Efficiency of Fuzzy Task Assignment in Heterogeneous Multi-robot System

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Abstract: Task assignment in heterogeneous multi-robot systems poses unique challenges due to the diverse capabilities of the robots. This article presents a study of a model in addressing the problem of task allocation within such systems, called task selection in heterogeneous mobile multi-robot systems, without communication, by decomposing complex tasks into elementary tasks. The study aims to reduce the time to complete tasks and improve the efficiency of the system. Ideal cooperation is defined by the criterion of accuracy in task selection by heterogeneous robots. The study shows that the problem is NP-hard when scaling by increasing the number of tasks and robots with different capabilities. The approach taken is called fuzzy decision making in selecting tasks. This latter is performed to evaluate a very high utility value related to the elementary task in the system, and another function is to evaluate the utility of the robot in the system that satisfies its capacity. The results show that our approach achieves better performance in terms of completion time, fairness of task distribution, and error probability. The approach can be applied to different real applications.

Keywords: Task Assignment, Multi-Robot,Accuracy, Utility, Fuzzy Decision

1. INTRODUCTION

In recent years, the field of robotics has witnessed significant advancements, particularly in the area of Heterogeneous Multi-Robot Systems (HMRS). These systems, consisting of multiple autonomous robots working together towards a common goal. With the advancement of technology and robotics research, the Heterogeneous Mobile Multi-Robot System (HMMRS) can play an increasingly important role by applying them in various fields, including (the military field, the commercial industrial field, etc..). Among these applications to name a few, the process of loading and unloading cargo in an industrial park Bauters et al. (2015). A (HMMRS) refers to a network of autonomous robots with diverse capabilities, physical characteristics, and functionalities cooperative to accomplish complex tasks, by distributing them to many robots Correll (2005). The heterogeneity of robots in a distributed multi-robot system brings forth numerous advantages. Firstly, different robot types can complement each other's strengths and weaknesses, allowing the system to handle a broader range of tasks Verma and Ranga (2021). Secondly, the diversity in robot capabilities enables allocation by decomposing the complex task within the system into elementary tasks. This decomposition can facilitate completing this complex task in parallel and distribute the sub-tasks among them Mataric (1994). Or what is known as Parallel Dynamic Task Allocation (PDTA) Teggar et al. (2021)Bai et al. (2022). Thirdly, heterogeneity enhances system resilience Prorok et al. (2021) and adaptability. In the face of failures or changing environmental conditions, heterogeneous systems can dynamically adjust their strategies and redistribute tasks among the available robots, ensuring that the complex task is still accomplished. However, HMMRS presents a special set of challenges to find the most effective collaboration strategy and best task distribution between robots in order to solve the problem of task allocation for each robot, and to get the most usefulness possible Gerkey and Mataric (2002)Hamza et al. (2022), in order to achieve standards such as reduced time and energy consumed Yan et al. (2012). In the literature, there are several approaches used in coordinating multi-robot systems and dealing with task allocation. Where these methods are classified according to the decision-making on how to allocate tasks. One approach is to use task allocation methods, where the tasks to be performed are assigned to different robots based on their capabilities and the requirements of the task. This can be done through a centralized or distributed mechanism, depending on the complexity of the task and the size of the system Gerkey and Mataric (2002) Liu et al. (2015). Another approach to achieving coordination in (HMMRS) is to use decentralized control techniques, where each robot makes decisions based on local information Verma and Ranga (2021). This approach is particularly useful in large-scale systems. There are two types of coordination in decentralized allocation . The first type, intentional coordination, refers to the explicit communication and collaboration strategies employed by the robots to achieve their common goals. There is also a second type of decentralized allocation, which is emergent coordination that can occur without explicit communication between the robots. These coordination mechanisms rely on local interactions and implicit information exchange. In emergent task allocation, robots dynamically self-organize to perform tasks without explicit communication. Each robot assesses its local environment and makes decisions based on its own knowledge and sensing capabilities Gerkey and Matarić (2004)Zlot et al. (2002)Teggar et al. (2021)Rechache and al (2022) .Through local interactions, the robots collectively achieve a global task allocation that optimizes overall system performance. We adopted this emerging coordination approach in our research. This paper investigates the challenge of assigning tasks to robots in (HMMRS) without direct communication, enabling them to collaboratively accomplish complex tasks by decomposing it into elementary tasks. Specifically, the complex task involves transferring various types of dispersed goods from source stations to a single consumer station in the desired proportions, considering each robot's capacity. The consumer station also requires specific quantities of each type of merchandise. Given the differences in robot capabilities and the increasing number of robots and tasks, the problem becomes NP-hard, necessitating approximate solutions. Our main contribution is the development of a fuzzy system called Fuzzy Decision-Making in Task Selection (FDM-TS) to address this challenge using fuzzy logic. This system allows robots to determine which tasks to undertake. The FDM-TS operates in two stages: the first stage evaluates and calculates the robot's utility function, and based on these results, the second stage is activated to evaluate and compute the task's utility function. This is how the rest of the article is structured. Works on the assignment problem are presented in the next section. Through Section 3 introduces, the complex task decomposition model and the suggested strategies in the task allocation model. The Task Selection process in Heterogeneous Mobile Multi-robot system (TSHMMR) is implemented using fuzzy logic, as described in Section 4. The analysis in Section 5 is followed by the discussion of the result. Section 6 that concludes the article.

2. RELATED WORK

Overall, task decomposition plays a crucial role in effectively accomplishing complex tasks in multi-robot systems Rizk et al. (2019). Task decomposition refers to breaking down a complex task into smaller sub-tasks , that propose the decomposition of complex tasks into independent sub-tasks using a tree structure. This decomposition allows for parallel execution of subtasks, which can lead to improved efficiency . For instance, the soccer robot system's task decomposition Chen et al. (2010). Many systems decompose a complex task manually, can break it down into sub-tasks Dorigo et al. (2013). Researchers have developed different models and algorithms to study emerging collaboration without communication and allocate tasks between robots. These models often rely on local interactions, where robots observe and respond to the behavior Zheng and Yuan (2021) and the state of their neighboring robots without explicitly exchanging information. A mathematical model based on the dynamic assignment of tasks without communication in in Gerkey and Matarić (2004), with the assumption that the robot evaluates the state of the environment, it can use these observations to make decisions regarding task selection and integration into its local plan. The specific form of a utility function can vary depending on the goals and criteria of the task assigned process. The purpose of the task assignment process is to maximize certain objectives or criteria, which could include factors like efficiency, cost-effectiveness Gerkey and Matarić (2004). In contrast to algorithms that allocate work in a static and random manner, and to calculate the value of the utility function, the author Dahl et al. (2009) proposed a method based on chains of vacancies for task distribution in a multi-robot system. Another research project about resilient task allocation in heterogeneous multi-robot systems by Mayya et al. (2021) refers to the process of efficiently assigning tasks to different robots with varying capabilities. There are several AI approaches that can be utilized in such systems to enhance their coordination, communication, and overall performance. Among these are those presented by Wang and de Silva (2008), A machine learning technique to direct robots and deal with the problem of task assignment in an erratic and dynamic environment. Another recently developed approach by Bai et al. (2022) called Group-based Distributed Auction Algorithms for Multi-Robot Task Assignment, entails having a big flotilla of robots to transfer a series of scattered packets from their originating points to the proper destinations within predetermined time intervals. To allocate tasks through the Task Allocation model in Heterogeneously mobile Multi-Robot System (TAHMMRS), and to calculate utility functions, we used fuzzy logic, which has been used in many studies. Of between it, a proposed method of dynamic task allocation by Tsalatsanis et al. (2012), Fuzzy logic has been used to compute utility functions, which measure the robot's capacity to execute a task. Fuzzy logic as well used in Islam and Akhtar (2017) the simulation was evaluated to show how well it reduced the amount of energy needed to perform the tasks in an ant colony. In addition, the Fuzzy predictor was used by Teggar et al. (2021), when sub-tasks are distributed to many robots at the same time, it is referred to as the Parallel Task Dynamic Assignment process (PTDA). In Rechache and al (2022) also, another method based on fuzzy decision-making has been used for task selection in multi-robot systems (TSMRS), without communication, based on decomposing complex tasks into elementary tasks. However, despite numerous studies in the field of robotics, there remains a shortage of research specifically addressing task allocation in multi-robot heterogeneous systems. In this research, we propose a method to enhance effectiveness and accuracy in solving task allocation challenges within these systems.

3. DESCRIPTION OF THE MODEL

3.1 Formulating the Problem

In the model depicted in Fig. 1, (Graphic representation A) the group of robots R utilizes an information library PI about their environment Z, to define the tasks to be performed, represented by a complex task T decomposed into sub-tasks. This model draws inspiration from warehouse management operations, where goods are transported from "source station" warehouses to "consumer station" destinations in accordance with regulatory constraints.

The proposed model, (Graphic representation B), for task selection relies on evaluating the accuracy and utility of task execution $U(t_i)$(including observations and error estimation) to minimize performance errors.

The utility $U(r_k)$ of the robots is determined by observing the type of task and their capacity. Tasks are selected based on information gathered at the control area before entering the operational area. Each robot gathers information about the operational area, considering the density of robots and type of tasks to be completed.

During the task planning process, robots assign tasks to themselves based on their capacities and the utility of tasks they have already undertaken.

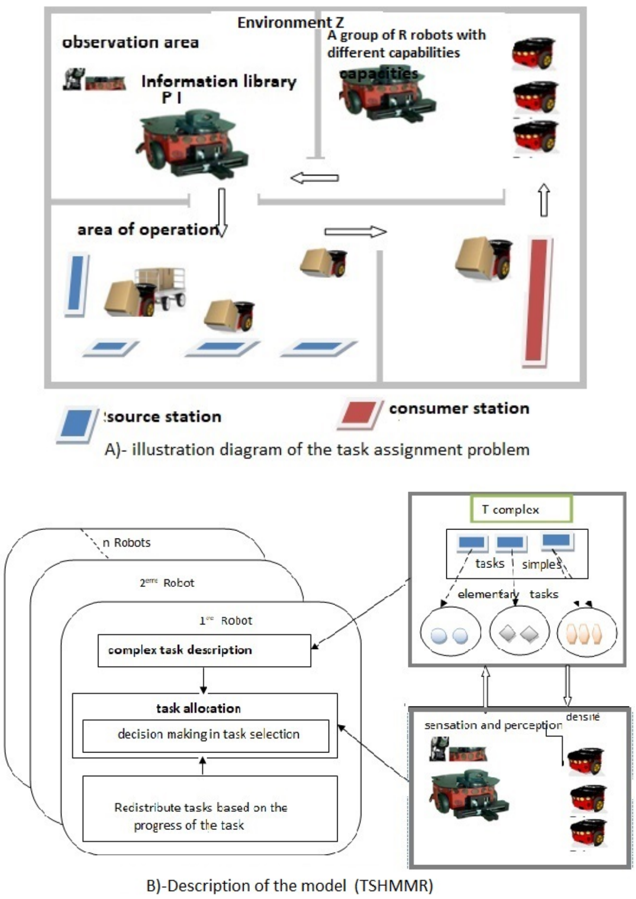

Fig. 1. Schematic diagram of task selection in heterogeneous mobile multi-robot systems.

3.2 The model(TSHMMR)

In this paper, the model revolves around Task Selection in Heterogeneous Mobile Multi-Robot Systems (TSHMMR). The robots self-organize, fostering cooperation among them without direct communication, to execute tasks based on their individual capacities.

The model (TSHMMR) is an extension of the model (PDTA) presented in (Teggar et al., 2021)(Hamza et al., 2022) by introducing new constraints on task assignment operations in multi-robot systems in a specific environment.

The proposed model is based on representing the complex task and selecting sub-tasks, depicted in Fig. 2. Fig. 3 illustrates the decomposition of a complex task into three hierarchical levels within a tree structure. The task assignment function specifies the elementary tasks that need execution at any given time. This selection is based on the progress of the complex task during execution. The ultimate goal is to minimize errors in task accomplished..

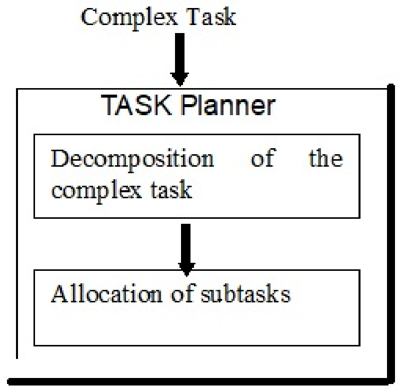

Fig. 2. Processes related to the proposed model.

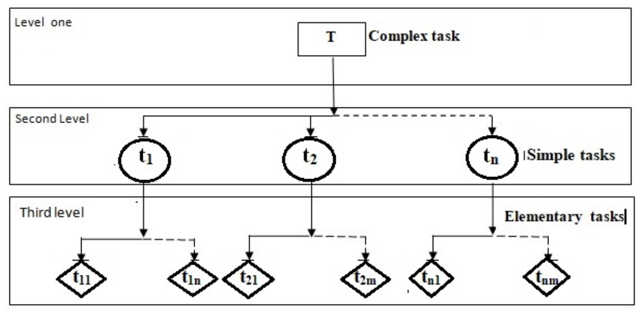

Fig. 3. Decomposition of complex task into 3 levels .

3.3 Decomposition of complex task

In this study, the proposed model initially involves decomposing complex tasks into three levels. The first-level node is the root T (representing the complex task T), and the n nodes at the second level represent a set of simpler tasks resulting from the decomposition of $T = t_1, t_2, .., t_n$ denoted as t_i. Each $t_i$is further decomposed into m elementary tasks, represented by nodes t_{ij} of the same type , at the third level, where $t_i = t_{i1}, t_{i2}, .t_{ij}, ..t_{im}$. The process for decomposing the complex task follows a predefined program.

In this model, elementary tasks can be performed concurrently (Teggar et al., 2021). Moving from an initial position (Ps) to an final point $(Pe)$is defined as completing one or more elementary tasks, represented as $t : Ps \mapsto Pe$.

Assuming that the number of elementary tasks Nt_i may vary across different simple tasks and NT represents the total number of elementary tasks composing T (task complex).

Each elementary task $\{t_{ij} \mid 1 \leq i \leq n$ **and** $1 \leq j \leq m\}$ cannot be decomposed, and each t_{ij} can only be accomplished by one robot. In the proposed model, the desired ratio of execution of a simple task i denoted by $\phi(t_i)$, is defined as follows:

$$\phi(t_i) = \frac{Nt_i}{NT} \; with \; NT = \sum_{i=1}^{n} Nt_i \tag{1}$$

For example, let the complex task $T = t_1, t_2, t_3$ **with** $t_1 = \{t_{11}, t_{12}\}$ **and** $t_2 = \{t_{21}, t_{22}, t_{23}, t_{24}\}$ **and** $t_3 = \{t_{31}, t_{32}, t_{33}\}$ then the ratios are $\phi(t_1) = 2/9$ **and** $\phi(t_2) = 4/9$ **and** $\phi(t_3) = 3/9$

3.4 ***Task selection in heterogeneous Mobile multi -robot systems (TSHMMR).***

The objective of this model is to provide a solution to the task allocation problem (HMRS), where robots engage in emergent cooperation. To address this, the task assignment problem is approached as a task selection issue within a heterogeneous multi-robot system (TSHMMR). Task selection involves robots reassigning tasks dynamically based on the progress made in completing a complex task.

The group of robots $R : \{r_1, r_2, ..., r_k\}$ consists of k heterogeneous robots capable of independently selecting and performing tasks of type t_i based on their capacities Cr_k, without direct communication. The set $\acute{T}$ represents the tasks actually completed by robots. Initially, $\acute{T} = \emptyset$ at the mission's outset, gradually populated as each robot finishes executing its elementary tasks t_{ij}. Each elementary task t_{ij} is executed by a robot according to its capacity and added to the corresponding set of the same type $\acute{t_i}$ indexed as t_{ix}, where $x = N\acute{t_i} + Cr_k$ and $N\acute{t_i}$ denotes the number of tasks executed. This information is stored in the control area for future reference by remaining robots preparing to enter the operational zone. There may be situations in the system where the number of tasks executed by the NB_r, number of robots may be higher. In other words, $Nt_i < N\acute{t_i}$ and $Nt_i < NB_r$, and every robot has decided to perform the same simple task t_i simultaneously.
Keeping in mind that the robots are fully autonomous, so a robot can only choose one or more elementary task t_{ij} if and only if :

$$\rho(t_i) < \phi(t_i) | \; \forall \; t_{ij} \in t_i \tag{2}$$

with $\phi(t_i)$ is the desired ratio in the execution of tasks of type i, $\rho(t_i)$ is the rate of progress given by:

$$\rho(t_i) = \frac{N\acute{t_i}}{NT} \tag{3}$$

$$\forall \; t_i \in T \; , \; \rho(t_i) > \phi(t_i) \tag{4}$$

Equation 4 is a criterion for stopping the task selection process.

Process of cooperation: This research develops a utility model to evaluate emergent cooperation in task assignment and the performance of robots to complete elementary tasks t_{ij} according to the desired ratio $\phi(t_i)$. In this section, new criteria are established to calculate the Accuracy of the cooperative process and assess the performance of the multi-robot system.

To enter the operational area, robots pass through the control area to gather information and determine their utility based on their capacity relative to the existing simple tasks t_i. Information about each simple task is represented by a Matrix Information (MI), where each task includes its own data tuple, as shown below:

$\{\rho(t_i), \phi(t_i), Nt_i, N\acute{t_i}\}$

Where $\rho(ti)$ denotes the progress of task t_i , $\phi(t_i)$ represents its desired ratio, Nt_i is the total number of elementary tasks of t_i, and $N\acute{t_i}$ is the number of elementary tasks executed for t_i .

Accordingly, the utility of each robot $\forall r_k \in R$ as a function of its capacity Cr_k for each task $\forall t_i \in T$ is calculated as follows:

$$U(r_k, t_i) = \begin{cases} \dfrac{Cr_k}{Nt_i} & if \; Cr_k \leq Nt_i \; and \; (\forall \; t_i \in T \; , \; \rho(t_i) < \phi(t_i)) \\ 1 & \text{Otherwise} \end{cases} \tag{5}$$

We take Example 1 to calculate the utility of a group of three robots, $R\{r_1, r_2, r_3\}$,each with its own capacity, $Cr = (3, 2, 1)$.
$Cr_1 > Nt_1 \; then \; U(r_1, t_1) = 1, \; U(r_1, t_2) = 3/4, \; U(r_1, t_3) = 3/3,$
$U(r_2, t_1) = 2/2, \; U(r_2, t_2) = 2/4, \; U(r_2, t_3) = 2/3$
$U(r_3, t_1) = 1/2, \; U(r_3, t_2) = 1/4, \; U(r_3, t_3) = 1/3.$

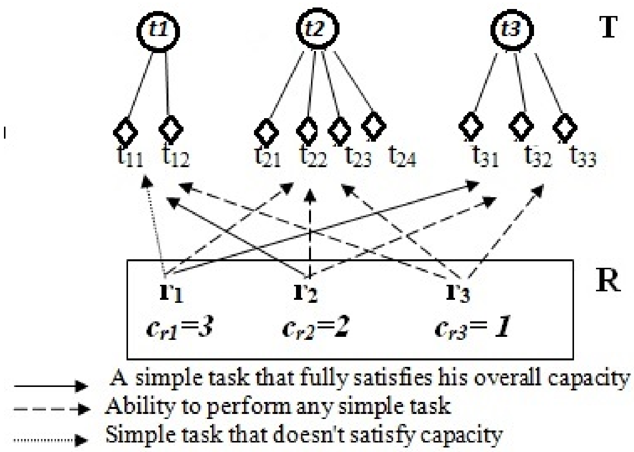

Fig. 4. illustrates the importance of calculating the utility of each robot according to its capacity regarding the simple tasks t_i that satisfy it.

The example shown in Fig. 4 demonstrates that robots can perform any task within the group, aiming to select tasks that are most suitable for them. However, robots may struggle with tasks that do not align with their capabilities.

This study focuses on the utility of robots when their capacity is less than or equal to the number of elementary tasks.

While task execution progress is below the system's desired ratio, all robots must continue working. That is,
$\forall t_i \in T \;\; \rho(t_i) < \phi(t_i)$.
We define the relative error E to assess the significance of

the decisions made by the robots when executing a simple task t_i by

$$E(t_i) = \frac{Nt_i - N\acute{t_i}}{Nt_i} \quad (6)$$

It can be expressed as follows:

$$E(t_i) = 1 - \frac{N\acute{t_i}}{Nt_i} \quad (7)$$

According to equation (7), the execution error of a complicated task is the total of all the absolute values of relative errors $E(t_i)$, granted by:

$$E(T) = \sum_{i=1}^{n} |E(t_i)| \quad (8)$$

and Accuracy is defined as :

$$A(T) = \begin{cases} \frac{1}{E(T)} & \text{if } E(T) \neq 0 \\ \epsilon & \text{if } E(T) = 0 \end{cases} \quad (9)$$

The parameter ϵ represents the threshold for absolute accuracy in the task assignment process. Additionally, ϵ serves as a criterion to determine when to terminate the task allocation process.

The objective of the systems (TSHDMR) method is to find a robot-task allocation that maximizes accuracy $Max(A(T)$ while minimizing decision-making errors $Min(E(T)$.

$$Max\left(\frac{1}{E(T)}\right)_{subject\ to\ E(T)\neq 0} \quad (10)$$

$$Min\left(\sum_{i=1}^{n} |E(t_i)|\right)_{subject\ to\ \rho(t_i)<\phi(t_i} \quad (11)$$

Determining the optimal solution becomes increasingly challenging as the number of tasks and robots grows, rendering it an NP-complete problem. Consequently, this necessitates the use of approximation techniques.

4. PROPOSED METHODOLOGY

4.1 Simple Strategy for Decision-Making in the Execution of Simple Tasks (DM-EST Strategy)

To evaluate the performance of the model, we define a simple strategy that allows the robot to make the decision to choose the type of its future tasks according to its absorption capacity, based on the prediction of the relative error, to minimize the complex task error.

Definition 1: Let's the Decision-Making be defined as follows:

$$\acute{E}(T, f) = \acute{E}(t_f) + ((E(T) - |E(t_f)|) \quad (12)$$

The Decision-Making $\acute{E}(T, f)$ allows for determining whether a simple task t_f will be executed in the future while performing the complex task T. Here, $\acute{E}(t_f)$ represents the decision-making process regarding the execution of the simple task t_f, enabling the robot r to select future elementary tasks associated with t_f based on its capacity Cr_k.

$$\acute{E}(t_f) = 1 - \frac{N\acute{t_f} + Cr_k}{Nt_f}_{\quad with 1\leq f\leq |T|} \quad (13)$$

Or

$$\acute{E}(t_f) = 1 - \left(\frac{N\acute{t_f}}{Nt_f} + \mu(r_k, t_f)\right)_{1\leq f\leq |T|} \quad (14)$$

Definition 2 : A simple strategy enables the selection of one or more tasks that match the utility and capacity of each robot from all potential future simple tasks. This strategy aims to minimize errors in the completion of complex tasks.

$$\begin{aligned} argmin\acute{E}(T, f)_{\substack{1\leq i \\ f\leq |T|}} &= \{t_f | \rho(t_i) < \phi(t_i \\ and\ \ \acute{E}(T, f) < \acute{E}(T, i)\ and\ Cr_K &\leq Nt_f\} \end{aligned} \quad (15)$$

In heterogeneous mobile multi-robot systems, where robots collaborate in task allocation without direct communication, multiple robots might independently select and attempt to execute the same tasks using a simplistic approach, which can lead to potential systemic dysfunction. To address this issue, a solution based on fuzzy decision-making has been proposed.

4.2 Fuzzy Decision-Making Strategy for Task Selection: FDM-TS

In this section, fuzzy logic is applied (Zadeh, 1965) to address the challenge of non-cooperative robot behaviors, specifically in decision-making (Hentout et al., 2023) when multiple robots attempt to execute the same task simultaneously. Thus, robots need to assess their decisions carefully to select the most appropriate task, considering both the utility of the robot in task execution and the anticipated error.

As discussed in the preceding Section 3, the proposed model focuses on enabling robots to decide on the execution of multiple tasks rather than just one. The utility of a task being performed by a robot r1 is represented as, $t_i = 1$, while for another robot r2, it might be $t_i = 0$. Moreover, the utility of a robot is determined by its capacity to execute a task, denoted as r=1 if capable, otherwise r=0.

The primary objective of this study is to maximize the utility of robots in task execution by fully utilizing their capacities, ensuring compatibility between the robot's capabilities and the type of task assigned, thereby optimizing task utility.

- A first utility function :$\mu_r : r_k \longrightarrow [0, 1]$ associates an importance value ranging from 0 and 1 of $r_k \in R$ / The highest value reflects the robot's capacity and capability to perform tasks effectively.
- Second utility function :$\mu_t : t_n \longrightarrow [0, 1]$ associates an importance value between 0 and 1 of $t_i \in t_n$ / The highest value is given to the task deemed most critical or essential . (Tsalatsanis et al., 2012).

In the proposed model, there isn't a mathematical method to explicitly define the utility function of tasks. Therefore, we propose describing these functions using variables within the framework of fuzzy logic (Zadeh, 1965).

By incorporating a fuzzy decision-making process, we assign a significant utility value to the simple task t_f that most effectively minimizes the error $E(T)$ associated with the complex task (Teggar et al., 2021; Rechache and al, 2022). It is important to note that the robot has the following knowledge :

- Decision-Making to choose t_f: $\acute{E}(T, f)$
- Robot observations r_k: $Ob(r_k)$ the density of active robots in the system.
- Observation of task type $t(i)$ suitability for each robot: $Ob(t_i)$

a- Variable Description

The robot's environment data is encapsulated in the following variables:

Task Observation: The variable $Ob(t_i)$ captures observations about the types of tasks that have not yet been executed. This information is collected at the control point before the robot enters the operational area. Using $Ob(t_i)$, each robot determines which future tasks align with its capacity and decides to undertake them accordingly.

Robot Density Observation: The variable $Ob(r_k)$ reflects the observation of the density of active robots within the operational area. Each robot relies on its sensors (e.g., cameras, proximity sensors) to detect the presence of other robots.

Error Prediction ($\acute{E}(T, f)$): Predicts errors associated with task execution.

These variables are continuously updated by each robot during decision-making cycles, allowing them to dynamically adjust their strategies based on current conditions.

To effectively predict the utility of future tasks t_f and the utility of the robot itself, the three variables—$\acute{E}(T, f)$, $Ob(t_i)$, and $Ob(r_k)$—serve as input parameters for the fuzzy decision-making process.

The fuzzy decision-making framework, based on Mamdani's model (Mamdani and Assilian, 1975), operates in two sequential phases. The first phase triggers the second phase upon reaching specific threshold values. The inference rules used to describe the fuzzy controller are interpreted as follows:

- Phase 1 *The Observation $Ob(t_i)$ of task type is used to determine the importance of the future task, through which he determines his robot utility, by comparing his capacities to the type of this task, which increases the selection decision if it is suitable for his capacity .*

If the desired value is satisfied, the second phase can be validated.

- Phase 2 *In the scenario when there is a very large density of active robots, the observation $Ob(r_k)$ is utilized to decrease the importance of the task t_f, and the value of $\acute{E}(T, f)$ is very low, because it is highly possible that another robot will choose a task of the same type of t_f as its future task. On the other hand, The predictor prioritizes another task t_i more highly such that $\acute{E}(T, i) > \acute{E}(T, f)$ however, an active robot is less likely to select it.*

b - FDM-TS Implementation

b.1 Fuzzification :Implements the fuzzy

Decision- Making by the following membership functions:

Function 1- input of the first fuzzy variable (Estimation of errors in the execution of complex tasks) Fig 5

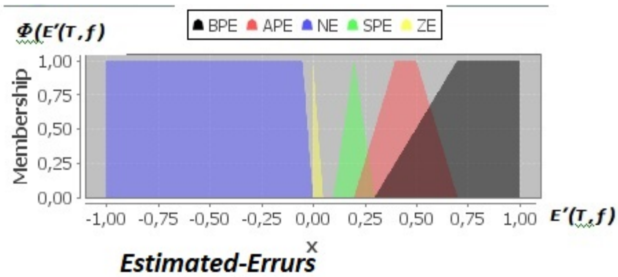

Fig. 5. Estimation of errors in the execution of complex tasks

Function 2- input of the second fuzzy variable (Observation on the density of active robots) Fig 6

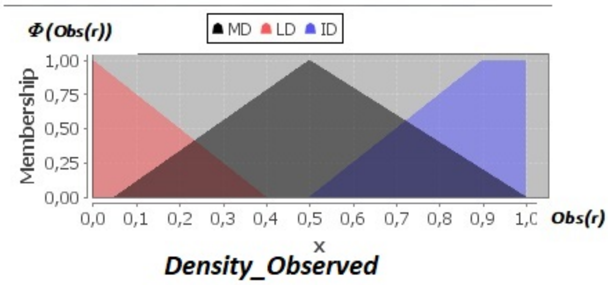

Fig. 6. Observation on the density of active robots

Function 3- the third fuzzy input variable (Observe the type simple task ti) en function of capacity robot Fig 7

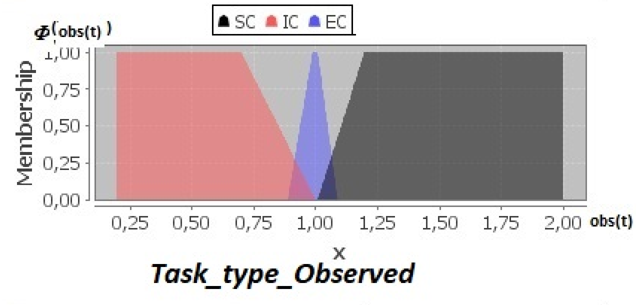

Fig. 7. Observation the type of simple task type t_i

Function 4- the fuzzy output variable (Utility robot) Fig 8

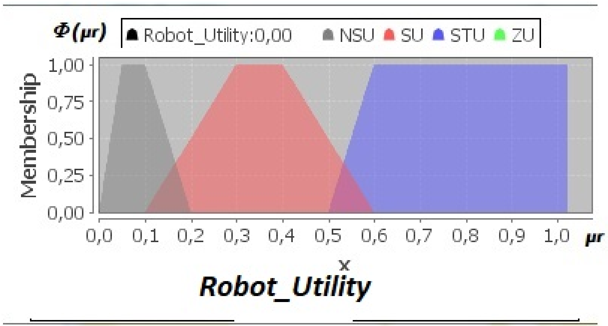

Fig. 8. Utility of Robot

Function 5- the fuzzy output variable (Utility of Future Tasks) Fig9

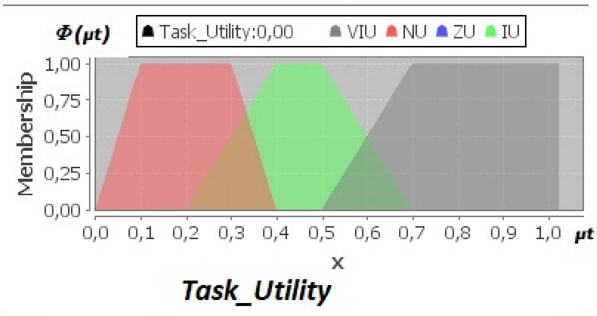

Fig. 9. Utility of Future Tasks

Table 1. fuzzy input variables

variable error	variable observation	variable observation type of task
ZE:zero error	LD:low Density	IC :Iinferior that Capacity of robot
SPE: Small positive error	MD:Moderate Density	EC: Equal that Capacity of robot
PE: Positive Error	ID:Intensive Density	SC: Superior that Capacity of robot
BPE:Big Positive Error		
NEG: Negative Error		

Table 2. fuzzy output variables

variable utility task	variable utility Robot
ZU:Zero Utility	NSU: No Satisfactory Utillity
NU:Negligible Utility	SU: Satisfactory Utility
IU:Important Utility	STU:Satisfactory Totally Utility
VIU:Very Important Utility	

- Inference rules

This step concerns the development of the rules, to define the utility of the robot by defining the importance of the future task of the robot that satisfies its capacity, according to its parameters.

As a first phase, for each set of input variable values, an action on the output variables is associated with it. In total, we obtain 9 fuzzy rules with one rules dominate. The following table summarizes all the rules:

Table 3. The inference rules of phase 1

Expected error	Observation Obs(t_i)		
	IC	EC	SC
ZE	STU	STU	NSU
SPE	SU	STU	NSU
PE	SU	STU	NSU
NEG		NSU	

Examples for illustrated this table as follows:

$1 - IF\ Error\ IS\ NEG\ THEN\ Robot\_Utility\ IS\ NSU$

$2 - IF\ Error\ IS\ ZE\ AND\ observation\_type\ IS\ IC\ THEN\ Robot\_utility\ IS\ STU$

$3 - IF\ Error\ IS\ SPE\ AND\ observation\_type\ IS\ IC\ THEN\ Robot\_utility\ IS\ SU$

....

Another step concerns the development of the rules, to define the utility of the tasks by defining the importance of the future task of the robot, compared to the density of active robots, according to its parameters.

This phase can be activated, when the domain of real values, in the defuzzification of first phase of robot utility fuzzufication reaches a desired value. (See b.2 - Defuzzification.)

Through the second phase, for each set of input variable values, an action on the output variables is associated with it. In total, we obtain 9 fuzzy rules, with one rules dominate. The following table summarizes all the rules:

Table 4. The inference rules of phase 2

Expected error	Observation Obs(t_r)		
	LD	MD	ID
ZE	VIU	NU	ZU
SPE	IU	NU	NU
PE	NU	IU	IU
NEG		ZU	

Examples for illustrated this table as follows:

$1 - IF\ Error\ IS\ NEG\ THEN\ Task\_Utility\ IS\ ZU$

$2 - IF\ Error\ IS\ ZE\ AND\ Observation\_robot\ IS\ LD\ THEN\ Task\_Utility\ IS\ VIU$

....

b.2- Defuzzification:

This point enables the transformation of the values of the linguistic variables used in decision-making from the fuzzy setting to the reals value domain. In the case of FDM.TS, we will use the center of gravity method (Mamdani and Assilian, 1975), which can be determined by

- In the first phase the defuzzification using the general relation:

$$\mu r_k^{*CDG} = \frac{\sum_{i=0}^{n} \mu r_k.\phi(\mu r_k)}{\sum_{i=0}^{n} \mu r_k} \quad (16)$$

Where μr_k^{*CDG} is the utility robot's actual value in relation to the task t_i that was chosen in the future. This valuse can be activates the second phase of fuzzufication to select future elemental task t_i when $\mu r_i >= 50$

- In the second phase the defuzzification using the general relation:

$$\mu t_f^{*CDG} = \frac{\sum_{i=0}^{n} \mu t_i.\phi(\mu t_i)}{\sum_{i=0}^{n} \mu t_i} \quad (17)$$

Where μt_f^{*CDG} represents the actual value utility associated with the robot's choice of the future task (t_i).

4.3 ***Fuzzy Decision-making algorithms***

Algorithms are used to apply the same rules of fuzzy decision-making on all robots.

- The robot makes the decision on future tasks to be assigned according to its capacity and observing the $ob(t)$ type of task by Algorithm 1 as follows:

Algorithm 1 (utility robot) Fuzzy Decision-making algorithm

```
input : T, T́, C_r, ob(t);
output t_f:
maxUtility(robot) = analyze the decision-making process using the inputs É(T, f), Ob(t_i);
t_f = t_1;
i = 2;
while (i ≤ |T|) do
  μr_k =estimate the Decision making with inputs. É(T, f), Ob(t_i) ;
  if (μr_k > maxUtility(robot)) then
    t_f = t_i
    maxUtility(robot) = μr_k
  end if
  i = i + 1
end while
if (maxUtility(robot) > 0) then
  return t_f
else
  return null;
end if
```

- To activate the second phase of decision making in task assignment, the following algorithm 2is used:

Algorithm 2 Fuzzy Decision-making algorithm activate

```
input the set : T, T́, μr_k
if the desired value μr_k is reached then
  activate the calculate (maxUtility(task)
else
  return null;
end if
```

- The robots activate the decision-making to assign the future tasks according to the observation of the robots density $ob(r)$ by the algorithm 2 as follows algorithm 3:

Algorithm 3 (utility task) Fuzzy Decision-making algorithm

```
input set : T, T́, ob(r)
output t_f
maxUtility(task) = analyze the decision-making process using the inputs É(T, f), Ob(r);
t_f = t_1;
i = 2;
while (i ≤ |T|) do
  μt_i = estimate the Decision making with inputs É(T, f), Ob(r) ;
  if (μt_i > maxUtility(task)) then
    t_f = t_i
    maxUtility(task) = μt_i
  end if
  i = i + 1
end while
if (maxUtility(task) > 0) then
  return t_f
else
  return null;
end if
```

5. SIMULATION EXPERIMENTS

5.1 ***Scenario Description:***

In the (HMMRS) that consists of a group of mobile robots where each robot has its own capacities, The tasks are to load the goods from the source stations and transport them to the consumer stations according to the capacities of each robot (loading/unloading), which requires the following:

- All robots in an environment are autonomous and have prior knowledge of the locations and status of the source stations and consumer station without any communication between them.

- Loading process from source stations: Each source station is temporarily occupied by one robot during the loading process, taking into account the capacity of the robot to ensure that it can handle the load of goods, with each station contains one specific type of goods.

- Task Priority: Some tasks may have higher priority than others, requiring them to be processed more quickly.

- Control of the performance progress: The system should provide the monitoring of the progress of an execution task for optimization.

- The elementary tasks in HMMRS are considered non-interruptible.

-The task itself is considered complete when the quantity of each type of commodity at the consumer station meets or exceeds the target quantity.

Furthermore, at the end of the task, the system aims to achieve a minimal difference between the rate of each type of commodity required by the consumer station and the rate actually achieved and strives to minimize differences between desired and achieved consumption rates.

By following this scenario, we can effectively allocate tasks in a heterogeneous distributed system for accomplishing the complex task, optimizing resource utilization, and minimizing time and cost.

5.2 *Realistic environment map*

To evaluate the effectiveness of the suggested algorithms by Fuzzy Decision-making for task allocation in (HMMRS) under various instances in the simulation environment, we can follow these steps:

Use of the MobileSim Omron (2018a) allows for the simulation of physically realistic mobile robots and their environments. It provides a platform to test and evaluate various robot behaviors and algorithms without the need for a physical robot setup.

In the experiment, the ARIA Java packages Omron (2018c) were utilized. It offers a set of tools and libraries for programming the operations of mobile robots using a high-level language. These packages enable to create Java client applications that can describe and control complex tasks for the simulated robots within Mobile Sim.

A heterogeneous team of robots can collaborate effectively by using realistic environment maps. we created realistic environment maps with Mapper3Basic (Omron, 2018c). Figure 10 displays the map that robots utilize. A heterogeneous team of robots was used for the experiments, and each robot its own capacity. Each robot has the ability to localize itself using estimated position. We identified three types of robots according to its different capabilities represented in Fig 10 with different colors each type of robot is represented by a color.

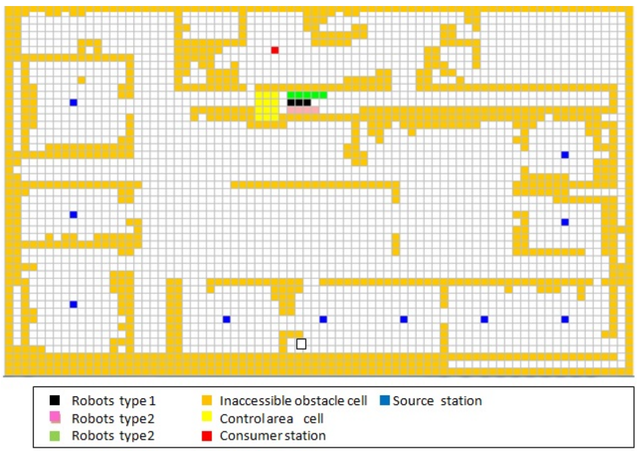

Fig. 10. Local environmental map using a binary occupancy grid (see online version for colours)

5.3 *The decision-making process for completing a complex task*

Executing a complex task T typically involves a structured approach to decision-making. This model focuses on the mission of transporting goods from various source stations to a consumer station. In this framework, each simple task $t_i$represents a source station responsible for handling a specific quantity $Q_i$of goods of type i. The elementary task t_{ij} denotes the process of transporting goods of type i from the source station for loading to the consumer station for unloading.

Robots perform multiple elementary tasks within a single cycle based on their capacity. This cycle of decision-making starting with the navigation to the source station, followed by task selection, and concluding with delivery to the consumer station. Robots determine their course of action by assessing the density of robots and the nature of tasks required, choosing the simplest task they can handle based on their capacity. The number of active robots is also tracked by monitoring occupied stations throughout the cycle.

To facilitate effective execution of elementary tasks by robots, the following behaviors are defined, aimed at ensuring adaptive navigation and decision-making throughout the task allocation process: Fig 11 describes these behaviors)

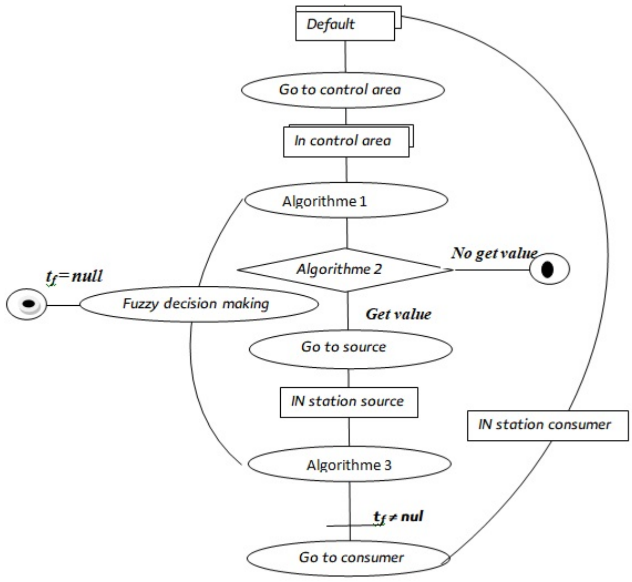

Fig. 11. Describe the fusion of the many robot behaviors.

- Move to Control Area: Initiated at the start of the complex task execution (beginning of decision-making using Algorithm 1), this behavior involves gathering data about the operational area. The robot observes suitable task types and notes the density of robots present.
- Move to Source: Triggered after acquiring information about the future task, this behavior aims to locate an available source terminal. The robot estimate a local environmental map using a binary occupancy grid (similar to Figure 10), where each cell represents 0.25 x 0.25 meters. The A-star algorithm (Hart et al., 1968) is employed to compute the shortest pathways on this map.
- Decision Making: Upon reaching the source station, the robot decides on its next task using Algorithm 3 proposed in Section 4.3 (activated by Algorithm 2). If no tasks are available, the robot ceases task searching. It updates its observations upon completing the decision-making process.
- Move to Consumer: After unloading goods, the robot returns to the consumer station.

5.4 *Analysis of the results*

Hypothesis: In all tests, the sum of the robots' capacity C_{rk} is assumed to be less than the sum of the elementary tasks t_{ij} of a complex task T .

$$\sum_{k=1}^{n} C_{rk} < NT \quad withe \quad NT = \sum_{i=1}^{n} Nt_i \qquad (18)$$

Table 5. The results of experiments for simple strategy

T complex	NB Robots R	$\sum_{k=1}^{n} C_{rk}$	(t_i)	NT	simple $N\acute{t}_i$	simple $E(T)$
T1	5	16	6	18	18	0.00
T2			7	24	51	1.33
T3			8	31	97	2.62
T4			10	48	187	4.40
T5			15	108	420	6.16
T6			20	193	798	6.99
T5	2	4	15	108	338	0.96
T5	3	7	15	108	319	1.59
T5	4	11	15	108	344	3.41
T5	6	22	15	108	590	9.35
T5	7	29	15	108	768	11.85

Table 6. The results of experiments for the fuzzy decision FDM-TS

T complex	NB Robots R	$\sum_{k=1}^{n} C_{rk}$	(t_i)	NT	Fuzzy $N\acute{t}_i$	Fuzzy $E(T)$
T1	5	16	6	18	18	0.00
T2			7	24	67	1.67
T3			8	31	95	2.60
T4			10	48	116	3.31
T5			15	108	380	3.62
T6			20	193	738	3.82
T5	2	4	15	108	338	0.96
T5	3	7	15	108	319	1.59
T5	4	11	15	108	344	3.41
T5	6	22	15	108	374	5.33
T5	7	29	15	108	474	7.30

To analyze the results [1] of simulation experiments, in which we tested the efficiency of the fuzzy strategy (FDM-TS) compared to a simple strategy in completing complex tasks. We used the Graphical representations to visualize data and make it easier to interpret the results presented in tables 5 and 6, can be expressed graphically through various in Figures 12, 13, 14.

Table 5 and table 6 summarizes the results obtained by conducting several experiments in two stages:

- In the first stage, we fixed the number of robots with a change in the number of simple tasks (complex tasks from 1 to 6). The tasks differ from each other in the number of simple tasks, as shown in Tables 5 and 6, with different desired ratios. The test results showed the efficiency of (FDM-TS) in the fuzzy strategy compared to the simple strategy, as shown in figure 12 and figure 13 in terms of the number of tasks performed and the error rate. We find that in (FDM-TS), $N\acute{s}_i$ represents the number of elementary tasks that the robots have already completed and the error estimate in completing these tasks is much lower than the simple strategy, as the number of tasks increases.

The graphs in Figures 11 and 12 summarize the results of the stage1

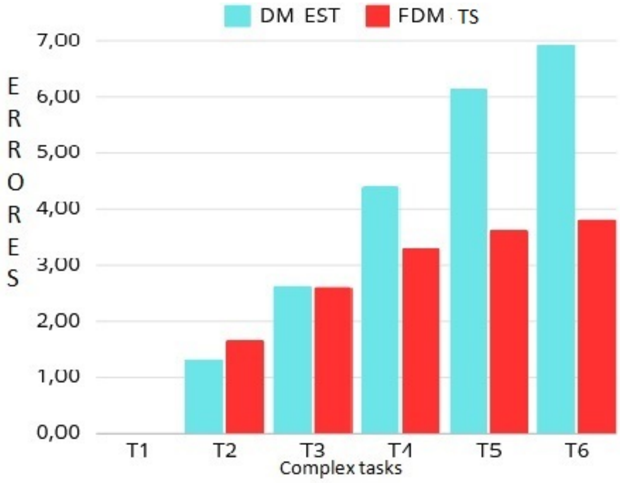

Fig. 12. Graph representing simulation results of the model (strategy simple $E(T)$ vs. strategy FDM-TS)

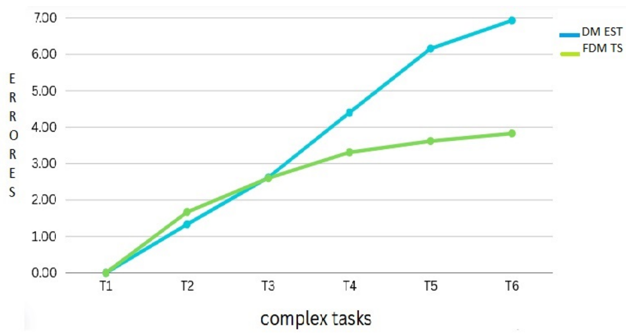

Fig. 13. Graph representing the results of the tests by increasing the number of Complex tasks (strategy simple $E(T)$ vs. strategy FDM-TS)

-The results of the second stage represented in Tables 5 and 6, by fixing the number of tasks (the experiments conducted on the complex task T5) and increasing the number of robots from 2 to 7 (respecting Hypothesis 1 (Equation 18)) and setting the total number of elemental tasks to 108, as shown in figure 14. The results showed the same thing, with the superiority of the algorithm (FDM-TS) based on the tasks selection strategy in (TSMMRS) in terms of the number of tasks actually completed and the error estimate is much lower than the results of the simple strategy.

[1] The results represent a comparison of the results obtained between the simple strategy vs the fuzzy decision according to the capacity of each robot.

The graph in Figure 14 summarizes the results of the stage2

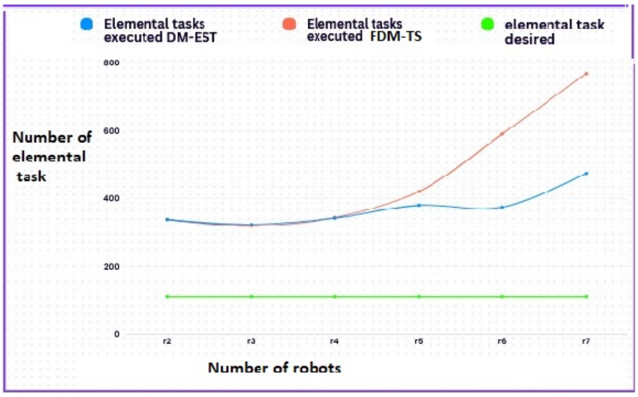

Fig. 14. Graph representing the results of the tests by increasing the number of robots (strategy simple $E(T)$ vs. strategy FDM-TS)

The test results also showed that applying the (FDM-TS) algorithms assigning tasks is a more accurate strategy in heterogeneous multi-robot systems by increasing the number of robots. Accordingly, we conclude that the goal can be achieved through the proposed approach (TSHMMR) of maximizing the accuracy efficiency of the system and minimizing proportional errors in task completion, leading to saving time and energy.

6. CONCLUSION

In this paper, we explored the task allocation problem in heterogeneous multi-robot systems, focusing on robots transporting goods from source stations to consumer stations based on their respective capacities. The task allocation model was approached as an optimization problem, revealing its NP-complete nature. We developed and implemented two algorithms: one to evaluate the utility of each robot, and another to assess the utility of tasks, particularly as the number of robots and tasks increases, to assign tasks effectively according to robot capacities. The primary aim of this study was to minimize task assignment time to enhance energy efficiency. Our results confirm that this objective was met. For future work, we propose further enhancement of the task allocation model by introducing new constraints to improve task assignment accuracy in (HMMRS) and minimize decision-making errors, especially when robot capacity exceeds the available number of tasks, thus optimizing the entire task allocation process.

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