Energy Optimized Path Planning and Decision Making for Multiple Robots in Rescue Operations

Dileep Sivaraman, Branesh M. Pillai, Songpol Ongwattanakul, and Jackrit Suthakorn

IECON 2022 – 48th Annual Conference of the IEEE Industrial Electronics Society | 978-1-6654-8025-3/22/$31.00 ©2022 IEEE | DOI: 10.1109/IECON49645.2022.9968971

Abstract—**Path planning strategies exist today for producing trajectories in Unmanned ground vehicles (UGV) that incorporate various navigation concerns, such as 3D navigation, obstacle avoidance, and path re-planning. These path generators mostly depend on the dynamics of the UGV's position and orientation. However, one significant issue with these methods is that it ignores the relationship between the path planning task and the energy consumption associated with battery performance. This paper presents a path planning algorithm for multiple unmanned robots that take into account battery performance. Subsequently, using the optimal trajectory of each robot within a multi-robot system and monitoring the battery state of each robot, an algorithm for determining the suitable robot for the instantaneous task during rescue operations is proposed. The simulation results show that the proposed energy optimization algorithm can be used to predict the energy consumption of the mobile robot maneuvering processes, in addition, to efficiently supporting to make decisions for mobile robots in rescue operations.**

Index Terms—**Unmanned tracked vehicle; Tracked vehicle dynamics; Battery management; Mobile autonomous robots**

I. Introduction

To create trajectories for UGVs that take into consideration diverse navigation challenges, such as 3D navigation, obstacle avoidance, and path re-planning, there have been impressive path planning algorithms developed. [12, 3, 14]. Such path generators are mostly based on the dynamics of the position and orientation of the UGVs. However, one of the main limitations of such methods is that they will not account for the relationship between path planning and robot energy consumption during missions. On account of limited battery backup on autonomous UGVs, the power supply of the robot has an impact on its performance and can cause the robot to stop in the middle of a mission. This failure has a direct impact on the specified task and/or success of the mission. To overcome this situation is to identify the energy consumption of each part individually and estimate and compensate for the power consumption.

Recent studies have succeeded in achieving the goal of saving energy through trajectory optimization [13, 6]. Since in rescue operations, robots must be able to function autonomously/ semi-autonomously or with minimal human interaction in potentially hazardous and dangerous environments. One of the major limitations of the studies that are mentioned above is that they fail to account for the relationship between the battery backup and the path of the robot [12, 3, 13, 6]. It is essential that robots use minimum energy in rescue operations. When multiple robots work together in rescue operations, they engage in their work in different positions. In this scenario, the selection of an appropriate robot for the instantaneous task is critical. Selecting such a robot from different positions depends on the time it takes to reach the goal, battery backup, and trajectory to the target.

In rescue operations, there are situations where the robot with the shortest path has insufficient enough battery life to complete the task, and also the robot with the most battery backup may not have the shortest path. In this situation, an algorithm is required to determine which robot is appropriate depending on its path and battery backup. In this paper, the authors propose an algorithm to determine the most appropriate robot based on calculating the robot's energy consumption, and trajectory from the robots distributed at various locations.

II. methodology

To improve the energy efficiency of the mobile robots in the rescue operation, a proper robust algorithm is necessary to calculate and predict energy consumption before making the decision, to enable energy-efficient strategies. To estimate the energy consumption of a mobile robot, three major factors must be considered: the motion system, the sensor system, and the control system [4]. The speed of the robots affects all of these systems both directly and indirectly.

The algorithm starts with collecting the real-time battery status data, including the battery capacity. In parallel, the mapping technique is implemented for each robot to forecast the shortest path, estimating the kinetic energy, energy consumption of the sensor system, and friction loss from the velocity of the robots for accomplishing the mission. And these data sets for the robots will be collected with the help of static and moving obstacles to estimate the shortest path because it depends on the position of the obstacles. Furthermore, by using this information, optimal path, and optimal energy path are predicted individually for all the mission robots. This allows for the calculation of each efficiency parameter of the robot. Additionally, it will determine the most appropriate robot for an unexpected task from other robots in different locations. The overview of the algorithm is illustrated in Fig.1.

The majority of the aforementioned trajectory generation algorithms determine only the shortest path, however, this does not necessarily mean that it is the best energy-efficient path for the robot. In order to optimize the path with regard

*This research is partially supported by the e-ASIA Joint Research Program (P-19-50869) Grant through the National Science and Technology Development Agency (NSTDA) and Mahidol University, Thailand.
The authors are with the Center for Biomedical and Robotics Technology (BART LAB), Faculty of Engineering, Mahidol University, Thailand. Email: jackrit.sut@mahidol.ac.th

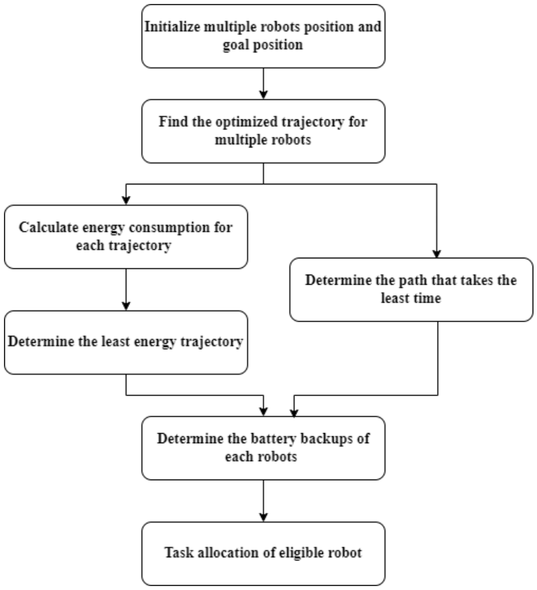

Fig. 1. Planning Framework

to energy and time, it is necessary to determine the overall energy consumption and losses throughout each operation. Additionally, it will also address the issues of path planning and identifying the proper robot. To do this, we need to evaluate the amount of energy utilized for the individual robots during the mission.

A. Energy Consumption Model

The power consumption of a rescue robot is an important factor that determines how much power is required during the mission; this will influence battery selection and specifics of battery management tactics. [11]. It is feasible to calculate the total power consumption of the robot by taking into account the power consumption of each electrical component. The total energy consumed by the robot is defined in equation (1)

$$E_{Total} = E_s + E_k + E_f + E_e + E_g \tag{1}$$

Where E_s, E_k, E_f, E_e, and E_g represent energy consumption by sensors, robot motion energy, friction energy losses, heat in the armatures of motors losses, and gear energy losses, respectively. The most energy-intensive components are motors, sensors, microcontrollers, and embedded computers [11]. The power consumption of these components could be estimated using power models [9]. Mechanical power is the sum of each actuator's torque and the motors' rotational angular velocity. As a result, the energy optimization problem has been transformed into a trajectory optimization problem [8]. From equation (1), the energy consumption of the mobile robot is divided into two parts: the sensors system, and the motion system.

1) Energy Consumption of the Sensor System: According to Huang, Jun S., et al., 2020 [4] the energy consumption of the sensor system is fairly constant. As a result, the electrical energy consumption (equation (2)) can be represented as

$$E_s = P_s \times dt \tag{2}$$

Where, P_s is the electrical power of the sensor system. In addition, the net energy consumption of the sensor is proportional to the speed of the robot [4]. So that, if V_{max} is the maximum speed of the robot then,

$$E_s = \frac{1}{V_{max}} \int (v * P_s) dt \tag{3}$$

2) Energy Consumption of the Motion System: Concerning the motion system, the energy consumed to attain and sustain robotic motion can be written as,

$$E_{motion} = E_k + E_f + E_e + E_g \tag{4}$$

Let E_k denote the kinetic energy of the robot, M_r denotes the mass of the robot and v represents the current moment speed of the robot, then

$$E_k = M_r * \frac{v^2}{2} \tag{5}$$

If μ is the friction coefficient between the wheel and the ground, then the equation (6) shows the friction dissipation during the movement of the robot is

$$E_f = \int (\mu * M_r * v) dt \tag{6}$$

In this study, we considered only the parameters E_f, E_K, E_S and because of their nonlinearity E_e and E_g are not included in this study as they require more attention and are being considered for future study.

III. Implementation of Algorithm

A. Dynamic Window Algorithm motion planning

Obstacle avoidance is a basic prerequisite for autonomous robots to move safely and perform tasks. [10]. The dynamic window approach (DWA) [1], unlike other avoidance approaches, is derived directly from the robot's dynamics and is specifically designed to deal with the constraints given by the robot's limited velocities and accelerations [7]. This is a velocity-based local planner that calculates a robot's ideal collision-free velocity for reaching its target. It converts a Cartesian goal (x, y) for a mobile robot into a velocity (v, ω) instruction. There are two main objectives to determine a valid velocity search space and to choose the best velocity. Given the set of velocities the robot can achieve in the next time slice provided its dynamics ('dynamic window'), the search space is created from the set of velocities, that produce a safe trajectory (i.e. allow the robot to stop before the collision). If v is the heading velocity and ω is the rotational velocity. Then, in order to prevent colliding with obstacles, a permissible speed set is determined [7] as follows:

$$V_a = \{(v, \omega) | v \leq \sqrt{2dist(v, \omega)\dot{v_b}} \wedge \omega \leq \sqrt{2dist(v, \omega)\dot{\omega_b}}\} \tag{7}$$

where dist(v, ω) is the shortest distance between the robot and the obstacle, and v_b and ω_b are the breakage accelerations. When the motors' accelerations are constrained, the entire search can be reduced into a dynamic window that only includes velocities that can be reached within the next time interval. The dynamic window V_d has the following definition [7]:

$$V_d = \{(v, \omega) | v \in [v_a - \dot{v}t, v_a + \dot{v}t] \wedge \omega \in [\omega_a - \dot{\omega}t, \omega_a + \dot{\omega}t]\} \quad (8)$$

where (v_a, w_a) is the actual velocity and t is the time interval during which v and w are applied. There are some scenarios where the Euclidean distance is insufficient to measure the actual distance traveled. [5]. Let x and y denote the Euclidean distance between two robots on the x- and y-axes. Then a robot's front view distance DS of a distant object is a Finsler distance provided by [5]

$$DS = x^4 + y^4 \quad (9)$$

It is the hypotenuse of formalized flying triangulation. The side view distance DB from a robot on a nearby object moving in a diagonal saddle is calculated as follows:

$$DB = x^2 y^2 \quad (10)$$

This is one of the right-angle edges. The variable then determines the distance between two moving robots. There is an aggregated measure f-norm called sum (AV) on a finite Finsler real manifold, where AV stands for Area Variable, a positive real number generated by a pair of neighbor points coordinate:

$$AV = \frac{\sqrt{DS - DB}}{2} \quad (11)$$

We made a simulation study on MATLAB (Mathworks Inc., USA). So as per the algorithm, the real-time battery state (Remaining energy) and optimum path of the individual mission robots will be estimated. From the trajectories of individual robots, it can identify which robot has the shortest trajectory. For the instantaneous operation identifying the proper robot depends not only on the trajectory of the robot but also on the energy consumption. Also, the closest Eucleadian distance of the robots to the target will not be easily achievable because of the obstacles around the robots. So, in order to avoid the obstacles robots need to consume so much energy. A robot must not only detect obstacles but also recalculate the detouring path and steer itself toward a safe and efficient path in real-time in order to avoid collision with them. When obstacles are in the path, the travel distance and time will increase as the robot spends more time and distance turning around the obstacles and avoiding collisions. It will result in motions depending on the sensing capabilities and the actual position of the mobile robot [2]. To do so, information from various sensors is received and integrated in order to determine the location of the robot, detect obstacles, and prevent collisions. To complete these tasks, the robot will require a better sensory system, a strong mechanical structure, and a reliable control system. As a result, more energy will be expended.

Secondly, the simulation will give the fastest robot (the robot that reaches the target first) and the value of the efficiency parameter can be calculated based on each robot that reaches the target. Let the real-time battery status of the individual mission robots is E_{bi}, the total energy consumption during the motion is E_{motion}, and the energy consumption of the sensor system is E_s, then the efficiency parameter:

$$K_i = \frac{E_{bi}}{E_{motion} + E_s} \quad (12)$$

The value of K can determine the most appropriate robot for assigning an instantaneous task during the rescue operation since the robots are distributed in different locations as mentioned above. From equation (12), the robot with a maximum value of K is the most suitable one; since the robot with the shortest trajectory does not necessarily have to satisfy the battery requirements of the task. Similarly, the path taken by the robot with the biggest battery backup is not the shortest. Likewise, the path of the robot with the largest battery backup will not be the shortest. A detailed description of the algorithm is represented in Figure. 2. A robot with maximum energy backup and with the least energy consumption will be the most eligible.

IV. Algorithm Evaluation and Result Analysis

The energy-optimized path planning and decision-making for multiple robots in the rescue operations method are tested here. It is used to evaluate and predict energy consumption and to provide a reference to avoid task interruption due to lack of energy. To validate this algorithm with simulation, we considered five similar robots distributed in different locations (Euclidian distances to the robots are different), and the battery state (battery backup) of the individual robots is considered constant and equal. The robot is then allowed to travel from different positions with the same friction coefficient. This path of each robot was generated using the Dynamic window approach. The maximum speed of all the robots is the same, but the number of obstacles that each robot must overcome is different. In the moving obstacle scenario, all the obstacles are moving at random velocity. Then we evaluated the energy consumption of each robot with the help of its velocity and meanwhile, it calculated the time for completing the task of each robot.

From the Figure. 3, we can see that all the robots are distributed in different positions, the horizontal and vertical axis describes the position of the robot and the blue squares represents the robot. Even if the goal (Red triangle) is the same, they have to overcome many moving and stable obstacles denoted by the black circles. And Figure. 4, 5, 6, and 7 denotes the kinetic energy, frictional loss, energy consumption of the sensor systems, and total energy used by the robots during the motion represented, respectively. In each figure,

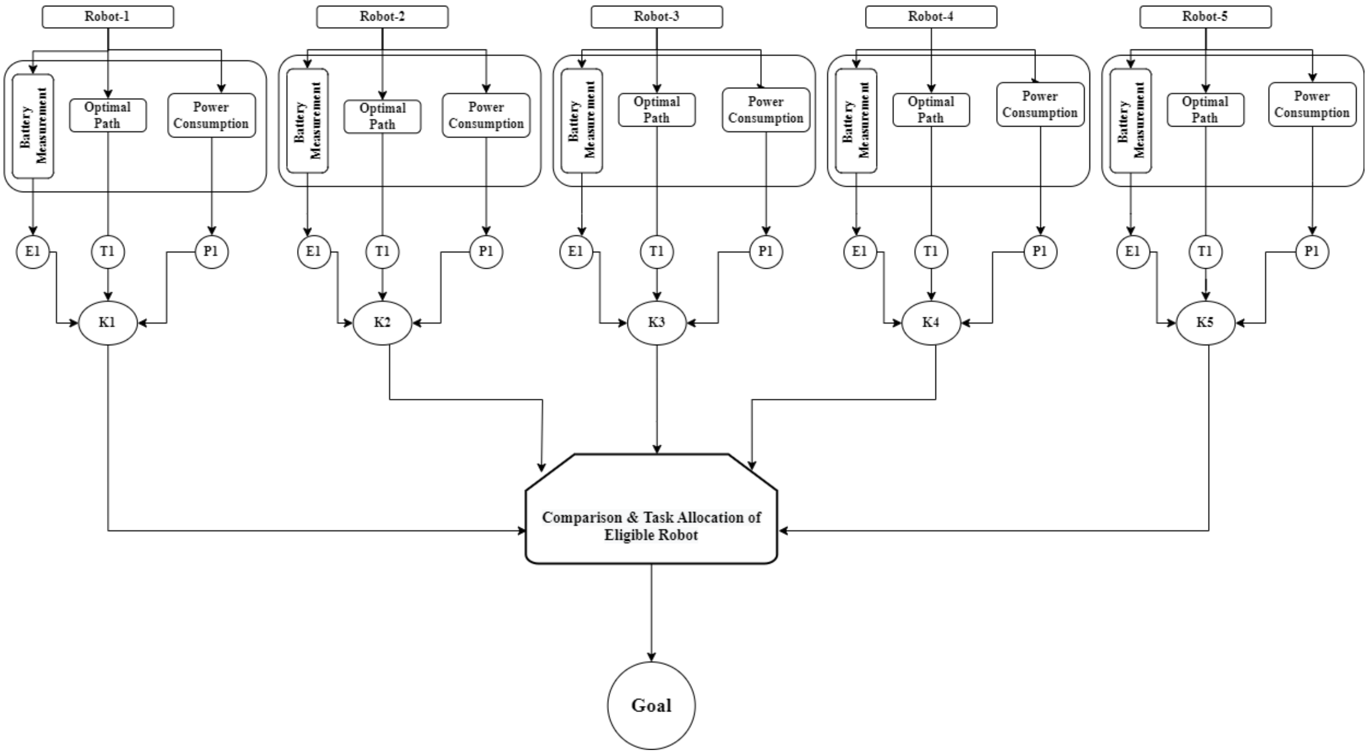

Fig. 2. Planning Framework

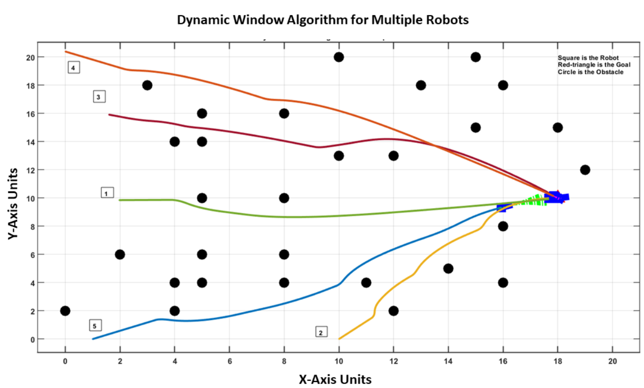

Fig. 3. The trajectory of robots through static obstacles

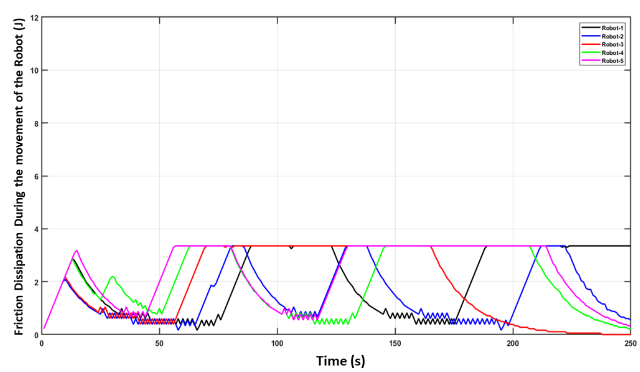

Fig. 5. The frictional loss of the robots

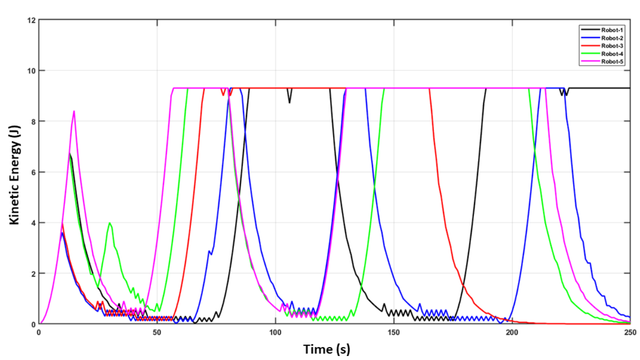

Fig. 4. The kinetic energy of the robots

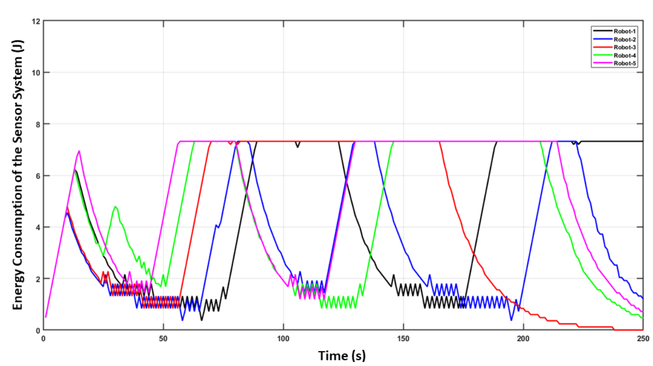

Fig. 6. Energy Consumption of the Sensor System

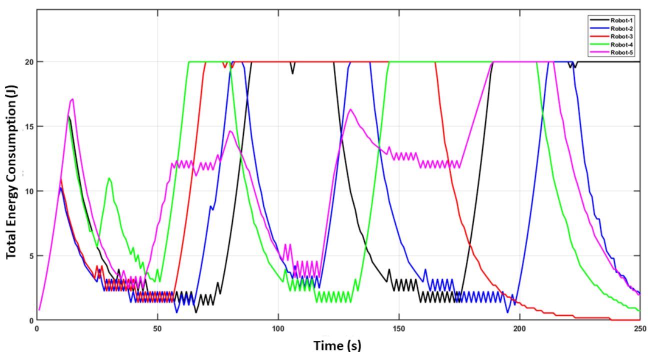

Fig. 7. The total energy used by the robots during the motion

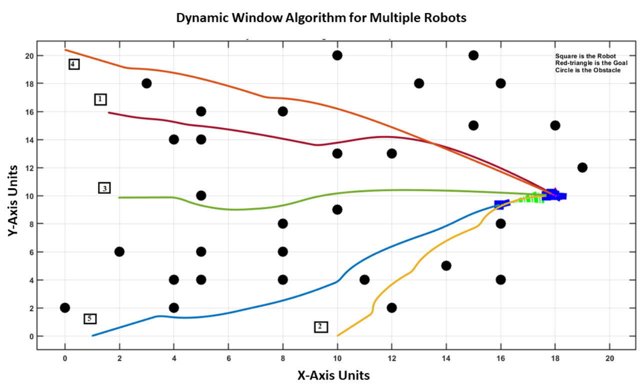

Fig. 8. The trajectory of robots through moving obstacles.

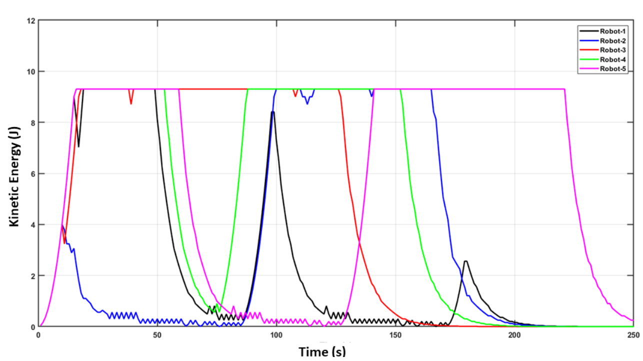

Fig. 9. The kinetic energy of the robots

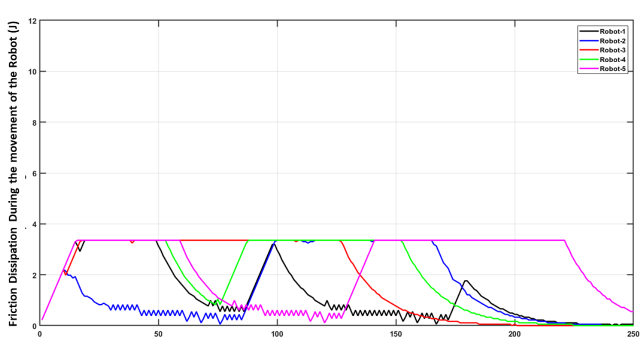

Fig. 10. The frictional loss of the robots

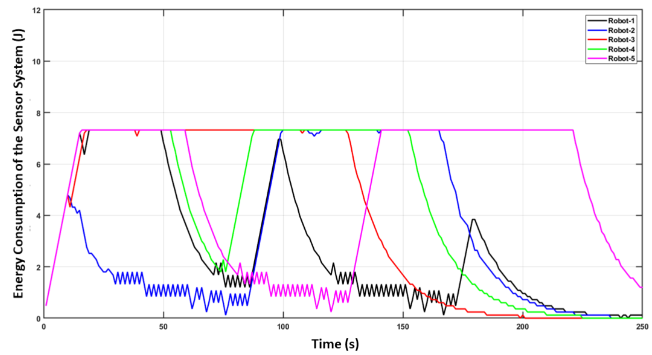

Fig. 11. Energy Consumption of the Sensor System

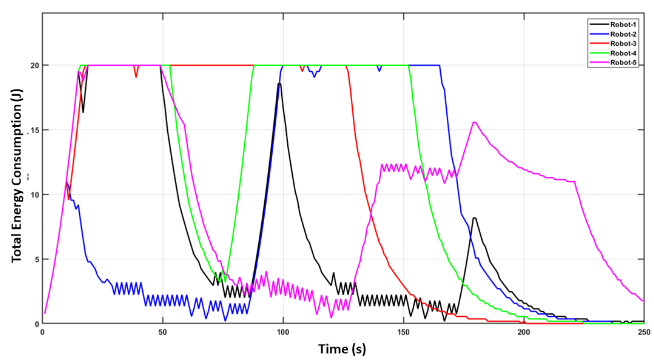

Fig. 12. The total energy used by the robots during the motion

the horizontal axis describes time, while the vertical axis highlights the energy consumed by each robot.

In the simulation Robot-1 reaches the target position firstly, then Robot-3, Robot-4, Robot-2, and Robot-5 reached the target respectively. But Robot-1consumes more energy than other robots, since it has fewer obstacles it was at maximum speed so it used maximum energy to reach the target. As mentioned earlier, the Dynamic-Window algorithm determines only the shortest path, however, this does not indicate that this path is the most energy-efficient. So, in order to avoid the obstacles robots need to consume so much energy and time. In the case of Robot-2, the linear distance to the target was shorter than other robots, but it only reached the fourth position, and Robot-5 was the last to arrive, taking a maximum of 299.96 seconds, and consuming as much energy as Robot-1. If Robot-3 consumes less power than Robot-1 and the battery backup of Robot-3 is higher than that of Robot-1, then it will be the most suitable robot for the task. From the figure, we can see Robot-3 consumed less energy than Robot-1 and arrived at the second position. But in the actual case, all robots will have different battery backups, which has to be considered important.

When considering the second scenario, where all the robots are maneuvering through moving obstacles(It is shown from Figure. 8 to Figure. 12). In the simulation, Robot-3 reaches the target position first, followed by Robot-2, Robot-1, Robot-4, and Robot-5 reach the target respectively. But Robot-3 consumes more energy than other robots as mentioned above. Since it has fewer obstacles, it was at maximum speed so it used maximum energy to reach the target. Even the linear distance to the target of the Robot-2 was shorter than other robots, but it was only able to reach second place. But in the midst of so many repetitions of the simulation, it got other positions. The last to arrive was Robot-5, which took the maximum amount of time (265.41 seconds) and expended the same amount of energy as Robot-3.

In the case of moving obstacles, the same robot will not be the first to arrive for every iteration, because its path is often created differently. Since their battery backup is a critical factor, it's important to know how much less power the arriver is using. But the simulations showed that the algorithm described here is feasible and effective. However, the experiments were carried out on a 2-D plane surface. The operation of a robot demands accelerating, stopping, turning, slowing down, moving uphill and downhill, and so on, all of which are not fully covered by the proposed simulation. And the time taken for simulation is also a concern, especially in moving obstacle scenarios. As a result, future studies should focus on completing the model based on all robot actions, and employ a better and more comprehensive experimental field. Moreover, the energy-optimized path planning and decision-making model is very important and is valid for the decision-making of autonomous rescue operations.

V. Conclusion

This study considered the challenges of decision-making and motion planning for multiple autonomous mobile robots in rescue operations, with the objective of energy optimization. An algorithm is developed to calculate and predict energy consumption before making a decision in order to improve the energy efficiency of a mobile robot in a rescue mission, which gives a solution to enable energy-efficient tactics. Four key components were addressed while evaluating the energy consumption of a mobile robot: the mobility system, the sensor system, the control system, and the trajectory of the robot. The results of the simulations indicate that the suggested energy model can be employed to estimate the energy consumption of robot rescue operations as well as can efficiently support the analysis of mobile robot energy consumption properties. The presented path planning algorithm can determine the suitable robot for the instantaneous task during rescue operations using the optimal trajectory of each robot with respect to the battery backup within a multi-robot system. Although all the operations of a robot are not entirely covered by the proposed simulation, it is still valid for the decision-making of autonomous rescue operations. Consequently, further research should aim to complete the model according to all robot actions and terrain.

References

[1] Dieter Fox, Wolfram Burgard, and Sebastian Thrun. "The dynamic window approach to collision avoidance". In: *IEEE Robotics & Automation Magazine* 4.1 (1997), pp. 23–33.

[2] Dieter Fox et al. "A hybrid collision avoidance method for mobile robots". In: *Proceedings. 1998 IEEE International Conference on Robotics and Automation (Cat. No. 98CH36146)*. Vol. 2. IEEE. 1998, pp. 1238–1243.

[3] Sajad Haghzad Klidbary, Saeed Bagheri Shouraki, and Soroush Sheikhpour Kourabbaslou. "Path planning of modular robots on various terrains using Q-learning versus optimization algorithms". In: *Intelligent Service Robotics* 10.2 (2017), pp. 121–136.

[4] Linfei Hou, Liang Zhang, and Jongwon Kim. "Energy modeling and power measurement for mobile robots". In: *Energies* 12.1 (2018), p. 27.

[5] Jun S Huang et al. "An Artificial Swan Formation Using the Finsler Measure in the Dynamic Window Control". In: *Int J Swarm Evol Comput* 9 (2020), p. 186.

[6] Haokun Kang, Caishan Liu, and Yan-Bin Jia. "Inverse dynamics and energy optimal trajectories for a wheeled mobile robot". In: *International Journal of Mechanical Sciences* 134 (2017), pp. 576–588.

[7] Xiuyun Li et al. "Obstacle avoidance for mobile robot based on improved dynamic window approach". In: *Turkish Journal of Electrical Engineering & Computer Sciences* 25.2 (2017), pp. 666–676.

[8] Changyou Ma et al. "Optimal energy consumption for mobile manipulators executing door-opening task". In: *Mathematical Problems in Engineering* 2018 (2018).

[9] Yongguo Mei et al. "A case study of mobile robot's energy consumption and conservation techniques". In: *ICAR'05. Proceedings., 12th International Conference on Advanced Robotics, 2005.* IEEE. 2005, pp. 492–497.

[10] Branesh M Pillai and Jackrit Suthakorn. "Challenges for novice developers in rough terrain rescue robots: A survey on motion control systems". In: *Journal of Control Science and Engineering* 2019 (2019).

[11] Preedipat Sattayasoonthorn and Jackrit Suthakorn. "Battery management for rescue robot operation". In: *2016 IEEE International Conference on Robotics and Biomimetics (ROBIO)*. IEEE. 2016, pp. 1227–1232.

[12] Bijo Sebastian and Pinhas Ben-Tzvi. "Physics based path planning for autonomous tracked vehicle in challenging terrain". In: *Journal of Intelligent & Robotic Systems* 95.2 (2019), pp. 511–526.

[13] Li Xie et al. "Power-minimization and energy-reduction autonomous navigation of an omnidirectional Mecanum robot via the dynamic window approach local trajectory planning". In: *International Journal of Advanced Robotic Systems* 15.1 (2018), p. 1729881418754563.

[14] Haojie Zhang, Yudong Zhang, and Tiantian Yang. "A survey of energy-efficient motion planning for wheeled mobile robots". In: *Industrial Robot: the international journal of robotics research and application* (2020).