (Oncan, Altinel, & Laporte, 2009), the shortest path problem (Wastlund, 2006), transportation problems (Bertsekas & Castañon, 1989), and to track moving objects in space (Burkard & Çela, 1999). A plethora of algorithms have been applied in attempts to find optimal or near-optimal solutions for various assignment problems. Extensive reviews of such attempts can be found in Abdel-Basset, Manogaran, Rashad, et al. (2018), Niknafs, Denzinger, and Ruhe (2013), and Pentico (2007). The improved Hungarian method, utilized in this paper is faster than the original Hungarian method and solves the matching problem. Still, as the assignment is unbalanced and occurs in a spatiotemporal context, we first define several concepts concerning the effective handling of emergency events, and then apply a specific process to run the algorithm to produce a time series (see Section 2).

The rest of this paper is organized as follows. Section 2 presents the study's theoretical approach for handling emergency events in a spatiotemporal context, and the formulation of the assignment algorithm. It also describes the main concepts of the evolutionary algorithm proposed for optimizing the ANN. Section 3 presents the case study and evaluates the computational results. Finally, section 4 discusses and concludes the overall approach, reflecting on various aspects of ongoing research.

2. Materials and methods

2.1. Conceptualizing spatiotemporal point emergency events

We introduce the following concepts and notions to enable better handling and modeling of spatiotemporal emergency events. Suppose that K and L are two given finite point sets of emergency events (EEs) in timestamps t and $t + 1$, respectively (see Fig. 1A). K consists of {i, i = 1,2, …m} EEs, and set L consists of {j, j = 1,2, …n} EEs.

We define as follows (see Fig. 1A and B):

Emergency Event- $\boldsymbol{EE_i^t}$**:** the location of the *i-th* EE that occurs in timestamp $\boldsymbol{t}$.

Timestamp $\boldsymbol{t}$**:** the time at which a set of EEs occurs. The step between successive timestamps is constant.

Polyevent $\boldsymbol{PE_i}$**:** $(EE_i^t \rightarrow EE_j^{t+1} \rightarrow \cdots EE_e^r)$ are sequential interconnected EEs in successive timestamps, where r is the total number of timestamps, and i, j, e are the *i-th, j-th*, and *e-th* EEs in time stamps t, $t + 1$, and r, respectively.

The proposed approach assigns m EEs of timestamp t to n EEs of timestamp $t + 1$, so that each EE of timestamp t is assigned to only one EE of timestamp $t + 1$ and vice versa. When three or more chronologically equally distanced timestamps exist, the process runs for each pair of successive timestamps (e.g., $(t,t + 1),(t + 1,t + 2)\ldots(r-1,r)$). Temporal distance depends on the problem at hand and data availability; it can take, for example, values such as hours, days, or weeks.

The sequential assignment of EEs creates spatiotemporal paths, which we call "Polyevents" (PEs; see Fig. 1B). In practice, matching EE sets is an unbalanced assignment problem, in which m agents are matched to n objects on a one-to-one basis to minimize costs or maximize benefits (Betts & Vasko, 2016, Yadaiah & Haragopal, 2016). The unbalanced assignment problem for modeling EEs is formulated as follows:

$$Minimize\ Z = \sum_{i=1}^{m} \sum_{j=1}^{n} d_{ij} X_{ij} \tag{1}$$

subject to.

$$\sum_{j=1}^{n} X_{ij} = 1, for\ i = 1, 2, 3, ..m \tag{2}$$

$$\sum_{i=1}^{m} X_{ij} = 1, for\ j = 1, 2, 3, ..n \tag{3}$$

where.

$$X_{ij} = \begin{cases} 1, \text{ if the } EE_i^t \text{ is assigned to } EE_j^{t+1} \\ 0, \text{ if the } EE_i^t \text{ is not assigned to } EE_j^{t+1} \end{cases} \text{ is the assignment matrix} \tag{4}$$

and d_{ij} is the Euclidean distance between EE_i and EE_j.when m equals n, we have the so-called "classical assignment problem" (Bertsekas, 1998), which can be solved using the well-known Hungarian method (also known as the Munkres algorithm; Kuhn, 1955). Although the Hungarian method has limitations, its main advantage is that it can easily be used for unbalanced assignments. This can be done by introducing dummy decision variables (Bhunia et al., 2017). Given the one-to-one restriction, some agents will remain unassigned when $m > n$ and some objects will be unassigned when $m < n$.

Likewise, when the number of EEs in one timestamp differs from the number of EEs in the next timestamp (as happens in practice), some EEs remain unassigned and do not participate in any PE (as a result of the one-to-one matching restriction). This may not be a problem in a typical unbalanced assignment. As we are interested in creating spatiotemporal paths for prediction, however, we need to retain as much data as possible. If we drop the unassigned EEs, we miss valuable information about their spatiotemporal distribution. For this reason, all EEs that are not initially assigned should be assigned in a second round of analysis.

All PEs that are complete (i.e., that have EEs for every single timestamp in a total of r) are called "first-order PEs," while PEs with EEs for fewer timestamps than r are called "second-order PEs." Both first-order (complete) and second-order (incomplete) PEs are used for the prediction process with the exception of second-order PEs with less than $r/2$ EEs (insufficient time series). For details on why the above notions are introduced as well as on the proposed approach, see the Discussion section.

An example of the process described above is shown in Fig. 2. Suppose we have four timestamps with six EEs in t_1, eight in t_2, four in t_3, and 10 in t_4 (see Fig. 2A). During the 1st algorithm run, four first-order PEs are produced (as many as the minimum number of EEs in t_3) (see Fig. 2B). In the second phase, the algorithm runs for the two EEs remaining in t_1, the four EEs in t_2, the zero EEs in t_3, and the six EEs in t_4 (see Fig. 2C). In practice, t_3 is no longer taken into account. The algorithm produces two second-order PEs with three EEs each. In the third run, there will be zero EEs in t_1, two in t_2, zero in t_3, and four in t_4 (see Fig. 2D). The process goes on between timestamps t_2 and t_4, generating two PEs with two EEs each.

2.2. ANNs and evolutionary hyper-parameters optimization

ANNs are inspired by the way the human brain works and aim to solve problems through extensive learning using data. A typical ANN

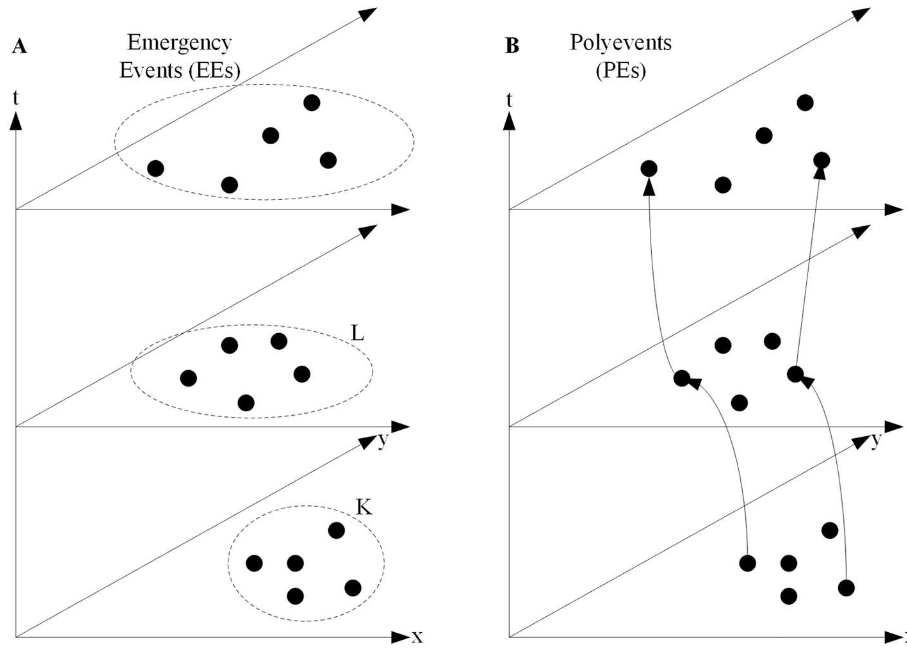

Fig. 1. A) EEs modeled as sets of points in sequential time intervals. B) The linkage of EEs creates time-series data (polyevents).

consists of connected neurons arranged in layers. An ANN with fewer than five layers is considered "shallow," while an ANN with five or more layers is considered a "deep learning" type (Goodfellow, Bengio, & Courville, 2016). One of the most commonly used ANNs in geographical analysis is the Multilayer Perceptron (MLP) (Gopal, 2017; Grekousis, 2019; Grekousis & Photis, 2013).

The MLP belongs to the feed-forward topology. In feed forward topology, information is transferred, through network's connections, in one direction, which is forward from the input layer to the hidden layers, and then to the output layer. In practice, each neuron receives inputs and activates outputs that are forwarded to the following layers (Openshaw & Openshaw, 1997). The input layer is the layer where we import the data. The output layer is used to compare results with known data (also called targets). The MLP learns by calibrating the weights of connections, so that the error between the known output and the network output is minimized. The error is calculated by a cost function and is then minimized by using an algorithm called a "learning algorithm." The most common supervised learning algorithm is the back-propagation with gradient descent. In backpropagation, the values calculated by the cost function are used to adjust the weights and biases back-to-back—from the last layer to the first. As we do not know which weights need to be corrected, all weights are adjusted (but not by the same amount) using the gradient descent method (for a more thorough explanation of MLP's architecture see Shalev-Shwartz & Ben-David, 2014).

Apart from the weights and biases, parameters known as "hyper-parameters" must also be adjusted (Bengio, 2012). Hyper-parameters are various settings that should be defined before training occurs; these include the learning rate, the momentum, the number of training iterations, the number of neurons, the number of hidden layers, and the weight decay regularization coefficient (L1 or L2), (Goodfellow et al., 2016). The process of identifying an appropriate value for a hyper-parameter is called "hyper-parameter optimization" (Bergstra & Bengio, 2012). Configuring the various architectural settings and hyper-parameter values of an ANN is challenging (Miikkulainen et al., 2018), mainly because the selection of a hyper-parameter value usually influences how another hyper-parameter performs. Thus, the order of hyper-parameter tuning is likely to influence the overall performance (LeCun, Yoshua, & Geoffrey, 2015).

There are three main hyper-parameter tuning methods: a) manually by trial and test, b) by grid or random search, c) by automated techniques such as Bayesian optimization or evolutionary optimization (Kotthoff, Thornton, Hoos, Hutter, & Leyton-Brown, 2017, Loshchilov & Hutter, 2016, Bengio, 2012, Snoek, Larochelle, & Adams, 2012, Bergstra, Bardenet, Bengio, & Kegl, 2011). As the complexity of ANNs (especially deep learning types) is increasing, the usual trial-and-test approach conducted by humans is becoming inefficient. Automated techniques such as evolutionary hyper-parameter optimization, which uses evolutionary algorithms, have started to emerge and are yielding promising results (Miikkulainen et al., 2018, Real, Moore, Selle, Saxena, et al., 2017, Loshchilov & Hutter, 2016, Young, Rose, Karnowski, Lim, & Patton, 2015).

Evolutionary algorithms (EAs) are heuristic search methods designed to mimic the evolution process. Types of EAs include evolutionary programming, evolution strategies, genetic programming, and genetic algorithms (Vikhar, 2016). Evolutionary algorithms are a flexible class of search algorithm that can generate new sample points in any search space utilizing genetic operators such as selection, mutation, and recombination. Although the general principles of EAs are common to all EA applications, there is no generic EA. Therefore, the user has to custom design the algorithm for the problem at hand (Alp, Erkut, & Drezner, 2003). This is not a trivial task since an EA requires many design decisions, such as the genetic coding, the initializing method, and the development of recombination and mutation operators; a weak choice may result in a poor algorithm regardless of its other features. Other essential decisions include the size of the population (i.e., the number of solutions), the selection of parents for offspring allocation, the replacement of one generation by the next, the method and frequency of mutations, and the overall number of generations.

Evolutionary algorithms have been studied extensively over the last few years regarding a variety of spatial problems, such as location-allocation problems (Comber, Sasaki, Suzuki, & Brunsdon, 2011; Doong, Lai, & Wu, 2007; Düzgün, Uşkay, & Aksoy, 2016; Indriasari, Mahmud, Ahmad, & Shariff, 2010) spatial clustering (Banerjee, 2013, Laszio & Mukherjee, 2007), and land use planning (Chen et al., 2019; Stewart, Janssen, & Herwijnen, 2004).

We develop a simple EA to fine-tune the hyper-parameters of a feed-forward MLP in order to predict EEs for optimal response service. We follow the typical steps of an EA as presented in Openshaw & Openshaw, 1997 while modifying them slightly to suit the specific

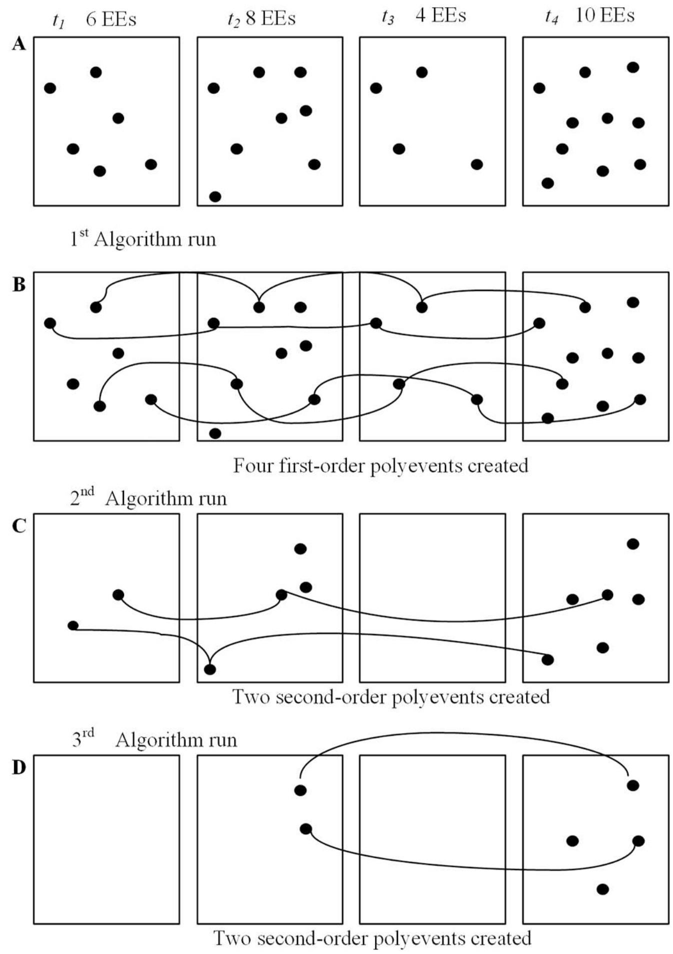

Fig. 2. A) The number of EEs per timestamp is usually different. B) In the first step, each EE of one timestamp is assigned to only one EE of the next timestamp and vice versa. Due to this restriction, some EEs will not be assigned to any EEs of the following timestamp. C) EEs that are left unassigned in a timestamp *t* due to the unbalanced assignment will be assigned to EEs of the following timestamp t + 1 or whichever timestamp after that has unassigned EEs. D) The process goes on until no further EE matching is possible.

needs of this study (see Fig. 3). First, an initial population of *N* MLP ANNs is randomly created, trained, validated, and tested. The ANNs are sorted in ascending order based on their mean square error (MSE). We then apply selection, mutation, and recombination operators. During selection, the top *X%* ANNs (with less MSE) are chosen for reproduction. Additionally, we randomly select *(X/2)%* of ANNs with low MSE to mix good and bad performers and to avoid local minima. On the selected ANNs, we then apply mutation and recombination. Mutation is used to randomly change the values of some hyperparameters of a fraction (*Y%*) of the selected ANNs. We then develop a simple recombination operator with a probability of *Z%* to give birth to offspring. This involves an exchange of hyper-parameter values among those selected. In particular, for any given set of two ANNs, we name the first ANN the "father" and the second the "mother." The first child inherits the same hyper-parameter values for the learning rate, the L1, and the momentum from the mother and inherits the rest from the father. The second child inherits the same hyper-parameter values for the learning rate, the L1, and the momentum from the father, and inherits the rest from the mother. Then, the offspring replace the worst ANNs of the previous generation. This process continues until a certain number of generations is reached or nothing further can be improved to minimize the MSE. (The proposed EA is not used to optimize the weights of the ANN, which are adjusted by the backpropagation learning algorithm with the gradient descent). The steps of the EA are as follows:

Step 1. Generate the initial population of *N* individual MLP ANNs randomly.

Step 2. Train, validate, and test the MLP ANNs of the generation using early stopping and L1 regularization, and calculate the cost function for each one of them (MSE). Sort the ANNs by MSE in ascending order.

Step 3. Select the top *X%* of the ANNs (with less MSE). Randomly select additional *(X/2)%* ANNs.

Step 4. Apply a mutation operator with a probability of *Y%*.

Step 5. Apply a recombination operator with a probability of *Z%* to give birth to offspring.

Step 6. Replace the worst ANNs of the population with the offspring and create a new generation.

Step 7. Go to step 2 or stop when nothing further can be improved to minimize the MSE or when the total number of generations is reached.

Finally, it has been empirically proven that large datasets prevent model overfitting and increase model accuracy (Goodfellow et al., 2016). Using artificial augmentation techniques is a common way to increase dataset size (Wong, Gatt, Stamatescu, & McDonnell, 2016; Zhang, Rong, Liang, Sun, & Xiong, 2017). We artificially augment the dataset by applying affine transformations such as shifting, flipping, and rotating. As the PEs can be seen as point trajectories (paths), it is easy to apply such transformations in the same way they are applied in ANNs for image classification problems (Krizhevsky, Sutskever, & Hinton, 2012; Szegedy et al., 2015).

2.3. P-center problem

The *p*-center problem (also known as *minmax*) in the EMS context is defined as locating *p* facilities (ambulances) on a network to minimize the maximum distance between demand nodes (emergencies) and their closest facility. If facilities can be placed only in the vertices of the network, the problem is called vertex *p*-center problem, while if facilities are allowed to be placed anywhere along the network, then the problem is called the absolute *p*-center problem (Daskin, 2013). If there are capacity restrictions on the facilities the problem is called the capacitated *p*-center problem.

Many exact, heuristics, and metaheuristics algorithms and approaches have been proposed to solve the *p*-center problem as reviewed by ReVelle et al. (2008) and de Smith, Goodchild, and Longley (2018). For example, Drezner (1984a), Daskin (2013), Calik and Tansel (2013), Chen and Chen (2013) proposed exact algorithms to solve the *p*-center problem under certain conditions. Still, exact algorithms may not be able to solve the *p*-center problem (Dantrakul, Likasiri, & Pongvuthithum, 2014) as this problem is NP-hard (Daskin, 2013). For this reason, heuristics and metaheuristics have been developed. For example, Caruso et al., (2003) introduced two exact and two heuristic algorithms to solve the *p*-center problem. Lagrangian relaxation-based heuristics have been also applied (Daskin, 2000, Albareda-Sambola, Diaz, & Fernandez, 2010). Moreover, Scaparra, Pallottino, and Scutellà (2004) used a local search heuristic to solve the capacitated *p*-center problem. Finally, metaheuristics such as tabu search and variable neighborhood search (Mladenovic, Labbe, & Hansen, 2003), genetic algorithms (Pullan, 2008), and bee colony optimization (Davidovic, Ramljak, Selmic, & Teodorovic, 2011) have been used to solve the *p*-center problem.

The *p*-center problem can be extended to solve the continuous area *p*-center problem. It can be defined as finding the *p* new facilities on the plane that minimize the maximum distance between each demand point (on the plane) and its nearest facility (Drezner, 1984b). Various methods have been proposed for solving the continuous *p*-center problem based mainly on the geometric properties of the region and on Voronoi diagram heuristics (Drezner, 1984b, Suzuki & Okabe, 1995, Suzuki & Drezner, 1996, Okabe & Suzuki, 1997, Wei, Murray, & Xiao,

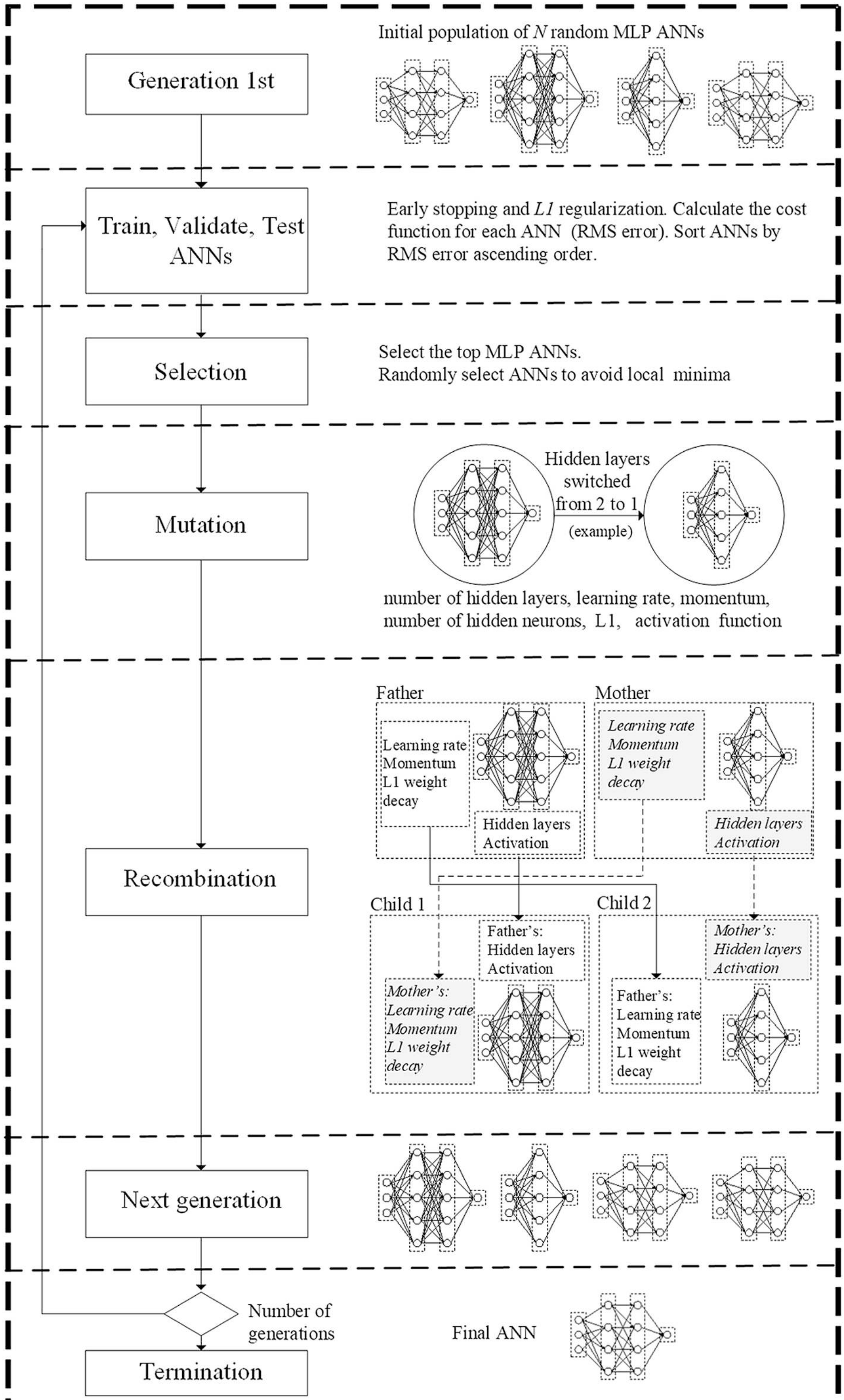

Fig. 3. Evolutionary algorithm for hyper-parameter optimization. An initial population with random MLP ANNs is generated. Based on their MSE, ANNS are selected and along with mutation and recombination operators, a new generation is created. After a cycle of continuous reproductions and generations, the algorithm ends at ANNs with low MSE.

2006, Novaes, Souza de Cursi, da Silva, & Souza, 2009). Still, the above approaches seem to get stuck in local optimums (Davoodi, Mohades, & Rezaei, 2011).

In this research we solve the vertex p-center problem with no capacity restrictions which is formulated according to Daskin (2013) as:

$$\text{Minimize } W \tag{5}$$

$$\text{Subject to: } \sum_{j \in J} Y_{ij} = 1 \ \forall \ i \in I \tag{6}$$

$$\sum_{j \in J} X_j = P \tag{7}$$

$$Y_{ij} \leq X_j \ \forall \ i \in I; j \in J \tag{8}$$

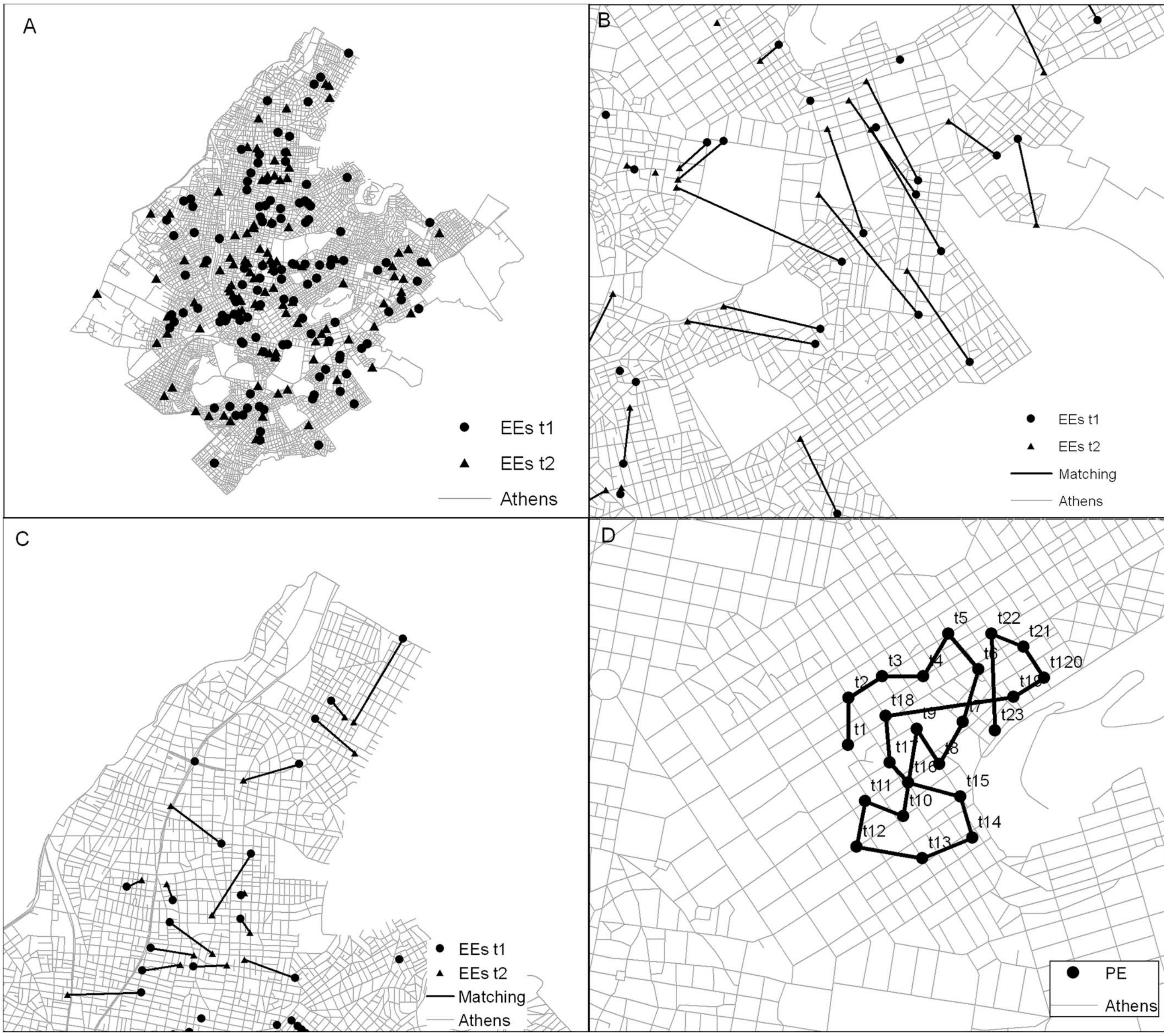

Fig. 4. A) EEs for time *t1* and *t2*. B) Assignment results zoomed in the eastern part of the case study area. Some EEs remain unmatched. C) Assignment results zoomed in the northern part of the case study area. D) A single PE created and depicted for the entire period *t1–t23*.

$$W \geq \sum_{j \in J} d_{ij} Y_{ij} \ \forall \ i \in I \tag{9}$$

$$X_j \in \{0, 1\} \ \forall \ j \in J \tag{10}$$

$$Y_{ij} \in \{0, 1\} \ \forall \ i \in I; j \in J \tag{11}$$

where W is the maximum distance between a demand node and the closest facility, I is the set of demand nodes (emergencies), J is the set of candidate locations (of ambulances), d_{ij} is the distance between demand node $i \in I$ to facility node $j \in J$, P the number of facilities, and X_j, Y_{ij} are defined as:

$$X_j = \begin{cases} 1, \ \textit{if an ambulance is located at cadidate site } j \in J \\ 0, \ \textit{if not} \end{cases}$$

Y_{ij} is the demand at node $i \in I$ that is served by an ambulance at node $j \in J$.

The objective function (5) in the EMS context minimizes the maximum distance of an emergency event to the nearest ambulance. Constraint (6) assigns each emergency to only one ambulance, while constraint (7) ensures that P ambulances will be located. Constraint (8) assigns an emergency to a node, only if there is an ambulance in this node. Constraint (9) ensures that the maximum distance between an emergency node and the closest ambulance is equal or larger than the distance between any emergency $i \in I$ and the ambulance $j \in J$ to which is assigned. Finally, constraints (10) and (11) are the integrality restrictions.

3. Case study

Our approach is tested in a case study involving 2851 EEs handled by the EMS in Athens, Greece over 24 weeks. Data for the first 23 weeks are used to calibrate the model, and data for the 24th week are used to test the model's prediction. Timestamps are consecutive and are selected so that the total number of emergencies per week does not deviate more than ± 20% from the average number of emergency events for the entire time period. In case that the number of emergency events, for a specific timestamp, deviates more, then we may omit this timestamp (in our case study, none week was omitted). This ± 20%

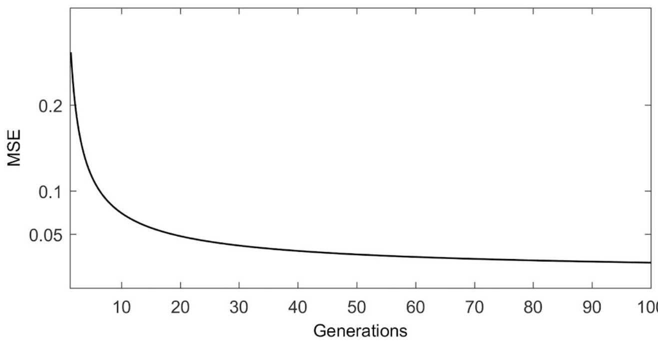

Fig. 5. Minimum test MSE error per generation.

boundary is imposed to avoid a) seasonality issues (for example, significant fall in the number of emergencies for one or more weeks during summer months), and b) a significant rise in emergency events due to an unexpected natural (e.g. earthquake) or human-caused (e.g. terrorist attack) disaster. In addition, by keeping variation in emergencies count relatively stable, we ensure that the number of expected emergency events will not be extremely large or small, facilitating thus the ANN to better identify patterns among data and achieve more accurate predictions. Further research should take into account seasonality issues and large fluctuations in demand, as also discussed in the Conclusions and Discussion section.

We apply a three-level process. First, PEs are created using the improved Hungarian algorithm. Second, an MLP ANN is used to predict EE locations in the 24th week based on the PEs (time series data) created in the previous step. We use evolutionary hyper-parameter optimization to select the ANN with the minimum generalization error. The results are evaluated a) using simple GIS techniques, such as buffer and overlay analysis to calculate the distance deviation of the predicted EEs from the actual EEs, and b) using the Nearest Neighbor analysis statistical test. This statistical test is applied to check if the point pattern of the predicted EEs (as produced from the ANN), is a random arrangement of events. In other words, we test whether the ANN identified any clustering patterns among the EEs through the PEs creation, or it just generated events in a random way. Third, a location-allocation model is applied to locate ambulances near expected EEs, and the results are evaluated based on four scenarios.

3.1. Formulating polyevents

The improved Hungarian method assigns EEs at successive timestamps (e.g., $(t_1,t_2),(t_2,t_3)\ldots(t_{22},t_{23})$, to create the PEs. As the total number of EEs differs for each timestamp, the assignment is unbalanced, and some EEs remain unassigned. During the first algorithm run, the algorithm formulates a total of 102 first-order PEs. As explained in section 2, the algorithm is applied again for only the unassigned EEs, creating a total of 27 seconds-order PEs. Of those, 11 PEs have > 12 EEs (half of the timestamps) and will be included in the final dataset. As the results of this process are lengthy, we present the assignment results only of (t_1,t_2) as well as the path of a single PE from t_1 to t_{23} (see Fig. 4). A more general view with all the PEs and assignments would be complex, as many PEs have crossing paths. Fig. 4A depicts the locations of the EEs for timestamp t_1 and t_2, while Fig. 4B and C depict the assignment of the EEs in the eastern and northern parts of the case study area. The path of a single PE for the entire period from t_1 to t_{23} is depicted in Fig. 4D. The final set of PEs is then used to feed the ANN that will be trained for the prediction task.

3.2. Neural network and evolutionary hyper-parameters optimization

Through the evolutionary algorithm, we test various feed-forward MLP ANNs to predict the locations of expected EEs in *t24*. We use the backpropagation learning algorithm with gradient descent, and we additionally apply the *L1* weight regularization and the early stopping method. Regularization *L1* is used to both detect when overfitting occurs and reduce the effects of overfitting. Early stopping prevents strong overfitting even if other hyper-parameters are not well-tuned (Bengio, 2012). The cost function to be minimized is the MSE between the target (actual EE locations) and the output values. The dataset consists of the PEs created for the period t_1–t_{23}. As mentioned in section 2, we artificially augment the PE dataset (point trajectories) by applying affine transformations such as shifting, flipping, and rotating in a way similar to that applied to image classification problems using ANN. These transformations increased the size of our training set tenfold.

Twenty percent of the dataset is selected as test data, 20% is selected as validation data, and the remaining 60% is selected as training data. The hyper-parameter optimization is conducted via the evolutionary algorithm, as presented in section 2. The hyper-parameters to be optimized are the number of hidden layers (one or two), the learning rate, the momentum, the number of hidden neurons, the L1 weight decay regularization coefficient, and the choice of activation function. The number of training iterations is fine-tuned using the early stopping method.

The settings of the EA (see Fig. 3) are as follows: $N = 40$ (initial population of MLP ANNs), $X = 20\%$ (selection), $Y = 10\%$, (randomly selection), Mutation probability = 20%, Recombination probability $Z = 80\%$, Generations = 100.

The EA runs for 100 generations, and the MSE of the test dataset is constantly decreasing (see Fig. 5). After the 60th generation, the MSE is almost stabilized to the value of 0.0468. To present the best ANN of this generation, we use a standardized way of reporting results as suggested by Grekousis (2019), (see Table 1). This reporting scheme aims to present the ANN's architecture, hyper-parameter settings, and outcomes during the research process so that, first, the results are presented in a consistent way across studies and, second, knowledge gained related to ANN setting is effectively disseminated to the scientific community.

This ANN is then used to predict the EEs of t_{24}, and the results are compared with the actual EEs available for this timestamp. To evaluate the prediction accuracy, we use the correlation coefficient r and the normalized mean square error (NMSE). The NMSE is frequently used to measure the difference between predicted and observed values. The NMSE is low (0.058); values near zero indicate a good fit for the network because the error is minimized. The correlation coefficient of the

Table 1
ANN results based on a standardized reporting format as proposed by Grekousis 2019.

ANN and Metrics	Value
Data and ANN	
Name of ANN	Multi-layer perceptron
Learning algorithm	Backpropagation with gradient descent
Training dataset	60%
Validation dataset	20%
Testing dataset	20%
Cost function	Mean square error (MSE)
Activation function	• Hyperbolic tangent
Hyperparameters	
Number of hidden layers	2
Learning rate	0.0016
Momentum	0.92
Number of epochs	504
Neurons per hidden layer	11
Regularization coefficient	L1 = 0.014
Evaluation	
Training error	0.0210
Validation error	0.0377
Testing error	0.0468
Correlation coefficient	0.93
Stopping criteria	Early stopping method

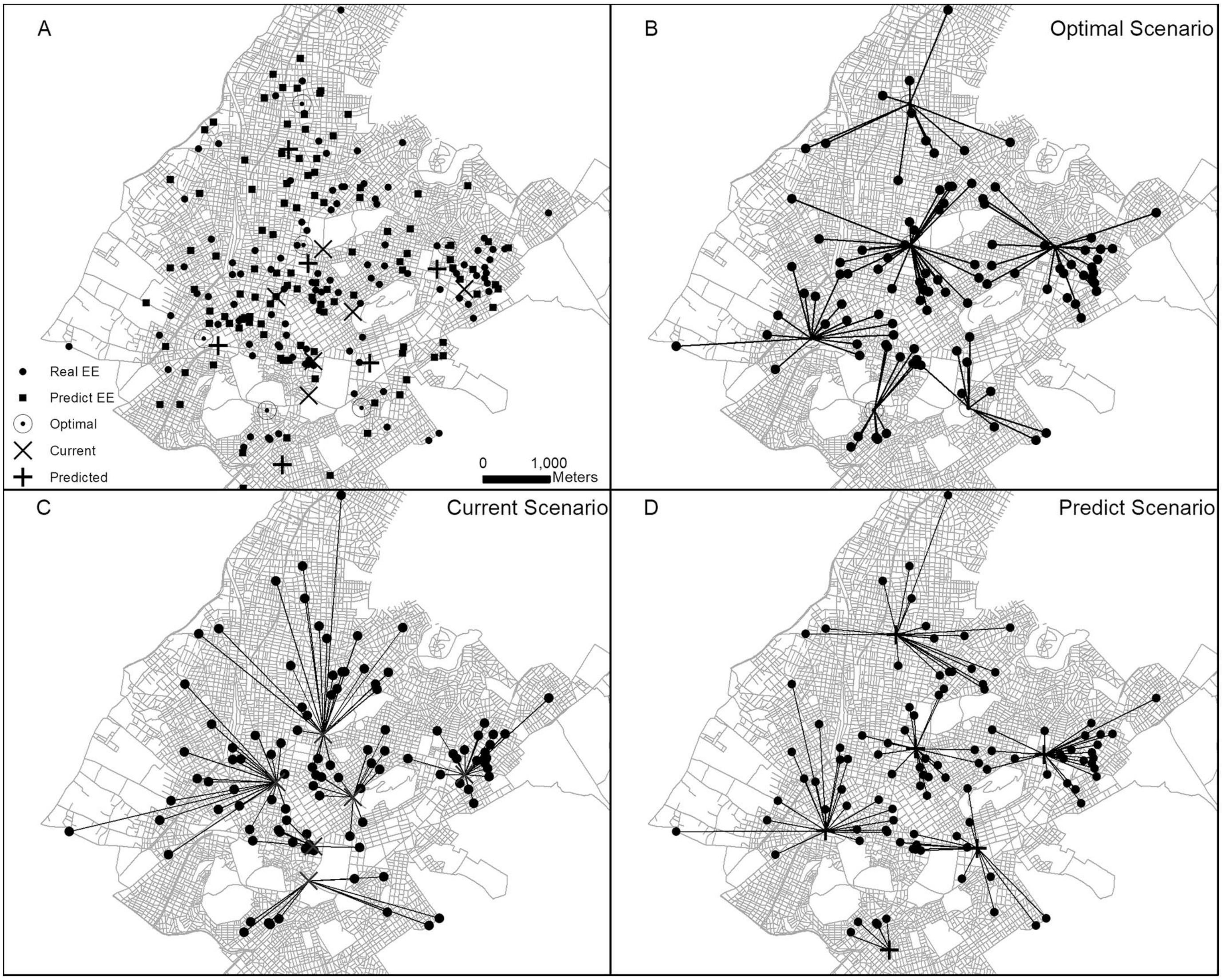

Fig. 6. A) Real and predicted EEs for t24. B) Location-allocation for 'Optimal scenario'. C) Location-allocation for 'Current scenario'. D) Location-allocation for 'Predict scenario'.

Table 2
Percentage of real EEs inside buffers around the predicted EEs.

Buffer(m)	EE
50	23.34%
100	42.45%
150	68.98%
200	75.89%
250	86.43%
< 500	100%

model is high (0.93), indicating a good fit. In addition, the locations of the predicted EEs are overlaid with the actual locations. By applying simple GIS buffer analysis, we calculate how many real EEs lie inside the buffers of the predicted EEs (see Fig. 6A and Table 2). The analysis indicates that 23.24% of real EEs are within 50 m of the predicted EEs and that 42.45% of real EEs are within 100 m the predicted EEs.

We also test if the predicted demand is significantly different from a random pattern of events. Specifically, we use the nearest neighbor statistical test to identify if the predicted demand forms a random, dispersed or clustered spatial pattern. We conduct this analysis for the actual events as well. Nearest neighbor analysis is a statistical test used to assess the spatial process a point pattern has been generated from (O'Sullivan & Unwin, 2014). The statistic tests the null hypothesis that the observed pattern is random and is generated by the complete spatial randomness, by calculating the nearest neighbor ratio R. A nearest neighbor ratio $R < 1$ indicates a process towards clustering while a value larger than 1, indicates that the pattern is. Results are evaluated based on z-scores and p-values, and are presented in Table 3. The spatial pattern of actual emergencies is clustered and given the z-score of -12.925, there is < 1% likelihood to be the result of a random process. For the predicted events, given the z-score of -2.770. there is a < 1% likelihood that this clustered pattern is the result of random chance. This result indicates that the point pattern generated by the ANN is not due to randomness but due to co-location patterns identified through

Table 3
Nearest neighbor analysis for actual and predicted spatial point patterns of demand.

Nearest Neighbor Analysis	R	z-score	Spatial Pattern
Actual	0.62***	−12.925	Clustered
Predicted	0.85***	−2.770	Clustered

p-value: *** $p \leq 0.001$.

the EEs and PEs analysis.

3.3. Location-allocation model and evaluation of results

We evaluate the results based on four scenarios. In the first, we locate six ambulances in the city road network based on the actual demand for t_{24}. In other words, we site the ambulances after the actual EEs have occurred. This is the a posteriori solution to the problem when ambulances are sited based on a given demand. We label this scenario "Optimal," and we use it to compare with the other scenarios, as it would be the ideal solution if the prediction were 100% accurate. In the second scenario, we locate six ambulances based on the predicted demand for t_{24}, and we label this scenario "Predict." In the third scenario, we use the currently applied policy according to which ambulances are waiting in a fixed set of six locations (also called "ambulance posts") to serve the expected EEs of t_{24}. We label this scenario "Current." These ambulance posts are sited in major squares and parks in Athens, with easy parking and quick access to the rest of the city. These posts have been identified over the years based on the experience of the personnel rather than spatial planning. Finally, the fourth scenario is called "Random". In section 3.2 we tested if the predicted EEs pattern is random and we concluded that it is a clustered pattern statistically significant from a random one. In this scenario though, we test if random points would provide similar, better or worst solution to the *p*-center problem in comparison to the predicted demand. This provides an additional evaluation for the ANN output. In other words, any events' arrangement would provide a solution to the above problem. So how different is the solution provided by the predicted set of events in comparison to a random set of events? To answer this question, we generate a random pattern of emergency events, and we compare the *p*-center solution for this random demand with the *p*-center solution of the predicted demand.

To locate the ambulances in each scenario, we use the *p*-center location-allocation model. The *p*-center location-allocation model places ambulances such that the maximum distance to any EE in the city is minimized. We use SITATION, a free software package able to optimally solve *p*-center problems up to 300 nodes using Lagrangian relaxation heuristic (Daskin, 2000; Daskin, 2013). It is available at the following web site: https://daskin.engin.umich.edu/network-discrete-location/.

The six centers, the objective function value, and the mean distance of an EE to the closest center for each scenario are presented in Fig. 6 and Table 4. The lines in Fig. 6B, C, and D represent the allocation of the EEs to the six corresponding ambulances for the first three scenarios. The optimal solution for this dataset using the *p*-center location-allocation model is given by the "Optimal scenario" as the centers are calculated based on the real events (see Fig. 6B and Table 4).

The "Current scenario" (predefined fixed posts) does not provide sufficient coverage (see Fig. 6C and Table 4). For example, the objective function of the "Current scenario" is 39.5% greater than that in the "Optimal scenario", while the mean distance between an EE and the nearest ambulance location is 91.4% larger (almost double). As explained earlier, the centers of the "Current scenario" were chosen mainly based on their importance as landmarks, their parking convenience, and the experience of the personnel. However, they cannot serve the demand sufficiently, leaving many areas without quick access such as the northern and southern neighborhoods.

On the other hand, the "Predict scenario" locates the six ambulances based on the predicted EE demand (see Fig. 6D, Table 4). The objective function deviates by 12% relative to the "Optimal scenario" and improves the "Current scenario" by 19.7%. The mean distance in the "Predict scenario" (between an EE and the nearest ambulance location) is 1345.36 m, a slight difference of 110.73 m from the mean distance achieved in the "Optimal scenario" (1234.63 m). Given the size of the case study area, this distance difference is reasonable and manageable for the EMS. The mean distance in the "Predict scenario" is significantly smaller (by 1017.95 m) than that in the "Current scenario" (2363.32). Thus, the "Predict scenario" improves the mean distance of an ambulance from the EE by 43%, and it is only 8.9% larger than in the optimal solution.

In the fourth scenario, we generate emergency events randomly and we a) locate 6 ambulances, and b) use these centers to allocate the actual demand. The generation of random patterns in a more statistically sound way, would require simulation and further statistical analysis through pseudo *p*-values, which is beyond the scopes of this research. We only generate a single random pattern to showcase how different a solution is compared to the optimal and the predict scenario. More specifically, 113 events (as many as the PEs) were randomly generated across the case study area. *P*-center was used to locate $p = 6$ centers. The objective function of the *p*-center model when using these centers for serving the actual demand is 197,923.12, which is 45.6% larger than the optimal scenario, 30.0% larger than the predict scenario, and 4.4% larger than the current scenario (Table 4). The 30% difference between the predicted demand and the random demand indicates that the result of the ANN is not due to randomness but due to regional co-location patterns identified through the emergency events' paths analysis. It's interesting to highlight the resemblance of the "Current" scenario to the "Random" scenario, showcasing that the way that ambulances have been deployed does not deviate a lot from a random arrangement, (as a result of locating ambulances not based on scientific methods), something that makes EMS highly inefficient.

Finally, as the *p*-center problem is sensitive to different *p* values we test our approach for *p* ranging from 1 to 10 (Fig. 7). In practice, using the predicted demand, we locate the ambulances locations for various *p* values and then we plug these locations to the actual demand to calculate how it is served. From the graph inspection, we observe that as *p* gets larger the predicted demand tends to produce worst solutions compared to the actual (Fig. 7). Although the trend is not stable, this outcome is rational. In the hypothesized case where $p = n$ (as many centers as the number of emergencies) then the objective function for the actual events would be zero (each event would be allocated to itself). To achieve this result with the predicted demand trough the ANN would require an exact prediction (prediction demand to be identical to the actual demand) something that is highly unlikely to occur as we cannot minimize the prediction error. Still, Fig. 7 shows that when using the predicted demand for a relatively small number of *p* in comparison to *n* the objective function does not deviate a lot from the objective function of the actual demand (for example the maximum deviation is 14.7% for $p = 9$). As such, the proposed approach for this specific dataset provides a good simulation of the expected events

Table 4
p-center model results for optimal, predict, current, and random scenario.

Scenario	Objective Function	Compared to current	Compared to optimal	Mean Distance	Less compared to current	More compared to optimal
Optimal	135,925.40	−28.3%	N/A	1234.63	−47.7%	N/A
Predict	152,254.28	−19.7%	+12.0%	1345.36	−43.0% (−1017.95 m)	+8.9% (+110,73 m)
Current	189,632.89		+39.5%	2363.31		+91.4%
Random*	197,923.12	+4.4%	+45.6%	N/A	N/A	N/A

* Random compared to Predict is +30.0% more. Random is only used to compare objective functions, not distances.

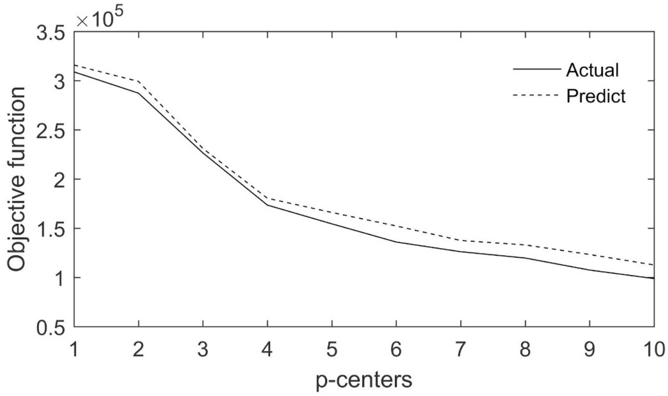

Fig. 7. Performance of *p*-center model for *p* values ranging from 1 to 10.

assisting thus in better spatial planning of EMS. A more thorough analysis would require to test the approach over varying demand and a larger range of *p*, as well as different location-allocation models. As this analysis is extensive, is left for future research.

4. Conclusions and discussion

This study introduces new concepts and notions to model EEs utilizing spatial analysis, artificial intelligence, and evolutionary algorithms, to enable EMS act preventively. The study proposes a novel approach that assigns EEs of sequential timestamps in order to formulate PEs. Using the improved Hungarian assignment algorithm, EEs in each timestamp are paired with those nearest in the next timestamp. Then, ANNs optimized using a proposed evolutionary algorithm are used to predict future EE patterns. From the policy perspective, various location-allocation models may be used to serve this demand, improving ambulance response times. The proposed approach facilitates improved policies and strategies, thus improving public safety.

The overall approach was applied to a real dataset containing 2851 EEs in Athens, Greece. The results show that expected EEs were predicted with high accuracy, taking into account the scale of analysis (city level). Specifically, 23.24% of real EEs lie within 50 m of the predicted ones, and nearly 70% of the real EEs lie no further away than 150 m. In absolute-value error terms, 50 m might seem a large deviation. From the policy perspective, however, it is a relatively small difference given that the case study area size is approximately 10 km by 10 km. An expected EE lying within a 50 m radius from the real one is just one or two blocks away. Such a distance adds only a few seconds of delay to the response time of an ambulance relative to the theoretically optimal solution, in which demand is provided in advance. Thus, although the ANN's accuracy can be further improved it offers a good approximation of the expected spatial pattern of demand.

The benefits of the overall approach are even more evident when the *p*-center location-allocation model is applied to the predicted EEs. The corresponding centers provided better coverage of the real EEs than the current solution, improving the objective function of the *p*-center model by 19.7%. More importantly, the mean distance between an EE and the nearest ambulance in the "Predict scenario" deviates by 110 m (or 8.9%) relative to the optimal solution and improves the current fixed solution by > 1 km (1017.95 m; see Table 4). The overall results show that the proposed approach can significantly assist EMS to cover the expected demand more effectively.

The rationale behind developing EEs and PEs notions is that they allow for better modeling emergency events through a spatiotemporal analysis lens. In specific, the proposed approach analyzes EEs as a set of interconnected points in space that create paths over time so that their next occurrence can be predicted, thus avoiding an aggregation of results at a regional level. Most existing approaches focus on how to predict the expected volume of future EEs. These predictions are based on the expected volume of EEs inside a zone and fail to predict their locations. By contrast, our approach locates the geographic locations of future EEs, which is more informative for EMS analysis and related response.

At a more conceptual level, the idea that EEs can be interconnected, formulating a single entity (the PE), might seem unconventional. It is true that EEs are (or at least seem to be) independent from each other (especially when they do not refer to some acute localized disaster, such as an earthquake). The central assumption is that exhibiting similar spatiotemporal co-location patterns (i.e., EEs are frequently close together) might indicate a trend that can be captured analytically and used for EE prediction. Based on the notions of spatial autocorrelation and spatial dependence, we hypothesize that future EEs are most likely to occur in locations near previous ones. Instead of using zones to aggregate and then analyzing them via conventional statistical analysis (regression) or spatial analysis techniques (e.g., geographically weighted regression), we link the nearest ones based on a one-to-one restriction so that the total distance cost is minimized. The one-to-one restriction is used to avoid having more than one EE of timestamp *t* assigned to the same EE of the next timestamp. This would leave many EEs unmatched and excluded from the study.

Assigning EEs so that the total distance cost is minimized (through the improved Hungarian algorithm) also ensures a local search for an EE, which means that each PE moves within a small neighborhood, thus simplifying the PE modeling and the projection of its trajectory. We thereby predict the future pattern by using ANNs via evolutionary optimization, which eventually can guide EMS adopt the appropriate policies.

This study's methodology has limitations that should be examined in future research. For example, when the EEs lie near the boundaries of the study area, their possible matching EEs may lie towards only certain directions. Furthermore, we do not address ambulance availability, traffic congestion, or seasonality in hourly cycles. Several interesting studies have addressed adjustments to the number of ambulances deployed based on the time of day (Channouf et al., 2007; Rajagopalan, Saydam, & Xiao, 2008), suggesting that aggregated forecasts for an area over an entire year will likely not help EMS because demand varies daily and hourly in space and magnitude. Future research could expand this study's proposed methodology to address seasonality regarding days (weekdays, weekends, holidays) and hours of the day. Future research could also test various location-allocation models, varying demand and number of facilities as well as taking into account the underlying population geography, other demographic data, or daily population shifts.

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