Optimal Distribution of Service Points in Holy Places

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Abstract

According to the 2030 Saudi vision, the annual number of pilgrims and visitors would increase to 30 million by 2030. In order to properly serve this large number of pilgrims and visitors, the maximum performance of already available service points should be exploited. In this paper, we propose a Genetic Algorithms (GA)-based methodology to optimize the distribution of these service points in any field, in order to realize their maximum performance. Our methodology could be used in the holy places, like Mina, Arafat, and the two holy mosques, to optimize the distribution of many service points, like police cars, ambulance cars, fire trucks, surveillance cameras, sensing circuits for different environmental parameters, and cars for food, water and beverage. Our methodology aims at minimizing the distance that should be traversed to acquire these services. Two distance metrics are considered for optimization, average and maximum distances. The former metric abstracts the average-case performance, whereas the later one represents the worst-case performance. As a proof of concept, a case study of distributing ambulance cars in Arafat is considered. Obtained results indicate that our methodology outperforms current as well as random distribution strategies with respect to both average and maximum distance metrics. The case study clearly shows the efficiency of our methodology in exploiting the maximum performance from any group of service points.

I. Introduction

Millions of Muslims from all over the world wait their turn to perform Umrah, and hopefully hajj. Every year, only few millions from this huge awaiting number manage to carry out their holy trip to Makkah and Madinah. In fulfilling its duty toward Muslims, the Saudi government aims at increasing the number of pilgrims and visitors that could annually be accommodated. According to the Saudi 2030 vision, the annual number of pilgrims and visitors would increase to 30 million by 2030 [1]. Indeed, this number is limited by the infrastructure and the services that could be introduced in holy places. Many services are currently available to serve pilgrims and visitors. Examples of these services are hospitals, medical centers, ambulance cars and jets, fire trucks, police cars, transportation buses, and cars for food, water, and beverage. Furthermore, in the future, many smart electronic equipments might be deployed throughout holy places for continuous monitoring, disaster prevention, and automatic control of critical situations. Examples of these smart electronic equipments are surveillance cameras and sensing circuits for different environmental conditions, like temperature and fires. In order to properly serve the increasing number of pilgrims and visitors, the performance of these services and equipments should be optimized. One aspect of this optimization problem is how to perfectly distribute these services and equipments to exploit the maximum performance from them. In this paper, we target this optimal distribution problem by presenting a methodology to perfectly spread services and equipments in holy places. For the rest of this paper, we use the term service points to represents both services and equipments.

According to deployment locations, distributing service points in any field could be formulated as an unconstrained or a constrained problem [2]. In the unconstrained distribution, service points could be placed anywhere in the field. Contrarily, the constrained formulation restricts the distribution of service points onto certain candidate locations. For holy places, the unconstrained distribution of service points is not practically possible due to physical obstacles in these places, like mountains and restricted zones. For example, we could not place an ambulance car above Alrahma mountain or inside Alkhaif mosque. Therefore, constrained distribution of service points is only considered in this paper.

The distribution of service points in any field is usually customized with respect to certain performance metrics. For holy places, one of the most important metrics, which needs to be minimized, is the distance [3]. For any location within the field, this metric represents the distance from this location to the nearest service point. Minimizing this metric not only reduces the distance that should be traversed to acquire the service, but it also increases the coverage metric. The coverage metric represents the total number of service points, which serve that location. In the literature, distributing service points in any field is a variant of the discrete facilities location problem, which is known to be an NP-hard one [4, 5]. Therefore, heuristics, approximation algorithms, and optimization-based techniques should be used to solve it [6]. In this paper, we present a Genetic Algorithm (GA)-based methodology that aims at optimally distributing service points in any field, specially holy places, to minimize the distance that should be traversed to acquire these services. Our methodology could be used to minimize one of two distance metrics. The first is the average distance, which is the mean of distances from all locations within the field to their nearest service points. The second metric is the maximum distance, which represents the farthest location from a service point. As a proof of concept, the distribution of ambulance cars in Arafat is considered. The obtained results prove that our methodology could significantly enhance the performance of these service points.

The rest of this paper is organized as follow. Sections II reviews the related work. Section III surveys GA as an optimization technique. Formulation of the problem and models of the two distance metrics are presented in Section IV. Section V discusses our GA-based methodology for the optimal distribution of service points. Section VI gives experimental results of our case study to validate our work. We draw conclusions and give directions for future work in Section VII. Finally, Section VIII summarizes our recommendations to enhance the performance of the current system of services.

II. Related Work

The distribution of service points in any field, which we target in this paper, is a variant of the discrete facility location problem [7]. The discrete facility location problem is studied with respect to many metrics. Out of these metrics, distance is the most considered one. Consequently, many previous research work aim at deciding the proper locations of service points, such that the distance to different locations within the field is minimized. Both the average and the maximum distances are considered for minimization. First, minimizing the average distance is named the p-median problem [8] or the minisum problem [9]. This problem aims at minimizing the mean of all distances from service points to different locations within the field. Therefore, it represents the average-case performance of a distribution. Second, minimizing the maximum distance is named the p-center problem [10] or the minimax problem [11]. This problem aims at minimizing the maximum distance from service points to the farthest locations from them. Therefore, it represents the worst-case performance.

Neither of the p-median nor the p-center problems is considered to optimally distribute service points in holy places. However, they are used for many other fields. Moreover, different techniques are used to solve the two problems. For example, the p-median problem is solved using GAs in [12]. An algorithm to speed up the solution of the p-center problem is presented in [13]. The case of uncertain distances for the p-center problem is targeted in [14]. In summary, a thorough survey about different formulations of the two problems and algorithms used to solve them is given in [15]. Finally, for holy places, a slightly related problem of distributing camps in Mina could be found in [16].

III. Genetic Algorithms (GA) optimization

GA is used to solve complex optimization problems, which could not be solved by conventional methods. It is a global optimization technique that mimics the evolution of human genes [17]. GA optimization starts by a set of chromosomes, which is named a generation. Each chromosome represents a possible solution of the optimization problem. All chromosomes within a generation are evaluated according to the optimization function. Continually, the optimization engine evolves new generations from the preceding ones until a certain stopping criterion terminates the execution. Famous stopping criteria are exceeding a maximum number of generations or a maximum allowable execution time. The evolution of one generation from the preceding one is done through three genetic operators: elitism, crossover, and mutation. In elitism, the best chromosome, or chromosomes, survive to represent the first portion of the new generation. In the crossover, two chromosomes mate together to generate two new ones. The resultant children from mating multiple pairs of chromosomes represent the second portion of the new generation. In the mutation, some chromosomes are slightly modified to prevent the optimization engine from being trapped in local minima or maxima. These modified chromosomes represent the last portion of the new generation.

IV. Problem formulation

In this section, we present the models of the two distance metrics, which we use in this paper. In Section IV, our GA-based methodology would minimize one of these two models to generate the optimal distribution of service points in any field of interest. In order to ensure covering the whole area of that field, a grid sampling strategy, similar to the one presented in [18], is employed. Accordingly, the field is partitioned into horizontal and vertical slices of infinitesimal δx and δy. This results in a grid of small rectangles. Points at the corners of these rectangles are uniformly distributed throughout the field with very small distances in between. Therefore, we name them sampling points and only consider them in our distance calculations. The distance metrics abstract the effort, the time, or the energy that are needed by a service point to reach a sampling point and vice versa. We start our modeling by finding the distance from each sampling point to its nearest service point. Consider S and P to represent the two sets of service points and sampling points, respectively. For any arbitrary sampling point, pi, the distance from that point, dij, to each service point, sj, is first calculated. The minimum of these distances, which represents the shortest path from that sampling point to a service point, is then found. This minimum constitutes the distance metric, di, of the arbitrary sampling point, pi, and could consequently be represented by

$$d_i = \min(d_{ij}) \qquad , \forall s_j \in S \qquad (1)$$

After finding the shortest path of every sampling point to a service point, we calculate our average and maximum distance metrics for any candidate distribution of service points. Any of these metrics could be used as an objective function, which would be minimized by our GA-based methodology. As the name implies, the average distance is the mean of all sampling points distance, as expressed by (1). The average distance metric, d_{avg}, therefore captures the overall performance of any distribution and could be represented by

$$d_{avg} = \text{mean}(d_i) \qquad , \forall p_i \in P \qquad (2)$$

The maximum distance, in turn, is the maximum of all sampling points distance, as expressed by (1). It represents the farthest sampling point from a service point. The maximum distance metric, d_{max}, therefore captures the worst-case performance of any distribution and could be represented by

$$d_{max} = \max(d_i) \qquad , \forall p_i \in P \qquad (3)$$

V. Proposed methodology

This section discusses our GA-based methodology for optimal distribution of service points in any field. As explained in Section II, applying GA requires representing possible distributions of service points in the form of chromosomes. In this paper, our GA-based methodology employs binary chromosome representation. The length of any chromosome is equal to the number of candidate locations of service points. Each gene within a chromosome is either 1 or 0 to indicate whether a service point is actually distributed to its corresponding location or not, respectively. The total number of 1’s of any chromosome should be equal to the number of actual service points. This is ensured by using special creation, crossover, and mutation functions. First, in our creation function, random genes, whose number is equal to that of actual service points, are set to 1. Second, in our crossover function, a single point crossover is regularly used. Thereafter, the legality of generated children is checked. According to the outcome of this check, random genes might be flipped to guarantee that the total number of ones is equal to that of actual service points. Third, in our mutation function, half of the chromosomes are generated completely random. This is done to introduce new distributions to the GA engine and prevent it from being trapped in a local optimum. For the second half of mutation chromosomes, arbitrary 1 and 0 in the most fitted chromosome are randomly selected and flipped. This is done to introduce minor changes to the best achieved distribution, in a hope to further enhance it.

Fig. 1 shows our methodology for optimal distribution of service points using GA. The GA optimization starts, in the first step, by reading the inputs required by the engine. These inputs are the description of the field, the candidate locations to which service points could be distributed, and the required number of service points that should be actually distributed. In the second step, grid sampling is carried out to ensure covering the whole area of the field, as discussed in Section III. Thereafter, the GA engine runs iteratively to find the best distribution of service points with respect to one of the two distance metrics. In the third step, a new generation of chromosomes is formed. For our initial population, random chromosomes are generated using our creation function. For all subsequent generations, elitism, crossover, and mutation are used to form them. Every chromosome within the generation is then evaluated by steps 4-6 of our methodology. In the fourth step, the distance metric of each sampling point is found, according to (1). Thereafter, in the fifth step, the metric for which optimization should be carried out is decided. In the sixth step, according to the required metric, either the average distance, over all sampling points, or the maximum distance is calculated, according to (2) or (3), respectively. The calculated distance is used to evaluate the fitness of each chromosome within the generation. Chromosomes are consequently ranked according to their fitness score. The rank of each chromosome decides if it would survive to the subsequent generation, through elitism, or be considered for crossover and mutation. In the seventh step, the exit criterion is checked. In the eighth step, if the exit criterion is satisfied, the GA engine finally generates the optimal distribution of service points within the field.

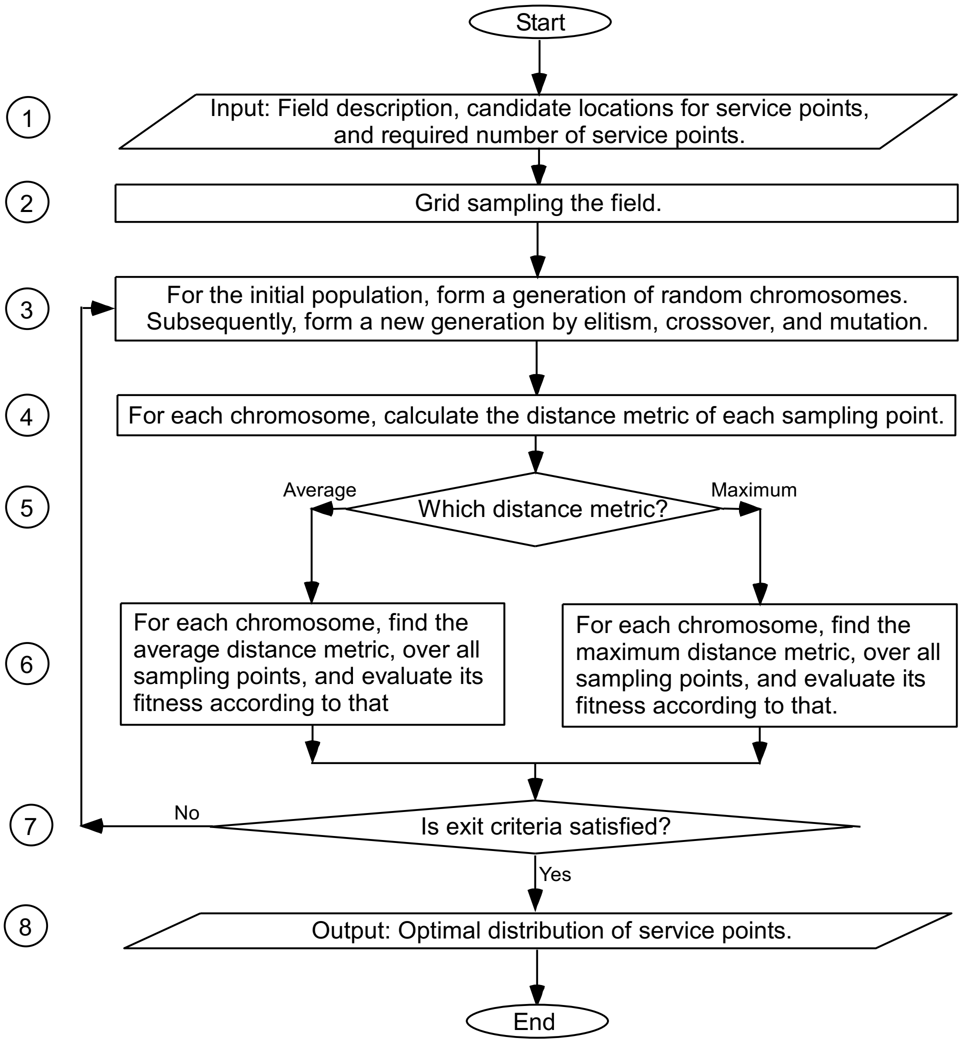


Fig. 1. GA-based methodology for optimal distribution of service points.

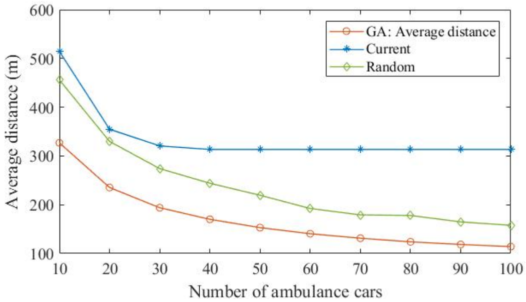
VI. Experimental results

In order to verify the efficiency of our GA-based methodology, we consider a case study of distributing ambulance cars in Arafat. Our selection of the case study is motivated by the fact that the Hajj is moving toward the summer. Indeed, the day during the summer is long and very hot. More pilgrims would be affected by the direct sunlight and the high temperature. Therefore, ambulance cars should optimally cover the whole area of Arafat and quickly move to provide immediate medical help.

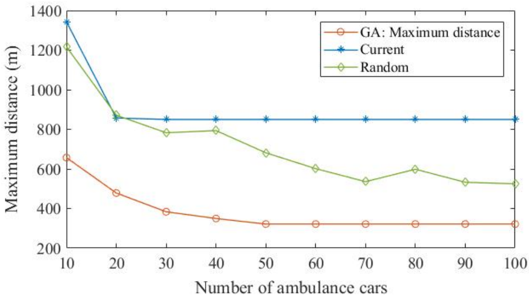
Before presenting and discussing our results, we herein summarize the tool, assumptions, and parameters used in getting these results. First, for the tool, the Matlab® global optimization toolbox [19] is used in solving the optimization problem in this paper. Each generation consists of 10 different chromosomes, representing 10 different distributions. Two chromosomes of the best fitness are allowed to survive from one generation to the next through elitism. Furthermore, crossover and mutation generate 4 chromosomes each. For our methodology, different numbers of chromosomes could be used for the generation size, the elitism, the crossover, and the mutation. However, the used values are found by experimentation to give the best convergence time. Those values also agree with the ones suggested in [20]. Second, for the candidate locations of service points, ambulance cars could only be distributed to the intersection of any two paved roads. This results in a total of 330 candidate locations for ambulance cars. This restriction aims at facilitating the movement of any car and helping it to reach the desired location quickly.

The two distance metrics presented in Section III are considered for comparison in this section. Accordingly, for each metric, we change the number of ambulance cars from 10 to 100 and compare the results of our methodology to those of the random as well as the currently employed distribution strategies. In the random distribution strategy, some of the aforementioned candidate road intersections are randomly selected as locations for ambulance cars. In the current distribution strategy, ambulance cars are only restricted to fixed locations. These are the locations of hospitals, medical centers, and red crescent centers. Fig. 2 shows the results of the three distribution strategies with respect to the two distance metrics. The results of our GA-based methodology are averages over 10 runs. In each subfigure, our GA-based methodology, the current distribution strategy, and the random distribution strategy are represented by a red line with circle markers, a blue line with star markers, and a green line with diamond markers, respectively.

The average distances resulted from the three distribution strategies are shown in Fig. 2(a). From this figure, we first notice the superiority of our methodology over the two other strategies. Depending on the number of ambulance cars, our GA-based methodology reduces the average distance by 33.7% to 63.6%, with respect to the current distribution strategy, and by 26.7% to 30.4%, with respect to the random distribution strategy. Second, the figure shows that the average distance of the current distribution strategy remains constant beyond 30 ambulance cars. As that strategy restricts the distribution of ambulance cars to fixed locations, it could not benefit from increasing the number of cars or even achieve an average distance as small as that of the random distribution strategy. From these results, we finally conclude that keeping services centralized in fixed locations prevents them from attaining the maximum possible performance.



(a) Average distance



(b) Maximum distance

Fig. 2. Comparison of our GA-based methodology to random and current distribution strategies with respect to different distance metrics.

The maximum distances resulted from the four distribution strategies are shown in Fig. 2(b). As mentioned in Section III, the maximum distance represents the farthest sampling location from an ambulance car. The figure first re-emphasizes the superiority of our methodology over the two other distribution strategies. Depending on the number of ambulance cars, our GA-based methodology reduces the maximum distance by 44.2% to 62.2%, with respect to the current distribution strategy, and by 38.7% to 56%, with respect to the random distribution strategy. Second, the figure again shows that the current distribution strategy could not even outperform the random distribution one with respect to the maximum distance metric. Furthermore, it could not benefit from increasing the number of ambulance cars and its maximum distance sticks beyond 20 cars.

VII. Conclusion and future work

In this paper, we present a methodology to optimize the distribution of service points in any field. The methodology is suitable for distributing services in holy places. The optimization process is carried out using Genetic Algorithms with binary chromosome representation. Our methodology considers two distance metrics, average and maximum distances. A case study of distributing ambulance cars within Arafat is given to validate the efficiency of our methodology. Results show that the proposed methodology could significantly reduce the distance compared to current as well as random distribution strategies.

Our work could be extended into different directions. First, more metrics could be considered. Second, the methodology could be modified to combine between stationary and movable service points. Finally, for any required level of performance, the methodology could be adapted to decide the minimum number of service points that are needed to achieve this target performance.

VIII. Recommendations

From the experience we got throughout our work and depending on the results we obtained in our case study, we give the following recommendations

1) There is a significant unused performance that should be better utilized from the current system of services. Therefore, for different types and aspects of already available services, optimization techniques should be employed to exploit the maximum performance from them.
2) The more we transform from centralized to de-centralized distribution of services, the higher the performance we get from these services. Accordingly, enhanced and high performance strategies, which properly distribute these services, are of great importance.
3) The distances between service points and different locations within holy places should be minimized. The benefits of this minimization are not only to save time, effort, and energy in acquiring these services, but also to increase their coverage. For emergency services, like ambulance cars and fire trucks, the benefits further extend to save pilgrims life.

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