Control of a robotic swarm for the elimination of marine oil pollutions

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Abstract – This paper presents the concept as well as first results of the EU-MOP ("Elimination Units for Marine Oil Pollutions") project[1]. The basic idea of this project is a swarm out of autonomous marine robots which are able to recover oil with the help of oil skimmers. In order to achieve a flexible and robust system, the swarm intelligence (SI) approach has been used as control paradigm for the EU-MOP robots. Within the SI approach interaction between the robots plays an important role for the performance of the whole multi robot system. Thus, three control approaches, all basing on SI, but with different levels of interaction, have been developed. Furthermore a method for the evaluation of swarms in comparison to single robot systems will be presented.

I. INTRODUCTION

A. Motivation

Oil spills, arising either from marine accidents or from routine shipping and refining operations, are one of the major causes of ocean pollution, producing both ecological and economical damages of wide public concern. Spilled oil can negatively influence the physiology, immunology, and development of many organisms, but the most evident effect is usually an important decrease or disappearance of populations of marine fauna and flora within the affected area. As for economical damages especially the influence of oil spills on fishing industries and the tourist sector has to be mentioned [1].

The EU-MOP project follows a new approach for oil spill response, namely the use of multi robot systems (MRS) [2], as such systems have the potential for several advantages, like an increased system performance, a higher flexibility and an increased fault-tolerance [3], [4], [5], [6].

B. The basic EU-MOP concept

Within the EU-MOP project different oil spill scenarios will be considered. Figure 1 shows the scheme of an oil spill response operation in an open sea scenario. After the detection of the oil spill and the initial phase, where the EU-MOP robots (synonymously called EU-MOP units) as well as a support vessel, the so-called mother ship (MS), will be prepared for the oil spill response operation, the robots will be transported to the operational area by the mother ship. The operational area is a predefined virtual limitation, which will ensure that the units will not move in areas that could endanger the units, animals or human beings. Afterwards the robots will start the oil recovery operation with the help of skimmers. As every unit has only limited energy supply and limited storage capacities onboard, they have to move back to the mother ship in the case its energy is running low or its oil storage is full. As soon as the whole oil spill is eliminated the units will move back to the mother ship [2].

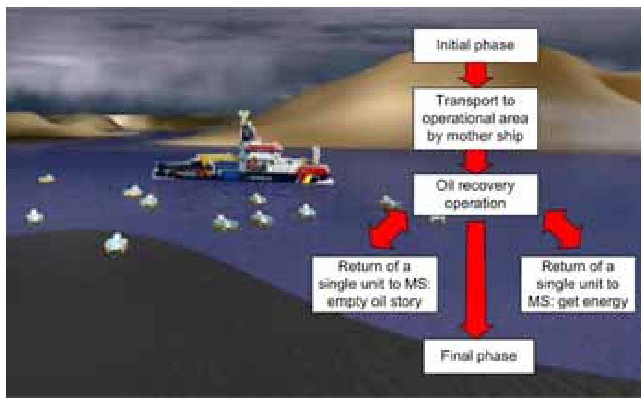

Fig. 1. Basic EU-MOP concept in an open sea scenario

C. Control of the EU-MOP swarm

The amount of oil ($V_{skimmedoil}$) which has been collected by a unit i up to time t can be calculated as follows

$$V_{skimmedoil,i}(t) = \int_y \int_x o_{thickness}(x, y, t)$$
$$\forall\, x, y \text{ with } (xpos_i(t) - x)^2 + (ypos_i(t) - y)^2 \le r_{unit,i}^{\;2} \tag{1}$$

where $o_{thickness}(x,y,t)$ represents the thickness of the oil slick at position (x,y) at time t, $r_{unit,i}$ represents the radius of unit i, $xpos_i(t)$ is the x-position and $ypos_i(t)$ the y-position of unit i at time t.

Nevertheless, the function $o_{thickness}(x,y,t)$ is unknown, as there is no technique available which will provide full information on the thickness of the oil slick at all positions (x,y) and at all times t [7]. As consequence, the movements

[1] EU-MOP is a research project co-funded by the European Commission in the context of the 6th Framework Programme. The project started in February of 2005 and has a duration of 3 years. The EU-MOP consortium is coordinated by the National Technical University of Athens (Greece), and also includes as partners the University of Glasgow and Strathclyde (UK), Sirehna S.A. (France), I (Portugal), BMT Ltd (UK), Cetemar S.L. (Spain), Environmental Protection Engineering S.A. (Greece), Aurensis S.L. (Spain), the University of Oxford (UK), Consultrans S.A. (Spain), the Institute of Shipping Economics and Logistics (Germany), and the Fraunhofer Institute for Manufacturing Engineering and Automation IPA (Germany).

of the robots cannot be planned by a central planning instance. Only a distributed approach, which allows the units to operate in an unknown environment, can be the basis for the control of the EU-MOP swarm.

In the last years, a lot of research has been done in the field of distributed problem solving algorithms. These studies show that concerning performance, robustness and flexibility the so-called swarm intelligence is one of the promising approaches for distributed problem solving [8], [9] and for the control of multi robot systems [10]. Thus the use of the SI approach as basis for the control of the EU-MOP robots will be examined in this paper.

II. SWARM INTELLIGENCE AS CONTROL PARADIGM OF THE EU-MOP ROBOTS

A. Swarm intelligence research axes

The expression swarm intelligence was introduced by Beni, Hackwood and Wang in the context of cellular robotic systems [11], [12], [13]. A cellular robotic system (CRS) "consists of a large number of robots operating in a cellular space under distributed control […]. All robots in the system have to cooperate in order to accomplish any global task" [14]. There is no synchronous clock or centralized control, limited communication exists only among adjacent robots. Each robot in the system has to make its own decisions autonomously based solely on sensed information on the environment and its internal state [14]. In this context swarm intelligence was defined as "a property of systems of non-intelligent robots exhibiting collectively intelligent behaviour" [12], [13].

The second research axis goes back on the work of Bonabeau, Dorigo and Theraulaz; they state that "using the expression 'swarm intelligence' to describe only this work seems unnecessarily restrictive" [15]. Basing on studies of the behaviour of social insects they extend this definition "to include any attempt to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insects and other animal societies" [15]. The behaviour of social insects bases on the use of pheromones; by laying and following pheromone trails ants for instance are able to forage in unknown environments. The algorithm basing on that behaviour is called ant system (AS), which was first applied to the travelling salesman problem. Due to many approaches for the modification and/or extension of this AS algorithm, Dorigo and Di Caro put these algorithms in a common framework by defining the Ant Colony Optimization (ACO) meta-heuristic [8]. So far, ACO has been applied to many applications, e.g. routing in telecommunication networks, but also in the field of robotics e.g. in cooperative transportation [8].

Finally, there is another research axis related to the expressions swarm and swarm intelligence: the so-called particle swarm optimization (PSO). PSO has roots in two main component methodologies: in artificial life (A-life), especially in bird flocking and fish schooling and it is also related to evolutionary computation, and has ties to both genetic algorithms and evolution strategies [9], [16], [17].

According to PSO, every potential solution to a given problem, called particle, is assigned a random velocity and a "position" in the hyperspace. Each position has a fitness value; and each particle "knows" its so-far best solution called pbest. Furthermore, the so-far global best solution of all particles, called gbest, is also known. In every iteration each particle sets its velocity according to the pbest and gbest values in order to find a better solution for the problem. Besides this global version of PSO there is a local version which replace gbest by a so-called lbest, which represents the pbest values of all particles in the neighbourhood of a particle [16], [17].

B. The importance of interaction for swarm intelligence

Although these three research axes have some differences, they have one important mechanism in common which is the key for the intelligence: the interaction of the agents.

Interaction can be classified into different categories. A very common classification bases on three categories: interaction through the environment, interaction through sensing, and interaction through communication [18].

Interaction through the environment is an indirect interaction. Each agent is able to modify the environment, and other agents respond to the new environment at a later time [8]. Thus, the environment itself is the communication medium. Stigmergy is one of the most common examples of this type of interaction. It is defined as "the process by which the coordination of tasks and the regulation of construction does not depend directly on the workers, but on the constructions themselves" [18], [19], [20], [21], [22]. Thus, stigmergy and interaction through the environment refers to the nest construction behaviour of termites or to the foraging behaviour of ants with pheromones.

Interaction through sensing refers to "local interactions that occur between agents as a result of agents sensing one another, but without explicit communication" [23]. The collective movement of fishes and birds is an example of interaction through sensing [24].

In the third category of interaction, interaction through communication, agents "may address other agents directly, either in a system-specific manner or through a standard agent communication protocol" [18]. Human communication is an example out of the biology for this category of interaction.

Each of the presented research axes of swarm intelligence bases on at least one of these interaction categories. The CRS approach mainly bases on interaction through sensing, ACO mainly bases on interaction through the environment, and PSO bases on interaction through communication (global version) and on interaction through sensing (local version).

Nevertheless, all types of interaction have a high potential for increasing the overall system performance of a multi robot system. Thus, in the context of the EU-MOP project a robotic swarm is a homogeneous group of robots that performs a predefined task by simple control strategies without any hierarchies and without any kind of central planning or control instance. The increased performance of a swarm arises from interaction of the agents, where interaction through the environment, interaction through sensing and interaction via communication is allowed.

In order to compare different types of interaction three different control concepts for the EU-MOP robots have been developed. These will be presented and compared in chapter III.

C. Assessment of robotic swarms

In order to compare different control concepts, assessment criteria will be needed. Liu and Passino state that “although many studies on swarm intelligence have been presented, there are no general criteria to evaluate a swarm intelligent system's performance” [25]. Fukuda et al. try to make an evaluation based on the flexibility [26]. Nevertheless, as in every oil response scenario the time to recover the oil (recovery time T_0) is crucial, a more specific criterion has been developed for the EU-MOP swarm.

This criterion is called swarm performance quotient (Q_{SP}). It bases on the idea that a swarm of N robots should have an increased performance compared to a single robot system. Thus the performance P_N of a swarm of N units has to be higher than N times the performance P_1 of 1 robot; performance can be considered as the quotient of the initial oil slick size V_0 and the time to recover the oil T_0.

$$P_N \overset{!}{\geq} N * P_1 \Rightarrow \frac{V_0}{T_{0,N}} \overset{!}{\geq} N * \frac{V_0}{T_{0,1}} \Rightarrow N * T_{o,N} \overset{!}{\leq} T_{0,1}$$
$$Q_{SP} = \frac{T_{0,1}}{N * T_{0,N}} \qquad (2)$$

where $T_{0,1}$ is the recovery time of 1 robot, and $T_{0,N}$ the time of a swarm with N robots. In other words: A EU-MOP swarm uses synergy effects and is thus better than a single robot system, if the quotient of the recovery time of one robot and N times the recovery time of N units is larger than 1.

D. Simulation of the behaviour of the EU-MOP swarm

Furthermore a C++ simulation has been developed in order to analyze the behaviour of the swarm and to estimate the recovery time of the different control concepts. Fig. 2 shows screenshots of the simulation with the EU-MOP robots, the oil slicks as well as the marine environment.

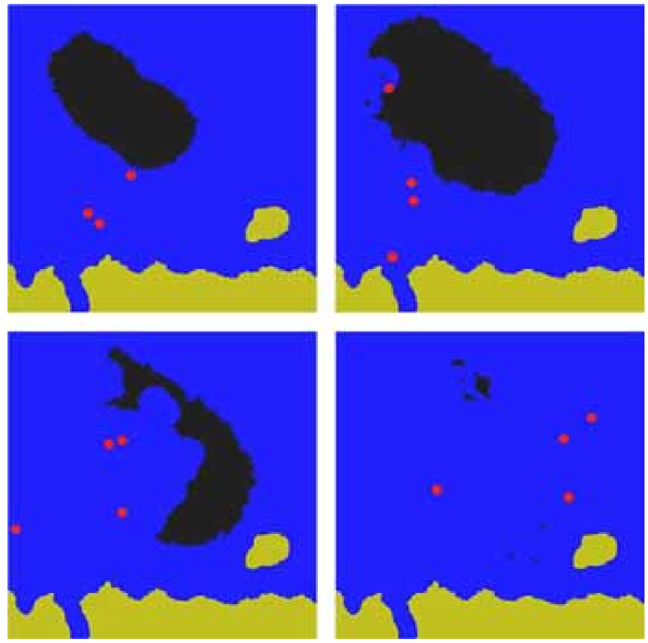

Fig. 2. Screenshots of the simulation with robots, oil slick and marine environment

In this simulation, the oil slick is spreading and weathering according to an oil fate model which has been developed by the University of Oxford within the EU-MOP project. The EU-MOP units behave according to the control systems described later in chapters III-V. The overall amount of skimmed oil by a swarm with N units up to time T is:

$$V_{skimmedoil}(T) = \int_{t=0}^{T} \sum_{i=1}^{N} V_{skimmedoil,i}(t) \qquad (3)$$

Input data of this simulation are the oil spill scenario (amount of oil, type of oil etc.), as well as typical data of the EU-MOP robots (size, speed etc.). The main output of this simulation is the recovery time T_0 where $V_{skimmedoil}(T_0) = 0$.

III. SIMULATION OF DIFFERENT CONTROL CONCEPTS OF THE EU-MOP SWARM

As mentioned above, three different control concepts will be presented, simulated and compared in this chapter. These control concepts differ in the level of interaction of the robots in a swarm; the three control concepts are:

- a low-level interaction control concept (type A),
- an interaction via environment control concept (type B) and
- an interaction via communication control concept (type C).

Due to the fact that the EU-MOP robots will have to work in a highly dynamic environment with strong winds, waves and currents the robots will not be able to connect each-other physically. Thus the aspect of self-assembling will not considered in this paper.

A. Low-level interaction control concept (type A)

According to this control concept the robots are only equipped with bumpers for the detection of collisions with other units and the environment. The robots will not be able to detect oil, or to cooperate with other units. The only interaction is that a robot will be influenced by another one, if there was a collision between both (and as the units are only equipped with bumpers, they are not able to differentiate between EU-MOP robots and other obstacles).

The control of the EU-MOP robots of this type (type A) is shown in the FSA diagram in Fig. 3.

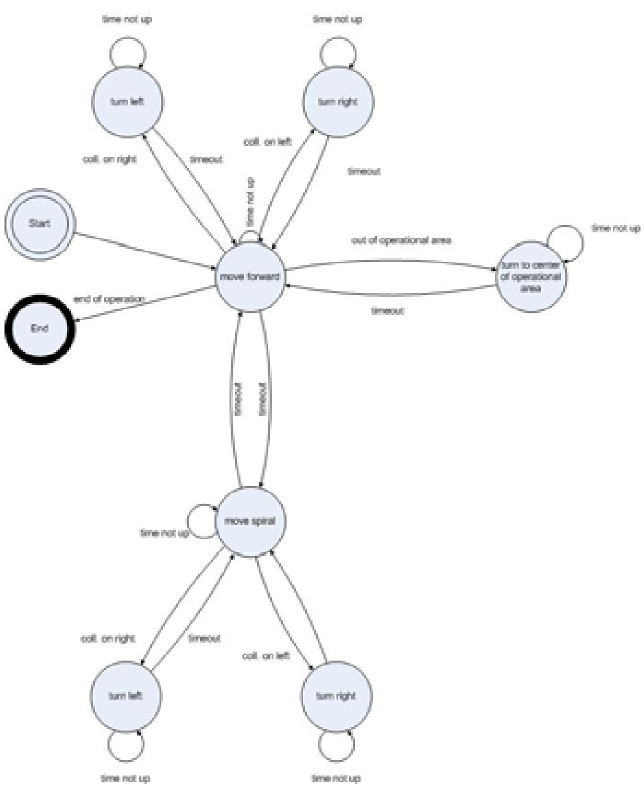

Fig. 3. FSA diagram of robots of type A

At the beginning of its operation each unit of type A will have the state "move forward", until one of the following events occurs:

- a collision occurs on the left which will be detected by the left bumper,
- a collision occurs on the right which will be detected by the right bumper,
- the unit moves out of a predefined operational area which will be detected by a GPS sensor or
- an internal timer will have a value of 0 (timeout).

A collision, either on the left or on the right, will change the state of the unit to the state turn left or turn right, respectively. In this state the unit will turn for a random time; as soon as timeout occurs, the unit will change its state back to "move forward".

If the unit is in the state "move forward" and it moves out of a predefined operational area, the unit will turn towards the centre of the operational area and change back to the state "move forward".

Each time the unit changes into the state "move forward" an internal timer will be set to a random value. As soon as the timer has a value of 0 (timeout), the unit will change into the state "move spiral", which means that it will turn left with an permanently increasing radius until, again, a timeout event occurs. The timeout event in the state "move spiral" will bring the unit back to the state "move forward". Of course, collisions can also occur in the state "move spiral". In this case, the units will handle collisions like in the state "move forward".

Furthermore each robot (type A, B and C) is equipped with a positioning system in order to move back to the MS if the oil storage is full. This is not shown in the FSA diagrams.

The following diagram shows the amount of oil on water at each time step for 0 units, 1 unit, 2 units, 5 units and 20 units of type A.

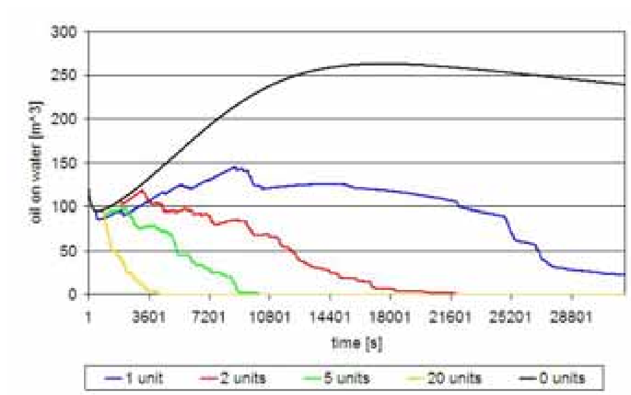

Fig. 4. Amount of oil in simulation of unit type A

The line "0 units" shows the changes of the amount of oil on the water surface without any oil response operation. This line is only influenced by spreading and weathering effects of the oil. Typical effects are evaporation which will lead to a decrease of the amount of oil on the water surface, and emulsification, which will lead to an increase of the oil volume. The diagram in Fig. 4 shows a small phase of decreasing oil volume, afterwards a phase of an increasing volume, and finally a phase of decreasing oil volume which ends in a saturation.

The line “1 unit” shows the amount of oil on the water surface if one unit is applied. This line consists of two different sequences: In those phases, where the robot is not in the oil slick, the amount of oil behaves according to the line “0 units”. If a unit is recovering oil, the line decreases faster. This line shows, that there are a lot of phases, where the unit does not recover oil, thus the total recovery time is very high.

The lines “2 units”, “5 units” and “20 units” show that if the number of units increases the amount of oil on the water surface decreases faster, as there are less times, where no unit recovers oil, and thus the total recovery time decreases also. The following table shows the recovery time and the swarm performance quotient as a function of the swarm size.

TABLE I
RESULTS OF THE SIMULATION OF THE TYPE A SWARM ROBOTS

Swarm size (N)	T_0 of units of type A [s]	Q_{SP} of units of type A [s]	Standard deviation of T_0 [s]
1	42499	1,00	2059,23
2	21893	0,97	1145,74
3	11938	1,19	619,33
4	9885	1,07	498,65
5	9702	0,88	470,30
10	4074	1,04	125,68
20	2810	0,76	94,97

The T_0 values base on 25 simulation runs with different random seeds for each swarm size.

Due to the selected scenario (including size of robots, size of oil slick, size of environment etc.) 20 units is more or less the maximum size of a swarm; with higher swarm sizes each robot will permanently avoid collisions with other robots which will lead to the same unit type independent behaviour.

The recovery time T_0 of these type A swarms is very bad (compared to those of the following swarm types B and C). Furthermore, the swarm performance quotient Q_{SP} reaches relatively bad values. The fact, that the Q_{SP} is sometimes above 1 and sometimes below 1 shows that there is now swarm “intelligence” behind this strategy. The low level of interaction of these robots is the reason for this bad swarm performance quotient. The only interaction in this scenario comes form the collisions between two units. After each collision both units will turn into a random direction, and this will lead to a better distribution of the units in the whole operational area. Nevertheless, this interaction is to low in order to reach a good Q_{SP}, and thus control concepts with more interaction will be needed.

B. Interaction via environment control concept (type B)

In this control concept each unit is additionally equipped with an oil detection sensor. These sensors will enable the units to move in a more intelligent way. The control of the EU-MOP robots of this type (type B) is shown in the FSA diagram in Fig. 5. According to this concept, a unit of type B will behave in the same way as a unit of type A if it does not detect oil. As soon as the unit detects oil it will switch into the state “move forward through oil”. Comparable to the state “move forward” each unit of type B which has the state “move forward through oil” will move straight ahead until

- a collision occurs on the left which will be detected by the left bumper,
- a collision occurs on the right which will be detected by the right bumper,
- the unit does not detect oil which will be detected by the oil sensors.

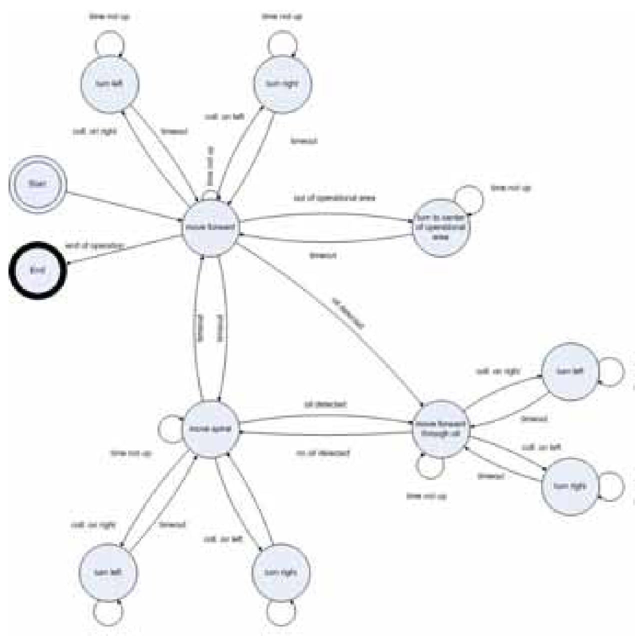

Fig. 5. FSA diagram of robots of type B

In the case of a collision on the left / on the right the unit will turn to the right / to the left and afterwards it will change into the state “move forward through oil”.

If a unit is in the state “move forward through oil” and the event “no oil detected” occurs, it will switch to the state “move spiral”. The idea behind this strategy is the following: A single unit detects oil and moves straight through the oil slick. If the unit has crossed this oil slick completely it will be split into two smaller oil slicks. If the unit is now moving a spiral it will be more or less immediately back in oil.

TABLE II
RESULTS OF THE SIMULATION OF THE TYPE B SWARM ROBOTS

Swarm size (N)	T_0 of units of type A [s]	Q_{SP} of units of type A [s]	Standard deviation of T_0 [s]
1	17802	1,00	915,63
2	4289	2,08	198,70
3	2625	2,26	119,18
4	2382	1,87	90,83
5	1960	1,82	68,64
10	1869	0,95	44,32
20	1807	0,49	53,80

The T_0 values base on 25 simulation runs with different random seeds for each swarm size.

The benefits of this strategy are illustrated in table II. This table shows that in both the recovery time T_0 and in the Q_{SP} a swarm of units of type B performs much better than a swarm of units of type A. This will be explained with the following figure.

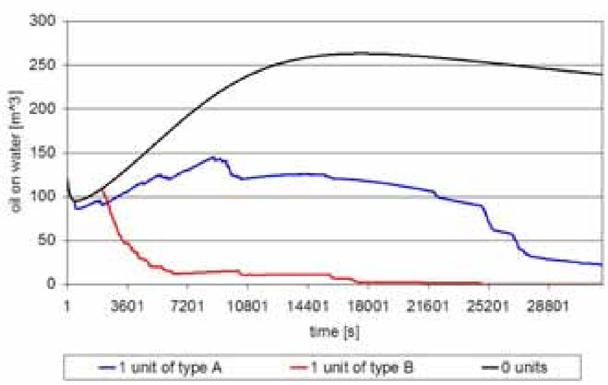

Fig. 6. Amount of oil on water for 0 units, 1 unit of type A and 1 unit of type B over time

The line "0 units" shows again the spreading and weathering effects of the oil. The line "1 unit of type A" shows the volume of the oil on water over time during an oil response operation of one unit of type A, the line "1 unit of type B" an oil response operation of one unit of type B respectively. Although in this example, the first time that a unit of type A removes oil is much earlier than a robot of type B, the recovery time of type B is much better. This is due to the oil detection sensor, which will enable a unit of type B to stay more or less always in the oil. Therefore, the line "1 unit of type B" decreases especially in the beginning much more than the line of type A.

Furthermore, the oil detection sensor enables an interaction via the environment. The fact, that a unit removes oil at a certain position may influence the behaviour of another unit at a later time. But, the oil has not the same effects as the pheromone in the ant-based robot swarms. If an ant smells pheromone, this means that another ant has definitely been at the same place. The sensor information "oil detected at present position" is not clear; it means that either no robot has been at this position before or that a robot has removed oil at this position, but due to spreading and weathering effects the oil moved back to this position. The information "no oil detected" means, that oil has been removed at this position or that no oil has ever been there.

Nevertheless, this swarm type reaches good Q_{SP} values; up to five units every additional unit will lead to an increased performance with a factor of about two.

C. Interaction via communication control concept (type C)

According to this concept, each unit is additionally equipped with a radio system, which will enable the robots to communicate. Thus, the following strategy comprises a state "move to oil unit", where a unit which does not detect oil will move towards the closest unit which detects oil. The following figure shows the FSA diagram of the robots of type C.

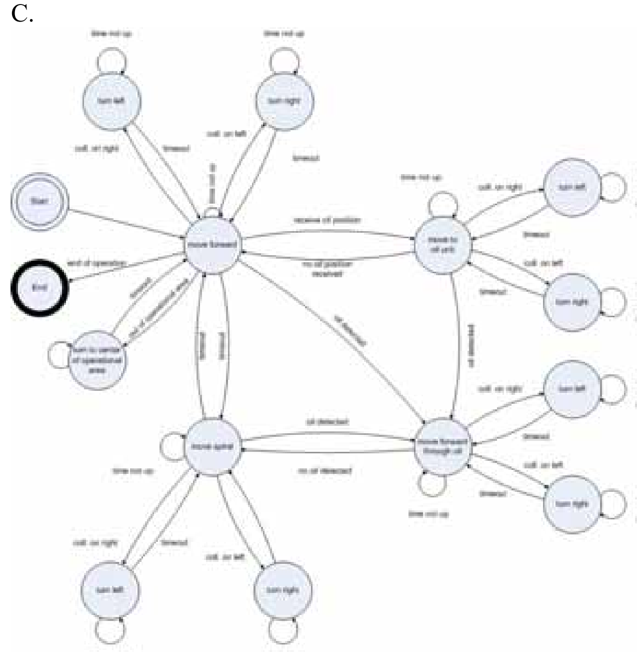

Fig. 7. FSA diagram of robots of type C

Table III shows the results of swarms of type C.

The additional sensor and the corresponding additional interaction (robots of type C uses interaction via communication and interaction via the environments) lead to better results than those of the robots of type A. With swarm sizes of more than two robots (in biology a swarm has at least 3 agents [26]) the robots of type C perform better as those of type B.

TABLE III
RESULTS OF THE SIMULATION OF THE TYPE C SWARM ROBOTS

Swarm size (N)	T_0 of units of type A [s]	Q_{SP} of units of type A [s]	Standard deviation of T_0 [s]
1	17805	1.00	843,64
2	7278	1,22	372,68
3	2459	2,41	104,74
4	1863	2,39	66,51
5	1703	2,09	53,06
10	1651	1,08	54,78
20	1620	0,55	54,52

The T_0 values base on 25 simulation runs with different random seeds for each swarm size.

Furthermore, swarms up to 10 robots have a good swarm performance quotient. This is due to the increased interaction capabilities of the robots. For swarms up to 2 units, swarms of type B perform better. This is due to the fact, that with the strategy of type C causes a certain clustering effect, especially in the beginning of the simulation, where the units are dropped in sequence into the water. Thus, the second type C robot will directly move towards the first robot, while the type B robots are moving less concentrated through the operational area. Nevertheless, comparing all three type of control concepts, the type C control concept produces the best results.

VI. CONCLUSION

Many optimization problems can be solved with the help of central problem solving algorithms. For instance: The problem of the allocation of machines in order to produce a certain number of different products is a classical application of the linear programming (LP). A central planning instance can optimize the output of this production system. But what happens, if one of the machines has an unexpected breakdown? The results of this LP optimization are wrong as this algorithm assumed that machines do not have breakdowns. Furthermore, what happens if the time which a machine needs in order to process one of these products is unknown? Then, again, the LP algorithm will not be applicable.

This example shows, that if an agent has to cope with an unknown and highly dynamic environment (where machines have breakdowns and where the behaviour of other objects in the environment is unknown), only distributed problem solving algorithms will be the basis for good solutions.

The swarm intelligence approach is a distributed problem solving algorithm which is supposed to produce very intelligent solutions with simple agents. In this paper we have shown with a concrete application, namely the elimination of marine oil pollutions, that a SI-based control of multi robot systems produces very good results. Furthermore, we have shown that interaction between agents is very important for the SI approach and that especially in the field of robotics the combination of different interaction principles leads to additional benefits.

Nevertheless, there are still further possibilities how to increase the interaction, e.g. the use of the interaction via sensing principle. Furthermore, these control concepts and interaction principles have just been simulated with the help of one concrete scenario. Thus, further research will be done in order to develop high-level interaction control strategies, which are able to cope with different oil spill scenarios.

VII. ACKNOWLEDGMENT

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VIII. REFERENCES

[1] Vieites, D. R.; Nieto-Romàn, S.; Palanca, A.; Ferrer, X.; Vences, M. (2004): European Atlantic: the hottest oil spill hotspot worldwide. In: Naturwissenschaften 91:535–538.

[2] Psaraftis, H. N.; Ventikos, N. P. (2006): An intelligent robot system to respond to oil spills: the EU-MOP Project. In: Proceedings of the INTERSPILL, London.

[3] Arkin, R. C.: Behavior-Based Robotics. Cambridge, MA: MIT Press, 1998.

[4] Uny Cao,Y.; Fukunaga, A.S.; Kahig, A.B. (1997): Cooperative mobile robots: Antecedents and directions. In: Autonomous robots, vol 4., Number 1, page 23.

[5] Matarić, M. J.; Sukhatme, G. S.; Østergaard, E. H. (2003): Multi-Robot Task Allocation in Uncertain Environments. In: Autonomous Robots, vol. 14, pages 255-263.

[6] Schenker, P.; Huntsberger, T.; Pirjanian, P.; Trebi-Ollennu, A.; Das, H.; Joshi, S.; Aghazarian, H.; Ganino, A.; Kennedy, B.; Garett, M. (2000): Robot work crews for planetary outposts: Close cooperation and coordination of multiple robots. In: Proceedings of SPIE Symposium on Sensor Fusion and Decentralized Control in Robotic Systems III, Boston, MA, vol. 4196.

[7] The International Tanker Owners Pollution Federation: ITOPF Handbook 2006/2007. Available at: www.itopf.com.

[8] Bonabeau, E.; Dorigo, M.; Theraulaz, G.: Swarm Intelligence: From Natural to Artificial Systems. New York, Oxford. Oxford University Press, 1999.

[9] Kennedy, J.; Eberhart, R.C.: Swarm Intelligence. Morgan Kaufmann Publishers: San Francisco, 2001.

[10] Schraft, R. D.; Hägele, M.; Wegener, K. (2004): Service Roboter Visionen. München: Hanser, 2004.

[11] Beni, G.: The concept of cellular robotic systems. In: Proceedings of the IEEE Symp. Intell. Contr., Arlington, VA, Aug. 1988, pp. 57–62.

[12] Beni G.; Wang J.: Swarm Intelligence in Cellular Robotic Systems,. In: Proceedings of the NATO Advanced Workshop on Robots and Biological Systems, I1 Ciocco, Tuscany, Italy, 1989.

[13] Hackwood, S.; Beni, G.: Self-organization of sensors for swarm intelligence. In: Proceedings of the IEEE International Conference on Robotics and Automation, pp.819-829 vol.1, 12-14 May 1992.

[14] Dorigo, M.; Di Caro, G.: Ant colony optimization: a new meta-heuristic. In: Proceedings of the 1999 Congress on Evolutionary Computation, vol.2, no.pp.-1477 Vol. 2, 1999.

[15] Kennedy, J.; Eberhart, R.: Particle swarm optimization. In: Proceedings of the IEEE International Conference on Neural Networks, vol.4, no.pp.1942-1948 vol.4, Nov/Dec 1995.

[16] Eberhart, R.; Kennedy, J.: A new optimizer using particle swarm theory. In: Proceedings of the Sixth International Symposium on Micro Machine and Human Science, pp.39-43, 4-6 Oct 1995.
[17] Jones, C.; Matarić, M. J.; Werger, B.: Cognitive Processing through the Interaction of Many Agents. In: Encyclopaedia of Cognitive Science. Nature Publishing Group, Macmillan Reference Limited, Nov. 2002.
[18] Holland, O., ; Melhuish, C.: Stigmergy, selforganization, and sorting in collective robotics. Artificial Life 5(2): 173-202. 1999.
[19] McFarland, D.: Animal Behaviour, Psychobiology, ethology and evolution. Addison Wesley Longman Ltd, fourth edition, 1999.
[20] Grassé, P.-P.: La Reconstruction du nid et les Coordinations Inter-Individuelles chez Bellicositermes Nataensis et Cubertimes sp. La théorie de la Stigmergy : Essai d'interpretation du Comportement des Termites Constructeurs. Insect. Soc. 6, pp. 41 – 80, 1959.
[21] Grassé, P.-P. : Termitologia, Tome II. Foundation des Sociétés. Construction. Paris, Masson, 1984.
[22] Cao, Y.; Fukunaga, A. S.; Kahng, A. B.; Meng, F.: Cooperative Mobile Robotics: Antecedents and Directions, in `IEEE/TSJ International Conference on Intelligent Robots and Systems', Yokohama, Japan, 1995.
[23] Reynolds, C. W.: Flocks, herds and schools: A distributed behavioral model. In Proceedings of the 14th Annual Conference on Computer Graphics and interactive Techniques M. C. Stone, Ed. SIGGRAPH 1987. ACM Press, New York, NY, 25-34.
[24] Liu, S.; Passino, K. Swarm intelligence: Literature overview. In Dept. of Electrical Engineering, The Ohio State University, 2015 Neil Ave., Columbus, OH 43210 (2000).
[25] Fukuda, T.; Funato, D.; Sekiyam, K.; Arai, F.: Evaluation on flexibility of swarm intelligent system. In: Proceedings of the 1998 IEEE International Conference on Robotics and Automation, pp. 3210-3215, 1998.
[26] Haken, H.; Haken-Krell, M.: Entstehung von biologischer Information und Ordnung. Darmstadt, Wissenschaftliche Buchgesellschaft, 1989.