Reducing Response Time of Ambulance Service by Utilizing the Knowledge of Service Location of Ambulance Drivers using Self-Organizing Map

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R. K. Jha

Manojit Chattopadhyay

Indian Institute of Management
(rohan.fpm@gmail.com)
(mchattopadhyay@iimraipur.ac.in)

Yuvraj Gajpal

University of Manitoba
(gajpaly@gmail.com)

Large numbers of people are dying because ambulances are taking too long to transport patients to hospital. This work addresses the issue of reducing response time by using knowledge of location of ambulance drivers. Kohonen's SOM was used to solve the ambulance driver-scheduling problem (ADS) problem owing to its ability to break the ADS problem into smaller and manageable parts using its unique visual approach. This approach would enable the ambulance company managers, most of who still rely on some crude non-computer based system, to visually solve the ADS problem. Numerical experiments were conducted using randomly generated data representing the ADS problem. Finally, performance of SOM was measured using grouping efficacy. This work can be used independently or it can be used as a plug-in in existing scheduling system to reduce response time.

Keywords: Response Time, Ambulance Service, Knowledge of Service, Location, Self-Organizing Map

1. Introduction

Ambulance companies provide for transportation of patients. One of the primary aims of managers at ambulance companies is to minimize the response time. Response time is minimized to avoid further deterioration of patient's health with time. A general criterion for ambulance scheduling is that the patients requiring immediate medical attention should reach the hospital within 15 minutes (Zhen et al, 2015). Yet all over the world large numbers of people are dying because ambulances are taking too long to transport patients to hospital. For example, in London almost fifty percent of ambulances called for emergency patients were late by more than 15 minutes¹. Further in England, one of the most developed economies of world, it has been reported that out of its 32 ambulance services only 3 were able to transport emergency patients as per prescribed guidelines².

¹ <http://www.dailymail.co.uk/health/article-55521/Thousands-die-ambulance-delays.html#ixzz4WflP5UYN>, accessed on 30 January 2017.

² *ibid*

One of the most important aspects in management of ambulance service is the fairness with which resources are being utilized (Aringhieri et al., 2017). We unlike in previous research papers on minimization of response time for patients have used the knowledge of a given service location of ambulance driver in minimizing the response time. Knowledge of service location becomes very important when ambulance service is to be provided in localities with no modern communication facilities, interior areas in historical/unplanned cities or when ambulances have to avoid traffic congestion (Figure 1). The in-depth knowledge of service location of ambulance drivers can enable early admission of patients in hospital which is very important given the fact that even a minute saved can potentially save a life (some experts estimate that around 3000 heart attack victims could be saved in England alone if ninety percent of emergency calls are answered on time³).

Figure 1 *Some Service Areas where Knowledge of Location of Ambulance Drivers can Reduce Response Time*

Generally an ambulance company has several bases (B1, B2, B3...) spread across its service area. Ambulances from these bases are sent to several service locations (we have divided the service area into several independent service location (L1, L2, L3...) like in case of Andersson and Värbrand (2007); Toro-DíAz et al. (2013)) to pick up patients. Figure 2 illustrates distribution of bases across service locations. The most intuitive way to schedule ambulances is to schedule them such that ambulances pick up patients closest to it. But, these schedules does not necessarily meet the criterion of ensuring large percentage of requests being fulfilled within 15 minutes (Zhen et al, 2015). Some of the most prominent challenges in scheduling of ambulances are:

- Accommodating the distribution of patients in various locations (Zhen et al, 2015)
- Accommodating ever changing traffic condition (Zhen et al, 2015)
- Accommodating knowledge of service location of ambulance driver

In existing literature different parameters such as position of ambulances, number of ambulances, medical facilities in ambulances, capacity of each ambulance and healthcare legislations specific to a country has been optimized in order to minimize response time for patients. In this work we have tried to further reduce response time

³ *ibid*

using a new resource i.e. knowledge of service location of ambulance drivers. Hence this work can be used independently or it can be used as a plug-in in existing ambulance scheduling systems to reduce response time.

We propose to use a novel visual hierarchical clustering approach using Kohonen’s SOM based algorithm to deal with the problem of incorporating knowledge of ambulance drivers in their scheduling. We call this problem ambulance driver-scheduling (ADS) problem. The computational complexity involved in this problem has been illustrated in section 3. We use SOM to break the complex ADS problem into smaller and manageable parts, as this is one of the biggest challenge in solving this type of problem (Uyeno and Seeberg, 1984). We do so with the purpose of solving the ADS problem using visual clustering properties of SOM. This would enable ambulance company managers (most of who still relies mostly on some crude non-computer based system (Patrick, Puterman & Queyranne, 2008), to visually solve the ADS problem. Unlike most existing work in literature, the visual results obtained from using SOM can be easily understood and interpreted by ambulance company managers. Some of the primary objectives of this work are:

- To use knowledge of service location of ambulance drivers in reducing response time.
- To decompose the ADS problem into smaller and manageable parts using self-organizing map (SOM) to help ambulance company managers in making real time decision.
- To illustrate the ability of SOM, in enabling smart decision-making while scheduling ambulance drivers to serve patients from different service locations.

To illustrate the ability of SOM, in enabling smart decision-making while scheduling ambulance drivers to serve patients from different service locations. The remaining work is organized as follows Section 2 covers relevant literature. Section 3 describes the problem. Section 4 describes the Kohonen’s SOM algorithm. Section 5 presents the numerical experiments conducted with randomly generated data whereas section 6 covers managerial implications and also concludes the work.

Figure 2 Distribution of Bases (B1, B2, B3...) Across Various Service Locations (L1, L2, L3...)

2. Literature Review

The scheduling of ambulances is a complex problem (Kim and Lee, 2016) and exact solutions are intractable when the number of vehicles is large (Jagtenberg, Bhulai and van der Mei, 2015) as illustrated in section 3. Generally the most used dispatching rule is to send ambulances from bases closest to patient in order to minimize the response time (Andersson, and Värbrand, 2007) but this rule does not always give optimal results (Carter, Chaiken and Ignall, 1972). As per the United States Emergency Medical Services Act (Ball and Lin, 1993) ambulances should reach 95 % patients in urban and rural areas in 10 minutes and 30 minutes respectively. 38% of service calls requires minimum one ambulance relocation (Brotcorne, Laporte and Semet, 2003) and knowledge of location can be very useful for ambulance drivers in reducing response time in case of relocations also. Decision-making in case of ambulance service arises at mainly three levels (Gendreau, Laporte, and Semet, 1997).

- Strategic level: Involves decision making such as location of service facility, recruitment of staff and purchase of necessary equipment.
- Tactical level: Scheduling of staff, deployment and relocation of ambulances, and positioning of ambulances.
- Operational level: Procedures for medical staff in accordance with nature of service being required.

The ADS problem being considered in this work is tactical in nature as it is concerned with scheduling of staff and most papers considered for review in this work falls under the category of minimization of response time. Literature reviews covering minimization of response time for ambulance are Marianov and Reville (1995); Brotcorne, Laporte and Semet (2003); Li et al., (2011), Aringhieri et al., (2017) etc. Table 1 illustrates some of the recent research papers in literature on reducing response time of ambulance service providers. In this work unlike existing work in literature we have used knowledge of location of ambulance drivers in reducing the response time.

It is possible to classify or cluster ambulance drivers based on their knowledge of a service location. Clustering of this kind will make it easier for ambulance company managers to decide which drivers are most prepared to pick up patients from a given service location. In the existing literature on scheduling of ambulances a number of factors have been considered to minimize the response time for patients but to the best of our knowledge no work has used the knowledge of service location of drivers in reducing response time. The clustering of ambulance drivers based on their knowledge of a given service location would give a cost-effective and easy to apply way of determining the best-suited ambulance drivers for picking up patients from a given service location.

Neural network (NN) and artificial intelligence (AI) based clustering techniques are presently one of the most used in the domain (Medhi and Mondal, 2016). There are two basic elements of an artificial neural network, nodes (these are the processing elements) and interconnections between them (Balakrishnan et al., 1996). The nodes are generally arranged in layers. There are three primary layers. The first layer receives input signals, the second layer processes the input data and the third layer is the output layer. One of the main advantages of computer based ANN or an AI technique is that they can be trained by historical data or by an expert. This enables a non-expert (here ambulance company managers) to consult the system when a similar kind of situation

is faced. The similarities in decision making between AI based technique and human being enables it to cope better with complexities and uncertainties (Guo, Rivero and Pazos, 2010).

Table 1 *Some Recent Research Papers on Reducing Response Time*

Reference	Contribution
Aboueljinane et al., (2014)	This paper found that repositioning of medical teams on the basis of a redeployment plan extracted from simulation optimization resulted in increasing coverage of ambulance services.
Aboueljinane, Jemai & Sahin, (2012)	The work tried to find out different ways of reducing response time for ambulance. They investigated several scenarios such as ones increasing the resources available, reducing process time and relocation of medical teams etc. This study established that reducing processing time has biggest impact on reducing overall response time (our research gap)
Andersson, and Varbrand, (2007)	The prime purpose of this work was to enhance the level of preparedness of ambulance companies in a given location with potential patients. Preparedness was defined based on ambulances available to serve a given zone and time taken to reach to a given zone.
Ingolfsson, Budge and Erkut (2008)	This work develops a model to reduce the response time while minimizing the number of ambulances required.
Jagtenberg, Bhulai and van der Mei, (2015)	The purpose of this work was to reduce the expected fraction of late arrival while making decisions in real time and at the same time taking into account the position of other vehicles and accidents.
Lee, (2012)	This paper proposed a centrality policy to reduce response time of ambulance. In this work the nearest neighbor dispatching policy for ambulances is extended to a centrality policy by including centrality along with closeness in dispatching policy for ambulances.
Lee, (2015)	This work proposed a preparedness policy with a simple form but with ability to perform efficiently in long run. This policy uses the notion of centrality and also involves a tuning parameter which is chosen as the existing scenario.
Li, D. (2015, June)	This work proposed the usage of software defined networking to enable early arrival of patients at hospital via ambulance.
Nogueira Jr., Pinto and Silva (2016)	This work optimizes the location of ambulances bases in order to reduce the response time
Sasaki et al. (2010)	This work has tried to reduce response time for ambulance service by using demand to identify optimal location for positioning of ambulances with an aim to reduce their response time.
Stein, Wallis and Adetunji, (2015)	This work found that increasing the number of ambulances reduced the response time only to a point and further increase in number of ambulances did not have any significant impact on reduction of response time.
Toro-Díaz et al., (2013)	This work used the closest dispatching rule to minimize the response time while taking care of total coverage areas of ambulances.

3. Driver Allocation Problem

The manager at ambulance companies faces two kinds of problem i.e. allocation problem and redeployment problem (Gendreau, Laporte, and Semet, 2001). The decision making concerned with which ambulance should serve which patient is covered under the allocation problem whereas the problem of relocating ambulances to appropriate bases in order to maximize their coverage comes under redeployment problem (Gendreau, Laporte, and Semet, 2001). This work deals with allocation of ambulances to patients while making use of knowledge of location of drivers.

The request for ambulance services is growing world over. Also the condition of traffic on roads is highly dynamic. The job of managers at ambulance companies is to ensure timely service. A general criterion for ambulance scheduling is that that patients requiring immediate medical attention should reach the hospital within 15 minutes (Zhen et al, 2015). Scheduling of ambulances is a computationally difficult because of following reasons (Ghosh and Varakantham, 2016):

- Large amount of input data such as several possible base locations
 - Allocation of large number of ambulances available to different patients.
- Combinatory explosion associated with scheduling of ambulances while considering the knowledge of service location (as shown in Figure 2) of a given ambulance driver at any given base can be calculated using McMullen, (2001). The number of sequences possible is

$$\text{Number of sequences possible} = \frac{(\sum_{k=1}^p n_k)!}{(\prod_{k=1}^p n_k!)} \quad (1)$$

Where,

n_k : number of service locations visited by i^{th} ambulance

p : total number of ambulances at any given base

For example, let us consider the case of a small base as shown in Figure 2 where number of service locations being visited by each ambulance is 15 and there are only 2 ambulances. Here it is assumed that only one driver is available for each ambulance.

Then using McMullen, (2001) as shown in Equation (1) number of possible sequences in which these ambulances can visit their respective locations are

$$\frac{(15+15)!}{15!.15!} = 155117520$$

The managers at ambulance companies have to constantly decide which driver is to be scheduled to pick up patient from which locality. The calls for ambulance service are random in nature. This means that scheduling ambulances with drivers to various localities is complex. To manage even a small fleet of ambulances, which visits only a small number of localities, is complex as illustrated above. Therefore a robust methodology is needed to cope with this problem due to the combinatorial complexity being involved with real life problem.

3.1 Defining Driver Allocation Problem

The service location and ambulance drivers can be represented as an $m \times n$ matrix where m represents ambulance drivers and n represents various service locations. This can be represented using Equation (2) as follows.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} = x_{ij} \quad (2)$$

Here, $x_j = (x_{1j}, x_{2j}, \dots, x_{pj})$ is the j^{th} data point (service location) with corresponding traits (ambulance drivers). The drivers either have knowledge of a location or not. Therefore, x_{ij} can take only two values i.e.

$$x_{ij} = \begin{cases} 1: \text{service location } j \text{ is known to ambulance driver } l \\ 0: \text{service location } j \text{ is not known to ambulance driver } l \end{cases}$$

The value x_{ij} shows the relationship between ambulance driver and service location. If value of $x_{ij} = 0$ then it represents that j^{th} service location is not known to l^{th} ambulance driver whereas if value of $x_{ij} = 1$ then it represents that j^{th} service location is known to l^{th} ambulance driver. The matrix also represents similarities in ambulance drivers and service location. The objective is to group ambulance drivers and service locations on the basis of similarities between them to break the scheduling problem defined here into smaller and manageable parts.

4. Kohonen's SOM Algorithm

In this work neural network is used to cluster data. A large proportion of literature on ANN application in domain has used Kohonen's self-organising map (SOM) (Mingoti and Lima 2006; Brusco et al. 2012). Kohonen's SOM has an additional input layer called Kohonen layer. This additional layer serves the purpose of preserving the topology which maps an input with n -dimensions into 2-dimensions (Mangiameli, Chen, and West 1996; Mingoti and Lima 2006). The kohonen layer is a competitive network and here the weights associated with winning nodes are updated with respect to certain rules. An unsupervised learning algorithm trains the SOM network. The rate of adjustment for the SOM network with respect to time is determined by absolute value of learning co-efficient. For preserving the topology the weight of nodes in neighborhood of winning node is considered via a neighbourhood function (Kohonen 1989).

Networks can be trained to identify similarities in input data. Input data on how much knowledge has an ambulance driver about a service location can train such networks. The networks, which are trained, can be used to identify ambulance drivers with similar kind of expertise on service location and this would be helpful for ambulance company managers.

Feature detection is an important function of neural networks. This is reduction of data dimensionality and can be used for pre-processing of input data. SOM has many advantages over other methods of classification (Medhi and Mondal, 2016). These networks have simple architecture but their self-organizing process contains considerable amount of subtleties (Medhi and Mondal, 2016).

4.1 SOM Algorithm

Self-organizing networks have the capability to learn and identify correlations and similarities in the input data (here data containing the ambulance drivers and their knowledge of a service location), and predict responses from it. Neurons in the competitive network learn to identify sets of similar input vectors while SOM learns to identify sets of similar input vectors in a way such that neurons present physically in proximity to each other in the neuron layer responds to alike input vectors (here sets of ambulance drivers knowing similar set of service location forms alike input vectors). SOM learns both the distribution and topology of the input vectors used to train them. The winning neuron is determined similarly for competitive layers. SOM updates a neighborhood of nodes around the winning node instead of updating only one node (Westerlund, 2005). The competitive learning algorithm applied to the network can be studied in more detail from Kaski (1997) and Kohonen (2001).

An input vector is given to the network and then using equation 3 and equation 4 the Euclidean distances between the input vector k_i and all the reference vectors v_i are calculated.

$$k_i = [k_1, k_2, \dots, k_n]^T \in \mathbb{R}^n, i=1, 2, \dots, N \quad (3)$$

$$v_i = [v_1, v_2, \dots, v_n]^T \in \mathbb{R}^n, i=1, 2, \dots, N \quad (4)$$

The best matching unit (BMU) v_c is chosen during the training process using equation 5 i.e. it is the unit for whom the reference vector has the least n -dimensional Euclidean distance with respect to the input vector.

$$\|x - v_c\| = \min_i (\|x - v_i\|) \quad (5)$$

At the same time, the closest neighbors of the BMU are activated as per a neighborhood function say, Gaussian distribution. Finally the reference vectors associated with all activated units are updated. The factor $h_{ci}(t)$ is called the learning rate and it determines the rate of change of the reference vectors.

$$v_i(t+1) = v_i(t) + h_{ci}(t) [k(t) - v_i(t)] \quad (6)$$

Where,

t : index of the iteration step,

$k(t)$: vector-valued input sample of k in the t^{th} iteration.

$h_{ci}(t)$: neighborhood function around winning node c .

During training process, $h_{ci}(t)$ is the decreasing function of the distance in between the i^{th} and c^{th} model of the map node. The necessary condition for convergence is $h_{ci}(t) \rightarrow 0$ when $t \rightarrow \infty$. Hence, the SOM learning process gradually transforms from an initial rough learning stage associated with a large influence neighborhood and fast-shifting prototype vectors unto a fine-tuning stage associated with little neighborhood radius and prototype vectors, which adapts gradually to the sample.

4.2 Visualization of SOM Clusters

In this work we use two visualization tools i.e. component planes and U-matrix. They use only prototype vectors and don't make use of the data vectors. The combined use of component planes and U-matrix provides information about similarities in variables (Chattopadhyay, Chattopadhyay and Dan, 2011).

4.2.1 U-Matrix

U-matrix is one of the most frequently used tools of SOM for visualizing patterns (Skupin and Agarwal, 2008). It uses a single plot to display the cluster boundaries in accordance with the dissimilarities existing in its neighboring units. The different clusters are represented by different colors. U-matrix is useful for visualizing clusters in the input data when there is no prior information about the clusters (K. Tasdemir, 2008).

4.2.2 Component Planes

Component plane is another visualization tool of SOM. It depicts the contribution of variables to cluster structure. Each component (here ambulance driver) is visualized in each neuron of trained SOM.

4.3 Measure of Map Quality

The purpose of measuring map quality is to measure how well has the topology been preserved in its projection onto the SOM's map grid (lower dimension). Topographic

error represents the accuracy of mapping while preserving topology (Kohonen, 2001) i.e. it basically measures continuity of the mapping. Topographic error can be mathematically computed in the map using equation 7 (Kiviluoto, 1996). Lower value of topographic error indicates better map quality.

$$\text{Topographic error} = \frac{\sum_{j=1}^N u(x_j)}{N} \quad (7)$$

Where,

N : number of input samples

$U(x_j)$: is 0 if the first and second BMUs of x_j are next to each other, otherwise $u(x_j)$ is 1.

4.4 Map Size and Structure

The specification of map size i.e. the number of output neurons in the training process of SOM is very vital to detect the deviation of the data. Smaller map size yields, outcome, which follows more general patterns (Vesanto et al., 2000). It has a drawback i.e. it may not reveal some of the significant differences, which should be detected. Larger map sizes on the other hand yields outcome into more detailed patterns. Its drawback is that it even highlights the differences, which are too small (Wilppu, 1997). The neurons connected to their adjacent neurons by the neighborhood relationship determine the structure of the map. The two most common 2-D grids are the hexagonal grid and the rectangular grid.

All experiments in the present study were performed using the Kohonen package with R software platform. The number of neurons by default was set to $5\sqrt{n}$ (Vesanto et al., 2000) with n being the number of training samples and the default structure is set to be hexagonal. To determine the optimum map size the number of neurons was initialized as $5\sqrt{n}$. We then kept on changing the number of neurons in our experiment till we achieved the map size with least topographic error.

4.5 Performance Measure

Kumar and Chandrasekhar an (1990) suggested grouping efficacy as a measure for goodness of output matrix. Grouping efficacy tries to minimize number of exceptional work orders while simultaneously maximizing number of work orders in cells. Grouping efficacy can be mathematically defined as,

$$\text{Grouping efficacy} = \frac{N_1 - N_1^{Out}}{N_1 + N_0^{In}} \quad (8)$$

Here, N_1 = total number of 1's in diagonal block; N_1^{Out} = total number of 1's outside the diagonal block and N_0^{In} = total number of 0's inside the diagonal block. The value of grouping efficacy when closer to 1 indicates better clustering.

5. Numerical Experiments with Randomly Generated Data

The solution method proposed in this work was tested with randomly generated dataset. The generated dataset is binary in nature. 1's represents that the ambulance driver knows the service location and 0's represents that they do not know the service

location (Table 2). As this dataset was generated randomly so the clusters were not known beforehand. This data set has 9 ambulance drivers and these drivers are scheduled in different shifts. The ambulance drivers in each shift have to cover 25 service locations.

5.1 Results and Analysis

The purpose of the numerical experiment is to gain new insights by exploring the artificially generated driver-service location dataset. During the training process the data was presented 100 times to the complete network before the map converged as shown in Figure 3. The U-matrix output obtained after application of SOM to the dataset showed the existence of 4 clusters as shown in Figure 4.

Table 2 Randomly Generated Data for Ambulance Drivers with Knowledge of Different Service Locations

	D1	D2	D3	D4	D5	D6	D7	D8	D9
L1	0	0	0	1	1	0	0	0	0
L2	0	0	0	0	0	1	0	1	0
L3	1	0	0	0	0	0	1	0	0
L4	0	0	0	1	1	0	0	0	0
L5	0	0	0	0	0	1	0	1	0
L6	0	1	0	0	0	0	1	0	0
L7	0	0	0	1	1	0	0	0	0
L8	0	0	0	0	0	0	1	0	0
L9	1	0	1	0	0	0	0	0	1
L10	0	0	0	1	1	0	0	0	0
L11	1	0	1	0	0	0	0	0	1
L12	0	0	0	1	1	0	0	0	0
L13	0	1	0	0	0	0	1	0	0
L14	0	0	0	0	0	0	0	1	0
L15	0	1	0	0	0	0	1	0	0
L16	0	0	0	0	0	0	1	0	0
L17	1	0	1	0	0	0	0	0	0
L18	0	0	0	0	0	1	0	1	0
L19	1	0	1	0	0	0	0	0	1
L20	0	0	0	1	1	0	0	0	0
L21	0	0	0	0	0	0	0	1	0
L22	0	0	0	0	0	0	0	1	0
L23	1	0	1	0	0	0	0	0	0
L24	1	0	1	0	0	0	0	0	1
L25	0	0	0	0	0	1	0	1	0

Figure 3 Training Process

Figure 4 U-Matrix

The cluster borders have been indicated with bold black color. The result obtained in Figure 4 was validated using sum of squares as shown in Figure 5. The component plane (Figure 6) shows the weights of ambulance drivers for service locations. The details of cluster membership (Table 3) obtained after applying SOM to data revealed which service locations belonged to which cluster.

Figure 5 Within Cluster Sum of Squares

Based on this information and the raw data D1, D3, D9; D4, D5; D6, D8 and D7, D2 seem to be the members of the four clusters suggested by Figure 3, Figure 5 and Table 3. The block diagonal was prepared in three steps.

- Step 1: Service locations belonging to first cluster are placed together in rows.
- Step 2: Service locations known to similar kinds of ambulance drivers were placed next to each other as far as possible. For example, ambulance drivers D1, D3 and D9 know service locations L9 and L19 and both the service locations belong to cluster-1 (Table 3) so they are placed next to each other in block diagonal.
- Step 3: The ambulance drivers knowing about a service location are placed first in columns and then ambulance drivers knowing next service location are placed in succeeding columns. For example, in case of first cluster L9 is known to three ambulance drivers (i.e. D1, D3, D9) and other locations in cluster 1 is also known to same set of ambulance drivers so we don't need to add further any ambulance drivers. But in case of cluster 2 the first location is known to another set of ambulance drivers i.e. D4 and D5, hence these ambulance drivers are added in succeeding columns. These steps are repeated for all the locations to prepare the block diagonal (Table 4).

Figure 6 Component Plane

Table 3 Cluster Details

Service location	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	L13	L14	L15	L16	L17	L18	L19	L20	L21	L22	L23	L24	L25
Cluster	2	3	4	2	3	4	2	4	1	2	1	2	4	3	4	4	1	3	1	2	3	3	1	1	3

Table 4 Block Diagram

	D1	D3	D9	D4	D5	D6	D8	D7	D2
L9	1	1	1						
L19	1	1	1						
L24	1	1	1						
L17	1	1	1						
L23	1	1	1						
L11	1	1	1						
L1				1	1				
L4				1	1				
L7				1	1				
L10				1	1				
L12				1	1				
L20				1	1				
L2						1	1		
L5						1	1		
L25						1	1		
L18						1	1		
L21								1	
L22								1	
L14								1	
L13									1
L6									1
L15									1
L3									1
L16									1
L8									1

Based on information in block diagonal (Table 4), grouping efficacy was calculated to be 86.36 % using Equation 8. Also topographic error was found to be 1.05. To increase the reliability of results obtained using SOM we used one form of heat map, which uses dendrogram to cluster service location and ambulance drivers available on R software. The results of the same have been shown in Figure 7. This numerical example demonstrates the applicability of SOM in situations where ambulance drivers if allocated to certain set of service locations can reduce response time by using their knowledge of service location.

Figure 7 Heatmap

6. Managerial Implications and Conclusions

A complex ambulance driver scheduling problem, which involves various service locations is difficult to solve due to combinatory explosion associated with it. A SOM based approach has been proposed and used in this paper to address the ambulance driver-scheduling problem. The performance was measured for the problem. Grouping efficacy (86.36%) was used as a measure of performance. A major finding of this study is that SOM can be used for scheduling of ambulance driver across service locations. Utilizing the proposed SOM approach, ambulance driver scheduling problem can be dynamically and virtually structured into relatively small and manageable parts. Unlike previous research work on ambulance driver scheduling the methodology proposed in this work gives the manager a visual solution to this problem. The visual navigability to ambulance driver scheduling problem along with the usage of knowledge of service location provided in this work makes it unique. The knowledge of service location of ambulance drivers available with ambulances companies can be used to reduce response time in some of the following ways:

- In case of traffic congestion the ambulance drivers with knowledge of certain service location can take certain routes to avoid traffic, which is generally not the case with all ambulance drivers.
- In case of locations with very complex structure of roads mostly in case of unplanned cities/historical cities they can pick up patients from interior areas at much faster rate as compared to drivers with no or very little understanding of these locations.
- In case of underdeveloped / interior locations (especially in case of third world countries) it is on several occasions impossible to reach to patients for ambulance drivers who do not have understanding of these service locations.
- The working hours for ambulance drivers in number of cases exceed their normal working hours (Rajagopalan et al, 2011) and managers need information as which set of drivers are best suited for extra working hours. The proposed approach can resolve this issue, as now managers know drivers with similar set of knowledge with respect to service location so depending upon demand they can decide which ambulance drivers are best suited for extra working hour. Also it would guide managers while recruiting ambulance drivers in future.
- This work would also assist managers in tackling uneven distribution of resources during night shifts (6 p.m. -6 a.m.), which has been found to be major cause of deaths in case of emergency patients admitted during these hours (Anderson et al. 2014). This work would enable managers to evenly distribute its resources throughout the various shifts by identifying drivers with similar kind of expertise i.e. it would enable them to distribute drivers with similar kind of expertise in all shifts.
- The condition of traffic changes with time of day say for example traffic on roads leading to offices and schools is higher during morning hours whereas traffic on roads leading to local markets/restaurants is higher late in evening. Now the managers can use this information along with knowledge of which pool of drivers are best suited to provide service in a given locations. The managers can decide how many drivers are to be recruited and then subsequently assign them in relevant working hours.

As a future research endeavor, the present work can be extended by accounting for other parameters in ambulance driver scheduling such as how to encounter disruptions in schedule caused by natural disasters or any other such untoward event. Further, the visual clustering approach based on SOM can be improved further by employing metaheuristic/heuristic or any other such approach.

7. Reference

1. Aboueljinane, L., Jemai, Z., & Sahin, E. (2012, December). Reducing ambulance response time using simulation: The case of Val-de-Marne department Emergency Medical Service. In *Proceedings of the Winter Simulation Conference* (p. 84). Winter Simulation Conference.
2. Aboueljinane, L., Sahin, E., Jemai, Z., & Marty, J. (2014). A simulation study to improve the performance of an emergency medical service: Application to the French Val-de-Marne department. *Simulation modelling practice and theory*, 47, 46-59.
3. Anderson D, Gao GG, Golden B (2014) Life is all about timing: an examination of differences in treatment quality for trauma patients based on hospital arrival time. *Prod Oper Manag* 23(12):2178–2190
4. Andersson, T., & Värbrand, P. (2007). Decision support tools for ambulance dispatch and relocation. *Journal of the Operational Research Society*, 58(2), 195-201.
5. Aringhieri, R., Bruni, M. E., Khodaparasti, S., & van Essen, J. T. (2017). Emergency medical services and beyond: Addressing new challenges through a wide literature review. *Computers & Operations Research*, 78, 349-368.
6. Balakrishnan, P. V., M. C. Cooper, V. S. Jacob, and P. A. Lewis. 1996. "Comparative Performance of the FSCL Neural Net and K-means Algorithm for Market Segmentation." *European Journal of Operational Research* 93 (2): 346–357.
7. Ball, M.O., Lin, L.F., 1993. A reliability model applied to emergency service vehicle location. *Operations Research* 41, 18–36.
8. Brotcorne, L., Laporte, G., & Semet, F. (2003). Ambulance location and relocation models. *European journal of operational research*, 147(3), 451-463.
9. Brusco, M. J., D. Steinley, J. D. Cradit, and R. Singh. 2012. "Emergent Clustering Methods for Empirical OM Research." *Journal of Operations Management* 30 (6): 454–466.
10. Carter G, Chaiken J and Ignall E (1972). Response areas for two emergency units. *Opns Res* 20(3): 571-5
11. Gendreau, M., Laporte, G., & Semet, F. (1997). Solving an ambulance location model by tabu search. *Location science*, 5(2), 75-88.
12. Gendreau, M., Laporte, G., & Semet, F. (2001). A dynamic model and parallel tabu search heuristic for real-time ambulance relocation. *Parallel computing*, 27(12), 1641-1653.
13. Ghosh, S., & Varakantham, P. (2016). Strategic Planning for Setting up Base Stations in Emergency Medical Systems. In *International Conference on Automated Planning and Scheduling (ICAPS)*.

14. Guo, L., D. Rivero, and A. Pazos. 2010. "Epileptic Seizure Detection Using Multiwavelet Transform Based Approximate Entropy and Artificial Neural Networks." *Journal of Neuroscience Methods* 193 (1): 156–163.
15. Ingolfsson, A., Budge, S., & Erkut, E. (2008). Optimal ambulance location with random delays and travel times. *Health Care Management Science*, 11(3), 262–274.
16. Jagtenberg, C. J., Bhulai, S., & van der Mei, R. D. (2015). An efficient heuristic for real-time ambulance redeployment. *Operations Research for Health Care*, 4, 27–35.
17. K. Tasdemir, Exploring topology preservation of SOMs with a graph based visualization Lecture Notes in Computer Science 5326 (2008) 180–187.
18. Kaski S.: Data Exploration Using Self-Organizing Maps, Acta Polytechnica Scandinavia, 82, 1997.
19. Kim, S. H., & Lee, Y. H. (2016). Iterative optimization algorithm with parameter estimation for the ambulance location problem. *Health care management science*, 19(4), 362–382.
20. Kivilnito, K., Topology preservation in self-organizing maps, In: Proceedings of ICNN'96, IEE International Conference on Neural Networks. IEEF, Service Center, Piscataway, pp. 294–299, 1996
21. Kohonen T., *self-organizing maps*, Springer, Berlin, Germany, 2001
22. Kohonen, T. 1989. Self-Organization and Associative Memory. 3rd Ed. New York: Springer-Verlag.
23. Lee, S. (2012). The role of centrality in ambulance dispatching. *Decision Support Systems*, 54(1), 282–291.
24. Lee, S. (2015). A new preparedness policy for EMS logistics. *Health care management science*, 1–10.
25. Li, D. (2015, June). Poster: A Time-Saving Scheme for Ambulance Transportation with Support of Software-Defined Networking. In *Proceedings of the 16th ACM International Symposium on Mobile Ad Hoc Networking and Computing* (pp. 391–392). ACM.
26. Li, X., Zhao, Z., Zhu, X., & Wyatt, T. (2011). Covering models and optimization techniques for emergency response facility location and planning: a review. *Mathematical Methods of Operations Research*, 74(3), 281–310.
27. M. Chattopadhyay, S. Chattopadhyay, P. Dan, Machine-part cell formation through visual decipherable clustering of self-organizing map, The International Journal of Advanced Manufacturing Technology 52 (9–12) (2011) 1019–1030.
28. Mangiameli, P., S. K. Chen, and D. West. 1996. "A Comparison of SOM Neural Network and Hierarchical Clustering Methods." *European Journal of Operational Research* 93 (2): 402–417.
29. Marianov, V., Reveille, C.S., 1995. Siting emergency services. In: Drezner, Z. (Ed.), *Facility Location*. Springer, New York, pp. 199–223.
30. McMullen, P. R. 2001. "An Ant Colony Optimization Approach to Addressing a JIT Sequencing Problem with Multiple Objectives." *Artificial Intelligence in Engineering* 15 (3): 309–317.

31. Medhi, P. K., & Mondal, S. (2016). A neural feature extraction model for classification of firms and prediction of outsourcing success: advantage of using relational sources of information for new suppliers. *International Journal of Production Research*, 54(20), 6071-6081.
32. Mingoti, S. A., and J. O. Lima. 2006. "Comparing SOM Neural Network with Fuzzy C-means, K-means and Traditional Hierarchical Clustering Algorithms." *European Journal of Operational Research* 174 (3): 1742–1759.
33. Nogueira Jr, L. C., Pinto, L. R., & Silva, P. M. S. (2016). Reducing Emergency Medical Service response time via the reallocation of ambulance bases. *Health care management science*, 19(1), 31-42.
34. Pankaj Kumar Medhi & Sandeep Mondal (2016) A neural feature extraction model for classification of firms and prediction of outsourcing success: advantage of using relational sources of information for new suppliers, *International Journal of Production Research*, 54:20, 6071-6081, DOI: 10.1080/00207543.2016.1174342
35. Patrick, J., Puterman, M. L., & Queyranne, M. (2008). Dynamic multipriority patient scheduling for a diagnostic resource. *Operations research*, 56(6), 1507-1525.
36. Rajagopalan, H. K., Saydam, C., Setzler, H., & Sharer, E. (2011). Ambulance deployment and shift scheduling: An integrated approach. *Journal of Service Science and Management*, 4(01), 66.
37. Sasaki, S., Comber, A. J., Suzuki, H., & Brunsdon, C. (2010). Using genetic algorithms to optimise current and future health planning-the example of ambulance locations. *International journal of health geographics*, 9(1), 1.
38. Skupin, P. Agarwal, What is a self-organizing map? In: P. Agarwal, A. Skupin (Eds.), *Self-organising Maps: Applications in Geographic Information Science*, John Wiley & Sons, Chichester, England, 2008, pp. 1–20.
39. Stein, C., Wallis, L., & Adetunji, O. (2015). Meeting national response time targets for priority 1 incidents in an urban emergency medical services system in South Africa: More ambulances won't help. *SAMJ: South African Medical Journal*, 105(10), 840-844.
40. Suresh Kumar, C., & Chandrasekhar an, M. P. (1990). Grouping efficacy: a quantitative criterion for goodness of block diagonal forms of binary matrices in group technology. *International Journal of Production Research*, 28(2), 233-243.
41. Toro-DíAz, H., Mayorga, M. E., Chanta, S., & Mclay, L. A. (2013). Joint location and dispatching decisions for emergency medical services. *Computers & Industrial Engineering*, 64(4), 917-928.
42. Uyeno, D. H., & Seeberg, C. (1984). A practical methodology for ambulance location. *Simulation*, 43(2), 79-87
43. Vesanto, J., Alhoniemi, E., Clustering of the Self-Organizing Map, *IEEE Transactions on Neural Networks*, 11(3), 586–600, 2000
44. Westerlund, M. L. (2005). Classification with Kohonen self-organizing maps. *Soft Computing, Haskoli Islands*.
45. Wilppu, R., the Visualisation Capability of Self-Organizing Maps to Detect Deviation in Distribution Control. TUCS Technical Report No. 153. Turku Centre for Computer Science, Finland, 1997

46. Zhen, L., Sheng, S., Xie, Z., & Wang, K. (2015). Decision rules for ambulance scheduling decision support systems. *Applied Soft Computing*, 26, 350-356.

About Our Authors

R.K. Jha is a management consultant. He holds a PhD (Business Management) in Production and Operations Management from Indian Institute of Management Raipur, India. His research interest lies in the area of scheduling, planning, healthcare supply chain management and digital strategies in business.

Manojit Chattopadhyay is an Associate Professor of Information Technology and Systems at Indian Institute of Management Raipur, India. He holds a PhD (Business Management) in the area of Decision Science and Systems from Department of Business Management, University of Calcutta and M. Phil (Management) in the area of Systems Management from West Bengal University of Technology. He has affiliations from, Dept. of Business Management of University of Calcutta, IIAS School of Education, affiliated to Visva Bharati, Industrial Engineering and Management department of West Bengal University of Technology and several other institutions of repute. His research interests mainly lie in business intelligence in decision making, modelling using artificial neural network/soft computing/visual data mining (clustering), cellular manufacturing system/group technology, digital strategies in business and social network analysis.

Yuvraj Gajpal is an Associate Professor of Supply Chain Management at Asper School of Business, University of Manitoba Winnipeg, Canada. He holds a PhD in Management Science from DeGroote School of Business at McMaster University Hamilton, Canada and Master in Industrial Management from Indian Institute of Technology (IIT) Madras, India. He has worked as a postdoctoral fellow at Interuniversity Research Center on Enterprise Networks, Logistics and Transportation (CIRRELT), University of Ontario Institute of Technology (UOIT) and McMaster University. He is a member of Institute for Operations Research and the Management Sciences (INFORMS) and Canadian Operational Research Society (CORS). His research interests mainly lie on application of heuristics and meta-heuristics on transportation and logistics management. His current research is focused on retail supply chain management where he is exploring the issue of contract between retailer and manufacturer and the effect of different inventory policy on their relationship.