International Conference on Automation, Control, Engineering and Computer Science (ACECS'14)
Proceedings - Copyright IPCO-2014, pp.180-186
ISSN 2356-5608

Effect of evaporation pheromone rate on multi-robots mines detection system based on modified ACO algorithms

Saaidia Riadh
Computer Laboratory for Industrial Systems (LISI)
National Institute of Applied Sciences and Technology
University of Carthage
Tunis, Tunisia
riadh.saaidia@insat.rnu.tn

Mohamed Sahbi Bellamine
Computer Laboratory for Industrial Systems (LISI)
National Institute of Applied Sciences and Technology
University of Carthage
Tunis, Tunisia
aroussia@insat.rnu.tn

Abdessattar Ben Amor
Computer Laboratory for Industrial Systems (LISI)
National Institute of Applied Sciences and Technology
University of Carthage
Tunis, Tunisia
mrdssrst@yahoo.fr

***Abstract*— Ensuring humanitarian demining operations required high level of reliability and accurate constraints. In order to enhance efficiency of demining operations, these constraints included more criteria in terms of time, cost, and safety enhancement of person and operation. In this article, we chose an automated approach for demining operations based on meta-heuristic algorithm. The demining system was represented by a multi-robotics system which operated in unknown landmines. The choice of meta-heuristic algorithms as coordinating strategy would improve temporal performances of the overall mine detection process. We studied temporal performances system through effects of minefields configuration variation and choice of coordinating algorithms. We presented a comparative study about use of ACO algorithm (as coordinating algorithm) for mine detection purpose. Especially we presented effect of evaporation pheromone rate variation on timing system performance. Multi-robotic demining systems were simulated for different mine land distributions and for three types of coordination algorithms.**

***Keywords*— multi-robotic, ACO algorithms, minefields distributions, evaporation pheromone rate, temporal performances.**

I. Introduction

At least, Standard demining clearance model operations (UNDHA standard) must ensure 99.6% rate of successful mine detection, and a 100% of the same rate according to International Mine Action Standards (IMAS)[1-3]. Timing demining process performances are less important than personal safety, reliability and accuracy of the demining process. Replacing manual methods as primary procedure for humanitarian demining by robotized solutions should increase productivity by speeding up demining process reliably and safely. Various demining treatments exit. This is due to use of different types of sensors and equipments to detect and neutralize landmines. In addition to this difficulty, the nature of landmines and the characterizations of any demining instrument, which should be 100% reliable, must be taken in consideration. the Application of Robotics research to demining operations purposes requires integration of various technologies including demining oriented functions like the adaptability to field mines distributions, type of control architecture, integration of heterogeneous sensors, autonomous navigation , coordination in the case of multi robots system, communication implementation, Machine intelligence and signal processing algorithms[1].

The exited robotic systems designed for demining operations have limited performances if we consider that these systems should explore unknown configuration field [4]. In addition, demining robots are equipped with high sophisticated technology instruments for mine detection and processing [5] rise mine clearance cost. Time optimization of demining operations becomes an important humanitarian objective if we consider the number of abandoned mines fields [6]. This optimization must respect security constraints attached to demining operator and enhance efficiency of demining tasks in time proceeding and energy consummation. According to [5, 6],various assistant tools were designed and tested to help automation demining process, limit risk of human error, and rise estimation of risk zone. Substitution of human operators by robotic agent participates with appropriate strategy in the realization of this goal [7]. However, the sophisticated robots agents and the distributions variety of mines field enhance the demining operations cost. This cost includes time demining operation, energy management, equipment, and security considerations. In this article, we explore the possible applications of multi-robot systems in time detection optimization of Mx% (maximum mine portion detected.) mines in particular case of field mine configuration. Adaptation of multi-robot systems for demining operations, induce the choice of an adaptable coordination algorithm. Demining operations are complex problems and they need meta-heuristic algorithms as coordination algorithms. Search and optimization algorithms have risen their exploration capabilities by including basic heuristic [8]. Many

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ISSN 2356-5608

evolutionary algorithms like ant colony optimization, genetic algorithms etc. solve difficult optimization problems in a reduced amount of time with approximate solution. At this stage, ACO algorithms represent a coordination algorithm used to optimize demining operations time with adaptable considerations as an example for solving foraging robots problem.

This paper is organized as follows. In Sect. 2, we present works related to multi-robots application on demining operations. In particular these works include configuration constraints in the case of mine distribution, type of meta-heuristics used for collaboration algorithms and performances metrics. Sect. 3 presents field mine distribution and collaboration models used in demining operations. Sect. 4 describes simulation considerations for performed experiences. Sect. 5 lists and analyzes the simulations results.

II. RELATED WORKS

Multi-robots application in demining operations for humanitarian purposes represents an evaluation example of coordination strategy performance. Many researches such as [9-11]use specific coordination strategy in order to evaluate some criteria performances. General research organization starts with definition of collaboration Algorithms used in order to perform specific task. In our case we choose demining operations. Demining process includes many constraints related to the nature of minefield distribution and performance evaluation criteria. Some researches as in [9, 11, 12]give statistical studies on variety of spatial mine distribution in minefield. In fact, mines field spatial distributions in conflict zones are highly complex and varied. Landmine descriptions can't be defined easily with deterministic clustering approaches. Landmine variety induces different mine distribution patterns. Different mines distribution can be used to test hypotheses for demining operations. However, other assumptions have influence on performances evaluation systems. Combining the different parameters (incidents, populations, roads, agriculture field, etc.) for defining mine field map, would allow the consideration of environmental and social conditions [6].

Simulation example given in [4] tests real case minefield distributions in order to realize an automatic estimator to mines localization. Mines distribution configuration represents limitation if we work in unknown environment. But in several cases, mines distribution can be modeled by stochastic model like in [5, 6, 12]. In other part efficiency of demining operations depend of scenario followed for each robotic agent.

In other part, the choice of collaboration strategy represents other constraint. In fact, demining operations with multi-robots systems rises complexity of collaboration interactions [9, 13]. In this case application of suitable meta-heuristic algorithms for multi-robot demining operations was performed in research such as [14-17]. Research studies focus on combined and modified heuristic (as is the case for Genetic algorithms, ACO algorithms, etc.) to enhance general performances of multi-robots systems. As a result, studies as [18] define evaluation metrics to quantify collaboration performance cost. Localization and distribution robotic agents' configuration was taken as evaluation criteria. These criteria depend on applications constraints like possible robot agents interference [19]. A set of generic performance metrics was employed to evaluate each aspect of robotic demining systems. These performance metrics include demining processing speed to measure time elapsed until demining operations can be totally or partially achieved. In the rest of experimentations we will focus on temporal performance optimization using modified meta-heuristic algorithms. In particular, configuration parameters for minefield and coordination algorithm heuristic, as type of mine distributions and effects of evaporation pheromone rate, were treated in experimentations. Other performance metrics like: robotic agents displacements which represents aggregation of the distances inter-agent position during demining operations (consumed energy), robotic Agents proportion of agents which ensure demining operations, robotic group size effect and communication flow exchanged between agents during robots interactions; represent other optimization objectives and they will be treated in further works.

III. METHODS AND HYPOTHESIS

This part represents general configuration parameters for tested environment. These parameters include minefield distribution and adaptation of ACO algorithms for collaborative demining robotic foraging.

A. *Field mine configuration*

Measurement of demining operations time was performed at different values of configuration parameters. In concordance with[20], we consider evaporation pheromone model as influential parameter. In fact, we fix robots/mines ratio and we vary evaporation pheromone rate and note detection mines time for different minefield proportion (Mx %). Tested mines proportion was been fixed to 60%, 70%, 80% and 90% for a total number of 50 mines [5].

In other part, mine spatial distribution has possible effect in mine detection time [5, 6]. We try different spatial distributions which include:

1st case: (random distribution) mines are placed randomly with uniform density of probability.

2nd case: (fixed spatial distribution) second distributions are destined for fixed mine position. We try two different dispositions with limited mined zone. These two tests are indicated in Fig 1 and Fig 2.In Fig 1 we divide mine field into two parts relatively to a vertical symmetry axe. P1 represents mined area zone. In figure 2 we divide mine field into four parts relatively to a vertical and horizontal symmetry axes and P3 represents mined area zone. Other parts are mine free. As presented in [21], in the case of environment symmetry, localization represents a complicated task. This complexity is

ISSN 2356-5608

due to correctness of robot position and orientation estimation (unknown mine land without specific information). Collaborative algorithms as for ACO algorithms can reduce elapsed time in mines research operations.

3rd case :(random line distribution: Fig 3) Mine lines are randomly placed along the line or dropped with a constant spacing. The random lines are given a very broad margin of placement error. The random spacing lines are assumed to represent positioning errors mainly due to navigation and drop timing errors. Random lines are assumed to have random orientation and mine spacing. But in this experimentations random mine lines are parallel[4].

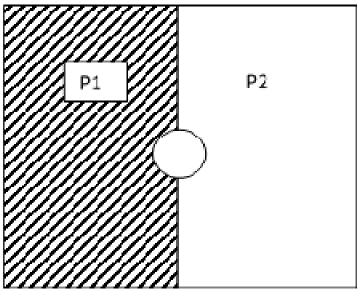

Fig. 1. Fixed spatial distribution 1.

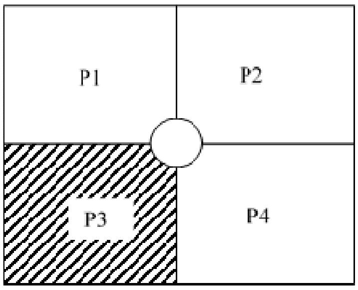

Fig. 2. Fixed spatial distribution 2.

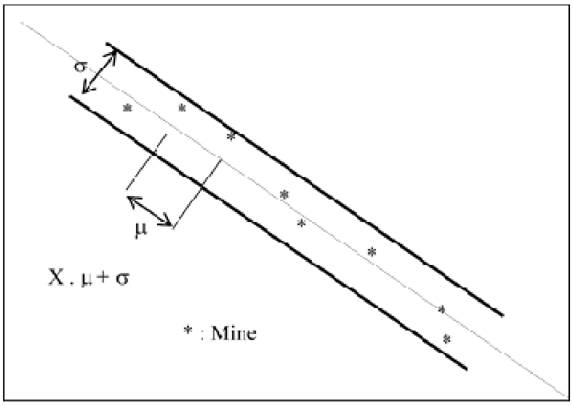

Fig. 3. Random line distribution (s=1,μ=3 and areas dimensions=16x16).

B. Navigation and research methods

In this part, we will present mine research methods adopted by different robot agents. The evaluation of this methods effect is based on the time detection mines quality. In this experimentation, three main collaborative navigation algorithms were performed:

1) Method1: (model BASE)

In this model, robot agents do not adopt a particular logic for mine research. So robot agents are not restricted with any constraints except some particular rule listed in fallow:

- R1: when robot agent finds a mine. It must return to the base for deactivation mine operation
- R2: used base is fixed
- R3: all robot agents are placed in the base at the demining operations beginning.

2) Method2: (model ACO)

In this part, robot agents adopt a mine research strategy based on ACO (Ant Colony Optimization) algorithm to find optimum demining operation. We save the same rules adopted in model BASE (R1 R2 R3). Used robot agents path is fixed by pheromone rate τ deposed by other searching agents. We adopt three main methods for pheromone rate calculation:

a) 1st case (static evaporation pheromone rate)

In this test we fixe evaporation pheromone rate ρ and we calculate pheromone rate as fallow [22]:

$$\tau(\kappa)=\tau(\kappa-1)(1-\rho) \qquad (1)$$

b) 2nd case(dynamic evaporation pheromone rate)

This ACO algorithm configuration adopts a programmable evaporation pheromone rate to calculate pheromone rate as fallow:

$$\tau(\kappa)=\tau(\kappa-1)(1-\rho)+(1-(1+Q)^{-1})\tau(\kappa-1) \qquad (2)$$

$$\rho=(1+(\tau-\alpha)^{4}(2\alpha)^{-0.5})^{-1}\text{ , }\alpha=0.5 \qquad (3)$$

$$Q= TP\ (TP+FN)^{-1}\ TN\ (FP+TN)^{-1} \qquad (4)$$

This equation is introduced as heuristic a Q factor, which represents an algorithm quality factor [20].α factor used in programmable evaporation pheromone rate was fixed to 0.3 and Q factor represents an algorithm appreciation for method research rule [9].In our case we define two main rules for demining research operations:

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- Dynamic rule 1 = mine research operation (TP, FP)
  - TP=find mine when trying to research mine
  - FP = robot do not find mine when trying to research mine
- Dynamic rule 2 = base return (TN, FN)
  - TN = robot already charging mine in return when trying to return to base
  - FN = mine discharged into the base

c) 3rd case (timed evaporation pheromone rate)

This case adopts also a programmable evaporation pheromone rate. But, evaporation pheromone rate is defined by determination of lost time elapsed between two succeeded mine detections as fallow:

$$\tau(\kappa)=\tau(\kappa-1)(1-\rho)+(1-(1+Q)^{-1})\tau(\kappa-1) \quad (4)$$

$$\rho=\Delta t(1+tM1) \quad (5)$$

$$\Delta t=tM1-tM2+1 \quad (6)$$

tM1=detection time for mine $_i$

tM2= detection time for mine $_{i-1}$

3) Method3: (model modified ACO)

The method adopted in this part is based on an ACO algorithm but with considering a mobile base in order to minimize base-mine displacement. Base coordinates are defined by P_x and P_y:

$$P_x(k)=0.5\,[\,P_x(k-1)+R_{ix}(k)\,] \quad (7)$$

$$P_y(k)=0.5\,[\,P_y(k-1)+R_{iy}(k)\,] \quad (8)$$

The ($R_{ix}(k)$, $R_{iy}(k)$) couple represent coordinates of recent detected mine$_i$. The idea presented was inspired from intensification and diversification [8, 23]. Diversification for robotic agent represents ability to demining many and different mine land regions. Intensification summarized in the ability of base guides demining operation in specific zones with high mine concentration. At this stage we can reserve robot agents for mine research and the base as a new agent for deactivating operations.

IV. SIMULATION PROTOCOL

In this section, we introduce general simulations protocols followed in collaborative algorithms efficiency validation. All simulations are performed with NetLogo [24, 25]. NetLogo is used as software platform to simulate robotic agents and landmine map. In fact, NetLogo supports advanced modeling of complex systems using a library of java programming primitives. In NetLogo simulation environment, robotic agents were modeled in simple design without consideration of collision avoidance. As given in Table 1 experience design was performed by variation of the evaporation pheromone rate and kind of landmine distributions. Each experience is repeated ten times using NetLogo API control. Mine detection time values was reported to MATLAB software platform in order to compare different configuration results.

A simplified foraging scenario was taken to describe demining operations. Robots states include the searching and homing state. When a robot detects a mine, it picks up and come back toward neutralizing base. Execution demining time is accounted while a robot is either in searching mode or homing. Time of other robots avoidance is not considered in demining scenario. Fig 4 shows the behavior diagram for demining operations scenario. Robotic agents detect, collect mines and bring them to a mine neutralizing base.

TABLE I. TABLE 1.SIMULATION PARAMETERS

Model	**Evaporation pheromone rate %**	**Distributions**
ACO	0%-100%	Random, fixed 1, fixed 2 and random line
Modified ACO	0%-100%	Random, fixed 1, fixed 2 and random line

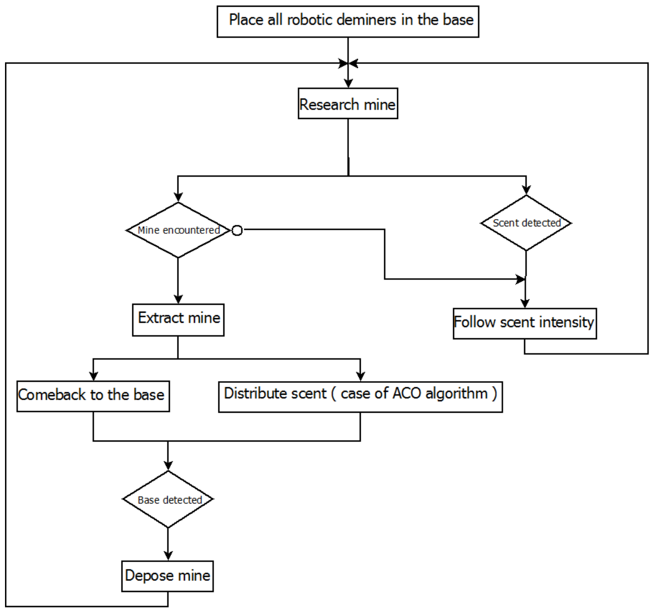

Fig. 4. behavior diagram of a multi-robot demining system.

V. RESULTS AND INTERPRETATION

Experimental studies in this article were performed for fixed mines/robots ratio. According to [19],rising robots/mines

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ratio beyond some limits don't affect time detection due to robotic agents interference and this time was stabilized. In order to test evaporation pheromone rate influence on time demining optimization; we start by testing available robots/mines ratio limits which don't modify temporal performances. Application of various mines/robots rate on presented mines distributions and collaboration models based on ACO algorithms, attest that rising robotic agents number (in order to minimize mine detection time) haven't influence on system timing performances. Figure 5 gives an example of time detection mine stabilization for base demining model with random distribution (robots/mines ratio = 50%, mean time values=129.17). Table 2 summarized means and deviation values of other stabilized time detection mine for different demining models (base, ACO and Modified ACO models) and detected mines proportion (60%-90%) ranges. Variation effects of distributions study cases are considered with mean values.

TABLE II. MEANS AND DEVIATIONS LIST OF MINE DETECTION TIME VALUES (RM% = 50%)

Model		Base	ACO	Modified ACO	Mean time for all models
Time for Mx%=90%	mean	129.13	149.92	118.67	132.57
	deviation	9.31	10.68	22.37	
Time for Mx%=80%	mean	100.88	117.25	93.04	103.72
	deviation	9.63	12.25	14.94	
Time for Mx%=70%	mean	83.42	97.25	76.71	85.79
	deviation	9.85	11.81	9.78	
Time for Mx%=60%	mean	70.17	80.54	64.79	71.83
	deviation	9.19	10.84	6.33	

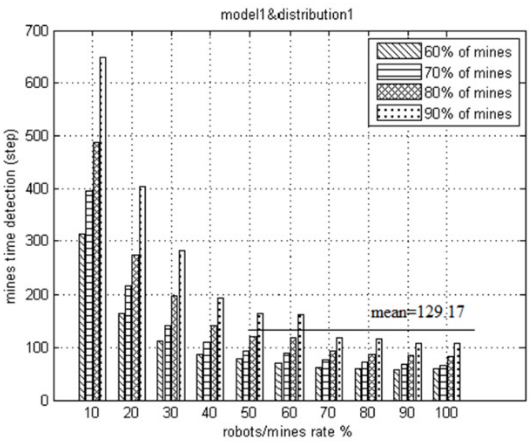

Fig. 5. Time detection mine using model BASE and random distribution.

In this part, we present possible effect of evaporation pheromone rate variation on demining time performances for both ACO and modified ACO algorithms (Mx%=90%). In each experimentation, we increase pheromone evaporation rate with 10%. Figures 6 and 7 represent detection time variation with consideration of mine field distribution type for both ACO and Modified ACO model. For lower pheromone evaporation rate, higher values of detection time results were taken with random distribution. Rising pheromone evaporation rate ameliorates temporal performances. But this mine detection time decrease was stabilized for high evaporation. In fact, detection time results were limited to a range of 200 s.t for evaporation pheromone rate > 60% in the case of ACO model and for evaporation pheromone rate > 30% in the case of modified ACO model.

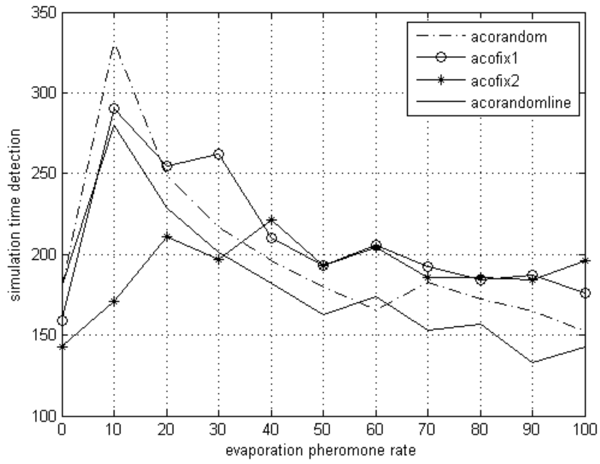

Fig. 6. Time detection results ACO model

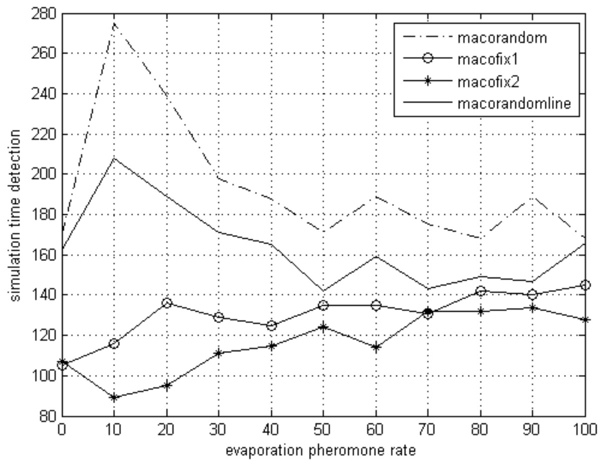

Fig. 7. Time detection results for modified ACO model

International Conference on Automation, Control, Engineering and Computer Science (ACECS'14)

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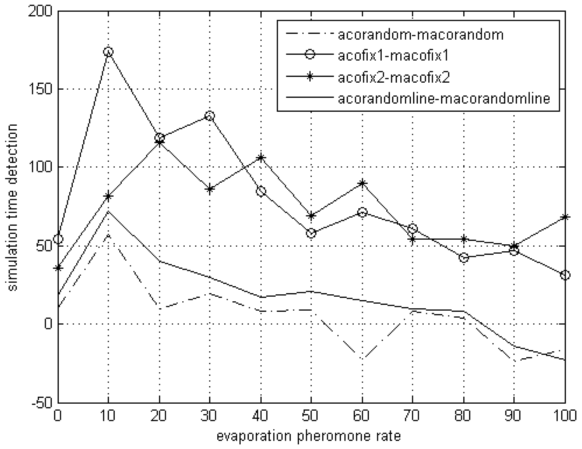

Fig. 8. Time detection comparison between ACO and modified ACO model

Figure 8 indicates time variation between ACO and modified ACO model. Modified ACO model presents better timing results than ACO model with lower pheromone evaporation rate (if we consider separately effect of mine field distribution type). ACO model presents better timing results than modified ACO model only in the case of fixed spatial distributions with high pheromone evaporation rate (>80%).

Pheromone evaporation rate impact on time system performances is noted in the beginning of solutions construction. Adopting a programmable pheromone evaporation rate which induces new solutions exploration should reduce time demining. Researches in [20, 26, 27], use different models of programmable evaporation rate based on mathematical formulation. We take the evaporation pheromone example given in [20], as reference to evaluate our evaporation pheromone rate model. Simplifying evaporation pheromone model was the principal motivation of selection of timed algorithm model.

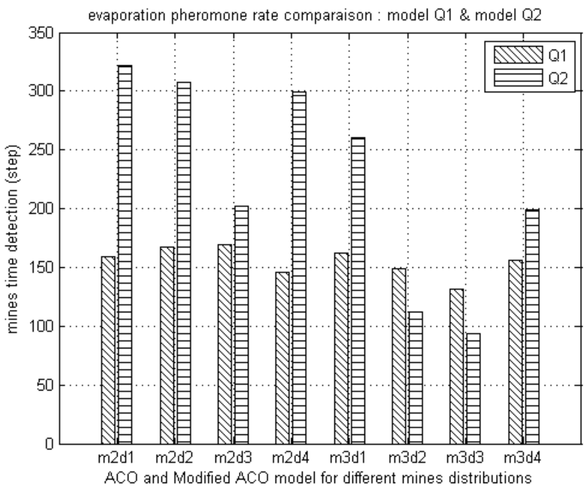

Fig. 9. Evaporation pheromone rate model comparison

In figure 9, we reported the temporal results difference between different evaporation pheromone models for ACO and Modified ACO collaborative algorithms. Mathematical evaporation pheromone rate model [20] is represented by Q1 model. Our evaporation pheromone rate model is represented by Q2 model. In the case of ACO model (m2d1, m2d2, m2d3 and m2d4), temporal results obtained with Q1 model are better than Q2 model except the result in fixed 2 distribution (m2d1). In fact system equipped by Q2 evaporation pheromone model takes double time to detect 90% of mines than Q1 model. This different change in the case of Modified ACO model and better temporal performances was detected with Q2 model in the case of fixed distributions. Multi-robots system experimentations were performed on software simulation platform. In real implementation, application of mathematical complex model for evaporation pheromone rate should require more hardware resources and reduce temporal performances.

VI. CONCLUSION

This paper presents pheromone evaporation rate experimentations. Effects of pheromone evaporation rate were noted for particular rates and we have better results with modified ACO algorithms. Temporal performance enhance of demining multi-robots systems was obtained by modification of ACO algorithms. But results still depend on environment configurations and other modifications can be performed on ACO algorithms especially with pheromone evaporation rate studies. Application of programmable evaporation pheromone rate helps to improve temporal performances. This improve use of evaporation pheromone rate pulse instead of high evaporation pheromone rate maintain. The Choice of evaporation pheromone rate model modifies temporal performances system. In our case, the additional experimentations on real implementation of multi-robot controller must be performed to evaluate algorithmic model of evaporation pheromone rate.

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