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Transportation Research Procedia 00 (2018) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2019 Mumbai 26-31 May 2019

Effective Handling of Emergencies in Resource Constrained Urban Areas by Considering Dynamics: A Performance Analysis

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Abstract

Emergency Response Services (ERS) in the developing countries often face the challenge of distributing the resources in a manner to provide optimal service. Moreover, the exclusion of heterogeneous urban fabric and considerable variations of travel time and coverage demand throughout the day often leads to inadequate solutions. Hence, we propose an approach to incorporate dynamic aspects like demand, travel time, and coverage area in developing an asset location model. We illustrate how the travel time distribution produces more reliable coverage results when compared to the model considering fixed travel times over the periods. We also incorporate the influence of urban settlement elements like built-up compactness etc. in the resource allocation. A machine learning based approach is proposed to estimate the varying demand. The prediction model predicts the firefighting vehicles demand with high accuracy. We formulate a mixed integer program to maximize the empirical demand coverage by firefighting vehicles. The proposed model is applied to the southern region of Mumbai, India. We use percentage coverage and coverage variation difference as the metrics to test the performance of the model. When compared to the static travel time model considering fixed average travel times the dynamic model showed more variability in the coverage. This supports our hypothesis that demand and the travel time variations influence the coverage. For the dynamic case, the maximum coverage variability for the vehicles was found to be in the range of 9%, whereas for the static case it was found to be in the range of 6%.

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Keywords: Data-driven optimization; Emergency response services; Resource allocation; Travel time and resource planning; Dynamic adaption; Sustainable cities

1. Introduction

Emergency incidents in urban areas of India have become frequent. For example, as per the India Risk Survey

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report published in 2016, a total of 3.16 lakh fire accident cases were reported in India between 2001 and 2014 (FICCI, 2016). Our analysis of the response time data acquired from Mumbai Fire Brigade (MFB) for the southern Mumbai region showed that only 4.82 percent of the total area was covered as per the response time guidelines of four minutes and 29.25 percentage of the entire area was covered in eight minutes.

As per the India risk survey report, there is an alarming deficit of 72.75 percent in the urban areas (FICCI, 2016). The city of Mumbai which is our study area lacks around 66 fire stations to match the global standards of 100 stations to cover the city in an acceptable range of eight minutes (Mumbai Fire Brigade, 2014). In such alarming resource-constrained conditions, the aim to serve maximum people becomes even more challenging. One of the solutions to ensure better efficiency can be tactically planned facility locations and the resources over them.

Nomenclature

MFB	Mumbai Fire Brigade
ERS	Emergency Response Services
EMS	Emergency Medical Services
ML	Machine Learning
GIS	Geographic Information System
FT	Fire Tenders
RT	Rescue Truck
WT	Water Truck
A	Ambulance
R	Residential areas
C	Commercial areas
I	Industrial areas
L	Low rise
H	High rise
M	Medium rise
RMSE	Root Mean Square Error

Several studies have provided essential insights into dynamic changes that occur throughout the day while planning the location and relocation strategy for Emergency Response Services (ERS) in an urban region. Deviation in demand, travel time and effective coverage has been reported concerning hours in a day and among days of a week (Degel et al., 2015). As neglecting these variations could lead to incorrect estimation of the time-dependent coverage, fleet size, and their positions, an appropriate approach is presented that incorporate these variations. The estimation becomes more complex in the case of firefighting, due to variation in vehicle types (Berg et al., 2016). Most of the existing models focus on fixed backup or double coverage that does not consider the much needed temporal and spatial variations of the demand and the travel time of the vehicles. We propose a model that incorporates these variations for maximizing the empirically determined coverage by firefighting vehicles.

The performance measure for emergency services focuses on reaching a percentage of area within a response time limit. Accurate prediction of such performance measures requires information about the distribution of response time which depends on the traffic congestions in the selected route. According to the BMC's Comprehensive Mobility Plan (CMP) report published in 2016, on 67% of road networks, vehicle speeds are less than 20kmph during the evening peak hours. In the western suburbs alone, 78% of road networks bring down the speed (MCGM, 2016). The report says 52% of road networks in the island city and 45% in the western suburbs saw vehicles moving at 20kmph or less. This highlights the importance of considering the travel time in decision making. The influence of time-dependent travel in identifying the ambulance locations has been studied by (Schmid and Doerner, 2010). Taking motivation from their work, we present a coverage based comparative performance analysis of the developed model considering static and dynamic travel time.

An efficient firefighting strategy requires a clear understanding of spatiotemporal fire incident patterns, role of built environment, urban settlement elements, and their interrelationships (Turner et al., 2017). The prior researches did not consider them collectively, leading to suboptimal responses to fire incidents. We argue that firefighting solutions must incorporate fine-grained urban details to make the solution feasible. For example, establishing a large number of fire stations might be a possible solution in a broader context, but it is impractical for a growing city like Mumbai with limited space and ever-increasing compactness of the urban sprawl. The idea of mini fire stations with fewer resources in high compact areas can be a good option for a quick response. It can also prove to be economical if the resources need to be relocated over a short time. To address these challenges, we develop an approach to show the importance of dynamic variations over various periods for influencing the tactical decisions related to resource distribution and positioning. Our model incorporates different urban environment variables like built-up compactness and settlement details to estimate the demand and to distribute the available resources over suitable locations.

The paper is organized as follows: We discuss related work in the next section. After listing the contributions, we then discuss the problem modeling framework followed by a case study. The section also details the various data-sets and the demand estimation technique. Lastly, we present the empirical results followed by conclusions.

2. Related work

2.1 Facility location models

Some of the earlier models and methods developed to improve the ERS services are (i) the p-median (minimum) problem (ii) the p-center (minimax) problem (iii) the Maximum Coverage Location Problem (MLCP), and iv) Set Covering Location Problem (SCLP) had a drawback of being static in nature (Simpson and Hancock, 2009). Also, these models did not consider the probability of resources being unavailable. MEXCLP, a version of the covering location problem incorporates busy fractions to determine the expected coverage (Repede and Bernardo, 1994). Apart from these, many variants like Capacitated Facility Location Problem (CFLP) and other methods based on heuristics and metaheuristics exist (Gholami-Zanjani et al., 2018). Average Response Time Model (ARTM) minimizes the average response time from the nearest base. Double Standard Model (DSM) incorporates the concept of backup coverage. Some of the other earlier models that discuss the idea of backup coverage include BACOP1, BACOP2, and MALP (Berg et al., 2016). However, these models are static and did not consider the dynamics of travel time, demand, or fleet size over time.

2.2 Dynamic coverage models

The work proposed by Li et al. (2015) considers traffic situations for estimating locating the facilities. TIMEXCLP is an extension of MEXCLP under dynamic settings (Li et al., 2011). It optimizes the expected coverage at various points considering time-varying travel times, demands and changing fleet sizes (TIMEXCLP). However, the model views each time period independently without linking the periods. Rajagopalan et al. (2005) presents a model to estimate the number of ambulances needed to satisfy specific coverage requirements during various time-periods. Degel et al. (2015) introduces an extension of the Double Standard Model which includes time-dependent travel time and empirically derived coverage in their model for the ambulances. Schmid and Doerner (2010) compare time-dependent over a time-independent model. However, they have not considered the ambulance types. Thus, coverage by any ambulance is considered the same. Berg et al. (2016) discuss the importance of considering vehicle types in firefighting. Their study introduces a firefighting specific coverage model which considers various types of firefighting vehicles. However, the work lacked time-dependent variations, and further considers a fixed coverage condition. Van den Berg and Aardal, (2015) presents an extension of MEXCLP with time-dependent demand coverage. It considers a demand point to be covered if covered by k ambulances are allocated in a time period. Boujemaa et al. (2018) introduces an extension of MCLP model which considers various ambulance types. However, the model does not consider time-dependent variations in the model. Most of these models are developed based on the usage pattern of an ambulance. This raises an important question over applicability and implementation of models developed in various ERS services. Berg et al. (2016) points out the specific differences in the working style and requirements of Emergency Medical Services (EMS) for fire services and proposed different models to make them more implementable. This work states that a lesser focus is given on developing the firefighting specific location models. One of the reason might be the lack of data, which is a concern in developing countries, and especially for resource deficient fire services. To the best of our knowledge, apart from no study in the literature discusses the importance of travel time in empirical demand coverage especially in the case of firefighting. Our data-driven approach influenced by TIMEXCLP incorporates firefighting specific characteristics to address the gap in the literature.

2.3 Role of urban spaces in firefighting

Effective firefighting not only incorporates response required in EMS but also demands a clear understanding of the surroundings, spatiotemporal pattern of incidents and the influence of urban elements that varies across countries and regions (Turner et al., 2017). Wang et al. (2013) argues that, until the fire station location model does not consider the complex urban and incident parameters, the model will not provide a realistic optimal solution. Sathyadevan et al. (2014) discuss the significance of urban data in delivering emergency services. Chakrabarti (2001) highlights resource and land use constraints as some of the major hurdles in developing countries for any infrastructure development. Limited literature can be found on the optimization of emergency response services in the context of resource-constrained societies, which considers the urban space details in determining the location of new emergency response services, especially fire services. This study aims to fill in the existing gap while analyzing the granular urban datasets for the case of Mumbai India.

2.4 Dynamically varying demand estimation

Predicting demand accurately at locations is critical for fleet management and dynamic deployment. Sari Rochman et al. (2018) apply Machine Learning (ML) based approach to estimate the number of patient visits to Dental Poli. Data mining techniques are applied for pre-positioning of ambulances in the Dhaka city (Maghfiroh et al., 2018). They use time series models to forecast the daily, and hourly EMS demands. However, capturing the critical spatial variation of the demand is not performed in their study. As incidents may occur temporally and spatially, incorporating the spatial information of the surroundings might improve the accuracy of the demand prediction. To mitigate the gaps in the literature, this research integrates granular urban settlement data together with fire incident datasets to predict the spatially and temporally varying demand of vehicles in the potential fire-prone areas using the supervised machine learning based Decision Tree (DT) algorithm.

3. Contribution

To overcome the previously discussed drawbacks, the contribution of the paper includes a new optimization model by considering:

1. Time and day dependent travel time and spatiotemporal demand variations.
2. Spatiotemporal demand variation based empirically calculated coverage level for the demand points.
3. Urban space specific characteristics like the built-up compactness of an area in determining the total allowed vehicles at a location.

The paper presents performance analysis of static and dynamic firefighting coverage models considering travel time variations. The results can pave the way for the decision makers to effectively plan the resources for better coverage of the demand in quick response time.

4. Research framework

To develop the location-allocation model considering dynamic variations study has been divided into various phases (Figure 1). Phase1 comprises of the task of data collection, filtering, and preparation. In the second phase, we apply different types of analysis techniques: temporal, spatial, and spatiotemporal to understand the dynamics of fire incidents. These analyses provide useful insights into fire management problems by revealing trends and patterns. Geographic Information System (GIS) has been used to manage, analyze and visualize the spatial data. To predict the spatiotemporal vehicle demand in the fire-prone areas, decision tree based regression model is trained.

Our prediction model uses the fire incident data obtained from the Mumbai Fire Brigade (MFB) and urban settlement elements as the informative variables in the training set. In the final phase of the study, we include the time-dependent travel time data and the estimated demand variations to calculate the resulting changes in coverage throughout the day. We then introduce a firefighting specific model which incorporates this information and allows vehicles to be redistributed to optimize the coverage at several points in time. We estimate the models independently for various points in time without considering the reallocation of resources. We present cases to stress the importance of quality of travel time data in such studies. The model determines the coverage and the distribution of the firefighting vehicles over the locations for different periods of a day.

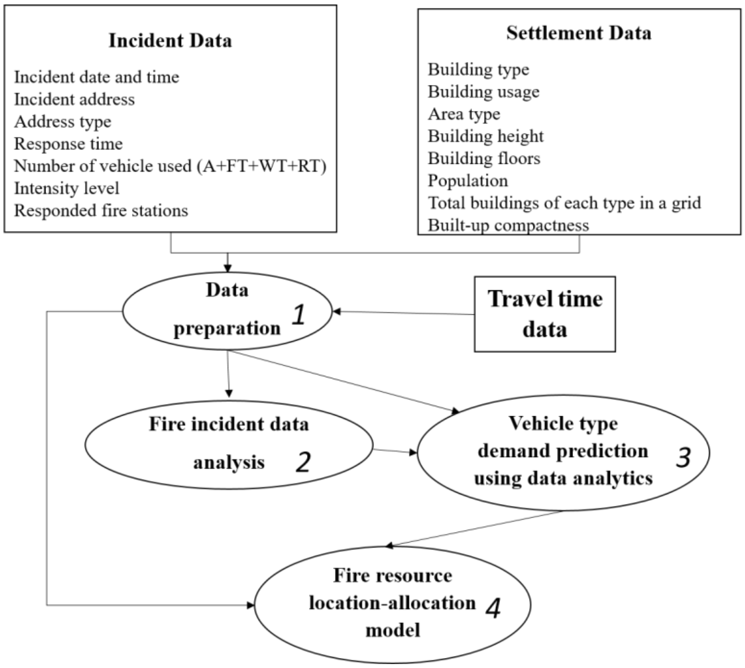


Figure 1. Approach of the study

5. Problem statement and modeling framework

We consider two separate conditions with no locations being given priority over other potential locations; a) actual travel time values, b) averaged travel time values. The model is formulated given:

- Vehicles types: Fire Tenders (FT), Rescue Truck (RT), WT (Water Truck), Ambulance (A).
- The travel time of a vehicle from point *a* to point *b* is independent of the vehicle types.

The objective of the model is to maximize the coverage of the demand areas by the appropriate vehicle type. We formulated the model as an integer linear programming model. This type of problem being NP-hard, in general, cannot be solved in polynomial time. However, many commercial solvers like Gurobi and CPLEX can provide an optimal solution for realistic instance sizes in reasonable time duration (Bixby, 2012; Lodi et al., 2010). In our study, we have used the Gurobi Optimizer. We include various types of vehicles in the optimization, which are used to serve different types of calls. We define a set V of vehicle types. The demand for a particular vehicle $v \in V$ from demand point $j \in J$ at a time period $t \in T$ is given by d_{jvt}, p_i denotes the total available vehicles at a location I, and p_v denotes the total available units of each vehicle types in a time period. The travel time between bases location $i \in I$ and demand point $j \in J$ is assumed to be fixed and independent of the vehicle type, and is denoted by t_{ij}. The response time target for each type of vehicle for every demand point is denoted by r_{iv} for all type of vehicles. Here, I_{jvt} denote the set of potential locations for a fire station, that can cover the demand points $j \in J$ under response time target r_{iv} by a vehicle

type $v \in V$ in the time period $t \in T$, is equal to $I_{jvt} = \{i \in I | t_{ij} \leq r_{iv}\}$. In the model formulation, we use two types of variables. The number of type v vehicles that are placed at potential base location i during the time period t is denoted by x_{ivt}. Second, a binary variable $y_{jd_{jvt}}$ indicates whether the demand point j is covered at-least d_{jvt} times by vehicle of type v during the time period t.
The model is defined as follows:

$$z = \sum_{t \in T} \sum_{j \in J} \sum_{v \in V} d_{jvt} y_{jd_{jvt}} \tag{1}$$

The objective function z maximizes the coverage overall demand points in all periods without considering the reallocations.
Subject to:

$$\sum_{i \in I_{jvt}} x_{ivt} \geq \sum_{1}^{d_{jvt}} y_{jd_{jvt}} \qquad \forall j \in J; v \in V; t \in T, \tag{2}$$

Constraint (2) states that demand point j is only covered by vehicle type v if there is at least n vehicle of type v at base locations close enough to demand point j, where n is equal to the total demand of a particular vehicle during time t denoted by (d_{jvt}). A base location to be close enough depends on the vehicle at that base, which is ensured by the set I_{jvt}.

$$\sum_{v \in V} x_{ivt} \leq p_i \qquad v \in V, t \in T, i \in I, \tag{3}$$

Constraints (3) states the maximum capacity of vehicles at a location i. In the empirical results section, we address how to determine the appropriate values of p_i.

$$\sum_{i \in I} x_{ivt} \leq p_v \qquad \forall\, v \in V, t \in T, \tag{4}$$

Constraints (4) limits the number of each vehicle type for every period.

$$\sum_{j \in J2} d_{jvt} y_{jd_{jvt}} \geq \alpha \sum_{j \in J2} d_{jvt} \qquad \forall\, v \in V, t \in T, \tag{5}$$

We give importance to the coverage of highly vulnerable demand areas. To do so, we define a variable $J2$, *where* $J2 = \{j \in J | a_j \geq Int\}$ denotes the demand points with intensity value (*Int*) greater or equal to four. A variable α is introduced, whose value indicates the required percentage coverage. Constraint (5) ensures that α % of the demand points with a fire intensity proneness value equal to or greater than four, which states that highest intensity fires must be covered by the vehicles of type v during the period t.

$$y_{jvt}, \in \{0, 1\} \qquad \forall\, v \in V, i \in I, j \in J, t \in T. \tag{6}$$

6. Case study and empirical results

To prove the effectiveness of the model, we empirically tested the model in the southern part of the city of Mumbai India (Figure 2). To incorporate the temporal aspect in estimating coverage one single day (24 hours, starting from midnight) was equally split into a set T of six time periods, each of length four hours. Changing the starting and ending time points for the periods may lead to significantly different spatial patterns of fire risk. We take into account the traffic congestion patterns during the day presented by (MCGM, 2016) and the study by (Degel et al., 2015) as the base for selecting our time periods., the model assumes the day to be divided into several time periods of the day by allowing distribution of the vehicles over the selected bases. After a description of the data, we present a machine learning based approach to estimate the varying spatiotemporal demand. We use the demand values in the model and to show the influence of travel time on coverage, we compare the execution results of a dynamic model with the static model with fixed travel time.

6.1 Data description

The considered region for the case study is the southern region of Mumbai, the capital of the state of Maharashtra in India. It is also rated as the second most densely populated city in the world (Figure 2). The south Mumbai region is having an area of 41.76 sq. km receives 40% of the total fire calls and has six fire stations out of the total 34 for all of Mumbai. Taking into account the land use and travel time variations we have selected this region as the study area. We divide the study area into 300 m*300 m equal area grids based on the recommendations in the Mumbai fire brigade report (Mumbai Fire Brigade 2014). A total of 464 points as the centroid of the grids are selected as the demand locations.

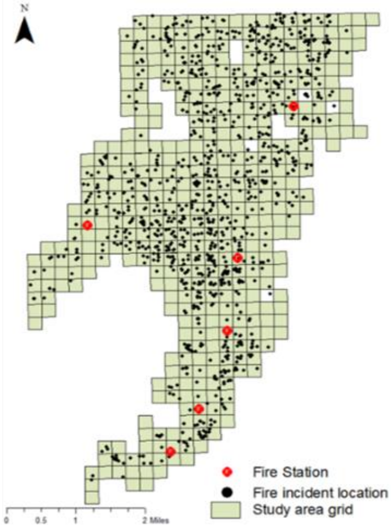


Figure 2. Study area grid with fire incidents and existing fire station locations

We remove the grids consisting of railway stations, water bodies, etc. and define the resulting set as potential base locations that can cover certain demand points (total: 432). The incidents locations, demand, and potential location sites are assigned the value of various urban attributes of the grid area by applying spatial tools.

6.1.1 The travel time data

The network travel time between potential location sites to the demand points during a period is calculated using Google Distance Matrix API. The Google Maps database provides access not only to the network geometry but also to the transport travel times. Google Maps Distance Matrix API as a service returns travel distance and time for an origin-destination (OD) pair at a specified departure time. The acquired information is based on the recommended network route between origin and destination, as calculated by the Google Maps Distance Matrix API. The mode of travel was kept constant ('driving') as further analysis is restricted to the motorized transport travel times on the urban street network (Dumbliauskas et al., 2017).

Figure 3 shows the methodology applied to calculate the travel time between demand and potential locations for time t_x, where, $x \in \{1,2,3,4,5,6\}$.

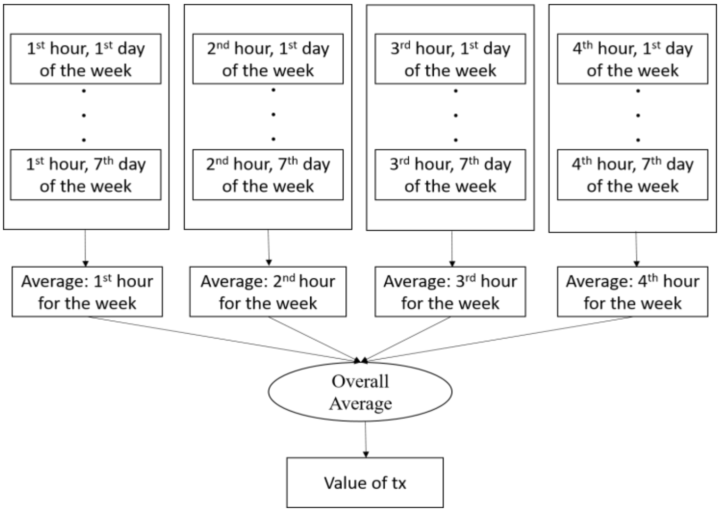


Figure 3. Approach to calculate travel time for a single time period

Every time-period (t_x) is of four-hour duration and every hour can have different travel time values. To incorporate the travel time variability over these duration, an average travel time value for all days in a week are averaged over the four hours is assigned to the respective period. Figure 4 shows the descriptive results of the acquired travel time data for two periods (morning 4 a.m. to 8 a.m. {a, b, c} and evening 4 p.m. to 8 p.m. {d, e, f}). Where figure 4a and figure 4d represent the maximum travel time values from potential site locations to each demand location in the morning and evening respectively. Figure 4b and Figure 4e represent the minimum travel time values from potential site locations to each demand location in the morning and evening respectively. Figure 4c and Figure 4f

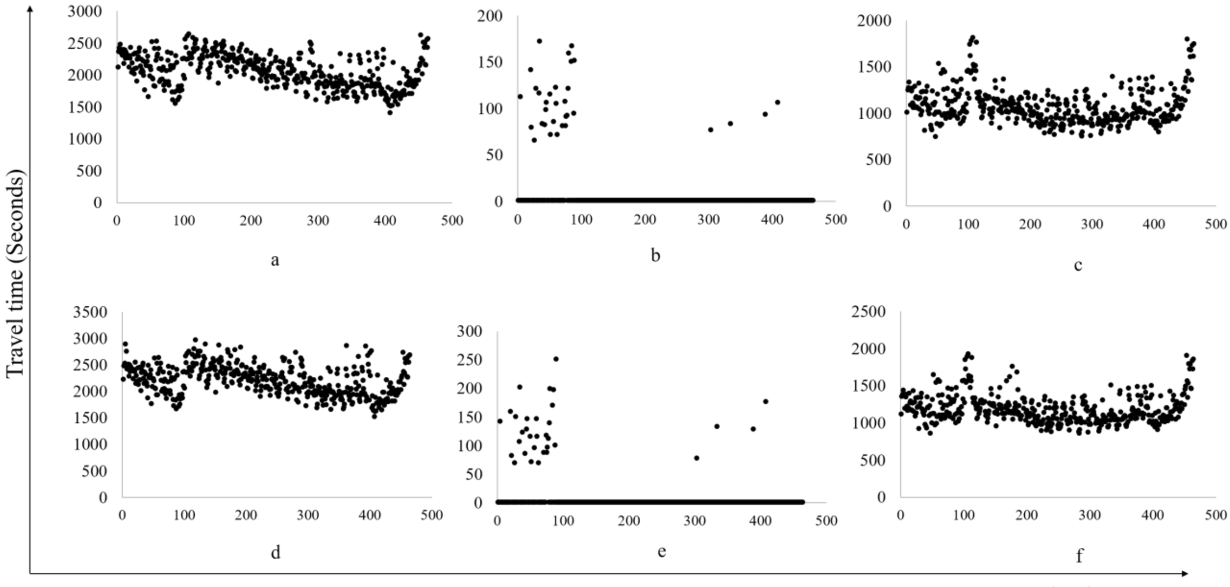


Figure 4. Descriptive results of travel time values for morning distribution 4 a.m. to 8 a.m. (morning) and 4 p.m. to 8 p.m. (evening). Maximum (morning, evening): (a, d); Minimum (morning, evening): (b, e); Mean (morning, evening): (c, f)

represent the mean travel time value from possible site locations to each demand location in the morning and evening respectively. For the computations value of response time target (r_{iv}) is considered independent of the vehicle types and is set to eight mins.

6.1.2 The historical Fire incident data

We have used fire incident records (total 19,504) provided by the Mumbai Fire Brigade (MFB) office from January 2015 to December 2016.

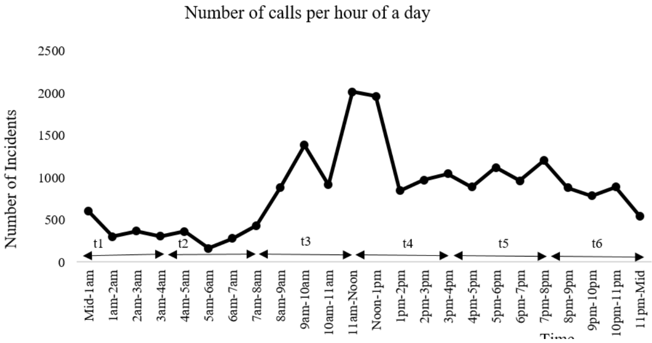


Figure 5. Number of calls per hours and for different time periods

Each record has a list of attributes such as location, address, response time, the cause of an incident, type of building, level of fire, surrounding area details, total number of fire engines used, etc. We added additional attributes for each record such as day of the week, the month of the year, distance to the nearest fire station, etc. Out of the total calls 59.12% calls were Other Service (OS) message calls, 0.27% False Alarm (FA), 36.98% Level1 (L1) fire calls, 1.8% Level2 (L2) fire calls, 1.13% Level3 (L3) fire calls, 0.5% Level4 (L4) and 0.2% Level5 (L5) fire calls. Figure 5 shows the cumulative number of fire emergency calls for Mumbai in 2015, 2016 aggregated for different periods. We filtered out the false alarm and OS calls and used only the fire calls which makes a total of 7,142 entries. A significantly high number of incident calls is reported during the afternoon (11am-1pm) and evening (6 pm to 9 pm).

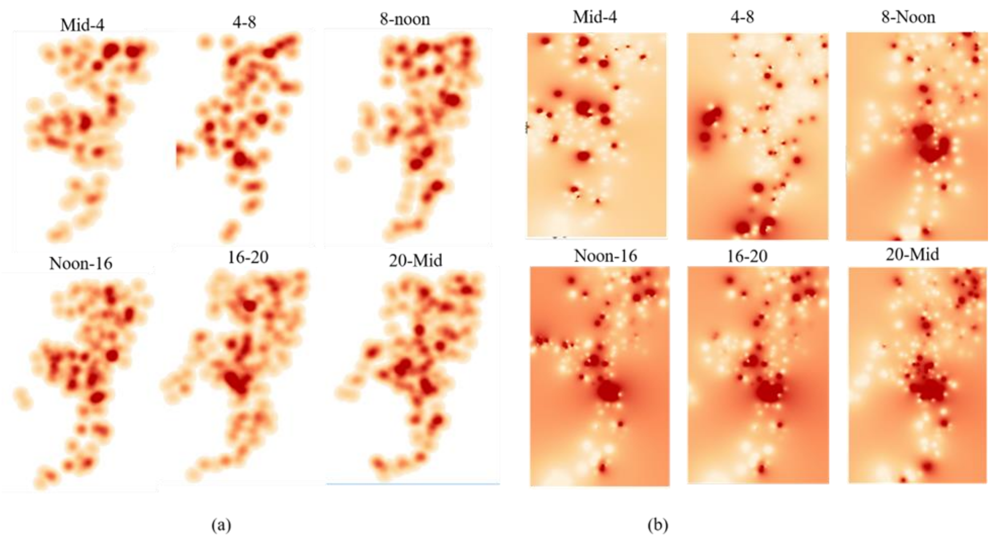


Figure 6. Spatiotemporal incident locations heat map of a) incident locations b) Spatiotemporal intensity

A weighted kernel density function (KDE) with a search radius 500 meters, when applied on the locations and with intensity as the weight, show significant spatiotemporal variations over a day (Figure 6 (a), 6 (b)). However, fewer variations are observed when the same is applied for the days of the week, so we deduce that fire incidents hourly patterns are mostly similar over the days.

6.1.3 The urban settlement dataset

Fire incidents mostly occur in buildings and the spread depends on built-up elements like compactness, land use and other environmental factors like wind, humidity, etc. Therefore, it is important to study the associated attributes for each building and the adjoining area to better understand the dynamics of fire vulnerability. However, we have not considered the environmental factors in the study scope of the paper. In this study, the buildings in the study area are classified (Figure 7 (a), 7 (b)) on the basis of usage and number of floors (Table 1)based on the recommendations mentioned in Bureau of Indian Standards 2015 report and Mumbai fire brigade report (2014) (Bureau of Indian Standards, 2015; Mumbai Fire Brigade, 2014). We used high-resolution landuse map, Google Earth satellite imagery, OpenStreetMap, ESRI topographic, ESRI industrial, and ESRI commercial maps to prepare the database. The built-up features were also validated through field surveys. Due to unavailability of the building height information, we assign floor height and the floor count values based on the standards mentioned in the general building requirement report (2014) (MoUD, GoI, 2014). These standards suggested different floor heights and number of floors, based on the building usage and building type. Google street view images and Wonobo web service were used to manually identify each building type, number of floors, and the floor variation in the areas. Further, field verifications were performed to validate the data sets. The selected number of floors and the floor height are: number of floor (nf):{2 (low rise), 5 (medium rise), 12 (high rise)}, height of floor (hf):{6 (low rise), 7 (medium rise), 7 (high rise)}. Note that this approach might have errors associated with it. Thus, further research is required to obtain the better quality of the built-up datasets. The various classes on the basis of building usage are R, S, C, I, RS, RC, RI, CI, CS, SI, RCS, RIC, RSI, and RSCI, Where R corresponds to residential areas, C: commercial areas, I: Industrial areas, S: Special buildings. The building are classified on the basis of height as: L, M, H, LH, LM, MH, and LMH where L corresponds to low rise, M: medium rise, H: high rise building. Built-up compactness of an area has been defined on the basis of various factors, the one adopted for this study is based upon built-up area density (Kotharkar et al., 2014).

Table 1. Land use and building classification based on usage

Residential (R)	Lodgings, Dwellings, Dormitories, Flats, Hotels etc.
Commercial (C)	Office, Shops, Stores, Restaurants, Market etc.
Industrial (I)	Assembly plants, Labs, Pumping stations, Refineries, Sawmills, All types of storages, Sheds, trucks & marine terminals, Garages, Hangars, Stables, Hazardous storage, etc.
Special (S)	Institutes, Hospitals, College, Schools, Homes for aged, Orphanages, Theatres, Assembly Halls, Auditorium, Assembly Halls, Auditorium, Airport, Railway, bus stations, Exhibition, Restaurants, Place of worship, Jails, Recreations, etc.
High rise (H)	High rise buildings
Low rise (L)	Low rise buildings
Medium Rise (M)	Medium rise buildings

By definition, we estimated the built-up compactness (Figure 7c) of a grid area using the proposed equation (7).

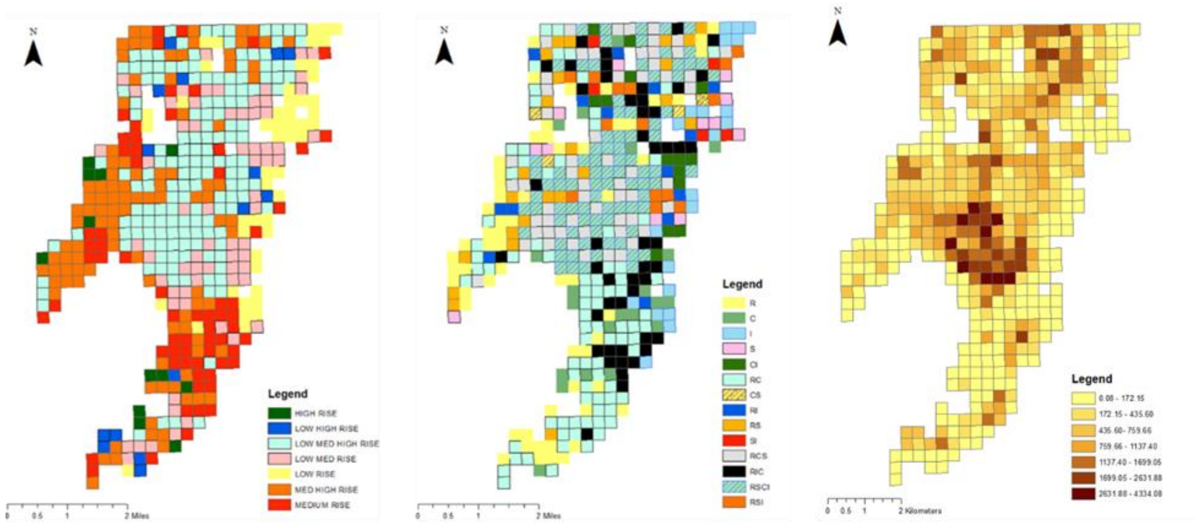
$$\text{Built-up compactness} = (nf_{med} * hf_{med} * F_{med} * N_{med} + nf_{high} * hf_{high} * F_{high} * N_{high} + nf_{low} * hf_{low} * F_{low} * N_{low}) / grid\ area \quad (7)$$

Where,

F_{high}, F_{med}, F_{low} = Mean of the total footprint area for a high rise, medium rise, and low rise buildings

nf_{high}, nf_{med}, nf_{low} = Number of floors for a high rise, medium rise, and low rise building.

hf_{high}, hf_{med}, hf_{low} = Floor height for a high rise, medium rise, and low rise building.



(a) (b) (c)

Figure 7. (a) Classified settlement (Building height) (b) Classified settlement (Building usage) (c) Built-up compactness distribution

6.2 Estimating the firefighting vehicles demand

The number and vehicle types needed during an incident not only depends on the fire intensity but also on the urban environment. The demand also varies with time and location. For calculating the weight d_{jvt}, we divide the fire incident dataset into various time periods and apply machine learning (ML) algorithm. Our prediction model uses the variables listed in Table 2 as the informative variables in the training data. The class attribute Y is individually modeled for all the four types of vehicles separately for each time duration. In our research, we apply the Classification and Regression Trees (CART) method to build and evaluate decision regression tree (Mahjoobi and Etemad-Shahidi, 2008). The algorithm is selected on the basis of work done by (Mahjoobi and Etemad-Shahidi, 2008; Tso and Yau, 2007). Root mean square error (RMSE) defined as the standard deviation of the residuals (prediction errors) is considered as the performance metric in the empirical evaluation of the applied algorithm. To minimize the bias related to data sampling, the 10-fold cross-validation is performed to estimate the performance of the model. Using the same dataset, the model is trained and tested ten times, with the 9-folds used as the training dataset and the remaining 1-fold as the testing dataset. For each set of training and testing RMSE values for every vehicle type is calculated.

Table 2. The labeled dataset used in training the model

Variable	Variable details	Type of variable
Vehicle Type and its count *(Y)*	Vehicle type (FT, WT, RV, and A) and their count used in the incident	Continuous
Incident level (X_1)	Incident level defined by MFB	Continuous
Population (X_2)	Population of the area grid	Continuous
Settlement (usage) (X_3)	Grid settlement classification based on usage (combination of R,S,C,I)	R, S,C,I, RS, RC, RI, CI, CS, SI, RCS, RIC, RSI, RSCI (Categorical)
Settlement (height) (X_4)	Grid settlement classification based on building height (combination of Low, Medium or High rise)	L, M, H, LH, LM, MH, LMH (Categorical)
Built-up Compactness (X_5)	Grid area built-up compactness	Continuous
High rise building count (X_6)	Total number of high rise buildings in the grid area	Continuous
Medium rise building count (X_7)	Total number of medium rise buildings in the grid area	Continuous
Low rise building count (X_8)	Total number of low rise buildings in the grid area	Continuous

Commercial building count *(X_9)*	Total number of commercial buildings in the grid area	Continuous
Residential building count *(X_{10})*	Total number of residential buildings in the grid area	Continuous
Industry building count *(X_{11})*	Total number of mixed buildings in the grid area	Continuous
Mixed building count *(X_{12})*	Total number of industrial buildings in the grid area	Continuous
Special building count *(X_{13})*	Total number of special buildings in the grid area	Continuous

The calculated RMSE value range for 10 fold cross validation for the various vehicles across all the periods are found to be in the range of 0.12 to 0.19 for FT, 0.12 to 0.17 for WT, 0.13 to 0.18 for RT and 0.12 to 0.16 for A respectively (Table 3). The important variables are determined on the basis of reduction of sum of squared error (SSE) after the splits on the variables. The split on the variable which leads to the largest reduction in SSE is marked as the most important variable. The most important variables are found to be: X_1, X_2, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, and X_{12}. The best performing model is applied to the demand points to estimate the demand weights (d_{jvt}). The RMSE values for demand weight estimation are FT: 0.1632, RT: 0.1576, WT: 0.1408, A: 0.1317.

Table 3. RMSE value ranges for 10 fold cross validation

Vehicle	RMSE (t1)	RMSE (t2)	RMSE (t3)	RMSE (t4)	RMSE (t5)	RMSE (t6)
FT	0.17±0.02	0.17±0.02	0.17±0.02	0.15±0.01	0.14±0.02	0.17±0.02
WT	0.15±0.01	0.14±0.02	0.15±0.02	0.14±0.01	0.16±0.01	0.14±0.02
RT	0.16±0.01	0.16±0.02	0.16±0.01	0.15±0.02	0.15±0.01	0.15±0.02
A	0.14±0.02	0.13±0.01	0.14±0.02	0.14±0.02	0.14±0.01	0.13±0.02

. Table 4 presents the predicted demand values for the demand points. The integration of GIS provides a visualization of the spatial variations of estimated values (Figure 8).

Table 4. Predicted demand weight *(d_{jvt})* value ranges across the time-periods

	t1:1	t2:2	t3:3	t4:4	t5:5	t6:6
FT:1	$1<=d_{j11}<=6$	$1<=d_{j12}<=7$	$1<=d_{j13}<=7$	$1<=d_{j14}<=6$	$1<=d_{j15}<=6$	$1<=d_{j16}<=6$
WT:2	$1<=d_{j21}<=6$	$1<=d_{j22}<=6$	$1<=d_{j23}<=7$	$1<=d_{j24}<=7$	$1<=d_{j25}<=7$	$1<=d_{j26}<=6$
RT:3	$1<=d_{j31}<=4$	$1<=d_{j32}<=5$	$1<=d_{j33}<=5$	$1<=d_{j34}<=5$	$1<=d_{j35}<=4$	$1<=d_{j36}<=5$
A:4	$1<=d_{j41}<=2$	$1<=d_{j42}<=2$	$1<=d_{j43}<=2$	$1<=d_{j44}<=2$	$1<=d_{j45}<=2$	$1<=d_{j46}<=2$

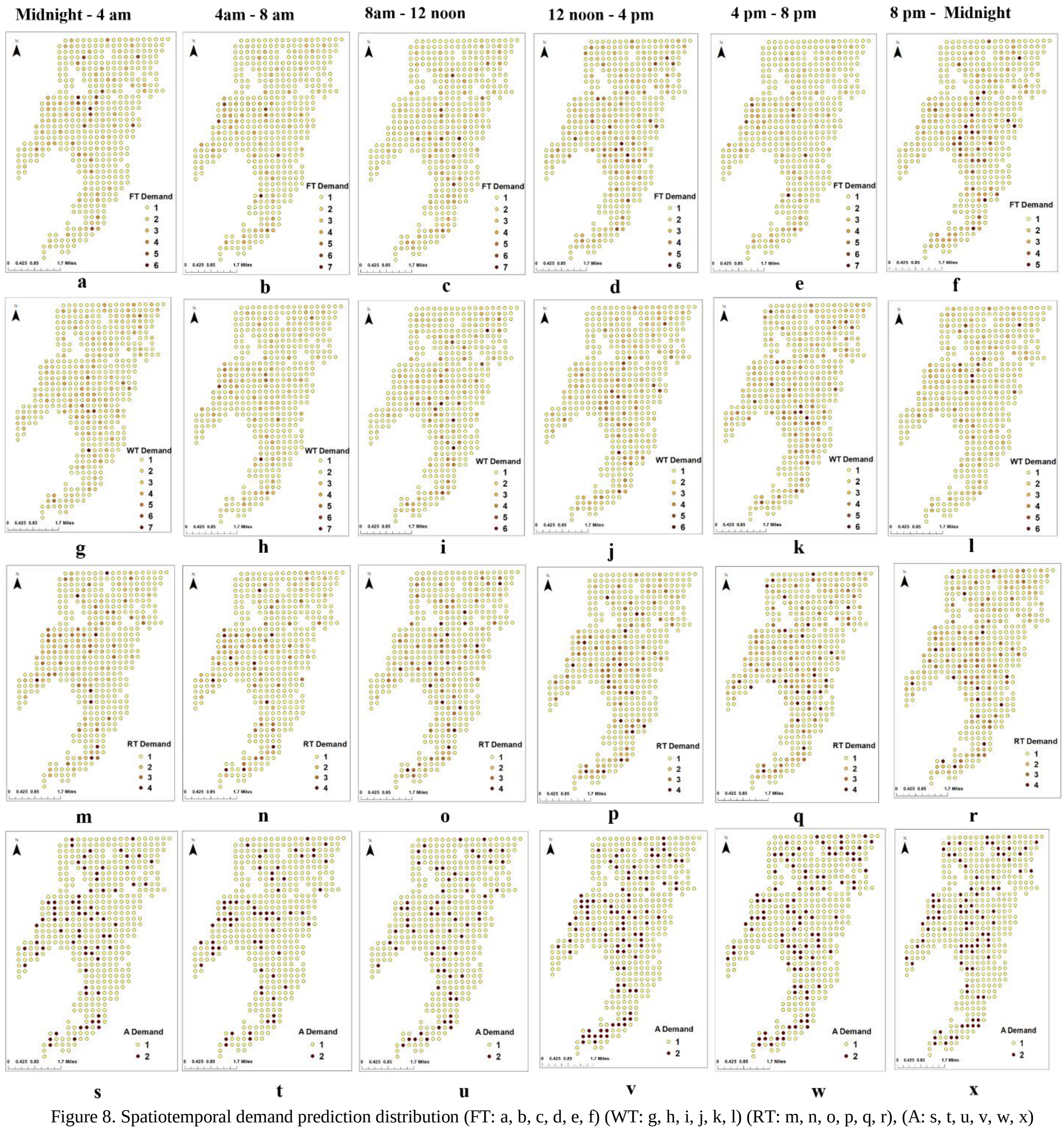


Figure 8. Spatiotemporal demand prediction distribution (FT: a, b, c, d, e, f) (WT: g, h, i, j, k, l) (RT: m, n, o, p, q, r), (A: s, t, u, v, w, x)

6.3 Empirical results

The maximum available number of vehicles (p_v) during various time-periods are; FT: 25, RT: 22, WT: 25 and A: 10, respectively. The value of r_{iv} is fixed to be eight minutes for all the cases; the variable α is set to be 70% which means a minimum of 70% cases of high-intensity prone demand areas must be covered. Total the value of p_i can be at most the total available vehicles, but allocating all the vehicles at one location would not be a prudent solution. In our experiments, this sum never exceeds 11. As a consequence, we can use 11 as the value for p_i in one time period. However, accommodating a certain number of vehicles depends on the urban space availability. To address this issue, we introduced a base location-dependent value for p_i, which depends on the built-up compactness value of the area. A very high built-up compactness value associated with a base location denotes that the base location does not have enough capacity for more than a certain number of vehicles. Thus we can decrease the value of p_i. We consider three classes of built-up compactness; High, Medium and Low. For a base station location with an associated Low built-up compact value (0-759.66), we define p_i value as 10. For a base station location with an associated medium built-up compact value (759.66- 1699), p_i value is defined to be 6. Lastly for the p_i value for base stations with an associated high built-up compactness value range (1699- 4334.08) is defined as 3.

a) Case1: actual travel time considerations (dynamic): We estimated the model by using the t_{ij} values. We named the above-defined settings as the 'base case (a)'. Further, two different model settings were tested: b) considering demand location as covered by minimum single coverage by any of the vehicle type, and c) existing locations of the fire stations as the potential locations for single coverage of the demand locations. Figure 9 (a, b, c) present the results of the model execution. It can be observed that the coverage varies significantly over the periods due to consideration of the dynamic variations. Further, it was found that the location and the resource distribution by the model provides a significant increase in the coverage as compared to the existing scenario (Figure 9b and Figure 9c). A notable variations in the coverage by the vehicles can be observed between empirical and single coverage (Figure 9a and Figure 9b). It demonstrates the importance of considerations of empirical coverage in the EMS services. Although the time-period t4 is not the peak travel time hours, still the coverage percentage is low compared to the evening and morning peak hours. This is because of the consideration of the variations in demand and the importance given to coverage of high-intensity fire risk by constraint (5). As the time-period t3 accounts for more high-intensity fire calls, the fixed number of available vehicles are distributed more at some locations to cover high-risk areas; thus, many low-intensity fire risk areas remain uncovered. To study the influence of available resources on coverage, we estimated the model by changing the value of p_v. The value of p_v is increased by 20. As a result, an increase in the coverage by each vehicle type is observed, i.e., 98.76 percentage of the demand is found to be covered by FT in the time-period t4.

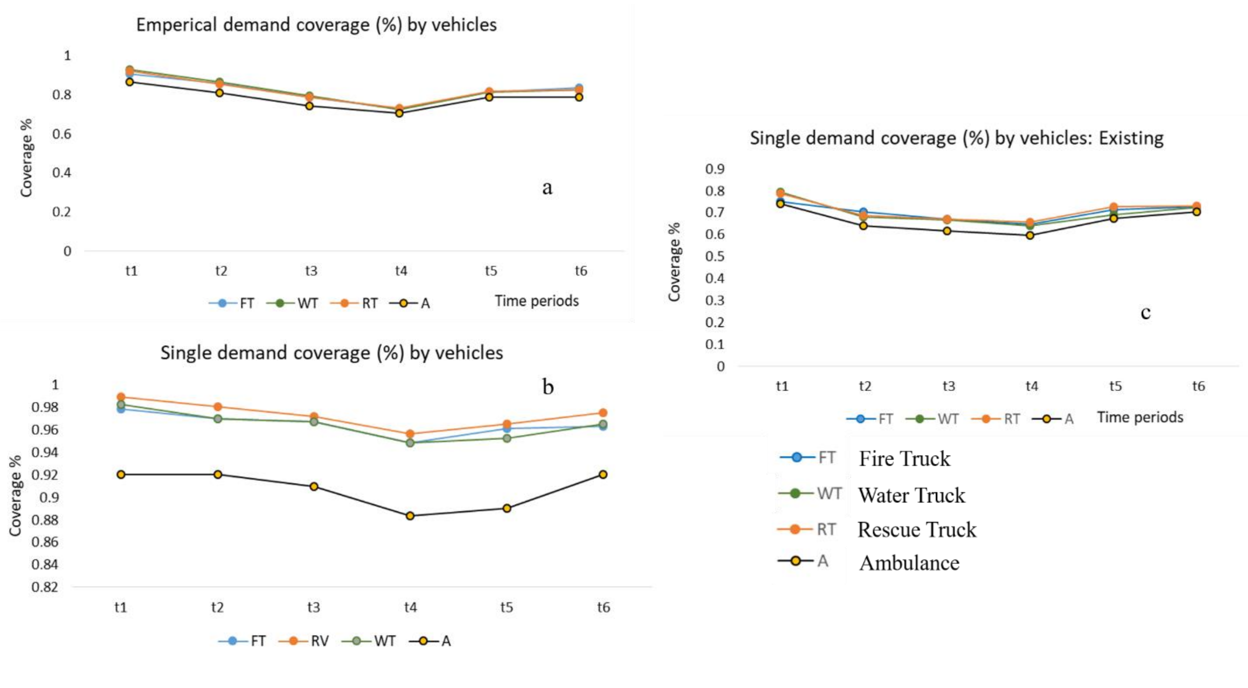


Figure 9. Case 1 a) Empirical demand coverage (base case) b) single demand coverage c) single demand coverage with existing fire station locations as the potential locations

b) Case2: averaged travel time considerations (static): In the second case, a common travel time value for all the time periods is calculated by taking the average of the travel times over all the time periods. The value is used in the model as the travel time value for every period. Execution results (Figure 10 (a-d)) show a decrease in the coverage for the time period t1, t2, and t6 and an increase in the coverage for t3, t4, and t5. This is because by averaging the travel time between the potential locations, the demand points increased for t1, t2, and t6; whereas, it decreased for t3, t4, and t5, when compared to the actual travel times.

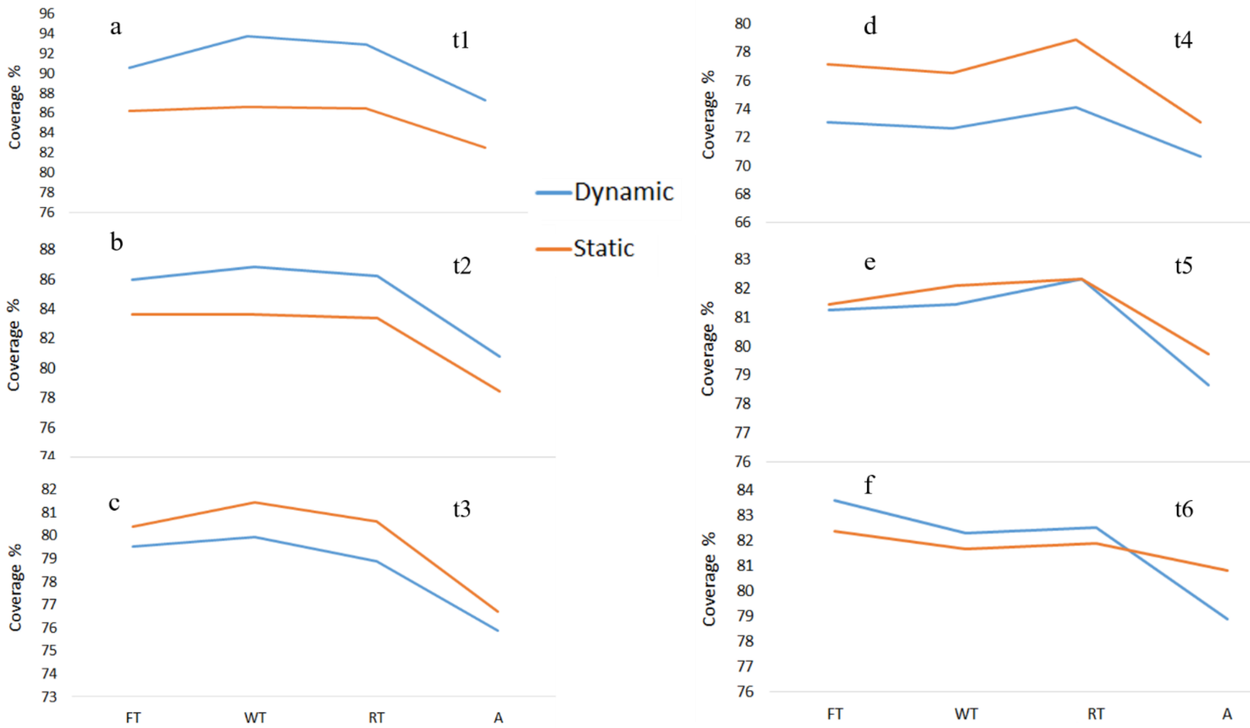


Figure 10. Dynamic and static coverage by the vehicles for a) t1 b) t2 c) t3 d) t4 e) t5 f) t6

To further understand the influence of travel time on the temporal coverage variability by the vehicles, we compare the absolute difference of temporal coverage by every vehicle (Figure11). Results show comparatively minor variations in the temporal coverage by the vehicles for case 2 as compared to case 1. The maximum coverage variations for the vehicles in the dynamic case lie in the range of 10, whereas, for the static case the maximum variations are lower in the range of 6. It can be deduced that by modeling static travel times over the period we lost the pragmatic variations and the observed temporal difference in the coverage is only because of the spatiotemporal variations in the fire occurrences. The above discussions show that travel time has a considerable role in the demand coverage and using impractical travel times in the models might suffer under or oversupply of the resources.

One of the crucial contributions of the study is the inclusion of urban space constraints in identifying the locations with a capacity to accommodate a certain number of vehicles. Ignoring the space constraints might lead to unreliable solutions. As without these constraints, the model can select a large fire station located in a highly compact area which might not be a practical solution. The variable pi ensures that vehicles are allocated based on the surrounding area details with a lesser number of vehicles located in the area with high built-up compactness. Such locations can be selected to build mini fire stations, while some of the locations in lesser compact regions can be considered for making larger fire stations. The integrated approach of considering complex urban details, firefighting specific features and the spatiotemporal variations of the fire events is one of the uniqueness of this study, which might be specifically applicable to cities of developing nations including India.

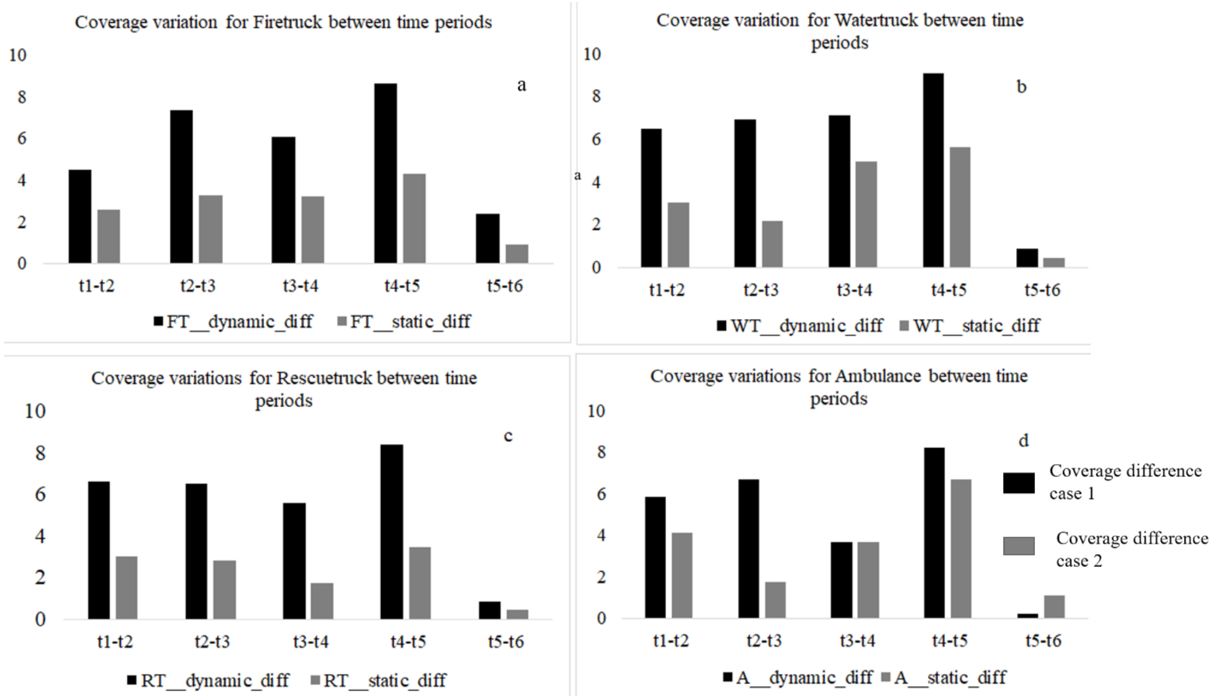


Figure 11. Temporal coverage variability by the fire fighting vehicles a) fire truck b) water truck c) rescue truck d) e) ambulance

7. Conclusions

This study presents a resource-allocation model to maximize the flexible instead of fixed demand coverage of firefighting vehicles given a response time threshold of eight minutes. The model differs from the previous works, as relevant parameters like varying demand, travel time, urban space dependent location selection are simultaneously modeled as time-dependent. The proposed model identifies the optimal spatiotemporal allocation of firefighting vehicles to achieve coverage requirements. A machine learning based approach is proposed to estimate the value and the coverage requirement of a specific vehicle type at the demand locations. The solution exploits the fact that urban variables influence disaster intensities. The analysis models fine-grained urban settlement elements as informative variables to predict the demand with good accuracy. We compare the dynamic model with the static fixed travel time-based model. Results of our model show that the static model increases the coverage percentage during non-peak times. Still, the results cannot be considered as reliable and thus should not be considered in decision making. Comparative results also show the high coverage variation between the time-periods for the dynamic model than the static models which is primarily because of the collective variations in demand and the travel time. Increase in the available resources further increases the coverage percentage. Distribution of the vehicles shows the importance of inclusion of urban constraints in the model as the model successfully identifies high compact regions as the favorable locations for fewer vehicles and vice versa. The analysis presented in the study has the potential to improve the firefighting in current and future cities. The study did not consider special situations like festivals, and so on, however, their inclusion in the future work can be an interesting aspect. Incorporation of firefighting crew details, resource redeployment, and reallocation cost and dynamic aspects of simultaneous fire might also be studied.

8. Acknowledgments

We thank all the authorities and volunteers of Mumbai fire brigade for providing us the fire incident data and helping us understand the firefighting process through organized drills. We also thank authorities of Municipal Corporation of Greater Mumbai (MCGM) to provide important settlement datasets. I also thank my friends for providing important feedbacks.

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