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MECHANICAL ENGINEERING | RESEARCH ARTICLE

Methods of obtaining, verifying, and reusing optimal biological solutions

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Abstract: The practice of using analogies to biological systems for deriving innovative solutions to difficult engineering problems is called biologically inspired design. Although some procedures and methodologies for biologically inspired design have been presented in the literature, they did not specifically support obtaining and applying optimal solutions in living organisms. This article fills this research gap by presenting two methods of obtaining, verifying, and reusing biological optimal solutions (refer to biological forms, shapes, and structures) to solve engineering optimisation problems. The first method develops an analytical model, formulates an optimisation problem explicitly, and then verifies the optimal solution theoretically. An application example of this method is provided. The second method is based on experiments, and uses experimental design and statistical analysis to verify the optimal solution. This method is applied to the design of the flapping Micro Air Vehicles, which reuse an optimal biological solution (the shape of dragonfly wing). The procedures, requirements and advantages of both methods are discussed. We show that by using the two methods, scientists and engineers can efficiently obtain, verify, and reuse the optimal solutions from biological organisms.

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PUBLIC INTEREST STATEMENT

Living organisms in nature often face optimisation problems similar to those of engineering products. This article proposes two methods of obtaining and reusing biological optimal solutions (refer to biological forms, shapes, and structures) to solve difficult optimisation problems in engineering product design. The procedures, requirements, advantages and application cases of these methods are presented. These methods help designers reuse the optimal form of a biological example even if the mechanism and theories in relevant areas are undiscovered or undeveloped. An engineering designer without advanced mathematical knowledge or optimisation skills can learn and reuse the most complicated biological form without developing mathematical functions to describe them. With the help of the two methods, engineers will be able to efficiently reuse biological forms to design high-performance products.

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1. Introduction

Living organisms in nature display abundant optimal designs, many of which have been found and reused by humans. The application of these optimal designs results in many new and astonishing technical solutions, such as lightweight shape-optimised technical structures (modelled according to trees and bones) (Mattheck, 1998) and streamlined shapes in technology for least resistance in travelling through air or water (modelled according to the trout or dolphin body) (Vogel, 1998). The practice of using analogies to biological systems for deriving innovative solutions to difficult engineering problems is called biologically inspired design (Vattam, Wiltgen, Helms, Goel, & Yen, 2011), also referred to as biomimetics, biomimicry, biognosis, bionics, bioinspiration, biomimetic design, or bioanalogous design.

This article studies the methods of obtaining, verifying, and reusing biological optimal solutions (refer to biological shapes, structures, and forms) to solve engineering optimisation problems. A product design for fulfilling a functional requirement can be viewed as a multiple-objective, multiple-constraint optimisation problem, which is to determine the detailed design and parameters for optimising the product performance. However, many optimisation problems in engineering are very difficult to solve.

Engineering design literature presents the following three approaches to solve design optimisation problems.

The first is an equation-based approach, which uses an explicit function to establish the relationship between the performance of a product and the design parameters. This method is often difficult, or even impossible in certain cases to implement, because it requires complete knowledge of the mechanism of the system. Even if the explicit function is formulated, Yates, Templeman, and Boffey (1982) pointed out that a feasible and an efficient algorithm which guarantees to find globally optimal discrete design is not achievable within the limits of our existing mathematical knowledge.

The second one is a meta-model-based approach (surrogate model), when the explicit functions are not available. A surrogate model based on a few real case data is built and simulation experiments are used to establish the relationship between the performance and input design parameters. Then the optimisation is performed on the surrogate model. This technique has been studied by Fujita and Yoshioka (2003), Ulrich and Eppinger (2004), Jiao and Tseng (2004), and Ponweiser, Wagner, and Vincze (2008). However, the experiment is possible only when the shape and structure of the physical part have already been designed. Even if such a relationship is established, the real global optimum may not be obtained with a small number of experiments.

The third approach is information content assessment, for similar designs that use identical components (Bahrami, 1994; Jiao & Tseng, 2004; Suh, 1990). This approach associates each critical characteristic of a physical part with a value representing the information content, which is a measure of probability that the part will satisfy the performance requirement. Then the performance of a physical part or a product is predicted. This method requires identical components to be used for the new design and relationships between the components and the product performance to be established.

The aforementioned three approaches are difficult to implement in practice. Because the form and structure of a part of a product are unknown, engineers cannot write explicit forms of the objective and constraint functions for the optimisation problems. These problems are categorised as HEB (High dimensionality, Computationally expensive and Black-box) problems, which widely exist in

engineering design optimisation and feature high dimensionality (with many decision variables), are computationally expensive, and possess black-box properties (unknown function properties).

Instead of attempting to solve these HEB problems with mathematical methods and optimisation skills (which is sometimes impossible), engineers can obtain the optimal solutions directly from nature. Living organisms in nature often face optimisation problems similar to those of engineering products. To survive in a competitive environment, a living organism must optimise in many aspects. Biological examples in nature display their forms explicitly, which are the optimal solutions for many optimisation problems.

This article studies the procedure and methodology for discovering and applying optimal biological solutions. Although some procedures and methodologies for biologically inspired design have been presented in the literature (Badarnah & Kadri, 2015; Biomimicry Institute, 2007; Coelho & Versos, 2012; Cohen & Reich, 2016; Colombo, 2007; Fu et al., 2015; Helms, Vattam, & Goel, 2009; Hill, 2005; Huang & Siao, 2016; Junior, Guanabara, Silva, & Platcheck, 2002; Kim & Lee, 2015; Kruiper, Chen-Burger, & Desmulliez, 2016; Lindemann & Gramann, 2004; Sartori, Pal, & Chakrabarti, 2010; Schild, Herstatt, & Luthje, 2004; Shu, Ueda, Chiu, & Cheong, 2011; Vandevenne, Verhaegen, Dewulf, & Duflou, 2016; Vincent, Bogatyreva, Pahl, Bogatyrev, & Bowyer, 2005), most of them are methodologies designed for general biologically inspired design, not specifically for obtaining, verifying and reusing optimal biological solutions.

A method for obtaining, identifying, and reusing optimal forms of living organisms should contain procedures or iterations with these elements: observing the biological examples, formulating an optimisation problem, obtaining a possible optimal solution (biological forms, shapes and structures) and verifying the optimal solution. Since a solution is only valid for a specific problem, the problem and the solution should be identified and expressed first. Then the optimality of the solution is verified either through theoretical analysis or through experiments. Only after verification, the optimal solution is eligible to be reused for similar engineering optimisation problems. A method for obtaining, verifying and reusing optimal biological solutions should provide detailed instructions for all of the above elements.

Unfortunately, most of the procedures presented in the literature lack these elements. They focus on the functions of the biological and engineering systems and the analogy between them, instead of the optimal solutions for the optimisation problems. However, functions are only part of the composition of the objective of an optimisation problem. For example, Hill (2005) proposed a process which analyses contradicting demands to determine basic functions. Helms et al. (2009) presented a process where a problem is defined as a function, and a complex function is decomposed into subfunctions. Sartori et al. (2010) developed a model for capturing the functionality of both biological and technical systems. Although some procedures in the literature mention abstracting the principles in biological systems, principles are not exactly optimal solutions. For instance, Huang and Siao (2016) proposed an integrated bionic design system that transfers biological principles into engineering design as well as uses a computer-aided engineering analysis and Taguchi's method to select the optimal design parameters from a given list. They did not mention the formulation of optimisation problems. Some researchers specifically mentioned shape optimisation. For example, Kim and Lee (2015) suggested a method to evaluate the aerodynamic characteristics of a biological model and modify the morphological parameters. However, they neither formulated an optimisation problem, nor conducted statistical analysis of the experiment results.

To the best of our knowledge, none of the methods presented to date adequately support obtaining and applying optimal solutions in biologically inspired design.

A systematic biologically inspired design procedure for optimisation solution discovery and reuse is crucial because it helps designers comprehend biological forms as well as facilitates the development of new technical solutions and industrial products. Because no procedure has been specifically

proposed for optimal solution discovery and reuse in biologically inspired design, this study fills this research gap by presenting two methods for obtaining, verifying, and reusing biologically optimal solutions. The first method develops an analytical model, formulates an optimisation problem explicitly, and then theoretically verifies the optimal solution. When theoretical and analytical models are difficult to obtain, the second method is applied, which is based on experiments and statistical analysis. It uses experimental design and hypothesis testing to verify the optimal solution, and does not require the explicit mathematical formulas or full understanding of the biological system's mechanism. These two methods are applicable to different biologically inspired design situations. Through the two methods, scientists and engineers can efficiently obtain, verify, and reuse the optimal solution from biological organisms.

The rest of this article is organised as follows. Sections 2 and 3 discuss the first and the second methods, respectively. These sections discuss the procedure, requirements, and advantages of each method; an application example of the first method and a case study of the second method are also provided. The final section summarises the contribution of this article and suggests future research directions.
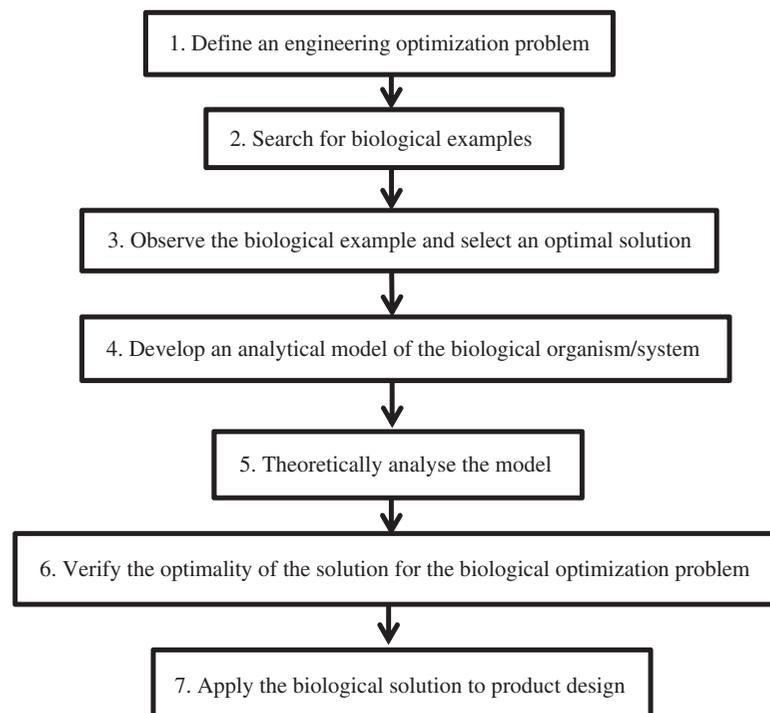
2. First method

2.1. Procedure of the first method

The brief procedure of the first method is shown by Figure 1. It involves the following seven steps:

Step 1: Define an engineering optimisation problem. To design an engineering product, the researcher must solve an optimisation problem (called Problem A). Due to lack of knowledge of the forms, shapes, and structures of the components and the product, the problem definition (its objective functions, design variables, and constraints) is not explicit without explicit mathematical formulas. It relies on concept description.

Figure 1. The procedure of the first method.

1. Define an engineering optimization problem
2. Search for biological examples
3. Observe the biological example and select an optimal solution
4. Develop an analytical model of the biological organism/system
5. Theoretically analyse the model
6. Verify the optimality of the solution for the biological optimization problem
7. Apply the biological solution to product design

Step 2: Search for biological examples. Living organisms in nature must solve optimisation problems similar to engineering problems for their survival. The following three methods are applicable in this step.

Method 1: Learn from biologists. Search biology journal papers, reports, books, and dictionaries for biological examples. To seek optimal biological solutions, the researcher should search by the keywords of the optimisation problem (the keywords are the objective function, the constraints, and the decision variables). Sometimes, the keywords of optimisation problems differ from the terms that are used commonly in biology. In that case, the synonyms of the keywords should be used instead.

Method 2: Search a nature-inspired solution database. Some databases that support biologically inspired design have been built in the literature, including those built by Vincent (2006), Bruck et al. (2006), the Biomimicry Institute (2007), Stroble, Stone, McAdams, and Watkins (2009) and Vattam et al. (2011). However, to the best of our knowledge, there is no database specialised for searching optimal solutions.

Method 3: Observe the example directly from nature. For example, to reduce the induced drag during flight, Mueller (2001) observed that most of the birds soaring over the land exhibit characteristic slotted wingtips. To apply this method, the designer may begin with a broad search space, and then screen the examples and gradually reduce the search space. The screening aims to find candidates with high potential to display the optimal solution for the engineering problem.

Step 3: Observe the biological example and select an optimal solution. Select one champion from the biological examples. Observe the form, shape, structure, and other features of this example. These are the possible optimal solutions for the optimisation problem.

Step 4: Develop an analytical model for the biological organism/system. Building an analytical model describes the working mechanism of a biological system. It is a mathematical expression constructed using well-known operations that are ready for calculation. The model should be a close approximation of the real system and incorporate most of its features; however, the model should not be too complex to understand and analyse. Building an analytical model often requires a comprehensive understanding of the mechanism and abundant knowledge of the biological organism/system.

Step 5: Theoretically analyse the model. Theoretically analyse the analytical model and develop closed-form mathematical functions. Formulate the optimisation problem faced by the biological example explicitly, which is called Problem B.

Step 6: Verify the optimality of the solution for the biological optimisation problem. Use scientific theories or mathematical algorithms to verify the optimality of the biological solution for Problem B. If the optimality of the biological solution is not verified, then the researcher should search for a new optimal solution and repeat Steps 2 to 6.

Step 7: Apply the biological solution to product design. By using knowledge of the forms of the components or the product, the objective functions and constraints of the engineering problem (Problem A) can be explicitly expressed as mathematical functions, which can substantially reduce the number of decision variables. Apply the biological optimal solution to the engineering problem. Some modification may be necessary due to the difference between Problems A and B.

2.2. Application example of the first method

The procedure of the first method is illustrated by a biologically inspired design example presented by Pasini and Burgess (2004). Seven steps are described as follows.

Step 1: Pasini and Burgess (2004) studied the optimality of the shape and size of the cross-section of a cantilever that supports the bending moment. They formulated the optimisation problem as follows:

$$\text{Max}\, p = f(F, D, S, M) \tag{1}$$

where p is a measure of mass efficiency, F is the function requirement, D describes the dimensions (width and height) of the cross-section envelope, S describes the shape of the cross-section, and M describes the material properties. F, D, S and M are four decision variables. The researchers attempted to determine efficient structures that can minimise mass and maximise p. Due to lack of knowledge of the form, shape and structure of the cantilever, the initial problem definition was not explicit.

Step 2: They observed the biological example directly from nature: a tree branch. The tree branch can be treated as a cantilever that supports the bending moment because of the self-weight of the branch. It contains several efficient structural features.

Step 3: They observed that the tree branch develops a structure in response to mechanical loading. The optimisation of form occurs in the transversal shape: the lower region is larger than the upper region (more cells grow at the lower region).The shape of the cross-section of the tree branch is the possible optimal solution to the optimisation problem.

Step 4: They developed an analytical model for the tree branch loading system and conducted mechanics analysis of the system. A tree branch can be treated as a cantilever. The wind loading produces bending moments and the self-weight of the tree produces compressive forces and bending moments. The upper region of the tree branch resists tensile stress and the lower region resists compressive stress.

Step 5: They theoretically analysed the model and developed closed-form mathematical functions. The function requirement F is defined as the bending failure moment. The performance index p is expressed as a function of the shape of the cross-section (S) and the area of the cross-section envelope (D). The readers are referred to Pasini and Burgess (2004) for the details of the functions.

Step 6: They used the functions and models to compare structures with different cross-section shapes. They proved theoretically that the cross-section of the tree branch has a better performance p than elliptical, rectangular, circular and any other cross-sections of man-made structures. For example, they proved that the tree branch saved 32% mass compared to a common rounded (circular) section for the same failure moment required. It is evident that the cross-section of the tree branch is the most efficient shape of the cantilever.
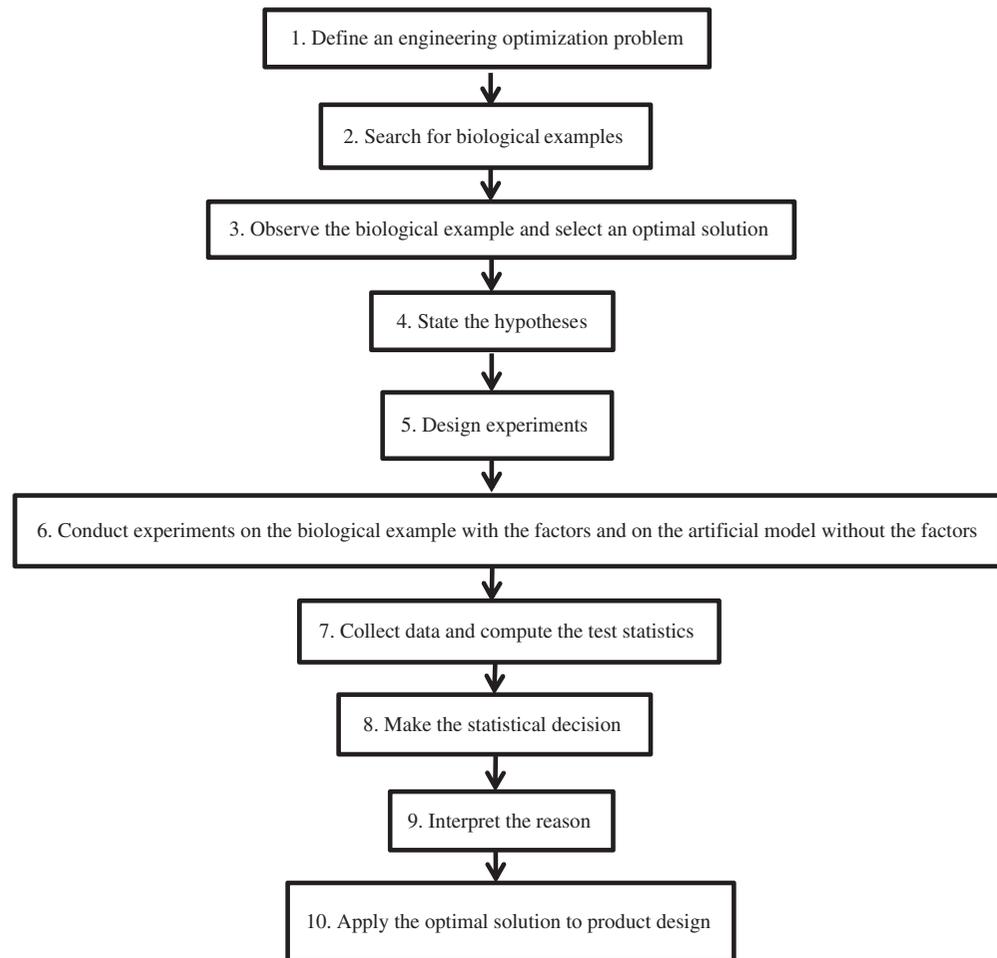
Step 7: The shape of the cross-section of a tree branch is the optimal solution to the engineering design problem and could be applied to design efficient cantilevers that support the bending moments.

2.3. Advantages and application requirements

The first method has the following advantages. First, it saves time and resources required in modelling and testing a product prototype by reusing the optimal solution of biological organisms. Second, it can solve the HEB problem effectively. Third, it helps researchers understand the biological example/system and establish new scientific theories by developing an explicit analytical model. Finally, the optimal parameters for a new product can be obtained by solving an explicit optimisation problem.

However, because this method requires developing an analytical model for a biological system, it imposes the following requirements for the designers. First, they should be knowledgeable of optimisation (mathematics), biology/biomechanics, and relevant engineering areas (such as mechanics, aerodynamics, and hydrodynamics). In addition, they should be able to analyse the form of the biological example and prove the optimality of a solution for an optimisation problem theoretically.

Figure 2. The procedure of the second method.

1. Define an engineering optimization problem

2. Search for biological examples

3. Observe the biological example and select an optimal solution

4. State the hypotheses

5. Design experiments

6. Conduct experiments on the biological example with the factors and on the artificial model without the factors

7. Collect data and compute the test statistics

8. Make the statistical decision

9. Interpret the reason

10. Apply the optimal solution to product design

3. Second method

3.1. Procedure of the second method

Sometimes, an analytical model of the biological system and the explicit formulation of the optimisation problem are difficult or impossible to obtain. The second method is proposed for this situation. It is based on statistical techniques. The brief procedure is shown by Figure 2. The method consists of the following ten steps (the first three steps are the same as those of the first method; thus, their details are omitted).

Step 1: Define an engineering optimisation problem.

Step 2: Search for biological examples.

Step 3: Observe the biological example, and select an optimal solution.

Step 4: State the hypotheses. The null and alternative hypotheses on the optimality of the biological solution are stated. The optimal solution from the biological organism (biological form) is defined as a factor. The researcher tests whether this factor contributes to the excellent performance of the biological organism.

Step 5: Design experiments. The researcher designs the experiments to measure the performance of the biological example with the factor and that of the artificial model without the factor. The performance is measured either through experimental instruments or through computer simulations.

If there is only one factor, two sample hypothesis testing is used, which tests whether the means of the two populations differ. If there is more than one factor, then the experiment design is complex. In this case, the researcher studies the relationship between independent variables (factors) and their interactions with a dependent variable (the performance index). Such an experiment design is called factorial design. For two factors, two-way ANOVA is used, and for k factors, a 2^k factorial design, and more complicated methods are used. Levine (2006) provided instructions and examples for factorial design.

Step 6: Conduct experiments on the biological example with the factors and on the artificial model without the factors. The biological example used in the experiment can be a real organism or a physical model built by the researcher that is analogous to the real organism and equipped with the investigated factors. The artificial model without the factors is a man-made model deriving from existing product designs or other common industry designs.

Step 7: Collect data and compute the test statistics. The sample performance indices from both the biological example and the artificial model are collected. The researcher determines the level of significance α, appropriate test statistic and other critical values used for hypothesis testing. Test statistics are calculated through statistic methods.

Step 8: Make the statistical decision. The research makes the statistical decision based on the result of statistical analysis: the factor either contributes to performance improvement with statistical significance or does not contribute to performance improvement with statistical significance. In the first case, the factor is considered an optimal solution for the optimisation problem. In the second case, the factor is not considered an optimal solution for the optimisation problem. The researcher should search for a new biological example and repeat the process from Steps 2 to 8.

Step 9: Interpret the reason. With engineering and science knowledge, the researcher attempts to determine why this factor contributes to performance improvement. If he or she succeeds, new knowledge and theories are explored and obtained. Nevertheless, the result may not be fully explained because of the limited knowledge of the researcher in the relevant area.

Step 10: Apply the optimal solution to product design. The researcher applies the factors (the optimal forms, shapes, and structures of the biological example) to a new product. The factors may be modified according to some engineering requirements (such as cost, material, and manufacturing methods). The researcher develops a product prototype, tests the performance, and modifies the design until the design is satisfactory.

Empirical modelling is another commonly used statistical method in studies. Through empirical modelling, scientists conduct experiments, collect data, and perform regressions to build an empirical model, which expresses a dependent variable (the performance index) as a function of several independent variables (the factors). The most common empirical model is a multi-regression linear model. Although empirical modelling is widely used in physics, biology, and other fields, it is rarely applied in biologically inspired design. The reason may be as follows. Regression modelling requires scientists to estimate the relationships between the dependent variable and independent variables before the experiment. The estimation is easy when the relationship forms are simple, such as linear, quadratic, and exponential. However, in most biological organisms, the relationship forms are very complicated and difficult to estimate correctly. Because there are scarce examples of using regression modelling in biologically inspired design, no empirical modelling method is proposed in this article.

3.2. Case study

A case study is used to illustrate the procedure of the second method. We aim to design the wing shape of the flapping Micro Air Vehicles (MAVs) which fly near the ground or the water surface. The case study is described step by step as follows.

Step 1: Define an engineering optimisation problem. The objective of the problem is to design the wing shape of MAVs to achieve excellent aerodynamic performance in ground effect (reduce the drag coefficient and enhance the lift coefficient) in the forward-flight mode.

Step 2: Search for biological examples.

We found the biological example by observing nature and searching the biology literature. The search space was screened and reduced twice.

First screening: the keyword "flapping wings" was used. Many living creatures, such as birds, insects, and mammals, have flapping wings. Among them, insects were chosen because they are likely to result in more ornithopter-like wings and wing actuation.

Second screening: the keyword "fluid aerodynamics of flapping wing in ground effect" was used. However, this keyword is rarely used in the biology literature, so it was replaced by two synonyms "flying efficiently" and "flying near the ground". Among the insects, dragonflies were chosen because they have an appropriate size and can fly efficiently near the ground and the water surface.

Step 3: Observe the biological example, and select an optimal solution.

We observe the dragonfly wing and also learned from previous studies on this object. Many features in a dragonfly may contribute to excellent fluid aerodynamics of flapping wing in ground effect. Among them, the shape of dragonfly wing cross-section is chosen as a possible optimal solution because it plays a significant role in aerodynamic performance.

Step 4: State the hypotheses. The optimal solution (the shape of dragonfly wing cross-section) is defined as a factor. We tests whether this factor contributes to the excellent aerodynamic performance. Since there is only one factor, two sample hypothesis testing is conducted. In this case, the aerodynamic performance of the airfoil is measured by the lift-to-drag coefficient. Two notations used in the hypothesis statements are defined as follows:

μ_1: the mean lift-to-drag coefficient of the dragonfly wing.

μ_2: the mean lift-to-drag coefficient of an artificial wing with different shape.

Since the wing with higher lift-to-drag coefficient implies better aerodynamic performance, the hypotheses about the lift-to-drag coefficient are stated as follows:

The null hypothesis H_0: $\mu_1 - \mu_2 = 0$

The alternative hypothesis H_1: $\mu_1 - \mu_2 \geq 0$

Step 5: Design experiments. The drag and lift coefficient in the forward flight mode will be obtained through numerical simulations. The recently developed Immersed Boundary-Lattice Boltzmann Method (IB-LBM) is adopted, which has been successfully employed to simulate various moving boundary problems. The details of the method are in Appendix 1. In the experiment, the Reynolds number Re is 730. 15 runs of the experiment are performed.

Step 6: Conduct experiments on the biological example with the factors and on the artificial model without the factors. The biological example used in the experiment is an airfoil which models the wing shape of ruddy darter (Sympetrum sanguineum), which is a kind of European species of dragonfly of the family Libellulidae. The artificial model is a NACA0012 airfoil.

Step 7: Collect data and compute the test statistics. The sample performance indices from both the biological example and the artificial model are collected. We conduct *F*-test two sample for variances on the lift-to-drag coefficients of both dragonfly wing and NACA0012 airfoil, and find that the two groups of data have equal variance with the level of significance $\alpha = 0.05$. Then we conduct *t*-test for comparing two populations of interval data with equal variance. *t* test statistic and P-value are obtained: $t = 94.496$ and $p = 6.36 \times e^{-36}$. The data obtained from the experiment and the calculation procedure of the test statistics are in Appendix 1.

Figure 3. The wing shape of the flapping micro air vehicle.
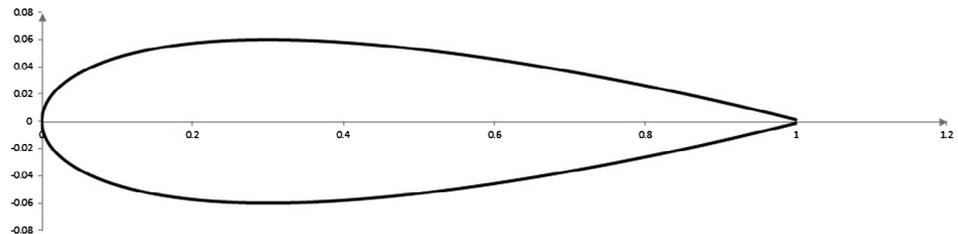
Step 8: Make the statistical decision. In one-factor analysis with a rejection region approach, the test statistic is compared with the critical value. At the level of significance $\alpha = 0.05$, the rejection region for H_0 is defined as $t \geq t_{0.05, 14, 14} = 1.701$. Since $t > 1.701$, the test statistic falls into the rejection region, then the null hypothesis H_0 is rejected in favour of the alternative hypothesis, implying that the performance of the biological example with the factor (the shape of dragonfly wing cross-section) is better than that of the artificial model (NACA0012 airfoil) without the factor. The same conclusion is drawn by *P*-value approach. Thus, the factor contributes to the excellent aerodynamic performance of flapping wing in ground effect with statistical significance.

Step 9: Interpret the reason. The drag and lift forces acted on the flapping foil are dependent on the shape of the airfoil. However, we have not fully understood the mechanism and could not build an analytical model yet. More detailed exploration of the force behaviour of the flapping foil in ground effect should be done in order to understand the mechanism.

Step 10: Apply the optimal solution to product design. The shape of dragonfly wing cross-section will be considered in the design of the flapping micro air vehicles (MAV) which fly near the ground or the water surface. The two-dimensional cross-section of the airfoil wing is sketched in Figure 3. We develop a regression model to approximate the shape. The details of the model are found in Appendix 1. The airfoil wing will be fabricated by a computer numerical control machine with the alloy of duralumin and titanium. However, more research work should be done before the airfoil wing is applied to the flapping MAV. The research includes mechanics tests of the airfoil wing produced by the machine, the design of the hinge system which links the wing to the vehicle body, the design of the assembling process and aerodynamics tests of the vehicle, etc. We will conduct these tests and design in future research.

3.3. Application area, advantages, and requirements of the second method

The second method is applied when the requirements for the first method are difficult to fulfil. It should be used in the following situations:

(1) The closed-form mathematical model for the optimisation problem is difficult to formulate;
(2) The analytic solutions for the optimisation problem are impossible or too complicated;
(3) Validating the mathematical model that describes the biological system or mechanism is impossible or too expensive;
(4) No knowledge or theories exist on the complex biological system/mechanism.

Compared with the first method, which uses theoretical analysis, the second method, with an experimental approach, has many advantages. First, it saves the time, resources, and effort that are required to study a complex biological system/mechanism. For example, in the case study, it is difficult to model the aerodynamics of the flapping wing in ground effect due to the complicated shape of the dragonfly wing. It may take years to fully understand the mechanism. Alternatively, we have applied the second method to verify the optimal solution through experiments. The process only took several months. Second, the second method helps designers reuse the optimal form of a biological example even if the mechanism and theories in this area are undiscovered or undeveloped. Third, no explicit mathematical problem needs to be written, and no HEB problems need to be solved; thus, an

engineering designer without advanced mathematical knowledge or optimisation skills can apply this method. Fourth, it directly proves the optimality of the solution through experimental data, and the conclusion is statistically significant. Fifth, designers can learn and reuse the most complicated form without fully understanding the mechanism or deriving mathematical functions to describe them. Finally, it directly tests the product performance on the basis of experimental data, which are more understandable than the optimal solution that is based on mathematical functions.

Nevertheless, applying this method generates some requirements for designers. First, they should be knowledgeable in biology in order to find biological examples in which optimisation problems similar to those of artificial products are faced. In addition, they should be able to efficiently develop an appropriate model with a design that is analogous to the real biological example, and design experiments to measure and test the performance of both the model and the biological example. Furthermore, they should be knowledgeable in statistics and be able to select appropriate statistical approaches to analyse the experimental data as well as perform hypothesis testing or factorial design.

4. Conclusion and future research

The optimal solutions (biological forms) of biological organisms can help solve difficult engineering optimisation problems. This article presents two methods for obtaining, verifying, and reusing the optimal designs from biological organisms. The first method develops an analytical model, formulates an optimisation problem explicitly, and then verifies the optimal solution theoretically. When theoretical and analytical models are difficult to obtain, the second method is applied, which is based on experiments and statistical analysis. Engineers should select a suitable method according to their capabilities, resources and knowledge of the biological system. With the help of the two methods, engineers without much biologically inspired design training will be able to obtain, verify and reuse biological forms, shapes and structures to design high-performance products.

In future research, the two methods will be applied to more case studies. The optimal solution identification and reuse method will be integrated with other processes and developed into a new product development methodology. In addition, a database that is designed for the storage of optimal solutions from nature will be constructed, so that product designers can search for the optimal solutions by using the keywords of their engineering optimisation problems.

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Appendix 1

Data analysis for the case study

In the case study, the aerodynamic performance of the airfoil is measured by the lift-to-drag coefficient C_L/C_D, where C_L is the lift coefficient and C_D is the drag coefficient. Other notations used in the case are defined as follows:

$C_{L,1}$: the lift coefficient of dragonfly wing.

$C_{D,1}$: the drag coefficient of dragonfly wing.

$C_{L,1}/C_{D,1}$: the lift-to-drag coefficient of dragonfly wing.

$C_{L,2}$: the lift coefficient of NACA0012 airfoil wing (an artificial wing with different shape).

$C_{D,2}$: the drag coefficient of NACA0012 airfoil wing.

$C_{L,2}/C_{D,2}$: the lift-to-drag coefficient of NACA0012 airfoil wing.

$\overline{C_{L,1}/C_{D,1}}$: the mean lift-to-drag coefficient of the dragonfly wing.

$\overline{C_{L,2}/C_{D,2}}$: the mean lift-to-drag coefficient of NACA0012 airfoil wing.

Since the wing with higher lift-to-drag coefficient implies better aerodynamic performance, the hypotheses about the lift-to-drag coefficient are stated as follows:

The null hypothesis H_0: $\overline{C_{L,1}/C_{D,1}} - \overline{C_{L,2}/C_{D,2}} = 0$

The alternative hypothesis H_1: $\overline{C_{L,1}/C_{D,1}} \geq \overline{C_{L,2}/C_{D,2}}$

The drag and lift coefficients in the forward flight mode are obtained through numerical simulations by the Immersed Boundary-Lattice Boltzmann Method (IB-LBM). The drag and lift coefficients are given by these functions:

$$C_D = \frac{2F_D}{\rho_\infty U_\infty^2 c} \text{ and } C_L = \frac{2F_L}{\rho_\infty U_\infty^2 c} \tag{2}$$

where F_D and F_L are the drag and life forces acted on the flapping foil, c is the chord of foil, ρ_∞ is the density of the fluid (air) and U_∞ is the free stream velocity. F_D and F_L are obtained by solving a mathematical equation system. Readers are referred to Wu and Shu (2009) for the details of the method.

In the experiment, the Reynolds number *Re* is 730, the angle of attack is 10 degree, and the amplitudes of plunging and pitching motions of the flapping foil are fixed at 0.4*c* and π/4 respectively. 15 runs of the experiment are performed.

The sample performance indices from both the biological example and the artificial model are collected. Table 1 lists the data obtained from 15 runs of the experiment.

Table 1. The lift coefficients, drag coefficients and lift-to-drag coefficients

Run	$C_{L,1}$	$C_{D,1}$	$C_{L,2}$	$C_{D,2}$	$C_{L,1}/C_{D,1}$	$C_{L,2}/C_{D,2}$
1	0.601	0.183	0.379	0.178	3.284	2.166
2	0.605	0.181	0.383	0.176	3.343	2.201
3	0.598	0.182	0.375	0.173	3.286	2.168
4	0.596	0.181	0.378	0.174	3.293	2.148
5	0.606	0.185	0.382	0.178	3.276	2.146
6	0.609	0.184	0.384	0.175	3.310	2.217
7	0.602	0.182	0.391	0.181	3.308	2.127
8	0.608	0.186	0.376	0.171	3.269	2.205
9	0.599	0.179	0.375	0.174	3.346	2.219
10	0.596	0.176	0.379	0.176	3.386	2.191
11	0.602	0.179	0.389	0.178	3.363	2.197
12	0.603	0.182	0.387	0.176	3.313	2.199
13	0.597	0.181	0.384	0.177	3.298	2.169
14	0.612	0.188	0.382	0.173	3.255	2.208
15	0.602	0.183	0.389	0.179	3.290	2.173

The sample means of the lift-to-drag coefficients of both dragonfly wing and NACA0012 airfoil are obtained:

$\overline{C_{L,1}/C_{D,1}} = 3.308$, $\overline{C_{L,2}/C_{D,2}} = 2.182$

We conduct *F*-test for the variances of the lift-to-drag coefficients of both dragonfly wing and NACA0012 airfoil. The hypothesis statement about the variances is as follows:

σ_1^2: the variance of the lift-to-drag coefficient sample of the dragonfly wing.

σ_2^2: the variance of the lift-to-drag coefficient sample of NACA0012 airfoil wing.

The null hypothesis H_0: $\sigma_1^2 - \sigma_2^2 = 0$
The alternative hypothesis H_1: $\sigma_1^2 - \sigma_2^2 \neq 0$

At the level of significance $\alpha = 0.05$, the rejection region for H_0 is defined as $F \geq 2.97$ or $F \leq 0.3336$. The test statistic *F* calculated from the data is 1.726. Since it does not fall into the rejection region, we could not reject H_0. Thus we conclude that the two groups of data have equal variance.

Then we conduct *t*-test for comparing two populations of interval data with equal variance. *t* test statistic and *P*-value are obtained: $t = 94.496$ and $P = 6.36 \times e^{-36}$. In one-factor analysis with a rejection region approach, the test statistic is compared with the critical value. At the level of significance $\alpha = 0.05$, the rejection region for H_0 is defined as $t \geq t_{0.05, 14, 14} = 1.701$. Since $t > 1.701$, the test statistic falls into the rejection region, then the null hypothesis H_0 is rejected in favour of the alternative hypothesis, indicating that the performance of the biological example with the factor (the shape of dragonfly wing cross-section) is better than that of the artificial model (NACA0012 airfoil) without the factor. The same conclusion is drawn by *P*-value approach. Thus, the factor contributes to the excellent aerodynamic performance of flapping wing in ground effect with statistical significance.

The shape of the dragonfly wing cross-section is considered in the design of the airfoil wing of the flapping micro air vehicles. The two-dimensional cross-section of the airfoil wing is sketched in Figure 3. The (*x*, *y*) coordinates of the points on the cross-section contour are displayed by Table 2.

Table 2. The (*x*, *y*) coordinates of the points on the cross-section contour

0 ≤ x < 0.3		0.3 ≤ x < 0.7		0.7 ≤ x ≤ 1	
x	*y*	*x*	*y*	*x*	*y*
0	0	0.3087	0.0600	0.7093	0.0357
3.8E-04	0.0035	0.3269	0.0599	0.7270	0.0340
0.0015	0.0069	0.3455	0.0596	0.7443	0.0322
0.0035	0.0102	0.3643	0.0592	0.7612	0.0304
0.0062	0.0135	0.3833	0.0586	0.7778	0.0287
0.0096	0.0167	0.4025	0.0579	0.7939	0.0269
0.0138	0.0199	0.4218	0.0571	0.8095	0.0252
0.0188	0.0229	0.4412	0.0562	0.8247	0.0235
0.0245	0.0259	0.4608	0.0552	0.8394	0.0218
0.0459	0.0343	0.4804	0.0541	0.8802	0.0169
0.0545	0.0369	0.5000	0.0529	0.8927	0.0154
0.0638	0.0393	0.5196	0.0517	0.9045	0.0139
0.0737	0.0417	0.5392	0.0503	0.9157	0.0125
0.0843	0.0439	0.5588	0.0489	0.9263	0.0111
0.1073	0.0480	0.5782	0.0474	0.9455	0.0087
0.1198	0.0499	0.5975	0.0458	0.9541	0.0075
0.1328	0.0515	0.6167	0.0442	0.9619	0.0065
0.1465	0.0531	0.6357	0.0426	0.9691	0.0055

(*Continued*)

Table 2. (Continued)

0 ≤ x < 0.3		0.3 ≤ x < 0.7		0.7 ≤ x ≤ 1	
x	*y*	*x*	*y*	*x*	*y*
0.1753	0.0557	0.6545	0.0409	0.9812	0.0039
0.2388	0.0591	0.6731	0.0392	0.9965	0.0017
0.2907	0.0600	0.6913	0.0375	1	0.0013

To fabricate the airfoil wing, we develop a regression model to describe the contour. Since the contour is symmetric, we only need build a regression model for the upper part. The contour is approximated by two three-order polynomial functions as follows:

$$y = 5.6866x^3 - 3.3858x^2 + 0.6921x + 0.0077, \quad 0 < x \le 0.3 \tag{3}$$

$$y = 0.04393x^3 - 0.1716x^2 + 0.0777x + 0.0514, \quad 0.3 < x < 1 \tag{4}$$

The adjusted R^2 statistics for function (3) and (4) are 0.987 and 0.999 respectively. The large adjusted R^2 statistics imply that the regression models provide adequate approximation to the contour.