Extended-Range Marine Unmanned Surface Vehicles for Border Surveillance Missions

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***Abstract*—This work focuses on the development of extended-range marine unmanned surface vehicles (USV) for border surveillance missions. USVs present many advantages for marine applications due to their energy-saving capabilities and lack of in-board pilot needs. Nevertheless, due to their small scales, USVs often present reduced mission ranges. In order to overcome this handicap, this work proposes the application of innovative energy management strategies to optimize the available energy during one mission. This solution is based on path and speed optimizations, taking into account the most probable weather and sea conditions, to define a mission plan. The proposed energy management optimization is supported by the USV simulation model. This model is calibrated and verified with two experimental tests: one in an indoor swimming pool and the other in an outdoor enclosed harbour. Applying the proposed optimization strategy results in energy savings between 10 and 35.9%, subject to the maximization of mission time. This work is carried out within the international project SEMS4USV, supported by Frontex.**

Keywords — Unmanned Surface Vehicle, Modelling, Energy Management System, Optimization.

I. INTRODUCTION

Unmanned marine surface vehicles (USVs) present many advantages for both missions and applications, due to their typically higher efficiencies and energy-saving qualities, while presenting higher safety due to their lack of in-board pilot need [1]. For example, in dangerous contexts, such as polluted areas, harsh environments, or nuclear-contaminated sites, USVs can carry out missions with no in-board pilot and crew safety concerns. In addition, USVs can also be used as generic platforms equipped with a variety of sensors and actuators to match different applications, and even adapted from existing manned vehicles [2]. USVs are a hot topic that is worth exploring, as they are being adapted to execute military and defence missions, such as border surveillance.

Due to their small scales (less than 5 meters), USVs are typically equipped with electric propulsion systems fed by batteries, leading to reduced mission ranges in the order of tens of kilometres. One possible solution to extend their range is including photovoltaic panels [3] and using energy management systems (EMS) to plan an optimized mission.

Regarding solar energy, some examples were already successfully tested in research projects. In [4], the Osaka Prefecture University propose a solar powered autonomous surface vehicle (ASV) with 81.2 kg weight, 2.87 m length, 0.79 m wide, and a maximum speed of 2 knots, that includes two 100 W solar panels, a charge controller and a 12 V battery (115 Ah). The vehicle was tested in confined waters, *i.e.*, a swimming pool. In [5], Emergent Space Technologies, Inc. proposes an ASV powered by photovoltaic panels (PV) for oceanographic and atmospheric scientific research. It has 5.5 m length, 1.5 m width, 1.8 m height, and 1360 kg weight. Finally, in [6], Villanova University propose a hybrid power system of a USV comprising a solar array, a fuel cell system and an ocean wave energy converter, that meets the USV's long-duration mission requirements by modelling and optimizing its hybrid power system.

While solar energy has proven to be a viable complementary energy source for these applications, some problems were clearly pointed out: (a) the degradation of PV system due to sea salinity [7]; (b) unpredictable disturbances caused by weather changes influence the power supply of marine vehicles; (c) consumption is typically proportional to the cube of the speed, thus limiting their maximum speed.

According to the previous references, it becomes clear that when dealing with limited energy and multiple sources of energy, the use of Energy Management System (EMS) is imperative for optimal operability. EMSs have been optimized through machine learning techniques, particle swarm optimization and predictive control-based algorithms to help solve the most common and important trade-offs: fuel consumption versus NOx emissions or autonomy versus mission time [8]-[11]. In [12], it is proposed an energy management system for hybrid ship propulsion. First, a detailed model of the main ship's components is presented: the propulsion system, ship dynamics, wave disturbance, engine-to-propeller performance (hybrid diesel and electric), and batteries. Next, based on experimental tests, the authors develop typical load profiles. This is done using machine learning and clustering, resulting in 20 typical load profiles. These are then used to proceed with the evaluation of the energy management strategy. The energy management system is based on a non-linear model predictive control. The selected cost function is used to optimize the variables related to the operator speed reference, the commands to the internal combustion engine and electric motor and a slack variable to include soft constraints, which, if not met, can be waved as a compromise to improve the objective function.

Another typical approach for energy optimization in patrol missions is to characterize the surroundings and establish the most effective path to be performed by the USV [14]-[16]. This is especially relevant when different weather and sea conditions affect a patrol zone, or when the patrol area is large. Some different approaches suggest that the first step should consist of the creation of a map related to the USV surroundings and further discretization of that map. In a second step, the use of optimization techniques will allow to cover the search area in the minimum time possible. In [17] and [18], the authors propose different optimization methods for optimal energy management systems, *e.g.*, dynamic programming, model predictive control, constant velocity prediction, stochastic control strategy, Pontryagin's minimum principle and artificial neural networks.

Following this research topic, within the SEMS4USV project [19], the authors propose to develop advanced technologies for environmentally sustainable systems and operations in border surveillance missions. The proposed project's objectives are: a) to demonstrate the feasibility of a fossil-free USV, with electric propulsion (batteries and electric propellers) and photovoltaic panels (PV), to extend the time and range of border surveillance missions; and b) to develop a smart energy management system (SEMS), considering the prediction of weather and sea conditions and also the mission profile, aiming to maximize the total mission range while minimizing risks of mission failure. The output of this project will be a USV prototype, Fig. 1 [20], validated experimentally under real river conditions.

In this specific work, the USV will be modelled, tested in pool and river conditions, and a smart energy management planning will be developed to maximize the USV mission range, Fig. 2. The mission profile is composed of a target path, the predicted weather and sea conditions and the mission constraints. These variables are used by the smart energy management planning to optimize both the USV path and speed to maximize its range. The energy optimization is based on a USV model that was calibrated experimentally and validated in pool and river conditions.

II. Border Surveillance Missions

The smart energy management system developed in this project takes into account the information about the mission

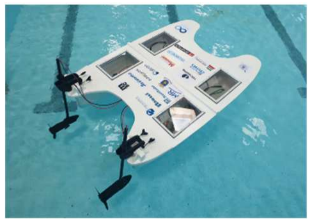


Fig. 1. USV prototype.

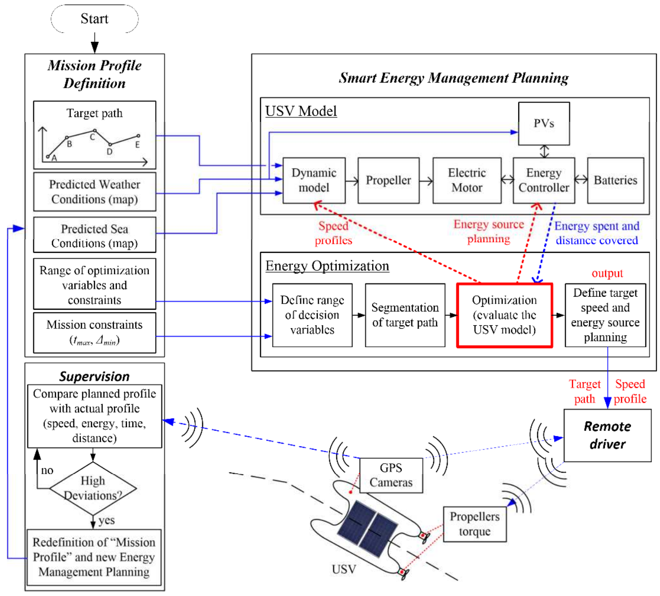


Fig. 2. Optimization strategy of the USV.

profile. For different mission profiles, the relevant objective functions are identified according to the needed variables, *e.g.*, time, speed or position accuracy. To accomplish efficient mission planning, environmental information is also crucial. The geolocation and forecast information should be included in the mission planning and execution. In addition, local sensors are essential to provide updated situational awareness for the mission's success.

The mission profiles are divided into long-endurance reconnaissance and time-sensitive delivery. Each profile is evaluated regarding the performance index of priority and the range achievement. The long-endurance missions are: a) persistent patrol / environmental monitoring; b) track vehicle/object; c) search and identify; d) stationary zone vigilance. The time-sensitive missions are: a) spill response; b) rescue and delivery aid; c) delivery goods. Each mission planning shall consider both weather and sea conditions. Using forecast site information for the predicted weather and sea conditions, and using the USV inboard sensors to obtain updated weather and sea conditions. In this work, a persistent patrol mission is considered as an example.

III. USV Modelling

The mission profiles and weather and sea conditions are the inputs to the USV model subsystems. This section concerns the modelling of the main subsystems of the USV that impact its energy consumption. In Fig. 3 is shown the block diagram of the USV model. The main input variables that will define the response of the USV are the USV speed, $\mathbf{V}$, the water currents speed, $\mathbf{V}_c$, waves height and period, w_h and w_p, wind speed, $\mathbf{V}_w$, irradiation, G, and temperature, T. Note that each speed is a vector quantity with the x- and y-axes components.

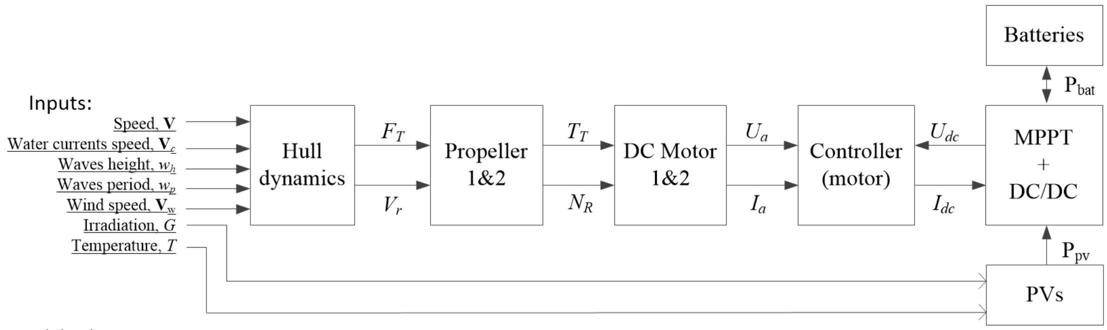


Fig. 3. USV model subsystems.

A. Hull dynamics

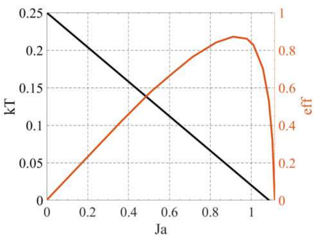
The hull dynamics has the main impact on the energy consumption of the USV. It models the drag forces acting upon the USV hull due to water currents, waves and wind. There are analytics that can be used for modelling; yet, since the USV was in-house designed, an experimental approach is preferred. The total hull resistance, when moving through the water, R_t, is computed based on (1), where ρ is the water density, S is the wetted surface area, V_{rc} is the USV relative speed to the water, $C_F(V_{rc})$ is the total drag coefficient computed experimentally. The latter is estimated based on experimental results, as explained in section IV.B and C.

$$R_t = \frac{1}{2}\rho C_F(V_{rc}) S {V_{rc}}^2 \tag{1}$$

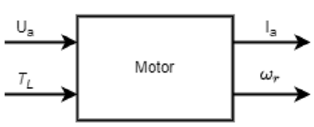
B. Propellers and Electric Motors

The current USV propellers and electric motors were characterized in [21]. Experimental tests were done on the propellers inside a water channel to characterize their torque, force and thrust coefficient k_T. Thrust coefficient and efficiency curves are presented in Fig. 4(a). Each propeller was equipped with a DC permanent magnet motor. From no-load, locked-rotor and load tests the motor's main electric and mechanical characteristics were obtained, Fig. 4(b) and TABLE 1. The motor model is developed for convenience with the voltage, U_a, and torque load, T_L, as input and the motor current, i_a, and speed, ω_r, as output, (2).

$$\begin{aligned} i_a &= \frac{1}{L_a}\int U_a - i_a R_a - k_\phi \omega_r dt \\ \omega_r &= \frac{1}{J}\int k_\phi i_a - T_L - \beta\omega_r - k_h dt \end{aligned} \tag{2}$$



(a)



(b)

Fig. 4. (a) Propeller coefficients; (b) DC motors model.

TABLE 1. DC MOTORS EQUIVALENT CIRCUIT PARAMETERS

R_a [Ω]	k_ϕ [Wb]	k_h [Nm]	β [N·m·s]	L_a [H]	J [kg·m²]
0.176	0.091	0.180	9.9x10^{-4}	8,9x10^{-4}	7.2x10^{-4}

C. Batteries

The batteries were modelled using a typical equivalent electric circuit. The fast transients of the batteries can be neglected in a long-time mission: these were only modelled using their open-circuit voltage, $V_{oc}(SOC)$, as a function of State of Charge (SOC), and their internal resistance R_0. In [22], the lead-acid batteries used in the USV were modelled. Their $Voc(SOC)$ was obtained experimentally and fit with $V_{oc}(SOC) = 12.47 \cdot SOC^{0.0995}$, as illustrated in Fig. 5, and their internal resistance was measured, R_0=10 mΩ.

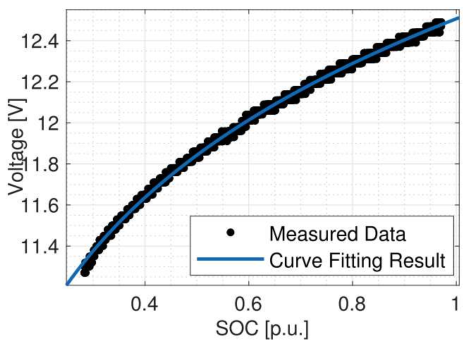
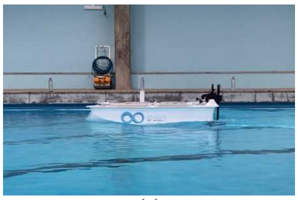


Fig. 5. Batteries $V_{OC}(SOC)$.

IV. EXPERIMENTAL TESTS

Experimental validation was performed in an indoor swimming pool and in an enclosed harbour at river Tejo, as illustrated in Fig. 6. The pool tests allowed for underlying the USV behaviour without wind, water current and waves, while the enclosed harbour tests allowed a more realistic context. With these, the hull and propeller models were calibrated to be further used in the optimization scenario.



(a)

(b)

Fig. 6. Photos of the experimental environments: (a) pool and (b) enclosed harbour.

A. Sensors

The USV is equipped with a microprocessor for data acquisition and the required communications for remote driving. During the experimental tests, voltage and current of the batteries and motors were registered as well as the location, orientation, and speed of the USV. The last signals were obtained using a GPS-RTK and an IMU.

B. Indoor swimming Pool tests

Data were acquired from two tests: first, for a set of constant USV speeds, where a constant throttle, between 20% and 100%, was applied to the motors. This allowed the calibration of the drag and propeller coefficients at different speeds; the second test corresponded to a set of deceleration tests, where the throttle of the USV is interrupted, and the transient behaviour of its speed is recorded. With this, it was possible to estimate the drag coefficients of the hull without dependence on the propeller behaviour.

Both experimental and simulation output power results for batteries, motors and propellers are shown in Fig. 7. To obtain the simulation results, the drag coefficient calibration was based on experimental measurement. As expected, the required power is proportional to the cube of the speed. The model results match the experimental ones in all three cases. Please note that the batteries supply two electric motors.

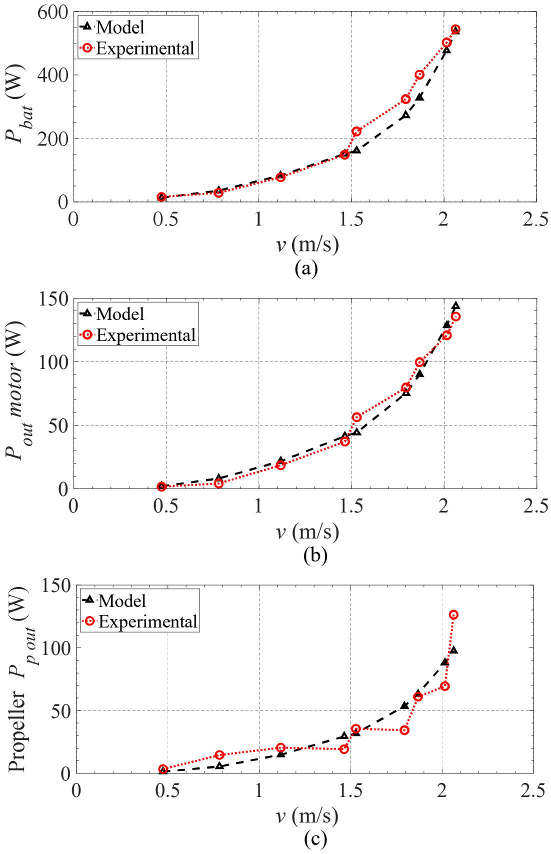


Fig. 7. Experimental and simulation results: (a) battery output power; (b) electric motors output power; (c) propellers output power.

C. Enclosed harbour tests

The enclosed harbour tests were performed at the river Tejo, Lisbon, to evaluate the USV resilience and estimate the increase of drag due to the presence of waves. No significant water currents and wind were verified during the experiments. A set of experimental tests were performed at four constant throttle values: 50%, 60%, 70% and 100%. After USV data processing, the evolution of the speed and power consumption of each motor and batteries was obtained. With this, the total drag coefficient, now due to the presence of waves, was calibrated, presenting now an increase of the total drag coefficient, Fig. 8. The waves amplitude and period were about 0.3m and 5s to 6s.

The USV model is then used to estimate the required power for the same experimental speed. Fig. 9(a) and (b) show the experimental and simulation results for a throttle of 50% and 100%, respectively. The left figures show the measured boat speed and angle, while the right figures show the predicted power, “Model”, and the experimental one, “Exp.”. The x-axis corresponds to the relative time related to the beginning of the experiments. The oscillatory behaviour is related to the waves' presence. When crossing a wave, the GPS speed first decreases and then increases. This creates an illusion of increase and decrease of power estimated by the model. However, the model results are oscillating around the experimental ones. In addition, Fig. 10 shows the time evolution of the energy consumption for the four scenarios. From the energy point of view, the achieved results clearly indicate that the developed USV simulation model is capable of obtaining accurate energy consumption for all different throttle values applied to the motors. These were obtained with the same total drag coefficient, Fig. 8. Therefore, one can have confidence in the developed USV simulation model to perform the optimization scenarios in section V.

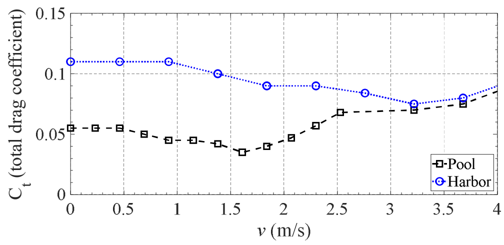


Fig. 8. Total drag coefficient obtained experimentally.

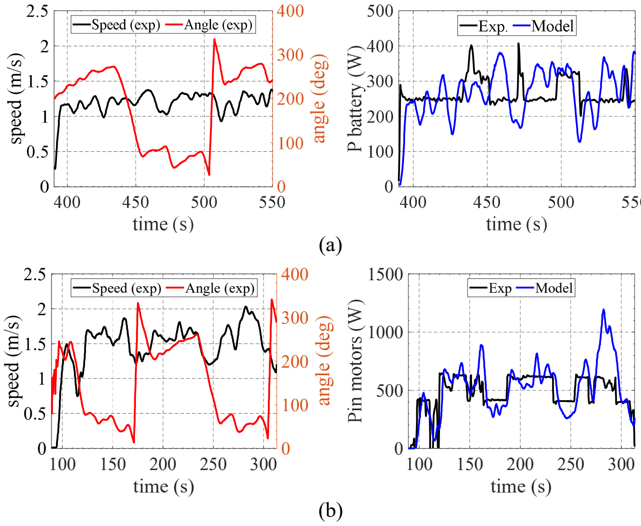


Fig. 9. Experimental and simulation results for the instantaneous battery power at (a) 50% and (b) 100% of throttle.

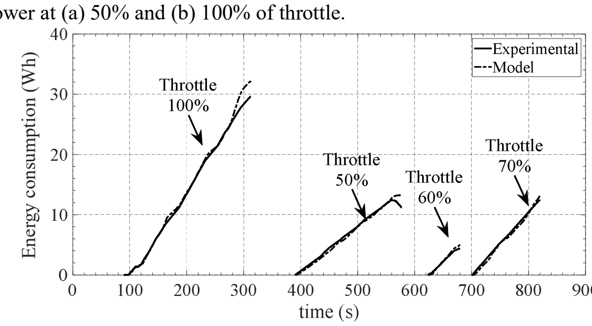


Fig. 10. Experimental and simulation results for the energy consumption at the different throttle levels.

V. Energy Management System / Extended Range Optimization

For a mission profile, there is a high number and types of variables that can be optimized. In this work, the path and speed of the USV are optimized to cover a mission profile defined by four target positions (A, B, C and D), Fig. 11. The USV should start and end its mission in point A, near Escola Superior Náutica Infante D. Henrique, Paço de Arcos, Portugal. Thus, the optimization was divided in two layers: (i) optimization of the path assuming a constant USV speed (1m/s), and (ii) a posterior optimization of the USV's speed after defining the optimized path. To evaluate this scenario, the water currents map was obtained for the river Tejo from the Portuguese Institute for Sea and Atmosphere (IPMA), Fig. 11, [23], and assumed to remain unchanged over time.

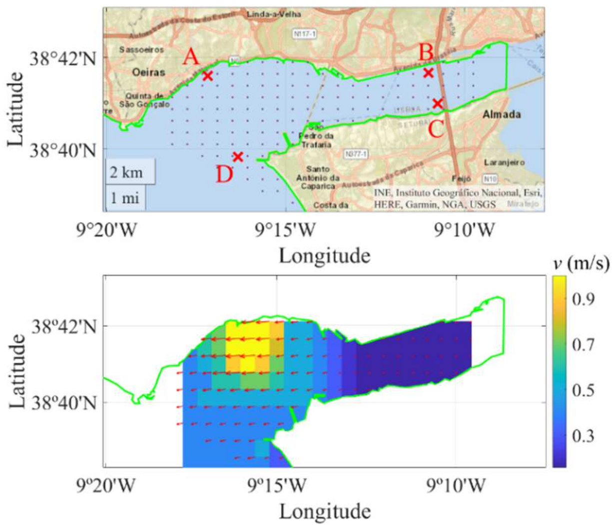


Fig. 11. Target points (A, B, C and D) and water currents' map.

A. Path optimization

The path optimization was performed using a grid of points distributed along the river, as shown in Fig. 11. Then, a bidirectional graph is constructed with all the possible solutions between points, where the edges between two points are represented by weights. After weight definition, a shortest path algorithm is applied to optimize the path.

Fig. 12 presents the results for the two path optimization scenarios. In Fig. 12(a) the optimization is carried out using the distance between two points as weights, this way finding the shortest path between points. Fig. 12(b) presents the results for the case where the weights represent the energy required to move between two points. In this case, weights are bidirectional due to the water's current direction.

These results are summarized in TABLE 2. When considering the minimum distance between points, Fig. 12(a), the USV is capable of finishing the mission in 6.69 h and requiring 2750 Wh. With the energy optimization, Fig. 12(b), the USV takes advantage of the low water currents near the south part of the river to reduce its energy consumption by crossing the river from D to A, in a zone where these currents are lower. Then, it uses the highly favourable currents to return to point A. This led to a reduction of about 10% of the energy consumption, at a cost of a higher mission time, 8.97h.

TABLE 2. ENERGY CONSUMPTION FOR DIFFERENT OPTIMIZATION SCENARIOS

Optimization scenario	*Mission time*	*Energy required*
(a) min(Distance)	6.69 h	2750 Wh
(b) min(Energy) (v = 1m/s)	8.97 h	2495 Wh (-10%)

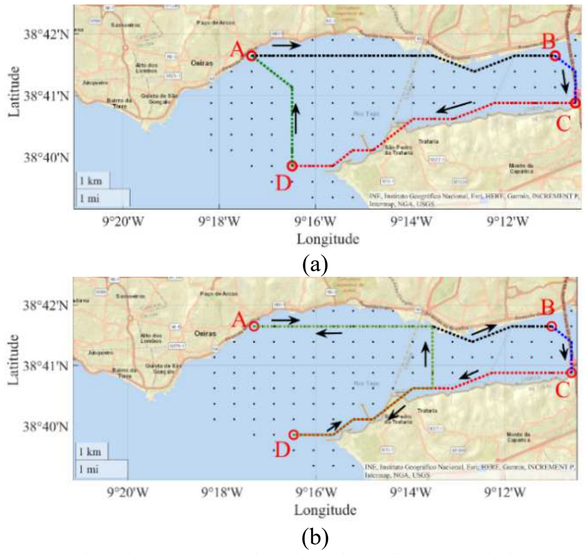


Fig. 12. Path optimization as a function of: (a) distance and, (b) energy.

B. Speed optimization

After the selection of the optimized path, a second optimization is carried out by optimizing the speed profile, along this path, to minimize the energy consumption. A trivial solution is to achieve a zero-speed. To avoid this, a time limit for the mission is defined, T_{max}. The speed optimization is obtained by assuming a constant speed at each segment of the path, between two points of the grids defined in Fig. 12(b). This optimization is done in Matlab [24] using the *fmincon* tool and the developed USV model. The results are shown in TABLE 3 for different values of T_{max}, presenting energy saving between 12.7 to 35.9%, when compared to the mission profile in Fig. 12(a).

TABLE 3. SPEED OPTIMIZATION

Optimized speed profile	*Energy required*
T_{max} = 12h	1763 Wh (-35.9%)
T_{max} = 11h	1780 Wh (-35.3%)
T_{max} = 10h	2021 Wh (-26.5%)
T_{max} = 9h	2188 Wh (-20.4%)
T_{max} = 8h	2402 Wh (-12.7%)

Fig. 13 shows the optimized speed profile for t_{max} =10 h. In addition, an illustration of the water currents direction, referred to the USV direction, is shown in blue arrows. As expected, the USV presents lower speeds when the current direction is opposite to it, and higher speeds when these are favourable. The optimization strategy allows extending the USV mission profiles, at the cost of a higher mission time.

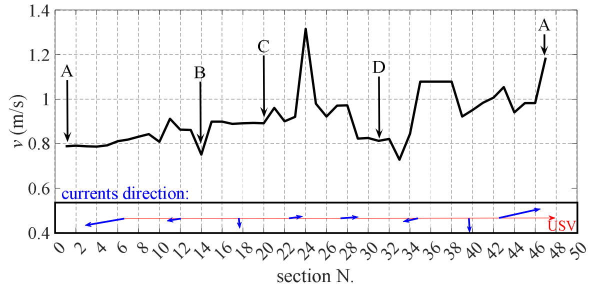


Fig. 13. Optimized speed profile (black lines) and illustration of currents direction (blue vectors).

Following this work, experimental tests will be carried out to validate the results. Due to the non-uniform weather conditions, a supervision loop should be implemented. In addition, new lithium batteries and PV will be installed in the USV to help extend its range. These activities are planned to be carried out during 2024, within the SEMS4USV project, financed by Frontex.

VI. Conclusions

In this work, a methodology for achieving extended-range USV was developed for marine border surveillance missions. An energy management strategy was developed based in two layers: (i) an optimization of the path assuming a constant USV speed, and (ii) a posterior optimization of the USV's speed after defining the optimized path. The optimization is carried out based on the expected behaviour of the USV and the predicted weather and sea conditions. The path optimization was carried out using a similar approach to the meshing of finite element models, where the domain is discretized in triangular elements.

The USV model was developed and verified under real conditions, in an indoor pool and an outdoor enclosed harbour. Experimental tests have shown the good accuracy of the model, even during real environmental conditions. With this model, an optimization scenario was carried out, for real weather conditions in the river Tejo. Results show that, while only path optimization allows for an energy saving of about 10%, when including speed optimization this saving increase from 12.7% to 35.9%. Of course, a higher energy saving is done at a cost of a higher mission time.

The importance of energy management strategies on these types of USV is evident. This is even more critical when including other sources of energy, such as photovoltaic panels, which will be included in the future of this project.

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