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TEMPORAL PERFORMANCES EVALUATION OF MULTI-ROBOT DEMINING SYSTEM INSPIRED BY ANT BEHAVIOR.

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Abstract

In this paper we adopt a cooperative strategy based on ACO (Ant Colony Optimization) algorithms to coordinate a Multi Robots System (MRS). Our principal objective is to evaluate temporal performances for this system by choosing demining operations as a benchmark problem. In this work, we try to adapt the ACO algorithm parameters for different mine distribution in order to reduce time demining operations. In particular, we report effects of evaporation pheromone rate model and minefield configuration on temporal performances.

Keywords: ACO algorithms, multi-robot system (MRS), evaporation pheromone rate, demining system.

1. Introduction

As stated in [1], the percentage of human victims and deaths caused by mine, improvised explosive device (IED) and explosive remain of war (ERW) has been declining since 1999. However, mine accidents number is still important, especially if we compare the civilian causalities percentage with military one, we find that it has risen for 73% in 2011 to 78% in 2012.

In 2012, the landmine report witnessed a high total number of 3628 mine/ERW/IED casualties especially among children and women. Also there is a detection of 1066 killed people and 2552 injuries. Despite all these figures, the real number of casualties is still unknown and related to world struggle. Although the clearness of landmine represents a recurrent problem because, the undamaged surface is extended yearly, and it needs efficient methods to ensure the clearance goal.

At least, both the standard demining clearance model operations (UNDHA) and Mine Action Standards (IMAS) must ensure 99.6% and 100% of successful mine detection [2-4].

Taking into consideration, the importance of personal safety even before timing demining process performances, the robots is used to replace the manual methods, in order to save the human being and improve the activity by speeding up reliably and safely the demining process.

In order to achieve these goals, it must pay attention to the nature of landmine and the characterization of demining instruments, also it must use different types of sensors and equipment of detecting landmines. The application of robotic research to demining operations purposes requires the 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 [2].

The operation of exploring unknown configuration minefield faces some difficulties which are: the limited performances of the existing robotic systems [5], also the highly sophisticated technology instrument on the robots [6].

In addition, timing optimization in this operation presents a challenge that must be taken into account because of its relation to humanitarian objective [7]. So in order to ensure the security restrictions different assistant devices were added to the goal of limiting the risk of human error and rising the estimation of risk zone. However, the objective is still hard to be fullfiled because of the sophisticated robot agents and the mines distribution variety which enhance the demining operations cost.

In this paper, there is a presentation of different applications of multi-robot systems, which are adapted to minimize the time detection of mines proportion (Mx%=90%) [8]. Due to the importance and complexity of the demining operations, it is obvious and necessary to adapt an efficient coordination algorithm. So, in this work, we adopt Ant colony optimization algorithm as an example of coordination algorithm based on meta-heuristic algorithms to treat complexity of demining problem and scale of landmine fields [9, 10].

The remainder of this paper is organized as follows. Sect. 2 focuses on different works where multi-robots are applied to ensure demining operations. In the case of mine distribution, type of meta-heuristics used for collaboration algorithms and performances metrics. Sect. 3 presents the field mine distribution and collaboration models used in demining operations. Sect. 4 describes the simulation considerations for performed experiences. Sect. 5 lists and analyzes the simulations results. Sect. 6 is reserved for results discussion.

2. Related works

Multi-robots application in demining operations for humanitarian purposes represents an evaluation example of coordination strategy performance. Many researches such as [11-13] use specific coordination strategy in order to evaluate some criteria performances. General research organization starts with the definition of collaboration algorithms used in order to perform specific task. Demining process, which is highlighted in this research, includes many constraints related to the nature of minefield distribution and performance evaluation criteria. Some researches as in [11, 13, 14] 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 cannot be defined easily with deterministic clustering approaches. Landmine variety induces different mine distribution patterns, that one 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 minefield map, would allow the consideration of environmental and social conditions [7].

Simulation example given in [5] tests real case minefield distributions in order to realize an automatic estimator to mines localization. Mines distribution configuration represents a limitation in the case of unknown mined environment. Nevertheless, in several cases, mines distribution can be modeled by stochastic model like in [6, 7, 14]. Moreover, the efficiency of demining operations depends on the scenario followed for each robotic agent.

On the other hand, the choice of collaboration strategy represents other constraints. In fact, demining operations with multi-robots systems raise complexity of collaboration interactions [11, 15]. In this case, the application of suitable meta-heuristic algorithms for multi-robot demining operations was performed in research such as [16-19]. 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 [20] define some evaluation metrics to quantify collaboration performance cost. Localization and distribution robotic agents configuration were taken as evaluation criteria. These criteria depend on the application of constraints like possible robot agents interference [21]. 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. The rest of experimentations focus on temporal performance optimization by 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 the 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.

3. 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. The measurement of demining operations time was performed at different values of configuration parameters. Tested mines proportion

(Mx %) has been fixed to 90% for a total number of 50 mines [6].

At the first level, robots/mines ratio (RM%) is tested as an influential parameter for time system performances. At the second level, different configurations of minefield distribution were evaluated. At the third level, evaporation pheromone model is studied as influential parameter for research navigation model based on ACO algorithms [22]. The evaporation pheromone rate is increased gradually and the operation of detection mines time is noted.

2.1 Mine configuration

The mine spatial distribution has possible effect in mine detection time [6, 7]. The performance of different collaborative navigation methods is evaluated by the consideration of three types of distribution models. These distributions include random distribution, fixed spatial distribution and random line distribution.

In the case of random distribution mines are placed randomly with uniform density of probability [23, 24], the second type of distributions are reserved to fixed mine position [25]. Two different dispositions with limited mined zone are evaluated. That type of distribution is based on normal mixture model (Figure. 2 and 3)[26, 27]. The definition of the mined zones in the version of fixed distributions depends on matrix variance normal distribution (Fixed 1: $\sigma_1^2=1$ and $\sigma_2^2=16$;Fixed 2: $\sigma_1^2=10$ and $\sigma_2^2=16$)[28].

As presented in [29], and in the case of environment symmetry the localization represents a complicated task. This complexity is due to the 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.

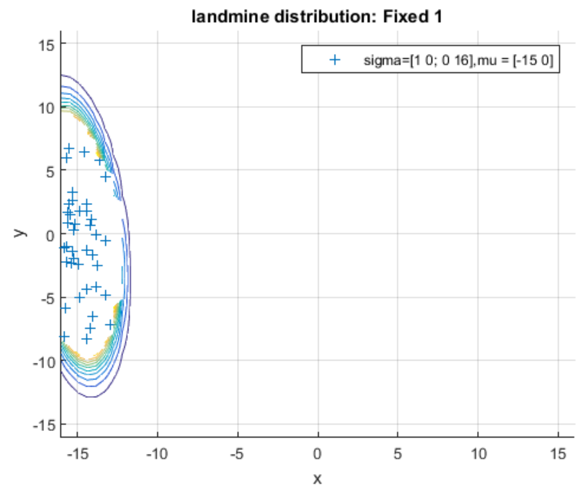


Fig. 1. Fixed spatial distribution 1.

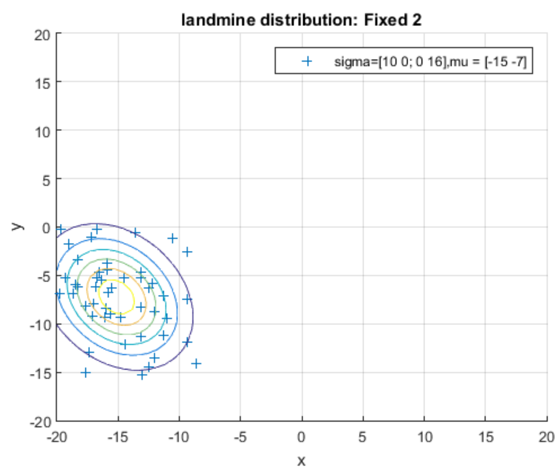


Fig. 2. Fixed spatial distribution 2.

In the case of random line distribution, 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. This distribution is based on Poisson mixture model [30, 31] with the probability to find a mine at the x position on the projected line is expressed as follow [5]:

$$P(X_N <= x)=(1- e^{-\lambda x})^N \tag{1}$$

With N is the number of mine detected and λ is the Poisson rate.

Random lines are assumed to have random orientation and mine spacing. But in these experimentations; random mine lines are parallel [5].

2.2 Navigation and research methods

This part includes the presentation of 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 including random research model (BASE), ant research model (AS-ACO) and modified ant research model (M-AS-ACO).

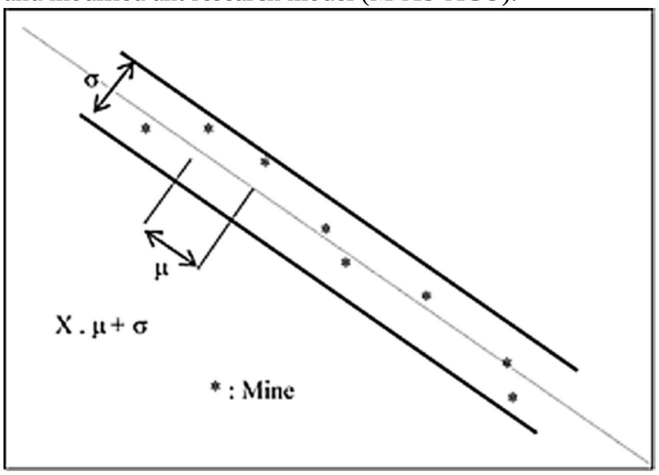


Fig. 3. Random line distribution (s=1,μ=3 and areas dimensions=16x16).

In the case of the BASE model, robot agents do not adopt a particular logic for mine research. So robot agents are not restricted to any constraint except some particular rules listed as fallows:

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

The robot agents of the AS-ACO model adopt a mine research strategy based on ACO algorithm to find optimum demining operation. The same rules adopted in BASE model (R1, R2 and R3) are retained. The used robot agents' path is fixed by pheromone rate τ deposited by other searching agents. Three main methods are adopted for pheromone rate calculation:

a) 1^{st} case:

In this test, the evaporation pheromone rate ρ (static evaporation pheromone rate) is fixed and the pheromone rate calculation is given as follows [32]:

$$\tau(k)=\tau(k-1)(1-\rho) \qquad (2)$$

b) 2nd case:

This ACO algorithm configuration adopts a programmable evaporation pheromone rate (dynamic evaporation pheromone rate) to calculate pheromone rate as follows:

$$\tau(k))=\tau(k-1)(1-\rho)+(1-(1+Q)^{-1})\ \tau(k-1) \qquad (3)$$

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

Eq. (3) introduces a heuristic Q factor, which represents an algorithm quality factor [22]. The α factor used in programmable evaporation pheromone rate was fixed to 0.3. The Q appreciation factor for method research rule is formulated as follows [11]:

$$Q=TP.(TP+FN)^{-1}.TN.(FP+TN)^{-1} \qquad (5)$$

Eq. (5) introduces two main rules for demining research operations:

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

c) 3rd case:

The navigation model in this case adopts also a programmable evaporation pheromone rate (timed evaporation pheromone rate). But, the evaporation pheromone rate is defined by the determination of wasted time elapsed between two successive mine detections as follows:

$$\rho= (1+tM1)^{-1}.\Delta t \qquad (5)$$

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

Where tM1=detection time for $mine_i$ and tM2= detection time for $mine_{i-1}$

The method adopted by M-AS-ACO model is also based on the ACO algorithm. This model considers a mobile base in order to minimize base-mine displacement. Base coordinates are defined by P_x and P_y:

$$P_x(k)=0.5\ (P_x(k-1)+R_{ix}(k)) \qquad (7)$$

$$P_y(k)=0.5\ (P_y(k-1)+R_{iy}(k)) \qquad (8)$$

The $(R_{ix}(k),\ R_{iy}(k))$ couple represents the coordinates of recent detected $mine_i$. The idea presented was inspired by the intensification and diversification [33, 34]. The diversification for robotic agent represents the ability to demine many and different mine land regions. Intensification is summarized in the ability of base guides demining operation in specific zones with high mine concentration. At this stage, the robot agents are reserved for mine research and the deactivating operations are assigned to the base as a new agent type.

4. Simulation protocol

This section introduces general simulation protocols followed in collaborative algorithms efficiency validation. All simulations are performed with NetLogo [35, 36]. NetLogo is used as a 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 are modeled in simple design without the consideration of collision avoidance.

As given in Table 1: the 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. The 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 it up and comes back toward neutralizing base. Execution demining time is accounted while a robot is either in searching or homing mode. Time of other robots avoidance is not considered in demining scenario. Fig. 4 shows the state diagram for demining operations scenario. Robotic agents detect, collect mines and bring them to a mine neutralizing base.

5. Result

Experimental studies in this manuscript were performed for different RM% ratio. According to [21], rising RM% ratio beyond some limits do not affect time detection because of the interference of robotic agents, which stabilizes the time result. In order to test evaporation pheromone rate influence on time demining optimization; some tests are performed with different RM% ratio. These tests identify limits that do not modify temporal performances. Additional experimentations, that perform the application of various RM% rate on presented mines distributions and collaboration models based on ACO algorithms, were conduct to verify the hypotheses. The rising robotic agents number (in order to minimize mine detection time) has no influence on system timing performances. Fig. 5 gives an example of time detection mine stabilization for BASE model with different distributions and RM%.

Table 1: Simulation parameters

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

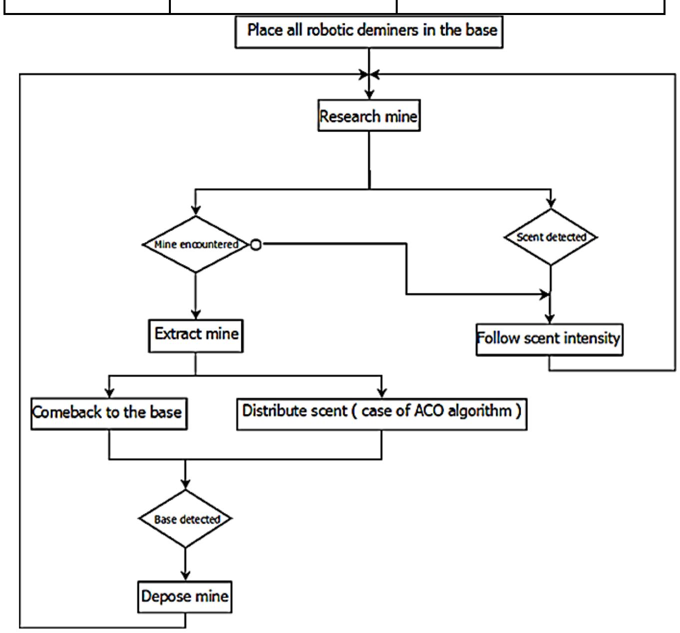
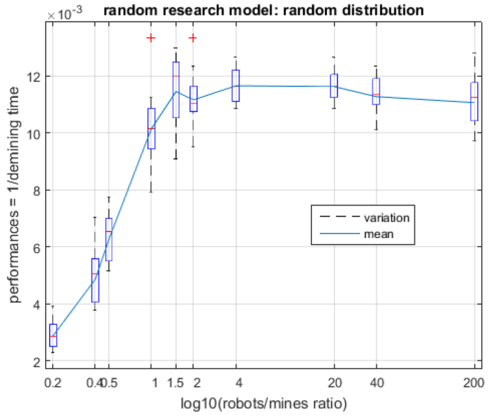
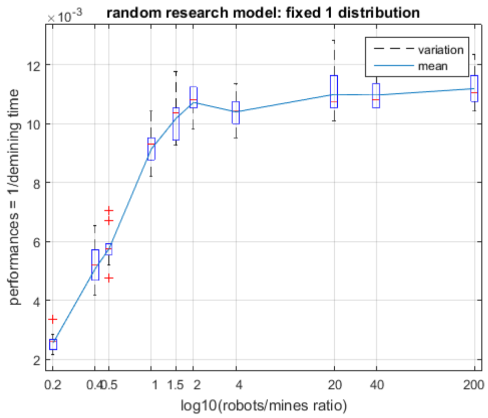


Fig. 4. Behavior diagram of a multi-robot demining system.

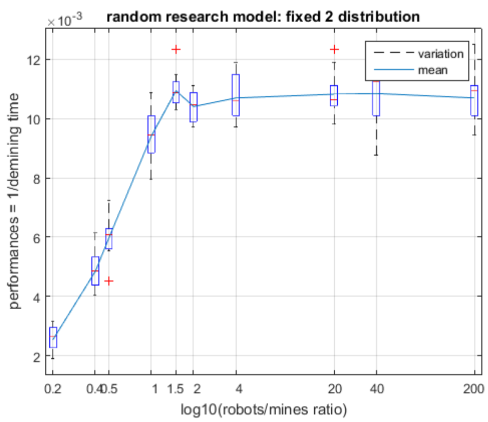
This part presents the possible effect of evaporation pheromone rate variation on demining time performances for both AS-ACO and M-AS-ACO algorithms (Mx%=90%). In each experimentation, pheromone evaporation rate is increased regularly by 10%.



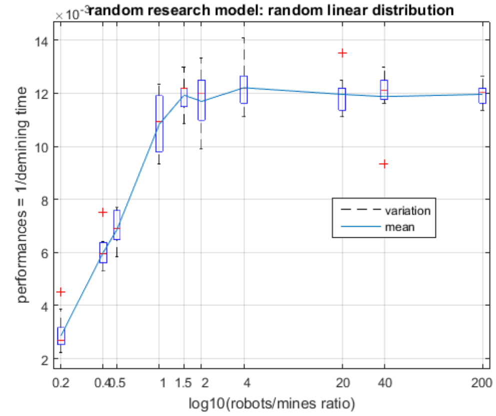
(a). random distribution.



(b). Fixed 1 spatial distribution.



(c). Fixed 2 spatial distribution.



(d). random line distribution.

Fig.5: Demining MRS performances (1/demining time) for different mine distributions in the case of BASE model

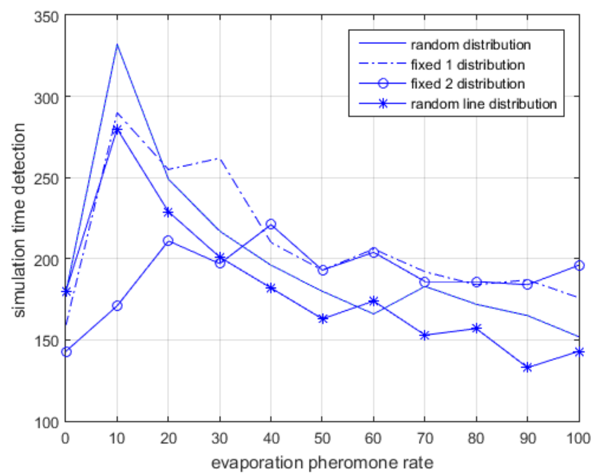


Fig. 6. Time detection results for the AS-ACO model

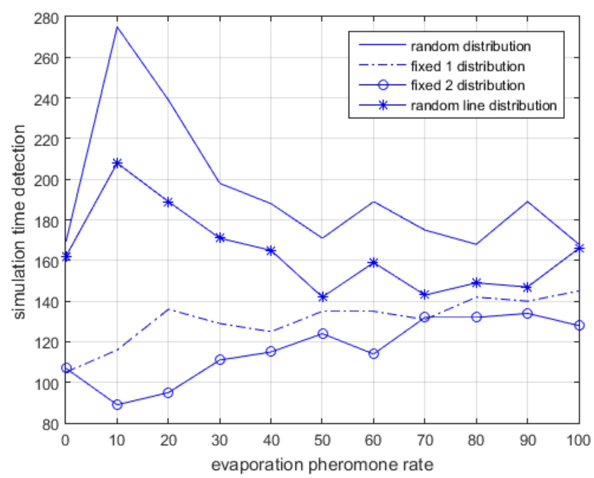


Fig. 7. Time detection results for the M-AS-ACO model

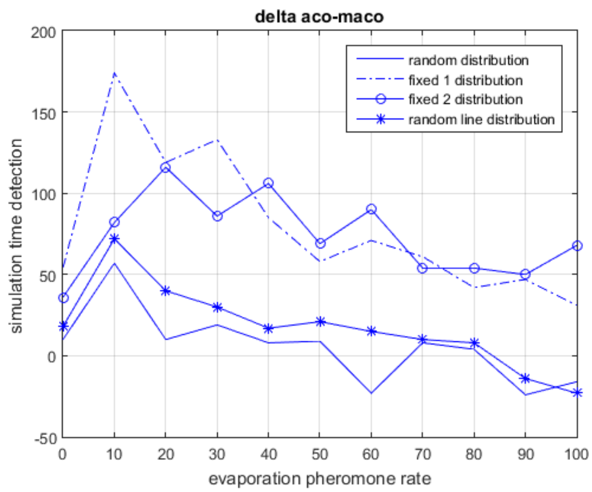


Fig. 8. Time detection comparison between AS-ACO and M-AS-ACO models

Fig.6 and 7 represent the detection time variation relating to the minefield distribution type for both AS-ACO and M-AS-ACO models. For lower pheromone evaporation rate, higher values of detection time results are taken with random distribution. The rising pheromone evaporation rate ameliorates temporal performances. However, this decrease of mine detection-time is stabilized for high evaporation. In fact, detection time results are limited to a range of 200 s.t for evaporation pheromone rate > 60% in the case of AS-ACO model and for evaporation pheromone rate > 30% in the case of M-AS-ACO model.

Fig. 8 indicates the time variation between AS-ACO and M-AS-ACO models. Considering the effect of minefield distribution type separately, M-AS-ACO model presents better timing results than AS-ACO model with lower pheromone evaporation rate. AS-ACO model presents better timing results than M-AS-ACO model only in the case of fixed spatial distributions with high pheromone evaporation rate (>80%).

The impact of pheromone evaporation rate on time system performances is noted at the beginning of the solutions construction. Adopting a programmable pheromone evaporation rate which induces new solution explorations should reduce time demining. Researches of [22, 37, 38], use different models of programmable evaporation rate based on a mathematical formulation. Dealing with the evaporation pheromone example given by [22], this model is taken as a reference to evaluate our evaporation pheromone rate model. Simplifying evaporation pheromone model is the principal motivation of selection of a timed algorithm model.

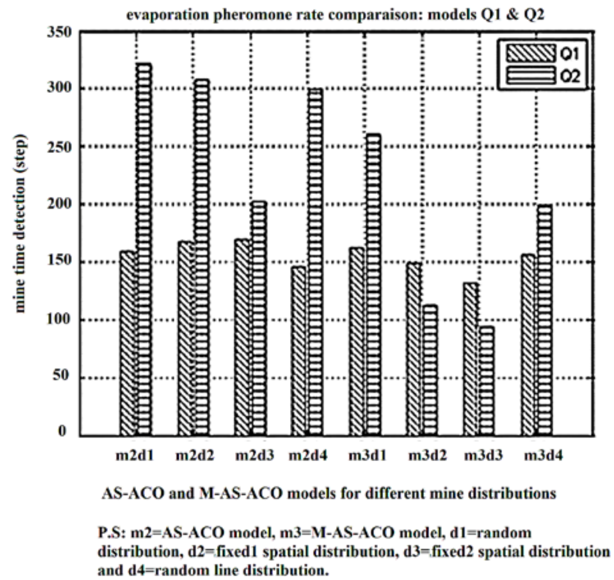


Fig. 9. Evaporation pheromone rate model comparison

Fig. 9 reports the temporal result difference between different evaporation pheromone models for AS-ACO and M-AS-ACO collaborative algorithms. Mathematical evaporation pheromone rate model [22] is represented by Q1 model. Our evaporation pheromone rate model is represented by Q2 model. In the case of AS-ACO model (m2d1, m2d2, m2d3 and m2d4); temporal results obtained with Q1 model are better than with Q2 model except the result in fixed 2 distribution (m2d1). In fact, the system equipped with Q2 evaporation pheromone model takes double time to detect 90% of mines compared to Q1 model. This different change in the case of M-AS-ACO model and better temporal performances is detected with Q2 model in the case of fixed distributions. Multi-robot system experimentations are performed on the software simulation platform. In real implementation, the application of mathematical complex model for evaporation pheromone rate should require more hardware resources and reduce temporal performances.

6. Discussion

The realized experimentations use a fixed setting of RM% rate. Generally, rising RM% rate is higher than 50% does not enhance cooperation impact on demining time optimization. These results were treated also in the previous researches [21].

The principal aim of research in this paper is the connection between evaporation pheromone rate and timing performance. In fact, as given in Fig. 6, 7 and 8 better timing results are detected for M-AS-ACO model (in most studied cases: Table 2).

Table 2: Summary of time result variation between AS-ACO and m-AS-ACO models

Distribution	***0%-50%***	***50%-70%***	***70%-80%***	***80%-100%***
Random	+	-	+	-
Fixed 1	+	+	+	+
Fixed 2	+	+	+	+
Random	+	+	-	-

(+/-) Sign of time result variation between AS-ACO and M-AS-ACO models for different static evaporation pheromone rates ($time_{AS\text{-}ACO} - time_{M\text{-}AS\text{-}ACO}$)

In general, ACO algorithms are made from ant foraging behavior. ACO optimization gives a short path solution to one source of food. In the case of demining problems, the mines are distributed in various positions. The best initial situation ACO algorithm consists of a limited zone mine concentration. This situation is given by fixed1 and fixed2 distributions. For these two mine distributions and at a lower evaporation pheromone rate, better timing results are obtained in comparison to the base model. However, with random distributions (random and random line distributions), time demining results are degraded with AS-ACO model in favor of the BASE or M-AS-ACO model. The Amelioration of the AS-ACO model results is given by the raising evaporation pheromone rate. In fact, this action helps robotic agents to forget the previous detected mine positions and forces the agents to explore new zones. Time result experimentations are reduced for the evaporation pheromone rate, which are higher than 60% in the case of AS-ACO model, and 30% rate in the case of M-AS-ACO model. The solution is ensured by M-AS-ACO model presents flexibility toward different mine distributions.

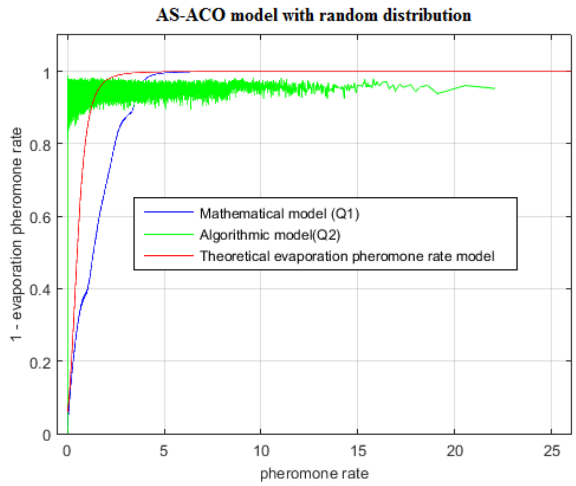
The variation of the evaporation pheromone rate has an impact on timing results. With this interpretation, some researchers [22, 39] applied a specific function to define the evaporation pheromone rate. In general, this function is bounded between 0 and 1. It rises exponentially with the pheromone rate. Our proposed evaporation pheromone rate Q2 gives lower timing performances for demining operations in the case of the AS-ACO model. The worst timing results are detected for random mine distribution (55% of time result reduction). However, the Q2 model gives better timing results in the case of the M-AS-ACO model with fixed mine distributions. The best results are detected for fixed 2 mine distribution. The evaporation pheromone Q1 model still has better results in random distributions (with M-AS-ACO model) but the timing performance differences between Q1 and Q2 models are reduced in comparison to AS-ACO model.

Table 3: Comparison time result between Q1 and Q2 models

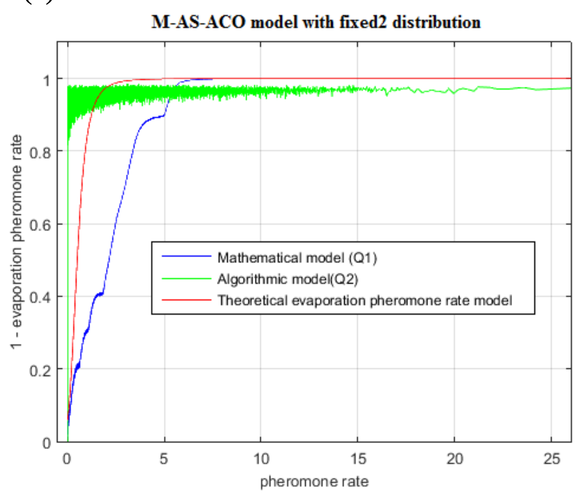
Distribution	***AS-ACO model***	***M-AS-ACO model***
Random	55%	32%
Fixed 1	46%	-8%
Fixed 2	12%	-27%
Random line	42%	28%

(*) %=($time_{Q2}$-$time_{Q1}$)/ $time_{Q2}$

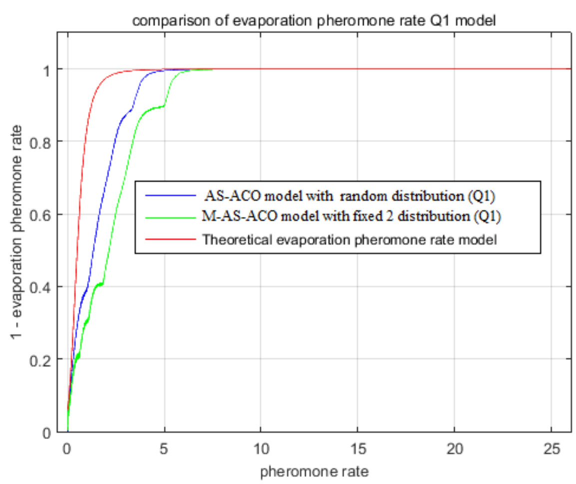
To explain the results given by Table 3, the worst and the best result for Q2 model are selected. The worst time result corresponds to the AS-ACO cooperative model with random distribution. The best time result corresponds to the M-AS-ACO cooperative model associated with fixed 2 mine distribution.



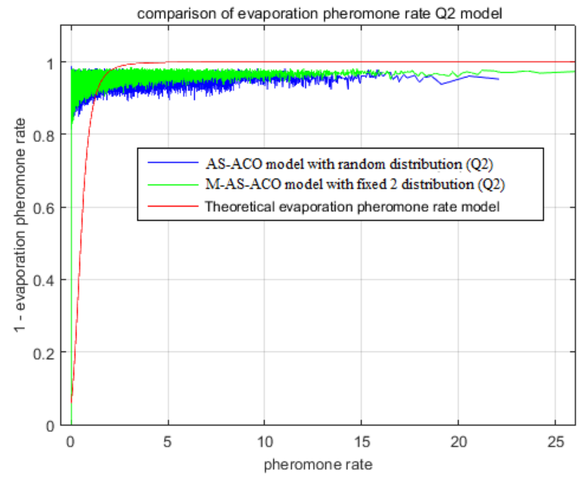
(a) AS-ACO model with random distribution



(b) M-AS-ACO model with fixed 2 distribution



(c) Comparison of evaporation pheromone rate Q1 model



(d) Comparison of evaporation pheromone rate Q2 model

Fig. 10. Evaluation of the evaporation pheromone rate model (Q1 and Q2 models) for AS-ACO and M-AS-ACO model

Fig. 10 reports the variation of the evaporation pheromone rate models in the worst time result (Fig. 10.a) and the best time result (Fig. 10.b). The recorded evaporation pheromone rate from Q1 model simulations differs from theoretical evaporation pheromone rate formulation (4). This difference is amplified for the M-AS-ACO model. In addition, the model guided by Q2 approaches the theoretical model but it presents higher sensitivity of the pheromone rate variation and saturates fast bounded limit. Fig. 10.c gives a comparison between Q1 model in the AS-ACO and M-AS-ACO model. Evaporation pheromone model converges to the theoretical model with additional delay in the M-AS-ACO model. In Fig. 10.d, the Q2 model preserves the same pattern and therefore gives better time results for fixed distributions.

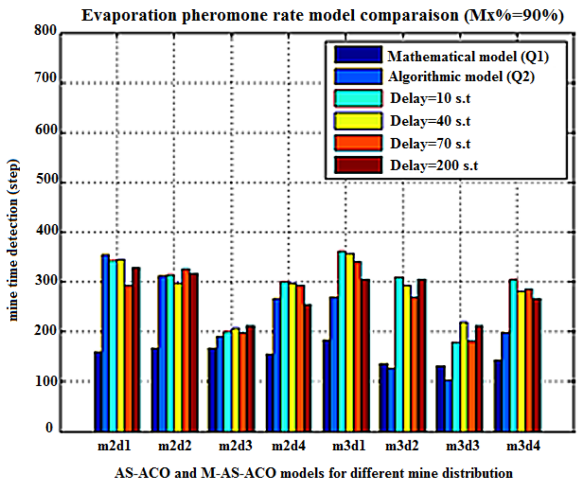


Fig. 11. Time results for different models of evaporation pheromone rate

Fig. 11 presents the time demining results for the reduction of evaporation pheromone rate sensitivity to variation of the pheromone rate. These attempts of Q2 model amelioration are based on the introduction of delay in the iterations of evaporation pheromone rate calculation. Some increasing values of delays (10 s.t, 40 s.t, 70 s.t and 200 s.t) are experimented. The general time performances of the demining system is degraded for the AS-ACO and M-AS-ACO models and there is no modification of evaporation pheromone rate pattern in the function of pheromone rate.

4. Conclusions

This paper presents the experimentations of the pheromone evaporation rate on the multi-robotic demining system. The effects of the pheromone evaporation rate are noted for particular rates and better results are obtained with M-AS-ACO algorithms. The temporal performance of demining multi-robot systems is obtained by modifying the ACO algorithms. However, results are still depending on the environment configurations and on the other modifications can be performed on ACO algorithms especially by studying the pheromone evaporation rate.

The application of programmable evaporation pheromone rate helps to improve temporal performances. The improvement of temporal performances is set up with the evaporation pheromone rate pulse (instead of high evaporation pheromone rate maintain). The choice of the model of evaporation pheromone rate modifies temporal performances of the demining system. The proposed evaporation pheromone rate Q2 enhances temporal performances of the demining operations for a particular configuration mainly with the M-AS-ACO model and fixed mine distribution. The studied Q1 model is an example of programmable evaporation pheromone rate. Other functional models can be tested. The aim of the algorithmic evaporation pheromone model is to simplify the implementation of this system. In our case, the additional experimentations on real implementation of multi-robot controller must be performed to evaluate the algorithmic model of evaporation pheromone rate. A collaborative model based on Ant Colony Optimization is selected. In addition, other meta-heuristic algorithms can be applied in the same case. In particular, hybrid meta-heuristic algorithms should be experimented on multi-robotic controllers.

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