Visualization of heuristic-based multi-objective design space exploration of embedded systems
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1 Introduction

1.1 Design Space Exploration in Embedded Systems Design

The design of modern embedded systems is quite complex. On one hand, these systems often target mass production and battery-based devices, and thus they should be low cost, small in size, light weight and be power efficient. On the other hand, they need to execute a wide range of functionalities, and therefore need to achieve high (real-time) performance and flexibility. To support such a wide spectrum of non-functional demands, modern embedded systems often have a heterogeneous system architecture. They consist of components that range from fully programmable processor cores to fully dedicated hardware components for time-critical application tasks. Increasingly, such heterogeneous system components reside together on a single chip, yielding heterogeneous Multi-Processor System-on-Chip (MPSoC) architectures that exploit task-level parallelism in applications. These MPSoC systems have now become the keystones in the development of today’s modern embedded systems, such as smart phones, digital televisions, game consoles and navigation systems.

The complexity of these systems forces designers to simulate systems and their components in the very early design stages. This is often referred to as "system-level design". The system-level models are applied at a high level of abstraction, thereby minimizing the modeling effort and optimizing the simulation speed that is needed for targeting the early design stages. Design Space Exploration (DSE) assesses alternative architectural solutions and plays a crucial role in system-level architecture design. It can have a large impact on the success or failure of the final product. Especially, exploration of different design choices during the early design stages, where the design space is still at its largest, is of eminent importance. Wrong decisions early in the design can be extremely costly in terms of re-design effort, or even deadly to the product’s success.

The heterogeneity of these embedded systems and at the same time their conflicting design criteria greatly complicate system design. A large number of alternative
combinations of design parameters have to be considered and tuned to find the "best" tradeoff in terms of multiple design criteria. Such design space exploration, during which multiple criteria should be considered simultaneously, is called Multi-Objective DSE. Since objectives are often in conflict, there cannot be a single optimum solution, which simultaneously optimizes all objectives. Therefore, optimal decisions need to be taken in the presence of trade-offs between multiple design criteria. A set of optimal solutions is denoted as the "Pareto optimal set". This is the set of those solutions for which one objective cannot be improved further without causing a simultaneous degradation in at least one other objective.

In Figure 1.1 we illustrate the design space exploration problem on a simple example. In this example, the application description consists of four computational tasks and four communication channels. The architecture platform contains two processors and one shared memory. Let us assume three design criteria to be minimized, which are execution time, architecture cost and power consumption. Different mappings of application tasks and communication channels to various architectural components should be evaluated by simulation to find the optimum mapping solutions under the aforementioned design criteria. Each mapping decision corresponds to a single point in the design space. Moreover, each mapping decision consists of two parts: allocation and binding. The allocation determines which architectural components are actually used. The binding indicates which application task is executed by which allocated processor and which communication channel is mapped on which allocated processor/memory. Note that if two communicating processes are mapped onto the same processor, then their communications are done internally and therefore communication channel(s) between them are mapped onto the processor in question.

It is clear from Figure 1.1 even without taking into account any system criteria, that the number of alternative mappings (i.e. the size of the design space) is extremely large as it grows exponentially with the size of the application model (i.e. number of compu-
1.2. THE NEED FOR VISUALIZATION

System-level simulation frameworks that aim for early design space exploration may produce vast amounts of data on various characteristics (performance, power consumption, reliability, etc.) for the architecture(s) under investigation. Interpreting and drawing the right conclusions from such copious simulation results may be extremely cumbersome. Typically, the results of simulations are summarized in a number of quantities, such as average load, throughput, latency, or power consumption. Such numbers are useful to compare different configurations, but from these numbers alone it is often impossible to understand the reasons behind these differences and to spot anomalous behavior. So, they do not facilitate the understanding of the landscape of the design space, i.e., understand the often subtle relations between design decisions and their effects. For this, the data has to be studied in much more detail, and visualization is the most effective approach to accomplish this. Because of exactly this reason, other domains that also struggle with interpreting massive amounts of data, such as scientific computing, data visualization has become an invaluable tool to facilitate the data analysis. As a result, visualization has become a research field in its own right in these domains. Such visualization, however, is often domain specific and therefore not necessarily applicable to other fields.

Despite the clear benefits, little research is being conducted on methods and techniques for visualizing the results of (system-level) computer architecture simulations. Even worse, visualization approaches to support the process of architectural DSE is very much an unexplored research field. Existing visualization work in the context of computer architecture simulation mainly focuses on visualization technology for educational purposes (e.g., [5][7]), tightly couples visualization to one particular architecture simulation environment (e.g., [8][11]), visualizes only one specific aspect of embedded applications, often lower than system-level, such as memory access patterns [12], cache behavior [13][15] and data dependencies [16], or only provides some basic support for the visualization of simulation results in the form of 2D (and sometimes 3D) graphs (e.g., [17]). However, as we will demonstrate in this thesis, visualization can be extremely helpful to a system designer in interpreting and analyzing the DSE results.
1.3 Problem Description

The purpose of this research study can be summarized in the following question:

How can interactive visualization help to improve and accelerate system-level design space exploration of computer architectures?

Visualization of computer architecture simulations, and especially of those that target system-level design space exploration, is a largely unexplored research area. We expect, however, that by embracing visualization techniques, as has been done in other domains such as scientific computing and software engineering, much can be gained to improve computer architecture design technology. To this end, in this thesis, we introduce the structural use of visualization techniques in the design of embedded systems, and specifically for supporting the design space exploration of embedded systems. We incorporated all the developed visualization techniques into a tool, called VMODEX[1]. Actually, we build a bridge between two previously separate research fields: data visualization and embedded system design, and show how our proposed visualization techniques can help designers for better understanding and analyzing the DSE results.

An important challenge in this respect is how to define suitable metaphors to represent the abstract concepts, such as execution time, energy consumption, power, etc, in a visual form that is clear and understandable. For visualizing the abstract information, there is no natural counterparts in the real world and therefore the user has no predetermined mental model to which the data can be automatically mapped. Another important issue that needed to be addressed is that the visualization approach should not be limited to only two or three variables. It should be extendable to show multivariate data. Furthermore, the visualization technique should be scalable to support large design spaces. It is essential to be able to handle the large-scale experimental and simulation data sets. The efficiency of the visualization should not be dependent on the size of the data (i.e. the usefulness of the visualization should not be reduced by increasing the amount of the visualized data). Our proposed visualization techniques address all the above challenges.

For developing an effective visualization of data and information, user interaction plays an essential role. It allows users to directly manipulate the representation and to explore the data actively in order to investigate the data from different perspectives and discover new insights. In VMODEX, we provide various interactive capabilities, which allow designers to play with data and find out interesting and important features that may not be found just by looking at the static visualization.

In this thesis, we propose visualization techniques that support system-level multiobjective design space exploration process. The designer can use our visualization tool to gain insight into the landscape of the design space and look at the explored data from different perspectives and at multiple levels of abstraction. Furthermore, additional capabilities are developed to understand the dynamic search behavior of heuris-

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[1]Visualization of Multi-Objective Design space Xploration
tic searching algorithms that are typically used in the DSE process (e.g. which parts of
the design space are not visited by the algorithm). Moreover, we have proposed new
visualization approaches to visualize the performance of different optimization meth-
ods from various points of view, which enable researchers to do detailed analysis of
the quality of the outcome of searching algorithms that are used for exploring the de-
sign space. In addition, we define new visual representations of the results of decision
making methods. These visualizations can help to gain a better understanding of the
trade-offs between different design criteria and provide some guidelines for choosing
the most preferred solution for the final implementation. For performing a comprehen-
sive study of the DSE process, we define three separate stages and for each stage, we
have developed several methods and visualization techniques to provide users a rapid
and more accurate analysis. In the next section, we explain these stages in details.

1.4 Multi-Objective DSE Stages

The process of multi-objective design space exploration is not just evaluating differ-
ent design points in terms of design criteria. There are some other issues that need
to be addressed to perform a comprehensive DSE process. One important issue is
developing an efficient searching algorithm for exploring the design space. This is
because the size of the design space is usually too large to be explored in an exhaus-
tive manner. Another problem is how one particular design point among the Pareto
optimal points can be selected for the final decision. This question arises since in
the presence of multiple conflicting objectives, there cannot be a single design point
that simultaneously optimizes all objectives. Instead, a set of Pareto optimal points
need to be found that provides trade-offs between multiple objectives. In the math-
ematical sense, all Pareto optimal solutions are regarded as equally desirable. Thus,
some multi-objective decision making methods should be used for choosing the most
preferred design point.

In this thesis, we define three stages for doing a comprehensive multi-objective design
space exploration:

1. Developing the best optimization algorithm that efficiently and effectively ex-
plores the design space.

2. Exploring the design space using the best optimization algorithm, finding the
Pareto optimal points and analyzing the DSE results (i.e. gaining insight into
the landscape of the design space).

3. Selecting the most satisfying solution from the Pareto optimal set for the final
implementation (i.e. multi-objective decision making).

Figure 1.2 shows the stages of multi-objective DSE. For each stage, we have developed
several methods and visualization techniques for performing a rapid and more accurate
analysis. Thus, using our proposed techniques, one can perform a comprehensive
1.4. **Multi-Objective DSE Stages**

Due to the sheer size of the design space in real problems, an exhaustive exploration of all possible alternatives is not feasible. Furthermore, usually multiple criteria need to be optimized simultaneously. Therefore, heuristic search techniques, such as Multi-Objective Evolutionary Algorithms (MOEAs), are often used for pruning an exponential design space and guiding the search process toward the most promising regions.

Although the goal of heuristic multi-objective optimization techniques is to find the Pareto optimal solutions with respect to the design criteria, there is no guarantee to reach real optimal solutions. This is because of the heuristic nature of these methods. They try to find optimal solutions. However, typically they are only able to find good approximations of optimal solutions that are not far away from the true optimal solutions. Furthermore, many different multi-objective optimization algorithms are proposed in literature, such as SPEA2 [18], NSGA-II [19], PAES [20], ACOG [21], AMOSA [22] etc., which may have a different performance on different problems, and there is no conclusive answer regarding to which algorithm is the best for a specific problem. On top of that, optimization algorithms are highly sensitive to the parameters being used, such as mutation rate, repair strategy, individual encoding, etc. These parameters have major effects on the performance of the algorithm and have to be fine-tuned by hand. Therefore, coming up with the best searching algorithm, which efficiently and effectively explores the design space and finds high quality solutions is

**Figure 1.2:** The stages of multi-objective design space exploration

...study on the entire design space exploration process. In the following subsections, we describe each stage with more details.

### 1.4.1 Developing the Best Optimization Algorithm

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Therefore, we have developed techniques to help algorithm developers to find the best optimization algorithm for their specific problem. These techniques have been incorporated in VMODEX. Thus, using VMODEX, algorithm developers can easily evaluate and compare the results of different optimization methods, with respect to their efficiency and effectiveness, in order to find the best approach. Then, the best optimization algorithm is used for exploring the design space and the results are delivered to the designers for analyzing the DSE process.

### 1.4.2 Exploring the Design Space

After finding the best optimization algorithm for a specific problem, this algorithm is used for exploring the design space and finding the Pareto optimal solutions. As the searched design space still is vast, interpreting all evaluation data and understanding how the optimization algorithm searches through or prunes the design space is cumbersome. Such analysis is, however, essential to the designer as it provides insight into the landscape of the design space (e.g., indicating which design parameters are more important than others). Therefore, we have developed a multi-objective DSE visualization, to understand how a heuristic optimization algorithm, searches the design space, where the optimum design points are located, how design parameters influence each objective, and provides insight into the relationship between the different objectives.

In addition, several interactive capabilities are provided, which enable the designer to analyze the data and explore the search result from different perspectives and at multiple levels of abstraction in order to discover interesting and important features that may not be found just by looking at the raw data or by using the traditional 2D/3D graphs.

### 1.4.3 Multi-Objective Decision Making

Finding the Pareto optimal points does not completely solve a multi-objective DSE Problem. The decision maker still has to choose one solution from this set to be implemented. However, the process of choosing the most preferred solution among the several Pareto optimal solutions is not trivial. Systematic approaches are needed to express preference information related to the multiple objectives and aid the decision maker to identify the most preferred solution. Without a systematic approach one cannot be sure that the proper decision has been made. In VMODEX, we have provided several decision making methods and visualization techniques to assist the decision makers to better understand the trade-offs between different criteria and guide them to make better decisions.
1.5 Thesis Organization and Contributions

In this thesis, we address the visualization of multi-objective design space exploration of multi-processor system-on-chip architectures. Actually, we build a bridge between two previously separate research fields. We introduce the structural usage of data visualization into the field of embedded systems design. This has not been done before, and in fact, we extend the boundaries of visualization to include new applications from other domains. We propose new visualization techniques for interpreting and analyzing the DSE results.

The main contributions of the thesis are presented in Chapters \( \text{3, 4 and 5} \), each focusing on a different stage in the process of multi-objective DSE, as explained in the previous section. The organization of the thesis and the main contributions of each chapter are as follows.

Chapter 2 gives an overview of the background information necessary for the rest of the thesis. We first describe the basic knowledge about multi-objective optimization problems. Then, we explain the multi-objective optimization problem in the context of design space exploration of embedded systems. This is followed by two subsections that describe two distinct issues in our DSE problem: the evaluation of a single design point and the searching strategy for exploring the design space. The first subsection introduces the Sesame system-level simulator \([23, 24]\), which is used for evaluating design points. In the second subsection, we describe multi-objective evolutionary algorithms as a heuristic searching method for solving the second issue. Afterwards, we discuss the benefits of using visualization techniques for exploring and analyzing the data. Finally, we conclude this chapter and illustrate the need for employing efficient visualization methods for interpreting and gaining insight into the DSE results.

Chapter 3 introduces our interactive visualization tool, which is specially developed for understanding the multi-objective DSE process of embedded systems that are based on heterogeneous multi-processor system-on-chip architectures. It provides insight into the search process of heuristic searching algorithms that are typically used in the DSE process. Several interactive capabilities are provided, which allow designers to play with data and find out some interesting and important features that may not be found just by looking at the static visualization of the data. This chapter supports the second stage of multi-objective DSE, as explained in Section 1.4.2 In the following, we summarize our main contributions in this chapter:

- We model the design space as a tree in which both the design parameters and criteria are shown in a single view.
- The proposed tree model enables us to visualize multivariate data. There is no limitation on the number of neither design parameters nor criteria.
- Several techniques are provided in VMODEX to be able to handle large design spaces.
- In our DSE tree model, the concepts of subspaces and local Pareto points are
proposed, which are new concepts in the multi-objective DSE process and have not been considered before.

• Various methods and visualization techniques are proposed for evaluating and comparing different subspaces of the design space.

• Additional visualization approaches are defined for showing different aspects of the characteristics of each design point. These aspects are referred to as secondary objectives in this chapter and allow designers to interpret the data from different perspectives and gain additional insight into the underlying information.

• Additional capabilities are provided to help designers to understand the dynamic search behavior in heuristic based design space exploration.

• We present an extensive case study to show the benefits of using our tool in the DSE process.

Chapter 4 is dedicated to the first stage of multi-objective DSE (see Section 1.4.1), which is evaluating the performance of different multi-objective optimizers and finding the best one for a specific problem. In this chapter, we introduce various performance metrics and their visualization methods we have provided in VMODEX for comparing the outcomes of different optimization methods from several points of view. In multi-objective optimization problems, several distinct goals need to be achieved and therefore there cannot be a single quality measure that indicates the performance of an optimization algorithm in an absolute sense. Thus, various metrics need to be used to perform a comprehensive analysis of the performance of an optimization approach. Our main contributions in this chapter are as follows:

• Proposing three new metrics for assessing the performance of optimization algorithms in the objective space, namely: WSGR, \( \sigma_{\text{rel}} \) and DFPOS.

• Turning the focus of attention from exclusively evaluating optimization success in the objective space to also considering the decision space.

• Defining new goals and subsequently new metrics to evaluate the behavior of optimization methods in the decision space.

• Proposing new visualization approaches for both existing and new metrics to enable algorithm developers a deeper and more accurate analysis of the performance assessment.

• Presenting a case study, which demonstrates the usefulness of using VMODEX for performing a comprehensive study on evaluating and comparing the performance of different optimization approaches.
Chapter 5 addresses the last stage of multi-objective DSE (see Section 1.4.3), which is the decision making process. As the last step of the multi-objective DSE process, the decision maker should select the most preferred design point from the set of Pareto optimal points. In this chapter, we explain the Multi-Objective Decision Making (MODM) methods that are provided in VMODEX and can help decision makers to understand the trade-offs between different criteria and select the final solution for the implementation. Furthermore, new visualization approaches are proposed, which provide the visual interpretation and detailed analysis of the results of the MODM methods. In this chapter, we describe the four basic problem formulations in MODM, which are: choice, classification/sorting, clustering and ranking problems. For each problem formulation, some decision making methodologies and their proposed visualizations are explained. Our main contributions in this chapter are as follows:

- We define a new method addressing the choice problem. Our method is based on the fuzzy dominance relations between the Pareto optimal points.

- We propose a new preference similarity measure for clustering the solutions. In our proposed similarity measure, unlike the conventional measures, the decision maker’s preferences are integrated in the multi-objective cluster analysis.

- We introduce a scheme for constructing the cluster centers, considering the properties of all solutions inside the same cluster. Some clustering approaches utilize the concept of cluster center for assigning the objects to different clusters.

- For each MODM method, we propose a new visualization approach. These visual representations allow decision makers to find out how and why a particular solution is considered as a most preferred solution with respect to a specific MODM method.

Finally in Chapter 6, we first look back and summarize what we have achieved, and then look ahead to outline what can be accomplished next.

This thesis work has resulted in several reviewed publications. The content of this thesis is mostly based on these publications. At the end of the thesis, a list of all our publications is given.