

# Interpreting Multi-objective Evolutionary Algorithms via *Sokoban* Level Generation

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**Abstract**—This paper presents an interactive platform to interpret multi-objective evolutionary algorithms. *Sokoban* level generation is selected as a showcase for its widespread use in procedural content generation. By balancing the emptiness and spatial diversity of *Sokoban* levels, we illustrate the improved two-archive algorithm, *Two\_Arch2*, a well-known multi-objective evolutionary algorithm. Our web-based platform integrates *Two\_Arch2* into an interface that visually and interactively demonstrates the evolutionary process in real-time. Designed to bridge theoretical optimisation strategies with practical game generation applications, the interface is also accessible to both researchers and beginners to multi-objective evolutionary algorithms or procedural content generation on a website. Through dynamic visualisations and interactive gameplay demonstrations, this web-based platform also has potential as an educational tool.

**Index Terms**—Procedural Content Generation, Multi-objective Optimisation, Multi-objective Evolutionary Algorithms, *Two\_Arch2*

## I. INTRODUCTION

Multi-objective optimisation problems (MOPs) are widespread across various domains [1], such as game optimisation [2], aero-engine calibration [3], trauma system design [4], and mitigating bias in decision making [5]. The literature demonstrates that multi-objective evolutionary algorithms (MOEAs) [1] can effectively address MOPs and produce diverse, high-quality solutions. However, studying MOEAs can be challenging for those unfamiliar with MOEAs. Motivated by this, we aim to develop a web-based interactive platform that visually demonstrates the optimisation process of MOEAs. This platform serves as a bridge between theoretical research and practical applications while meeting the needs of educators, students, researchers, and practitioners. Procedural content generation (PCG) often involves multi-objective optimisation challenges [6]–[8], such as balancing desired characteristics in game levels, like

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emptiness [9] and diversity [10], [11]. Moreover, the well-defined problem and the visually understandable solutions make PCG an ideal testbed for elucidating the mechanisms of MOEAs. Our web-based platform considers searching for levels of *Sokoban*, a puzzle game in which players push boxes onto targets, with design preferences such as minimalistic (emptiness) and diverse content (spatial diversity). Our platform integrates *Two\_Arch2* [12], a popular and effective MOEA, and interactively demonstrate its optimisation steps. Users can better understand the algorithm and its impact on game content and gameplay by interacting with our platform and through level visualisations, as shown in Fig. 1.



Fig. 1: Contributions of our web-based platform

## II. CONCEPT AND DESIGN

Section II-A briefly introduces *Two\_Arch2* and how it is adapted to *Sokoban* level generations. Section II-B details the design features for enhancing user understanding. The platform is publically accessible at <https://aingames.cn/demo/mopcg/index.html>.

### A. Searching for diverse game levels with *Two\_Arch2*

Our website is designed for visualising and searching for game content through MOEAs, particularly *Two\_Arch2* [12]. As shown in Fig. 2, *Two\_Arch2* adheres to the foundational principles of MOEAs, involving mating selection, reproduction, and survivor selection. The distinctive features of *Two\_Arch2* involve maintaining two archives during the evolutionary process: *convergence archive* (CA), which guides the population toward the *Pareto front* (PF) in terms of convergence, and *diversity archive* (DA), which ensures a rich diversity within the population, crucial for avoiding local optima. Besides the playability, we focus on spatial diversity (denoted as  $f_{div}$ ) [10] and emptiness (denoted as  $f_{emp}$ ) [9] to address multi-dimensional diversity [11], formulated as

$$\text{maximise } \{f_{emp}(\text{level}), f_{div}(\text{level})\}, \quad (1)$$

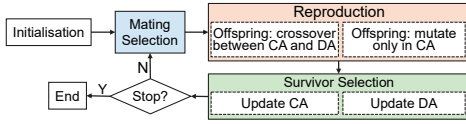


Fig. 2: Algorithmic process of Two\_Arch2

where  $f_{emp}$  represents the percentage of empty tiles within a *Sokoban* level, and  $f_{div}$ , defined as  $-\frac{1}{\log n} \sum_{i=1}^n \frac{\alpha p_i}{n} \log \frac{\alpha p_i}{n}$  within  $[0, 1]$ . A *level* is segmented into  $n$  parts, with each row representing a segment.  $p_i$  denotes the proportion of empty spaces within each segment, and  $\alpha$  is a normalisation factor, ensuring that  $\sum_{i=1}^n \alpha p_i = 1$ . A higher  $f_{div}$  indicates greater spatial diversity within a level, while a higher  $f_{emp}$  suggests the level is more minimalistic. Fig. 4c is an example captured from our website, a PF is observed in the space of emptiness and spatial diversity through Two\_Arch2 through our website.

### B. Website Features

The website integrates the process of generating *Sokoban* levels via Two\_Arch2 into a user-friendly interface that visualises the evolutionary process step by step. All interactive content is highlighted with the same *gesture* as in the example shown in Fig. 3. The design features include the following.

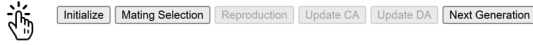


Fig. 3: Example of symbol and buttons for interactive content

1) *Background introduction and game settings*: The website starts with a basic introduction to MOEA and *Sokoban* levels represented as chromosomes. Users can customise the level parameters, such as size and layouts. An interface is designed for real-time modifications of the chromosome representations in response to the customised changes.

2) *Dynamic visualisation*: The current evolutionary process is dynamically highlighted in a chart of the overall process and one or more scatter graphs, characterised by emptiness and spatial diversity, representing the optimised level sets. Each point on a scatter graph represents a level individual, showcasing the progression, and providing visual feedback on the optimisation process, as shown in Fig. 4c.

3) *Step-by-step guidance and overview*: The demo provides a step-by-step explanation of Two\_Arch2 and includes information about each component, from chromosome representation, mating selection, reproduction (crossover and mutation, cf. Figs. 4a and 4b), to survivor selection processes. This educational strategy is designed to simplify complex optimisation processes for those new to evolutionary algorithms, multi-objective optimisation, or procedural level generation. It features tangible visualisations of *Sokoban* levels, enhancing user engagement and understanding. An overview section provides a comprehensive insight into the algorithm and displays the trends in the CA and DA over generations. Users can select any generated level from this overview to engage with in subsequent gameplay sessions designed by [13], thereby

deepening their understanding of the objectives of emptiness and spatial diversity.

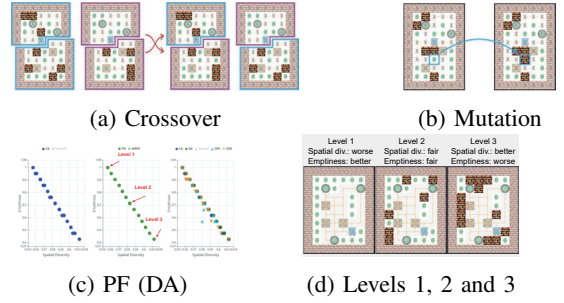


Fig. 4: Screenshots of some interactive content

### III. CONCLUSION

Our platform offers an interactive tool that enables diverse audiences to practically explore various fields, including multi-objective optimisation, evolutionary computation, and search-based level generation, making theoretical outcomes tangible. The platform is also suitable for various educational scenarios such as self-study and classroom use. In the future, it will enhance our platform by implementing various algorithms, allowing for a broader range of learning opportunities.

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