Mission based Optimum System Selector for Bio-inspired Unmanned Untethered Underwater Vehicles

Maryam Haroutunian
School of Marine Science and Technology,
Armstrong Bld.
Newcastle University, NE1 7RU
Newcastle upon Tyne - UK
maryam.haroutunian@ncl.ac.uk

Dr. Alan J Murphy
School of Marine Science and Technology,
Armstrong Bld.
Newcastle University, NE1 7RU
Newcastle upon Tyne - UK
a.j.murphy@ncl.ac.uk

***Abstract*—This paper is a part of the Nature in Engineering for Monitoring the Oceans (NEMO) project, investigating bio-inspiration to improve the performance of Unmanned Untethered Underwater Vehicles (UUUVs). Since biological systems (i.e. marine animals) are natives to the oceans, successfully surviving through time, they have been the source of this approach.**

NEMO's earlier investigations highlighted biological capabilities desirable for UUUV operations, including speed, speed range and manoeuvrability. These are significantly superior compared to current engineered systems. However, not all desirable characteristics are evident in the same species. Considering the mismatch between the "missions" of biological and engineered systems, no single specific biological system is able to fulfil all the desired UUUV mission requirements. Therefore, means are required to obtain the myriad of information from the biological world and adjust them to engineering needs.

This paper describes the algorithm of an Optimum System Selector (OSS) demonstrating its methodology and explaining modules such as estimating the drag of biological systems and indication of their propulsive efficiency. The OSS is implemented to output the appropriate combination for a bio-inspired UUUV design, based on its mission.

The OSS comprises missions as inputs, the decision maker, and the outputs. Mission profiles also account for capabilities unique to biological systems such as high manoeuvrability. The decision maker takes into account three main modules; speed and propulsion, manoeuvrability and upright stability. The fitness-for-purpose function of the selector consists of the energetic cost of the proposed combination, as well as the trade-off between the three modules due to the multi-functionality of the biological systems. The output consists of body and control surfaces design, propulsion and manoeuvring systems.

Through this method, OSS is an excellent guide to transform complex biological data for the future design and development of UUUVs.

Keywords-Bio-inspiration; AUV; Mission profile; Optimisation

Nomenclature and Abbreviations

AR……….	Aspect Ratio
AUV……..	Autonomous Underwater Vehicle
A_{WS}………	Wetted Surface Area $[m^2]$
BH……….	Body Height $[m]$
BMS……..	Biological Marine System
BUUUV….	Bio-inspired Unmanned Untethered Underwater Vehicle
BW……….	Body Width $[m]$
C_D…………	Drag Coefficient
C_f…………	Friction Coefficient
CFD……...	Computational Fluid Dynamics
COT………	Cost of Transport $[^J/_{kg.m}]$
D_{BB}………….	Bare Body Drag $[N]$
D_e………..	Equivalent Diameter $[m]$
GA……….	Genetic Algorithm
G/B………	Gearbox
EL………..	Elliptical Length $[m]$
FF………..	Fitness Function
M………...	Mass $[kg]$
MOGA…...	Multiple Objective Genetic Algorithm
NN………	Neural Network
OSS……...	Optimum System Selector
P_B………..	Brake Power $[W]$
P_E………..	Effective Power $[W]$
P_H………..	Hotel Load $[W]$
P_M………..	Muscle Power $[W]$
Re………...	Reynolds Number
R_{Yaw}……..	Yaw Radius$[m]$
TL………..	Total Length $[m]$
U_a………..	Advance Speed $[^m/_s]$
U_{Max}……...	Maximum Speed $[^m/_s]$
U_{opt}……….	Optimum Speed $[^m/_s]$
U_{Turn}…….	Turning Speed $[^\circ/_s]$
η_C………...	Conversion Efficiency
$\propto$………...	Added Drag Coefficient
η_B……….	Behind Efficiency
η_D………..	Delivered Efficiency
η_H……….	Hull Efficiency
η_{Ped}……...	Peduncle Efficiency
η_s………...	Shaft Efficiency
η_{Total}……..	Total Efficiency

I. INTRODUCTION

Mankind has a long history in ocean exploration and exploitation. The introduction of underwater vehicles in the past few decades - especially Autonomous Underwater Vehicles (AUVs) - facilitated these explorations and has made many scientific, military and industrial operations possible in previously unreachable waters. Nowadays expectations have increased and underwater vehicle users and clients are demanding faster, more manoeuvrable vehicles that are able to reach the deepest depths of the oceans with greater endurance at lower cost.

There are various approaches to investigate possible means of improving the performance of underwater vehicles. However, the longest surviving types of underwater systems are marine animals, which will be referred to as Biological Marine Systems (BMS) in this paper. Native to the oceans, they evolve and survive the harshest conditions underwater. Nature in Engineering for Monitoring the Oceans (NEMO) project is investigating novel technologies and generating bio-inspired design techniques & implementation methods based on these BMSs to improve current underwater vehicles performance. This is achieved by fulfilling two main objectives:

- Investigating bio-inspiration, and
- Application of bio-inspiration

The main focus is on increasing the speed, manoeuvrability and depth capability of unmanned underwater vehicles while reducing weight and energy consumption.

A. Investigating bio-inspiration: The contrast between BMS and AUV capabilities

As part of this research, studies were carried out on means to compare BMSs with engineered vehicles, to investigate whether bio-inspiration is a promising approach. However, originally, animals are studied by scientists whereas engineers study vehicles; in bio-inspiration, the two are combined. This is where the challenge stands; the key is to understand the mechanism of both systems and unify the definitions and measurements, in order to conduct a valid comparison. One significant challenge in this research was investigating the energetics comparison of animals and vehicles. For vehicles, energetic cost is calculated from knowledge of the energy stored in the batteries and its subsequent consumption, which is well defined and specified. However for BMSs with limited available data, the calculation is rather complicated. Therefore, a formulation of the physical factors associated with biological & engineered systems energy usage was presented for energetic cost comparison [1]. Since BMSs from many and various biological classes of species are investigated in this research, there were a number of principal challenges to be overcome. These challenges were unifying body measurements, comparing speed and depth capabilities which, due to size and taxonomy differences for BMSs, proved to be complicated also comparing scientific and engineered definitions, calculations and measurement of drag and power which are explained in Section IV.

B. A general challenge in bio-inspiration

Gathered data for BMSs is based on experiments carried out on each animal by external sources or the authors' observations and measurements from videos and photos taken from the animals. Unlike engineered vehicles, which have a well-defined capability, the performance of a specific species is a variable depending on the physical and environmental parameters of the samples, e.g. animal body size. Consequently for a given species every characteristic is specified over a range and not given as a specific value and therefore, in many cases values are an average of multiple experiments.

By overcoming the abovementioned challenges, a database of BMSs has been gathered and the parameters are shown Table I, Table II provides some explanatory notes to Table I.

TABLE I. KNOWN PARAMETERS FOR EACH BMS

Known Characteristics	***Parameters***	***Unit or description***
Body design	Body Form	General form of the body known for BMSs; e.g. Fusiform
	Cross Section Type	General shape of the body cross sectional area
	Average Mass	$[kg]$
	Maximum body height (BH)	Greatest height of the BMS along the body
	Maximum body width (BW)	Greatest width of the BMS along the body
	Elliptical Length	Length of the equivalent ellipsoid of the BMS body
	Peduncle Length	Length of the area connecting the elliptical BMS body to the rear fin
	Total Length (TL)	Overall length from the snout to the end of the rear fin
	"a" & "b" factors (*)	$\mathrm{Mass} = \mathrm{a}(\mathrm{Length})^{\mathrm{b}}$
Taxonomy (**)	Full name	Common Name & Binominal Name
	Family, Order, Class	-
Swimming	Swimming Mode	Various body & rear fin or paried fin swimming modes; e.g. Thunniform
	Optimum Speed	$Uopt\ [\frac{m}{s}]$
	Maximum Speed	$Umax\ [\frac{m}{s}]$

Known Characteristics	*Parameters*	*Unit or description*
Manoeuvring (***)	Turning (yaw) radius	R_{Yaw}
	Turning Speed	U_{Turn}
Control surfaces: Rear fin Side fins Top fin(s) Bottom fin (s) Side stabilising fins	Numbers or pairs	-
	Chord	$[m]$
	Span	$[m]$
	Area	$[m^2]$
	Aspect ratio	$AR = \frac{Span \times Chord}{Area}$
	Position from the snout	$[m]$
Diving	Maximum Depth	$[m]$
	Depth Range	$[m]$
Energetics	Cost of transport	$\left[\frac{J}{kg.m}\right]$
	Endurance (****)	$[km]$ or $[h]$
	Fat tissue storage	Can aid to estimate the energy reserve

TABLE II. EXPLANATORY NOTES TO TABLE I

Note	Description
*	Empirically obtained for each species based on measurements
**	All data is not available for every species, therefore taxonomy helps to relate data collected to similar animals. In this research taxonomy data are coded numerically for simplicity.
***	Turning speed is inversely proportional to the speed of the animal, therefore maximum turning speed and lowest yaw radius is usually achieved by unpowered turns. An example of conducted experiments on various marine mammals illustrates this fact [2].
****	Usually measured during long migration.
Note that all parameters are not known for the more than 200 animals in the database, therefore only the ones with available data are used when deriving calculations.	

A similar database was gathered for AUVs and the body design, speed and depth capabilities, manoeuvrability and energetics of various classes of marine species were compared with current AUVs. As a result of these comparisons, capabilities of BMSs with significant superiority over AUVs were identified; these characteristics, which include speed, speed range and manoeuvrability, were highlighted across a broad range of species [3]. The next step is to find a means to apply them to AUV design.

This paper explains the challenges involved in the application of bio-inspiration to AUV engineering. The rationale behind an Optimum System Selector (OSS) is explained and its algorithm described; this includes demonstrating its methodology and explaining its modules. The purpose of the described selector is to output the appropriate parameters required to aid the design of a bio-inspired UUUV, based on the vehicle's mission.

II. Application of Bio-Inspiration

In order to apply the findings of this earlier research to Bio-inspired Unmanned Untethered Underwater Vehicle (BUUUV) design, the design procedure of BMSs must be understood and as for any other system the "purpose" or mission plays an important role. For an AUV user, "best" option is not always the vehicle that does the maximum in any single performance characteristic, but the one that fulfils the requirements of the user across a combination of speed capability and range, manoeuvrability, depth capability, endurance, energetic cost and weight. Therefore, the bio-inspired technology should attempt to find the optimum option that nature has to offer for a corresponding AUV mission.

While missions are not formally defined for BMSs, they are in fact a consequence of an evolutionary process, subject to highly varied evolutionary pressures. Consequently, some are highly manoeuvrable, e.g. black ghost, some exhibit high speed, e.g. sailfish, and some have high acceleration characteristics, such as the barracuda. Although animals are highly capable, their main aim is to survive and reproduce and the data gathered from them can always be biased by other factors such as the physical and mental condition of the BMS at the time of data collection.

However, AUV missions are varied and different to ones of an animal; in addition, the superiority of BMSs is spread over a wide range of marine animals and they use various methods and systems which are interrelated with their other functions; i.e. no specific BMS is able to fulfil all desired mission profiles of an AUV. In addition, unlike engineered vehicles, BMSs sub-systems are multi-functional, which makes it impossible to investigate them as stand-alone systems.

For an engineering perspective, therefore, it is not a complete BMS that is sought, rather particular sub-systems of BMSs; which of course is unnatural and defines the challenge that this research attempts to overcome.

In addressing this challenge a simple approach could be to search the database of BMSs and find a system which fulfils all engineering requirements.

As part of the research this simple approach was examined. Consider the algorithm in Figure 1 as the system selector for a BUUUV; for each mission scenario, mission requirements are input to the selector and the capabilities of BMSs is gathered in a large database as shown in Table I. These capabilities are then sorted based on fulfilling each mission requirement and the most capable BMSs are extracted; however:

1. Many of the BMSs will be excluded from the sorting system due to failing even a single mission requirement.

2. Since overall ranking is considered based on how much of the mission is fulfilled by the system, in many mission scenarios, systems with close ranks would vary in capabilities.

3. This system only selects the existing best option but cannot consider “optimisation”.

This method therefore provided little useful insight to assist the design of a BUUUV. Therefore, means are required to output the appropriate combination for a bio-inspired design based on a particular mission profile. This is called the Optimum System Selector (OSS). OSS attempts to solve the abovementioned challenge of associating biological capability with engineering requirement.

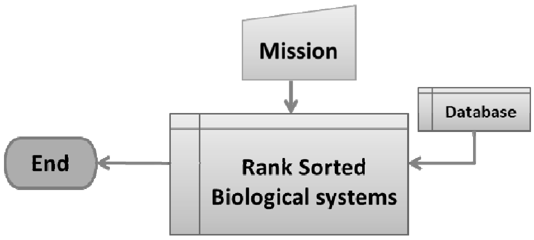

Figure 1 Simple algorithm to find best biological option

III. The Concept of an Optimum System Selector (OSS)

Figure 2 shows the algorithm modified for the OSS. In this algorithm, for every input, the BMS database is compared against the desired mission specifications; similar to the initial algorithm in Figure 1. If the requirements are met by any BMS, then the corresponding system is the output; however, for many mission profiles that is not the case and instead subsets of BMSs which meet at least one of the mission specifications are selected.

To optimise this initial subset, a decision maker is used. In nature, this is done through breeding and evolution; therefore being inspired by nature, the decision maker is designed to accelerate evolution by using a genetic algorithm (GA).

GAs take an initial potential group as parents and breed a new generation. The off-spring are then evaluated and ones with superior performance are used as new parents for the next generation. The cycle carries on until the desired performance characteristics are fulfilled or until the continuation of the GA will not improve the results any further. In this research, due to numerous influencing factors, there are multiple equations to be solved simultaneously; therefore a Multiple Objective Genetic Algorithm (MOGA) is implemented within the OSS.

The desired mission specifications are input as the GA constrains and the BMS subset from the database of existing species is input as the first generation.

The initial selection of the BMSs also ensures that animals that are by no means fit to fulfil any of the mission requirements are eliminated at an early stage to facilitate the task of the decision maker.

The decision maker then generates off-springs of the initial BMSs as a new generation, calculates their performance, and based on the mission input targets, decides which ones survive and the process continues until the desired results are achieved.

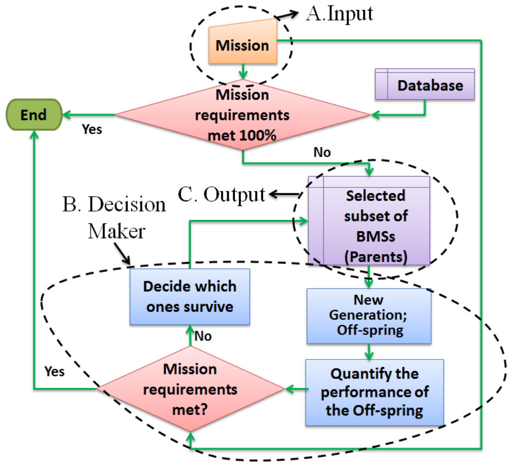

Figure 2 The algorithm modified for the OSS

The sub-algorithms of the OSS as indicated by dashed lines in Figure 2 are:

A. Missions

B. The Decision maker, and

C. Output;

These are explained next.

A. Missions

Desired AUV mission specifications are specified by the user. A manoeuvrability factor is included which may be achieved by using biological techniques as explained in Section IV. These mission specifications are shown in Table III.

The term “importance weight factor” for each mission specification is used to weight it against other inputs when evaluating the overall performance of systems and making the decision on the optimum off-spring. These are used to derive the weight factor, w_i, in (1).

TABLE III. Mission Inputs

Input	***Sub-input(s)***	***Unit(s)***
Size	Body length (EL)	$[m]$
	Mass (M)	$[kg]$
Speed	Optimum speed (U_{opt})	$[m/s]$
	Maximum speed (U_{Max})	$[m/s]$
Depth	Maximum Depth	$[m]$
Energetics and	Energetic cost of Transport (COT)	$[J/kg.m]$
	Endurance	$[km$ or $h]$
Manoeuvrability	Turning Radius (R_{Yaw})	$[m]$
	Turning speed (U_{Turn})	$[°/s]$
Importance weight factors		

B. The decision maker

The decision maker takes the selected sub-set of BMSs and produces off-spring with optimised performance. Optimising the performance of the off-spring consists of minimising the energetic cost of the off-spring, as well as the trade-off between speed and propulsion, manoeuvrability, and stability due to the multi-functionality of the BMSs. As mentioned previously, these are known for the parents, but they must be calculated for the subsequent generations which are defined by the genetic algorithm. Since the decision maker makes the selection based on the estimated performance of the off-springs, it is crucial to minimise the calculation or estimation error.

However, due to the complexity of BMSs and data being sparse, for the purpose of this research a variety of methods are used. The parameters are divided into two groups as follows:

- Calculable Parameters which include body drag, energetic cost, efficiency, stability and body flexibility. These parameters are calculable by deriving formulae based on physical arguments or trends discovered by analysing the performance of BMSs from the data on existing species.

- Complex parameters which include manoeuvrability and defining propulsion mode. These parameters are a consequence of the multi-functionality of the systems; therefore it is necessary to understand the impact of each parameter to the overall performance of the system. However, some parameters are either dependent on multiple variables, various systems are involved to perform the task (multi-functionality) or the relations are non-linear. These parameters are difficult to estimate with a one-fits-all method. To solve this challenge, Neural Networks (NN) are being investigated to estimate the relation of the variables and predict the desirable parameters.

The details of the calculations and estimations are explained in Section IV. All the formulae defined and used in this research are tested against the first generation of BMSs to ensure their validity.

C. Output

The final off-spring generation produced by the decision maker is sorted in order by using linear programming which uses a Fitness Function (FF) [4] in the form of:

$$a_1 w_1 + a_2 w_2 + \cdots + a_n w_n = FF \qquad (1)$$

Where w_1 is the importance weight factor of each parameter and $\mathrm{a_i}$ is calculated as:

$$a_i = \frac{Value_{Obtained} - Value_{Desired}}{Value_{Desired}} \qquad (2)$$

e.g. for speed a_i is calculated as:

$$a_i = \frac{\mathrm{U}_{off-spring} - \mathrm{U_{Desired}}}{\mathrm{U_{Desired}}} \qquad (3)$$

The sorted collection will output specifications for body geometry, control surfaces & propulsion method and an estimate of speed and energetic cost. Outputs are shown in TABLE IV; the 2nd column is output directly generated by the OSS and the 3rd column can be then derived from these output parameters.

TABLE IV. OUTPTS OF THE OSS

Categories	***Outputs from the OSS***	***Later stage output***
Size	EL, BH, BW $[m]$	Propulsion mode
	$Mass$ $[kg]$	
Speed	U [m/s]	
Maneouvrability	Flexibility No.	
	Turning Radius [m]	-
Body control surfaces (Important for stability, diving and surfacing, propulsion & manoeuvre)	Area of each control surface	Chord, span and length of the control surface
Energetics	Transport cost	-
Overall efficiency	Overall efficieny	-

IV. CALCULATION OF PARAMETERS

This section describes the details of calculations required to quantify the specifications of the off-spring generated by the decision maker. These are as follows:

A. Calculation of the energetic cost

B. Estimate of stability

C. Manoeuvrability assessment

D. Swimming mode selection

Each method will be explained next.

A. Calculation of the energetic cost

As explained by Phillips et al [1], the energetic cost of transport for biological and engineered vehicles is calculated as:

$$COT = \frac{P_H}{MU} + \frac{D_{BB}}{\xi M} \qquad (4)$$

where M is the mass,

U is the speed,

D_{BB} is the bare body drag,

P_H is the hotel load, and

$$\xi = \frac{\eta_{Total}}{\propto} \qquad (5)$$

where η_{Total} is the total efficiency and

$\propto$ is a coefficient which accounts for additional components of drag caused by appendages such as control surfaces, body roughness and gills of BMSs.

It is evident from literature that the definition of total efficiency is inconsistent when applied to BMSs and in some cases unclear; therefore to elaborate further on the definition of η_{Total}, this is given special treatment in Section V.

To solve (4), U and M are known and P_H is estimated using an empirical formula in the form of $P_H = x(Mass^y)$ obtained from multiple sources as discussed by Phillips et al [1]. Drag and ξ must be calculated.

Although BMSs have a wide speed range, two specific speeds have significant importance when investigating the performance of systems; optimum speed, U_{opt}, and maximum speed, U_{max}, and COT is calculated for these two speeds. The optimum speed of a BMS is the speed at which the energetic cost is minimum and is marginally lower than cruising speed. In engineering terms this is referred to as the economic speed of the vehicles.

- Calculation of drag

In engineering bare body drag, D_{BB}, is calculated as:

$$D_{BB} = 0.5\rho C_D A_{WS} U^2 \qquad (6)$$

Where:

C_D is the drag coefficient and A_{WS} is the wetted surface area and both must be estimated to calculate drag. As part of this research it has been concluded that, for the purposes of providing sufficiently accurate drag estimates, BMSs body forms can be idealised using a tri-axial ellipsoid [3], as illustrated in Figure 3. From this wetted surface area and drag coefficient can be estimated.

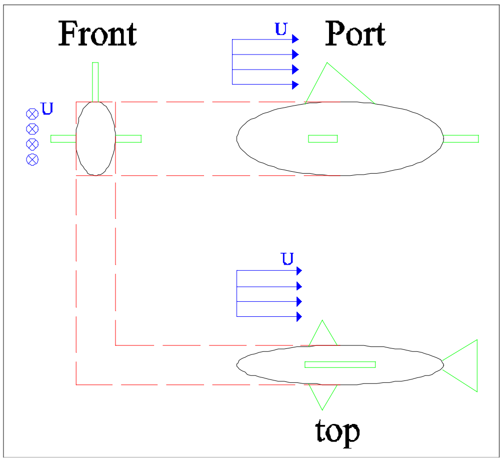

Figure 3 Three-view schematic design of a Marine Mammal

Although no analytical formula is defined to calculate the surface area of a tri-axial ellipsoid, a number of approximation formulae exist and the one used in this research is the Knud-Thomsen formula [5] which estimates A_{WS} with less than 1% error.

The Knud-Thomsen formula for a BMS is:

$$A_{WS} = \pi\left(\frac{\left(EL(BW+BH)\right)^{1.6075} + (BW \times BH)^{1.6075}}{3}\right)^{\frac{1}{1.6075}} \qquad (7)$$

Where BW and BH are maximum body width and height and EL is elliptical length. EL is used as the length of the main body, instead of total length, TL, or standard length, SL. This is because TL includes the rear fin and SL includes the length of the peduncle.

The drag coefficient is in the form of:

$$C_D = C_f(1+k) \qquad (8)$$

Where C_f is the friction coefficient and $(1+k)$ is the form factor.

To estimate C_f for vehicles the Prandtl-von Karman formula is used, that is:

$$C_f = 0.072Re^{-0.2} \qquad (9)$$

Where Re is the Reynolds number.

The values obtained by using this formula were compared to examples tested in CFD software and the results show less than 4% error.

Hoerner, 1965 [6] estimates the $(1+k)$ value, for Spheroids:

$$1+k = \left(1 + 1.5\left(\frac{BD}{EL}\right)^{\frac{3}{2}} + 7\left(\frac{BD}{EL}\right)^{3}\right) \qquad (10)$$

where BD and EL are the diameter and length of the spheroid respectively. The equivalent diameter for a tri-axial ellipsoid can be calculated from (11).

$$D_e = \sqrt{BH \times BW} \qquad (11)$$

By substituting D_e in (11), for BD in (10), the results obtained using (10) closely correspond with results from CFD, therefore results from Hoerner, 1965 formula are valid estimates of the form factor for a tri-axial ellipsoid.

- Estimate of ξ_{Uopt}

As mentioned earlier, COT must be calculated for optimum and maximum speed (U_{opt}, and U_{max}), therefore ξ must be estimated for these two speeds.

To estimate ξ at optimum speed, ξ_{Uopt}, COT is differentiated with respect to U:

$$\frac{dCOT}{dU} = \frac{1}{M}\left(\frac{-P_H}{U^2} + \frac{1.8 \times bU^{0.8}}{\xi}\right) \qquad (12)$$

The optimum COT is found at the speed, U_{opt}, when $\frac{dCOT}{dU} = 0$.

Therefore,

$$\xi_{Uopt} = \frac{1.8bU_{opt}^{2.8}}{P_H} \quad (13)$$

where b is:

$$b = 0.5\rho(1+k) \times 0.072\left(\frac{10^6 EL}{1.19}\right)^{-0.2} \times A_{WS} \quad (14)$$

- Estimate of ξ_{Umax}

For vehicles motor brake power is related to efficiency as follows:

$$P_B = U \times D_{BB} \times \frac{\propto}{\eta_{Total}} \quad (15)$$

Where P_B is the motor brake power; therefore:

$$\xi_{Umax} = \frac{Umax \times D_{BB\,Umax}}{P_{B\,Umax}} \quad (16)$$

To estimate ξ at maximum speed, ξ_{Umax}, the propulsion power at maximum speed must be quantified. For BMSs muscle power corresponds to the motor power and the power output of both red and white muscle fibres have been obtained from reference [7].

ξ_{Umax} is estimated by substituting the maximum available muscle powers in (16).

At this point all terms to calculate COT are known and (4) can be solved.

B. Estimate of stability

For the purpose of this research three main stabilities are considered for underwater vehicles as follows:

- **Yaw stability** is provided by the top and bottom fins and increases with increasing area of those fins. This improves manoeuvrability but increases appendage drag and hence ∝.
- **Pitch stability** is provided by a relatively flat body and is therefore increased with the value of $\frac{BW}{BH}$. This stability is useful when diving and surfacing but reduces the yaw stability.
- **Roll stability** is provided by side fins and increases with increasing area of those fins. This improves upright stability but increases appendage drag and hence ∝.

Based on the importance of each specification the OSS will select one of a few possible options for different missions; e.g. if pitch stability is more important than yaw stability, the off-spring with higher $\frac{BW}{BH}$ will be ranked higher.

C. Manoeuvrability assessment

Many parameters are involved in the manoeuvrability of a vehicle. One term which is specific to BMSs is flexibility. Although it is difficult to quantify flexibility, it is required to have an understanding of the effects of it on manoeuvrability. Therefore, investigations are being carried out to quantify the flexibility of a BMS by comparing their ability to turn with one of a solid body.

It is possible to estimate a flexibility number, however, predicting the manoeuvrability of a system is difficult because it depends on the area of the fins, the propulsion mode, the stability, the flexibility of the system, etc. For this purpose a neural network is being investigated to estimate the manoeuvrability of a system by predicting the turning radius based on known parameters.

D. Swimming mode selection

The resistance and propulsion characteristics are calculated numerically as discussed in this paper, and specifications of BUUUVs are selected by the OSS. From these calculations the swimming mode type can be determined by estimating what mode would be likely to achieve the outcomes of the OSS, based on observations from existing BMSs. This is achieved by using a categorising neural network. This particular network is trained by the available data for the BMSs and the existing data are categorised into various biological propulsion modes. The data of off-spring are then input into the trained neural network. The result is the swimming mode most appropriate for the off-spring.

V. DEFINITION OF EFFICIENCY

This section provides a detailed explanation of propulsion energy usage for BMSs and AUVs. This is to resolve the issue of inconsistent and unclear definitions and use of propulsive efficiency when applied to BMSs, as noted in Section II. This leads to a clear and consistent definition of propulsive efficiency.

Batteries are the energy store of AUVs which corresponds to food and fat for marine animals. As energy flows from the battery to eventually move the vehicle forward, some energy losses occur from the system. Figure 4.a illustrates the flow of power and efficiency relationships in an AUV propulsion system and Figure 4.b. is the equivalent concept presented for a BMS. Table V provides explanatory notes to Figure 4.

From the descriptions in Table V, it is realised that the total efficiency for BMSs, η_{Total}, is:

$$\eta_{Total} = \frac{DU_{BMS}}{\mathrm{P_M}} \quad (17)$$

Where D is the drag,
U_{BMS} is the BMS speed and
P_M is the muscle power.

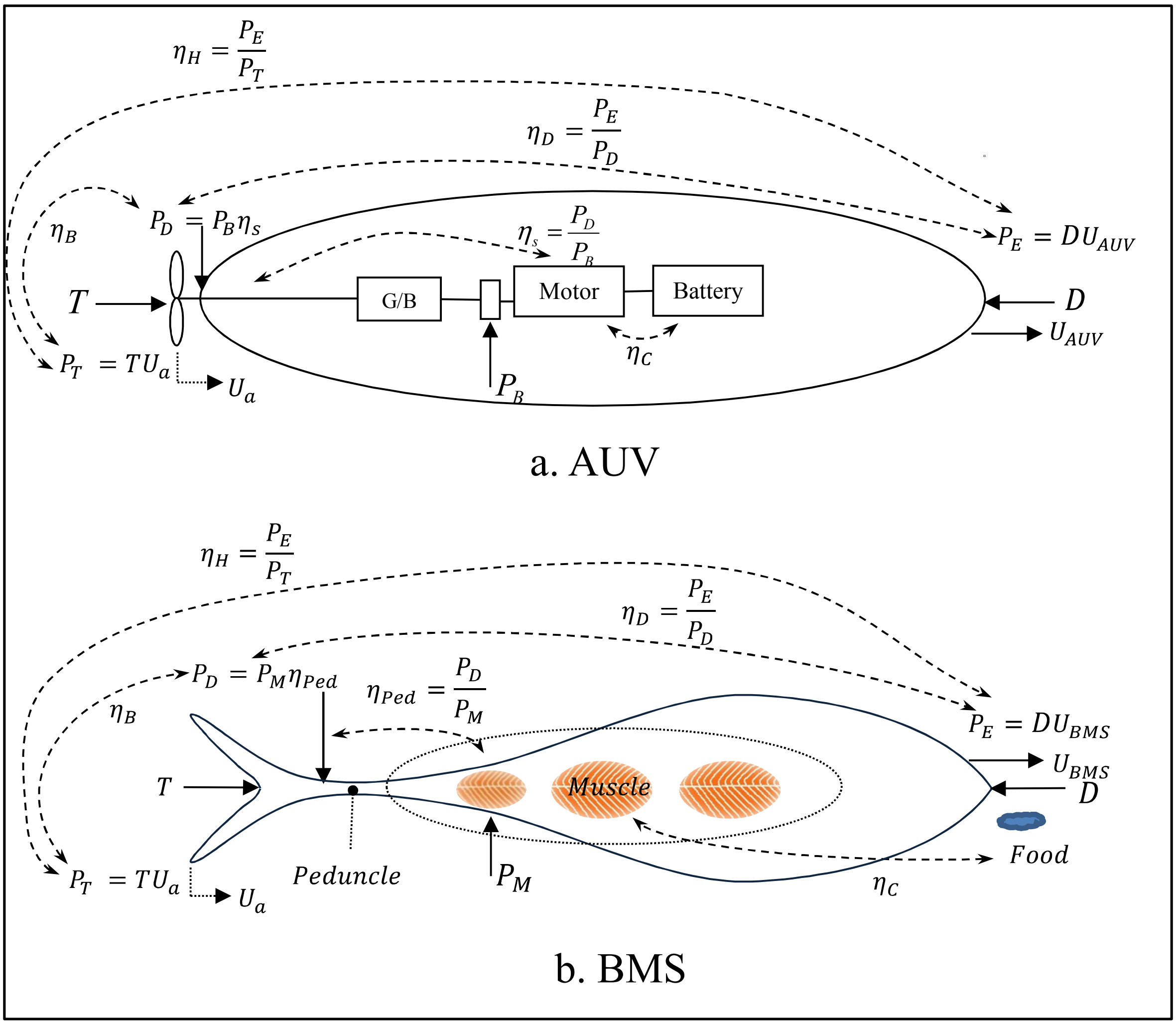

Figure 4 Comparison of power delivery in engineered vehicles and BMSs

TABLE V. EXPLANATORY NOTES TO THE POWER TRANSITIONS AND EFFICIENCIES ILLUSTRATED IN FIGURE 4

Process in AUV	**Corresponding Process in BMS**
Energy is lost when chemical energy in the battery is converted into electrical energy in the motor.	Energy loss when food and fat are converted into protein for muscle operation. (*)
In this research the efficiency associated with this this energy loss is called the conversion efficiency, η_C	Similar to an AUV
Energy is lost from friction when it is transferred through the drive chain to the propulsor.	Energy loss when energy is transferred from the muscle to the tail through the peduncle.(**)
The efficiency associated with this energy loss is known as the transmission, or shaft efficiency, η_S. $$\eta_s = \frac{P_D}{P_B}$$ Where P_D is the delivered power to the propeller and P_B is the brake power from the motor	The efficiency associated with this energy loss is the peduncle efficiency, η_{Ped}. $$\eta_{Ped} = \frac{P_D}{P_M}$$ Where P_D is the delivered power to the rear fin (the tail) and P_M is the muscle power
Energy is lost due to the propeller working in the flow field behind the AUV. In the desipline of naval architecture this is usually considered in two parts, namely with the propeller operating in the so-called open water condition with another adjustment for the effect of the wake behind the vehicle.[8]	Energy is lost due to the tail working in the flow field behind the BMS.
The efficiency associated with this energy loss is known as the "behind efficiency", η_B. $$\eta_B = \frac{P_T}{P_D}$$ Where P_T is the thrust power and is calculated as: $$P_T = TU_a$$ Where T is the thrust and U_a is the advance speed	In this research the efficiency associated with this energy loss is called the behind efficiency, η_B. $$\eta_B = \frac{P_T}{P_D}$$ Where P_T is the thrust power and is calculated as: $$P_T = TU_a$$ Where T is the thrust and U_a is the advance speed Note that T for a flapping tail is the mean net thrust derived over a complete oscillation.

There is a difference between the power developped at the propeller as compared to the effective power of the AUV overcoming drag at a given AUV speed.	There is a difference between the power developped at the tail compared to the effective power of the BMS overcoming drag at a given speed.
This power loss is referred as the hull efficiency, η_H. $$\eta_H = \frac{P_E}{P_T}$$ Where $P_E$is the effective power and is calculated as: $$P_E = DU_{AUV}$$	This power loss can be referred to as the hull or BMS body efficiency, η_H. $$\eta_H = \frac{P_E}{P_T}$$ Where $P_E$is the effective power and is calculated as: $$P_E = DU_{BMS}$$
From the explanations given above:	
$$\eta_{Total} = \eta_s \times \eta_B \times \eta_H$$ and in fact: $$\eta_B \times \eta_H = \eta_D = \frac{P_E}{P_D}$$ Where η_D is the delivered efficiency, therefore: $$\eta_{Total} = \eta_s \times \eta_D = \frac{P_E}{P_B} = \frac{DU_{AUV}}{P_B}$$	$$\eta_{Total} = \eta_{Ped} \times \eta_B \times \eta_H$$ And in fact: $$\eta_B \times \eta_H = \eta_D = \frac{P_E}{P_D}$$ Where η_D is the delivered efficiency, therefore: $$\eta_{Total} = \eta_{Ped} \times \eta_D = \frac{P_E}{P_M} = \frac{DU_{BMS}}{P_M}$$
In BMS: * Food corresponds to the battery and muscle to the motor of an AUV. ** Peduncle corresponds the propeller shaft and the propulsion fin; e.g. the tail to the propeller of an AUV	

In much of the literature which considers the locomotive and/or propulsive efficiency of BMSs, it is often unclear where the starting point in the energy flow in Figure 4 is. Therefore, claims of very high propulsive efficiency are often quoted as being a "total" efficiency, whereas, in reality they are more likely one of the sub-set of the efficiency terms illustrated in Figure 4 and explained in Table V which by definition will be higher than the real total efficiency.

VI. CONCLUSION

The superior performance of BMSs is apparent compared to engineered vehicles; however, no specific system is able to completely fulfil desired AUV mission requirements.

In this paper an Optimum System Selector (OSS) is described which combines BMSs to find an optimised solution for specific desired mission specifications. Therefore, it is crucial to calculate accurately the performance of the off-spring generated by the MOGA. The use of these calculation methods were described and justified in this paper.

Through considering multi-functionality and interaction of various biological sub-systems, OSS is an excellent guide to transform complex biological data for future vehicle design.

To realise the full potential of bio-inspiration, research is continuing by resolving the flexibility and depth-capability challenges and estimating the efficiency of the systems accurately.

ACKNOWLEDGMENT

NEMO is a collaboration between Newcastle University (NCL), University of Southampton (UoS) and the National Oceanography Centre (NOC) and it is sponsored by the Engineering and Physical Sciences Research Council (EPSRC) - Funding reference: EP/F066767/1.

REFERENCES

[1] Phillips, A. B., Haroutunian, M., Man, S. K., Murphy, A. J., Boyd, S. W., Blake, J. I. R. & Griffiths, G. (2012-a). "Nature in Engineering for Monitoring the Oceans: Comparison of the energetic costs of marine animals and AUVs". In: Sutton, R. and Roberts, G. (Ed.) Further Advances in Unmanned Marine Vehicles. The Institution of Engineering and Technology (IET). ISBN: 978-1-84919-479-2

[2] Fish, F. E. (2002). "Balancing Requirements for Stability and Maneuverability in Cetaceans". In: Integrative and Comparative Biology. Vol. 42, no. 1, pp. 85-93. DOI: 10.1093/icb/42.1.85

[3] Murphy, A.J. and Haroutunian, M. (2011). "Using Bio-Inspiration to Improve Capabilities of Underwater Vehicles". In: 17th International Unmanned Untethered Submersible Technology Conference (UUST 2011), 21-24 August, Portsmouth-USA. Curran Associates, Inc. pp. 20-31. ISBN: 978-1-61839-927-4

[4] Kreyszing, E. (1999). "Advanced Engineering Mathematics". John Wiley & Sons. 8th Edition, p.994. ISBN-10: 047133328X.

[5] Michon, G. P. (2012). "Final Answers". URL: http://www.numericana.com/answer/ellipsoid.htm. [Accessed: 04.2012]

[6] Hoerner, S. F. (1965). "Fluid-Dynamic Drag. Theoretical, experimental and statistical information". Hoerner Fluid Dynamics.

[7] Altringham, J. D. and Johnston, I.A. (1990)."Modelling Muscle Power output in a Swimming fish". In: Journal of experimental biology.Vol.148, pp.395-402.

[8] Lewis, Edward V., Principles of Naval Architecture, Society of Naval Architects and Marine Engineers, 1989, Volumes II.