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Resiliency and reliability of the power grid in the time of COVID-19: An integrated ABC-K-means model for optimal positioning of repair crew

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ABSTRACT

More than one year has passed since the outbreak of a new phenomenon in the world, a phenomenon that has affected and transformed all aspects of human life, it is nothing but pandemic of COVID-19. The field of electrical energy is no exception to this rule and has faced many changes and challenges over the 2020. In this paper, by applying artificial intelligence and the integrated clustering model, by k-means technique, combined with the meta-heuristic artificial bee colony (ABC) algorithm a new methodology is presented in order to optimal positioning of the repair crew based on annual data of power grid under situation of COVID-19 to improve the reliability and resiliency of the network due to the importance of electricity for medical purposes, home quarantine, telecommuting, and electronic services. Current research benefits from real interruption data related to year 2020 in Isfahan Province (Iran), reflexing both the huge changes in patterns of power consumption and dispatching as well as novel geographical distribution of blackouts due to COVID pandemic. The temporal distribution of interruptions is very close to the uniform distribution and the geographical distribution of interruptions relative to the density of subscribers had a normal distribution. Accordingly, proposed model is implemented for clustering the spatial data of blackouts recorded during 2020. The number of clusters is equal to the number of repair teams which in this study is considered equal to three. In the next step, the average spatial coordinates of the points of each cluster are calculated, which after reviewing the geographical conditions in the geo-spatial information system (GIS), indicates the optimal point for the deployment of electrical repair crew related to that cluster. The research findings show that after using the optimal points for a month, system average interruption duration index (SAIDI) decreased by an average of 23% compared to the same period of the 2020.

1. Introduction

Power grids have long been vulnerable to natural disasters; However, both the rate of natural disasters has been lower in the past and the dependence of human life on the reliability of electricity services has not been as great as the current age. Today, urban and even rural life are somehow tied to access to electricity, and the occurrence of widespread, albeit short-term, blackouts has serious economic and human consequences. On the other hand, due to the dependence of the correct operation of infrastructure systems on each other, with the occurrence of a blackout for several hours in an area, the performance of other infrastructure systems such as water supply networks or telecommunication systems is disrupted and this causes power outages on a larger scale. Obviously, in such circumstances, maintaining the security of operation of a power system in the event of low-impact and high-probability accidents is no longer sufficient, and another feature of this system should be considered that reflects its behavior to high-impact and low-probability accidents. This feature, known as resilience, indicates the degree of robustness, vulnerability and recoverability of an infrastructure system in the event of a severe accident [1].

Electricity distribution networks, under the influence of technical and non-technical factors, including power consumption and network load status, depreciation of network equipment, weather conditions (storms, snow and rain), human factors (manipulation of power facilities by unskilled people, Equipment theft) and many other factors cause blackouts (local power outages). At this time, the electrical repair teams are sent to the blackout site according to the current instructions in the distribution companies, and take corrective actions in order to repair the
breakdown and establish the power supply. One of the most important performance standard indicators of power distribution companies around the world, which shows the reliability of the network, is called SAIDI, which is: system average interruption duration index and is equal to: the ratio of total blackouts of subscribers in a system to total number of subscribers in the study period. Operational resiliency, meaning the operational components of the resiliency, including readiness, responsiveness and recovery of the initial situation, is of great importance in the research literature, which leads to a decrease in the average interruption duration of the system (SAIDI) and thus improve the network reliability index [2].

The world has been exposed to the spread of the coronavirus (COVID-19) over the past year in 2020, and many aspects of human life have been affected by this [3]. The COVID pandemic has significantly affected the economy, communities and daily life of the people [4]. The field of electrical energy is no exception and has received many effects due to changes in people’s lifestyles and work plans of organizations and industries, which are: changes in customer consumption patterns, changes in time consumption trends, and changes in network load. Electricity, on the other hand, is critical to health care providers, changes in time consumption trends, and changes in network load. Electricity, on the other hand, is critical to health care providers, patients undergoing home medical care, people under quarantine, telecommuting, and e-services to maintain social distance. Therefore, maintaining the reliability and resiliency of the electricity network in the current situation, has been increasingly considered by energy policymakers.

In the other word, COVID-19 has led to extreme changes in the consumption patterns during 2020 [3], a decrease in industrial and commercial sectors as well as a huge increase in residential and medical sectors, and consequently significant changes in network local load which caused blackouts and interruptions in the sections with more residential, medical and health care consumers. Improving reliability in sections of the power grid with heavier load under COVID conditions requires analysis of 2020 blackout data and improvement measures. One of the improvement measures is optimal relocation of the repair teams, which is discussed in current paper. Because, the speed with which the repair crew reaches the scene of an outage, the quick connecting of power current, and the prevention of an increase in the SAIDI index are of great importance to power distribution companies. Hence one of the available solutions is: Deploy repair crew in the optimal locations with a minimum distance to blackouts; which has been focused in this research.

It should be noted that this solution requires the use of geo-spatial information system (GIS) and registration of spatial coordinates of blackouts, which fortunately in recent years in the Isfahan Electricity Distribution Company has been implemented and is running [5-7]. Due to the fact that the electricity departments of the counties of Isfahan province each have a covered area, repair units and a certain number of dedicated repair crew, each county can be studied separately. Therefore, in the first phase, one of the major cities of the province, which has a significant geographical distribution, has been studied. The title of the proposed method is: Spatial clustering of outage points using the integrated ABC k-means algorithm.

The remarkable innovation that puts the current research in a unique position is that the ABC-k-means hybrid model has not been used to solve a real problem so far, and this paper is its first application in a real problem, especially in the field of energy. Fortunately, optimality, performance and time productivity of the ABC-k-means hybrid model has strongly confirmed compared to other alternatives by Armano and Farmani [8] and Tran et al. [9].

2. Literature review

2.1. Resiliency in power grids

Resilience is a concept that has been explored in the social, economic and managerial fields before being introduced in the fields of engineering. In social systems, resilience refers to the ability of a society to withstand pressures and events resulting from political, social and economic changes in that society [10]. In an economic system, resilience means: responding to different risks so that different individuals and groups can protect themselves from some economic losses in the market [11]. In the field of management and organizational systems, the ability of an organization to identify various risks and manage events is called organizational resilience [12]. What is quite colorful in these definitions is the existence of definitions such as resistance to accidents, protection from casualties and accident management. In other words, the main emphasis of these definitions is on the lack of vulnerability to accidents and although there is no implicit reference to post-injury recovery. This is due to the extreme inertia of social, economic and managerial systems and the slowness of the processes of positive change in them. This means that the specialists of these systems correctly consider the preventive approach and consider the treatment process after the occurrence of a serious injury and do not consider it very effective [13]. For example, if a society does not provide the necessary cultural care and the culture in that society is damaged, cultural recovery is needed and return to the period of cultural flourishing in that society will never be possible easily and quickly. Or if corruption is rooted in one economic structure, it is far from expected to reform that economic structure in the short term. But in engineering systems, especially infrastructure systems, the problem is different. In an engineering system whose equipment is prone to failure and various inherent, natural and human factors constantly threaten the health of the equipment, one can not hope for the correct operation of the system only with preventive actions. In these systems, equipment maintenance and repair is an integral part of the operation process. Also, after an accident and system failure, service recovery and repair of its structure, which is an inevitable and of course practically possible [14]. Therefore, the definition of resilience in infrastructure systems should focus on both robustness against accident and rapid post-accident recovery [15]. The ability of the system to reduce the duration and severity of disturbances; In other words, the system’s ability to predict, tolerate and adapt to various disturbances and fast recovery is called resilience [16].

In the case of power systems, although the above definition is correct and usable for resilience, it should be emphasized that disturbances refer to high-impact, low-probability events. These events, which can be of natural or human origin, are either rare or never experienced. The occurrence of such disturbances covers a wide geographical area and removes several equipment simultaneously from the circuit, complicating the recovery process and, of course, prolonging it. In other words, these perturbations leave spatial-temporal correlation effects. Another unique feature of these disturbances is that if they have a natural origin, they affect several infrastructure systems such as electricity network, telecommunication system, gas supply and distribution infrastructure, water supply network, etc. simultaneously. These critical situations, on the one hand, increase the depth of the catastrophe and, on the other hand, make the recovery process more difficult. Unlike reliability studies, which consider a set of events together and provide system
behavior by general indicators, a resilience study is conducted specifically for an event. The system may be designed to increase the system’s resilience to one accident but at the same time reduce its resilience to another. For instance, if the network designer decides to run power distribution feeders by underground cables to make it more resilient to storms and hurricanes, the system will be less resistant to flooding compared to air feeders [17].

Fig. 1 shows the resilience components of a system in the event of a severe disturbance. As can be seen in Fig. 1, after a disturbance occurs and damage to a number of equipment, the system, according to its adaptability, adapts itself properly to the post-accident conditions to the extent of shutdown and service interruption be minimized. In such cases, the system operator must have sufficient tools to be aware of the extent and severity of the damage, healthy equipment, available production sources, and loads with shutdowns and interruptions. Then, the operator, based on the resources at his disposal as well as his knowledge and experience, begins to recover the extinguished loads. However, due to limited resources, some of the network loads may not be recoverable and the return of services to them may be delayed until the damaged parts are repaired. It is worth noting that similarity in adaptability, recovery and speed of operation requires both hardware tools and arrangements as well as operating measures [2].

2.2. Repair crew optimal placement

There are several studies about optimal placement of repair teams in various condition during previous years. Proactive preparedness to cope with emergencies significantly improves the resilience and minimizes the restoration cost of electric power systems. Arab et al. proposed a stochastic proactive resource allocation model for repair and restoration of potential damages to the power system infrastructure located on the path of an upcoming hurricane [18]. Reddy et al. presented fuzzy approaches for restoration of distribution system during post natural disasters which fill the gap present in the existing methods by explaining the theoretical solutions to ranking of load points, locations, crew selection, estimation of repair times, and prioritization of the damaged regions [19]. Predictive planning for restoration and emergency reaction before occurrence of hurricane is an effective action in reducing time and cost of electricity interruption and improving resilience in overhead distribution networks [20]. Khomami and Sepasian proposed pre-hurricane repair team placement model (PHRTPM), using Monte Carlo simulation method and fragility curves. They generated different failure samples of poles and conductors of medium voltage distribution network according to the predicted speed of hurricane. A forward dynamic programming algorithm is used to determine the path of the repair teams; using a square grid topology, the optimum locations of utility teams are achieved [20]. Repair crews (RCs) and mobile power sources (MPSs) are critical resources for distribution system (DS) outage management after a natural disaster. Lei et al. proposed a resilient scheme for disaster recovery logistics to co-optimize DS restoration with the dispatch of RCs and MPSs. They generated resilient recovery strategies to enhance service restoration, especially by dynamic formation of microgrids that are powered by MPSs and topologized by repair actions of RCs and network reconfiguration of the DS [21]. Lin et al. proposed a combined repair crew dispatch problem for the interdependent power and natural gas systems. The repair schedule of the two systems is coordinated and co-optimized. Both power system topology reconfiguration and intentional DG islanding are modeled as operational measures to further improve the resilience of the interdependent systems [22].

2.3. Power systems under COVID-19 conditions

The electricity sector has been severely affected and challenged by COVID-19. Due to restrictive policies, large consumers of electricity, such as factories and commercial buildings, are forced to shut down or move to a minimum level of operation. Because people are limited to staying at home, the load of residential subscribers is greater. This change in work and lifestyle leads to a significant change in the level of electricity demand, profiles, composition and distribution of electricity. Changing the load pattern further affects the performance and control of the power system. Due to the unprecedented growth of the Corona pandemic and the rapid control and anti-epidemic policies, the performance of the power system is also facing a greater degree of uncertainty. In addition, the policy of forced closure and supply chain severance poses a direct obstacle to the maintenance and management of assets. In
addition to technical issues, the economic and environmental aspects of the electricity industry are also affected. The reduction in electricity prices and the reduction in carbon dioxide emissions from electricity generation were observed immediately after the restriction policies, which was due to the reduction in electricity demand and the increase in the ratio of renewable production [3].

Several reports have highlighted the adverse effects of the Corona pandemic on the electricity and clean energy sectors, including undermining operational resiliency, lowering wholesale prices, and delaying investment activities [23–25]. Analysis of electricity consumption by regional transmission organizations (RTOs) also shows an overall reduction in energy consumption, especially in areas with large commercial activity [26–28]. Fig. 2 shows daily electricity consumption from January to May 2018 to 2020 in four countries: Italy, Japan, the United States and Brazil. Compared to the 2018 and 2019 profiles, electricity demand shows a significant decrease in Italy, the United States and Brazil [3]. In the United Kingdom in lockdown situation, the load on weekdays was similar to weekends, and the morning peak slope was reported to be twice as low as usual [29]. The “duck-shaped curve” intensified in California, USA, following the “stay at home” policy [30], which was due to declining demand and an increase in the share of solar production.

Using night time light (NTL) data from satellite imagery, Fig. 3 illustrates the impact of COVID-19 on New York City electricity consumption. The reduction in NTL brightness provides a strong visual representation of the impact of COVID-19 on electricity consumption in such major metropolitan areas, where a significant portion of electricity consumption involves large commercial loads. This result serves as a preview of the insights gained from statistical analysis and show that the level of business activity is the main factor in the change in electricity consumption during COVID-19 [23]. Pandemics also cause maintenance and management problems for the power system. Maintenance of networks and generators is affected by lockdown, traffic bans, and supply chain interruptions. Periodic maintenance activities are usually scheduled years in advance. But in the pandemic period, such actions are somewhat postponed or even canceled [3]. In New Zealand and Australia, scheduled outages for maintenance work were delayed, with only those that were critical to the safety of the system being operated on schedule [31]. Power plant maintenance work has also been delayed in some US states to avoid the risk of COVID-19 exposure for workers [32].

The Electric Power Research Institute (EPRI) in the United States summarizes the operating strategies of power distribution companies during the outbreak. To minimize the impact of the virus and keep the control center operational, service companies implement strategies such as using backup control centers, implementing a work rotation plan, separating essential operational groups in the control center, and rigorous cleaning and disinfection actions [33]. Applying and development of electronic service platforms, including mobile applications and virtual two-way communication with customers has also been considered by utilities [34].

2.4. Data clustering: k-means method

Clustering analysis is one of the main analytical methods in data mining, the technique of clustering algorithm directly affects the clustering results. The common k-means algorithm is one of the most widely used clustering algorithms. This algorithm is classified as a partial, or non-hierarchical method [35]. In this algorithm, the number of clusters is assumed to be equal to the constant value k. By assigning data to the nearest cluster and then changing the membership of the clusters based on the error function, repeatedly until there is no significant change in the value of the error function, or the membership of the clusters does not change [36].

Its algorithm is as follows:

Prequisites: data set D, number of clusters k, dimensions d:
Ci: i th my cluster.
Initial phase:
Initial classification D: (C1, C2, ..., Ck)
Repeat phase:
repeat
Distance between data i and cluster j = dij;
For at least dij per 1 ≤ j ≤ k – ni;
Assign data i to cluster ni;
Recalculate the center of the clusters according to the above changes
As long as there is no change in the membership of the clusters in a complete iteration.
Output Results [37]

2.5. Artificial bee colony (ABC) meta-heuristic algorithm

This algorithm was introduced by Karaboga in 2005 to real optimize the parameters. This algorithm is a newly introduced optimization algorithm that simulates bee colony exploration behavior for unlimited optimization problems. To solve constraint optimization problems, a constraint management method is combined with this algorithm. In a real bee colony, there are tasks performed by specialized bees. These specialized bees try to maximize the amount of nectar stored in the hive by performing division of labor and effective self-organization. The minimum model of food search selection by intelligent bee groups in a bee colony, adopted by the ABC algorithm, includes three types of bees: worker bees, observer bees, and scout bees [38].

Half of the colony contains worker bees and the other half includes observer bees. Worker bees are responsible for exploiting the sources of nectar that have already been discovered, as well as giving information to other waiting bees in the hive about the quality of the food they are extracting. Observer bees stay in the hive and decide on a food source to be exploited based on information shared by worker bees. Scouts...
randomly search the environment to find a new food source based on an intrinsic motivation or external or random evidence [39].

The main steps of the ABC algorithm that simulates this behavior are as follows:

1. Initialization of food resource situations
2. Each worker bee produces a new food source in its food source location and extracts a better source.
3. Each scout bee selects a source depending on the quality of its solution and produces a new food source at the location of the selected food source and extracts a better source.
4. Determining the source that should be abandoned and allocating its worker bees as a pioneer in search of new food sources.
5. Remembering the best food source found so far.
6. Repeat steps 2 to 5 until the stop criterion is appropriate [38].

In the first step of the algorithm, \( x_i \ (i = 1, \ldots, SN) \) solutions are generated randomly in which \( SN \) is the number of food sources. In the second stage of the algorithm, for each worker bee, whose total number is equal to half the number of food sources, a new solution is generated by the following equation:

\[
v_i = x_0 + \phi_i (x_j - x_0)
\]  

where \( \phi_i \) is a random number with uniform distribution in the interval \([-1,1]\) that controls the production of the position of neighboring food sources around \( x_i \), \( k \) is the solution index randomly selected from the colony \( (k = \text{int} (\text{rand} \times SN) + 1) \), \( j = 1, \ldots, D \), and \( D \) is the dimension of the problem. After producing \( v_i \), this new solution is compared to \( x_i \) and the worker bee extracts a better source. In the third step of the algorithm, an observer bee selects a food source with probability (2) and generates a new source at the location of the food source selected by (1), and in the same way the worker bee method is a better source for extraction is decided.

\[
p_i = \frac{f_{i_0}}{\sum_{n=1}^{SN} f_{i_n}}
\]

After all the observing bees have been distributed to the sources, the sources are examined to see if they should be abandoned. If the number of cycles in which a resource cannot be recovered is greater than a predetermined range, that resource is considered an exhausted resource. The worker bee is related to the exhausted source of a scout bee and creates a random search in the problem area [38, 40]. Detailed pseudo-code of the ABC algorithm is given below [39]:

1: Initialize the population of solutions \( x_i \), \( i = 1, \ldots, SN \)
2: Evaluate the population
3: Cycle = 1
4: repeat
5: Produce new solutions \( v_i \) for the employed bees by using (1) and evaluate them
6: Apply the greedy selection process for the employed bees
7: Calculate the probability values \( P_i \) for the solutions \( x_i \) by (2)
8: Produce the new solutions \( v_i \) for the onlookers from the solutions \( x_i \) selected depending on \( P_i \) and evaluate them
9: Apply the greedy selection process for the onlookers
10: Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution \( x_i \)
11: Memorize the best solution achieved so far
12: Cycle = Cycle + 1
13: until Cycle = MCN

All the procedure is shown as a flowchart on Fig. 4 [40].

2.6. ABC-k-means hybrid algorithm

In the case of hybrid clustering algorithms using the k-means technique and the artificial bee colony algorithm, very limited research has been done before which just has dealt with theoretical aspects rather than real practical application [8, 9]. Fortunately, optimality, performance and time productivity of the ABC-k-means hybrid model has strongly confirmed compared to other alternatives by Armano and Farmani [8] and Tran et al. [9]. The remarkable novelty that puts the current research in a unique position is that this algorithm has not been used to solve a real problem so far, and this is its first application in a real problem, especially in the field of energy.

3. Methodology

In this paper, the integrated k-means and artificial bee colony (ABC) algorithm is used to cluster the data of the optimal positioning of the power repair teams’ locations. According to what has been stated, one of the existing solutions in order to improve the resilience of electricity networks after the accident in the field of ‘recovery and speed of repair’ is:

• Deploy repair crew in optimal locations with a minimum distance to blackouts.
To clarify the relationship between COVID-19 and the proposed method, it should be noted that the pandemic has led to extreme changes in the consumption patterns during 2020, a decrease in industrial and commercial sectors as well as a huge increase in residential and medical sectors, and consequently significant changes in network local load which caused blackouts and interruptions in the sections with more residential, medical and health care consumers. Improving reliability in sections of the power grid with heavier load under COVID conditions requires analysis of 2020 blackout data and improvement measures. One of the improvement measures is optimal relocation of the repair teams, which is discussed in current paper. Because, the speed with which the repair crew reaches the scene of an outage, the quick connecting of power current, and the prevention of an increase in the SAIDI index are of great importance to power distribution companies. Hence one of the available solutions is: Deploy repair crew in optimal locations with a minimum distance to blackouts.

The remarkable innovation that puts the current research in a unique position is that the ABC-k-means hybrid model has not been used to...
solve a real problem so far, and this is its first application in a real problem, especially in the field of energy.

This solution requires the use of geospatial information system (GIS) and registration of spatial coordinates of blackouts over time and at the time of the accident, which fortunately in recent years in the Isfahan Electricity Distribution Company is being implemented and is run.

Due to the fact that the cities of Isfahan province each have their own coverage area, repair units and special repair crew with a certain number, each city can be studied separately. Therefore, in the first phase, one of the major cities of the province, which has the geographical extent, population and distribution of the electricity network is studied and the problem is defined and solved as follows.

- Title of the problem: Positioning the optimal locations of repair teams
- Proposed solution method: Spatial Clustering of outage points using integrated ABC-k-means algorithm

The above problem is solved in two steps:

1- Clustering the location points of blackouts, in which the number of clusters is determined equal to the number of city repair crew. The output of this step determines the area covered by each team.
2- Determining the optimal point coordinates for the deployment of the repair crew in each cluster, which is the average coordinates of the points of each cluster.

The problem data is as follows:

- Spatial data of blackouts of the year 2020 in the studied city with 2181 UTM points, which are related to the COVID-19 conditions. It should be noted that the temporal distribution of blackouts was very close to the uniform distribution and the geographical distribution of

| Cluster number | Number of cluster points | Initial coordinates of deployment of repair crew (UTM) | Minimum cost |
|----------------|--------------------------|--------------------------------------------------------|--------------|
| Cluster 1      | 743                      | 554,427 3,633,650                                       |              |
| Cluster 2      | 719                      | 546,740 3,639,044                                       |              |
| Cluster 3      | 719                      | 540,862 3,660,179                                       |              |
| All Data       | 2181                     | – –                                                   | 1,152,758,788|

![Fig. 7. Problem data clustering results.](image)

![Fig. 8. Clustering results on the roadmap.](image)
blackouts relative to the density of subscribers had a normal distribution.
• The number of repair teams in the studied city is equal to 3 teams.
• The total number of subscribers in the studied city is equal to 133,344 subscribers.

4. Data analysis and research findings

Data of 2181 UTM points related to blackouts in 2020 of the studied city were imported in MATLAB software and then stored as a file with .m extension. Then, in the ABC-k-means clustering algorithm, the relevant data were entered with the load command. The scatter plot diagram of the problem in MATLAB software can be seen in Fig. 5.

Using the k-means clustering algorithm and combining it with the artificial bee colony meta-heuristic algorithm (ABC), the problem data are clustered in three clusters (nk = 3). To solve the problem in MATLAB software, the number of iterations of ABC algorithm is equal to 200 and the number of scout bees is equal to 50. The process of reducing costs and achieving the optimal answer can be seen in Fig. 6.

After clustering the data, in order to determine the optimal point coordinates for the deployment of the repair crew in each cluster, the average point coordinates of each cluster are calculated, which is described in Table (1). As shown in Table (1), the minimum total intra-cluster distances (Minimum Cost) is equal to 1,152,758,788.

The clustering results of the problem data and the initial locations of the repair crew are shown in Fig. 7 on the terrain map. The points of the first to third clusters are shown in red, green and blue, respectively, and the locations of the three power repair teams are shown with a “+” sign. Examining the status of the three points obtained, in the earth feature map (Fig. 7) and the road map (Fig. 8), it is observed that the locations of clusters 2 and 3 require a slight displacement in order to access the appropriate road. Therefore, after reviewing the geographical conditions in the geospatial information system (GIS), the required corrections and the final optimal points of deployment of repair teams for all three clusters are shown in Fig. 9 and their UTM coordinates are in accordance with Table 2.

The three points obtained according to Table 2, in the study county, were implemented for one month and SAIDI was calculated monthly. Findings show that the system average interruption duration index in the test month in 2020 was 19.8 min which decreased to 15.2 min in 2021. That illustrates more than 23% SAIDI reduction in 2021 resulted by applying the proposed model compared to the same period of the previous year.

5. Conclusion

One of the most important components of power grid resiliency is recovery and speed of operation. Considering the magnitude of COVID-19 situation and the notability of subscribers to have sustainable
electricity and the need to maintain reliability and improve network resilience, due to the vital role of electricity for medical centers, subscribers under home quarantine, telecommuting infrastructure, and electronic services, In this paper in order to increase the speed of repairing and timely presence of repair crew at the shutdown point which leads to improve resilience and reliability of power network, with the approach of using artificial intelligence in planning and decision making in the field of operational resilience in the utilization of distribution networks, a novel integrated clustering model using k-means method in combination with the artificial bee colony algorithm (ABC) is presented in order to locate the optimal positions of power repair crew. The proposed model was implemented on the real data of annual blackouts related to one of the big counties covered by Isfahan Province Electricity Distribution Company. The temporal distribution of blackouts was very close to the uniform distribution and the geographical distribution of blackouts relative to the density of consumers had a normal distribution. Accordingly, the spatial data of blackouts recorded during 2020, which are related to the COVID-19 conditions, are analyzed and clustered with the proposed algorithm using MATLAB software. The number of clusters determined based on the number of repair crew in the county, which in this study is equal to 3. In the next step, the average spatial coordinates of each of the clusters resulting from the clustering of blackout points are calculated and reviewed in GIS based on their status in the earth features map and road map. The results indicate the optimum location of 3 repair teams of the studied county. These locations were implemented for one month and SAIDI was calculated monthly. Our findings show that the average system interruption duration in the test month decreased by more than 23% compared to the same period of the previous year. Base on the research results, with careful and scientific planning, effective steps can be taken to increase network resilience and improve reliability indicators.

Authors statement
Both authors have the same contributions in this study.

Declaration of Competing Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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