GWO Model for Optimal Localization of IoT-Enabled Sensor Nodes in Smart Parking Systems

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***Abstract*— Due to rapid growth in urban population and advances in the automotive industry, the number of vehicles is increasing exponentially, posing the parking challenges. Automated parking systems provide efficient and optimal parking solution so that the drivers can have hassle free and quick parking. One of the demanding requirements is the design of smart parking systems, not only for comfort but also of economic interest. With the advancements in the Internet of Things (IoT), wireless sensors-based parking systems are the promising solutions for the deployment. Optimal positioning of IoT enabled wireless sensor nodes in the parking area is a crucial factor for the efficient parking model with the lower cost. In this paper, we propose a novel multi-objective grey wolf optimization technique for node localization with an objective to minimize a localization error. Two objective functions are considered for distance and geometric topology constraints. The proposed algorithm is compared with other node localization algorithms. Our algorithm outperforms the existing algorithms. The result shows that localization error is reduced up to 17% in comparison with the other algorithms. The proposed algorithm is computationally efficient due to the choice of fast converging parameters.**

***Index Terms*— Smart parking, Internet of Things, node localization, multi-objective optimization, grey wolf optimization, Pareto optimal set.**

I. Introduction

TRAFFIC congestion due to the increasing number of vehicles is an alarming problem on a global scale and aggravating day by day. It has been estimated that every day, around 30% of traffic congestion in the cities around the world is caused by vehicles searching for the parking space, and it takes the driver an average of 7 - 8 minutes to find a parking space [1]. Such scenarios' results into the traffic congestion, and leads to the wastage of time and fuel not only of the driver searching for parking but also increases waiting time of other drivers in the congestion. Vehicle parking problem needs the optimized solution for saving time of the user, reducing the pollution, and economic losses. Rapid growth in the IoT and artificial intelligence is contributing a lot towards smart, digitized and networked lifestyle [2]. With the help of innovative and reliable IoT solutions [3], smart parking systems can be tackled by integrating different resources to enhance the facilities and management. These parking systems can provide real-time updates to the users about available parking spaces and other information in a specific topographical area. It can also offer smart parking application to book, check, and navigate the vacant parking lots remotely. Such parking systems are comprised of low-cost sensors, real-time data pooling and aggregation, and cell phone enabled automated payment systems for reservation. After identifying parking lot, additional features like fast car retrieval, parking regulation, parking gate management, and other services can also be provided using RFID identification devices. Smart parking can be modeled as a parking gate and parking lot monitoring problem. At each parking slot, a sensor is placed to identify the presence or absence of vehicle which builds the availability map for parking guidance and other services. Such a system can also be considered as multi-parking management problem since it has to manage multiple parking lots distributed in various indoor and outdoor areas.

To design the smart parking systems, the correlation of sensor measurements with a physical location is necessary. Hence, self-organization and localization capabilities are the key requirements in the sensor networks. Use of the global navigation satellite systems such as GPS in the sensor nodes provides location awareness. However, it is not always feasible since sensor network consists of a large number of nodes and the solution may not be economical in such situations. These solutions are also not well suited for indoor environments. Rather than deploying all the nodes with GPS capabilities, it is preferred to have only a few nodes of the network to be endowed with their exact position through GPS or manual placement. These nodes are called as the anchor or reference nodes. Other nodes in the network will be able to identify their position to the nearby anchor nodes by measuring the received signal strength (RSS) and time of arrival. Conventionally, most of the approaches in the literature are focused on the use of single objective optimization with the space distance constraint to solve the localization problem of sensor nodes. These approaches have achieved

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substantial improvement in the accuracy and computational time. However single-objective function fails to address the major affecting factor of geometric topology constraint due to ranging errors. Hence, it is more reasonable to model the node localization problem as a multi-objective optimization problem, and that can be described as solving a Pareto optimal solution.

Our research aims to develop a multi-objective grey wolf optimization-based model for optimal localization of IoT-enabled wireless sensor nodes to determine their positions in the smart parking. The optimization algorithm is used to minimize localization error. The objective functions have included the distance and topological constraints. Pareto optimal solution for determining optimal solution is attained by using multi-objective grey wolf optimization (MOGWO). The objective of localization is to achieve efficiency and reduce the number of anchor nodes. The remaining structure of the paper is organized as: Section II discusses literature study related to smart parking models and node localization techniques. Section III describes the proposed smart parking system and its mathematical model. Section IV discusses localization based on MOGWO. Section V presents a novel MOGWO based localization algorithm (MOGWOLA) by adding Pareto optimal front to tackle sensor localization problem for smart parking. Section VI discusses results and performance analysis whereas the paper is concluded in Section VII.

II. Literature Review

In the recent past, several models for smart parking are reported. Optimal allocation of resources and reservation-based smart parking scheme [4] allocate parking space by considering the objective function of the user based on the destination and cost. Mixed-integer linear optimization is used in sequential time for the number of wireless sensor network (WSN) nodes in the parking lot. Mono parking management system [5], [6] uses one sensor per parking lot. Extension of mono parking to the multi-parking [7], [8] for larger-scale parking navigates the users to the appropriate parking lot within the area. It may necessitate alliance among all the parking service providers in that area. Parking regulation system based on intelligent WSN [9] proposes equipping each parking lot with virtual coordination system and display units with the aim of proper guidance to the user for occupying nearest parking spot.

A model in [10] provides parking lot and gate monitoring scheme use WSN and active RFID for a parking lot and gate monitoring, respectively. Gate monitoring is a low-cost and simple model in which RFID tags are assumed to be allocated to subscribed users, or it can be provided dynamically at the entrance to the momentary users. Zigbee and GSM based parking scheme [11] provides secured car parking by entering two-way passwords. Cloud-based intelligent car parking system for the smart cities [12] follows the personal software process approach. Automated parking management and parking fee collection using number plate recognition [13] reduces the hassles and increase accessibility and security. In KATHODIGOS [14], a smart parking system, the gateway transmits the status of parking availability at the roadside parking spaces to the central information system. VANET communication [8] for the large parking lots is described by restricted stock units to observe and manage the parking lot. Smart parking model for the smart cities [15] based on integer linear programming optimization with a focus on coverage and lifetime of the network is proposed.

Most of the reported schemes have used WSN and RFID with a focus on organized sensor placement in the parking lot. The feedforward neural network, and the generalized regression neural network is used in [16] for node localization. The parameters considered are average localization error, the minimum localization error and the localization error mid-value. Since the complexity of the algorithm is closely related to the input vector therefore the calculating and locating time of this localization technique is quite long. Particle swarm optimization (PSO) based wireless sensor node localization model [17] is effective in terms of computational time but does not shows much improvement in localization error. Bat algorithm for wireless sensor node localization [18] imitates behavior of bats for finding prey in the complete darkness with the help of echolocation. In this work, researchers have attuned bat calculation with chemotactic progress of bacterial sponging calculation to enhance the restriction precision in the short calculation time period. In the decision theory based WSN localization algorithm for smart cities [19], the simulations were carried out for different simple parking situations such as open space, underground, streets, and shows good adaptability for all the situations.

Grey wolf optimization (GWO) [20] is one of the newest bio-inspired techniques, mimics the hunting process of a pack of grey wolves in nature. It gives better results than other bio-inspired optimization techniques and can be used for smart parking optimization. Hunting strategy followed in grey wolf optimization helps to localize the maximum number of nodes than the other approaches.

III. The Smart Parking System

We have considered smart parking model based on the actual parking prototype proposed by Karbab *et al.* [10], which was experimented for outdoor parking in Algeria. This prototype has a multilayered sensors-based framework and provides modularity, scalability and aims to offer diverse parking services to distinct users. It includes sensing, networking, middleware, and application layer as shown in Fig.1.

In the sensing layer, sensor nodes are deployed in the parking lot and classified into two categories, viz. IoT-enabled simple WSN (transmitter) nodes, and anchor nodes. Additionally, RFID devices are placed at the parking gates. The cars are identified by using the RFID tags. Networking layer provides forward communication from the transmitter to anchor nodes and then to the gateway, and finally to the users. Optimization algorithms and the competent visualization techniques are used in the middleware layer for identifying the situation and providing smart services. Application layer defines and delivers various services to distinct users. User devices generally, cell phones are linked

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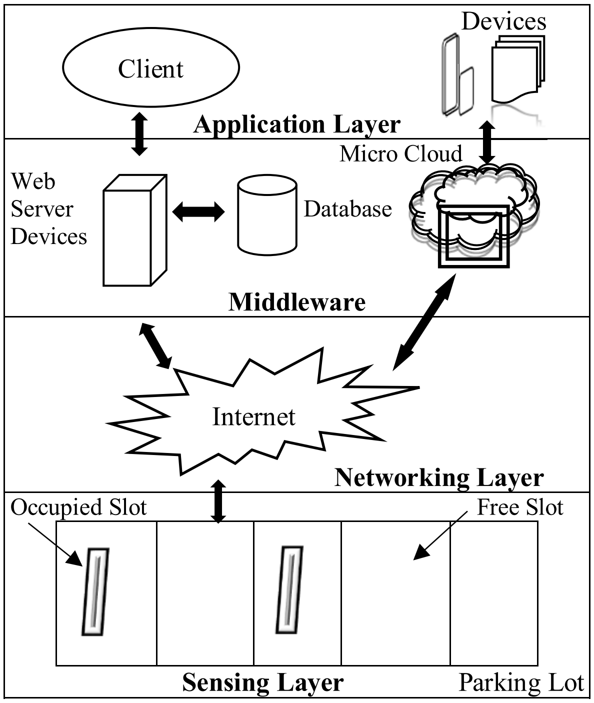

Fig. 1. Smart parking framework.

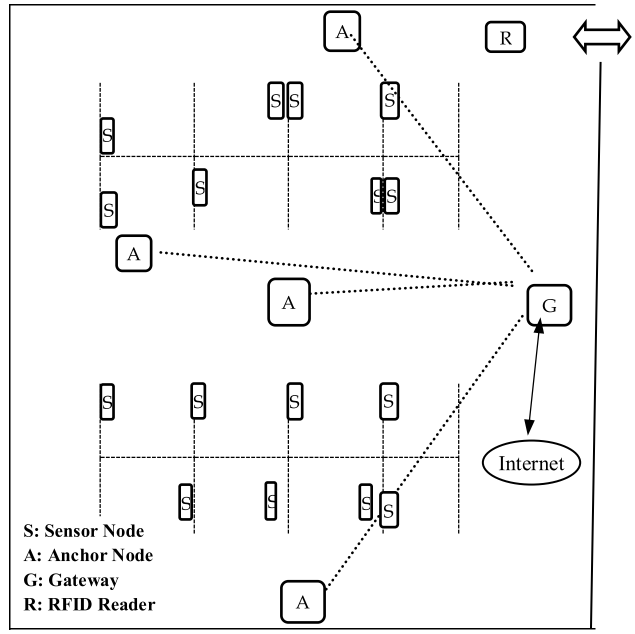

Fig. 2. Sensor placement for smart parking.

to a parking database and updated in real-time for the status of parking lots.

In the proposed smart parking system, RFID tags are assumed to be assigned to the subscribed users, or it can be provided dynamically at the entrance to the momentary users. The system provides automated ticket and guidance to move towards a pre-allotted parking slot. If there is no pre-allocation of parking slot, the nearest available slot is retrieved and allocated by considering the current location of the car. The system can also offer car retrieval service. Parking regulations are observed in case of slot pre-allocation or reservation. The layout of a smart parking system in which the anchor nodes are to be localized is depicted in Fig. 2.

Each parking slot has an IoT-enabled simple WSN node with an ultrasonic sensor. Once a car is detected in a parking slot, the address and location of the sensor node installed in that slot is communicated to the parking manager via nearest anchor node. This enables the parking management system to update the database, to charge the tariff, and also in verifying whether the identified car is authorized to access the slot or not.

In most of the smart parking models reported, the WSN nodes are placed in the parking lot with the geolocation constraints, leading to poor coverage and inability to communicate the sensed data to the gateway. Hence, the anchor nodes are incorporated into the smart parking system with optimal localization to increase sensor nodes coverage and connectivity.

A. Multi-Objective Optimization Problem

In the design of efficient and low-cost smart parking, optimal positioning of anchor nodes and other sensor nodes is very crucial. Localization or positioning is the process of evaluating the physical coordinates of transmitter nodes based on the position of anchor nodes. For anchor node localization, most of the researchers have proposed techniques based on single objective optimization by considering latitude and longitude as coordinates. In these studies, space distance between the prefixed anchor nodes and nodes to be localized is considered as a constraint. Single objective function considers one of the constraints, ignoring others. In the node localization problem, space distance constraint is well addressed, but the geometric topology is ignored because of the ranging errors. The multi-objective optimization is efficient in resolving the conflict of multiple objectives [21]. In the smart parking problem, the constraints such as node localization, lifetime expansion, and low energy consumption can be modeled as a multi-objective optimization function. In this paper, we propose a multi-objective grey wolf optimization localization (MOGWOLA) model for node localization in smart parking, considering the distance and topological constraints.

B. Mathematical Model

For the optimal positioning of the anchor and transmitter nodes in the parking lot, we assume that WSN with M anchor and N transmitter nodes ($M < N$) are deployed in two-dimensional space. The model has two objective functions to determine the coordinates of N transmitter nodes using the information about the location of anchor nodes. These coordinates satisfy space distance and geometric topology constraints. The constraints will make the evaluated coordinates close to near values and also generate unique topology.

For space distance constraint, the objective function has a two-step process. In the first step, the transmitter node determines its ranging distance from the anchor node by using received signal strength indicator (RSSI) and time of arrival of

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the received signal from the anchor node. In the second step, information retrieved in the first step is used to determine the position of transmitter nodes. The optimization algorithm is used to minimize the localization error with the assumption that anchor node l and other node m lie in each other's communication range and influence of noise measurement is also simulated. Every anchor node in the area determines its distance from all of its adjacent transmitter nodes. Internode ranging distance i_{lm} is calculated as

$$i_{lm} = a_{lm} + e_{lm} \tag{1}$$

where a_{lm} is actual distance between node l and node m nodes as determined by (2) and e_{lm} is ranging error.

$$a_{lm} = \sqrt{(u_l - u_m)^2 + (v_l - v_m)^2} \tag{2}$$

(u_l, v_l) and (u_m, v_m) are the coordinate positions of node l and m, respectively. If C is the communication range of anchor node l then the set of nodes that can be connected with the anchor node is N_{lm}, and its complement is N_{lm}^c. If $a_{lm} \le C$, then $(u_m, v_m) \in N_{lm}$ and if $a_{lm} > C$, then $(u_m, v_m) \in N_{lm}^c$. The ranging error, e_{lm} possess random value uniformly distributed in the range $\left[d_l - d_l \frac{P_n}{100}, d_l + d_l \frac{P_n}{100}\right], 0 \le P_n \le 1$ and d_l is the distance between anchor node l and any node. In the second step, objective functions for space distance constraint and geometric topology constraint are defined in (3) and (5), respectively.

$$f_1 = \sum_{l=M+1}^{N} \left(\sum_{m \in A_i} \left(\overline{i_{lm}} - i_{lm} \right)^2 \right) \tag{3}$$

where $\overline{i_{lm}}$ is expected distance among node l and m, calculated by (4)

$$\overline{i_{lm}} = \begin{cases} \sqrt{(\overline{u_l} - u_m)^2 + (\overline{v_l} - v_m)^2}, & \text{if } m \text{ is an anchor node} \\ \sqrt{(\overline{u_l} - \overline{u_m})^2 + (\overline{v_l} - \overline{v_m})^2}, & \text{otherwise} \end{cases} \tag{4}$$

$$f_2 = \sum_{l=M+1}^{N} \left(\sum_{m \in N_{lm}} x_{lm} + \sum_{m \in N_{lm}^c} (1 - x_{lm}) \right) \tag{5}$$

$$x_{lm} = \begin{cases} 1, & if\ \overline{i_{lm}} > C \\ 0, & Otherwise \end{cases} \tag{6}$$

Geometric topology constraint takes care of the connectivity of the network. Both the constraints together indicate the precision of node coordinates. High precision for unidentified node subsequently leads to the smaller values of the objective function. Hence, determining coordinates of unidentified nodes can be treated as exploring the optimal solution for multi-objective optimization, which can be achieved by reducing values of both the objective functions.

IV. Localization by Multi-Objective Grey Wolf Optimization

The preliminary version of grey wolf optimization (GWO) is used for a single objective function only. Here, we propose a multi-objective grey wolf optimization-based localization algorithm with Pareto optimal front to handle sensor localization problem in smart parking systems.

A. Gray Wolf Optimization

The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Generally, grey wolves live in a pack of 5 - 12 wolves and have a strict social dominant hierarchy. Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. The three main steps of hunting, viz. searching for prey, encircling prey, and attacking prey are implemented to perform optimization [20].

Alpha, generally a pair of wolves is the leader and makes decisions and hunting. The betas are secondary wolves, and they help alphas in the decision-making process. The beta wolves respect the alpha but rule the other lower-level wolves. The beta reinforces alpha orders all over the pack and provides feedback to the alpha. The omega wolves have to follow all other leading wolves. The delta wolves also rule omega and work as such as detectives, guards, elders, hunters, and caretakers.

In the mathematical model for the GWO, the acceptable solution is called the alpha (α). The second and third best solutions are beta (β) and delta (δ), respectively. The rest of the candidate solutions are assumed to be omega (ω). The hunting is guided by α, β, δ, and ω follow these three candidates solution. The first step in hunting is encircling a prey. The mathematical model for encircling behavior is given as

$$\overline{S}(t+1) = \overline{S_p}(t) - \overline{U}.\overline{V} \tag{7}$$

$$\overline{V} = \left| \overline{W}.\overline{S_p}(t) - \overline{S}(t) \right| \tag{8}$$

where $\overline{V}$ is the distance vector, t is iteration number, $\overline{S_P}$ is the location of prey and $\overline{S}$ is the location of grey wolf, $\overline{U}$ and $\overline{W}$ are coefficient vectors given by

$$\overline{U} = 2k.\overline{r_1} - k \tag{9}$$

$$\overline{W} = 2.\overline{r_2} \tag{10}$$

where k is linearly decreased from 2 to 0 over the successive iterations, and $\overline{r_1}$, $\overline{r_2}$ are random vectors in [0, 1]. The hunt is generally led by the alpha. Occasionally the beta and delta wolves also contribute to hunting. To simulate the hunting behavior of grey wolves mathematically, α (best candidate solution), β (second-best candidate solution), and δ (third-best candidate solution) are expected to have better knowledge about the probable location of prey. The first three best candidate solutions obtained so far are saved and communicated with the other search agents, including the omegas, for updating their locations with respect to the location of the best search agents. For updating the wolves location, we have

$$\overline{S}(t+1) = \frac{\overline{S_1} + \overline{S_2} + \overline{S_3}}{3} \tag{11}$$

$$\overline{S_1} = \left| \overline{S_\propto} - \overline{U_1}.\overline{V_\propto} \right| \tag{12}$$

$$\overline{S_2} = \left| \overline{S_\beta} - \overline{U_2}.\overline{V_\beta} \right| \tag{13}$$

$$\overline{S_3} = \left| \overline{S_\delta} - \overline{U_3}.\overline{V_\delta} \right| \tag{14}$$

where $\overline{S_1}$, $\overline{S_2}$ and $\overline{S_3}$ are the first three best solution candidates in the group at a given iteration t. $\overline{U_1}$, $\overline{U_2}$ and $\overline{U_3}$ are as

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defined (9), and $\overline{V_\propto}$, $\overline{V_\beta}$, $\overline{V_\delta}$ are position vectors defined as

$$\overline{V_\propto} = \left|\overline{W_1}.\overline{S_\propto} - \overline{S}\right| \quad (15)$$

$$\overline{V_\beta} = \left|\overline{W_2}.\overline{S_\beta} - \overline{S}\right| \quad (16)$$

$$\overline{V_\delta} = \left|\overline{W_3}.\overline{S_\delta} - \overline{S}\right| \quad (17)$$

where $\overline{W_1}$, $\overline{W_2}$, $\overline{W_3}$ are the coefficient vectors calculated using (10), representing the alpha, beta and delta wolves respectively. The parameter k controls the tradeoff between the search for prey (exploration) and converges while attacking prey (exploitation) in successive iterations. To update parameter k linearly in each iteration [20] with the range from 2 to 0 is proposed as

$$k = 2\left(1 - \frac{t^2}{T^2}\right) \quad (18)$$

where T is the total number of iterations allowed for optimization. Grey wolves diverge from each other during exploration and converge during the exploitation process. The choice of k speeds up the algorithm to move towards the best candidate solution. $\overline{U}$ can be used to decide divergence or convergence as given,

$|\overline{U}| > 1$, enforces divergence and moves to find the next better position.

$|\overline{U}| < 1$, enforces convergence and update the position as the best solution.

The proposed parameter k for fast convergence is different from than the parameter defined in the original GWO [20].

B. Pareto Optimal Front

For minimization problem, vector $u = (u_1, u_2, \ldots, u_n)$ dominates vector $v = (v_1, v_2, \ldots, v_n)$ if and only if $u_l \leq v_l$ for all $l \in 1, 2, \ldots,$ n and also there exists $l \in 1, 2, \ldots, n$ such that $u_l < v_l$. Hence for domination, at least one element of vector u should be less than the respective elements of vector v and remaining elements should be less or equal. Hence dominance correlation is given as

$$u \leq v \leftrightarrow u_l < v_l \vee u_l = v_l, \quad \text{where } l \in 1, 2, \ldots, n \quad (19)$$

An element u_l is called non-dominated if there does not exist any point that is greater or equal to it. Pareto front of the multi-objective function is the collection of all non-dominated elements. For the set of solution vectors V, Pareto front is as defined as

$$\text{PF} = \{\text{u} \in \text{V} / \nexists \text{ v} \in \text{V such that u} \leq \text{v}\} \quad (20)$$

The pseudo-code of the multi-objective GWO algorithm is as shown in Fig. 3.

With the initialization of the grey wolf population and coefficient vectors *k, U, W*; the fitness function of the search agent is evaluated. Further, the best solutions are identified and ranked for alpha, beta and delta. If the termination condition is satisfied, it stops the process and initializes the best agent. If the termination condition is not satisfied, it updates the search agent and coefficient vectors using (11) - (17). It evaluates the fitness of a new position of search agent. If new search agent is better than the current search agent then updates the alpha, beta, delta, and continues until the termination gets satisfied.

```
Initialize the Grey Wolf population S_r (r = 1, 2, ..., n)
Initialize k, U and W
Determine objective values for every search agent
Identify the non-dominated solutions and initialize archive
S_α= SelectLeader (archive)
Eliminate alpha temporarily from the archive to avoid repetition
S_β= SelectLeader (archive)
Eliminate beta temporarily from the archive to avoid repetition
S_δ= SelectLeader (archive)
Add back alpha and beta to the archive
t=l;
while (t < Max number of iterations)
    for each search agent
        Update the position of the current search agent using (11)-(17)
    end for
        Update k, U and W
        Determine the objective values of all search agents
        Calculate the nondominated solutions
        Update archive using determined non-dominated solutions.
    If the limiting value of archive is achieved
        Apply the grid mechanism to delete one of the
        present archive members
        Add new solution to the archive
    end if
    If any of the newly added solution in the archive falls
        outside the hypercubes
        Update the grid
    end if
  S_α= SelectLeader (archive)
  Eliminate alpha temporarily from archive to avoid
  repetition
  S_β= SelectLeader (archive)
  Eliminate beta temporarily from archive to avoid
  repetition
  S_δ= SelectLeader (archive)
  Add back alpha and beta to the archive
   t = l+1
end while
 return back to archive
```

Fig. 3. Pseudo-code of the multi-objective GWO algorithm.

V. Multi-Objective GWO For Localization (MOGWOLA)

We have added two additional features in the MOGWO [22]. The first feature is, an archive is generated to store or retrieve non-dominated Pareto optimal solutions obtained so far and second is the strategy for leader selection on the basis of first three best solutions from the archive as candidate solutions of the optimization process. Archive controller monitors the space availability in an archive, and non-dominated solutions obtained during the iteration process are simultaneously compared with existing elements in the archive.

The optimal solution of multi-objective optimization can be obtained from the Pareto optimal solution. Minimization of multiple objective functions as a multi-objective optimization of m-dimensional decision vector for n objective functions is structure as

$$Minimise F(u) = \{f_1(u), f_2(u), \ldots.., f_n(u)\} \quad \text{where } u \in [u_{lb}, u_{ub}] \quad (21)$$

where, $F(u)$ is the objective function with the objective vector $V = (f_1, f_2, \ldots, f_n) \in R^n$. Lower and upper limits for the searching range are u_{lb} and u_{ub}, respectively. The decision vector $U = (U_1, U_2, \ldots, U_N) \in R^m$, where each U_i is m-dimensional vector. It corresponds to the m-dimensional search space of wolves in GWO. The objective function $F(u)$ belongs to the n-dimensional objective space V, in which it is mapping function from the decision space to the objective space,

$$\emptyset = \left\{u \epsilon R^m / u \in [u_{lb}, u_{ub}]\right\} \tag{22}$$

For the maximum number of iterations, the process of iterations starts for evaluating the optimal position of sensor nodes and comparison with other nodes positions. For the combined best solution, random weight vector gets generated, and non-dominated vectors get preceded to the next iteration. After the maximum number of iterations, it performs approximations of the true Pareto front with the help of non-dominated vectors. Summation of random weight vectors generated during the process of optimization is given as

$$F(u) = W_\upsilon f_1 + (1 - W_\upsilon) f_2, \quad \sum\nolimits_{\upsilon=1}^{R} W_\upsilon = 1 \tag{23}$$

where, W_υ is the weight vector that is generated by r_υ / R, r_υ are random numbers and R is uniformly generated by rescaling operator. In the leader selection process, the three best solutions attained so far are considered as alpha, beta and delta. These solutions guide the other search agents to move towards the promising region of the search space with confidence to get the solution close to the global optimum. In this way, an archive of best non-dominated solutions gets generated. Search agent selects the least loaded sector of the search space and selects one of the non-dominated solutions as alpha, beta and delta. When the number of obtained solutions decreases in the hypercube, the probability of selection of the leader from the hypercube also increases. In the successive steps, MOGWOLA avoids selection of the leaders which are already chosen, by removing them from archive temporarily. Consequently, the search is always towards the unexplored area of the search space since the leader selection process prefers the least crowded hypercube and offers leaders from various segments. The active external archive saves the best non-dominated solutions so far. The algorithm in terms of the pseudo-code of multi-objective GWO for node localization is as given in Fig. 4.

The algorithm defines the objective function and initializes target node h and anchor node k. It calculates the distance between the target node and anchor node using the Pareto front. If the anchor node is within the transmission range and constraints are satisfied, it initializes search agent using MOGWOLA. If the anchor node k falls outside the transmission range, it checks for another anchor node $k+1$. If the maximum number of iterations is completed, then it returns to the localized node. If not then update the search agent using MOGWOLA.

```
Define objective function F(u) = f1(u), f2(u)
where u ∈ (u1, u2, ..., um)^t
Initialize population of P wolves uh(h = 1, 2, ..., p)
while t < (MaxGeneration)
  for h, k = 1 to P
    determine approximation PFh andPFk to the Pareto front
    if h ≠ k and when all the constraints are satisfied
    if PFh dominates PFk
      Optimize with GWO
      generate new ones if all the constraints not satisfied by
      moves
     end if
     if no non-dominated solutions can be determined
      Generate random weights wr(r = 1, 2, ..., q)
      Find best solution to minimize Eq. (23)
     end if
     end if
  Update and pass the non-dominated solutions to next iterations
   end for
 Sort and find the current best approximation to the Pareto front
 Update t = t+1
end while
```

Fig. 4. Pseudo-code of the multi-objective GWO for localization algorithm.

TABLE I
METRICS FOR PERFORMANCE ANALYSIS

Metric	Notation and Description
Number nodes localized	N_L
Root Mean Square Localization Error	$RMSLE = \sqrt{\sum_{k=1}^{N} \frac{(u_k - \bar{u}_k)^2 + (v_k - \bar{v}_k)^2}{N_L}}$ (u_k, v_k) and $(\bar{u}_k, \bar{v}_k)$ are actual and obtained positions of the node, respectively, and N_L is a number of nodes localized.
Computational time	T

VI. EXPERIMENTATION AND PERFORMANCE ANALYSIS

For testing and analyzing the performance of the proposed approach for smart parking systems, extensive simulations are carried out. The sensor nodes are randomly deployed in the localization area to test the accuracy of every localization algorithm. Localization error is defined as the distance between the actual coordinates of unknown nodes (u_0, v_0) and estimated coordinates (u, v). The results are compared with three localization algorithms as proposed in [16], [17] and [19]. The performance is measured on the basis of the metrics listed in Table I.

We have used root mean square error (RMSE) as a standard statistical metric to measure performance since for a data with more samples, reconstructing error distribution is more reliable. RMSE satisfies the triangle inequality for a distance function metric that is necessary for the space distance constraint used in our model. Additionally, RMSE is a better metric for normal distribution rather than a uniform distribution. Localization of sensor nodes falls in the category of normal distribution.

Simulations are performed for 200 m × 200 m area for 200 randomly distributed sensor nodes in a region to produce M anchor nodes. It is assumed that RSSI ranging error follows Gaussian distribution and transmission range is between 10 m to 40 m. The number of anchor nodes is varied from 20 to 60 for better accuracy in determining the position of sensor

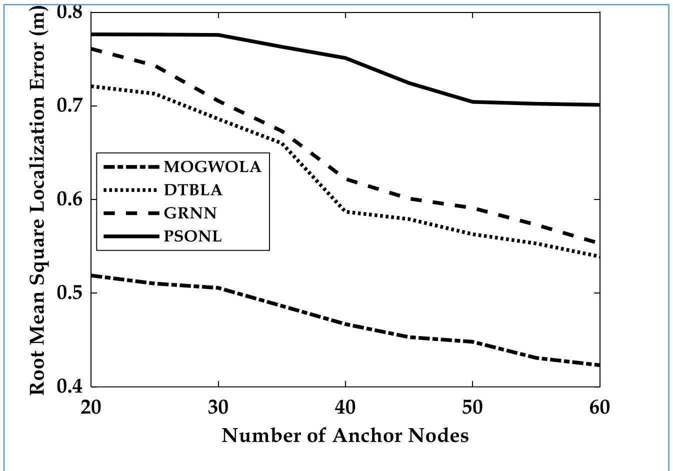

Fig. 5. Root mean square localization error for the different number of anchor nodes.

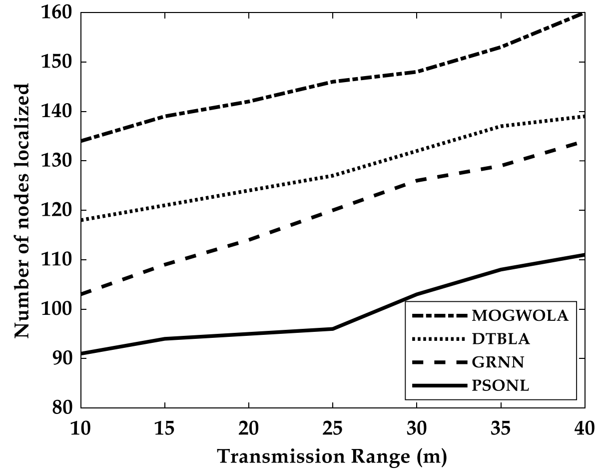

Fig. 6. Number of localized noes for distinct transmission range.

TABLE II
NUMBER OF LOCALIZED NODES AND COMPUTATIONAL TIME

No. of Anchor Nodes	MOGWOLA		DTBLA		GRNN		PSONL	
	N_L	T (Sec)	N_L	T (Sec)	N_L	T (Sec)	N_L	T (Sec)
20	134	2.20	118	2.48	103	3.01	91	3.41
25	139	2.41	121	2.57	109	3.36	94	3.56
30	142	2.53	124	3.25	114	4.00	95	4.03
35	146	2.57	127	3.36	120	4.21	96	4.51
40	148	2.33	132	3.47	126	5.03	103	5.11
45	153	2.67	137	3.32	129	4.59	108	5.17
50	160	2.37	139	3.25	134	4.18	111	4.49
55	171	2.41	147	3.11	140	5.11	116	5.27
60	186	2.45	160	3.33	148	5.37	124	5.59

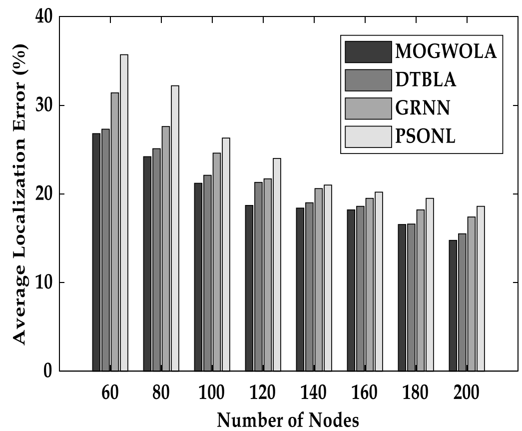

Fig. 7. Percentage of average localization error for various node density.

nodes. We have calculated the average of 10 different runs for each algorithm.

Figure 5 shows the root mean square localization error for the different number of anchor nodes for four different algorithms. With the increase in a number of anchor nodes, localization error decreases for all the four algorithms, but it also results in incurring more cost. However, localization error is significantly reduced in the proposed algorithm for the lesser number of nodes. The objective function used aims to minimize localization error since the parameter k steadily reduces and selects the nearest anchor node for the respective sensor node. Localization error obtained by MOGWOLA is reduced by 26%, 20% and 17% in comparison with GRNN [16], PSONL [17] and DTBLA [19], respectively.

The proposed algorithm localizes a large number of the node due to the hunting strategy of GWO, which benefits in locating the position of unidentified nodes. For determining execution time, we have simulated all the algorithms on the same machine. With the increase in a number of anchor nodes, the running time over 10 iterations is calculated. The number of nodes localized and the required computation time for each algorithm is summarized in Table II. Convergence rate of MOGWOLA is quite fast and generates optimal solution quickly for node localization.

Transmission range of the sensor node is an important parameter in node localization. Figure 6 illustrates the number of sensor nodes localized for the transmission range from 10 m to 40 m. The results show that the number of nodes localized by each algorithm gradually increases with the increase in transmission range. The proposed algorithm outperforms all others as the maximum numbers of sensor nodes are localized.

We have also evaluated the performance by changing node densities, anchor nodes and variety of Pareto solutions to optimize node localization. Average localization error for distinct network node densities with the assumption that 20% of the nodes are anchor nodes is as shown in Fig. 7. Error percentage in MOGWOLA based localization is comparatively lesser for all the node densities than others and shows the efficiency of two objective functions in optimizing localization problem for smart parking.

VII. CONCLUSION

A grey wolf optimization based multi-objective algorithm for optimal localization of sensor nodes for smart parking applications is proposed. Proposed objective functions

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minimize localization error and also reduce the requirement of the number of anchor nodes in the sensor network, leading to cost minimization without compromising the efficiency and connectivity. Results demonstrate that the proposed algorithm outperforms the existing optimization approaches by substantially reducing the localization error and maximizing localized nodes. The algorithm computes the optimal solution in lesser time, enabling the faster node positioning and improvement in network performance.

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