



# Forecasting design and decision paths in ship design using the ship-centric Markov decision process model



Austin A. Kana\*

Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology, Mekelweg 2, 2628 CD, Delft, the Netherlands

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## ABSTRACT

This paper introduces a decision-making model for forecasting design and decision paths in ship design by applying eigenvector analysis to the ship-centric Markov decision process (SC-MDP) model. This paper uses the concept of composite reducible Markov processes to identify various independent design absorbing paths. An absorbing path represents the long term behavior of a temporal decision process. This method identifies the set of absorbing paths by decomposing the process into sets of inherently independent parts and thus also gives insight into the structure and relationships of the decision process. This is done by examining the set of principal eigenvectors. Two metrics are introduced. First, the set of principal eigenvectors is used to identify all independent design absorbing paths without the need for full examination of all initial conditions. Second, through the use of the Moore-Penrose pseudo-inverse, the set of principal eigenvectors is used to estimate the optimal life cycle strategy of the decision process. A case study is presented involving life cycle planning for ballast water treatment compliance of a notional container ship to show the utility of these methods and metrics.

## 1. Introduction

This paper presents an eigenvector approach to the ship-centric Markov decision process (SC-MDP) model designed to forecast design and decision paths of maritime engineering design decisions. Specifically, this paper shows how the set of principal eigenvectors stemming from the SC-MDP model can be used as a leading indicator to identify and quantify the set of viable paths the design will converge to in the long term. These paths are defined as the absorbing paths of the process. This method decomposes the decision process into inherently independent parts that then provide insight into the absorbing paths. This paper follows in a series of publications aimed at exploring the applicability of the SC-MDP model to ship design and decision making. This introduction first lays out the problem background that lead to the initial need for the SC-MDP model, and second it highlights previous SC-MDP work to help place this particular paper in context.

Kana et al. (2016b) described many of the problems associated with making sound maritime engineering design decisions. They discussed how maritime design decisions are inherently sequential in nature and are influenced by uncertainty. The decisions made early in the process can have a disproportional impact on the final design, despite the lack of detailed information that is present early on (De Nucci and Hopman,

2012; Andrews et al., 2006). Uncertainty exists not only in regards to the lack of detailed information, but also in regards to future impacts of these decisions as there are currently no standard metrics for defining the future impact of design decisions or quantifying their costs (ONR, 2011). These decisions inevitably reduce design freedom moving forward and may cause design lock-in (Niese et al., 2015; Mavris and De Laurentis, 2000). Poor decision making can have negative impacts on the final design (De Nucci and Hopman, 2012), and can possibly lead to design changes later in the process. The costs of these design changes become exceedingly higher later in the design and life cycle of the vessel (Keane and Tibbitts, 1996). This causes a need for making sound decisions early, even in the face of uncertainty.

These decisions also have relationships and dependencies that may not be immediately obvious to the decision maker. These dependencies may influence other decisions, or they may relate to the interplay between the design problem statement and the design generation (Kana et al., 2016b). For instance, how does the decision to require the installation of a specific ballast water system during the construction of the vessel affect the opportunity to choose a different technology at some later point during its life cycle? This initial decision may be related to a strategic partnership between the company and the vendor, or it may be dependent on available technologies that meet a specific regional regulation. This is particularly challenging when making

E-mail address: [A.A.Kana@tudelft.nl](mailto:A.A.Kana@tudelft.nl).

\* This work was performed at the University of Michigan.

decisions regarding technologies that may still be under development. Understanding how decisions relate to each other and understanding their future impact on the final design is thus important during the design process and life cycle of the vessel.

Maritime design is also extremely sensitive to externalities, both throughout the design process, and throughout the life cycle of the vessel. These externalities may include upcoming regulations, changing economy, or posturing of economic competitors (Kana and Harrison, 2017). Due to the long time frame and high expense of the ship design and production process, decisions about vessels must be made well in advance without complete knowledge of future developments. Failure to properly navigate this landscape can have significant ramifications for the vessel or economic viability of the company. Being able to simulate various future scenarios to test their impact on design decisions made today could be very beneficial.

To approach this problem of evaluating design decision in the face of temporal uncertainty, Niese and Singer (2013) developed the SC-MDP model. The model was originally created to study life cycle decision making in the face of evolving environmental regulations. To do this, the SC-MDP model was developed to generate and analyze time domain ship design data under uncertainty. The SC-MDP model is defined as applying Markov decision processes to ship design and decision making. The model has previously been used to study a broad spectrum of attributes related to ship design decision making. This model has been used to study optimal decision paths for vessel technologies in the face of uncertain environmental policies, such as ballast water treatment compliance (Niese and Singer, 2013), the Energy Efficiency Design Index (EEDI) (Niese et al., 2015), and Emission Control Area (ECA) regulations (Kana et al., 2015). The previous research worked to quantify probabilistically what the best sequence of decisions that one should take to minimize their costs when regulations change.

Niese and Singer (2014) also studied the changeability of a vessel design throughout its life cycle in the face of uncertainty external pressures. They introduced new metrics on quantifying when costs are incurred and how much, and when, active management may be necessary for a specific ballast water system on a given ship. Niese et al. (2015) then later analyzed initial ship design alternatives and the presence of design lock-in given uncertain future scenarios. This previous work performed by Niese and his co-authors was based around performing simulations through the SC-MDP model to examine how certain decisions may constrain future opportunities and to discern differences in seemingly similar solutions.

Kana et al. (2016a) recognized that one limitation of these analysis techniques is that in many complex situations there are a vast number of possible paths available to the decision maker. Here, simply obtaining the final result does not provide sufficient insight, especially if it not clear how those results were obtained (Klein et al., 2009). In these cases, forecasting specific decision paths to gain an understanding of the structure, relationships, and sensitivities of these decisions may prove to be invaluable when trying to obtain specific results. For instance, how do you filter all the available design and decision options down to only those that are technically and economically viable? Is it possible to do this without full enumeration of all possible design options and all possible initial conditions? For these reasons, Kana et al. (2016a), Kana and Singer (2016) introduced a means to perform eigenvalue analysis to the SC-MDP model. This was done to quantify changes in individual decisions and to forecast the number of independent design and decision paths the process may follow.

This paper extends this work by introducing temporal eigenvector methods to gain a deeper understanding of the driving forces behind the different decision making scenarios, as well as quantifying their differences. To forecast future implications of the decision process, this paper discusses the concept of absorbing paths. An absorbing path represents the long term behavior of a non-stationary decision process. More than

one absorbing path may exist for the whole decision process, each one being dependent on the initial state of the system. These specific initial states of the system are considered the initial conditions of the system in this paper. Sensitivities to initial conditions has been known for decades to be a challenge when studying path dependent systems (Liebowitz and Margolis, 1995). Niese et al. (2015) discussed the importance of identifying the presence of multiple absorbing paths. They discussed that differing absorbing paths may mean that differing decision sequences may be viewed as only locally optimal. They were able to identify the multiple paths via simulation studies. This paper, on the other hand, claims that these differing paths are in fact dependent on where the system initially starts. Also, this paper uses eigenvector analysis as a leading indicator metric to identify these multiple absorbing paths without the need for potentially costly simulations and recursive investigation of the initial conditions. By developing a leading indicator metric for the design absorbing paths, the structure and dependencies of the decision process may become more clear.

As no single model can handle all aspects of design decision making or types of marine design vessels, (Andrews, 2016; Seram, 2013; Reich, 1995) this papers helps to provide one unique perspective on approaching this difficult problem. A case study discussing life cycle planning for ballast water treatment compliance is presented to demonstrate the significance of the set of principal eigenvectors in forecasting future scenarios and on identifying various inherently independent design absorbing paths.

## 2. Methods

The methods presented in this paper involve the following four primary steps. Each step is presented in more detail below.

1. Obtain the decision policy and associated expected utilities by solving the standard ship-centric Markov decision process.
2. From the set of decisions, develop a series of representative transition matrices,  $\mathbf{M}$ , for each decision epoch. The eigenvectors are then generated from  $\mathbf{M}$ .
3. Identify the absorbing paths of the decision process by decomposing  $\mathbf{M}$  into its set of principal eigenvectors. These principal eigenvectors define the absorbing paths. This follows the concept of composite reducible Markov processes.
4. Use the Moore-Penrose pseudo-inverse of  $\mathbf{M}$  to generate an estimation for the optimal behavior of the decision process. This step highlights the relationship between the principal eigenvectors of the system and its physical behavior.

### 2.1. The markov decision process

Markov decision processes are a mathematical model designed to handle dynamic sequential decision-making problems under uncertainty. They represent uncertain systems, can differentiate actions, and can handle temporal system variations. An MDP consists of a set of states,  $S$ , a set of actions,  $A$ , a set of probabilities,  $T$ , of transitioning between different states, and a set of rewards,  $R$ , received after landing in a given state,  $s$ , after taking a specific action,  $a$ . The objective of an MDP is to identify the decision policy that maximizes the cumulative, long term expected utility of the system. This policy takes into account both the outcomes of current decisions and future opportunities. The expected utility of the MDP can be obtained via Eq. (1), known as the Bellman equation, where  $U$  is the expected utility,  $\gamma$  is the discount factor, and  $s'$  is the future state.

$$U(s) = R(s) + \gamma \max_a \sum_{s'} T(s, a, s') U(s') \quad (1)$$

The decision policy,  $\pi$ , is found by taking the argument of Eq. (1), as defined in Eq. (2) (Russell and Norvig, 2003).

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