

## Article

# An Optimized Energy and Time Constraints-Based Path Planning for the Navigation of Mobile Robots Using an Intelligent Particle Swarm Optimization Technique

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**Abstract:** Mobile robots (MRs) typically require running for many hours on one charge of the battery. Electric autonomous mobile robots (AMRs) have become increasingly common in the manufacturing process in the last few years. MRs must often complete difficult assignments while gathering information across an unknown area involving energy constraints and time-sensitive preferences. This paper estimates the information collection assignment for surveillance as a multi-objective optimization dilemma with both energy and time constraints. In this study, three main objectives during acquiring data are taken into consideration, including the greatest quantity of data acquired for surveillance, following a path where obstacles are least likely to be experienced, and traveling the smallest feasible path. To obtain the optimal path for an MR by addressing the presented issue, this approach presents an intelligent particle swarm optimization (PSO) technique that determines fitness value by simplifying the optimization task for achieving the shortest path for MR navigation. It allows particles to execute variable operations while maintaining most of the prior search information. The findings of the simulation show that this technique of the PSO algorithm can realize swift convergence and high accuracy when compared with different benchmark functions derived for PSO. A comparative discussion on various energy-efficient navigation techniques for MRs is also provided. Lastly, this study describes the possible future research directions.



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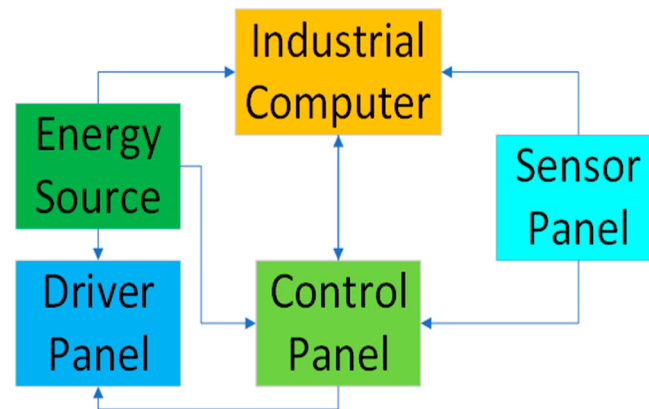
**Keywords:** data acquisition; energy; mobile robot (MR); navigation; path planning; particle swarm optimization (PSO); time

## 1. Introduction

MRs are sophisticated machines that implement preprogramming to perceive, analyze, communicate, and carry out a wide range of activities, including warehouse operations, military and civilian surveillance, healthcare support, customer support, and many more [1]. Also, MRs have been used to acquire data in a wide range of applications, including the inspection of electricity grids, the gathering of traffic-related information, tracking of chemical and biological contamination in major waterways, combat search and rescue, maritime surveillance, agricultural assessments, and environmental assessment [2,3]. Energy efficiency is an important challenge to the performance of MRs since their mobility is restricted by robust and costly batteries. The lifespan and operating duration of autonomous frameworks can be estimated by anticipating and regulating their consumption of energy and time duration, which are crucial. The importance of investigating how much energy MRs utilize cannot be underestimated [4].

To fulfill the objectives of minimizing energy usage that also helps to reduce the operating time, the energy issue of MRs has received greater prominence. The consumption of energy and time constraints-based modeling of MRs through computational equations might be highly rigorous for the assessment of the impact of operational situations on energy intake, which serves as a roadmap to support energy-efficient and time constraints

techniques [5]. Since the MR itself can comprehend the quantity of energy needed for motion along with the precise consumption of energy for every component, energy usage can be adjusted to fit various circumstances, and thus, the amount of available energy backup can be determined. Consumption of Energy must be taken into consideration when performing acquisition activities because of the inadequate power available to MRs, and it is essential to ensure time constraints for job completion to accomplish time-sensitive tasks. Figure 1 describes the complete scenarios of energy requirements by the different parts of the MR.



**Figure 1.** Block diagram of energy requirements by a mobile robot.

Additionally, an MR might collide with dynamic obstacles during its movements. For instance, a driverless car might come across pedestrians and traffic signals while gathering traffic-related information. Therefore, while collecting data, an MR must be fully conscious of both energy and time and always be ready to re-plan its movement direction as needed. In relation to path re-planning, various researchers have conducted several investigations and studies. The path-planning techniques in unknown and dynamic environments are provided in [6–9], and the path re-planning techniques in urgent scenarios have been researched in [10,11]. In the last century, for optimization purposes, numerous evolutionary algorithm (EA)-based heuristic algorithms have been proposed [12], including ant colony optimization (ACO) [13], artificial bee colony (ABC) [14], differential evolution (DE) [15], fireworks algorithm (FWA) [16], genetic algorithm (GA) [17], and PSO [18]. The PSO technique is widely used for the navigation of a MR to optimize the energy and minimize the time required by them to accomplish predefined tasks with higher accuracy and efficiency.

Initially, by the inspiration of fish schooling and bird flocking, Kennedy and Eberhart developed PSO dependent upon a population-based optimization method. Nowadays, PSO has emerged as one of the most well-liked optimization methods and can be efficiently used to address a variety of real-world issues due to its ease of usage and quick convergence [19–21]. Particles within a solution region are initially created arbitrarily for the very first PSO. The positions and velocities are evolved as Equations (1) and (2) [22]:

$$v_i^d = v_i^d + c_1 r_1^d (pbest_i^d - x_i^d) + c_2 r_2^d (gbest^d - x_i^d), \quad (1)$$

$$x_i^d = x_i^d + v_i^d, \quad (2)$$

where  $V_i = (v_i^1, v_i^2, v_i^3, v_i^4, \dots, v_i^D)$  is the  $i$ th particle velocity,  $X_i = (x_i^1, x_i^2, x_i^3, x_i^4, \dots, x_i^D)$  is the  $i$ th particle position,  $c_1$  and  $c_2$  are two coefficients of acceleration,  $r_1^d$  and  $r_2^d$  are two numbers selected randomly within the range of [0, 1],  $gbest = (gbest^1, gbest^2, \dots, gbest^d)$  is the greatest place found by swarm so far,  $pbest_i = (pbest_i^1, pbest_i^2, pbest_i^3, pbest_i^4, \dots, pbest_i^D)$

is the “personal best position” of  $i$ th particle achieved by itself, the dimension of an optimization problem is  $D$ , and  $d \in \{1, 2, \dots, D\}$ .

In this paper, we develop the collection of information tasks for MRs in the form of multi-objective optimization under time and energy limitations. To be more specific, three goals are taken into consideration for surveillance: acquiring the greatest amount of data, going through the route with the least likelihood of hitting obstacles, and covering the shortest distance. In fact, numerous approaches are available to tackle multi-objective optimization problems, including genetic algorithms [23] and deep learning [24]. In comparison, the PSO algorithm is comparatively easy to understand and simple to implement in comparison to them. Thus, for addressing tasks involving multi-objective optimization, we switch toward the PSO algorithms technique. PSO was developed in part to address situations where the best answer is a location in a space with multiple dimensions of the variables, like the scenario with information flow and social interaction in schools of fish and flocks of birds. Differential objective functions and constraints are not required for PSO to achieve the global optimal solution with very high accuracy.

In this work, we consider three goals and describe each objective as a multi-objective constraint optimization issue. Further, multi-objective optimization is analyzed for the navigation of MRs by keeping time and energy constraints in mind. Additionally, this paper provides an intelligent PSO technique for multi-objective problems in optimization, resulting in more rapid convergence and higher fitness. Listed below are some of the major significant contributions of this paper:

1. We model the wireless data collecting operation as a multi-objective confined optimization challenge that optimizes civilian or military surveillance, reduces the likelihood of encountering obstacles, and shortens the route. The main goal of mobile surveillance is supposed to be to optimize the quantity of data gathered, considering the limits of MR energy and job completion time;
2. To reduce the overall length the MRs travel throughout their movements, as well as the energy and time required for MR to locate its optimal location, routes are developed using the lengths between the present MR locations and the probable ones in the coming generations;
3. We provide an intelligent PSO approach to address the given optimization issue. The simulation outcomes show that the presented advanced PSO method can attain faster convergence and greater accuracy compared to conventional PSO techniques;
4. The minimum–maximal normalization strategy is used to standardize numerous variables while evaluating the quality of the PSO technique, therefore eliminating the dimension discrepancy in multi-objective optimizations;
5. This approach shows that the PSO technique can minimize the energy requirement by MR, minimize the operational time, and select the shortest path to accomplishing their predefined tasks of data acquisition for the surveillance.

This article is further divided into the following parts: Section 2. Provides the idea of research motivation, Section 3. Contains the most important literature survey, Section 4. Explains the background information, Section 5. Describes the proposed methodologies, Section 6. Provides the simulation and analysis, Section 7. Illustrates a comparative discussion between different energy efficient navigation system, Section 8 Demonstrates the future research directions and Section 9. Contains conclusion.

## 2. Research Motivation

The principal objective of this paper is to provide the algorithms and methods necessary for MRs to operate effectively in unpredictable environments whilst taking time and energy constraints into consideration. MRs can navigate in their surroundings on their own without assistance. MRs have actuators, sensors, and embedded processing to sense their surroundings, provide conclusions, and perform operations. For MRs, choosing the best routes for traveling with avoidance of obstacles is an essential aspect of navigation. For AMRs, particularly those driven by power sources, energy consumption is an important

factor. For an AMR to stay operational for a longer duration, recharge less frequently, and operate more effectively generally, the use of energy needs to be optimized. MRs can move by keeping cognizance of energy constraints and then find actions that utilize the lowest possible amount of energy despite accomplishing their targets. Also, time constraints can originate through the need to accomplish work in an allocated time or simply the necessity of responding fast to the variation in environmental conditions. MRs can decide how to utilize the available time most effectively by introducing time constraints into the navigation strategies. The ultimate motivation for this research is to address the concerns with conserving energy, battery limitations, time-sensitive assignments, and unpredictable conditions and to advocate ecological responsibility; studies on the optimization of time and energy constraints for the navigation of MRs have been performed. Thus, we can enhance the functionality, independence, and general feasibility of MR systems in many kinds of applications.

### 3. Literature Survey

In recent decades, many researchers have focused on optimizing energy and time constraints for the optimal navigation of MR using different techniques.

Szelag et al. [25] describe the MR control technique by keeping travel time, energy consumption, and path length as a base of study. The controlling method directs how the robot moves in line with the planned module's pathway determination, while the correctness of the route's modeling is crucial. A criterion is developed to control the navigation of MR. A QBot2e MR is used for the experiment, which works on the principle of differential drive dynamics. This work shows an optimization of energy and time constraints with the shortest path length taken by MR during the experiment.

Rapalski et al. [26] explain how we can optimize the energy for a wheeled MR during navigation. This work used a vision mapping technique and some major navigation algorithms, including A-star and RRT, for analysis. Using the foundation of forward movement modeling and odometry observations, the navigational outcomes are analyzed. An RGBW camera is utilized for making obstacles containing mapping. Also, binary occupation mapping was created to estimate the traffic path. This paper demonstrates that the RRT-star technique needs the least energy during navigation from the starting point to the target point.

Mohammadpour et al. [27] examine recent research on energy-efficient techniques for autonomous wheeled MRs to navigate various stages. To determine research gaps, the chosen papers in this study have been separated into fields for planning and controlling motions. Through multiple simulations and assessments, this paper demonstrates the immediate impact of the motion control step on the overall consumption of energy employing a manufacturing self-guided vehicle (SGV). The findings suggest that the quantity of energy utilized might differ depending on how the SGV responds to unanticipated obstacles. This study explains that, while creating an action plan, energy limits need to be taken into consideration.

Hou et al. [28] propose a new modeling of energy approach for MRs is suggested to increase the efficiency of energy use for an MR. Modeling of the energy utilization system for MR is done based on three features, including the motion system, the control system, and the sensor system. Mathematical formulas are used to further explain the association among all three of the features. Then, the mathematical framework is subsequently utilized in a four-wheeled Mecanum MR, where it is practically evaluated. The outcomes of this study indicated that the suggested energy modeling might be utilized to forecast the consumption of energy for MR mobility activities.

Sun et al. [29] present a strategy to find the best-suited path for MR on terrains with the lowest energy requirements. This research examines the issue of estimating the most effective routes for an MR to take on various terrains, whereas the associated expense of a route can be expressed as the energy required to compensate for resistance and gravitational. Certain upper- and lower-bound findings about the cumulative length of ideal pathways on

landscapes in this paradigm are used. An effective approximation technique is described in this article that estimates a route between two supplied places where the price falls under a user-defined relative deviation proportion.

Liu et al. [30] describe a new approach for optimal movement planning with the objective of reducing the requirements of energy for a wheeled MR within applications involving robotics. Firstly, a model is generated and might be employed to estimate the amount of energy required to overcome friction resistance and convert the energy into kinetic energy. A proper coming velocity and time of the mentioned directions are chosen for the least amount of energy to deliver an easy trajectory throughout the created track. This simulation can be used as a foundation to optimize the usage of energy for MR by applying efficient planning of motion.

Le et al. [31] realized the optimization of an energy model for a floor-cleaning robot that works on a differential drive algorithm dependent upon self-organized behavior. The capacity of customizable robots to vary their size necessitates the implementation of a dynamic estimating energy model, which makes the analysis energy-aware for full coverage planning of paths with these robots extremely fascinating. This study shows the consumption of energy can be measured by journey lengths, taking into consideration how differential drive functions of the floor cleaning frame dynamic patterns operate to complete actions of translation, correction of orientation, and transformation during robot navigation from the origin route-point to the final target route-point.

Wang et al. [32] designed an indoor carriage robotic for persons having physical disabilities, wherein it is essential to precisely trace the intended route. Monitoring is severely constrained by the robot's parameter uncertainty and disruptions. A brand-new, reliable tracking controller is proposed that must take into consideration both route monitoring optimization and energy usage reduction. The findings demonstrate that this innovative method can effectively decrease errors in monitoring by 0.2 m to 0.006 m while ensuring the least amount of consumed energy.

Ramos et al. [33] propose a numerical optimal control strategy that uses non-linear robot physics along its movement and considers minimizing energy and end-duration optimization. By explicitly deriving this strategy based on optimality criteria, the optimal control issue is transformed through an issue of boundary values that might be addressed using state-of-the-art numerical solvers. This technique has been examined in several applications, and the outcomes demonstrate its effective application using a non-holonomic robotic architecture.

Pant et al. [34] explore ways in which platform-level enhancements impact the throughput and energy of computations, along with ways to exploit this decision to lesser energy consumed by the computation part without significantly affecting control and throughput performances. This technique employs an offline assessment step of the perceptual algorithm to provide throughput vs. energy graphs for a variety of processing frequencies and different sequencing of its perceiving codes on the central processing unit (CPU) and graphics processing unit (GPU). Based on the results of experiments, this approach might save up to 20% of the energy used while only losing 1% of the overall efficiency of the control system.

When the environment is not very complicated, and the optimization terrain is not overly rough, PSO can perform effectively for relatively straightforward navigation tasks. Other approaches, including A\* search, genetic algorithms, simultaneous localization and mapping (slam), and reinforcement learning methods, can perform more effectively in environments that are more complicated and difficult. Whenever used to solve particular issues, PSO can swiftly converge to a solution. However, this feature can vary according to the dimensionality, structure, and PSO algorithm parameters of the problem. The factors used, including the number of particles, inertia weight, and cognitive and social aspects, determine the robustness of PSO. Inappropriate tuning of parameters can result in late or early convergence or in the inability to identify a satisfactory solution. Potential field approaches, including rapidly exploring random trees (RRT), have been specially developed

to tackle real-time navigation issues and can outperform PSO in such situations. Here, we are considering a situation where obstacles are static, and properties of the environment are also static; thus, PSO will be better than other techniques because of its higher rate of convergence. There are many techniques discussed in the literature survey that are useful for some specific situations.

#### 4. Background Information

Variability within the surroundings makes it difficult for MRs to plan their paths while collecting information. For the experiment, we have created a hypothetical environment. An energy-efficient path planning is considered during the surveillance through MR in this article. The following background information is required to proceed with further research in this experiment.

##### 4.1. Energy Conservation for Mobile Robots

Mobile robots must efficiently control their energy consumption whenever performing both alone and in groupings. A swarm of MRs working on a task might never be able to finish it or might become less tolerant of adverse situations that occur while the task is being carried out due to unequal energy distribution. The energy consumption varies depending on the behavior since the MR employs various sensors during varied behaviors. The energy level of MRs is mostly influenced by the energy consumed by their sensors and motors. An MR's overall energy capacity, or the quantity accessible after its battery is completely charged, is a definite amount. The amount of remaining energy ( $E_{remaining}$ ) after performing surveillance tasks for MRs can be calculated by Equation (3).

$$E_{remaining} = (E_{initial} - E_U) \quad (3)$$

where  $E_{initial}$  is the initial energy of MR means with a fully charged battery and  $E_U$  is the total energy used during the surveillance.

##### 4.2. Distribution Functions of Rational Data and Effective Information

Determining the quantity of data collected from the surveillance spaces is the primary objective of the explored monitoring task. The following definitions are initially introduced to make sure we can understand how to estimate the quantity of collected data [35].

**Definition 1.** *Helpful information gets acquired through tracking objects, which additionally represent the surveillance of object features, denoted by  $I_h$ .*

**Definition 2.** *The helpful information ( $I_h$ ) volume per unit area is known as information density. Let us consider the region area is  $A$ , then the density of information ( $\rho_A$ ) is denoted by Equation (4):*

$$\rho_A = \frac{I_h}{A}, \quad (4)$$

**Definition 3.** *The density of information has been utilized for constructing the distribution function of information  $\{F(x, y)\}$ , that describes an information transmission within the surveillance domain. This model enables the surveillance region's sites to collect the information quantity at any place.*

For further analysis, it is necessary to create the information density function. By applying the measured density of discrete information, users will be likely to estimate the unidentified quantity for additional coordinates places in the region under surveillance. While dealing with discrete data, the fitting procedure is appropriate. The method of fitting is to develop a function of mathematics that most accurately fits with a collection containing

discrete points of information. The minimization problem is derived from the relationship between  $F(x, y)$  and  $\rho$  in Equation (5) [35,36]:

$$\min_{F \in \Pi_n^2} \sum_k F(x_k, y_k) - \rho_k^2, \quad (5)$$

where the distribution function for information is denoted by  $F$  and collected from  $\Pi_n^2$ . Let us consider that provided  $n$  points available at places  $(x_k, y_k)$  in  $\mathbb{R}^2$ , where  $k \in (1, 2, 3, \dots, n)$ . The information density is  $\rho_k$  for the area of  $i$ th grid. The value of  $F(x, y)$  is denoted by  $F(x_k, y_k)$  at the position  $(x_k, y_k)$  that estimates the provided scalar quantities  $\rho_k$ .

#### 4.3. Path Planning for Surveillance Tasks

We consider that the surveillance area is  $S$ , and a representation of an environment for MRs that is illustrated in Figure 2. The distribution function of information for the surveillance area is described by  $F(x, y)$ . The quantity of information is given in Equation (6), for the entire surveillance area is denoted by  $I_S$  [36].

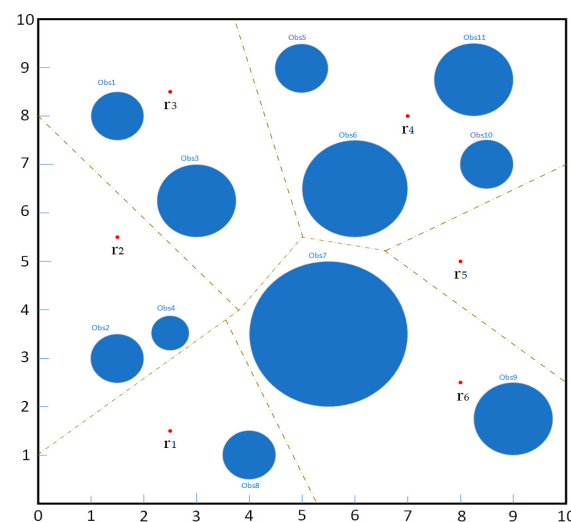
$$I_S = \iint_{A_S} F(x, y) dx dy, \quad (6)$$

where  $A_S$  is the area of the entire surveillance place. It is typically challenging to gather information from every spot within the surveillance area because of physical constraints. To create the group of remarkable places, we have chosen multiple dispersed locations, and this group is abbreviated as  $R$ , which is shown in Equation (7).

$$R = \{r_1, r_2, \dots, r_m\}, \quad (7)$$

$$r_i = i_{(x_i, y_i)}$$

where the coordinates are  $(x_i, y_i)$  for the  $i$ th interested place. At such places, an MR conducts inspection operations and obtains information.



**Figure 2.** Voronoi division of different environments for multiple MR surveillance.

Planner areas can easily be discretized well into basic geometrical simplex sets using Voronoi nets [37]. We split the surveillance region into multiple grids containing obstacles based on the Voronoi concept. Figure 2 provides an instance of the Voronoi segmentation of the surveillance zone within which the MR performs surveillance. The entire surveillance zone is divided into six parts,  $m = 6$  and there are total six surveillance locations, which are denoted by  $r_1, r_2, \dots$ , and  $r_6$  respectively.

The mathematical optimization for grids transforms the informational domain of the entire area, and the information related to the places is used for its representation. The quantity of data acquired by the MR is abbreviated in Equation (8) [36]:

$$I_M = \sum_{i=1}^n F(x_i, y_i) A_{r_i} \quad (8)$$

where  $A_{r_i}$  shows the Voronoi space of the surveillance place  $r_i$ . The number of surveillance places is  $n$ , for which real data is gathered. For  $n = m$ , the MR will be able to monitor the entire region of the Voronoi diagram and can collect data as well.

To study how to formulate the issue of a MR's surveillance tasks, we assume that each surveillance place is the coordinate of the path-following MR to perform surveillance tasks. The MR initializes the surveillance task at the first monitored place to gather data and get back to the same place after finishing surveillance work. The distance between each monitored place is given, and the coordinates of each starting place are predefined. The time and energy needed for each surveillance task are also given. The MR velocity and the consumption of energy per unit length are provided.

Whenever an unusual event is encountered by the MR, the position, the MR's remaining energy, and entry points for the monitored sites cannot be obtainable in the easiest way. The MR must be allowed to ascertain his position now. The proximity concept applies, which means that the accessible acquisition point that is nearest to the MR is considered the beginning place of re-planning, while the autonomous system is traveling between the two places that are considered for the experiment. Acquiring activities are unclear due to variable obstacles within the surroundings. An avoiding obstacle approach needs to be used by an MR while traveling across an unstable obstacle that can choose to stop moving forward, although performing so will delay the work of surveillance. It can additionally accelerate or follow another route, both of which require additional energy. After all criteria are satisfied, an efficient route from the starting position towards every capturing the data position must be identified, which might meet the needs for obtaining the quantity of information possible throughout the surveillance work.

## 5. Proposed Methodology

If the energy is limited and operational time is predefined for the MR to perform surveillance tasks, we aim to gather optimal information from the surveillance zone while the probability of facing obstacles must be minimal. The mobile surveillance task is a problem related to multi-objective optimization. In this paper, we enhanced the original PSO algorithm to create an intelligent PSO for getting an optimal path to perform operations of surveillance.

### 5.1. Mathematical Analysis and Proof

We used the methodologies mentioned in [36] to formulate this experiment for the simulation. Let us consider that  $S$  is the collection of routes linking the two surveillance places.  $S = \{l_{i,j} | i \neq j, i, j \in R\}$ , where  $l_{i,j}$  shows the path length between  $r_i$  and  $r_j$  for MR. It is possible that the MR might move across dynamic obstacles while it accomplishes the surveillance objectives between the two gathering spots. The probability that an MR will come across an obstacle along its intended path has been designated by a set  $P$ .  $P = \{P_{l_{i,j}}^* | i \neq j \forall i, j \in R\}$ , where  $P_{l_{i,j}}^*$  denotes the probability of facing obstacles by an MR on the route  $l_{i,j}$ . The MRs need more energy while facing obstacles and delays of the surveillance problems; thus, it is required during the planning of the path to encounter fewer obstacles while navigating.

The interoperability of the surveillance places seems to be taken for assumption. For the real project, whenever a path is not available between  $r_i$  and  $r_j$ , we can fix  $l_{i,j} = \infty$  and  $P_{l_{i,j}}^* = 1$ . Let the series of surveillance places dependent upon a specific route of the MR passing along the surveillance zone as  $R^n$ . Where  $R^n \subseteq R$ .  $Q^n$  is assigned as the collection

in route lengths generated by  $R$ . Where  $Q^n \subseteq S$ . MRs traveling on such paths have a sequence of confronting obstacle probabilities that can be expressed as  $P^n$ . Where  $P^n \subseteq P$ . The quantity of information gathered by the MR from the surveillance zone is estimated by Equation (9) [36]:

$$I_M(R^n, Q^n, P^n) = \sum_{i=1, r_i \in R^n}^n F(x_i, y_i) A_{r_i} \quad (9)$$

where  $A_{r_i}$  shows the Voronoi region of surveillance location  $r_i$ . The total number of surveillance places is  $n$ , for the MR where actual surveillance happened. Whenever the MR gathers the entire data from the desired sites, the  $m = n$  and  $R^n = R$ . The complete length of every planned route for MR is abbreviated as  $dist_M$  in Equation (10) [36].

$$dist_M(R^n, Q^n, P^n) = \sum_{l_{i,j} \in Q^n} l_{i,j} \quad (10)$$

The route has been designed to ensure it faces a minimal likelihood of striking obstacles with the objective of lowering a MR's energy use and shortening the duration required to acquire information. For an MR, the median possibility of hitting obstacles throughout each section of a predefined route might be estimated using Equation (11) [36].

$$obst_M(R^n, Q^n, P^n) = \frac{\sum_{l_{i,j} \in P^n} P_{l_{i,j}}^*}{n - 1} \quad (11)$$

We suppose that while performing surveillance mission, the MR will move with a constant velocity of  $v_n$ . The energy required for the MR per unit length is  $E_l$ . The required energy for the MR to carry out the surveillance work at the surveillance location is  $E_r$ . The time required for the MR to perform surveillance is  $t_r$ . The initial energy of MR before starting the surveillance task is  $E_{initial}$ . For accomplishing the surveillance task, we allocated a time of  $t_{initial}$ . The start and end locations for the navigation of MR while performing tasks is  $r_1$ . Firstly, MR gathers information of  $r_2$  location and return to  $r_1$  location after gathering the information of  $m - 1$  desired places and the information of  $r_1$  location. Information for  $r_1$  might be specified as being gathered after it returns in and only gathered once.

The MR needs to employ a collision-avoiding approach while traversing across an unstable obstacle. It can decide to halt moving forward, although doing so will lead to the process of obtaining information consuming a longer time. It might additionally accelerate or follow an alternate route, both of which require extra power. Acquisition operations are undefined because of variable obstacles throughout the surveillance domain. It might restrict the MR from using its remaining energy to get back to the place of origin within the specified time. Therefore, this makes it essential to perform re-planning during the surveillance operation.

When  $R \neq 0$ , then the surveillance process will start. As per the trajectory in  $Q$ , the MR reaches the subsequent surveillance location. The route taken through the preceding surveillance spot to the present surveillance spot is deducted from  $Q$ , which means  $(Q - l_{j,i})$ , whenever the surveillance work has been obtained. The accessible surveillance site will be eliminated from  $R$ , which means  $R = (R - r_i)$ , soon after the information about a prospective position has been successfully gathered. The surveillance task is completed after  $R = 0$ . Subsequently, it is essential to check the remaining time  $(t_{initial} - t_U)$  and energy  $(E_{initial} - E_U)$ , where  $t_U$  and  $E_U$  are the used time and energy consecutively before MR reaches a surveillance place.

The loss of power is substantial whenever the MR's energy reserve is unable to facilitate a trip back toward its place of origin. The amount of time left over will not be adequate to gather information from all the surveillance zones because the MR takes up a large portion of time. For these circumstances, re-planning is necessary. This is required to determine the MR's latest acquisition position; we suppose it is  $r_L$ . The surveillance place for re-planning is reserved in  $R'$ , and the starting  $R$  is reformed. The re-planned path

is reserved in  $Q'$ , and the starting  $Q$  is reformed. The obtaining for possibilities facing obstacles is updated concurrently. Thus, a group that includes re-planning routes remains in  $P'$ , and initial  $P$  is updated as the  $P'$ . The MR surveillance work formulation has been described in Equations (12)–(14) [36].

$$\max I_M(R^n, Q^n, P^n) = \max_{R^n \subseteq R, Q^n \subseteq Q, P^n \subseteq P} \sum_{i=1}^n F(x_i, y_i) A r_i \quad (12)$$

$$\min \text{dist}_M(R^n, Q^n, P^n) = \min_{R^n \subseteq R, Q^n \subseteq Q, P^n \subseteq P} \sum_{l_{i,j} \in Q^n} l_{i,j} \quad (13)$$

$$\min \text{obst}_M(R^n, Q^n, P^n) = \min_{R^n \subseteq R, Q^n \subseteq Q, P^n \subseteq P} \frac{\sum_{l_{i,j} \in P^n} P_{l_{i,j}}^*}{n-1} \quad (14)$$

Equation (12) is used for the purpose of maximizing the gathered information from the surveillance zone, Equation (13) is used for minimizing the distance traveled by MR during surveillance, and Equation (14) is used to minimize the possibility of encountering obstacles. When obstacles are likely to be encountered frequently, both time and energy become wasted, which ultimately lowers the quantity of data acquired during surveillance. As a result, we must design a route that has plenty of data and little chance of hitting obstacles. Equations (15) and (16) show the energy and time constraints respectively [35,36].

$$\sum_{l_{i,j} \in Q^n}^{n-1} l_{i,j} E_l + \sum_{i=1}^n E_r \leq (E_{\text{initial}} - E_U) \quad (15)$$

$$\sum_{l_{i,j} \in Q^n}^{n-1} \frac{l_{i,j}}{v_n} + \sum_{i=1}^n t_r \leq (t_{\text{initial}} - t_U) \quad (16)$$

where the consumption of energy while the MR travels along the planned path for surveillance is  $\sum_{l_{i,j} \in Q^n}^{n-1} l_{i,j} E_l$  and energy required by the MR at the acquisition place during surveillance is  $\sum_{i=1}^n E_r$ . The remaining energy and time for accomplishing the surveillance task are denoted by  $(E_{\text{initial}} - E_U)$  and  $(t_{\text{initial}} - t_U)$ . It is clear from Equation (15) that the required energy is less or the same as the remaining energy. The time used by the MR while moving at the predefined path is  $\sum_{l_{i,j} \in Q^n}^{n-1} \frac{l_{i,j}}{v_n}$  and time utilized by the MR during the acquisition of data from the surveillance site is  $\sum_{i=1}^n t_r$ . From Equation (16), it is proven that the required time is less or equal to the remaining time for accomplishing surveillance work.

## 5.2. Particle Swarm Optimization

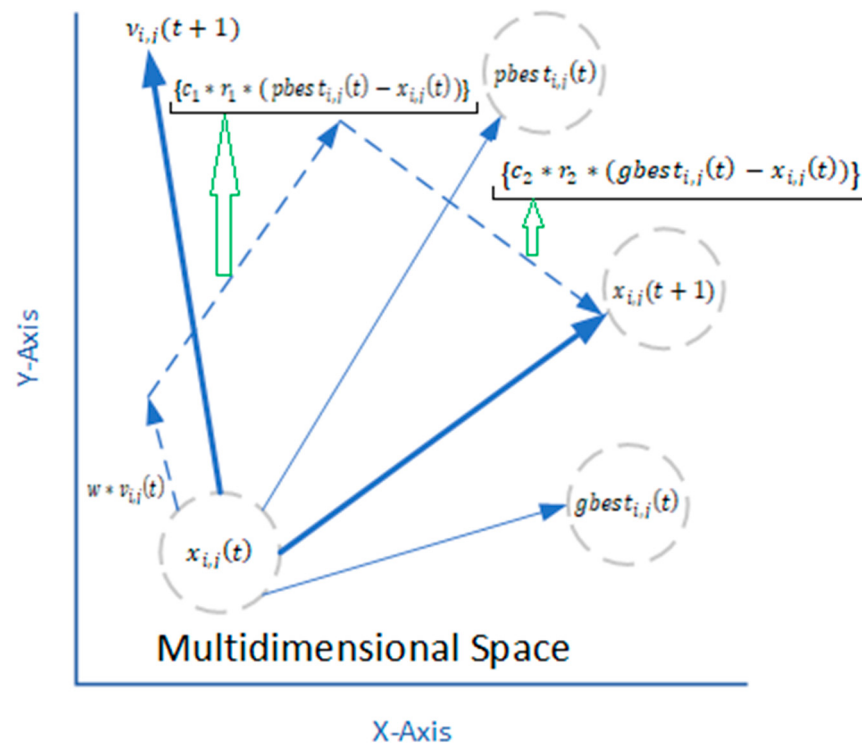
The technique used for optimizing non-linear continuous functions is called PSO. PSO is simple to use and can locate optimum or nearly perfect solutions. The most important work for the PSO technique is the information exchange among the swarm of particles. To allow us to discover the best response inside the search area, each particle can be looked after. Both the collective and personal information from the whole swarm of particles contributes to directing the search mechanism. The PSO technique is a special type of iterative algorithm. Each individual particle tries to move nearer to the perfect outcome throughout each successive iteration. Each iteration ends with a comment about the swarm's greatest choice among the past various options. The PSO is an efficient technique for path planning in this experiment to get the shortest path between each coordinate of a predefined surveillance location available inside the surveillance zone. Thus, after obtaining to the shortest path, we can optimize the energy efficiency of MR during navigation.

By PSO, each particle combines its individual search track record along with the histories of the remaining particles to find the problem's solution. It might ultimately discover the suboptimal or optimal approach for an issue over multiple iterations [37]. The enhanced PSO, which is considered an intelligent PSO during this experiment, can be abbreviated in Equations (17) and (18) using Equations (1) and (2) [38].

$$v_{i,j}(t+1) = w * v_{i,j}(t) + c_1 * r_1 * (pbest_{i,j}(t) - x_{i,j}(t)) + c_2 * r_2 * (gbest_{i,j}(t) - x_{i,j}(t)), \quad (17)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1), \quad (18)$$

where the  $i$ th particle is  $i$ ,  $d$ th dimension for the particle is  $j$  and  $t$ th generation is  $t$ . The learning factors denoted by  $c_1$  and  $c_2$ , within the range between 0 and 2. The independent random functions are denoted by  $r_1$  and  $r_2$ . Figure 3 represents the model of intelligent PSO used in this paper. Where, the position and velocity of the particle upon each iteration are represented by the bold arrows, global best position and personal best position are depicted by light arrows, and components of equation 17 are depicted by dotted arrows respectively.



**Figure 3.** Model representation of particle swarm optimization.

The updated velocity in Equation (17) consists of mainly three sections, including inertia weight, cognition section, and social section. The inertia weight section is represented as the influence factor for the velocity of particles by inertia. The cognition section is for the influence factor of the individual optimal value, and the social section provides the influence factor for the global optimum. Because of its simplicity and effective performance, the conventional PSO strategy outlined above is being utilized extensively in a range of optimizing scenarios, and several types of techniques have also been developed to enhance the classical PSO's functionality [39]. Shi and Eberhart presented a technique in [40–42] for the inertia weight  $w$  as linearity decrement on the generations of iteration. The current weight for the inertia weight  $w$  can be estimated as Equation (19):

$$w_c = (w_i - w_f) * \frac{(Max_{iter} - iter)}{Max_{iter}} + w_f, \quad (19)$$

where the initial and final inertia weights are  $w_i$  and  $w_f$  respectively; the number of maximum iterations is  $Max_{iter}$ , and the current iteration number is denoted by  $iter$ . In general, an increased inertia weight can lead the PSO to support extensive exploration, whereas a smaller value might result in limited exploration. That is why  $w_i$  and  $w_f$  frequently default to 0.9 and 0.4, consequently, as their starting and end values. In improved PSO, the ratio between both exploration and extraction is frequently adjusted using dynamic and time-

dependent inertia weights. This can result in faster convergence times and higher-quality solutions. During the beginning, a time-varying accelerating coefficient (TVAC) is added to PSO along with the time-dependent inertia weight parameter as a way to successfully coordinate local search operations and converge to the best possible global outcome. The TVAC-PSO technique is proposed for the estimation of acceleration coefficients according to Equations (20) and (21) [43].

$$c_1 = (c_{1i} - c_{1f}) * \frac{(Max_{iter} - iter)}{Max_{iter}} + c_{1f}, \quad (20)$$

$$c_2 = (c_{2i} - c_{2f}) * \frac{(Max_{iter} - iter)}{Max_{iter}} + c_{2f}, \quad (21)$$

where the initial values are  $c_{1i}$  and  $c_{2i}$ , and the final values are  $c_{1f}$  and  $c_{2f}$  for the acceleration coefficient final values  $c_1$  and  $c_2$ , respectively. Generally, we keep  $c_{1i} = c_{2f} = 2.5$ , and  $c_{1f} = c_{2i} = 0.5$  in this technique.

### 5.3. Multiobjective for Surveillance

Surveillance tasks associated with MRs are basically multi-objective optimization challenges. A possible approach to resolving multi-objective optimization tasks is the PSO method. The planning pathway is represented by a particle's movement. A particle estimates its surveillance locations set as  $R^n$ , path length set as  $Q^n$ , and the probability of facing obstacles set is  $P^n$ . Let us consider the relationship between the  $i$ th particle  $X_i$  and  $R^n$ ,  $Q^n$ , and  $P^n$  as given in Equations (22)–(24) [36].

$$R^n = con(rdl(X_i)) \quad (22)$$

$$Q^n = len(rdl(X_i)) \quad (23)$$

$$P^n = pro(rdl(X_i)) \quad (24)$$

where  $rdl()$  function is used to remove duplicate positions for  $X_i$  particle. Whenever a particle changes its position vector  $X_i = [x_{i,1}, x_{i,2}, x_{i,3}, \dots, x_{i,j}]$ , repeated positions can be created; thus, these duplicate places must be removed. The remainder of the spots make up the anticipated list of acquisition sites. For obtaining the length between two places of acquisition, function  $len()$  is used in a particle  $X_i$ . The function  $con()$  is used to change the position of the particle to a surveillance place. The function  $pro()$  is used for finding the set of probabilities when facing obstacles within the locations of acquisitions related to the particle's locations. The place  $x_{i,j}$  in the site vector  $X_i = [x_{i,1}, x_{i,2}, x_{i,3}, \dots, x_{i,j}]$ , for  $X_i$ -particle will be indexed at the acquisition place  $r_i$ . The Euclidean distance has been employed for estimating the width between acquisition places, and then, the resulting list of path lengths across data spots can be gathered.

### 5.4. Fitness Function

In PSO, fitness functions are crucial in the planning of routes related to a particular particle. Depending on the quantity of information acquired, the total distance traveled, and the average risk of striking into obstacles, distinct path sets, acquisitions site sets, and possible groups of crossing into obstacles obtain varying fitness values. The multi-objective situation can be simplified to a single-objective issue to simplify the level of difficulty of multi-objective solution finding. Several optimization goals include gathering as much data as feasible, minimizing the mean chances of hitting obstacles, and traveling the shortest distances.

The goal of a fitness function is to connect an optimization algorithm for motion planning to the real world [44]. The fitness function assesses the overall performance of a

particle's route. The PSO algorithm's convergence behavior and search efficiency might be affected by the swarm's particle population. PSO follows a population-based optimization approach in which each particle in PSO stands for a potential response to the optimization issue. Based on each particle's best-known location and the most effective available location of the swarm, the particles explore across space to find the perfect solution. The search space is typically extensively explored when there are more particles present. This increases the likelihood that the swarm will cover a greater area of the solution space, possibly boosting the likelihood of discovering the global optimal solution. That means a higher number of particles provides higher fitness values. The closer a particle's journey is to its destination, the higher its fitness.

## 6. Simulation and Discussion

Among population-based metaheuristic optimization methods, PSO is one of the most widely used. PSO has been effectively applied in a variety of scientific disciplines, including advanced physics, engineering, chemistry, and the humanities. However, even though it is well recognized that population size has a significant impact on how well metaheuristics work, there has not been a thorough study on the optimal PSO swarm size to far. The majority of the latest upgraded PSO techniques establish the weights and learning variable settings explicitly. Particles must possess proper specifications for every fitness and variety because they might be nearer to the optimum output. Additionally, compared to previous algorithms, our method incorporates appropriate intelligence. The key concept in the presented PSO methodology is that the estimated speed for the updated particles relies intelligently on the cognition of particles.

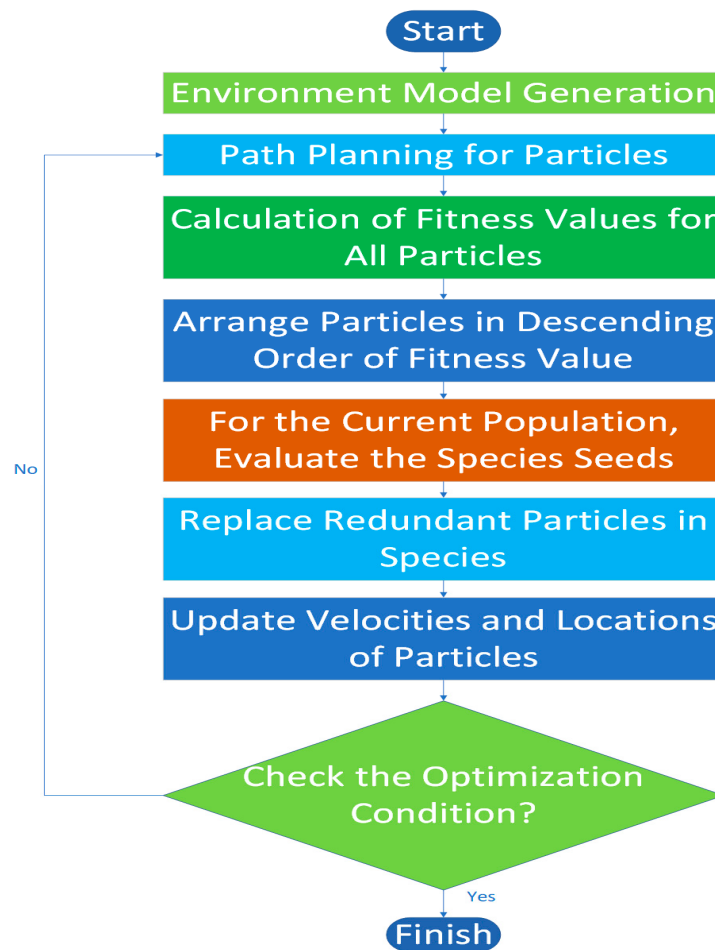
PSO's enhanced version strives for enhancements in its convergence speed, response quality, and resilience. Enhanced PSO algorithms can involve techniques for achieving a better balance, including dynamic variable adaptation, dynamic neighborhood explorations, or integration with other algorithms. Enhanced PSO algorithms might incorporate domain-driven information or problem-specific algorithms to drive the optimization procedure more accurately. PSO can be modified to discover an optimal or nearly optimal path that decreases energy usage while fulfilling the time limitations when energy and time constraints are taken into consideration during path design. Particle exploration can be improved more precisely, and the regional exploration variety of particles might be expanded by adding an intelligent cognition parameter. Table 1 illustrates the pseudocode of PSO algorithms.

**Table 1.** Pseudocode of intelligent PSO algorithm.

| Pseudocode of Intelligent PSO |                                                                                                           |
|-------------------------------|-----------------------------------------------------------------------------------------------------------|
| -                             | Initialize all particles within predefined conditions;                                                    |
| -                             | (The values of the initial best position will be like the particle position)                              |
| -                             | Define a decision variable within the range [1, number of unknown decision variables].                    |
| -                             | While (number of iterations < maximum number of iterations):                                              |
| -                             | For all particles, compute the fitness value using the cost function;                                     |
| -                             | For all particles, update the values of best position based on fitness values;                            |
| -                             | Determine new positions for all particles using Equations (17) and (18);                                  |
| -                             | Control all particles that violate the 'decision variable' parameter, then renew the redundant particles. |
| End                           |                                                                                                           |

We also evaluate the mixture of acquired positions, thereby assisting the PSO algorithm in providing an improved beginning state. Figure 4 shows the complete optimization task working scenarios. This approach is particularly relevant in multidimensional optimization issues. The most effective response can be obtained through particle search because of this technique. Speed and learning factors have been especially significant for PSOs since they

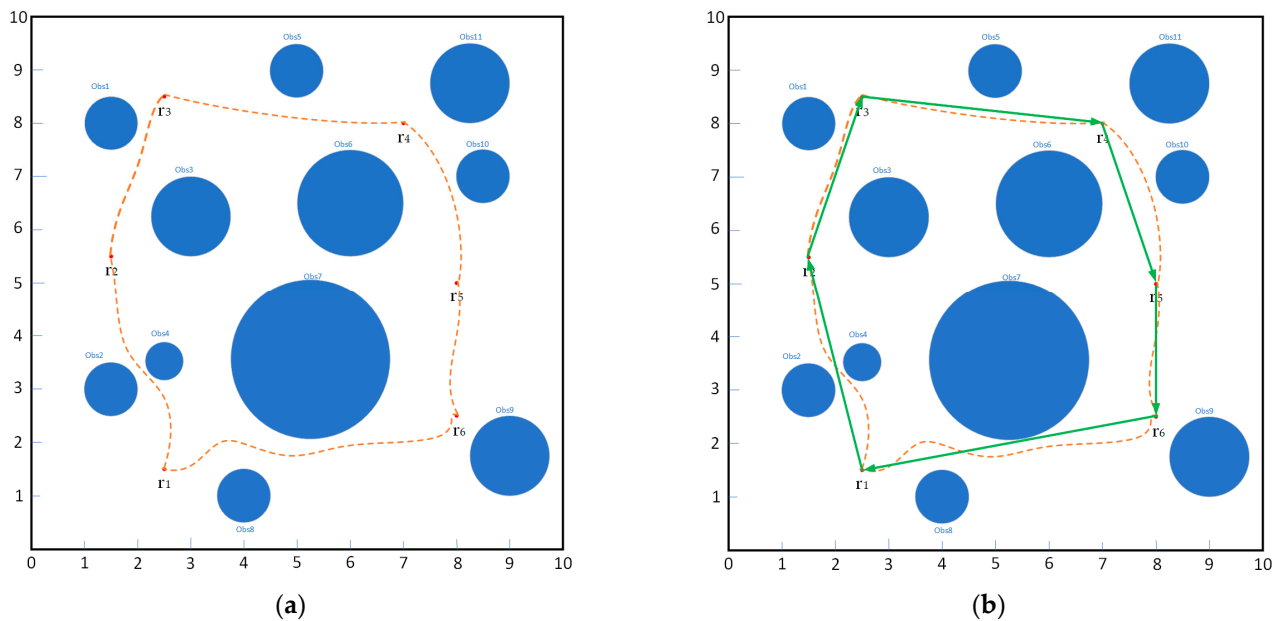
have an immediate influence on how effectively PSOs perform. To improve the population's variation along with encouraging particles to run away from nearby obstacles.



**Figure 4.** Flowchart of the proposed algorithm.

This approach has been proposed for addressing the problem where the route points generated with PSO contain several instances of duplicate path points and for optimizing the overall route. The planning of paths is done using enhanced algorithms, environment simulation, and various other techniques. The objective is to identify a population of particles that actively look for the best answer within a predefined search space.

We create an environment scenario using MATLAB R2023a and subsequently utilize the modified PSO for simulating the planning of the path for a MR's navigation with the objective of validating the algorithm's performance. A real-world investigation of airborne micro-robotic swarms acts as the source of inspiration for this research's basic concept. The planned application of the proposed framework and its related characteristics is to give an effective algorithmic structure of both energy usage and surveillance within the flying swarm. Establishing a baseline for more feasible investigations is the objective of the experiments. The MR route is designed to prevent collisions with obstacles, which is accomplished by implementing a collision monitoring and avoidance algorithm. Figure 5 shows the complete surveillance zone, the green line shows the optimized shortest distance between two surveillance locations, and the red dotted line shows the normal shortest distance while avoiding obstacles.



**Figure 5.** Illustration of the shortest path for performing surveillance tasks at different locations be listed as (a) shortest path between each surveillance location as a red dotted line without optimization and (b) optimized shortest path between each surveillance location shown as a green path and without optimized is the dotted path.

We perform simulations to demonstrate the efficiency of our presented intelligent PSO approach while comparing it to various widely recognized PSOs. The following is a list of the parameter configurations. The  $x$ -range can be expressed as the difference between the particle's highest and lowest velocities, which are 10% of the search space's radius. The highest and lowest velocities of particles for the Sphere function ( $f_s$ ) in this methodology is  $[10, -10]$ . The level-by-level competitive technique determines the learning and weight variables in intelligent PSO. The number of particles and iterations are 300 and 1000, respectively. The particle dimension is considered as 30, and each experiment is repeated 50 times. The median outcome is then given after the findings are evaluated individually to remove the random contribution. Table 2 describes the X and Y coordinates of different data acquisition locations inside the surveillance zone.

**Table 2.** Illustration of data acquisition locations in the surveillance region.

| Coordinates | $r_1$ | $r_2$ | $r_3$ | $r_4$ | $r_5$ | $r_6$ |
|-------------|-------|-------|-------|-------|-------|-------|
| X           | 2.5   | 1.5   | 2.5   | 7     | 8     | 8     |
| Y           | 1.5   | 5.5   | 8.5   | 8     | 5     | 2.5   |

We consider that the surveillance region is a type of rectangular area with 10 units in length and 10 units in width. The location of the start has been considered as being at the lower left corner. A total of six data acquisition locations have been generated randomly in the surveillance zone, and their coordinates are described in Table 1. Here,  $r_1$  is the starting and final position for the surveillance zone. The required energy for MR for each data acquisition place is five units,  $E_r = 5$ . The used energy per unit length is 1 unit,  $E_l = 1$ . The total used time by MRs at every data acquisition place is 2,  $t_r = 2$ . The total distance traveled by MR per unit of time is 0.5,  $t_n = 0.5$ . Let us consider the energy and time left for the re-planning of surveillance tasks are 90 and 100 units, which means  $(E_{initial} - E_U) = 90$ , and  $(t_{initial} - t_U) = 100$ . There are a total of 11 obstacles available inside the surveillance zone, which are taken randomly with different shapes and locations. Table 3 describes the X and Y coordinates and the radius of obstacles available inside the surveillance zone.

**Table 3.** Illustration of the location and size of obstacles located inside the surveillance zone.

| Coordinates | Obs1 | Obs2 | Obs3 | Obs4 | Obs5 | Obs6 | Obs7 | Obs8 | Obs9 | Obs10 | Obs11 |
|-------------|------|------|------|------|------|------|------|------|------|-------|-------|
| X           | 1.5  | 1.5  | 3.0  | 2.5  | 5.0  | 6.0  | 5.25 | 4.0  | 9.0  | 8.5   | 8.25  |
| Y           | 8.0  | 3.0  | 6.25 | 3.5  | 9.0  | 6.5  | 3.5  | 1.0  | 1.75 | 7.0   | 8.75  |
| Radius      | 0.5  | 0.5  | 0.75 | 0.25 | 0.5  | 1.0  | 1.5  | 0.5  | 0.75 | 0.5   | 0.75  |

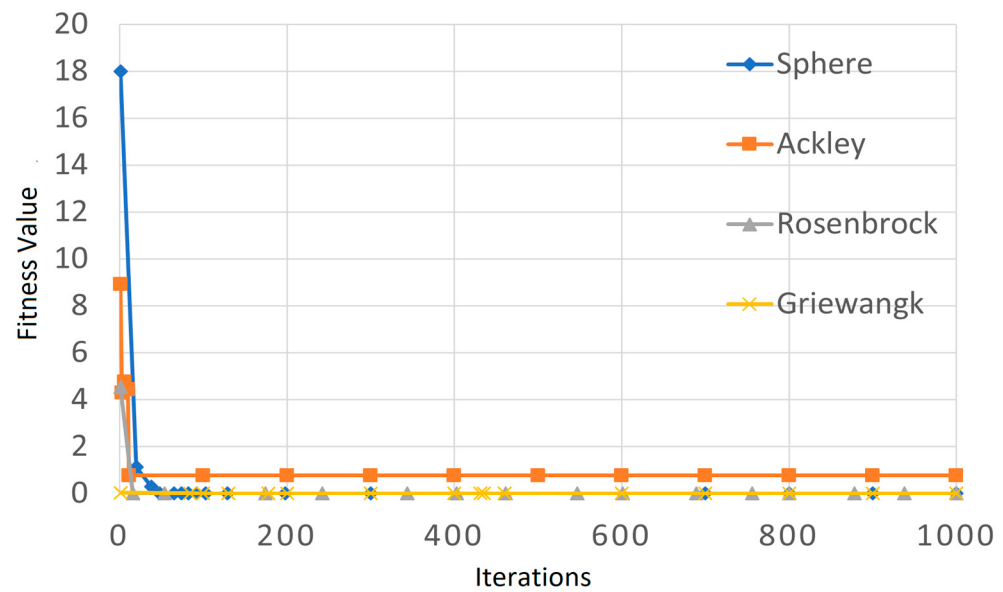
The distance traveled by a MR during surveillance through defined surveillance locations is abbreviated in Table 3. The distance traveled by a MR from  $r_1$  to  $r_2$  is 4.12, the distance traveled by a MR from  $r_2$  to  $r_3$  is 3.16, the distance traveled by a MR from  $r_3$  to  $r_4$  is 4.52, the distance traveled by a MR from  $r_4$  to  $r_5$  is 3.16, distance traveled by a MR from  $r_5$  to  $r_6$  is 5.50, and distance traveled by a MR from  $r_6$  to  $r_1$  is 5.59 units. Thus, the total distance traveled by a MR during the surveillance is 26.05 units. The required energy and time for a MR navigation from one coordinate to another coordinate in the surveillance zone and the distance traveled by a MR are illustrated in Table 4. The total energy used by a MR during the performance of the surveillance task is 56.05 units, and the total time spent by a MR during the surveillance task is 25.03 units. Thus, the remaining energy and time that can be estimated for the navigation of a MR at the shortest path determined by the PSO technique during surveillance will be 33.95 and 74.97 units, respectively.

**Table 4.** Illustration of total distance covered, total used energy, and total required time for the navigation of a MR between one surveillance location to another surveillance location.

| Calculated Value | $r_1 - r_2$ | $r_2 - r_3$ | $r_3 - r_4$ | $r_4 - r_5$ | $r_5 - r_6$ | $r_6 - r_1$ |
|------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Distance         | 4.12        | 3.16        | 4.52        | 3.16        | 5.50        | 5.59        |
| Energy           | 9.12        | 8.16        | 9.52        | 8.16        | 10.50       | 10.59       |
| Time             | 4.06        | 3.58        | 4.26        | 3.58        | 4.75        | 4.80        |

The enhanced intelligent PSO algorithm provides more efficient iterations, a reduced anticipated illustrates path, and optimized required energy and time with higher data acquisition for the surveillance, as demonstrated by a comparison with simulated analyses that illustrates the technique's performance. The benchmark functions from [45], including the Sphere function, Ackley function, Rosenbrock function, and Griewangk function, are used for the comparative analysis of the presented technique.

A fitness function must be built in order to assess if the present route is superior to the prior one and whether it is the global preferred option while evaluating the path that PSO sought. Tracking the fitness value across PSO iterations is essential for interpreting the convergence behavior and algorithmic performance. The term “fitness value over iterations” describes how a PSO algorithm's level of accuracy in solutions evolves over time, whether through iterative refinement or generational growth. Figure 6 presents a comparative analysis between different benchmark functions for fitness value over the number of iterations. The fitness value versus iterations graph shows higher convergence with several iterations during simulation. A greater level of convergence is achieved, and localized capture events are less common during the simulation. This enhanced PSO algorithm includes local search techniques for refining responses within very small areas surrounding the present particle positions, which helps during the fine-tuning of responses and might result in a more efficient use of search space. Improved PSO algorithms use better starting techniques to properly disperse particles over the search space, preventing early convergence to poor responses.



**Figure 6.** Comparison between different benchmark functions for the illustration of the algorithm.

## 7. Comparative Discussion on Various Energy-Efficient Navigation Systems

MRs need energy-efficient navigation systems to extend their operating range and decrease their reliance on external energy resources. It is essential to remember that the selection of the navigational system is determined by several parameters, including the intended use of the MR, the environment where it works, the accessible computing power, and the required degree of energy efficiency. For the greatest outcomes in certain situations, an integration of multiple approaches might prove appropriate. Energy-conscious planning of paths techniques provides an explicit emphasis on conserving energy consumption while navigating. Algorithms consider factors including battery lifespan, motor effectiveness, topographical features, and energy expenses related to various MR actions. MRs can choose routes with minimal energy consumption by considering these aspects while developing routes.

Under the constraints of time and energy, a mobile robot can only manage to execute a portion of the operation from the predefined whole tasks, but it can also actively re-plan its travel route within a complex environment by being conscious of its surroundings and completing its predefined work. PSO technique-based path planning strategies are easy and energy efficient when compared with other techniques. For better conservation of energy, any one of the navigational strategies listed below can be integrated with PSO technique-based path planning.

### 7.1. Deliberative Navigation Systems

In deliberative navigation systems, the environment is mapped out, and the best routes are chosen based on the map. Simultaneous localization and mapping (SLAM) algorithms are usually used to make the map, and several path planning algorithms, including A\* and Dijkstra, are used in the deliberative navigation systems. As algorithms enable a MR to anticipate and optimize its path according to the consumption of energy, deliberative navigation systems are often energy efficient [46]. However, route planning control is referred to as a deliberate technique since the MR is intended to give precise planning to attain a goal based on the environment's geometric model and the applicable theory [47]. However, the start of the mapping method along with ongoing planning of paths might need more energy. The decision between PSO-based navigation and deliberative navigation is influenced by the unique needs of the robot's mission as well as the features of the surroundings. Deliberative algorithms excel in established domains with complicated

barriers, but PSO-based navigation excels in dynamic and unknown situations requiring real-time adaptability.

### *7.2. Reactive Navigation Systems*

Reactive navigation systems depend on real-time data collected by the sensors to respond and navigate the environment. To provide quick reactions to environmental variations, they frequently apply techniques for obstacle identification and avoidance [48]. Due to the emphasis on quick decisions and lack of need for lengthy mapping or planning, reactive navigation systems are often proven energy efficient. However, reactive navigation methods are not always optimized for long-term energy conservation and can fail in complex circumstances. The characteristics of the environment, the required level of optimization, and the unique needs of the MR's job all influence the decision between PSO-based navigation and reactive navigation. Reactive navigation is best suited for real-time adaptability and simple surroundings, whereas PSO-based navigation is better suited for global optimization and dealing with difficult conditions.

### *7.3. Machine Learning-Based Navigation Systems*

MR navigation constraints can be trained using machine learning (ML) approaches, including reinforcement learning (RL) [49]. This type of system generates navigational decisions based on knowledge and experience. ML-based navigation systems can maximize energy efficiency by learning strategies that minimize unnecessary motions and use less energy. But initially, training the models might require a lot of computing time and energy. Thus, the PSO technique is better for energy conservation when compared with other ML-based navigation systems. The quantity and quality of training data, the quantity of required flexibility, the preferred degree of optimization, and the inherent complexity of the surroundings will all impact the decision between PSO-based navigation and ML-based navigation. PSO-based navigation is focused on optimization and is excellent for difficult path-planning problems, whereas ML-based navigation is adaptive and data-driven [50].

### *7.4. Hybrid Navigation Systems*

Both reactive and deliberative strategies are incorporated in hybrid navigation systems. In Hybrid navigation systems, reactive behaviors are utilized to avoid obstacles swiftly, and deliberative planning is implemented to optimize paths over a period. An infrared sensor and GPS navigation technique can be implemented together for the navigation of a MR. MR navigation systems might be used for an extended duration without being required to recharge their batteries because renewable energy can be used for data acquisition and interpretation [51]. With these technologies, real-time responsiveness and energy-conscious planning are balanced. Hybrid navigation systems can achieve efficient consumption of energy by continuously adapting the amount of awareness that depends on the complex nature of the surroundings.

## **8. Future Research Trends**

This paper is mostly focused on the optimization of time and energy constraints for MR navigation. However, there are other collections of objectives, including motion smoothness, sensor noise, multi-robot systems, and many more, that must be considered for further research. MR mobility in the real world frequently suffers from uncertainties and sensor noise. Also, development can involve looking at ways to modify a strategy when working across multiple robot systems, landscapes, or energy resources while preserving or enhancing functionality. The optimization approach can be expanded in the near future to address multi-robot systems and resolve issues with coordination, avoidance of collisions, and distribution of tasks for large-scale operations [52,53]. The inclusion of complex frameworks and noisy sensors within the optimization paradigm might become a topic for prospective exploration. To guarantee that the robot's strategy for navigation maintains efficiency despite an environment of uncertainty, that might utilize approaches including

Bayesian optimization, stochastic simulation, or robust optimization processes [54]. The planning and re-planning routes described in this paper can be used to gather relevant physical characteristics, including variations in temperature, wind speed, etc., that can further be implemented for the surveillance associated with firefighting and border surveillance.

An analytical approach and simulation-based findings are presented in this study. Further research might focus on applying the intelligent PSO method to live robots along with testing its accuracy in real-world situations. This might include taking responsibility for the limitations associated with actual equipment, coping with constraints on time, and solving everyday challenges with a sensor interface and communications. Subsequent research might examine how the strategy for optimization can be applied to various additional robot types, limitations, and environments. For instance, to enable collaboration in making decisions between the MR and its human user, additional studies will investigate ways to include human behavior and restrictions within the optimization paradigm [55]. By addressing these problems and factors that develop throughout real-world environments and extending limitations for MR navigation, we can extend both the scope and application of the optimization approach for future research.

## 9. Conclusions

In this paper, we developed the subject of a collection of data for surveillance as a multi-objective optimization task for MR navigation involving optimizing acquiring data, reducing the likelihood of running into obstacles, and reducing the journey distance. To address this optimization task, we present an intelligent PSO algorithm. The velocity updated formula of each particle has been modified by our method to incorporate an additional intelligence element. Such a component comprises the particle's perception of society along with its own personalized intelligence. In PSO, learning and weight components are crucial. Traditional methods rely heavily on expertise and thus are inadequate to address the complex problems raised by our specified problem. This article presented a technique for choosing the finest copied particles through competitions at each stage depending upon the concept of removing the fittest. The system we developed can take both learning and weight parameters from the best-replicated particles, which contributes to enhanced fitness instantly with improved particle movement. The intelligent PSO method for path planning is successfully shown in simulation, which further demonstrates its reliability and superior accuracy when compared with conventional techniques. A comparative discussion with other energy-efficient navigation systems is also provided in this article. The simulation result shows optimized energy and time constraints for the Navigation of MRs using an intelligent PSO methodology. Thus, this technique can be implemented in real-world scenarios for energy conservation in MR navigation.

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