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RESEARCH PAPER

Optimized Deployment of Telecom Field Teams across the Pakistan for better Telecom Service Performance: A Novel Technique

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ABSTRACT

Deployment of Telecom teams, comprising of engineers, technicians, installers etc for field services or trouble shootings of deployed telecom installations or circuits like VSAT, Radio towers, BTS sites and mobile towers at different geographical locations is always a challenging task for telecom companies. The objectives of the study were to evaluate the response time and distance to telecom sites by proposing new geo-graphical positions of field workforce and to compare the mean response time and mean distance to telecom sites of proposed geographical locations with the existing techniques. It was a novel experimental study in which k-means clustering algorithm was used for estimating geographical locations for deployment of teams. Mean distances of circuits, mean response time, mean areas of clusters and mean inter-centroid distances were calculated and independent t test was applied to determine the difference in these means of initially selected big cities and proposed locations using k-means algorithm. A significant difference was observed in mean response time, mean inter-centroid distance, mean areas of clusters and mean inter-centroid distances with p-values of 0.03, 0.03, 0.002 and 0.0001respectively. It is concluded that proposed geographical locations for team deployment may improve service quality and upsurge customer satisfaction in Telecommunication market.

KEYWORDS Clustering, Customer Expectations, Customer Satisfaction, Field Service, K-Means Clustering Algorithm, Service Quality, Workforce Optimization

Introduction

Effectiveness of any service provided by telecom organization depends upon various factors and one of them is efficient use of resources without compromising customer satisfaction(Shakya et al., 2017) (Ferreyra et al., 2017) Telecom companies usually deploy teams in developed and big cities and some companies deploy them at locations near to the maximum number of circuits or locations which are closer to the customer premises thus reducing response time. But there was no define pattern exists for team deployment which was a major gap in this direction. The reduction in response time directly affects cost of services and trouble shootings, service quality, customer satisfaction and overall performance of a company. Reduction in distance and response time can be done by deploying telecom teams in a vicinity closer and surrounded by maximum number of telecom installations at one or more than one geographical region. Number of deployed technical teams in any one cluster of telecom installations or circuits usually depends on the type, sensitivity and services of telecom installations. Some telecom companies deploy one while others deploy two or more technical teams for one cluster of telecom circuits depending on cluster size.

Various researchers proposed different techniques for efficient utilization of workforce. Some recommended the Augmented Reality (AR) system based on fuzzy logic which is beneficial in providing assistance to deployed teams in accessing company's resources using private maps.(Peña-Rios et al., 2017) Starkey et al proposed a multi-objective genetic type-2 fuzzy logic system to increase the efficiency of working areas with field personnel.(Starkey, Hagras, Shakya, & Owusu, 2016b) In another research additional engineers were appraised using type-2 Fuzzy Logic System (FLS) for different activities.(Ferreyra et al., 2017) Some researchers also proposed certain algorithms for workforce and service optimization. (Shakya et al., 2017)(Starkey, Hagras, Shakya, & Owusu, 2016a)(Starkey, Hagras, Shakya, Owusu, et al., 2016). In another study resource allocation issue in rural areas was addressed using k-means clustering as a graph theory problem.(Alsabti, 2015)

K-means clustering is linear non-overlapping and fast converging algorithm.(Meng et al., 2018)(Abo-Elnaga & Nasr, 2022) As compared to Hierarchical Clustering, its results are always different from previous obtained final results after iterations. K-means clustering is sensitive to outliers.(Meng et al., 2018) Different techniques proposed for further optimization of k-means clustering algorithm. (Hakim, 2022)(Gbadoubissa et al., 2020)(Kaushik & Mathur, 2014)

Contrary to these different techniques, a novel technique of team deployment as per existing telecom circuits was proposed in this research. It was hypothesized that if we used K-means clustering algorithm for deployment of different teams at different geographical locations, the efficiency and overall performance of Telecom service delivery especially for VSAT circuits would significantly improve.

Simple steps of k-means clustering algorithm(Meng et al., 2018)(Yang et al., 2010)

- Step 1. Define k number of clusters for a given data set or objects.
- Step 2. Consider k points or centers as initial centroids in data set.
- Step 3. Measure distance of each datum with new centroids by using Euclidean distance.
- Step 4. Assign closet objects to corresponding centroids. These groups of objects with new centroids are new clusters.
- Step 5. Re-calculate the centroids of each cluster.
- Step 6. Repeat step 3, until no further change in position of centroids observed.

Literature Review

A simulation model was made by considering a widespread diversity of indecisions in real-world problems, such as issues in the obtainability of trained technical teams, unclear travel and job closing times etc (Shakya et al., 2017). Focus points were service delivery locations for each working part as input. One-day simulation was performed, with each engineer to compute the cost of this distribution for dissimilar purposes and results analyzed. Two important tasks were Maximization of coverage and minimize the distance travelled which is calculated as a mean distance moved by all technical teams in the geographical area in KMs.

Estimation was being done for requirement of additional/extra technical staff for allocation of different tasks (Ferreyra et al., 2017). Domain data and decision were developed automatically by static and dynamic methods using Fuzzy Logic System, with training data sets. It was built on a type-1 fuzzy logic system in the allocation domain which turns into type-2 fuzzy logic system. The method described in this paper is proficient enough of gathering information from data inputs (available tasks, scheduled tasks, available engineers, additional engineers needed).

Augmented Reality (AR) being used in combination with Fuzzy Logic for service alignment and optimization (Peña-Rios et al., 2017). The major task of this combination was to facilitate the user to provide the asset location with directions. By using this method, Geographical layout of particular areas, field teams could trace the cabling with instructions to track the specific equipment in the design. Mobile helps in finding geo-graphical location of the technical team member and directs this data to server which estimates the difference between technical team member's location as per GPS, and equipment location.

A simulation model was made by considering widespread diversities of indecisions in real-world problems, such as issues in the obtainability of trained technical teams, unclear travel and job closing times etc (Starkey, A., Hagras, H., Shakya, S., & Owusu, G., 2016b). Focus points were service delivery locations for each working part as input. One-day simulation was performed, with each engineer to compute the cost of this distribution for dissimilar purposes and results analyzed. Two important tasks were Maximization of coverage and minimize the distance travelled which is calculated as a mean distance moved by all technical teams in the geographical area in KMs.

Multiobjective Type-2 evolutionary algorithm was used to explain the problem of working unit strategy (Starkey, A., Hagras, H., Shakya, S., & Owusu, G., 2016). Optimal design of working areas, for a large-scale mobile workforce for maximizing the utilization of the workforce, Optimization of WAs (working areas) involves clustering or re-clustering these Service Distribution Points based on the latest demand and capacity information. They associated a GA based solution with workforce allocation problem, alongside a particle swarm optimization-based solution.

Material and Methods

It was an experimental study design. In this study, geographical locations where teams deployed were labelled as centroids, telecom installations as "circuits", services or trouble shootings as "services" and deployed technical teams as "teams".

Independent variables were team positions at different geographical locations. Longitudes and Latitudes were considered as site coordinates for geographical location of each team and circuit location. Major dependent variables were distance of circuit from team location in a cluster and corresponding response time. Other dependent variables were inter-centroid distances, inert-circuits distances, area and circuit density of each cluster.

For assessment of better geographical team locations, two structures were formed and compared;

1. Clusters for selected Big cities
2. Clusters for proposed centroids using k-means algorithm

Clusters for Big cities

Initially there were five sets of data.

First two sets of data consist of randomly selected site coordinates as geographical locations of circuits across Pakistan. Each geographical location is represented as a pair of longitudes and latitudes. First set of data K_{Lo}, consists of unique longitudes and second set of data K_{La}, consists of unique latitudes for geographical locations of circuits. So

$L_{Lo1}, L_{Lo2}, \ldots, L_{LoN} \in K_{Lo}$

and

$L_{La1}, L_{La2}, \ldots, L_{LaN} \in K_{La}$

L_{Lo1} represents longitude of first location of circuit, L_{Lo2} second and so on.

Similarly L_{La1} represented latitude of first location of circuit, L_{La2} second and so on.

Pair of L_{Lo1} and L_{La1} represented corresponding longitude and latitude of first location of circuit, pair of L_{Lo2} and L_{La2} represented second and so on.

N is the total number of telecom circuits, selected randomly across Pakistan, which were 4000.

Number of elements in both the sets K_{Lo} and K_{La} were equal.

The geographical locations of different circuits are shown in Fig.1

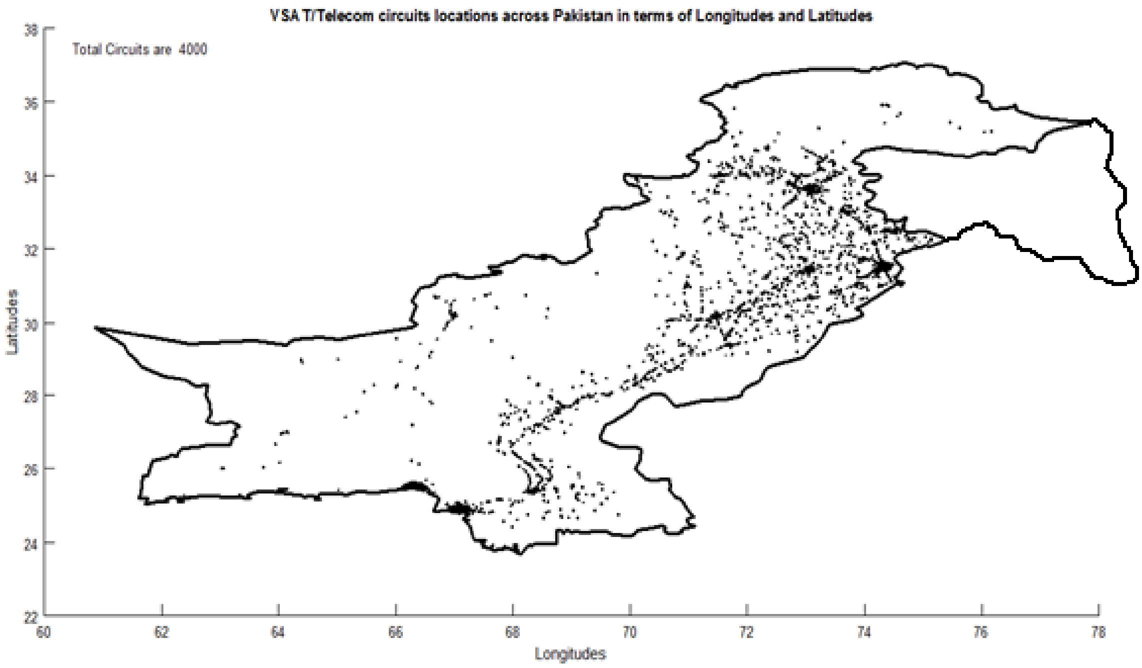


Fig.1. Geographical locations of circuits

Third and fourth sets of data consist of site coordinates of geographical locations in big cities across Pakistan where teams can be deployed. Each geographical location in each big city was represented as a pair of longitudes and latitudes. Third set of data B_{Lo}, consists of unique longitudes and fourth set of data B_{La}, consists of unique latitudes for geographical locations of deployed teams in big cities. So

$B_{Lo1}, B_{Lo2}, \ldots, B_{LoM} \in B_{Lo}$

and

$B_{La1}, B_{La2}, \ldots, B_{LaM} \in B_{La}$

B_{Lo1} represented longitude of first location of team, B_{Lo2} second and so on.

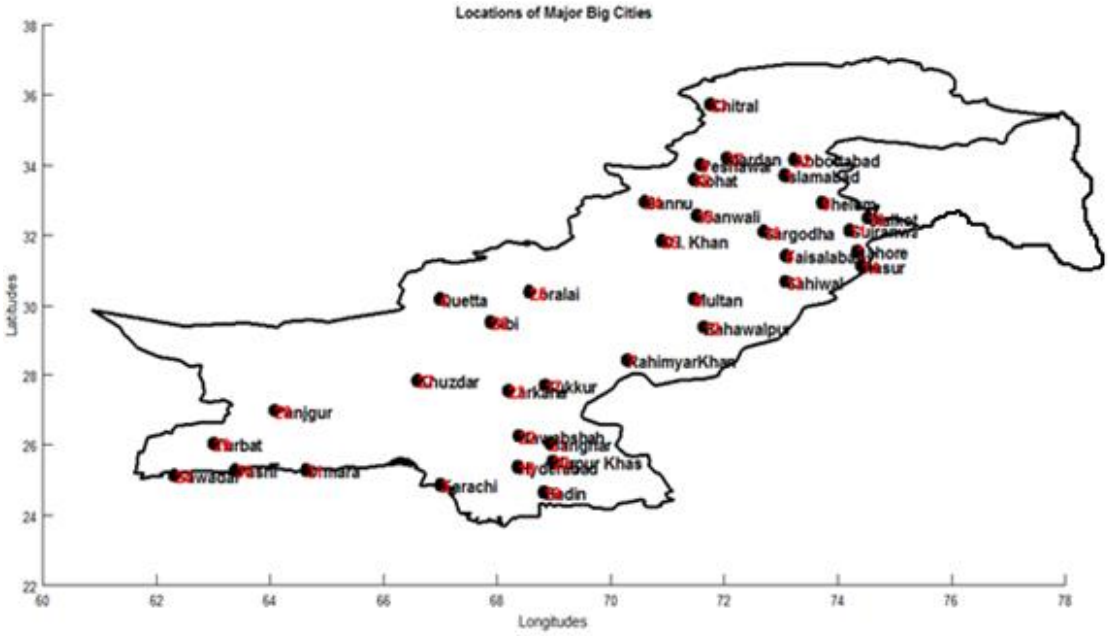
While B_{La1} represented latitude of first location of team, B_{La2} second and so on.

Pair of B_{Lo1} and B_{La1} denoted corresponding longitude and latitude of first location of team, pair of B_{Lo2} and B_{La2} second and so on.

M is the total number of teams deployed in big cities were 20.

Number of elements in both the sets B_{Lo} and B_{La} were equal.

The geographical locations in 37 big cities where teams can be deployed are presented in Fig.2a and 37 big cities together with circuits are shown in Fig.2b.



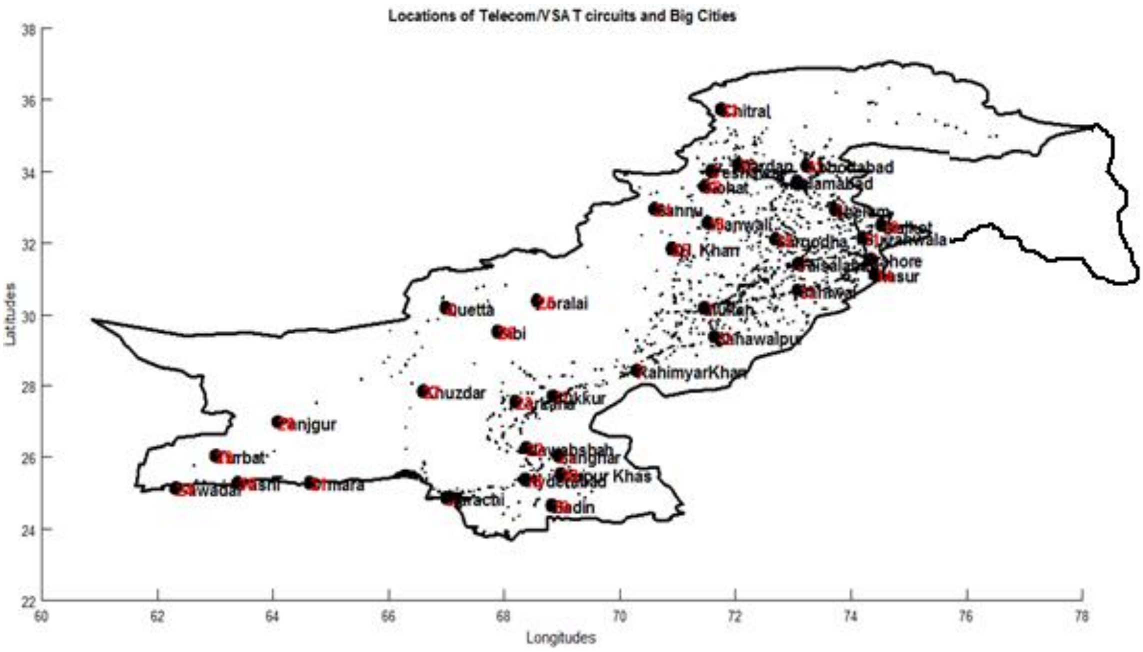


Fig.2. (a). **Geographical locations in 37 big cities where teams can be deployed.**

(b). 37 **Big Cities with circuits in terms of Longitudes and Latitudes across Pakistan.**

Since there was one team deployed in one big city for research convenience so,

Number of Teams = Number of selected big cities = M.

Fifth set of data Na consists of names of big cities across Pakistan where teams can be deployed. So

$Na_1, Na_2, \ldots, Na_M \in Na$

Na_1 represented the name of first big city, Na_2 second and so on.

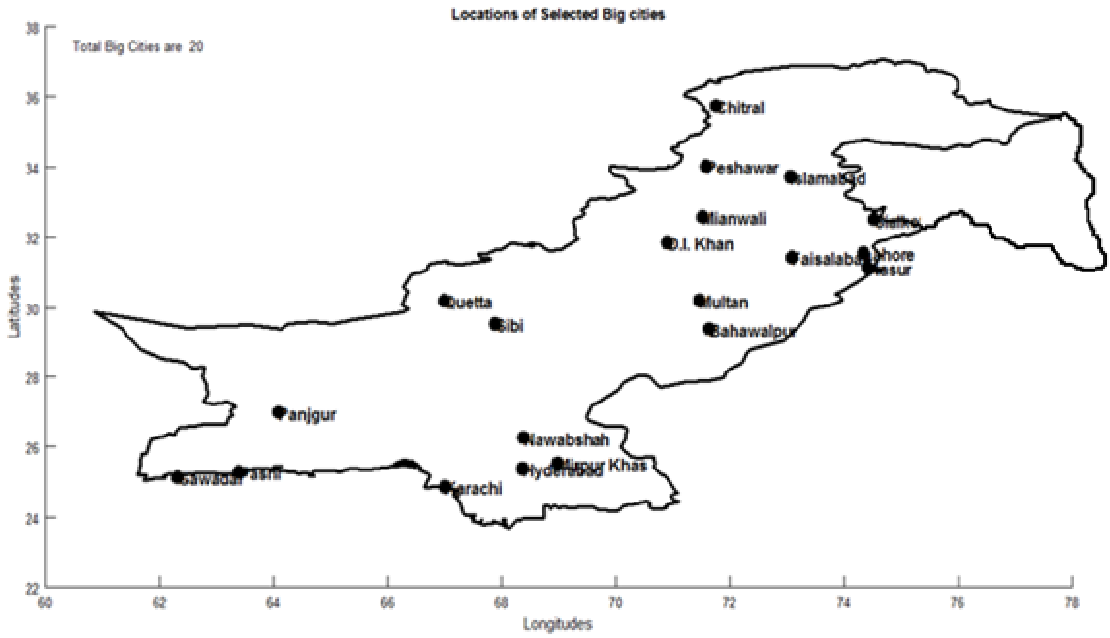
So five data sets were K_{Lo}, K_{La}, B_{Lo}, B_{La} and Na.

As usual practice and requirement by telecom companies, N is always greater than M.

$N > M$

This implies that number of elements in sets K_{Lo} and B_{Lo} was greater than number of elements in sets K_{La} and B_{La}. Number of elements in sets Na, B_{Lo} and set B_{La} was equal.

The selected cities were Islamabad, Lahore, Karachi, Quetta, Peshawar, Sialkot, Kasur, Faisalabad, Multan, Bahawalpur, Mianwali, Sukkar, Larkana, Gawadar, Pasni, Panjgur, Sibi, D.I. Khan, Chitral, Nawabshah, Hyderabad and Mirpur Khas as shown in Fig.3a and the selected cities with circuits are mentioned in Fig.3b.



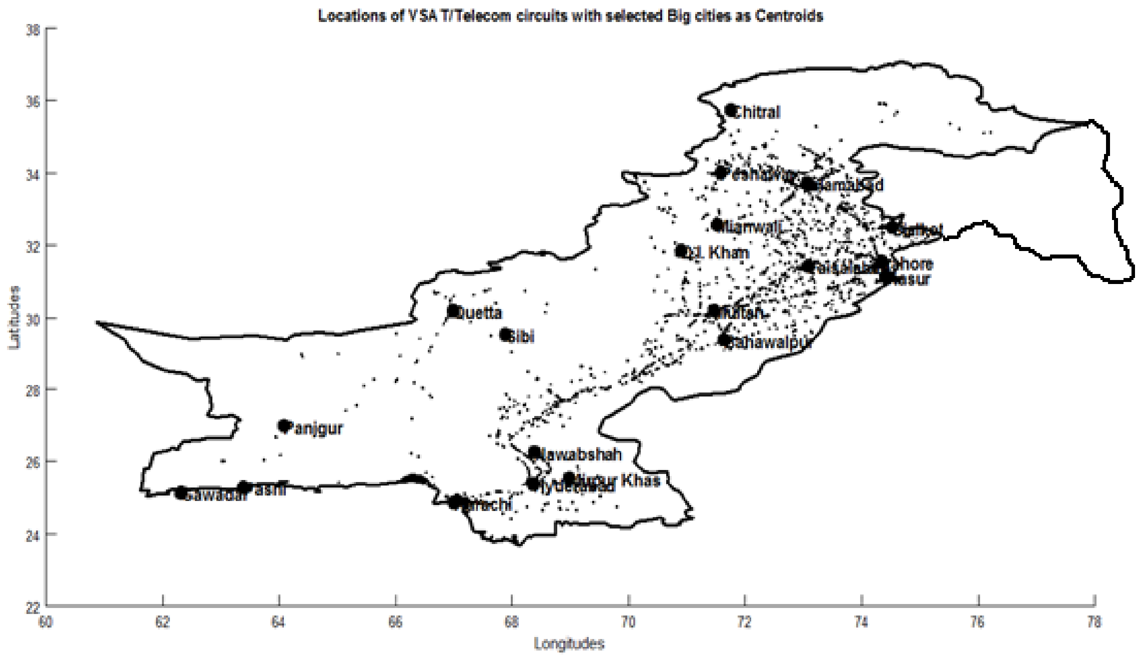


Fig.3.(a) Selected Big Cities in terms of Longitudes and Latitudes across Pakistan.

(b). Selected Big Cities with circuits in terms of Longitudes and Latitudes across Pakistan.

Circuits which were most closed to deployed teams in each big city were selected. So nearest circuits along with the particular team were considered as one cluster. Selection was made by calculating the distance of each circuit to all teams deployed in all big cities.

Distance between two geographical locations was calculated by using built in function of Matlab, based on the Haversine' formula (Tzortzis & Likas, 2014) in kilometer. This formula calculate the great-circle distance between two points – that is, the shortest distance over the earth's surface using Longitude and Latitude of a point on earth giving "as-the-crow-flies" distance between two points ignoring any hills or irregular surface they fly over.

Harversine formula is given below

$$a = \sin^2(\Delta\varphi/2)+\cos\varphi_1\cdot\cos\varphi_2 \cdot \sin^2(\Delta\lambda/2)$$

$$c = 2 \cdot \operatorname{atan2}(\sqrt{a},\sqrt{(1-a)})$$

$$d = R \cdot c$$

where φ is latitude, λ is longitude, R is earth's radius (mean radius = 6,371km). Angles are in radians for trigonometric functions whereas longitudes and Latitudes are in degrees.

Mean Distances and Response Times

Mean distance is the average distance of team location to all circuits in a cluster. Data set MDbig of mean distances for all M clusters is given below.

$MDb_1, MDb_2, MDb_3, \ldots, MDb_M \in MDbig$

where MDb_1 is the mean distance of team location to all circuits in cluster number 1, MDb_2 for cluster 2 and so on.

Response time is a time taken by deployed team from its position to a particular circuit and its based on geographical area. Hilly area consumed much time as compared to plain field area. For research convenience travelling speed as 2 minutes per Km was selected as an average in all types of areas for all clusters.

Data set TMDbig of mean response time in big cities for all M clusters is given below.

$TMDb_1, TMDb_2, TMDb_3, \ldots, TMDb_M \in TMDbig$

where $TMDb_1$ is the mean response time of team location to all circuits in cluster number 1, $TMDb_2$ for cluster 2 and so on.

Areas and Circuit densities of clusters in big cities

Distance between farthest circuit in a cluster and the team location was considered as radius to calculate the circular area of each cluster.

Data set Abig for areas of all M clusters is given below.

$Ab_1, Ab_2, Ab_3, \ldots, Ab_M \in Abig$

where Ab_1 is the area of cluster number 1, Ab_2 for cluster 2 and so on.

Circuit density is a number of circuits per unit area of a cluster. Circuit densities of all clusters for selected big cities were calculated.

Data set Dbig for circuit densities of all M clusters is given below.

$Db_1, Db_2, Db_3, \ldots, Db_M \in Dbig$

where Db_1 is the circuit density of cluster number 1, Db_2 for cluster 2 and so on.

Inter-Circuit Distances and Inter-centroid distances

Inter-circuit distance is the Mean distance of each circuit to all other circuits in a cluster. Mean inter-circuit distance of a cluster is the mean of inter-circuit distances for that cluster.

Data set IMDbig of mean Inter-circuit distances for all M clusters is given below.

$IMDb_1, IMDb_2, IMDb_3, \ldots, IMDb_M \in IMDbig$

where $IMDb_1$ is the mean Inter-circuit distance of cluster number 1, $IMDb_2$ for cluster 2 and so on.

Inter-centroid distance is the distance between team locations in two clusters.

Data set MICDbig of mean Inter-centroid distances for all M clusters of selected big cities is given below.

$MICDb_1, MICDb_2, MICDb_3, \ldots, MICDb_M \in MICDbig$

where $MICDb_1$ is the mean Inter-centroid distance of centroid for cluster number 1 with other centroids, $MICDb_2$ for cluster 2 and so on.

So data sets for selected big cities are

$K_{Lo} = \{L_{Lo1}, L_{Lo2},\ldots, L_{LoN}\}$,

$K_{La} = \{L_{La1}, L_{La2},\ldots, L_{LaN}\}$,

$B_{Lo} = \{B_{Lo1}, B_{Lo2},\ldots, B_{LoM}\}$,

$B_{La} = \{B_{La1}, B_{La2},\ldots, B_{LaM}\}$,

$Na = \{Na_1, Na_2,\ldots, Na_M\}$,

$MDbig = \{MDb_1, MDb_2, \ldots, MDb_M\}$,

$TMDbig = \{TMDb_1, TMDb_2, \ldots, TMDb_M\}$,

$Abig = \{Ab_1, Ab_2, Ab_3, \ldots, Ab_M\}$,

$Dbig = \{Db_1, Db_2, Db_3, \ldots, Db_M\}$,

$IMDbig = \{IMDb_1, IMDb_2, \ldots, IMDb_M\}$,

$MICDbig = \{MICDb_1, MICDb_2, \ldots, MICDb_M\}$

Overall means of sets for selected big cities were calculated as follows.

$MDb = mean(\{MDb_1, MDb_2, \ldots, MDb_M\})$,

$TMDb = mean(\{TMDb_1, TMDb_2, \ldots, TMDb_M\})$,

$Ab = mean(\{Ab_1, Ab_2, Ab_3, \ldots, Ab_M\})$,

$Db = mean(\{Db_1, Db_2, Db_3, \ldots, Db_M\})$,

$IMDb = mean(\{IMDb_1, IMDb_2, \ldots, IMDb_M\})$,

$MICDb = mean(\{MICDb_1, MICDb_2, \ldots, MICDb_M\})$

Where MDb, TMDb, Ab, Db, IMDb and MICD are mean distance of all circuits to team locations, mean response time, mean area, mean circuit density, mean inter-circuit distance and mean inter-centroid distance respectively.

Mathematically

$MDb = \frac{\sum_{i=1}^{M} \mathrm{MDb}_i}{M}$,

$TMDb = \frac{\sum_{i=1}^{M} \mathrm{TMDb}_i}{M}$,

$Ab = \frac{\sum_{i=1}^{M} \mathrm{Ab}_i}{M}$,

$Db = \frac{\sum_{i=1}^{M} \mathrm{Db}_i}{M}$,

$IMDb = \frac{\sum_{i=1}^{M} \mathrm{IMDb}_i}{M}$,

$$\text{MICDb} = \frac{\sum_{i=1}^{M} \text{MICDb}_i}{M}$$

M should be a positive integer.

Clusters for proposed centroids using k-means algorithm

In this new proposed novel technique, K-means clustering algorithm was used on two data sets K_{Lo} and K_{La} to find new centroids. K-means clustering algorithm as compared to Hierarchical clustering algorithm is more dynamic and flexible. Results of K-means clustering algorithm may change on every running. But differences in overall results are minimal.

New centroids were the new proposed locations of teams instead of previous locations in big cities, which might be or might not be in the same locations in big cities. Circuits in each new proposed centroid might come from different clusters.

Number of new clusters were the same as for big cities. So as a novel technique this research proposed new geographical locations for teams instead of usual practice of team deployment in big cities.

New proposed geographical locations obtained after several iterations of K-means clustering algorithm. Note that in this algorithm, longitudes and latitudes were used as x and y co-ordinates. So after several iterations, two data sets were obtained. First set of data P_{Lo}, consists of unique longitudes and second set of data P_{La}, consists of unique latitudes for new proposed geographical locations of teams. So

$P_{Lo1}, P_{Lo2}, \ldots, P_{LoM} \in P_{Lo}$

and

$P_{La1}, P_{La2}, \ldots, P_{LaM} \in P_{La}$

P_{Lo1} represented longitude of first proposed location of team, P_{Lo2} second and so on.

P_{La1} represented latitude of first proposed location of team, P_{La2} second and so on.

Pair of P_{Lo1} and P_{La1} represented corresponding longitude and latitude of first proposed location of a team, pair of P_{Lo2} and P_{La2} represented 2nd proposed location of another team and so on.

Mean Distances and Response Times using k-means

Data set MDp of mean distances for all M proposed clusters is given below.

$MDp_1, MDp_2, MDp_3, \ldots, MDp_M \in MDp$

where MDp_1 is the mean distance of proposed team location to all circuits in proposed cluster number 1, MDp_2 for cluster number 2 and so on.

Data set TMDp of mean response time from proposed locations of teams to all circuits in all M proposed clusters is given below.

$TMDp_1, TMDp_2, TMDp_3, \ldots, TMDp_M \in TMDp$

where $TMDp_1$ is the mean response time of proposed team location to all circuits in proposed cluster number 1, $TMDp_2$ for cluster number 2 and so on.

Areas and Circuit densities of proposed cluster

Distance between farthest circuit in a cluster and the proposed team location was considered as radius to calculate the circular area of each proposed cluster.

Data set Ap for areas of all proposed M clusters is given below.

$Ap_1, Ap_2, Ap_3, \ldots, Ap_M \in Ap$

where Ap_1 is the area of proposed cluster number 1, Ap_2 for cluster 2 and so on.

Data set Dp for circuit densities of all proposed M clusters is given below.

$Dp_1, Dp_2, Dp_3, \ldots, Dp_M \in Dp$

where Dp_1 is the circuit density of proposed cluster number 1, Dp_2 for cluster number 2 and so on.

Inter-Circuit Distances and Inter-centroid distances

Data set IMDp of mean Inter-circuit distances for all proposed M clusters is given below.

$IMDp_1, IMDp_2, IMDp_3, \ldots, IMDp_M \in IMDp$

where $IMDp_1$ is the mean Inter-circuit distance of proposed cluster number 1, $IMDb_2$ for cluster 2 and so on.

Data set MICDp of mean Inter-centroid distances for all proposed M clusters is given below.

$MICDp_1, MICDp_2, MICDp_3, \ldots, MICDp_M \in MICDp$

where $MICDp_1$ is the mean Inter-centroid distance of centroid for proposed cluster number 1 with other proposed centroids, $MICDp_2$ for cluster 2 and so on.

K_{Lo} and K_{La} were same as for selected big cities.

So data sets for proposed centroids are mentioned as follows.

$K_{Lo} = \{L_{Lo1}, L_{Lo2}, \ldots, L_{LoN}\}$,

$K_{La} = \{L_{La1}, L_{La2}, \ldots, L_{LaN}\}$,

$P_{Lo} = \{P_{Lo1}, P_{Lo2}, \ldots, P_{LoM}\}$,

$P_{La} = \{P_{La1}, P_{La2}, \ldots, P_{LaM}\}$,

$MDp = \{MDp_1, MDp_2, \ldots, MDp_M\}$,

$TMDp = \{TMDp_1, TMDp_2, \ldots, TMDp_M\}$,

$Ap = \{Ap_1, Ap_2, Ap_3, \ldots, Ap_M\}$,

$Dp = \{Dp_1, Dp_2, Dp_3, \ldots, Dp_M\}$,

$IMDp = \{IMDp_1, IMDp_2, \ldots, IMDp_M\}$,

$MICDp = \{MICDp_1, MICDp_2, \ldots, MICDp_M\}$

Overall means of each of above last six data sets for proposed clusters were calculated as follows.

$MDp = mean(\{MDp_1, MDp_2, \ldots, MDp_M\})$,

$TMDp = mean(\{TMDp_1, TMDp_2, \ldots, TMDp_M\})$,

$Ap = mean(\{Ap_1, Ap_2, Ap_3, \ldots, Ap_M\})$,

$Dp = mean(\{Dp_1, Dp_2, Dp_3, \ldots, Dp_M\})$,

$IMDp = mean(\{IMDp_1, IMDp_2, \ldots, IMDp_M\})$,

$MICDp = mean(\{MICDp_1, MICDp_2, \ldots, MICDp_M\})$

Where MDp, TMDp, Ap, Dp, IMDp and MICDp are mean distance of all circuits to team locations, mean response time, mean area, mean circuit density, mean inter-circuit distance and mean inter-centroid distance respectively in proposed clusters.

Mathematically

$MDp = \frac{\sum_{i=1}^{M} \mathrm{MDp}_i}{M}$,

$TMDp = \frac{\sum_{i=1}^{M} \mathrm{TMDp}_i}{M}$,

$Ap = \frac{\sum_{i=1}^{M} \mathrm{Ap}_i}{M}$,

$Dp = \frac{\sum_{i=1}^{M} \mathrm{Dp}_i}{M}$,

$IMDp = \frac{\sum_{i=1}^{M} \mathrm{IMDp}_i}{M}$

$MICDp = \frac{\sum_{i=1}^{M} \mathrm{MICDp}_i}{M}$

M should be a positive integer.

Six sets of means obtained by using above two structures were {Ab, Ap}, {Db, Dp}, {TMDb, TMDp}, {MDb, MDp}, {IMDb, MICDp} and {IMDb, MICDp}. Descriptive statistics including means of variables in the above six sets were calculated and t-test was applied to find out the significant differences between data sets of big cities and proposed clusters. The p-value of less than 0.05 was considered significant.

Statistical Analysis

In the study, 20 big cities were selected with 20 teams so M = 20, total circuits were 4000 i.e N = 4000 and travelling speed was considered as 2 minutes per Km as an average in all types of areas for all clusters. MATLAB was being used for simulations.

Results and Discussion

Distances of each circuit to team locations in selected big cities were calculated. Clusters composed of circuits closed to nearest teams in big cities as centroids is shown in fig.4.

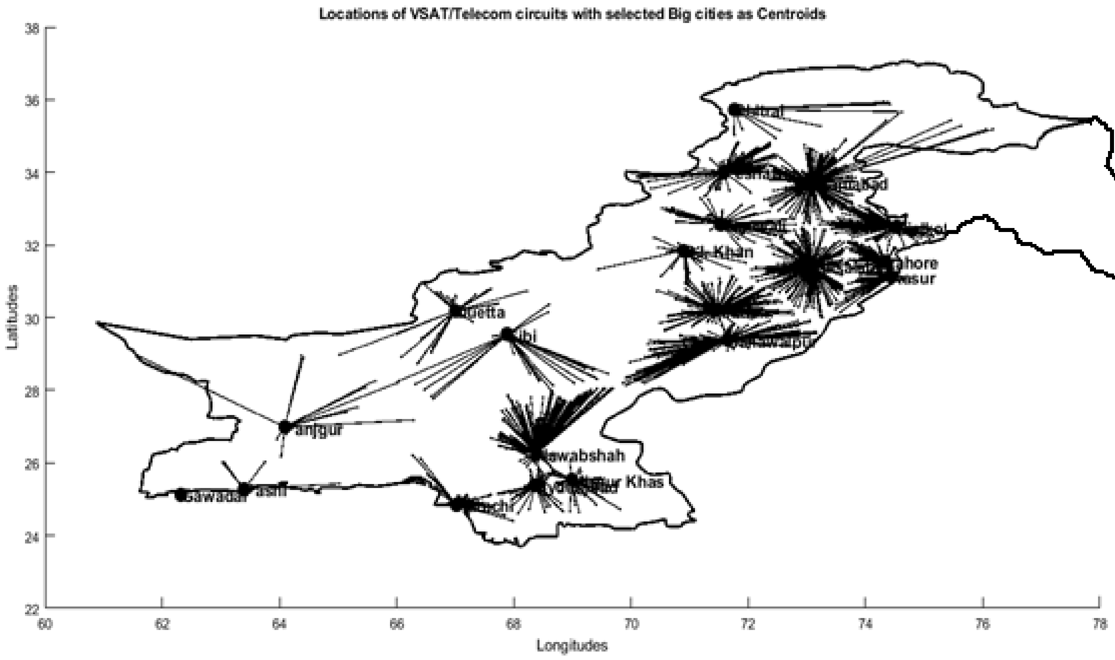
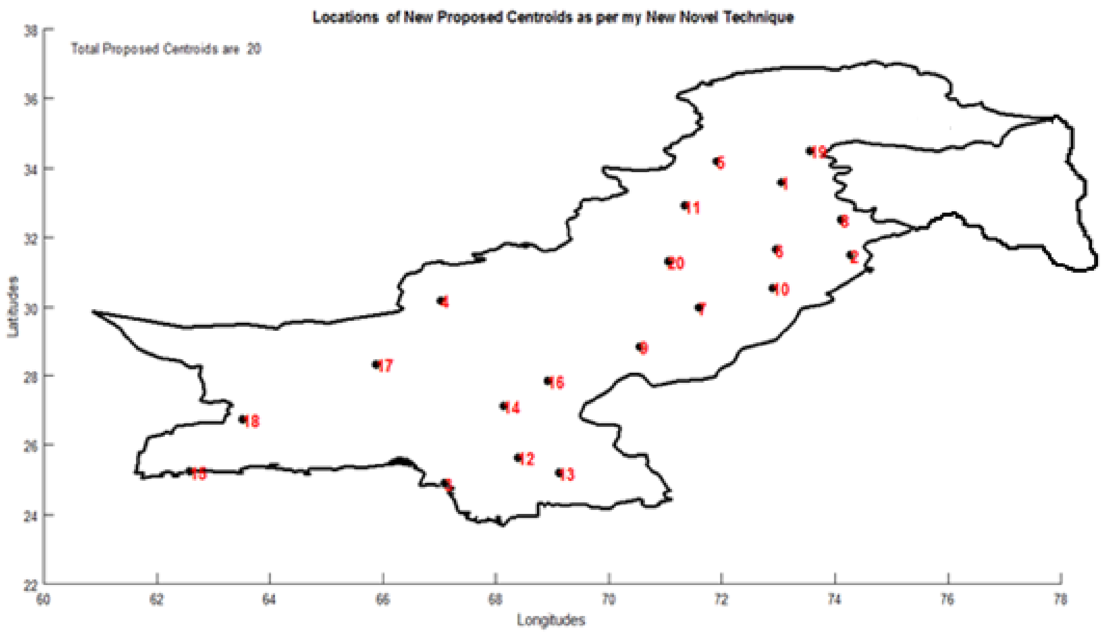


Figure 4. Clusters of circuits with Selected Big Cities as centroids.

This Novel technique using K-means clustering algorithm proposed new locations as centroids for teams and the locations of teams in terms of Longitudes and Latitudes across Pakistan are shown in Figure 5a while proposed geographical locations of teams together with circuits are shown in Figure 5b. Clusters composed of circuits with proposed centroids are shown in fig.6 and the comparison of proposed geographical locations of teams with selected big cities is depicted in Figure7.



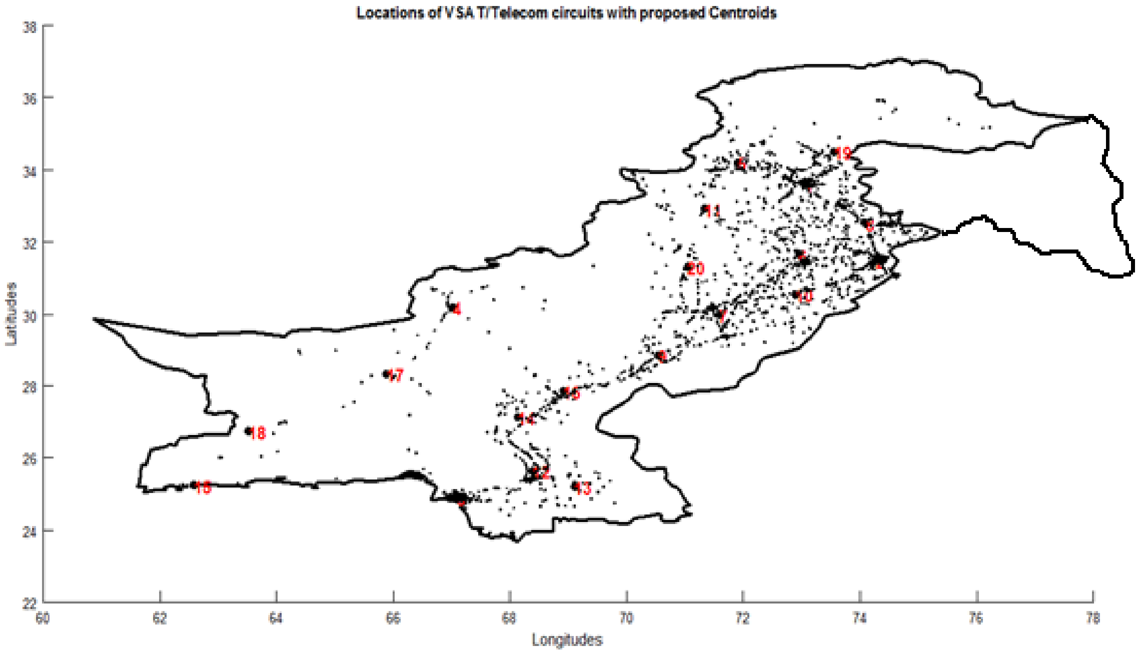


Figure.5. (a) New proposed geographical locations of teams using k-means.

(b) Proposed geographical locations of teams together with circuits.

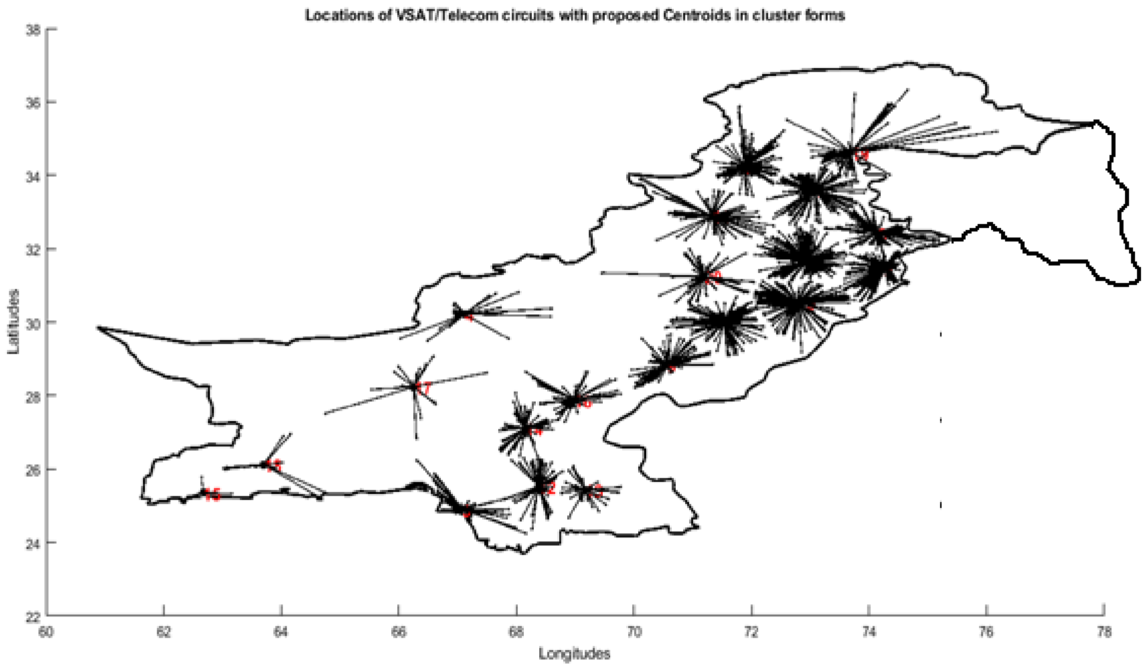


Figure.6. Clusters of circuits with new proposed centroids.

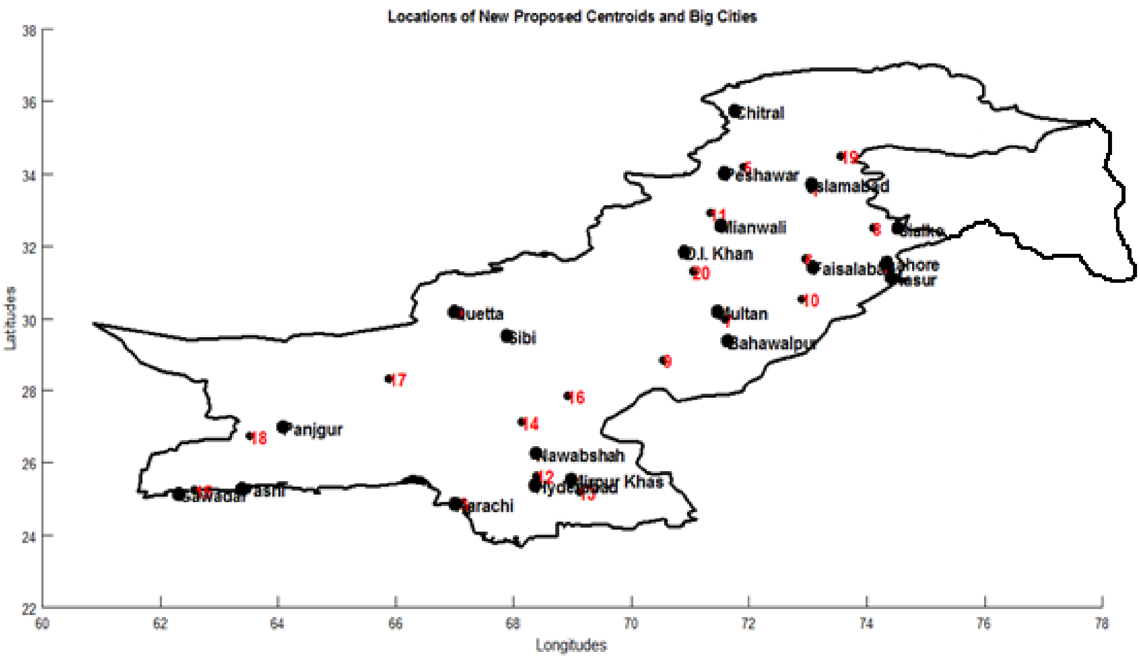


Fig.7. Comparison of proposed geographical locations of teams with selected big cities.

Mean and standard deviations of performance parameters of initially selected big cities and proposed locations using k-means are shown in Table.1.

Table 1
Descriptive statistics of performance parameters of Selected Big cities and Proposed Locations

Selected Big Cities		Proposed Centroids		P value
MDb	65.67 Km	MDp	43.88 Km	0.033321
TMDb	2.18 Hrs	TMDp	1.46 Hrs	0.033321
Ab	93208.13 Sq.Km	Ap	30255.57 Sq.Km	0.000827
MICDb	608.90 Km	MICDp	565.32 Km	0.000062
Db	0.0035	Dp	0.0442	0.212826

The t-test applied on Mean distances of circuits, Mean response time, Mean areas of clusters and Mean inter-centroid distances of initially selected big cities and proposed locations, showed significant difference while mean densities showed insignificant difference.

The results of the study indicate that the performance of teams will definitely improve by applying this novel technique. In the proposed technique, the anticipated locations were more central and look natural as compared to initially selected big cities and the locations obtained by applying density-based clustering algorithm DBSCAN(Moreno, Munari, et al., 2020), Genetic Algorithm(Ajam et al., 2022) streaming k-means clustering algorithm(Mesbahi et al., 2019) are also not so natural and centric.

Number of circuits in a cluster for each initially big city might be or might not be the same as number of circuits in a cluster for each new proposed location but there was a remarkable difference in Mean distances of team locations to circuits in clusters for initially deployed teams in big cities and proposed team locations using k-means algorithm; distance of proposed team locations was much lower as compared to the initially big cities locations for teams. Similarly, time taken by the teams to reach the circuits was significantly less if deployed at the proposed locations. So, if we use proposed locations for team deployment, identified by the novel technique, both the efficiency and effectiveness of any telecom company will increase.

Methodology used for minimizing response time and distance in this technique is more simpler as compared to the methodologies used by others like heterogeneous Multi Crew Scheduling and Routing problem, MCSRP(Li & Xing, 2019b), Branch-and-Benders-Cut, BBC, Genetic algorithm, Hybrid BBC, HBBC(Li & Xing, 2019a) and other mathematical models(Li & Xing, 2019c). Calculations are very simple as compared to the other techniques of service enhancement like team-based approach(Moreno, Alem, et al., 2020).

High circuit density clusters was obtained by using this Novel technique while circuit density was very less for clusters made by using initially selected big cities. Less dense circuit clusters, means circuits are far to each other in a cluster so require more time and distance to travel.

There is a remarkable difference in mean Inter-circuit distances of initially selected Big cities and proposed centroids. Value for IMDp is less than IMDb which shows that circuits are more crowded in clusters for proposed centroids as compared to clusters for selected big cities. So, movement of technical teams from one circuit to another will consume less time and distance. Less time will be required for team movement from one circuit to another in a same cluster, in case of any trouble shooting. If IMDp is less than IMDb then a company can safe enough time, revenue and resources by mobilizing a team from one circuit to another circuit in a particular cluster.

This novel technique proposed a greater number of circuits in comparatively less area which can be understood by comparing Ab and Ap values. It means circuits were more crowded near to the location of each team on proposed centroids in clusters, so less time will be required for movement of team to particular circuit location in a particular cluster.

Proposed algorithm also impacts on overall mean Inter-centroid distance of proposed centroids. There is less overall mean inter-centroid distance for proposed centroids as compared to initially selected big cities. Value for MICDp is higher than MICDb which shows that centroids are more crowded for selected big cities as compared to the clusters for proposed centroids. One point is worth mentioning that the comparison between MICDp and MICDb also depends on orientation of overall circuits.

User can select any number of big cities other than 20 as mentioned here, depending on locations of existing telecom circuits.

The performance parameters impact directly on overall performance and revenue of any telecom company or organization who will adopt this technique. Results can vary by changing the number of circuits and corresponding teams without disturbing the overall efficiency. This novel technique proposed the strong orientation of team's locations as per requirement of telecom circuits.

Since team orientation is quite cumbersome for large number of circuits so this proposed technique is useful for large telecom companies and organizations who have large number of telecom circuits and technical teams.

Conclusions

It is concluded that team deployment by this novel technique remarkably reduce the time and the distance of team movement to circuit in a particular cluster, which help in reduction in cost required for team mobilization. Further, implementation of this proposed algorithm reduces the area of each cluster which otherwise require large time and distance as in selected big cities. Reduced area of each cluster in proposed technique, increased the circuit density which helps in team movement to a specific circuit in a short time. Increased circuit density also helps the team to move from one circuit to another circuit in a minimum time. This algorithm also reduces the mean inter-centroid distances, which helps the team for troubleshooting of circuit from their cluster to another nearby cluster in case of emergency in a short possible time.

These findings have vast practical as well as theoretical implications in cost and service quality which are the major requirement of telecom companies. Implementation of this proposed technique, impacts on overall revenue, service quality and customer satisfaction of telecom companies.

Recommendations:

In this work, travelling speed is being considered as 2 minutes per Km as an average in all types of areas for all clusters. But team movement also depends on the geo-graphical area and road status etc. So, in future work, results can be further optimized by monitoring and observing all areas separately. In the proposed technique, one team in one cluster is being considered but number of teams in one cluster can be changed according to the requirement of circuits. Further work can be done in this direction. Further work can also be done by considering sub-clusters within one cluster. It also depends on the requirement of telecom circuits.

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