Modeling Sequential Design Decisions Using Fine-Grained Empirical Data

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1. Highlights

The authors propose a Markov decision process (MDP) based framework to model sequential design decisions in engineering systems design using fine-grained design action data logged by computer-aided design (CAD) software. This preliminary work is focused on testing the predictive performance of four autonomous learning models, including a Markov chain model (MCM), a hidden Markov model (HMM), a feedforward neural network (FNN) model, and a recurrent neural network (RNN) model without constructing the reward function in MDP. The models are applied to predict design processes (i.e., the data transformed from design actions using design process models) in a solarized house design problem, and the results indicate that RNN best predict the next design process with an accuracy of 56.4%.

2. Research Questions

Design involves finding problems and solving them. The first stage is a process of transforming design problems from ill-defined to well-defined for design requirements extraction and design constraints development. This stage defines the design space. The second stage is focused on decisions of searching for solution points within the design space identified. The decisions in this stage are stepwise and iterative, thus often referred to as *sequential design decisions*. The entire design process flows from requirement analysis (customer domain) through product evaluation and realization (process domain) in a sequential yet iterative manner. Therefore, sequential decision-making plays an essential role in engineering design process. It has significant impact on the quality of design outcomes and the resources needed to achieve the outcomes. Despite much effort in theoretical modeling of sequential design decision-making, there is a lack of foundational understanding on *how* and *why* particular design sequences emerge in the context of systems design. Existing studies are often conducted in simplified scenarios, limiting the generalizability of their findings to design at the systems level. To fill the gap, we aim to answer the following **research question: what are the explanatory models for designers' sequential decision-making behaviors in systems design?** The hypothesis is that the behaviors can be modeled as MDP and designers' decision-making strategies can be learned with deep neural network methods.

3. Main Contributions

The major contributions of this study are manifested in two aspects, as summarized as follows.

3.1 Modeling sequential design decisions as a reward-driven decision-making using MDP

A *Markov decision process* (MDP) is a stochastic process in which a system transitions among a set of states [1]. Despite various applications of MDP ranging from intelligent robots to game playing, its application in engineering design field remains to be fully utilized. In this project, we take a step towards demonstrating the utility of MDP in modeling human sequential decision-making in engineering design. In the design context, states are the cognitive states-of-mind through which a designer passes while working on a systems design project using CAD software, and transitions are initiated by the

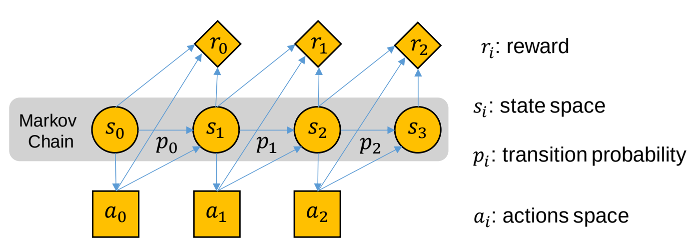

Figure 1. Using the Markov decision process to characterize a sequential design decision-making process

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actions/operations that a designer performs. By using an MDP to model transitions between states, we can gain important insights into designers' cognitive processes. A diagram of the problem is shown in Figure 1. Circles represent states. These are hidden from observation but are of primary interest in our study. Squares represent the actions that designers take. They are assumed to be the product of an unknown function of the current state. An important step in this study is to learn a model of that unknown function from observed data. Diamonds represent the rewards that designers have been instructed to pursue, i.e., the design objective. The reward is a quantitative assessment of the extent to which the designer has achieved that objective. When these components are put together, our model provides an explanatory framework to answer why certain design actions are followed in addition to understanding how likely transitions would happen between design actions.

3.2 Identification of data requirements for machine learning sequential design decisions

In design community, empirical studies have been a common practice for studying engineering design thinking. Fine-grained temporal data captured by CAD software may provide a high-resolution lens for probing into designer thinking. To successfully answer the research question, the data is critical and specific requirements deserves careful attention. We identified five points:

a) *Intra-stage and inter-stage design iteration.* Design iteration does not only occur within each stage but also between stages [2]. The decisions made during such an iteration plays a vital role in assuring a successful design. The collection of design process data and design actions in both *intra-stage* and *inter-stage* iterations is required.
b) *High fidelity*. In a design process, ad-hoc decisions are often made. Unnoticeable actions could be nontrivial information reflecting useful decision-making strategies. The data should be a collective memory of the complete output and all iterations in design.
c) *Non-intrusive collection*. Intrusive data collection (e.g., interviews) is time-consuming, thus often restricts research scale [3, 4]. Such a process could easily add cognitive loads to designers, thus contributes biases toward the observed behaviors, which can diminish the validity of results. The data should be collected without disturbing the design process in a non-intrusive manner.
d) *Rational behavior*. Most decision theories assume rational behaviors, but designers have bounded rationality [5]. When collecting behavioral data, designers' irrational behaviors should be mitigated to assure the quality of the data.
e) *Multiple forms.* The data should be a combination of operational, textual and even video data to support the cross validation of the research methodology.

4. Preliminary Work and Closing Remarks

We designed a field experiment to collect data satisfying the above requirements. A subject is tasked with designing a solarized house, maximizing energy efficiency while limiting the overall building cost. Subjects designed the houses in Energy3D, a software that automatically logs every action as they performed. A Function-Behavior-Structure (FBS) based design process model is adopted to code the design actions into seven design process categories that reflect designers' decision-making. With these data, four different models, including the MCM, the HMM, the FNN, and the RNN, are tested in predicting the sequential design processes. The prediction accuracies are 55.51%, 56.07%, 55.34%, 56.43%, respectively. The results show that both of the HMM and the RNN that capture information about other time steps encoding certain degree of memory effect outperform the two models (the MCM and the FFN) that do not. We also observe that the RNN outperforms the HMM, demonstrating that the neural network model is able to capture more information than those traditionally used in this field.

In the future study, on the one hand, we aim to construct a complete MDP model (as shown in Figure 1) by taking the reward structure into account and integrating the RNN to predict design actions. On the other hand, we plan to develop a model to better understand and predict human sequential decisions in engineering design, meanwhile capturing system design features, such as nonparametric forms, coupled design variables, and ill-defined constraints [6], and many factors in systems thinking, such as the capability of handling problem complexity [7] and uncertainties [8], that can influence designers' sequential actions and final design quality.

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