Interactive Visual Analysis of Robot Base Placement and Trajectory Optimization

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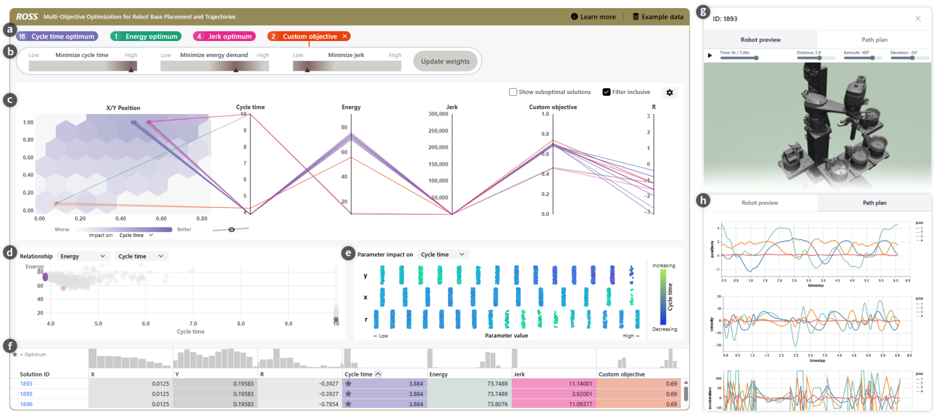

Figure 1: *ROSS consists of multiple coordinated views: (a) color legends indicate objective optima and enable toggling of corresponding solutions; (b) optional custom objective with adjustable weights; (c) spatially-linked parallel coordinates plot with an integrated base position map; (d) scatter plot for pairwise relationship analysis; (e) parameter impact view for a single selected objective; (f) multi-attribute ranking of solution instances; and (g) detail view with a 3D robot simulation, which can be switched to (h) multi-series joint trajectories.*

Abstract

Optimization procedures for industrial robot base placement and trajectory planning typically result in the selection of a single solution and provide limited support for understanding the broader solution space or reasoning about trade-offs between conflicting objectives. The high-dimensional data, including spatial dependencies and derived performance metrics, requires tailored visual analysis support. To address this gap, we present ROSS, a design study for exploring ensembles of optimization results for robot base placement and trajectory planning. We propose a spatially-linked parallel coordinates plot to increase the analytical prominence of x/y base positions within the high-dimensional data. We gathered formative feedback from industry practitioners and conducted six summative semi-structured interviews. Preliminary findings indicate that complementary visual encodings support distinct analysis strategies and reasoning about trade-offs.

CCS Concepts

• ***Human-centered computing*** $\rightarrow$ ***Visualization application domains;***

1. Introduction

Industrial manufacturing environments increasingly rely on flexible robotic work cells to support product individualization, small batch sizes, and frequent reconfigurations [PGMDM21, ZLL*18, BNR21]. In this context, robot base placement and trajectory planning are key aspects for achieving optimal performance. Due to the limited workspace of industrial robots, suboptimal base placement can lead to increased cycle times, higher energy consumption, and costly manual repositioning [WHNK21].

Recent advances in robot base placement and trajectory optimization address these challenges through optimization procedures that compute feasible solutions under environmental constraints [SCB*16, WHNK24, SSCN24]. Such approaches typically evaluate large parameter spaces and optimize one or multiple objectives, such as cycle time or energy demand. In practice, these optimization workflows often culminate in the selection of a single solution, which is then inspected or validated using a robotic simulation. However, this workflow provides limited support for understanding the broader solution space, reasoning about trade-offs, or explaining why certain configurations perform better than others. Visualization techniques for multi-objective decision making [OCW*24] and parameter space analysis [SHB*14] provide mechanisms to explore trade-offs, compare alternatives, and articulate preferences. However, the problem scenario and optimization results exhibit characteristics that require tailored support. The resulting solution space is high-dimensional and its analysis involves competing objectives that can vary across scenarios.

Through a visualization design study [SMM12], conducted in collaboration with robotics researchers as well as industrial domain experts, we investigate the exploration of such optimization results. This work is guided by the following research question: *How can visual analysis support users in exploring and reasoning about solution spaces for robot base placement and trajectory optimization through different visual encodings?*

We contribute 1) an analysis and abstraction of data and tasks for exploring robot base placement and trajectory optimization results; 2) the design and implementation of ROSS, a visual analysis tool supporting such tasks; and 3) qualitative insights from formative industry feedback and a small-scale summative user study, highlighting how different visual encodings complement each other and accommodate different analysis strategies and user preferences.

2. Related Work

Recent algorithmic methods for robot base placement and trajectory planning significantly advanced the state of the art in robotic optimization but emphasize the computation of a single optimal solution or a small set of candidates [WKHN24, WHNK24, WHNK21, SGK25]. Support for systematically exploring the solution space and reasoning about trade-offs remains limited in this context. Prior work on human-centered approaches in industrial robotics emphasize the importance of transparency, interpretability, and trust in design and planning processes [Nah19]. This motivates approaches that support human sensemaking of optimization results alongside automated algorithmic procedures [WFMD21].

Visualization techniques for industrial robots and manufacturing [ZLL*19] include reachability and capability maps [ZBWH13], inverse reachability analysis [MG18], and trajectory visualizations [FTG*20]. Several works suggest methods on summarizing robot trajectories using static 2D images [RMG16, JDR23]. These approaches support feasibility assessment and motion understanding, but typically focus on individual configurations rather than ensembles of optimization results and provide limited support for comparative analysis. Motion Comparator [WPJG24] enables the comparison of multiple robot motions in 3D. Hägele et al. [HAO*20] proposed a visual analytics approach for analyzing optimization runs in robot motion planning, but focuses exclusively on trajectories. More broadly, a wide range of visual analytics techniques have been proposed to support multi-objective decision making [OCW*23] and spatiotemporal data analysis [AAG03]. However, the given optimization scenario introduces specific requirements, including high-dimensional spaces of spatial parameters, temporal trajectories, and derived performance metrics. In addition to dimensionality reduction techniques [CAFS20], parallel coordinates plots (PCP) are frequently used to visualize high-dimensional data [Ins85, Weg90], and are often embedded in coordinated multiple-view systems [HRM*22]. PAVED [CMMK20] extends PCPs to support the exploration of design alternatives with conflicting criteria, and WeightLifter [PSTW*16] facilitates the analysis of weight spaces in multi-objective settings.

Our work builds on these approaches by adapting and combining visual encodings and interaction mechanisms to support the exploration of robot base placement and trajectory optimization solution spaces. In particular, we introduce a spatially-linked parallel coordinates plot inspired by the Geo-Coordinated Parallel Coordinates [EMH15] and Map-in-Parallel-Coordinates Plot [LWJ*23].

3. Data and Task Abstraction

3.1. Data

The data is generated by an optimization model that evaluates feasible combinations of multi-joint industrial robot base positions and trajectories under given constraints and task-specific requirements, which together form a high-dimensional solution space. Each solution instance consists of three main categories of attributes:

Robot base parameters describe the spatial placement of the robot base in the work cell. In the demo setting, these include planar position and orientation (e.g., x, y, rotation), and can be extended to additional parameters depending on the robot type and setup.

Trajectory data represent robot motion as multivariate time-series over a common time axis that capture kinematic variables such as joint positions, velocities, and accelerations, with one time series per joint and attribute.

Derived outcome metrics are quantitative performance measures computed for each solution instance, including cycle time (total time required to complete the defined sequence), energy demand, and jerk (rate of change of acceleration). Additional performance measures may be incorporated depending on the problem scenario.

The size of the solution space can range from hundreds to thousands of instances, depending on the parameter discretization and constraints. Example datasets were provided by our research collaborators and are based on test configurations with assumptions intended to mimic realistic industrial scenarios.

3.2. Analysis Tasks

The exploration of robot base placement and trajectory optimization results is a recurring challenge for practitioners involved in the design and configuration of robotic work cells (see supplemental CAD illustrations: https://osf.io/u4ky5). They must interpret optimization results, justify design decisions, and adapt solutions to practical constraints that are not fully captured by formal models. Through formative interviews with our industry partner, we learned that such reasoning processes are central to onboarding and skill development. Practitioners emphasized the importance of building intuition about trade-offs between competing objectives and understanding the impact of parameter settings. While cycle time has historically been the predominant target, additional factors such as energy efficiency and mechanical wear are becoming increasingly relevant. In a broader context, increasing automation combined with higher workforce fluctuation heighten the risk of knowledge erosion [RKPS*23], which interviewees identified as a major concern. Although a computed optimal solution may be sufficient for routine operational tasks, they highlighted the need for tools that support questioning results, diagnosing issues, and understanding alternative configurations, rather than relying exclusively on automated outputs. Through our engagement with research and industry collaborators, we distilled four high-level analysis tasks:

T1: Overview. Obtain an initial understanding of the distribution and structure of feasible solutions, including parameter ranges, objective values, and patterns or outliers.

T2: Refinement. Narrow the solution space by adjusting parameter ranges, comparing objectives, and exploring custom weights.

T3: Comparison. Compare subsets of solutions to reason about trade-offs and evaluate alternatives across multiple objectives.

T4: Inspection. Examine individual solutions to review detailed parameters and performance metrics.

This abstraction of data and tasks guided the iterative development of ROSS, described in the following section.

4. ROSS: Visual Exploration of the Solution Space

ROSS is a web-based interactive visualization tool designed to support the exploration of robot base placement and trajectory optimization solution spaces (Fig. 1; implementation details at https://osf.io/u4ky5). The interface consists of multiple views connected through brushing and linking, visualizing ensembles of solutions from an external optimization model and enables users to examine data at different levels of abstraction, ranging from aggregated overviews to individual configurations. By default, only solutions that are optimal with respect to the selected objective are displayed. Alternative solutions that may provide near-optimal trade-offs with minor reductions in the primary objective can be explored, to support a broader exploration of the solution space.

Spatially linked parallel coordinates plot. The view at the top (Fig. 1c) combines a hexbin map with a parallel coordinates plot (PCP) to visualize the high-dimensional data. The 2D robot base map in the background uses hexagonal binning [COW92] to aggregate base positions for the selected objective, reducing overplotting and revealing spatial patterns. Parallel coordinates enable the inspection of distributions and correlations across configurable parameters and objectives. We adopted this combined representation after preliminary testing with (a) PCP alone and (b) with PCP and a separate hexbin map. Integrating both into a spatially linked view improved the interpretability of spatial effects and increased the analytical prominence of the x/y positions. Inspired by the Map-in-Parallel-Coordinates Plot [LWJ*23], we directly connect the polylines of selected solutions to their corresponding robot base positions in the spatial map. This view supports analysis at different levels of granularity (Tasks T1-T3), and although overplotting remains an inherent limitation, interactive highlighting and filtering provide control over visible subsets of the data.

Exploring relationships between dimensions. A scatter plot (Fig. 1d) supports the analysis of pairwise relationships between dimensions, including both parameters and objectives. This view primarily addresses Task T2 by enabling users to examine correlations and trade-offs between selected dimensions; particularly in two-objective scenarios. Through linked highlighting with other views, users can compare trade-off patterns with specific regions in the parameter space and identify tipping points where small variations correspond to substantial differences in performance outcomes.

Understanding parameter importance. To support reasoning about which parameters strongly influence specific performance outcomes, ROSS includes a parameter impact view (Fig. 1e) derived from SHAP summary plots [LEL19]. Each row represents a parameter. Individual solutions are shown as points positioned along the horizontal axis according to their value, with vertical jitter to reduce overplotting. Color encodes whether the parameter contributes positively or negatively to the selected objective. This view primarily addresses T1 by providing a compact and extensible (e.g., z-position) overview of influential parameters. A limitation of this view is its focus on a single objective at a time and the initial orientation required due to the less familiar encoding.

Multi-attribute ranking. The scrollable panel at the bottom provides a multi-attribute ranking (Fig. 1f) in which each row represents a solution instance and columns correspond to parameters and objectives. The view supports several analysis activities: obtaining an overview through histograms embedded in the column headers (T1), identifying trends across selected subsets (T2-T3), selecting candidates for detailed inspection (T3), and retrieving exact values for individual solutions (T4). Cells are color-coded to support pattern detection and systematic comparison across solutions.

Preference articulation. Users can define a custom objective by interactively assigning weights to predefined objectives (Fig. 1b), in addition to manually comparing solutions and identifying suitable trade-offs. Solutions that align with the specified weights are highlighted across all views. The design is derived from Probability Distribution Sliders [GSK*17] to frame weight adjustment as coarse preference articulation. The current demo implementation is based on precomputed solutions and identifies configurations that best match the specified weighting through filtering; these may not correspond to the mathematically optimal solution. Nevertheless, the interaction paradigm is designed to support future re-execution of the optimization model using refined objective specifications.

Detailed inspection of individual solutions. Users can select a solution from the ranking to inspect it in a sidebar overlay. The first tab presents a 3D robot simulation (Fig. 1g), while the second provides small-multiple line charts showing joint-level position, velocity, and acceleration over time (Fig. 1h). These representations follow established conventions in robotics. Although the multi-series line charts may appear visually crowded to non-experts, they represent a familiar domain-specific visualization used to assess joint limits and identify characteristic motion patterns.

4.1. Formative Feedback

The iterative design process involved two visualization researchers and two robotics and automation researchers (co-authors), as well as external industry stakeholders. Following the design study methodology [SMM12], we conducted an iterative requirement analysis with early data sketches and progressively refined them into the ROSS prototype. With the industry partner, we conducted four online expert interview sessions, including one individual session and three group sessions, involving seven participants in total from innovation management, data science, engineering and mechanical construction. Initial discussions were based on early data sketches that had been internally validated within the research team. The diversity of stakeholder roles revealed differing perspectives on potential usage scenarios and surfaced requirements that were not initially central to our design; similar to observations reported in data-first design studies [OM20]. In particular, participants emphasized that the tool could serve as a means for building expertise, onboarding new employees, and fostering a deeper understanding of how parameter settings influence performance.

Although we planned to progressively increase complexity by exposing additional data, stakeholders consistently preferred simple and familiar encodings. The feedback led to several design revisions. For example, we replaced the dark mode with a light mode to improve color discrimination under overplotting and occlusion. We changed the default view from displaying the full solution space to highlighting objective-specific optima, to provide clearer initial guidance. A major revision concerned the multi-attribute ranking. Earlier versions included trajectories, also shown in the line charts (Fig. 1f) for individual solutions, which we compressed using binning and heatmap encodings. However, discussions revealed that they did not directly support core analytical tasks (T1-T4). Stakeholders indicated that joint limits are inherently respected by the optimization model and that higher-level performance metrics provide sufficient information for comparisons. We simplified the ranking to focus on key parameters and objectives, and display more detailed trajectory data in the sidebar view on demand.

4.2. Summative Feedback

We conducted a qualitative study to assess the perceived utility of ROSS, its benefits, and limitations.

Participants were recruited through outreach at a university institute. Six Master's students (aged 24–26) participated. Five were enrolled in Automation and Robotic Systems and one in Electrical Energy Engineering. All had prior experience with robot path and trajectory planning and were familiar with multi-objective optimization, but had limited exposure to robot base positioning.

Procedure. We conducted individual 40-minute online interviews. Participants interacted directly with ROSS via screen sharing. Each session followed a task-driven, semi-structured protocol aligned with Tasks T1–T4, starting from an overview to detailed inspection. Participants were encouraged to think aloud. Each session concluded with a short questionnaire. All interviews were recorded.

Results. All participants completed the tasks efficiently and reported that ROSS supported the identification of patterns and trade-offs. We observed distinct analysis strategies. Four participants followed a *multi-view scanning* strategy, where they initially scanned several views to form a mental model of the solution space before narrowing their focus. Two participants followed an *anchor-view strategy*, centering their analysis on the spatially-linked parallel coordinates plot. Preferences also differed regarding decision guidance. Three participants chose the custom objective option to *algorithmically* narrow the solution space, whereas three preferred *manual visual exploration* before applying weights, and described the automation as potentially opaque. The parameter impact view was primarily used for explanatory support rather than selection. Three participants considered it highly relevant for understanding parameter influence, particularly in scenarios with a larger number of parameters, whereas three expressed skepticism due to its focus on a single objective at a time.

5. Discussion and Conclusion

This work provides preliminary evidence how interactive visual analysis can support reasoning about optimization results for robot base placement and trajectory planning. Industry stakeholders and study participants used ROSS to identify trade-offs and relate performance outcomes to spatial parameters, and articulate preferences under conflicting objectives. These findings complement prior work on multi-objective decision and reasoning support through an industrial robotics use case.

A recurring observation is that the visual encodings were used as *complementary* rather than competing. Although some views expose overlapping relationships (e.g., scatter plot and the spatially-linked parallel coordinates plot), users valued multiple perspectives. Brushing and linking enabled quick transitions between single-objective inspection, and two- or three-objective comparison, as well as between global overviews and subset analysis. Extending ROSS to scenarios with additional objectives and parameters remains an important direction.

We acknowledge several limitations. The summative evaluation involved a small, homogeneous sample and a single dataset; broader studies and additional industrial scenarios are needed to assess generalizability. Moreover, the observed analysis strategies may have been influenced by the layout and default configuration, suggesting that interface structure itself affects the exploration. Industry exchanges also revealed barriers for deployment in practice, including fragmented tooling and data transfer between optimization, simulation, and engineering environments. A promising next step is to embed ROSS, and decision-support tools in general, within existing CAD workflows to reduce context switching and support day-to-day work practices.

Finally, participants differed in how they used manual exploration and algorithmic support. These findings suggest that automated mechanisms should be carefully integrated and made available on demand rather than imposed. More broadly, an important direction for future work is to investigate how mixed-initiative design and interaction paradigms can preserve user agency while supporting more efficient analysis and reasoning tasks.

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