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Oil Spill trajectory tracking using Swarm Intelligence and Hybrid fuzzy system

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***Abstract*—Increase of the offshore industrial activities is highly affecting marine milieu. For example, discharge of liquid petroleum on water surface, oil spill, frequently happens because of the offshore well vessels failure or transportation accidents. Numerous occurrences of the oil spills are obvious examples of affecting ecology by industrialization. Therefore, information about the exact location and real-time situation of an oil spill can significantly facilitate to plan for diminishing the spot, in time. This research proposes a hybrid fuzzy algorithm for individuals of swarm robots, in order to track the boundaries of a simulated oil spill which is influenced by environmental factors such as wind and wave currents. Simulation results prove the feasibility of engaging swarm robotics in this application.**

I. Introduction

Nowadays, growing the offshore industrial activities is highly affecting marine milieu. Discharges of liquid petroleum on water surface, known as oil spills, frequently take place due to offshore well vessels failure or transportation accidents. For example, at least twenty huge oil spills are reported [1] in the last four decades, in addition of the abundant small and local oil spills occurrences [2]. Furthermore, numerous physical, chemical, and even biological factors influence the spread of the oil on a water surface. Wind, sea currents, tide, oil properties, and so many more elements cause complex and variable distribution of the oil spill [3]. Obviously, prior estimation about potential behaviour of suspended oil on the water surface directs to more efficient treatment of the slicked oil, consequently, modelling of leaking oil is a significant necessity.

Currently, there are several researches aimed to propose a numerical model of the oil spill such as [3, 4]. However, due to vast numbers of influencing factors and complexities, their results need to be verified with external observations which are highly labour intensive [5]. In addition, there are other kinds of studies to track the spills trajectory technically, such as satellite imagery captures [6]. Nevertheless, they also experience different obstacles such as light reflection, cloud occupations and noisy images, even though these types of solution are not practically applicable for the small spills.

On the other hand, swarm intelligence is a well-known solution for the complex problems. Furthermore, recent progresses in robotics and electronic facilities make it possible to engage a swarm of mobile sensors to track the fate and trajectory of the spill, accurately and interactively. Since the spread of the slicking oil is the most important concern, in this paper, we propose an innovative and intuitive algorithm, aimed to track the boundaries of oil spills, by a set of synchronized robots.

Despite the term of *Swarm Intelligence* is generally known for some of famous algorithms such as PSO, ABC, and etc, but since in the proposed method, robots work in a coordinated group; and they cannot perform individually also without other synchronized mates as particles of an intelligent swarm, so, literally it may be possible to categorize this technique as a swarm intelligence method.

The rest of this paper is continued by the preliminary acquaintance about diffusion principles and equations, followed by the methodology of proposing algorithm, and finally ended with a discussion about the simulation results.

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II. Preliminaries

Numerical model of Oil spill

There are many comprehensive researches presenting numerical models of the slicking oil on the water surface which are widely discussed in [1], [3], and [7]. According to the Fick's diffusion law [8], the discharging oil concentration disperses over the time as a function of diffusion coefficients, $D_{x,y}$, and environmental factors such as winds and water currents resultant $U_{x,y}$.

$$\frac{\partial c}{\partial t} = D_x \frac{\partial^2 c}{\partial x^2} + D_y \frac{\partial^2 c}{\partial y^2} - U_x \frac{\partial c}{\partial x} - U_y \frac{\partial c}{\partial y} \tag{1}$$

Considering the instantaneous v_t volume of oil release, the equation (2) describes distortion of the oil based on time and location:

$$c(x, y, t) = \frac{v_t}{4\pi\sqrt{D_x D_y}}.exp\,[-\frac{x - U_x t^2}{4D_x t} - \frac{y - U_y t^2}{4D_y t}] \tag{2}$$

However, if release rate of the oil is recorded as $\omega(t)$ over the time iterations, derived from superposition principle, the allotment of the oil on the water surface is:

$$C(x, y, t) = \int_{-\infty}^{t} \omega(\tau)\, c(x, y, \tau) d\tau \tag{3}$$

On the other hand, Fay [9] suggested an estimation of slicking oil area versus the whole volume of discharged mass, rooted in his several experimental observations:

$$A = \eta.(V)^{(3/4)} \quad (4)$$

While in the metric system, A is in the square meter, and V is scaled in cubic meters, η is recommended to be 10^5. In addition, the resultant effect of winds and water currents [10] with amplitude of ρ, and direction of θ, can be assumed as a normal distribution with a mean of μ and standard deviation of σ^2, respectively [7]:

$$\vec{U} = \mathcal{N}\left(\mu_\rho, \sigma_\rho^2\right).\exp\left[-i.\mathcal{N}(\mu_\theta, \sigma_\theta^2)\right] \quad (5)$$

III. Methodology

In a general overview, our proposed algorithm is a method which engages a swarm of robots to track the oil spill on the water surface. Each individual of the robots as a particle of the swarm updates its position based on the sensory measurements and the position of the other robots. In this order, there are some elementary assumptions which should be noticed regarding the simulation of the robots' behaviours. First of all, it is assumed that robots are able to thoroughly navigate themselves on the water surface, and every robot can locate itself using positioning facilities such as GPS [11] or APM [12] modules. Meanwhile, they should be capable of communicating to each other through a network, so that they can share their position in a regular schedule. Therefore, they potentially can calculate their iterative destination using the available information.

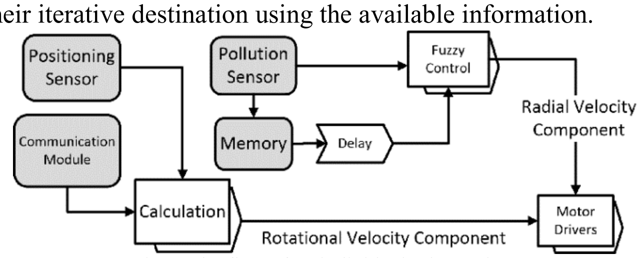

Fig. 1 The flow of an individual robot tasks

Figure 1 shows the outline of an individual robot tasks, which leads to contributing the position of the oil spill boundaries. A hybrid fuzzy control system is defined to update motors speed of the robots in direction and magnitude. The pseudo code of ten steps cycle procedure of individual robots is as follows:

1. *Read the position. (GPS)*
2. *Share the position in the network.*
3. *Get the other robots' position from the network.*
4. *Calculate the swarm centre, and positions reference to the centre point in the polar system.*
5. *Read the Pollutant sensor.*
6. *Save the measured pollution in the Memory.*
7. *Read the Memory. (Previous amount of the sensor)*
8. *Obtain the radial component of the velocity update. (Fuzzy Control)*
9. *Calculate the rotational component of the velocity.*
10. *Apply the new velocity to the motors.*

Since robots are engaged in a swarm, the centre of their positions is considered as the reference of their computations, and obviously it may relocate in every iteration.

$$C = \begin{bmatrix} \bar{X} \\ \bar{Y} \end{bmatrix} \quad (6)$$

A. Dynamic effect of Currents, Waves and Wind on robots position

Since the robots are considered buoyant on the water surface, therefore, they are affected by environmental forces such as currents and wind, in addition of their controlled engine power. Therefore, in simulation of their position at every time step, the effect of environmental forces is initially applied on each robot position based on local force resultant, before its engine command from intelligence module.

B. Profiling the spill, based on robots position

The situation of each robot particle in the swarm contributes a position of local information about the oil spill borders, rather than the point C in the polar system. Therefore, the profile of the slicked oil is obtained, based on a 360 degrees interpolation with the gathered information from particles' position.

C. Navigation Control

Navigation control includes computing of each robot's velocity, based on the gathered information such as position of itself and the mates, concentration of measured pollutant, and the previous measured amount which is saved in the memory. In addition, two components of robots' velocity are determined separately, in a polar system reference to the point C in (6); while the radial component, ρ, is coming from a fuzzy controlling system, the rotational element of speed, φ, is administrated based on a geometric calculation.

1) Radial direction

One of the major benefits of the fuzzy control systems is providing a simple look-up table for robots, leading to a faster and simpler processing. Thus, terms of pollutant concentration and robot speed are defined as fuzzy membership functions. Therefore, the fuzzy system controls the amplitude of the robot's speed in the radial aspect based on measuring the amount of pollutant at the instant time iteration and the previous time step, which is recorded in memory.

In this regard, a Mamdani Fuzzy system is defined with two inputs of instantaneous and previous measured concentration from the sensor and memory, respectively. Three membership functions of concentration are defined based on [9] as "Diluted Area", "Boundaries Area", and "Concentrated Area". The output of the fuzzy system determines the robot speed motor which is defuzzified with centroid method whether in positive – far from swarm centre – or negative – close to the centre – amount in the range of negative maximum speeds of motors till positive, divided by root square of two. There are five membership functions named "FastFar", "MedFar", "Slow", "MedClose", and "FastClose" represent the fuzzy output. Table I, listed the rule table of this fuzzy system.

2) Rotational component

On the other side, the uniform distribution of particles along the spill perimeter is crucial. Therefore, we have proposed a computational algorithm to update rotational component of velocity of the robots. Through this computation, the robots adjust their angular speed component to keep the maximum angular distance time-by-time.

$$\varphi_i(t+1) = \varphi_i(t) + \sum_{j=1}^{N} \frac{\operatorname{sign}(\varphi_i - \varphi_j)}{D_{i,j}} \cos\left(\frac{\varphi_i - \varphi_j}{2}\right) \tag{7}$$

While, φ_i is the angle of ith robot in the polar system reference to centre of the swarm and the east axis, $D_{i,j}$ represent distance between the ith and jth robot, calculating:

$$D_{i,j} = \sqrt{\rho_i^2 + \rho_j^2 - 2\rho_i\rho_j\cos(\varphi_i - \varphi_j)} \tag{8}$$

TABLE I
RULE TABLE OF FUZZY CONTROLLER

Current Position	Previous Position	Consequent
Concentrated	Concentrated	FastFar
Concentrated	Boundary	MedFar
Concentrated	Dilute	FastFar
Boundary	Concentrated	MedFar
Boundary	Boundary	Slow
Boundary	Dilute	MedClose
Dilute	Concentrated	FastClose
Dilute	Boundary	MedClose
Dilute	Dilute	FastClose

IV. RESULTS AND DISCUSSION

The simulation results for 8-robot-swarm are illustrated in Figures 3 to 9. Figure 2 shows the resultant vectors of the wind and current forces [10] as input information of the simulation. The resultant is considered as a normal distribution of U in both direction and amplitude (grey scale), with the mean of 7 m/s and standard deviation of 0.2 m/s. They are also distributed normally in the direction (arrows in the figure) with the mean of 115 degrees and standard deviation of 0.15 degrees.

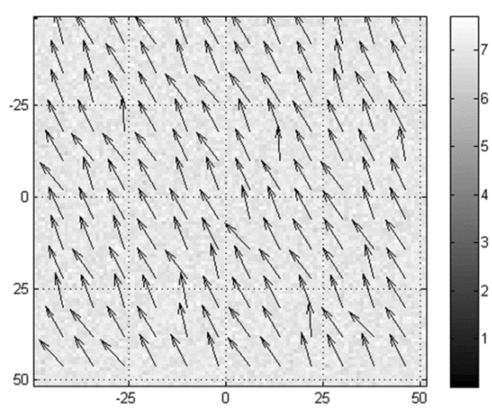

Fig. 2 The resultant of Wind and Current, for $U = \mathcal{N}(7m/s, 0.2).\exp[-i.\mathcal{N}(115°, 0.15)]$

For all diagrams of 3 to 9, x and y directions refer to positions, scaled in meter, and in the zonal and meridional directions, correspondingly. In addition, the bar in the right side indicates the concentration of pollutant in the grey scale. Furthermore, the dashed bound indicates the proposing profile of the oil spill based on robots position. Figure 3 shows the initial positions of robots (black circles) which are determined by the user, even though, they could be set randomly around the discharge location.

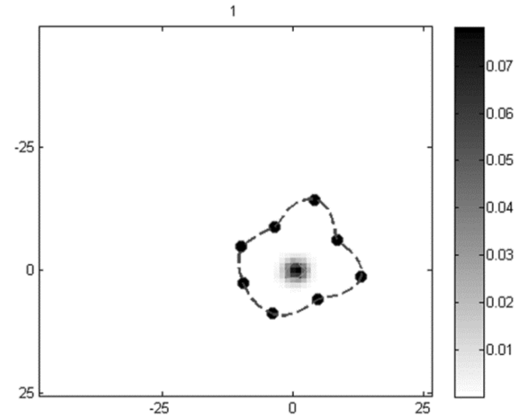

Fig. 3 Initial Positions of 8 robots and oil spill.

The collapse of the swarm is shown in Figure 4, when they navigate in *closer* direction to the centre of the cluster in the fifth time iteration.

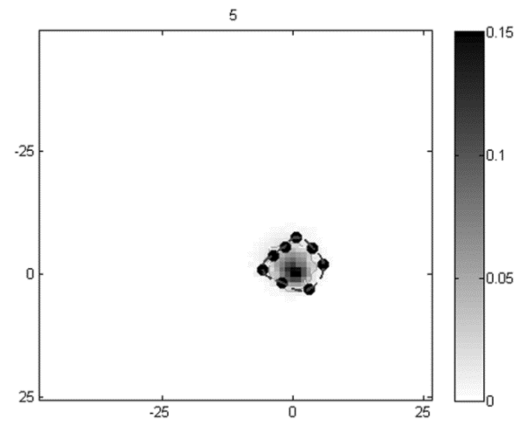

Fig. 4 Oil spill situation and robot position after five iterations.

However, they tend to extend afterward, since the oil spill is growing onward in figures 5, 6, and 7, respectively in time iterations 10, 20, and 30.

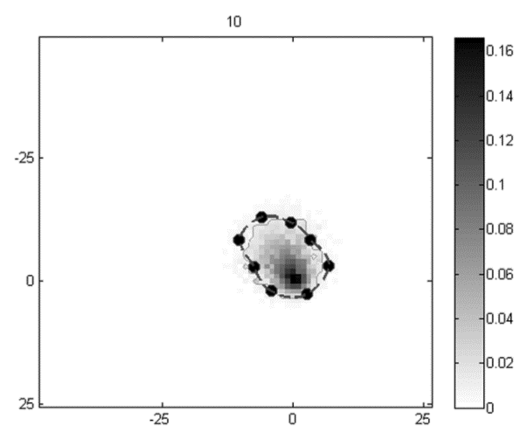

Fig. 5 Oil spill situation and robot position after 10 iterations.

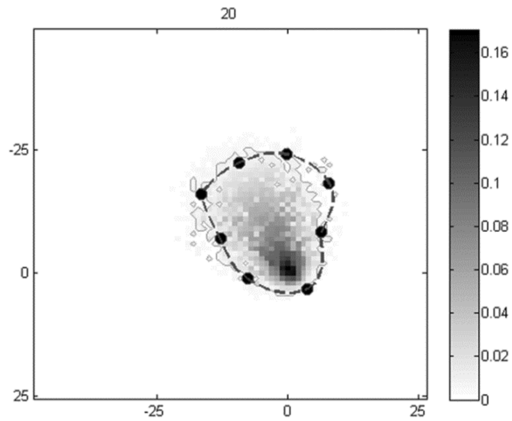

Fig. 6 Oil spill situation and robot position after 20 iterations.

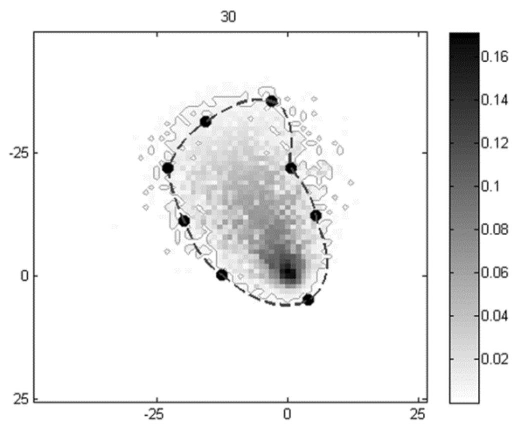

Fig. 7 Oil spill situation and robot position after 30 iterations.

Another simulation test was running with a different condition which was the cut-off of leakage sources at the time iteration 15. The consequent results are shown in figure 8 and 9 in time step of 20, and 30. The advection of oil spill concentration centre rather than the figures 6 and 7 is noticeable. However, robots comprehensively track the spill in this condition, either.

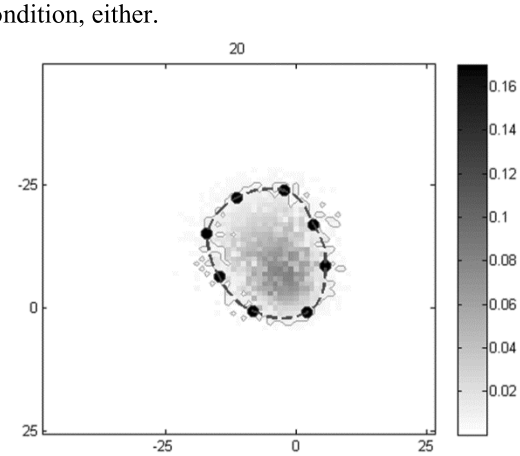

Fig. 8 Oil spill situation and robot position after 20 iterations.

In addition, the fuzzy hybrid method has been evaluated and compared with the fully numerical control method [7]. To do so, some terms should be explained, first.

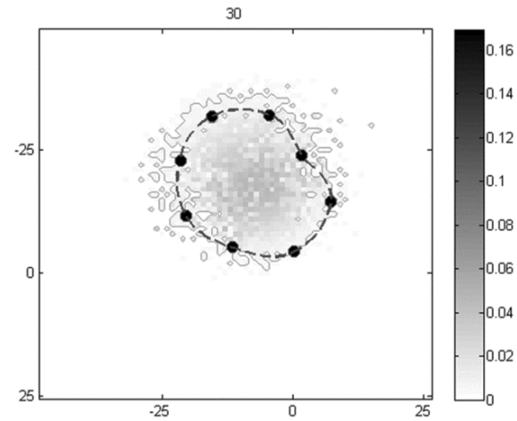

Fig. 9 Oil spill situation and robot position after 30 iterations.

Since evaluation of robots behaviour in this research is main concern, the numerical model of the oil spill – which is described in preliminary section – in the background is considered as ground truth. Therefore, the term “True Positive” (TP) indicates the areas that are occupied either by the oil spill from the numerical model or surrounded by the swarm. Term “False Positive” (FP) refers to areas which are closed by robots, while they are not specified as oil spill according to the ground truth. “True Negative” (TN) is that areas which, both the ground truth and robot swarm show out of the slick, whereas the “False Negative” (FN) point to regions that are truly in the oil spill but out of the swarm circumference. Consequently, based on these four elements, “Accuracy” and “Positive Predictive Value” or “Precision” is defined [13].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

$$Percision = \frac{TP}{TP + FP} \tag{10}$$

Figure 10 shows the True Positive, False Positive, Precision, and Accuracy evaluations of the conventional fully numerical control (FNC) method as described in [7], over the time iterations, while the figure 11 illustrated same evaluations for fuzzy hybrid (FH) method in this paper. The comparison between two figures shows that the “True Positive” is more stable in the FNC algorithm. It keeps more than 90% -except in iteration 4-, while in the FH method decrease to even less than 80%. However, “False Positive” term also, drops faster in the FH technique, whilst it smoothly drops in FNC and finally gets stable around 30%, but, in the FH it rapidly decreases after fifth iteration and even drops to less than 10%. Consequently, the term of Accuracy and Precision in the FH method have greater grown and converged on 85% and 90% in order, however they fixed only at 85% and 75% in FNC method. Finally, the time processing comparison is demonstrated in figure 12. The black bars indicate the processing times in each iteration for FNC algorithm, and the whites belong to FH method in a portion of a second(s). In the first iteration probably fetching the look-up table to the memory caused a delay. Therefore, despite the first iteration, it is clearly obvious that FH is the faster one in performance.

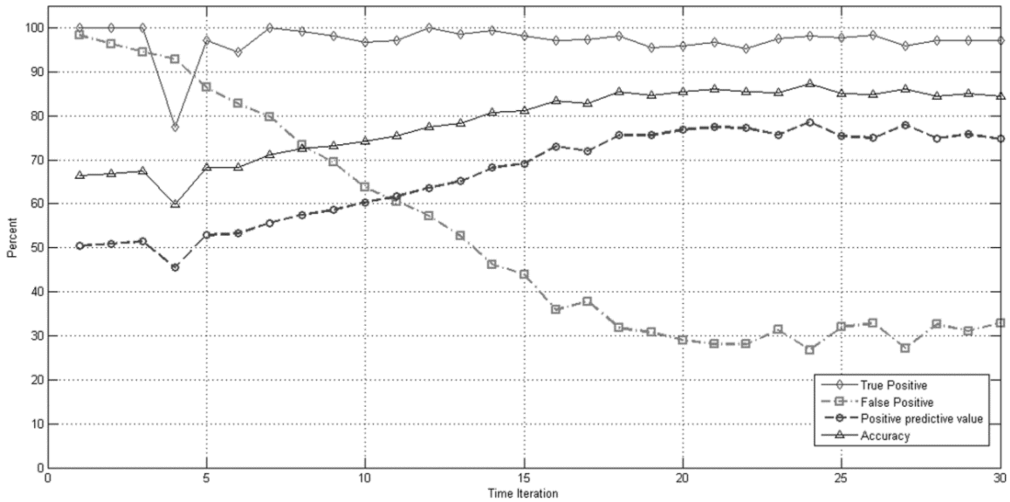

Fig. 10 Evaluation parameters of fully numerical control (FNC) method [7]

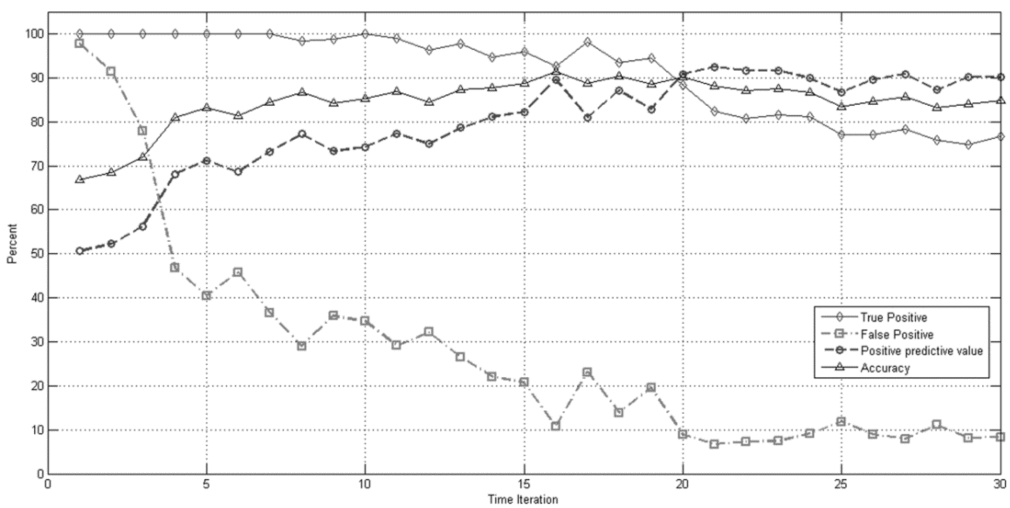

Fig. 11 Evaluation parameters of fuzzy hybrid (FH) method

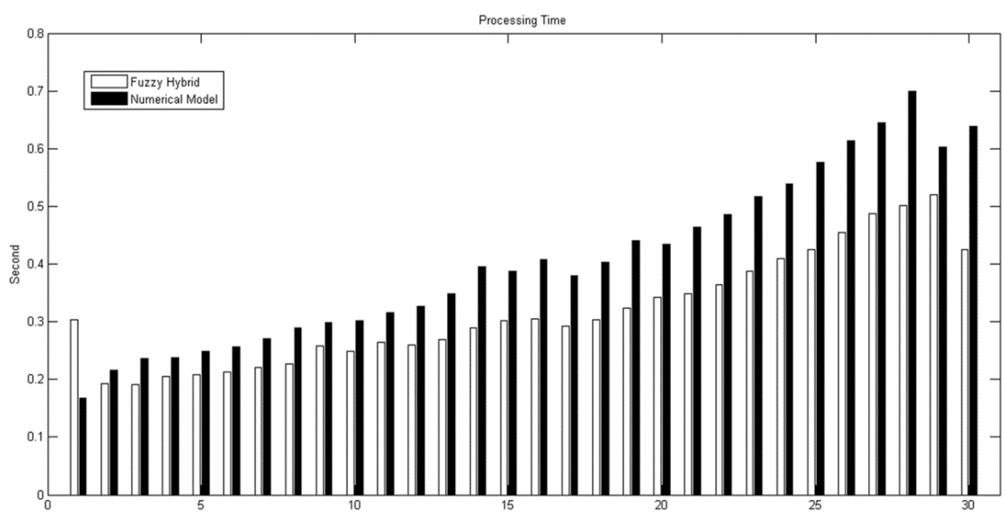

Fig. 12 Bar chart of time processing comparison between fully numerical (FNC) method [7] and fuzzy hybrid (FH) method

V. CONCLUSION

A novel strategy is proposed in this research, in order to employ a swarm of autonomous floating robots to track the fate and trajectory of oil spill influenced by environmental factors such as wind and sea currents. Indeed, we suggest a fuzzy hybrid controlling system to enhance the accuracy and precision of profiling the oil spill, simultaneously with faster processing procedure. Simulation results prove the feasibility of engaging swarm robotic in this application.

VI. FUTURE WORK

In this project, we aimed to follow the slicking oil fate on the water surface based on known environmental influences, however, it is also possible to predict and forecast trajectory of oil spill in the different probability of meteorological condition.

Moreover, applying these algorithms on the embedded mobile platform will be useful for other water pollution applications such as algae or toxic mass materials by replacing only the pollutant sensors.

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