An Ant-Inspired Task Allocation software Implementation for Swarms of Robots

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# Abstract

Say also that is intends to explore task allocation in swarm 3 independent task blahblah

This paper proposes a software implementation of an ant-inspired mathematical task allocation model created by Alejandro Cornejo et Al. [link]. Moreover, it declines the implementation in two architecture of the swarm robotic paradigm; A centralized and a distributed version. Through a set of experiments and thorough comparisons against strong task allocation methods, is has been proven that .. Also speak about PSI RND and GTA More……

# Introduction

Ants are great social insects in many ways. From their adaptability to a great range of environments, to the extremely high level of self-organization in colonies reaching to sometimes up to 10 millions of individuals, they are a great source of inspiration for robotic and swarm intelligence. Their most interesting feature is their maximization of the distribution of labour to sustain the colony’s need to periods of over decades and how it can be applied to today’s swarm robotic challenges. Swarm robotic can be defined as « a new approach to the coordination of multi-robot systems which consist of large numbers of relatively simple robots which takes its inspiration from social insects. The most remarkable characteristic of swarm robots are the ability to work cooperatively to achieve a common goal. ». [1]. The studies of task allocation systems related to swarms of robots is mainly used to understand how a complex system of task can be solved using multiple agents [link 2-4 symmetry]. The tasks can either be achieved by an individual, alone, or by a group or robots, cooperatively [link?]. Existing practical applications of swarm robotic includes … LOOK FOR EXAMPLES.

Distribution of labor in groups of individuals can be considered done in two ways: Firstly, given that the environment is limited in its growth, one can implement pre-determined task allocation strategy, such as robot-planning [LINK], where the individuals will be able to perform a set of given task with time and precision. The second is task allocation is dynamic environments where robots are given a set of behavior-based mechanisms and the task allocation strategy has to be adaptive. The main challenges faced by swarm robotic when dealing with dynamic environment are the following:

* Coordination of a large groups of individuals is exponentially harder as the task’s complexity increases and the environment grows
* Pre-determined task allocation strategy will suffer from a lack of versatility in dynamic environments as
* Inaccuracy and inconsistency in dynamic system can exponentially grow if non-resolved, resulting in a high energy consumption.

The proposed ant-inspired task allocation implementation hops to resolve the beforementioned challenges by:

* Dynamically allocating individual considering the current environmental demand.
* Reducing inconsistency in task switch, thereby reducing energy consumption.
* Being adaptive to a large and un-defined number of task for as large of a group of individual as possible while keeping accurate distribution of labour.

Moreover, this project intends to provide a framework of precisely defined environment and experiments description for everyone to reproduce the work and improve the implementation or compare it. To address the mentioned improvement, this paper explore the implementation of an ant-inspired algorithm via two architectures of the swarm robotic paradigm through the implementation of …. Firstly, the centralized one (see figure n), where the information about the environment is not shared among all the individuals but is rather kept in a single entity that any robot can reach out to given deterministic conditions (space and time). This single entity is usually referred to as the leader and can be anything from a robot to a static information center and is also responsible for delivering a task allocation for any robot requesting one. The centralized architecture is well suited for a small number of robots [link] but has obvious downsides when the group of robots become larger as the communication failure (information loss) and overhead quickly creates a disturbance in the system [link]. Moreover, this system has what is commonly referred to as a single point of failure, where if the information center breaks or stops functioning, the entire swarm is impacted and cannot perform further action [link]. The second architecture is the distributed architecture. This time, the information is shared among all individuals through local communication where each robot shares its state and is responsible for understanding their environment and assigning a task to themselves. Given the mode of communication, this architecture does not suffer the same downsides as the centralized one. It is scalable and robust to failure as if one of few robots are removed, the rest of the swarm keeps sharing their state and the system keeps working. Moreover, this architecture is expected to suffer less from communication failure and overhead as if such happens it is only locally to one robot, which does not impact the rest of the swarm.

[link file:///Users/freak/Downloads/bxy107.pdf]

As said in the paper, they provide a framework that let us choose ant feature and more

**This paragraph can also easily go somewhere else more introduction**

**Maybe that a bit bold of an assumption to say that I want to explore that, then I need to discuss it big time in the discussion, also because I kind of let AITA apart**

- Also, my system AITA was not implemented ANYWHERE (on the web that is, no paper has done it) so it’s nice that I provide a proof

My thesis is also an experiment proposal so that hopefully people can use it afterward with their own system. Also, it is meant to be use for overly simplistic robot as ants.

Explain what I will do and from who I will “copy”

**Say something about task allocation .. swarm .. the future .. refer to other paper, they might’ve the answer**

Talk about response treshold

**I think mine is treshhold as well.**

**[1]**

**“un mot qui veut dire avertissement sur »**

*#! I know I want to use robot simulated because I want to assess the efficenicy of the allocation system for robots. Doing it with few robot wouldn’t prove so much.*

<https://www.frontiersin.org/articles/10.3389/frobt.2020.00036/full> -> this website explain why is swarm robotic. Maybe I can have a reflexion part on the thesis, and transpose it to the ants. Like it says

“ **Group size regulation** allows the robots in the swarm to form groups of desired size. If the size of the swarm exceeds the desired group size, it splits into multiple groups.” But ants don’t have such complex system.

**[0]**

## Related work

[1]

Small chapter here that will define the set of dependent task, why it work and why it is relevant

-> will have to explain how some model are based on ant characteristic and why I don’t use them

Also cite a bunch of paper and what they did there.

<https://www.google.com/search?q=task+allocation+in+autonomous+swarm+robot&oq=task&aqs=chrome.0.69i59j69i57j69i59j69i61l3j69i65l2.832j0j7&sourceid=chrome&ie=UTF-8>

<file:///Users/freak/Downloads/Distributed_Task_Allocation_in_Swarms_of_Robots.pdf>

-> this one for instance talk about “scalability” and how it is important that the task changes in function of the needs. This is different from my task allocation system as as of now, the robot cannot quantify needs.

My robot are made to solve a set of task from A to Z without any arrogance on the speed of the execution

<https://people.idsia.ch/~frederick/taskallocation.pdf> -> this one has flying robot .. not yet relevant to me.

<https://core.ac.uk/download/pdf/188778566.pdf> -> AUCTION!

<https://www.researchgate.net/publication/2472396_ALLIANCE_An_Architecture_for_Fault_Tolerant_Multi-Robot_Cooperation>

Ant-Inspired Task Allocation Model Within a Swarm of Homogeneous Simulated Robotic-Agents

<file:///Users/freak/Downloads/paper_preV.pdf>

Payam paper, could be used in the “related work”

<file:///Users/freak/Downloads/Task_Allocation_in_Robotic_Swarms_Explicit_Communi.pdf>

Heavily interesting, it says that

“This leads to a huge amount of differently designed global missions and as a result to many different solutions which are hard to compare[3]. Thus in most of the proposed methods in this area, researchers have only introduced their own methods and refrained from comparing with other methods. Our scenario also possesses different features, goals and finally distinct global foraging mission compared to previous scenarios in task allocation field”

<file:///Users/freak/Downloads/AnInterruptibleTaskAllocationModel%20(2).pdf>

<https://ieeexplore.ieee.org/document/4803959>

<https://ieeexplore.ieee.org/document/8023527>

- Maybe I can slo defend why interaction rate is not optimal because it’s too localisation and time based. ()

**Talk about the model**

* **Talk about task in general, “task allocation generalist” is a paper defining the use of specifc task from specific ants. It could be interesting to talk about it**

# Ant-Inspired Task Allocation Algorithm

This section describes the main algorithm used for the swarm of robots to achieve task allocation, and how it is integrated to the simulation. Throughout the section, the terms AITA, CAITA, DAITA will be used. AITA stands for **A**nt-**I**nspired **T**ask **A**llocation and is the implemented algorithm, CAITA stand for **C**entralized **A**nt-**I**nspired **T**ask **A**llocation (a centralized version of AITA), and DAITA for **D**istributed **A**nt-**I**nspired **T**ask **A**llocation (a distributed version of AITA).

Maybe somewhere talk about the strensght of the system envisaged by Alejandro

## Introduction

The ant-inspired task allocation algorithm used for this research has been designed in 2014 by Alejandro Cornejo et al. [link] and takes the form of a mathematical model. Furthermore, the system has not been implemented or tested in a simulation environment at the time this paper is written (Q2 - 2021), which makes it a good candidate for experiments. The algorithm is a crossover between a multitude of studies of ant’s task allocation models such as the threshold algorithm [link] or the interaction-rate model [link]. -> more here

Here say on what the model is based… “the model is based on the idea that ant can quantify…[…]…”

Say what is interesting in the algorithm over others..

## Paper’s assumptions

Have a part where I test its assumptions and then the comparison with all other Tas?

Alejendro et al. (todo) define an optimal task allocation as being one that optimizes the square difference betweenen the energy demands and the energy supplied.

if one task can be set to an equilibrium, then all other task will be served .. because when eq. reached, the robot are reassigned -> to be verified

## The system model

Alejandro Cornejo et al. introduce four quantifier helpers that help a worker telling whether a task is in energy deficit or surplus. To begin with, they define a function **d**(T, t) as being the **demand** for a task t at a given time T. The **demand** function can depend on any aspect of the current environment, such as weather conditions, the location of the colony (in the world),the current number of ants in the colony, etc. Secondly, the function **e**(T, a, t) yields how much **energy** [NDPDB] an ant can provide to a task t at a given time T. The **energy**an ant can provide to a task depends on environmental variables, but also on ants’ characteristics and previous experiences of the specific task. Thirdly, they define the **energy supplied** to a task t at a given time T **w**(T,t) as being the sum of the **energy** **e**(T, a,t) currently provided by all ant performing the task. Finally, they define **q**(T,t) as being **d**(T,t) – **w**(T,t), or; the current demand for a task minus the energy currently supplied by all ant to that task at a specific given time T (this paper will refer **w**(T,t) as being the **energy difference**).

Moreover, they define a satisfying task assignment as being one where no task is in energy deficit, that is, the task is in equilibrium. Being in equilibrium for a task means that the **energy supplied** to a task t exactly matches the **demand** of the task. (maybe that’s repetition)

TODO NDBDP:

As described in the original paper (Alejandro Cornejo et al, 2014), the energy unit can be any kind of energy (watt, joules, etc..) as long as one keeps it consistent throughout the implementation.

## Model restrictions

The previous secton mentions four helpers, however, it is still unclear how they exactly work as it only has been mentions of potential “environmental variable” for the demand or “ant’s characteristics and experiences” for the energy. It is because the environmental variables, ant’s characteristics, and experience settings are so phenomenally broad that it is impossible to include every one of them in the model. Indeed, even Alejandro Cornejo et Al. have decided to leave this choice to someone else who would implement the task allocation they have created, as they highlight how the complexity of individual variation quickly results in an “intractable task allocation formulation”. Being an intractable formulation means that there is no efficient way to solve the task allocation problem [Link]. Intractable problems are commonly referred to as NP-complete problems [Link],.

The robot will have to collect resources and 1 resources is a demand of 1. More in section ..

As will be elaborated later, the simulated individuals are a set of homogeneous robots which all share the same skills and characteristics to solve a given task. Sharing the same abilities to solve a task is important as it already narrows down the expectations and reflections around the energy a worker can supply to a task, as no robot can perform a given task better than the others. Moreover, since the simulated environment is controlled and not meant to reflect hard environment such as a jungle or a desert, but rather meant to reflect the use of such a system in placed such as a depot or a hangar, its effect is limited. Finally, it has been chosen that a robot does not have memory of past experience, which means that the energy supplied by a robot to a task can be set to 1 for any robot and any given task.

To conclude, this leaves the following model restrictions: a robot can carry out on a task as its ability to solve it is 1 and each time a robot finishes its task, the demand decreases by 1.

## Task allocation algorithm

This section is an overview of the AITA algorithm. The complete algorithm can be found in Alejandro Cornejo et Al’s research paper.

### The binary feedback function

The algorithm is based on the worker’s ability to sense its direct and local environment through a binary-feedback function f(T, i). Recall the helper function q(T,t) which is the energy difference for a task t at a given time T. The binary feedback function yields 1 if the energy difference for a task is in equilibrium or in energy surplus, -1 otherwise (not that the binary feedback function does not provide enough information for the workers to tell whether a task has reach exact equilibrium). The paper also introduces other binary feedback functions in their further work section, which will not be covered in this paper. Sensing the energy difference for a task through a binary function means that a worker is unable to quantify by how much a task is in energy deficit or surplus. This is very important as it fundamentally shapes the way the task allocation system works. Being able to sense only little and local information is also biologically accurate as ants don’t have the exact knowledge of the energy supplied to a task [link] in the sometimes up to 1’000’000 million individual nests [link].

### Algorithm

The algorithm (which considers the size of the colony |A| as being fixed) works as follows: Firstly, all worker executing the algorithm maintain a current task *currentT* and can be found in one of the five following states: Resting, FirstReserve, SecondReserve, TempWorker, and CoreWorker. Moreover, workers carry a table of potentials Q for each task which is used to determine which task a worker will be executing next. The table of potentials Q is updated via the binary feedback function, tasks in energy surplus or equilibrium get a potential of 0, and tasks in energy deficit see their potential increasing (up to 3). Worker first start idle and in the Resting state, and fill up a candidate list which contains task with potential of 3. With equal distribution, a worker will choose a task from the candidate list and leave the Resting state to move to the TempWorker state. Moreover, the paper states that:

*“Ants in the TempWorker state and CoreWorker state work on the task specified by currentT ask (ants in all other states are idle). Specifically, ants in the TempWorker state transition to the FirstReserve state if there is a surplus of energy in currentT ask, and otherwise transition to the CoreWorker state. Ants in the CoreWorker state transition to the TempWorker state if*

*there is a surplus of energy in currentT ask, and otherwise remain in the CoreWorker state. The result is that when there is a surplus of energy all ants in the TempWorker state will become idle before any ants in the CoreWorker state. Ants in the FirstReserve state and SecondReserve are state idle, but unlike ants in the Resting state (which are also idle) if they start working they will do so at the task they were last working on. Ants in the FirstReserve state transition to the Resting state if there is a surplus of energy in currentT ask, and otherwise they transition to the TempWorker state with constant probability or join the SecondReserve state. Ants in the SecondReserve state transition to the Resting state if there is a surplus of energy currentT ask, and otherwise transition to the TempWorker state.”*

For more detail, refer to the original paper.

The complete original algorithm is shown in Figure N. Figure N depicts a correction made to the algorithm, explained in the section “correction on the original algorithm TODO”.

## Original algorithm correction

Throughout the implementation and tests conducted on the original algorithm, it has been found that there was an issue with the increase of potential for a task in table Q (see Figure N, todo line x to y). Indeed, imagine the following quite likely situation: All tasks are in energy deficit, and one (or more) worker is in the Resting-state.

When a task is in energy deficit, the algorithm will increase its potential in the table of potential Q. However, the algorithm yields that the new value is either 3 or higher which is problematic for the following reason: When the value for a task in table Q is 3, it is added to the candidate list. However, it is not given that this task is selected as the worker selects a new task with probability ½. This means that first, a task of potential equal to 3 can re-enter the code on todo line x to y, and end up with a value higher than 3 which defeats [todo paper name]’s definition of the values the table Q can take:” [..] The potential for every task is a two-bit value {0, 1, 2, 3} [..]”, and secondly, if all tasks are higher than 3, none of them are added to the candidate list and the robot is stuck without any assignment until eventually a task is in energy surplus and the worker assigns its value to 0 in table Q.

To overcome this situation, line 3 in figure N has been updated to

…

And line N todo has been updated to:

..

This way, the task assignment can be satisfied, the algorithm works as intended by the original creator and a worker cannot be stuck without task assignment when tasks are in energy deficit.

Table

Description automatically generatedA picture containing table

Description automatically generated

**Here, redo the algorithm as I know how it should be, no copy past the algo from pseudo code**

**Centralized and Distributed**

The beforementioned algorithm has been implemented in both a centralized fashion - where a communication area (the nest) severs as an information center - and in a distributed fashion where the information about the demand and the current task assignment is shared globally throughout all the individuals.

**Centralized AITA**

The centralized ant-inspired task allocation implementation or CAITA works as follows (as shown in Figure N): At their initialization, each robot is given the initial demand for each task which is defined by an outside person. The robots then have to perform a set of 3 dependent tasks (more on this in section TODO) while periodically reporting their status to the information center (Note that: a robot is not being assigned a new task if it carries a payload). Each time a robot reports its status, it shares its identification number, its current task, its current state, and what it has been working on since the last report. Once the information center receives these pieces of information, it updates a table of global knowledge and decides on a new task assignment for the robot.

Mechanisms for improving the robustness of the system against potential robots' failures have been implemented. Each time a robot does not report within 2000 simulation steps, it is considered gone and its status in the global table of knowledge switches to "gone" which changes the energy supplied to the task the missing robot was performing, leaving place for another potential idle, first reserve, or second reserve robot to take over its work.

Talk here about shift error knowledge if not introduced further down?

**Distributed AITA**

Significant changes are made in the distributed version of AITA. This time, the memory is not contained in a single place but rather is shared throughout the entire swarm. To do so, each worker holds an array of demands for each task initialized at the start of the simulation. Along with this array, each robot has a memory of every other robot’s state. At each simulation step, every robot tries to broadcast its current status – I.e. its identification number, current task, state, and its current “advancement” on each task. As another robot receives this information, it updates its memory on the robot and runs the AITA algorithm to be attributed a task.

Robustness mechanisms similar to the one implemented for CAITA are also present in DAITA. This time, each robot keeps track of the last time it has encountered a robot. If this elapsed time goes over a specific pre-defined simulation step, the robot is considered gone from the other robot’s system to be potentially replaced.

# RND, GTA and PSI

**other chapter)**

## RND, GTA and PSI

To give a more in-depth analysis of CAITA and DAITA, it has been chosen to implement three other algorithms that would evolve and be experimented on in the same environment with the same set of tasks to perform. This section provides an overview of each of them, highlighting why they have been chosen over others and what can be expected from every one of them.

### Random Task Allocation Algorithm

The random task allocation algorithm, or RND, is a system where each individual, given that it is not currently performing a task (currently performing a task means currently carrying a payload), is attributed a new task every 600 simulation step (after thorough experiments, 600 simulation step has been seen to be the most optimal task time) following a uniform distribution (that is, no task as more chance to be selected over another). Since the robots do not require sharing any kind of information and don't need to be aware of the current world state, this task allocation system does not suffer any kind of communication failure or overhead, which makes him highly scalable and robust.

This algorithm has been chosen because it is the simplest algorithm one can design, and thus serves as a lower boundary as to what the ant-inspired algorithm (and any other elaborated algorithm) should not go below. It is expected that this algorithm performs the poorest as it does not worry about the current world's state and is very inconsistent (for instance, even though the probability is extremely low, one could end up in a system where only the foraging task is performed throughout the entire lifetime of a simulation).

### Greedy Task Allocation Algorithm

The greedy task allocation algorithm, or GTA, is a system where the robots share their states to others within the swarm and coordinate to cover the task that requires the most attention. As for the CAITA, DAITA, and RND, a robot cannot be attributed to a new task if it is currently performing one. Because the information is distributed among the entire system (the memory and communication systems are the ones used by DAITA), this algorithm suffers the same challenges as DAITA, that is, communication failure and system disturbance.

A greedy algorithm has been selected because itusually perform very well in a wide range of situations, but consume a lot of computational power. Thus, this algorithm is expected to perform well but at computational costs that are high compared to other systems.

### Partitioning social inhibition Task Allocation Algorithm

The Partitioning Social Inhibition task allocation algorithm, or PSI, is a system issued from a research paper "Division of Labor in a Swarm of Autonomous Underwater Robots by Improved Partitioning Social Inhibition" (Zahadat et al. [link]). Zahadat et al. claim that "The PSI algorithm maintains a division of labor and allocation of tasks to different members of a swarm. It is adaptive to changes in the swarm size and relative demands for different tasks." Being adaptive to changes in the swarm size and demand for the tasks is important because it is part of what the other TAs are being experimented on. PSI is also interesting because it does not fall under the category of algorithms that are easily applicable to any kind of situation, rather they are robotic related or not (such as GTA and RND) since it is also an attempt at solving the task allocation problem. This sub-section is an overview of the algorithm and the way it has been implemented within the system developed for this project.

For this research paper, Payam Zahadat has been kind enough to provide the student with the C++ code with which the simulation was run. The algorithm has then been transferred to the Python code the student is working with and adapted to the current environment and communication mechanisms. This adaptation means that PSI is executing the same set of tasks as all of the other TAs, which provides fair and accurate data. Overall, the algorithm is expected to perform as well as in Zahadat et al.'s experiment, but the system is also expected to suffer from the consequences of applying the algorithm to the student's environment (which is discussed under the discussion section TODO).

Each robot of the swarm holds an x value that represents their physiological age – A value that represent the biological real state of a living things (In the original paper, the analogy is made between the robots and honeybees, from which PSI is inspired). This x value is distributed over a range of xmin and xmax (the value of the variables are defined in table n) where the range is split equally by the number of tasks so that each task gets the same amount of distribution (see figure n). PSI aims to distribute each individual's x value relative to the current demands for the tasks to achieve equilibrium (recall that the equilibrium is when the number of robots assigned for a task matches or covers the current demand of the task). PSI uses the same communication system as DAITA and is thus distributed. Using the same system means that PSI is expected to suffer from the same challenges as DAITA (communication failure and system disturbance). The value x changes through time and local interaction with the member of the swarm, but this paper does not intend to cover that. For further information on how the local interaction within individual changes the x values, please refer to the original paper.

As mentioned above, PSI has not been written to run under the same kind of environment as for the one DAITA and the other algorithms have been designed for, meaning that PSI has been adapted to fit this project's simulation and its constraints. The two impacted areas are the demand and the specific condition under which a worker can be allocated a new task.

##### Demand

The current implementation of the environment yields that a demand for a task can variate from -inf to inf, whereas in Payam et al.'s system the tasks have a value that represents a fraction of the current demand and usually variates between 1 and some positive number. This means that in the PSI's original system, no task can have a negative demand or a demand of 0. To counter that, it has been chosen to map the actual demand of the environment to a 1 - 20 scale (only for PSI) as follows:

Imagine the following sequence of demand [23, 132, 12], where 23 is the current demand for the foraging task, 132 is the current demand for the nest processing task, and 12 is the demand for the current cleaning task.

**TODO** put that into equations:

# First, the highest demand is determined

max\_demand = max(23, 132, 12)

# Then each demand is mapped to the 1-20 system following this equation where x is the input demand:

f(x) = math.ceil(x / max\_demand \* 20)

return f(x) if demand > 1

1 otherwise

A wide range of tests and experiments have proven that this system accurately complies with how the PSI's task allocation algorithm is designed to work. The tests and experiments are not shown in this project as the goal is only to get as close as possible to the performance of PSI under its original setup.

## PSI starting variables (TODO MOVE TO PSI DEF?)

In order for anyone to reproduce this paper’s work, this section quickly defines PSI task allocation system includes some variables that one can act on, table N defines what values have been chosen for each variable. More information about what each variable mean and the what influence it has on the PSI system can be found in the original paper [link].

TODO add table.

|  |  |
| --- | --- |
| Xmin | 0 |
| Xmax | 512 |
| Noise on x | 0 |
| Phi | 1 |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |

##### Condition under which a worker can be attributed a new task

As for all the other algorithms, PSI cannot attribute a task if the robot is currently performing one. What it means for PSI is that the value x of each individual is delayed as long as the worker is currently carrying a payload. Tests have shows that it does not impact the efficiency of PSI.

# Experiments

This section precisely describes the set of variables and assumptions used for the system and the experiments. Moreover, it shows and discuss the results of the experiments conducted over the different parameters of the simulation and the different methods of task allocation.

## Environment

The different task allocation methods, CAITA, DAITA, PSI, RND, and GTA, are tested and experimented on in an agent-based simulation built by Alexandre Vanini written in Python. The model of the simulation (figure N) consists of a 2D environment wide of 10 meters and tall of 7 meters, populated with 4 types of agents (idle, foragers, nest processors, and cleaners), a nest including 3 main areas (or chambers), the dump area (in blue, 1.4 meters x 1.4 meters), where resources collected from the outside world are stored and also serves as an information place/centre for the robot’s using CAITA’s algorithm to report their status. The transit area (in pink, 1.4 meters x 1.4 meters), where resources processed from the dump area are stored. Finally, the waste area (in orange, 1.4 meters x 1.4 meters) where resources stored in the transit area are trashed. Everything that is not one of these 3 areas is considered a foraging area where 2000 food items are distributed at the start of each simulation following a random uniform distribution (the uniform distribution is chosen so that the distribution of resources in the arena does not play a role in the effective performances of the different TAs). The topology of the world is a rectangle box bounded in all its directions.

Workers can carry out four kinds of tasks depending on the demand of the colony: Firstly, the idle task – which consists of being at rest in the nest (not moving) waiting to be attributed a task. Workers carrying out the idle task are shown in black, see Figure N. Secondly, resource collecting or foraging - where workers wander outside the nest and collect resources to then bring them back to the dump area. Workers carrying out the foraging task are shown in red. Thirdly, nest processors – i.e. to process the resources brought back by the foragers and move them to the transit area. Workers carrying out the nest processing task are shown in green. Finally, the cleaners collect the resources deposed in the transit area and move them to the waste area. Once a resource reaches the waste area, it is considered fully processed and will not be moved any further. Workers carrying out the cleaning task are shown in blue.

Moreover, each time a resource is carried out by a worker and processed, it changes its colour and type. The resources outside the nest area (shown in green) switch from the *foraging* type to the *dumped* type. Resources in the dump area (shown in grey) switch from the *dumped* type to the *transit* type. Finally, resources in the transit area (shown in red) switch from the *transit* type to the *waste* type (shown in blue) once placed in the waste area. Furthermore, workers working on specific tasks will only recognize the resources of their current task – i.e. a forager will only be able to sense the resources of type *foraging* and a robot performing the cleaning task will only be able to sense resources of type *waste*.

This set of tasks (foraging, nest processing, and cleaning. Idle is omitted as it is more a state than a task) are 3 dependent tasks which means that the demand in the foraging task always influences the future need in the 2 others. In other words, for the demand to raise in the nest processing task, a resource has first to be collected in the foraging area and brought back home, and for the demand to raise in the cleaning task, a resource first has to be collected outside and brought back home and then has to be processed by the nest processors and move to the transit area. This three dependent task setup can easily relate to real-life like tasks such as collecting warehouse supplies and carrying them out to other parts of a hangar in the transit area to be processed. Note that: this set of task is not representative or limiting the application of the AITA algorithm, but is only highlighting the performances of this algorithm compared to other methods in a specific environment.

Scatter chart

Description automatically generated

* Maybe have a better one that shows also every kind of resources and robots and less points (like 500) (colors).

## Environment setting

In order for the experiment to be as fair as possible and to make sure each task allocation method is given the same chance at succeeding, the environment is framed with a set of assumption an variables. Firstly, the environment assumes that all the simulated agents are a set of homogeneous Thymio-II robots [link?] (a pre-built ready-to-use robot equipped with built-in sensors and communication system). Using a set of homogenous robots means that all the robots are the same, share the same capabilities and skills. Moreover, all the robots have the same navigation and object avoidance system. A robot is able to somewhat precisely move to a given coordinate in the plan during the simulation.

For the CAITA system, the communication has no overhead and happens a soon as a robot enters the information center. The information center is assumed to be able to communicate back and forth with every robot at the same time. As for CAITA, The DAITA system assumes a instant communication transmission time when sharing its information to someone. Unlike CAITA, robots in DAITA cannot receive a packet information from each robot at the same time. Indeed, since this time it is the robots that receive the packet and not an information center it has been decided to implement a random mechanisms that decides from which signal the robot will choose its packet (each signal is given the same chance to be received, see figure N todo). Moreover, a robot can only receive one packet per simulation step. This system ensures fairness and reality in the communication. GTA and PSI who both use the DAITA communication system suffers the same communication restrictions and challenges.

TODO signal reception graph.

**TITLE about variable that one can act on?**

A set of specific variable can be changed prior to run a simulation, and it is expected that each of these variables have high impact on the system depending on their value:

* The number of robots
* The noise / the probability of communication failure
* The communication range
* The demand for each task
* Increase of demand in the foraging task

Increase in the ForagingTask’s demand

This parameters can be seen as being useless as the goal is to compare how fast a system can for instance, collect N resources or how does a system do over a given period. However, the author argues that this periodical increase helps to keep the experiment as fair as possible for the following reason: the AITA algorithm makes sure that the demand for a task always meets equilibrium, given that enough workforce is available. This means that if the goal of an experiment is to collect 300 resources with 40 robots, and the starting demand for the *ForagingTask* is set to 300 and there is no increase in the demand, AITA will deploy its 40 robots on the *ForagingTask* to collect 300 resources as this, as long as the task is in energy deficit. This means that

Goal: keep the system busy

What do I want to experiment? -> Yes and no..

The experiments intend to assess the efficiency of the system over five categories that are commonly referred to as being what a swarm robotic system should be good at, namely: Its scalability, which is the system's ability to adapt to a change of workforce (whether it is adding or removing individuals). Its robustness, or how well the system does against communication or robot failures. Its versatility, which states that the system should apply to a wide range of tasks. Its adaptability, or how good can the system adapts to dynamic environments. And finally, the reliability of the system stating that the robot should be consistent in its probability of solving a given task. Along with this five categories, the systems are tested upon Alejendro TODO’s metric of stable task allocation system – the minimalization of the squared difference between the energy demands and the energy supplied, and their energy consumption.

In order to evaluate the performances of the proposed methods upon the defined categories, different metrics are taken into consideration; The task completion rate, the total covered distance for all robots, the distribution of robots in the different classes of workers, the number of task switch per robot and the demand and the energy supplied for each task. For systems that have a distributed communication (DAITA, GTA, and PSI), the average sensed demand by each worker is also compared to what the real demand for each task is. For CAITA, the demand sensed by the information centre is compared to the current environment as well as for the robot currently assigned to a specific task. Each experiments is run 5 times and averaged to give the fairest outcome compared to a single run.

## Experiments on parameters settings

In order to best see the robustness and reliability of the CAITA and DAITA system, but also to choose variables that are be the same for every task allocation methods, tests upon communication failure/noise and change in the communication range have been conducted.

### Noise (here nice past tense because it’s prior to the exps and results in time)

The noise is implemented as a communication failure mechanism, that is, whenever a robot tries to broadcast its current knowledge of the world (DAITA) or report to the information center (CAITA), there’s a probability Pnoise that the communication with the receiver fails. Both CAITA and DAITA use the following system for this experiment: The tests run 40 robots, they have to collect 150 resources and fully process them as fast as possible. Each 500 simulation step, the demand for the foraging task increases of 5. This system assumes that the communication range covers the entire arena. WHAT is the starting need ?

**Noise DAITA**

The tests are first run with a probability of communication failure Pnoise of 0 and Pnoise is gradually increased to finally reach Pnoise = 0.99. As can be seen in figure N (todo), the different levels of noise tested don’t show any kind of significant variation in the task completion rate (the rate at which the given task is completed). Nonetheless, a small variation of the completion rate for Pnoise = 0.99 can be seen in Figure N, where the system completes its task sooner than the others.

Chart, line chart

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These variations could mean that the system is highly robust even when 99% of the communications are lost. However, to furthermore explore the incidence of the noise on the system, one can look at swarm’s perception error e of the actual environment:

Figure N depicts the metric where it can be seen that both Pnoise = 0, Pnoise = 0.3, and Pnoise = 0.7 have around the same error over a same period, reaching low fluctuation with an averaged error of TODO N, X, A for Pnoise = 0, 0.3, and 0.7 respectively. These slight variations even at high noise level such as Pnoise = 0.7 are plausible and are the result of the communication system implemented in DAITA. In the DAITA communication system, with each simulation step, every robot broadcasts its current knowledge of the world to all of the others individuals. In a system of 40 robots and a probability of success of 1 (that is, Pnoise is set to 0), the number of successfully sent and received packets is; 1 \* 39 = 39. Moreover, recall that each robot can only receive one packet per simulation step which means that in this system the robot has a likelihood of successfully receiving a packet equal to 100%. Now, in a system where the probability of success is 0.3 (that is, Pnoise is set to 0.7), the number of successfully sent and received packets is; 0.3 \* 39 = 11.7. The receiver (who can still only receive one packet per round) is probabilistically speaking receiving 11.7 packets on average each round, more than 1, enough for the system to update and spread the shared information globally. However, when the probability of success drops at 0.01 the robot is receiving on average 0.39 packet each simulation step, or less than 1 each round which means that successful communication can take up to on average 2.56 rounds to happen. This can be seen in the swarm’s perception error e of the actual environment shown in figure N were when the noise reaches a high level, the error skyrockets. Nevertheless, given enough time the error e plummets and the system stabilizes to reach just above the same error e as the other, or XX todo on average. This adaptation means that under the before-defined environment and these specific starting conditions, the system is robust to communication failure over time.

As the probability in communication failure reaches a high level, the success rate can become so low that the swarm struggles to agree on the current state of the environment. This tendency of difference between the status of the environment and what is seen by the swarm can further be seen in Figure M where when the noise is low (for Pnoise = 0 and 0.3), the current knowledge of the world is high (as information is shared faster) resulting in the robots adapting faster to the environment – Which means high oscillations in the task allocation resulting in a high number of task switch per robot. Inversely, for a high probability of communication failure, the swarm struggles to adapt quickly to the changing environment as failure in communication means the information is shared at a slower pace, which results in a low oscillation in the distribution of labor, leading to a lower number of task switch per robot. The consequence of delay in information sharing caused by high probability in communication failure, also called *knowledge error shift* can further be seen in Figure N where as the demand for resource collecting gently drops, the average sensed demand (in yellow) is slightly shifted compared to the actual demand (in green) as noise slows down the rate of information sharing, leading the swarm to over-collect resources. This also explain why for Pnoise = 0.99 the curve slightly variates in Figure N and the system finishes before the others. As the *shift* is big, the system struggles to adapt and fails at optimal labor distribution and over-collect resources, leading the swarm to take a time advantage over the other noise system.

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TODO add foraging demand graphs for each

Maybe in legeng of row[3], the no foraging at 2000 can be seen in the error graph (it is the spike). tODO above, can’t tell which graph is what lol

**Noise CAITA**

In the case of CAITA and unlike DAITA, the task completion rate graph in Figure N clearly shows signs of weakness when the level of noise Pnoise reaches 0.99. However, the other level of noise seems to achieve the same performances. Recall that the communication system of CAITA is fundamentally different that the one implemented on DAITA. In CAITA, each worker have to report to a central which then distributes tasks. This means that there’s twice as much more chance that a communication between a transmitter and a receiver fails as the robot first have to communicate, and then the nest send out the new task assignment.

???????

In conclusion, both DAITA and CAITA have shown high level of robustness to communication failures. Furthermore, even though the higher the probability of communication of failure is the more “messy” the knowledge error is, both systems seem to be able to compensate over time this problem and are expected to keep a healthy system for long periods of test. However, if the system is highly dynamic (lots of changes) it is expected that systems with high noise is be performing worse than system with low noise as system with high noise cannot adapt fast enough to the situation, leading into the knowledge error shift to be incontrollable, however, not covered in this paper (as shown in figure N, TODO where the system increases its foraging demand of a high random number from 5 to 15 every 500 hundred simulation step).

**Chosen Pnoise parameter**

For the rest of this document, each experiment assumes a noise level Pnoise of 0.3. This noise level still offers consistent results and a fast adaptation to the environment and remains a high number of communication failures, which should be a proof of the robustness of AITA.

### Communication

The influence in the change of communication range has also been tested before the experiments to observe and highlight the effects of it on the system. The test assumes that a communication device such as …. [TODOlink] which can communicate up to ???, is placed on top of the agents to enable multidirectional short-range/long-range communication (multidirectional - whether the robot receiving the signal is in front or behind does not matter as long as it is within the range). Moreover, the system assumes that there is no noise in the communication. The test consisted of using DAITA (workers in CAITA can share information as soon as they are on the communication area) with 40 robots and make it collect 150 resources as fast as possible, with increasing demand in the foraging task of 5 every 500 simulation step WHAT IS THE DEMAND. The range is first of 10 centimetres and increases to reach 13 meters, which covers the entire arena. The result are shown in Figure N.

Chart, line chart

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Among all the experimental settings tested, the task completion rate of range 0.1 is significantly higher than the others, reaching 1 20’000 simulation step later. Ranges 5, 7 and 13 meters offer the most consistent result as their task completion rates are similar looking, whereas ranges 0.5 and 1 meter show slight variations and are the fastest at reaching 1. As for the section NOISETODO, this alone is not enough to demonstrate the consequences of short communication ranges over different task allocation methods. This is why the swarm’s perception error e of the actual environment has been recorded and is shown in Figure N.

Chart, line chart

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As can be seen in figure N, the ranges of 0.1 and 0.5 meters offer the worst speed in environment adaptation resulting in a high swarm’s perception error whereas ranges over 1 meter (included) offer a low level of error. This can furthermore be seen in the number of task switch per robot shown in Figure N. Systems that have slow adaptability to the environment have fewer task switch as the need for tasks struggles to be shared globally, whereas robots with long-range communication access the information faster resulting in a higher number of task switch per robot as the workers can quickly adapt to the dynamic environment.

The effect of a short-range communication distance can be correlated to the *knowledge error shift* from the section NOISETODO as the shorter the range is, the slower the robots are notified about changes in the environment. This effect explains why short-range communication systems demonstrate a faster task completion rate than long-range communication systems in Figure N, as

As mentioned in the “NOISETODO” section, a direct consequence of a high *knowledge error shift* is the over-collection of resources. This effect on different ranges of communication can be seen in figure N or figure A (todo FF0) for range 0.1 and .5 meters respectively, where the demand sensed by the individuals is once again shifted from the actual demand of the environment. Over short periods, over-collecting can be harmless as the distribution of labor is good enough for the swarm to process the collected resources. However, long-period simulations, over-collecting becomes harmful as the swarm struggles to quickly adapt to the environment and get overwhelmed by the amount of resources it has to process. As the range of communication gets longer, the problem fades and almost disappear resulting in no over-collection of resources.

A solid feature of the environment that is directly related to a healthy system is the periodically visible peaks in the distribution of labor as seen in the series of graphs in Figure N. These periodical peaks happen as the demand periodically increases, a sign of the swarm adapting to the demand. The first two graphs are the labor distribution of the range 0.1 meters and 0.5 meters respectively where it can be seen that as there’s no spike, there’s no sign of the swarm adapting to the periodical increase of demand in the foraging task, which direct consequence is a sign of a high *knowledge error shift*. Inversely, the two other graphs show the distribution of labor for range 7 meters and the entire arena where clear signs of swarm adaptation are seen as periodical peaks are present throughout the entire period.

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0.1 TODO inverser les graphs ligne 2 et 3 1 7 13

**choose communication range parameter**

From now on, each new experiment assumes that the range of communication for DAITA, GTA, and PSI covers the entire arena. Indeed, as ranges below 5 meters suffer inconsistency and a high *knowledge error shift* they are disregarded. As for ranges of 5 and 7 meters, they do both offer consistency and fast environment adaptability, which underline that using a range that covers the entire arena will have the same effect but will offer the maximum consistency and accuracy in experiment results.

## Experiments

The systems through a set of experiments to best describe, observe and highlight how well or how bad they perform in the five categories. Then a first experiment intends to highlight the efficiency of the DAITA system in relationship to its communication performances. A second experiment observes the task completion rate of each system and comparisons are made backed with metrics. Then, tests on the robustness of the different systems are performed. Finally, tests and comparisons on the systems' ability to adapt in the change of workforce are tested and comapred and backup with metrics.

The values for each experiments are set as shown in Table N

|  |  |
| --- | --- |
| Number of resources | 2000 |
| Noise | 0.3 |
| Range | 13 meters |
| And so on? |  |
|  |  |

TODO: Make sure that there is a clear winner for each, reflect on it in disuccsion

*TODO, try to have something more scientific and call all :ForagingTask, NestProcessingTask, CleaningTask for instance.*

## Task completion rate

The task completion rate is meant to observe the speed at which a group of individual can complete a given task. Moreover, task completion rate can be used as a optimization goal as the sooner the swarm complete the task, the better the system is. In order to experiment the task completion rate, experiment 1 is defined.

Experiment 1 consists of collecting, processing, and cleaning 150 resources as fast as possible [NDPDB]. At each new start, the demand for the *ForagingTask* is 50 resources, the demand for the *NestProcessingTask* and *CleaningTask* are both set to 0, and the demand for the *ForagingTask* increases by 7 for every 500 simulation steps to keep the system busy. Tests have proven that increasing the demand by 7 resources at every 500 simulation step keeps the system busy at its max capacity for the whole period, which maximize the task completion rate of CAITA and DAITA as unlike GTA, RND and PSI, they use idle state where if the demand for a task is met, other robots remain idle. If one chooses to use an increase of 6 or less for this experiment, it will keep the system in a lazy state, with more or less half of the workers busy on average (dependent of the increase), over the whole period. The relationship between the demand for the *ForagingTask* and a periodically increasing demand is furthermore elaborated in the next chapter -> cool here, symmetry only talks about it at the same time?.

**Relationship between the periodcal increase of the demand and the starting demand of the *ForagingTask***

Montrer des graphs, dire que les selected ration on pour but de garder le system busy (montrer 70 :5)

The relationship between the periodical increase of the demand in the *ForagingTask* and its starting demand can be seen as a ratio *StartingDemand*:*PeriodicalIncrease* that one can experiment with to obtain different kinds of business in a AITA system.

???

This paper tends to push the business of the AITA system at its maximum over all the experiment to keep fairness in the results as a ratio such as 20:2 would take a longer time to complete experiment 1 compared to a ratio such as 50:7

[NDBDP] : Experiences have been stop at 40’000 simulation as some experiment could take over 200’000 simulation steps

TODO verififer each time qu’on est bien sur du 50 :7

**Task completion rate on variating number of robots over CAITA and DAITA**

The first set of tests performed on the CAITA and DAITA systems with the number of robots variating from 10, 20, 30, 40, 50, 70 to 100 shown in figure N and N, show that the task completion rate with 40 and 50 robots is significantly higher than for 10, 20, and 30 robots. This trend shows a direct relationship between the number of robots performing a task and the completion rate of a task. Furthermore, the trend shows that it is not given that within the same environment, the more robots used to complete a task, the faster the swarm reaches its goal, as both CAITA and DAITA demonstrate struggle when the number of robots goes above 50. In the former, using 70 robots or 100 robots is barely as good as using 50 robots as they achieve the same performances. In the latter, using 50 robots and 40 robots remain the overall fastest as 70 robots and 100 robots obtain a lower task completion rate. A Part of this drop in performances when as the number of robots increases is due to robot congestion (as shown in the figure) – i.e. when multiple robots try to reach a similar goal and struggle to find their way through as they are blocked by others. Furthermore, congestion implies that optimization of the task completion rate by improvement of the positioning of the different areas is possible, however not covered in the experiments, but rather reflected upon in the discussion part. Another part belongs to how AITA has been designed to deal with this type of situation. As explained previously, the algorithm intends to deploy as many robots as needed on a task to reach equilibrium (when the energy supplied to a task is the same as the demand of the task). Seeking equilibrium means that in a world where there exist 70 or 100 robots but the demand is only of 50 resources the algorithm will only deploy 50 robots to cover it. This behavior can be thought of as being “underperforming”, but it just is the AITA algorithm not using more energy than needed to complete a given task.

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**Task completion rate on different task allocation systems**

The same experiment is conducted on RND, GTA and PSI with 40 robots and compared to the two previous systems. Among all the experimental methods, Figure N shows that GTA achieves the best task completion rate than any other system. DAITA is as performant as PSI whereas CAITA is slightly off compared to two distributed systems. RND shows clear sign of under-performance due to its overwhelming over-collection of resources.

Chart, line chart

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## TODO faire attention de pas TOUT comparer, just AITA CORE au reste

## Robustness -> is it really a robustness experiment .. no

The second experiment (EXP2) is a robustness experiment designed for the TAs to show their performances over a period of 30’000 simulation steps. The system starts with a foraging demand of 50 and both the nest processing demand and the cleaning demand set to 0 (Note de bas de page 1:). Then, the demand for the foraging task increases by 7 for every 500 simulation timestep. The goal is to minimize the square error of task assignment -> optimization goal -> namely, reach equilibrium as most as possible TODO what is the squared diff? Also explained that minimizing task switch is minimizing energy consumption as robots stay consistently in the same task

GTA: 186

psi: 99

DAITA: 44

CAITA: 96

RND: 41484

**Robustness of the different task allocation method**

**TODO? Include task swtich?**

Chart

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Figure N shows the squared error for the mode CAITA, DAITA, PSI, GTA, and RND models. RND is shown in a transparent gray and its scale is on the right rather than on the left, as it is significantly performing worse than the other TA’s. It can be observed that methods which consider the demands in their task allocation algorithm do highly better than the one who does not, such as RND. RND reaches an average of 41484 squared error and the trend shows that this number is not falling. This is due to RND disregarding the current need of the environment and rather distributing equally its workforce over the three tasks, leading it to over-collect resources (behavior discussed in section TODO, see graph TODO), and thus leading to an increasing error as the demand for each task is not met.

CAITA, with a 96 squared error, and DAITA, with a 44 squared error show a similar trend with a first pick as the overflow of resources overwhelmed the system. Once this flooding of collected resources is handled, both system tends toward an almost null squared error, leaving only the picks from the periodically increasing demand in foraging task as a variation in the curve. (TODO maybe move it in the discussion area) This shows that both algorithms are reaching equilibrium in their task sooner or later, minimizing their squared error. PSI performs better (TODO in the discussion I guess I have to say why it might perform better? Or maybe here and keep conclusion to re assamble everything) than CAITA with an averaged squared error of 194 and shows the same downward trend as CAITA and DAITA. GTA also performs better than CAITA with an averaged squared error of 241, but shows a higher inconsistency in the curve and no downward trend, meaning that over time it will perform worse than PSI, CAITA, and DAITA.

TODO remettre la photo au propre.

## Adaptive change in workforce

The adaptive change in workforce is meant to observe the speed at which and how well a group of individual can adapt to a sudden change in the number of workers performing a task. The adaptive change in workforce can also be used as optimization goal as changing variables of the environments such as the communication efficiency, the robot’s efficiency at task solving, the number of robots and more can influence it (however not discussed in this paper). To observe the effect in the adaptive change of workforce, experiment number 3 is defined; Experiment number 3 tests the scalability, robustness, and adaptability of the system. The experiment consists of removing a class of workers at a given timestep, and re-introduce it later on. The system starts with a foraging demand of 25 (Note de bas de page 1), and with an increasing demand 7 in the foraging task in order to see how the adaptive change in workforce is influenced by a busy system. The nest processors are removed at the 20’000 simulation step, which gives the system enough time to start and stabilized itself. Then, the class of workers is re-introduced at the 40’000 simulation step and the simulation stops at the 60’000 simulation step. During the time the class of workers is gone and soon after the class is re-introduced, adaptability in the current environment is expected to be observed.

As the goal of this experiment is to observe how robots adapt to a change of workforce and not specifically a change in the nest processing workforce, GTA is removed from this experiment. Indeed, in GTA as all robot switch to the task with the highest demand, it means that usually all robot are in one task (it may happened that, due to communication delay, a robot changes later than its neighbors). Moreover, there is a likelihood of 2/3 that every robot are not in the nest processing task, meaning that no robot would effectively be removed if it was the case, preventing any relevant data to be generated.

*Note de bas de page 1: Since the CAITA and DAITA systems make use of idle states, one could think it is unfair to start the system with a foraging demand of 25 as for a simulation of i.e: 40 robots, 15 of them would be inactive at the start compared to 0 for PSI and RND (since none of them uses idle robots). However, and as will be visible in the result section, even though the system partially starts inactive, it quickly becomes busy resulting in all robots being requested for work, keeping the experiment fair and accurate.*

The comparisons of the adaptive change in workforce on different task allocation system is run with 40 robots and shown in Figure N. Figure N shows that the general trend shows that each TA suffers from the removal of individual as 20’000 simulation step and 40’000 simulation step clearly show signs of change for each curve. RND suffers the least from a change of workforce, highly explainable as its task allocation system is not based on interaction with the current environment situation but rather on individuals will to select a random task. Figure A todo shows how RND adapts to the situation, just by distributing the rest of the remaining robot equally over all other tasks. DAITA and PSI do not highly suffer from the lost in their workforce, and as can be seen they are able to heal from it when robots are re-introduce, as their task completion rate goes back to normal. CAITA however, seems to suffer more from the loss of individual as even though it was as performant as DAITA and PSI, its task completion rate drops and never catches up with the two other. Nevertheless, CAITA and DAITA show clear sign of adaptation in the change of workforce as shown in figure N and M where figure N shows the distribution of labor over the entire period for CAITA and figure M shows the same for DAITA respectively.

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Chart, histogram

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Chart, histogram

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Chart

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## A Comparison of the Total Distance Traveled by Robots with Different Task Allocation Methods

THIS IS ALSO ALIGNED ON 50:7

TODO update with new graph

The total covered distance of the entire swarm reflects the energy consumption of the different task allocation methods. The more distance is travelled the more energy a system has consumed over its lifetime. The relationship between energy consumption and covered distance is an optimization goal the different methods have to optimize. This section reflects on the covered distance following the experimental setup used for the section “Robutsness TODO”

Chart, line chart

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### Figure N shows that over a given period, DAITA uses the less energy by having covered a distance of 12816m, 557m less than the second to best in energy consumption, PSI, with a covered distance of 13373m. PSI, GTA and CAITA cover almost the same distance with 13373m, 13451m, and 13591m each respectively and in increasing order of covered distance. In comparison, RND has a high energy consumption with a total covered distance of 14801m. The performances achieved by DAITA can be explained as the AITA algorithm has been designed to optimize the number of allocated workers to a task related to its demand. In most cases, this means that if all tasks are already in equilibrium, task-less robots will remain idle, effectively not moving and consuming less energy. However, this is only efficient for DAITA has its communication system is fast enough for the swarm to adapt to the change and deploy as few workers as needed. CAITA having covered a significantly higher distance than DAITA is a clear sign of a weakness in the information-sharing center and swarm adaption to dynamic environments.

# Task switching title

Mybe say “uses experiment 1 result” that’s 50:7 EXP2

TODO mettre PSI sur le graph en double

The number of switch per robot is also an optimization goal that each TA should minimize as the lower the number of switch is, the less disturbance there is on the system. This experiment follows the setup used for the section (TODO TASK COMPLETION RATE NAME). Figure N shows the number of task switch per robot for each system. It can be seen that PSI has the highest number of task switch per robot compared to the other TAs. The other TA do not show extensive number of task switch over the experiment, however, CAITA if the methods that performs the best, followed by DAITA and RND.

Uses setup as exp2

Chart, line chart

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## Results

For me, robot that are not temp or core are considered as unassigned. But they are effectively assigned to a task, just waiting for the demand to raise to a level for which they would actually have to work

* Talk about the ratio
* **Talk about task allocation, demand and how energy supply could’ve and could impact the result**
* As of now I have a lot of congestion in my system, maybe talk about how I could prevent it and cite “Task allocation pitonakova”
* I imagine it is going to be interesting to assess how many robot it needs for a set of task to be at an equilibrium
* Say that psi was not designed for such task, which will explain a lot of thinngngngnggs

**Discuss and experiment on lemmas and theorem of the task allocation model**

* I can also say (this paper does not intend to cover the proof established in the paper, but more to assess its efficiency though a set of experiments and comparisons to established and well tested models such as .. “

They made assumption that I need to verify and discuss

“How much robot does it take to have n task at equilibrium” “following lemma tatata .. let’s try and see” “it did not reach .. but if we do that .. the result are better .. blah blah blah”

“How much task can n robot whit stand”

*#! as of now, the task handler makes sure the robot is not assigned a new task if he carries a resource*

As mentioned in the section TODO, an optimization variable is the location of the different deposit area within the arena. Indeed, the current implementation makes the robot deposed their payload in the center of each zone which drastically increase the time-to-find a resources as robot will usually crawl at the edges of a zone due to their stay in zone behaviour. Mechanisms to improve either the placement of the resources within the area of the resources detections can thus be implemented to improve it. Moreover, congestion also discussed in the same section can be something one can improve. The implemented robot avoidance behaviour is not optimal and thus does not offer the best chance for each robot to escape a congestion situation.

*#! ob: when more demand than robot, no oscilliation*

*#! ob: when too much osc the robot struggles to complete a task because it is always pulled somewhere else.*

*# ? my tweak with the >=3 fixes it*

*#! obs: sometimes an ant nest processing can lose its task assignemnt by going outside the border and be replaced by another once.*

*#! that is the same issues as descibred line 276*

*#!obs: a robot with AITA will not change task unless its task's demand is satisfied first. even if the other task has hiiigh demand.*

*#!obs seems to bring a lot of congestion since they are all trying to go at the same place*

*#! sometimes the robot will be oscilliating between task and no task, the sensor will go outside the zone*

*#! > even though the robot did not intend to leave the area, but because outside HOME, the robot keeps its task.*

*#! > it varies between has\_to\_work and not has\_to\_work so when the sensors leave the area HOME the robot does not have to report*

*#! > and will keep its state ...*

*# ? but is what I did the best option now? (go\_and\_stay\_home)*

## Discussions / Conclusion -> sort of

Here faire un retro de toutes les exps et dire genre (ouais bah si GTA était bon la en revanche il est nul la .. »

**Discuss possible variable and how they have impacted the task allocation model**

1. the paper proposes initial condition (such as no mouvement in task needs for a define amount of time) -> maybe I could propose stress test to relate to real life condition

-maybe say here that the robustness has been proven by the noise experiment?

For the conclusion

Maybe the greedy woul’dve perform worse with more task? Take the experiment from which I stole all the graphs idea because they were comparing GTA over 100 task and with other TAs and it was the worse

* GTA first -> It can be that the system in not challenging enough­
  + Also its trend is more or less to have these weird flat line each time
* Say somewhere that RND and GTA and PSI overperform as they don’t have mechanisms that prevent them to no allocate robot if task is good

# Future work

# The paper says it could also be impacted by previous experience .. maybe the robot can have a short memory

# That would say "ho .. I was close to food 10 timestep ago.. it is likely that I still have food nearby"

# The robot cannot sense their long-range environment, but maybe, for task such as food, we could sense the short # environment and say "if I sense food then the energy I can provide is higher"

# ? maybe .. if the robots know about any last foraging point .. then maybe the energy it can supply is greater?

#! or .. if you already are on the area for the task .. maybe increase?

In realf life it would be different, maybe reflect here with some paper from Gordon

**Possible improvements to the math model**

* **Share your entire memory to a robot instead of just your understanding, making it even more robutst.**

Given the exact implementation of the math model, the experiments have reach a certain result, but it could be changed so that ..

1. Every n step, re assign every robot with the current world state -> my take is that the distribution is going to be better
2. maybe the robots could "see" or "reassess" the needs when entering an area or something .. idk (even though it says that they would not try to assess how much energy can an ant give to a task as it makes the problem NP-complete)
3. maybe the gordon idea with the map could be tested as improvement (even though it says that they would not try to assess how much energy can an ant give to a task as it makes the problem NP-complete)
4. sometimes some ants are not even allocated .. maybe if all task have enough ants some idle should be attributed a random task=

Also the real-life implementation

Read payam’s email, I think she mention somewhere something that could potentially be future work

# Conclusion