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Implementing Value-Driven Design in Modelica for a racing solar boat

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Abstract

Research has shown that current design approaches, such as requirement-based design or Cost As Independent Variable (CAIV), may fundamentally yield suboptimal designs. In response to the need for better systems, new design techniques that are based on optimization and decision-making have been proposed. In this paper, we show how Modelica can be used to implement and operationalize Value-Driven Design (VDD) in concept selection. Modelica's object-oriented strengths are employed to model design alternatives and its capability to execute Monte Carlo simulation enables the introduction of uncertainty in models and assessment. The proposed approach has been applied to the conceptual design of an unmanned, autonomous solar powered boat, which is aimed at racing in a student competition. Value has been defined as a function of the probability to win the said race, which expands usual examples of value functions to non-monetary ones. This paper describes the approach as well as the benefits, limitations, and obstacles encountered during its implementation.

Keywords: Value-Driven Design; VDD; Conceptual Design; Modelica; System Modeling; Monte Carlo.

1. Introduction

In system development, early stage conceptual design plays a significant role in the chances to succeed in maximizing the value associated to the users' perceived satisfaction [1]. Research has shown that current design approaches, such as requirement-based design or Cost As Independent Variable (CAIV), may fundamentally yield suboptimal systems [2]. In response to the need for better systems, the Value-Driven Design (VDD), which is built on the pillars of optimization and decision-making, has been proposed [2, 3]. In VDD, a value function that relates system attributes to the level of satisfaction that is experienced by the corporation developing the system, usually through a user's demand function, is defined. Then, a particular design is optimized by modifying system attributes and evaluating their effect on system value [2].

This paper builds upon the authors' previous work on creating and assessing conceptual designs by means of hierarchical functional decomposition in Object Process Methodology [4, 5] and subsequent assessment by way of the simulation of Modelica models [4–6]. It provides two primary contributions. First, it integrates the VDD methodology explicitly within Modelica´s object oriented design environment. And second, while most of published applications of VDD have employed financial value functions, primarily economic profit, the work presented in this paper utilizes a non-monetary value function (the probability of winning the race), which helps in generalizing the application of VDD. This is applied to the early stage design of an unmanned solar racing for a student competition as a test case.

2. Background

2.1. Value-Driven Design (VDD)

In VDD, a particular design is optimized by modifying system attributes and evaluating their effect on system value [2]. Value is defined in this framework as a level of satisfaction that is experienced by the corporation developing the system and is usually monetized to profit. In Decision-Based Engineering Design, the attributes of a system are modified until the utility of the system is maximized, with respect to corporate preferences [7]. In this case, the definition of utility is directly taken from economics [8].

This contrasts with requirements-based design where prior to completing the design it is decided what performance the system and its components must exhibit and thus ignoring the uncertainty fundamentally associated with creating a new system [2]. Given the magnitude of the change required in systems engineering to move from requirements-based design to VDD a workshop was held by the US National Science Foundation in 2010 to compare the two approaches, the content of which is described by Collopy in [9]. It is suggested that while requirements-based approaches are embedded in industry today successfully, allowing for contracting between customers and suppliers, they continue to fail at capturing what the customer prefers and prevent the search for better designs. While the concept of VDD is embraced by academia, it remains a challenge to operationalize it in real projects. Hence, further research is required.

2.2. System Modeling

A large amount of engineering effort is spent in developing models of designs such that prediction can be made of their expected performance before they are built, avoiding in this way costly trial and error. SEBoK [10] lists various types of models divided between abstract models and physical models. With abstract models being further divided into descriptive models (describing logical relationships) and analytical models (describing mathematical relationships). Dynamic models are a sub category of analytical models and are appropriate for modeling the performance of systems with time-varying states and as such clearly applicable for modeling vehicles in motion.

The ease at which sufficiently accurate models can be created is clearly an important consideration on any project and object oriented approaches have successfully enabled the software industry to develop ever more complicated products by building and utilizing libraries enabled by object oriented technology. For engineers looking to create dynamic models in an object-oriented paradigm, Simulink and Modelica are both viable options and both popular in industry for the design of vehicle systems.

In Modelica and Simulink the behavior of components is captured in equations and these components are connected together to develop subsystems and ultimately form the system being designed. While superficially sounding similar, Modelica offers benefits over Simulink for this research. Primarily, as components can be connected with acausal connections (e.g. electrical current can flow in both directions) and physical equations can be simply declared with the solver handling how to execute them, Modelica enables the engineer to focus on the physical reality of the systems being designed. This avoids some errors associated with attempting to code a model of the system.

2.3. Modelica and VDD

Modelica has been used extensively in industry and research to assess the performance of systems before they are realized physically. Reviewing the most cited past work it tends to be focused on describing the language (e.g. [11, 12]), developing highly accurate modelling libraries for a particular domain (e.g. [13, 14]) or on the generation of Modelica models from other modeling languages (e.g. [15]). Modelica has been used as the assessment mechanism for design methodologies in the past such as described in [16], but such approaches focused on multi-objective optimization as opposed to supporting VDD.

Further literature review found one example attempting to describe VDD assessment being performed using Modelica by Du et al [17]. However, Du's work does not consolidate the value quantities and instead plots performance of various designs against surrogates of maintenance cost and capital cost. Hence, there is no attempt to rank the designs and select the one that provides the most value.

3. Methodology

An overview of the approach advocated in this paper is shown in Fig. 1, which for illustration shows the solar boat case study (referred to in this paper as SolarBoat).

First, we define the value function of the system being designed, which for SolarBoat we declare as the probability of winning the race subject to costing not more than a fixed budget.

On deciding the external factors interacting with all SolarBoats, it is possible for the value function and the infrastructure to assess each SolarBoat design modeled in Modelica, which for this research is known as a “Level 0 Environment Interface” (red dashed box in Fig. 1), within which a common base class for all SolarBoat designs is created known as “Level 1 SolarBoat Interface”. It is as if a socket has been created into which alternative SolarBoat designs can be placed (orange box in Fig. 1).

Then, we model the SolarBoat itself (i.e. the system of interest we are trying to design) from the common base class, hence utilizing a Modelica language feature that is well suited to comparing various different designs, as it is possible to enforce a particular interface and have variables common to all alternatives. This approach simplifies the creation and comparison of different designs that can have significantly different architectures. This is illustrated in Fig. 1 by the swapping in of various different SolarBoat alternatives.

We incorporate uncertainty by modeling external factors as probability density functions, which for SolarBoat are water current, solar irradiance and ambient temperature. Using Monte Carlo simulation we then compute the expected value of the system by consolidating the results of multiple trials into a cumulative probability distribution.

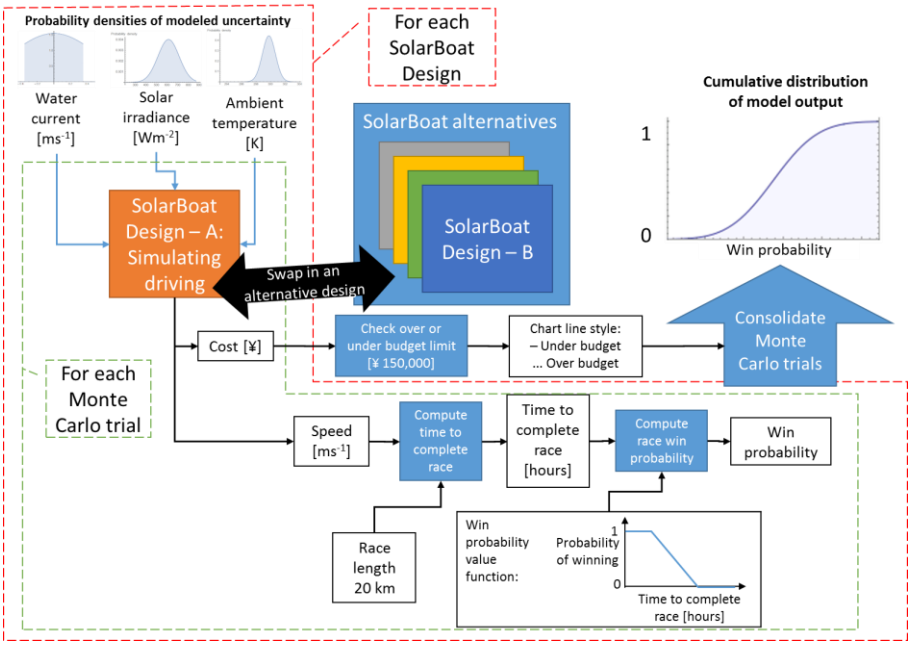


Fig. 1. Process overview.

4. Application

4.1. Problem description

The SolarBoat race occurs every year at the end of August on Lake Biwa in Japan, where different student teams race solar powered autonomous boats they have designed, built and tested over the previous semester. The competition involves two days of racing with the results of both days combined. On both days, the boats are challenged to travel 20km on a predefined course with three waypoints (see as Fig. 2

left side). The race organizers set design constraints on the power train in the form of maximum solar panel size of $2m^2$ and a maximum of 20Wh of lead based batteries (control systems can have additional batteries of any type). In addition, the boats are required to carry a payload from the race organizers. An example boat design is shown in the right side of Fig. 2.

To complete the project the University of Tokyo team typically has a budget of 300,000 Japanese Yen (¥), the final design's component bill typically incorporates no more than half of the budget (¥150,000), but students can make use of components from previous years for free. Given labor is free (students do the work), the sum of the component costs is an adequate model of the cost of the boat.

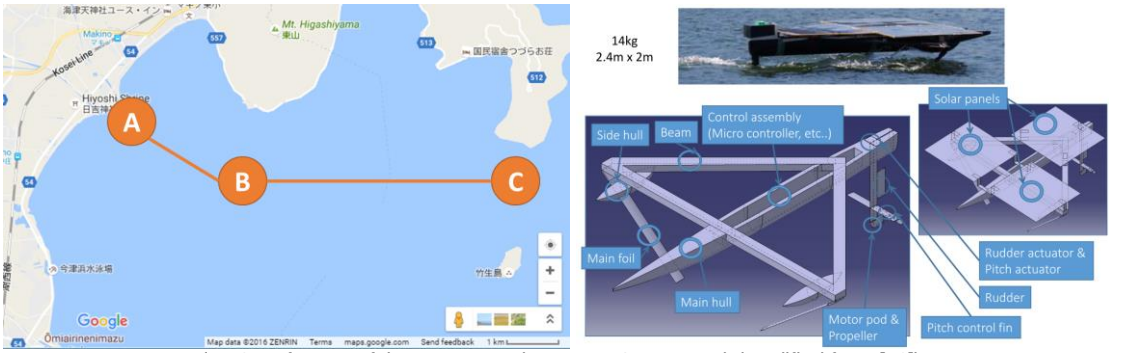


Fig. 2. Left: Map of the race route (A -> B -> C -> B -> A) (modified from [18])
Right: An example SolarBoat design (a hydrofoil from 2014) from [19]

For this study, the boat is assumed to travel in a straight line for 20km removing the need to model turning behavior. Further, the boat steady state speed is assumed to be reached at a time equal to 100 seconds in the simulation and then assumed to remain constant (thus acceleration is not assessed). This velocity is used to calculate total time to complete the race, which is mapped to probability of winning the race by way of the value function described in Section 4.2. The environmental inputs (water current, solar irradiance and ambient temperature) that affect the boat are described in Section 4.3.

4.2. Value function

The value function used in this work is shown in Fig. 3. It is believed that finishing the race in 1 hour or less guarantees winning the race, while finishing in 2.5 hours or more would guarantee losing. Winning is defined as finishing in 1st position in the race. Losing is defined as not winning. The bases for these two extremes is from limited data from previous races (which unfortunately does not specify the weather conditions experienced during the race), specifically:

- In 2015 Race Tokyo finished 2nd with 2 hour 6 minutes.
- In 2010 Race Tokyo won the race and set the all-time race record with 1 hour 40 minutes.

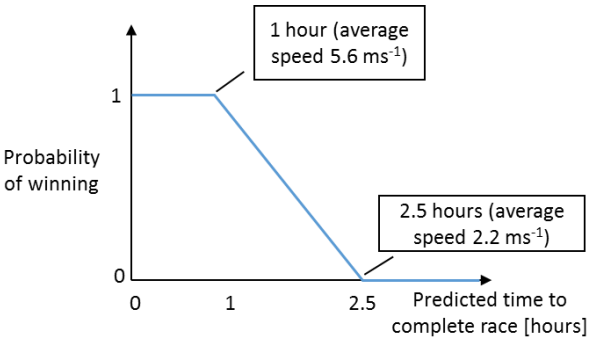


Fig. 3. Win probability value function.

The probability of winning for finishing times between 1 hour and 2.5 hours is believed to behave linearly. We have not elicited this function from existing data at this point, but we consider that it does not negatively affect the objectives of this paper. Furthermore, other effects such as weather or sea conditions are considered to be compounded in the given value function. Future work is planned to show how the different conditions can be compounded to a single value function through Bayesian probabilities.

It should be noted that the actual competition consists of two races held on two days with the results combined. This has been ignored in this paper for simplicity, since it does not affect negatively the purpose of the paper.

However, unconstrained optimization of the designs with regard to probability of winning is insufficient as the project has a spending limit. Therefore, any designs that cost more than the ¥150,000 cost limit are considered infeasible and marked as such.

4.3. External environment

Previous experiences in the SolarBoat race competition inform that water current, solar irradiance, and ambient temperature constituting the external environment drivers for boat performance in terms of finishing time. They have been modeled as probability density functions, in line with findings in literature. Their probabilistic models are provided in Table 1. While there are some dependencies between the three elements, independence has been assumed for simplicity purposes in this paper. It should further be noted that wind and air resistance are ignored, this is justified as the density of water is 1000 times more than air and all SolarBoat designs are assumed to have a low exposed area to the airflow (i.e. no sails or tall cargo) thus hydrodynamic forces dominate aerodynamic forces. While these assumptions do reduce the accuracy of the models, they do not negatively affect the objectives of this paper.

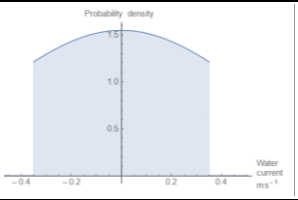
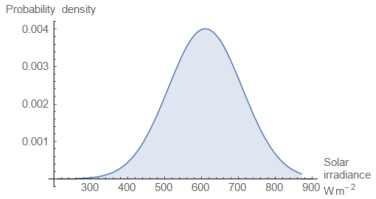
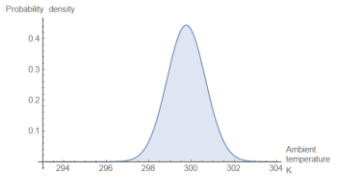
Environmental input	**Probability distribution used**		**Description**
Water current [ms^{-1}]		Truncated Normal Distribution: SD: 0.5 Cut off: -0.35 ms^{-1} Mean: 0 ms^{-1} Cut off: 0.35 ms^{-1}	Water currents maximum and minimum taken from the work of Endoh [20]. We assume due to long running processes even large lake currents are experienced.
Solar irradiance [Wm^{-2}]		Truncated Normal Distribution: SD: 100 Cut off: 260 Wm^{-2} Mean: 610 Wm^{-2} Cut off: 870 Wm^{-2}	Past work on the project had found the maximum and minimum solar irradiance. Extreme values are not expected frequently.
Ambient temperature [K]		Truncated Normal Distribution: SD: 0.9 Cut off: 294.25 K Mean: 299.75 K Cut off: 306.35 K	Dry bulb temperature data from NOAA [21].

Table 1. Uncertainty models used.

4.4. System model

To translate the problem description and assumptions into a computational model, initially a partial Modelica model was created with an interface defined for the SolarBoats to be placed and assessed. Fig. 4 left side depicts this with a diagram and right side shows the truncated Modelica code for the same model. The diagram view shows the interface for the SolarBoat clearly, while the truncated code shows that the assessment of the probability of winning is computed from the predicted time to complete the race, with the boats velocity and cost being extracted from the boat model.

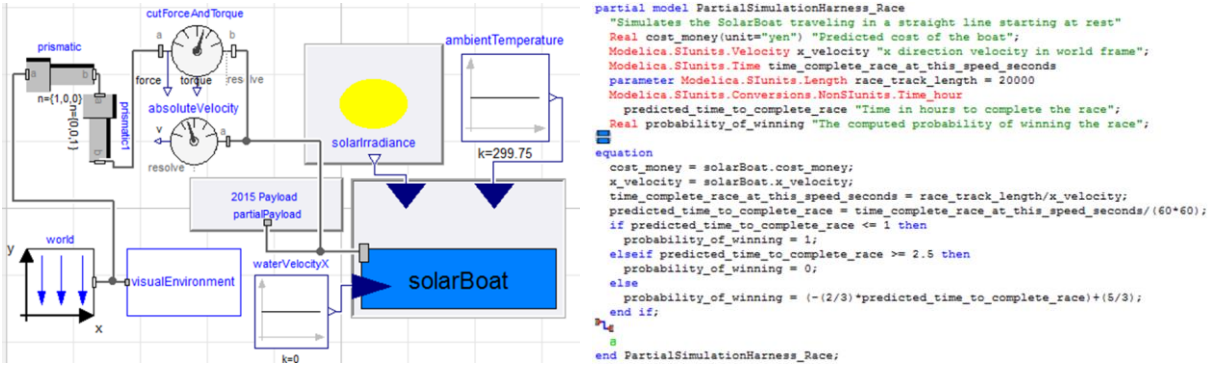


Fig. 4 Modelica model PartialSimulationHarness_Race. Known as a "Level 0 Environment Interface".

Left: Diagram view. Right: Text view (code is truncated for ease of reading).

Fig. 5 left side shows the Modelica diagram view of the SolarBoat interface, showing that the engineer has much freedom to implement the design as they think best, but then consistently assess it with the model shown in Fig. 4. Fig. 5 right side is a representation of the interface at Level 0, populated with different System of Interest designs (SolarBoats with different architectures, hence the different subsystems and subsystem components) and with SolarBoat designs being assigned Hierarchy Level 1 and Subsystems Hierarchy Level 2 and Subsystem-Components Hierarchy Level 3. As such, it is possible to assess all the alternative designs by the same method.

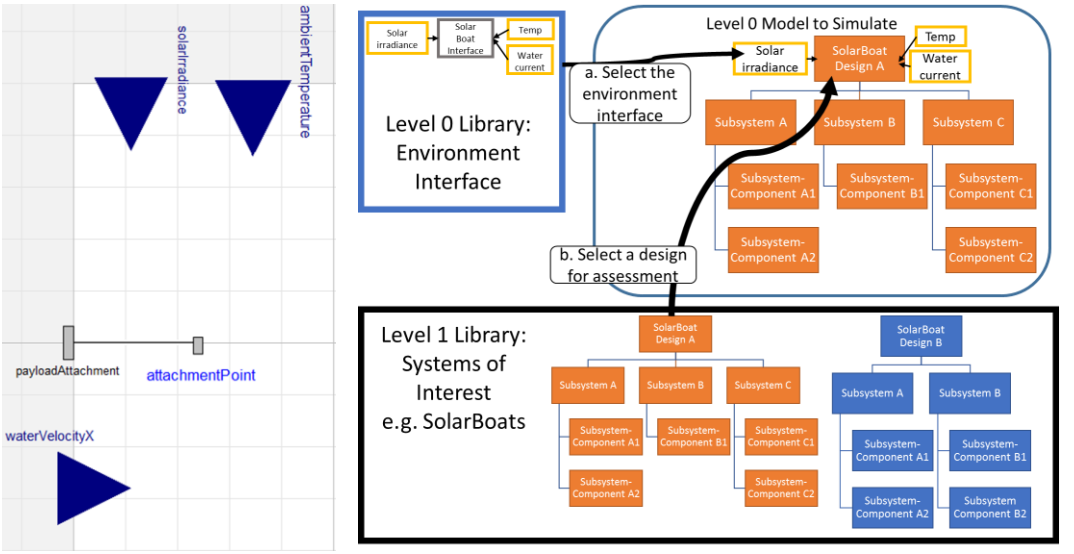


Fig. 5. Left: Modelica model of the "Level 1 SolarBoat Interface".

Right: Representation of combining SolarBoat designs (Level 1) with the Environmental Interface.

4.5. Design alternatives

Seven design alternatives are considered in this application (ref. Table 2). All the alternatives have the same subsystems of "Electrical to Thrust", "Buoyancy Generation", "Solar to Electrical" and "Overhead components." Thus, they all share the same architecture at Hierarchy Level 2. These subsystems are then decomposed into subsystem-components and specific designs are created by assigning specific subsystem-component implementations to the architecture. The resulting approach is similar to a morphological box technique, but with the synthesis of the functionality required of the subsystems being identified by the utilization of previous research by the authors which utilized OPM (Object Process Methodology) [4, 5]. The designs were selected to show a range of performances, not an optimally designed

boat. Description of each component is provided in Table 3. In addition, all designs contain the same overhead components (control and structure). These are not displayed in Table 2 because of page limitations.

			Subsystem to Subsystem-Component Decomposition:				
			Electrical to Thrust:			Buoyancy Generation:	Solar to Electrical:
Design:	**Cost:**	**Mass:**	**Motor**	**Gearbox**	**Propeller**	**Displacement hull**	**Solar panels**
SB1	¥ 39,400	9.18 kg	L3040A-480G	13:1	200mm	Single hull	FT-136SE
SB2	¥ 39,400	9.18 kg	L3040A-480G	13:1	220mm	Single hull	FT-136SE
SB3	¥ 20,000	10.9 kg	S13560_260R	3:1	220mm	Single hull	FT-136SE
SB4	¥ 20,000	10.7 kg	S13560_260R	None	160mm	Single hull	FT-136SE
SB5	¥ 451,500	13.76kg	S13560_260R	3:1	220mm	Dual hull	SP50f
SB6	¥ 20,000	10.9 kg	S13560_260R	3:1	160mm	Single hull	FT-136SE
SB7	¥ 20,000	10.7 kg	S13560_260R	None	220mm	Single hull	FT-136SE

Table 2. Subsystem-components used in the designs. Descriptions of the components are provided in Table 3. Note all designs contain both overhead components.

Component type:	**Name:**	**Cost (¥)**	**Mass (kg)**	**Further details**
Motor	L3040A-480G	2,100	0.19	Low mass low torque (Kv = 480 rpm / Volt).
	S13560_260R	0 (Retail 202,500)	1.75	Retained from previous years. (Kv = 69 rpm / Volt).
Gearbox	13:1	17,300	0.03	Compact planetary gearbox.
	3:1	0	0.2	Made by students from existing parts.
	None	0	0	For architectures with no gearbox.
Propeller	220, 200 or 160 mm	0	0.02	Made by students. 220, 200 or 160 mm diameter. 2 blades.
Hull	Single hull	20,000	0.69	Made by students but requires much material. 2.3m x 0.17m x 0.19,
	Dual hull	40,000	1.39	Made by students but requires much material. 2.3m x 0.17m x 0.19,
Solar panels	FT-136SE	0 (Retail 450,000)	3.24	Retained from previous years. 6 panel array.13.5% efficient.
	SP50f	411,500	5.4	6 panel array. 20.5% efficient.
Overhead	Control	0	2.7	Control system. All boats assumed to have this. From previous years.
	Structure	0	2.3	Miscellaneous extra mass. All boats assumed to have this.

Table 3. SolarBoat designs used in this example.

4.6. Simulation conditions

100 Monte Carlo trials were run for each design, selecting environmental variables from probability distributions presented in Table 1. Simulation was conducted in Dassault Systèmes Dymola.

4.7. Results

The results of the assessment of the various designs are presented in Fig. 6. The left side plot shows the cumulative predicted time to complete the race. The right side plot shows the cumulative probability of winning. Designs found to be over the budget limit are marked by the fine dashed line (i.e. SB5 is too expensive). Because of the uncertainty associated with these results, SB3 was simulated for 10, 100 and 500 trials to test the effects of number of Monte Carlo trials. Fig. 6 shows that when 10 trials are used, SB3's performance is significantly different than with 100 and 500 trials. The similarity of 100 and 500 trials indicates that 100 is sufficient. However, this experiment shows SB2 and SB3 are producing very similar performance and the difference in the simulation is likely uncertainty. As such, for designs with value predicted to be somewhat similar the engineer should exercise caution and investigate further.

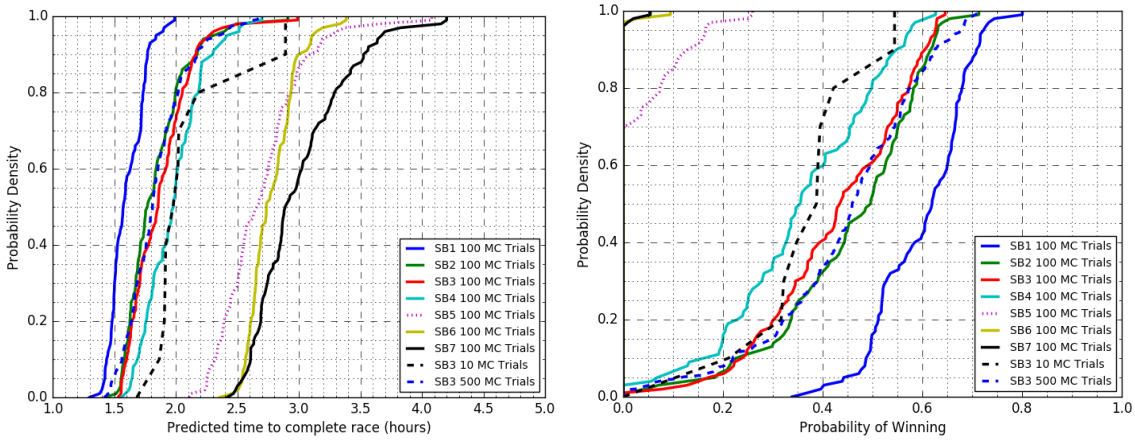


Fig. 6 Cumulative Probability density functions for predicted time to complete race (left side) and probability of winning the race (right side) for multiple SolarBoat designs (Table 3). Note the fine dash line indicates the design is beyond the budget i.e. SB5.

Of the designs, SB1 strongly dominates the alternatives. To investigate SB1 further in comparison to SB2 and SB3, all three were simulated under mean environmental conditions (results in Table 4). It reveals that SB1 is the fastest despite not having the highest steady state thrust. Thrust generated is a complex interaction between the spin speed of the powertrain and the boat velocity. Reviewing the thrust profiles (Fig. 7 left) shows SB1 has a wider thrust band enabling the boat to accelerate for a longer period of time. Reviewing the motor spin speeds (Fig. 7 right) shows SB1 is the only one to reach the nominal speed. Given SB1 scores so well the importance of good powertrain matching is clear. In 2015, a design using SB2's drive train had been selected based on static thrust testing, the research presented here indicates the smaller propeller of SB1 would be higher performance if the boat were moving.

Design:	Results at 100 seconds				
	Velocity (ms^{-1})	Drag (N)	Thrust (N)	Motor nominal speed (rad s^{-1})	Motor speed (rad s^{-1})
SB1	3.5	16.9	16.9	949	1030
SB2	3.1	14.4	14.4	949	918
SB3	3.1	17.0	17.0	272	217

Table 4. SolarBoat designs used in this example.

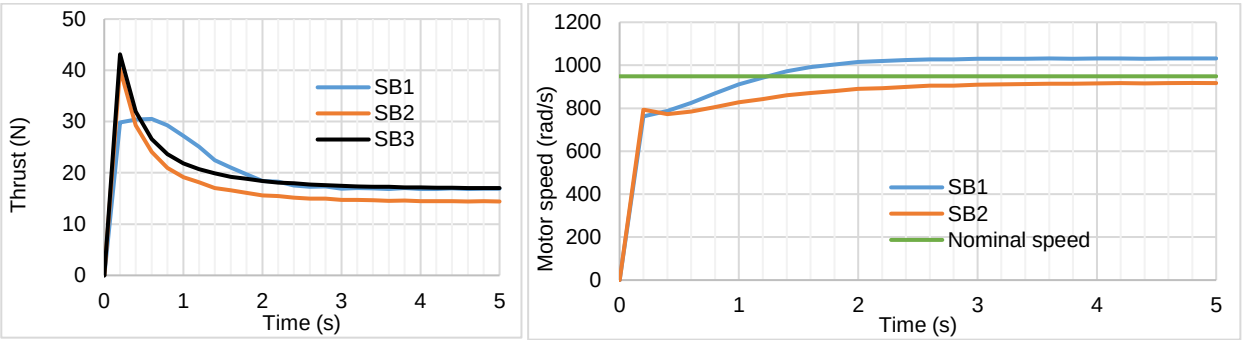


Fig. 7 Left: Thrust profiles for three solar boat designs. Right: Motor spin speed comparison.

5. Discussion

5.1. Benefits

The proposed approach makes it possible to logically compare and subsequently select alternative designs that are subject to uncertain environments by providing an assessment of the expected value created by each alternative and a measure of uncertainty associated with the said value measure. For the

case study of the SolarBoat, this measure was the probability to win the race, for which cumulative probability distributions were created for each alternative design (Fig. 6 right side). This operationalization of VDD enables the project team to explicitly target the metric of success and model it explicitly (i.e. the value function displayed in Fig. 3 for the running case study), enabling the logical ranking of the performance of various designs. This contrasts with the authors' past work where either a multi objective value function was used [4, 6] or the time to complete the race was predicted [5] which then created optimization problems which do not focus what the team is ultimately trying to achieve (i.e. win the race). By adopting VDD for this paper the team can focus clearly on this value, thus, the expected benefits of VDD have been demonstrated.

Given the uncertainty present in the environment that the design operates in, it is critical to capture this to the best of our knowledge and use it to make informed decisions. The use of a Monte Carlo method and comparison of cumulative probability distributions provided a method to achieve this. Previous work by the authors simulated for a range of weather conditions but did not take into regard the likelihood for each of those weather conditions. This paper integrates the various weather conditions based on their individual likelihoods and thus provides an overall likelihood of a particular design to win the race.

Further, similar to the authors' previous studies the use of the hierarchical object oriented features of Modelica enabled the rapid comparison of alternative designs such that there can be encouragement to review significantly different designs (which can all utilize the same interface) and so consider designs which might otherwise not be considered. All of which can now be assessed against the primary value of winning the race.

5.2. Limitations

The models presented of the environment, race and boats are likely not sufficient to provide the information needed to make all the decisions regarding what system architecture to build and race. Therefore, their fidelity should be improved. Further, the results output (Fig. 6 right side) lacks any assessment of the uncertainty that these results are subject to, making it potentially difficult to select between designs.

Finally, the synthesis process for the creation of design alternatives is only described briefly and needs to be expanded, particularly with regard to the flow down of the value function such that subsystems and subsystem components can be designed contributing to the overall project value.

6. Conclusions and future work

Given VDD is seen as a promising alternative to the inadequacies of the current design approaches, such as requirement-based design and Cost As Independent Variable (CAIV), the aim of this paper was to show how Modelica can be used to operationalize VDD and demonstrate its use on a novel case study. We applied the approach to the selection of a conceptual design for a student autonomous solar powered boat race, which given its novel nature, required a non-monetary value function (probability to win the race) to be used. Modelica's object-oriented features were shown to enable the assessment of all the designs consistently and Monte Carlo simulation allowed the introduction of uncertainty.

While the approach was shown to provide much benefit for implementing VDD, there are limitations and obstacles identified that should be addressed in future work. We identified primarily four key topic areas of interest: the creation of higher fidelity models, uncertainty assessment of the results, the design synthesis approach, and value model decomposition. Each of these are addressed below.

Firstly, the limitations of the models used in the research have been described in detail previously. Specifically, to address the environmental model, the independence of environmental variables should be removed and additional environmental variables introduced (e.g. waves and gusts of wind). This would then lead to more accurate modeling of the race of which a more accurate value model could be created making use of more data points of past race performances and incorporate the weather conditions to represent the beliefs the team has that the boat will win for a range of environmental conditions. As for the boat designs, currently the boat is not simulating turning functionality and thus not simulating the full journey between the

waypoints. In addition, reliability performance is critical for project success and thus should be included in the model with breakdowns increasing the time to complete the race.

Secondly, an appreciation of the uncertainty in the results would be beneficial for decision making (e.g. add *thickness* to the results plots in Fig. 6).

Thirdly, this paper uses System of Interest models (i.e. SolarBoat designs) that were created in prior research; there is no attempt to provide an explicit methodology for the synthesis process (of function, system architecture or parameters). Past work by the authors in [4] has attempted research in this area by means of the OPM language. However, further work is required as this offers an avenue to which this work can be generalized to other domains.

This leads to the forth topic for further work; value model decomposition, as the synthesis of designs will require such decomposition to enable the synthesis of a set of subsystems and subsystem-components which themselves address their own value functions derived from the whole system value function.

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