

12<sup>th</sup> ICCRTS  
“Adapting C<sup>2</sup> to the 21<sup>st</sup> century”

---

**A Multiagent Coordination Algorithm for Weapon  
Assignment in Ship Self Defense**

**Authors**

Besse Camille<sup>1,2</sup>, Cinq-Mars Patrick<sup>1,2</sup>, Gagné Olivier<sup>1,2</sup>, Chouinard Sébastien<sup>1,2</sup>,  
Chaib-draa Brahim<sup>2</sup>, Blodgett Dale<sup>3</sup> and Benaskeur Abder Rezak<sup>4</sup>

---

**Topics**

Track 1: C<sup>2</sup> Concepts, Theory, and Policy  
Track 3: Modeling and Simulation  
Track 4: Cognitive and Social Issues

**Contact**

Camille Besse

**Organization**

DAMAS Research Group

**Address**

Department of Computer Science  
Laval University  
Ste-Foy, QC, Canada, G1K 7P4

**Telephone**

1 (418) 656-2131 # 4505

**E-mail & Website**

besse@damas.ift.ulaval.ca  
<http://www.damas.ift.ulaval.ca>

---

<sup>1</sup> STUDENTS

<sup>2</sup> Department of Computer Science of Laval University. Quebec (QC), Canada.

<sup>3</sup> Lockheed Martin Canada, Halifax (NB), Canada.

<sup>4</sup> DRDC Valcartier, Quebec (QC), Canada.

---

# A Multiagent Coordination Algorithm for Weapon Assignment in Ship Self Defense

Besse Camille<sup>1,2</sup>, Cinq-Mars Patrick<sup>1,2</sup>, Gagné Olivier<sup>1,2</sup>, Chouinard Sébastien<sup>5,2</sup>,  
Chaib-draa Brahim<sup>6</sup>, Blodgett Dale<sup>7</sup> and Benaskeur Abder Rezak<sup>8</sup>

---

## Abstract

Many defensive weapons have been developed in recent years to counter anti-ship missiles that nowadays are the most dangerous threats to naval platforms. These defense systems are conventionally divided into hardkill and softkill types. Hardkill encompasses the classical kinematic kill which destroys the threats while softkill is aimed at the control and guidance subsystems of the threats and diverts it away from the ship at a significantly lower cost.

This paper reports a development methodology of a decision support system for command and control of a single warship. This methodology mainly consists in first teaching softkill strategies using Monte-Carlo methods to a softkill agent and then to enhance their effectiveness by adding rule-based hardkill strategies chosen by a hardkill agent. A self-synchronizing approach is then used so that an effective engagement plan is proposed to the frigate tactical officer.

These self-synchronized agents have finally been implemented and evaluated in a professional engagement simulation tool (BAE System's SADM). Results show that this coordination improves the overall survivability of the ship and minimize the engagement cost comparing to each agent acting separately.

---

<sup>5</sup> STUDENTS

<sup>6</sup> Department of Computer Science of Laval University. Quebec (QC), Canada.

<sup>7</sup> Lockheed Martin Canada, Halifax (NB), Canada.

<sup>8</sup> DRDC Valcartier, Quebec (QC), Canada.

# A Multi-Agent Coordination Algorithm for Weapon Assignment in Ship Self Defense

Besse Camille<sup>1</sup>, Cinq-Mars Patrick<sup>1</sup>, Gagné Olivier<sup>1</sup>, Chouinard Sébastien<sup>1</sup>,  
Chaib-draa Brahim<sup>1</sup>, Benaskeur Abder Rezak<sup>2</sup> & Blodgett Dale<sup>3</sup>

<sup>1</sup> Computer Science & Software Engineering Dept.,  
Laval University, Québec (Qc) , Canada,  
{besse, pcm, gagne, chouinard, chaib}@damas.ift.ulaval.ca,  
<http://www.damas.ift.ulaval.ca/>

<sup>2</sup> Defence R&D Canada – Valcartier,  
Quebec (Qc), Canada,  
abderrezak.benaskeur@drdc-rddc.gc.ca

<sup>3</sup> Lockheed Martin Canada,  
CFB Halifax (NS), Canada,  
dale.blodgett@lmco.com

**Abstract.** Many defensive weapons have been developed in recent years to counter anti-ship missiles that nowadays are the most dangerous threats to naval platforms. These defense systems are conventionally divided into hardkill and softkill types. Hardkill encompasses the classical kinematic kill which destroys the threats while softkill is aimed at the control and guidance subsystems of the threats and diverts it away from the ship at a significantly lower cost.

This paper reports a development methodology of a decision support system for command and control of a single warship. This methodology mainly consists in first teaching softkill strategies using Monte-Carlo methods to a softkill agent and then to enhance their effectiveness by adding rule-based hardkill strategies chosen by a hardkill agent. A self-synchronizing approach is then used so that an effective engagement plan is proposed to the frigate tactical officer.

These self-synchronized agents have finally been implemented and evaluated in a professional engagement simulation tool (BAE System's SADM). Results show that this coordination improves the overall survivability of the ship and minimize the engagement cost comparing to each agent acting separately.

## 1 Introduction

Since Second World War, air strikes have posed the most dangerous threat to naval ships. Advances made in air-surface weapon domain have further enhanced this threat. Thus, Anti-ship cruise missiles (ASCMs) are able to damage seriously a capital ship of a super power.

Many defensive weapons have been developed in recent years to counter the ASCM threat. These defense systems are conventionally divided into either hardkill or softkill types. Hardkill (HK) encompasses the classical kinematic kill which destroys the threat either by collision or by explosion. Softkill (SK) is aimed at the control and guidance subsystems of the threats and divert it away from the ship through confusion, distraction or seduction. Hardkill consists in a long range (up to 20 Km) surface-to-air missile (SAM), a medium range gun and a close-in weapon system (CIWS). Softkill consists in an onboard jammer and some chaff rounds.

Jammer manipulates received radar energy and retransmit it to change the return that the radar sees. This technique can change the range the threat's radar detects the ship by changing the delay in transmission of pulses. Chaff is made of different length metallic strips, which reflect different frequencies, so as to create a large area of false returns in which a real contact would be difficult to detect. It is also possible to coordinate them by launching a chaff behind the ship relatively to the threat and to jam the threat in order to pull off its range gate on the chaff.

This paper reports a policy development methodology of a pure softkill reflex planning agent and its enhancement by a hardkill one. It also presents an improvement of the coordinated approach proposed by Huang and Kar (1). The solution have been implemented and evaluated in an engagement simulation tool provided by the research and development center of Canadian army based in Valcartier (Qc). We first present the formalization of the naval problem, then, the policy development methodology is described. Second coordination algorithms are given and explained. Finally, implementation results are presented and a conclusion is made.

## 2 Problem modelization

A way to formalize this problem is to consider the Dynamic Weapon-Target Allocation (DWTA) problem described by Hosein *et al.* (2) which have been shown to be NP-complete (3) even in the static unconstrained case.

Our DWTA problem is described as follows: Consider a platform attacked by a set  $\mathcal{M}$  of  $m$  threats. This platform owns a set  $\mathcal{W}$  of  $w$  weapons with limited ammunitions to defend itself on a finite temporal horizon  $T$ . Thus its objective is to survive the attack by destroying threats with its weapons. Unfortunately, weapons are unreliable and weapon  $w_i$  have a probability  $p_{ij}^t$  to destroy or deceive a threat  $m_j$  at time  $t \in \{0, \dots, T\}$ . As a result, the problem can be formally described by:

$$\begin{aligned} \text{Maximize : } & \sum_{t=1}^T \sum_{i=1}^m \left[ 1 - \prod_{j=1}^w (1 - \alpha_{ij}^t p_{ij}^t) \right] \\ \text{under } & \alpha_{ij}^t \in \{0, 1\} \quad \text{and} \quad \sum_{i=1}^m \sum_{j=1}^w \alpha_{ij}^t = 1 \\ & t \in \{1, \dots, T\} \end{aligned}$$

Moreover, the time for weapon to intercept a threat depends on the range, the type and the speed of the threat and weapons also cannot freely fire at threats. Some constraints apply depending on their incoming azimuth and their distance from the platform. In our example, we consider that the platform is equipped with two Separate & Track Illumination Radar (STIR), two Ship-Air Missiles (SAM) launchers, a Gun and a Close-In Weapon System (CIWS) for hardkills and with four chaff launchers and one jammer for softkills. To ease example understanding all threats are assume to be the same type but with different starting range and speed<sup>4</sup>. The table 1 describes how weapons are constrained and what are their probability of success.

In this application, weapons are constrained during an episode: There exists unary constraints that specify which threats are reachable regarding their distance from platform and the range of weapon, and binary constraints that bind firing weapons to STIRs depending on threats STIRs can “see”. Few constraint of resource limitations already exists.

On the other hand, softkill modelization is more complex. In our model, chaffs can be launched following four fixed directions given in figure 1 and using two mode, seduction or distraction. Seduction must be used when a threat already locked the platform so as to propose another target to it, and then using jammer to deviate it on the seduction-mode chaff. Distraction must be used when a threat has not locked yet so as to propose another target before it lock. Chaffs effectiveness is unknown *a priori* and probably depends on the azimuth of threats. Furthermore, the jammer may be coordinated with chaff to increase their effectiveness. However, if a chaff is addressing a threat or a group of threats, it may affects the effectiveness of hardkills since a chaff deceive threats as it disturb STIR’s illumination and targeting. Thus we first learn what are softkills effectiveness alone and then try to coordinate them with hardkills.

<sup>4</sup> Threats speed is assume to remain constant all over an episode.

### Hardkill Constraints

- $C_1$ : A SAM must be guided by a STIR from fire time to interception time,
- $C_2$ : A Gun must use a STIR at fire time,
- $C_3$ : Two STIRs cannot target the same threat.

### Hardkill Blind Zones

Base State	0 to 360°	1 STIR, 1 Gun, 1 CIWS, 2 SAMs
Sector	Angles	Difference from Base state
A	345 to 15°	No CIWS
B	15 to 60°	No difference – Base state
C	60 to 120°	An additional STIR
D	120 to 145°	No difference – Base state
E	145 to 215°	No Gun
F	215 to 240°	No difference – Base state
G	240 to 300°	An additional STIR
H	300 to 345°	No difference – Base state

Weapon	Range	Probability of success
SAM	From 2.2 to 20km	95%
Gun	From 1.5 to 5km	50%
CIWS	From 0.2 to 2km	10%

Table 1. Examples of DWTA constraints

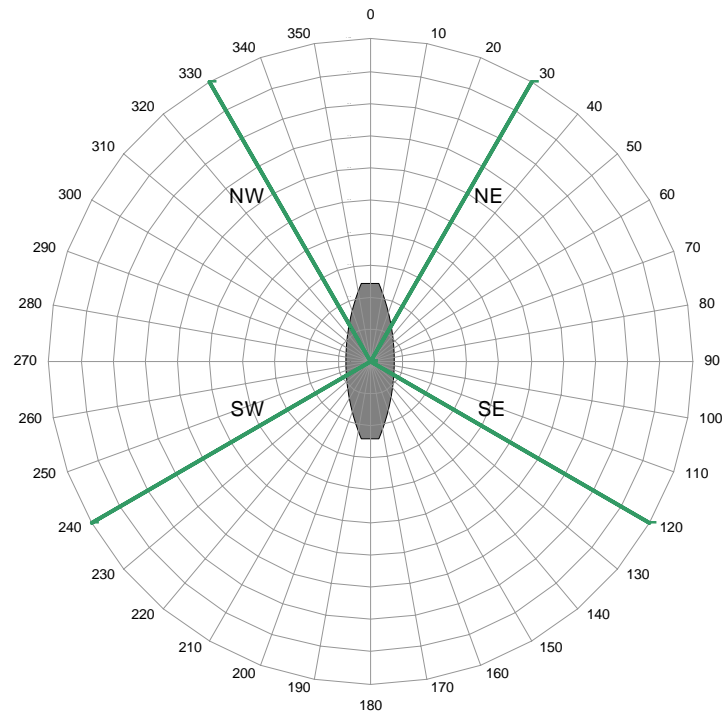


Fig. 1. Directions where chaff can be launched

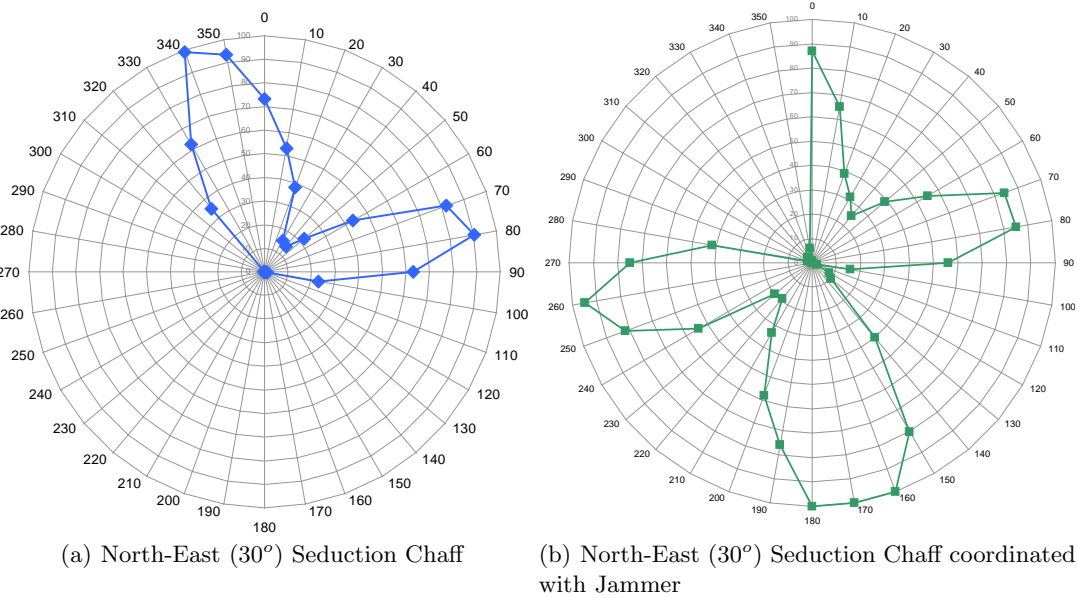
## 3 Policy Development Methodology

### 3.1 Softkill Basic Behavior

As chaffs effectiveness is unknown *a priori*, their probability distributions of deceiving a threat is evaluated with Monte-Carlo simulations and estimations as proposed in Sutton and Barto's

book (4). These distributions models what will be the softkill agent behavior. As a consequence, the softkill agent will have to choose an action to do among sixteen possible action (4 directions  $\times$  2 modes  $\times$  Jammer or not) each time it wants to engage a threat. We first estimate the effectiveness of one chaff against one threat and obtain probability distributions of deceiving a threat depending on action chosen and azimuth of th threat.

For instance, the effectiveness of a chaff launched in seduction mode is shown in figure 2(a) and the same located chaff launched in coordination with a jammer is shown in figure 2(b). The loss of efficiency in figure 2(b) from  $320^\circ$  to  $360^\circ$  is due to the fact that jammer may attract the threat on the boat instead of deceiving it if it is used too longer. This fact must be also taken into account in the coordinating agent.



**Fig. 2.** % effectiveness relatively to threat azimuth.

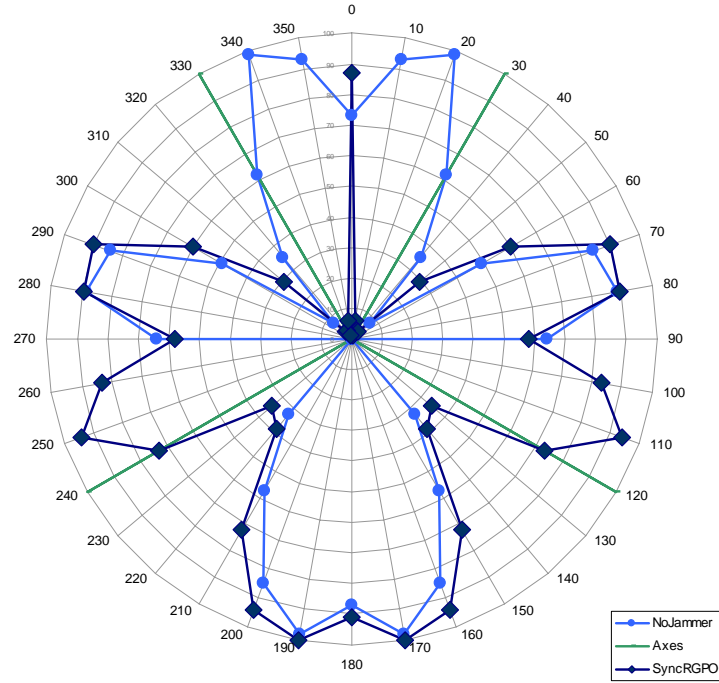
These graphics show the percentage of *softkilled* threats depending on their incoming azimuth. Results are obtained by simulating apparition of threats uniformly around the ship and evaluating the percentage of deceiving each chaff have depending on azimuth and jammer utilisation.

### 3.2 Developed Policies

Once probability distributions obtained, some theoretical policies were developed. In fact, these policies are the product of a conjunction of measurements following a given criteria. For instance, the policy given by figure 3 ensure the best chaff to launch to counter a threat and what is the gain if we synchronize it with the jammer. Samples of the chaff and the mode to choose and its probability of success to counter the threat is given in table 2.

We also developed two other policies, each of them related with given criteria : one which maximize overall survivability percentage but losses a more considerable if jammer is not available (figure 4(a) called 'risked-actions policy'), one which exploits the manoeuvring ability of the ship by rotating when threats income in blind zones (figure 4(b)).

On the other hand, allowing the ship to maneuver could improve softkill defense in some cases but could also decrease it in other cases. Thus, we decided to improve ship's survivability



**Fig. 3.** Policy % effectiveness based on results of learning. Light gray curve shows the chaff-only policy, the dark gray one shows improvement made by synchronizing the Jammer with the chaff.

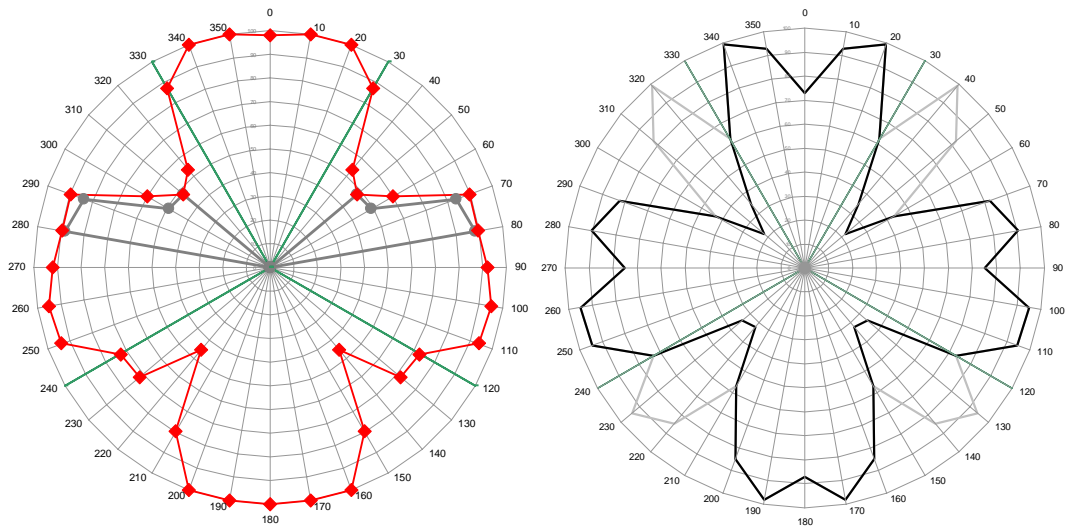
	% No Jammer	% Jammer	Action
0	73	87	NE Seduction
10	93	6	NW Seduction
20	99	1	NW Seduction
...	...	...	...
120	0	73	SW Seduction
130	0	34	SW Seduction
140	32	38	SE Seduction
150	57	72	SE Seduction
160	85	94	SE Seduction
...	...	...	...
220	32	38	SW Seduction
230	0	34	SE Seduction
240	0	73	SE Seduction
...	...	...	...
340	99	1	NE Seduction
350	93	6	NE Seduction

**Table 2.** Policy % effectiveness based on results of learning. Chaff to launch is indicated in the *Action* column.

by allocating blind-zone incoming threats to a reflex hardkill agent. This aspect of coordination will be explained in next section.

### 3.3 Policies Evaluation

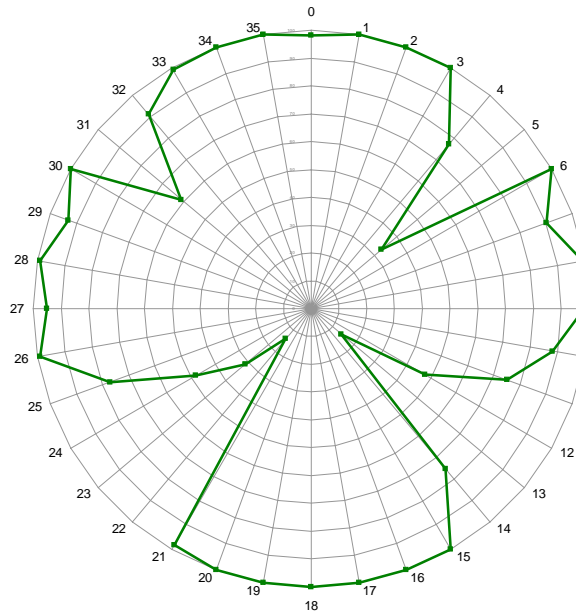
However, these policies are theoretical by the fact they are based on an assumption about symmetrical effectiveness of chaff. So we implant them to verify their real effectiveness in our



(a) Dark gray curve shows the maximized policy (b) Black curve shows the policy maximizing available coordinating chaff and jammer, the light gray one shows what happened if jammer is unavailable. The light gray one shows what gain obtained when rotating.

**Fig. 4.** Policy % effectiveness based on results of learning.

simulated environment. Results show that chaff are symmetrically effective in first approximation but there are some variance due to uncertainty and complexity of models that simulator employs. Thus, an empirical optimal policy for a reflex pure softkill agent is shown in figure 5



**Fig. 5.** Policy % effectiveness based on empirical tests.



## 4 Softkill & Hardkill Planning

As stated before, we have two agents, one for the softkill system and the other for the hardkill system. When they face one or several threats, these two specific agents plan the use of weapon resources of the ship for countering the threats. Planning weapon resources in this context means allocating and scheduling the deployment of the ship's weapon resources against threats with a precise order on the intervention time.

### 4.1 Softkill Reflex Planning Agent

Generally, reactive planning uses very low-level reasoning techniques for a simple response to a situation to give a very short reaction time. This is very important in our context because defending ship brings a very hard and usually very short time constraint.

Based on policies described in previous section, the softkill agent first wait until one threat begin to search after the ship (line 3 of algorithm 1). Then the agent uses known threats to regroup them (line 6) in order to turn the ship to minimize number of threats in blind zones (line 10). Finally, it apply policy given by methodology explained above.

---

**Algorithm 1** Softkill agent algorithm

---

```
1: Inputs: Threats: Threats list;  
2:           Policy: Policy given in section 3;  
3: Wait until threats going to lock.  
4: {Threats pre-treatment:}  
5: Threats  $\leftarrow$  EvaluateAndOrder(Threats)  
6: ThreatGroups  $\leftarrow$  Group(Threats)  
7: ThreatGroups  $\leftarrow$  Evaluate(ThreatGroups)  
8: {Maneuvers:}  
9: {Choose direction which maximize softkill effectiveness:}  
10: newHeading  $\leftarrow$  BestDirection(ThreatGroups)  
11: SetShipSpeed(maxSpeed knots)  
12: SetShipHeading(newHeading)  
13: wait for currentHeading = newHeading  
14: SetShipSpeed(baseSpeed)  
15: {Launch chaff according to given policy}  
16: LaunchChaff(Policy)
```

---

### 4.2 Hardkill Reflex Planning Agent

To construct a reflex plan, the hardkill agent maintains a list of threats coming on the ship. This list is sorted according to some threat evaluation (i. e., the list is sorted from the most to the least dangerous threat). Then, it applies some predefined rules for allocating the resources. These predefined rules are given by algorithm 2.

Though these rules are simple, they allow using all available resources in an efficient way. Unfortunately, the available resources are only allocated to the two most dangerous threats, and all others in the list (if any) are not considered in the reactive plan. In the case where a kill assessment indicates that a hostile threat has been destroyed, the resources that have been allocated to this threat become available for the next most dangerous threat in the list.

---

**Algorithm 2** Hardkill agent algorithm

---

- 1: **Inputs:** *Threats*: Threats list;
- 2: **Wait until** threats into range.
- 3: {Threats pre-treatment:}
- 4: *Threats*  $\leftarrow$  Evaluate(*Threats*)
- 5:  $1^{st}Threat \leftarrow$  First(*Threats*)
- 6:  $2^{nd}Threat \leftarrow$  Second(*Threats*)
- 7: {allocating a SAM and a gun to the most dangerous threat}
- 8: AssignSAM( $1^{st}Threat$ )
- 9: AssignGUN( $1^{st}Threat$ )
- 10: {allocating a SAM to the second most dangerous threat}
- 11: AssignSAM( $2^{nd}Threat$ )
- 12: {allocating the CIWS to all threats that enter into the CIWS's range.}
- 13: AssignCIWS(*AllThreatsInRange*)

---

### 4.3 Hardkill & Softkill Coordination

There are many ways to coordinate the hardkill and softkill agents. For instance, Blodgett *and al.* (5) used a Central Coordinator to merge plans after receiving them from each agent. If there are some negative interactions between the planned actions, it will modify the plans to eliminate these negative interactions, or if not possible, it will try to reduce their effects.

Another option is to use a direct method where agents communicate with each other and try to coordinate their actions. In this case, communications can be used for commitments and convention as suggested by Jennings (6), and they can be used for synchronizing plans and conflict solving.

A third method might be a kind of whiteboard (a common data space) in which the hardkill and softkill agents will construct a coordinated plan by some successive refinements. In this case, the coordination will be implicit because they will work on the same plan. Similar to this is the mediator, which in fact plays the role of a Central Coordinator with the possibility of communication and negotiation with softkill and hardkill agents on synchronizing plans and conflicts resolution. In fact, many different communications meanings could be used with their own advantages and drawbacks.

However, methods which use communication and negotiation are time consuming and therefore could decrease the quality of the produced plan. For this reason, the investigation is for a centralized coordinator that does not use communication between agents. In fact, we choose the softkill agent to coordinate actions due to its large perception and the fact that we want to prioritize it higher than the hardkill one. As a result the softkill agent will avoid the hardkill agent to engage the same threats as the softkill one does. To do so the agent just decreases their priority in hardkill agent's priority list. The corresponding algorithm is given by algorithm 3. Consequently, the hardkill agent will consider threats engaged by the softkill one once it has destroyed all threats with a better priority.

## 5 Results

Results were obtained by implementing our algorithms and testing them in a professional engagement simulation tool. Ship Air Defence Model (SADM from BAE Systems) models perfectly engagements in a naval context. Figure 6 shows what is the effectiveness of the coordinating agent versus the hardkill agent and the softkill agent alone while being attacked by numerous threats. Other curves show the average cost of an engagement for each number of threats<sup>5</sup>. Costs clearly reveals the advantage to use chaff despite their poor effectiveness when facing numerous threats. Coordination is thus a good compromise between cost and efficiency.

---

<sup>5</sup> A SAM costs 1.2 billions US\$, a chaff 10K US\$.

---

**Algorithm 3** Coordination algorithm

---

```
1: Inputs: Threats: Threats list;  
2: Wait until threats into range.  
3: {Threats pre-treatment:}  
4: Threats  $\leftarrow$  Evaluate(Threats)  
5: {in a same manner as hardkill agent does}  
  
6: for all group  $g \in$  Threats do  
7:   {get the best threat group to engage}  
8:    $P_g \leftarrow$  SeductionGroupProba( $g, Policy$ )  
9:   if  $P_g >$  SeductionGroupProba(BestGroup, Policy) then  
10:     BestGroup  $\leftarrow$   $g$   
11:   end if  
12: end for  
13: for all Threat  $i \in$  BestGroup do  
14:   {decrease their priority according to the probability to deceive it}  
15:    $P_i \leftarrow$  SeductionProba(Threat, Policy)  
16:    $Priority_i \leftarrow Priority_i * P_i$   
17: end for  
  
18: {Plan Softkill and Hardkill}  
19: Softkill planning on BestGroup  
20: Hardkill planning on Threats updated
```

---

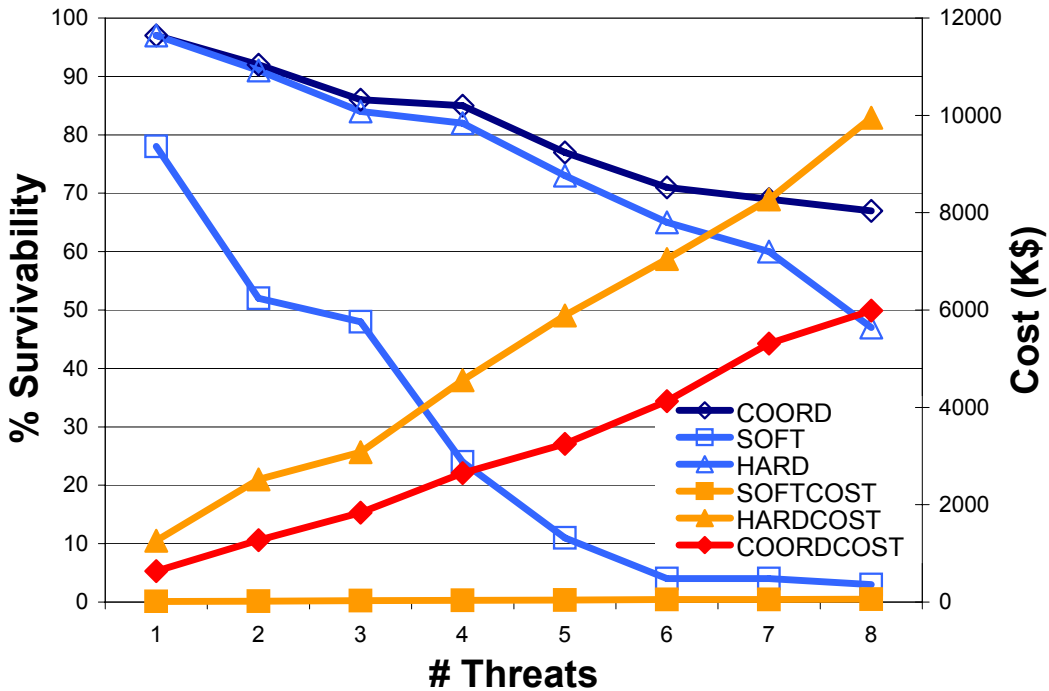


Fig. 6. Coordination % effectiveness vs Harkills & Softkills only

## 6 Discussion

We show in this paper that a reactive approach could bring encouraging results on survivability of a naval platform against numerous threats. Moreover, there are many possible ways to improve our approach. First, a possible improvement in the sector decomposition could be made in order to facilitate learning of the softkill agent. For instance, a simple decomposition

in height sectors (four of effectiveness, four of ineffectiveness) may probably give better results, a second decomposition could be calculated using Uther and Veloso's U-Tree algorithm (7) and then using reinforcement learning for choosing the best action to do.

An other feasible enhancement consists in choosing a way to reengage a threat by the hardkill agent that we consider that it have not be *softkilled* but further searches are needed to decide when a threat is decided as *softkilled*. Finally, our coordination maximize the ratio simplicity comparatively to ways to avoid negative interactions between hardkill and softkill. Next step consists in increasing survivability by considering positive interactions that could occur too.

## Bibliography

- [1] P. Huang and P. Kar, “An autonomous optimal weapon assignment algorithm for ship self defense”, in *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics*, 1994, vol. 3, pp. 2544–2549.
- [2] P.A. Hosein, M. Athans, and J. Walton, “Dynamic weapon-target assignment problems with vulnerable c2 nodes”, in *Proceedings of the 1988 Command and Control Symposium*, 1988, pp. 240–245.
- [3] S. P. Lloyd and H. S. Witsenhausen, “Weapons allocation is np-complete”, in *Proceedings of the 1986 Summer Computer Simulation Conference*, Reno, Nevada, 1986.
- [4] R Sutton and A Barto, *Reinforcement Learning: An Introduction*, MIT Press, Cambridge, 1998.
- [5] D. E. Blodgett, B. Chaib-draa, P. Plamondon, P. Kropf, and E. Bossé, “A method to optimize ship maneuvers for the coordination of hardkill and softkill weapons within a frigate”, in *Proceedings of the 7th International Command and Control Research and Technology Symposium*, 2002.
- [6] N. R. Jennings, *Cooperation in industrial multi-agent systems*, World Scientific Publishing Co., Inc., River Edge, NJ, USA, 1994.
- [7] William T. B. Uther and Manuela M. Veloso, “Tree based discretization for continuous state space reinforcement learning”, in *Proceedings of the Fifteenth National/Tenth Conference on Artificial intelligence/innovative Applications of Artificial intelligence*, CA American Association for Artificial Intelligence, Menlo Park, Ed., 1998, pp. 769–774.