

InsightXR: Operative Generative Design in Augmented Reality

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Abstract

This paper introduces InsightXR, an augmented reality application for early-stage massing studies in architecture. InsightXR uses an operative generative design algorithm using Non-Dominated Sorting Genetic Algorithm II (NSGA-II) in the Pymoo framework. To test InsightXR's capabilities, a case study is introduced to generate 3D design alternatives in real-time for a mixed-use project in San Francisco, USA. Design alternatives are generated for 5 generations and visualized in InsightXR.

1. Introduction

InsightXR is an augmented reality (AR) platform that enables user participation in the generative design process. The focus of InsightXR is early-stage massing studies. Integrating immersive technology such as augmented reality in the early-stage generative design process can help with immersion into the design along with

fostering a better understanding of the project's scale and overall geometry. InsightXR uses the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to generate design alternatives inspired by the volumetric operations discussed by Mari and Yoo [12]. InsightXR uses the operative NSGA-II algorithm introduced by Bailey and Caldas [1]. This paper focuses on the application of Operative Generative NSGA-II in InsightXR [1]. The design operations explored in this paper are expansion and carving [1]. In the proposed workflow, the operative NSGA-II algorithm is accessed using Amazon Web Services (AWS), and the users visualize selected design alternatives from each generation using InsightXR [15]. To reduce user fatigue during this interactive process, InsightXR only shows 3 design alternatives sampled based on the shape similarity of meshes over the five generations [2]. In this paper, the proposed generative design process in augmented reality is introduced using a case study. To assess the capabilities of the proposed algorithm in augmented reality, design alternatives are generated using the following objective functions: Roof and Best Oriented Surfaces (RBOS), Usable Open Space (UOS), and Area Violation (AV). RBOS explores maximizing the total area of the best-oriented facades, which can result in an increase in the potential for renewable energy in addition to an increase in

daylighting [1]. UOS is defined as the total unbuilt area of the site, which is calculated by subtracting the ground floor area from the lot area. The goal of this research is to maximize the UOS value. AV is a constraint violation used as an objective function in this paper [1].

2. Background

2.1 Augmented Reality

Augmented reality (AR) uses computer graphics to overlay virtual content on the physical world [9]. In architectural design, the use of AR has been focused on topics including integration with location-specific information (such as a Building Information Modeling (BIM) model containing different layers of construction details) and portable AR devices in the field [3]. In addition to the use of handheld devices for augmented reality, the use of Head Mounted Display (HMD) AR technology, such as Microsoft HoloLens, enables a hands-free AR experience [6]. Using AR technology can help with providing a realistic representation of the design along with allowing better engagement of stakeholders with the design [4]. In computational design, immersive design research has been focused on topics including exploring real-time object manipulations and visualizations, remote collaborations, and participatory design [10]. The interaction of users and designers during the design and review process can be mediated using AR technologies. Due to a desire to maintain wide accessibility, using AR in handheld devices (iPad Pro) is explored in this paper.

2.2 NSGA-II Algorithms

Evolutionary algorithms are metaheuristic algorithms that apply the concept of Darwin's survival of the fittest [7]. These algorithms apply operators, including mutation and cross-over, to create new individuals for the next generation [7]. Genetic algorithms are a type of evolutionary algorithm that John Holland first introduced in 1975 [11]. In this paper, Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used for generating the design solutions in InsightXR. Non-Dominated Sorting Genetic Algorithms (NSGA) were introduced by Deb and Srinivas [14]. NSGA-II algorithms were proposed later to solve issues such as lack of elitism and the restrictions of sharing parameters in NSGA algorithms [5].

3. Methods

InsightXR uses the Pymoo's framework in Python to run a NSGA-II algorithm inspired by the Operative Generative Design proposed by Bailey and Caldas [1], [16]. The algorithm is run on a local server and generates massing options as OBJ files uploaded to the Cloud using AWS and visualized in InsightXR's AR platform in real-time. In the proposed workflow, the designers will have access to the generated database of different design alternatives produced using InsightXR, and they can decide on the design outcome with full access to that knowledge. InsightXR is created using Unity Game Engine, and the AR capabilities of InsightXR use the AR Foundation framework within Unity.

A case study is introduced to test the capabilities of InsightXR with respect to applying Operative Generative Design in augmented reality. In addition, the proposed case study is used to assess

the proposed clustering methods for visualizing selected design options [1]. This case study explores early-stage massing studies for a mixed-use building on a site located at 74 Mission Rock St, San Francisco, CA 94158 [1]. The site covers an area of 4800 m² and is 80 m by 60 m [1]. The explored objectives, as discussed in the Introduction, include: 1. Roofs and Best Oriented Surfaces (RBOS), 2. Usable Open Space (UOS). Area Violation (AV) is a constraint violation in this case study and is used as an objective. The goal of is to maximize the RBOS and UOS while minimizing the AV. The population size in the NSGA-II algorithm is 30 individuals, with the simulated binary crossover set to 0.9. After 5 generations, the optimization is terminated. Design operations explored in this case study are Carving and Expansion (applied by adjusting the roof mesh points). In each generation, a selection of design alternatives is presented to the users. At the end of the process, the Pareto Front can be visualized for further investigation of the solution space.

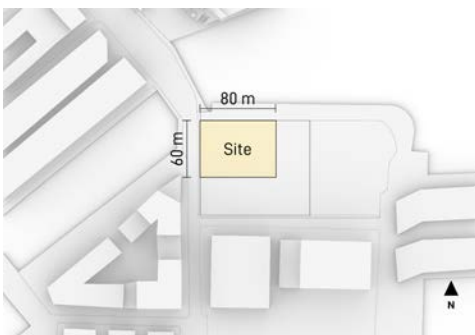


Figure 1. The case study site used in this research [1]

The overall generative design workflow in InsightXR can be described as follows:

- The applied NSGA-II algorithm runs on a local server for the initial generation and creates the first generation of individuals.
- A k-means clustering algorithm based on the Scikit-learn Python module is applied to the initial population to create 3 clusters [13]. Clustering is defined based on fitness values.
- Each cluster's solutions are analyzed using a shape similarity algorithm using the sum of Euclidean distances between each vertex of meshes [2]. The values are then used to rank each cluster's design alternatives from most similar to least. The most representative design alternative from each cluster is selected to be viewed in AR.
- OBJ files representing each selected design alternative are generated and uploaded on AWS.
- In InsightXR, users are provided an interface to visualize the first generation's design alternatives.
- These steps are repeated for each generation until the termination criterion is satisfied (defined as 5th generation).
- In the end, a Pareto-front is generated.

During the experience, the 3D site model is first visualized by finding a predefined QR code in the physical world using the AR camera. Each design alternative's 3D model is created by generating an OBJ file format from the NSGA-II algorithm and uploading the design alternative on an S3 bucket, a dedicated storage space for the algorithm on AWS. Selected design options using the clustering method described earlier are downloaded

from AWS throughout the experience and are visualized in InsightXR.

4. Case Study Results

To discuss the characteristics of the non-dominated solutions, 4 design options are visualized in Figure 2. As the AV increases, UOS increases due to the smaller gross floor area.

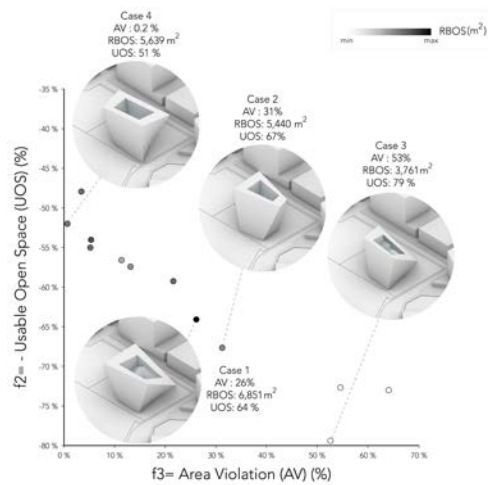


Figure 2. Non-dominated solutions. RBOS is represented using color. Darker color represents higher values.

Case 1 is a hybrid design option (carving and expansion), with the roof facing south and maximizing the roof area. Case 1 provides the maximum RBOS value. Case 2 has an increased height with a reduced value for RBOS compared to Cases 4 and 1 while increasing the UOS value. Case 3 is a hybrid option (carving and expansion) with the highest UOS value while increasing the AV by reducing the gross floor area of the building. Case 4 is a courtyard solution, with carving as the applied operation. Case 4 reaches the maximum height allowed on the site (61 m) while creating a deep courtyard.

This case aims to reach the maximum areas for the southern and northern facades while reducing the first-floor area. Figure 3 shows non-dominated solutions with RBOS and UOS on the horizontal and vertical axes and AV as the third objective using color.

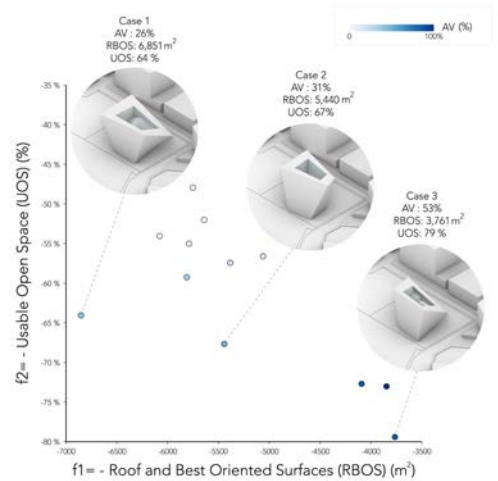


Figure 3. Non-dominated solutions. AV is represented using color. Darker color represents higher values.

4.1 Generation 1

At this step, the initial population of solutions is generated using the applied NSGA-II algorithm. The solutions are then divided into three clusters using the k-means clustering algorithm discussed in section 3. Figure 4 shows the three design options visualized in InsightXR. Case 1 is a result of expansion operation, with a low AV value and a high RBOS value (Figure 5). Case 2 is a hybrid, resulting from expansion and carving. This case maximizes the southern facade and roof area while increasing the UOS. Case 3 is an expansion design option with a low RBOS and UOS value.

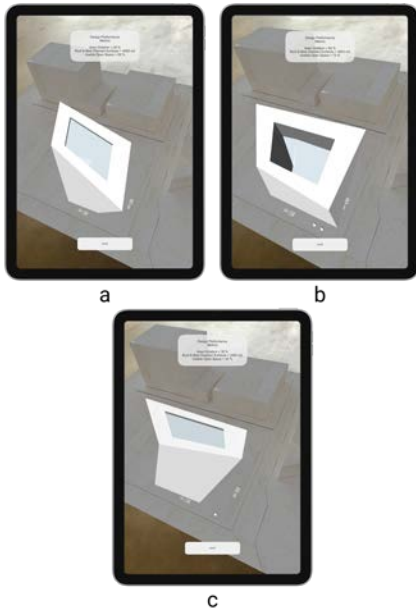


Figure 4. Generation 1 solutions. A. Case 1, b. Case 2, c. Case 3.

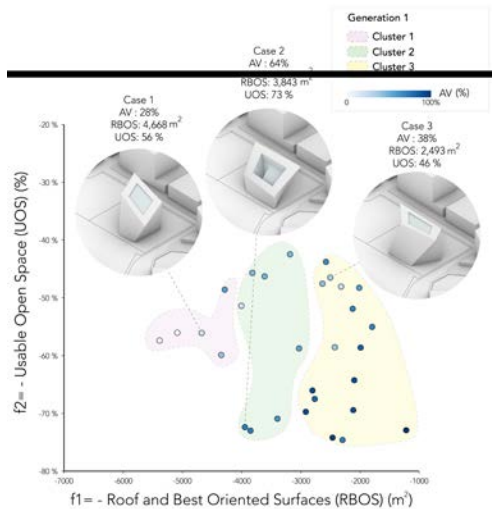


Figure 5. Generation 1 solutions. AV is represented using color. Darker color represents higher values.

Overall, cluster 1 includes options with higher RBOS values and lower AV values, cluster 2 is a trade-off between

cluster 1 and 3 in terms of AV and RBOS values, and cluster 3 includes options with higher AV and lower RBOS values. Cases 1 and 3 have shallow skylights, and in this research, shallow skylights (under one story height) are not considered a courtyard.

4.2 Generation 2

Generation two's clusters are defined similarly to generation one, where cluster 1 includes options with higher RBOS values and lower AV values, which is desired in this case study (Figure 7). Cluster 2 is a trade-off between RBOS and UOS values, and cluster 3 options have the lowest RBOS values and highest UOS values.

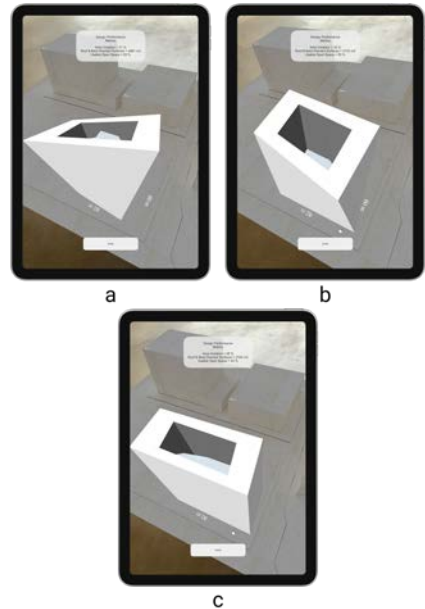


Figure 6. Generation 2 solutions. A. Case 1, b. Case 2, c. Case 3.

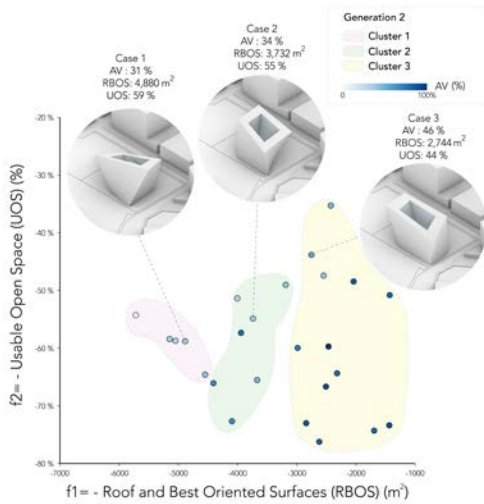


Figure 7. Generation 2 solutions. AV is represented using color. Darker color represents higher values.

Cluster 3 design options have the highest AV values among all options, which is due to their deep courtyards (carving) resulting in smaller floor plates. Similar to generation one, three design options are selected using the algorithm and visualized in InsightXR (Figure 6). Case 1 is a hybrid design option (expansion and carving) with a high RBOS value. Case 2 is a trade-off between Case 1 and 3 in RBOS and AV values. Cluster 3 has the widest variety of UOS values. Case 3 has a lower UOS value and RBOS value, and high AV values.

4.3 Generation 3

Cluster one includes options with the highest RBOS and lowest AV values among all solutions while having UOS values between 50 and 60 percent (Figure 9). On the other hand, cluster two includes solutions with tradeoffs between RBOS, UOS, and AV values compared to the other two clusters.

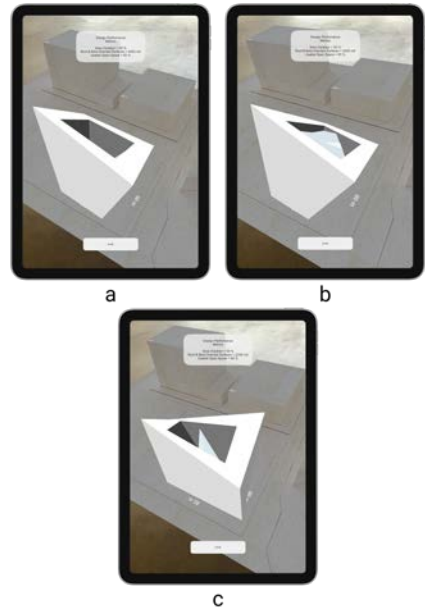


Figure 8. Generation 3 solutions. A. Case 1, b. Case 2, c. Case 3.

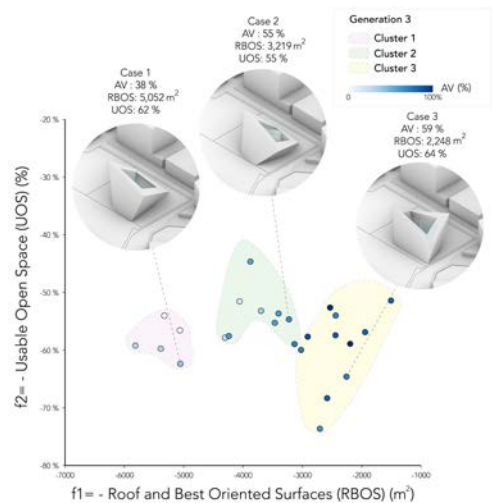


Figure 9. Generation 3 solutions. AV is represented using color. Darker color represents higher values.

Cluster 3 includes solutions with lower RBOS values and higher AV values,

which are not desired, while providing higher values of UOS, which can result in smaller floor plates or larger courtyards. Case 3 provides the highest UOS among the three selected cases while providing the lowest RBOS. Case 3 is a hybrid design option (carving and expansion) with a high AV value that doesn't provide the desired gross floor area. Figure 8 shows the visualized Cases 1, 2 and 3 in InsightXR.

4.4 Generation 4

Generation four's design options are more diversified compared to the previous generations (Figure 11). Cluster 1 includes solutions with the highest RBOS values and the lowest AV values, and as can be seen in Case 1, this option uses carving that includes large floor plates with a shallow courtyard.

Cluster 2, on the other hand, provides a compromise between clusters 1 and 3, where its solutions provide lower RBOS values compared to cluster 1 but higher RBOS values compared to cluster 3. Cluster 3 includes design options with lower RBOS values and higher AV values, and as can be seen in Case 3, smaller facade and roof areas result in a lower RBOS value compared to Case 1 and Case 2. Case 3 is a hybrid solution with a high AV value, which is due to its small floor plates. Case 2 provides a trade-off between Case 1 and 3 in terms of RBOS and AV values and is a hybrid design solution. Figure 10 shows the visualized Cases 1, 2 and 3 in InsightXR.

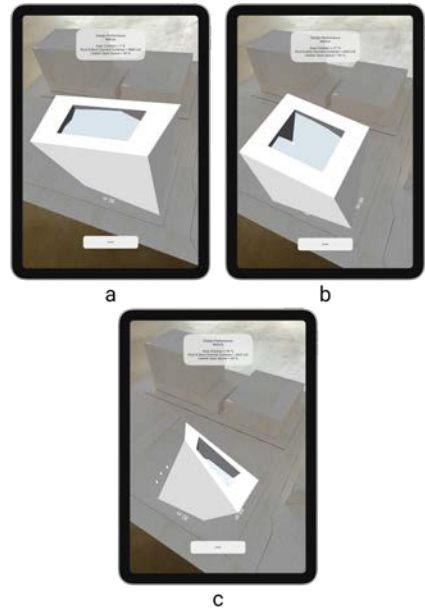


Figure 10. Generation 4 solutions. A. Case 1, b. Case 2, c. Case 3.

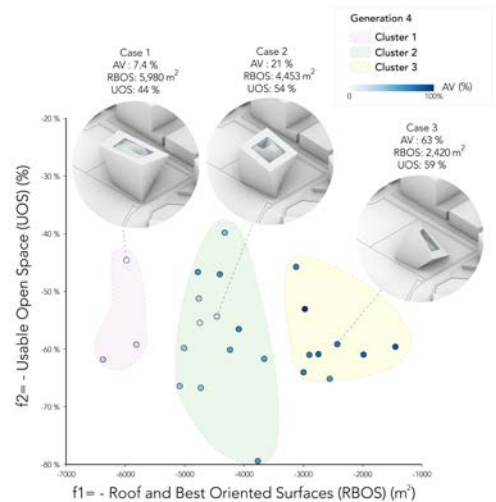


Figure 11. Generation 4 solutions. AV is represented using color. Darker color represents higher values.

4.5 Generation 5

Generation five's clusters are similar to previous generations, where cluster 1 includes design options with higher RBOS and lower AV values (Figure 13). Case 1 is the result of a carving operation with a deep courtyard while providing the lowest AV value among solutions. Cluster 2 includes solutions with a trade-off between RBOS and AV values compared to the other two clusters. Cluster 3 includes design options with lower RBOS and higher AV values. Case 2 is a hybrid solution (carving and expansion) with a tilted roof orientated West. Case 2 has the lowest UOS value. Case 3 provides a higher UOS value with a lower RBOS value compared to the two other cases. Figure 12 shows the visualized Cases 1, 2 and 3 in InsightXR.

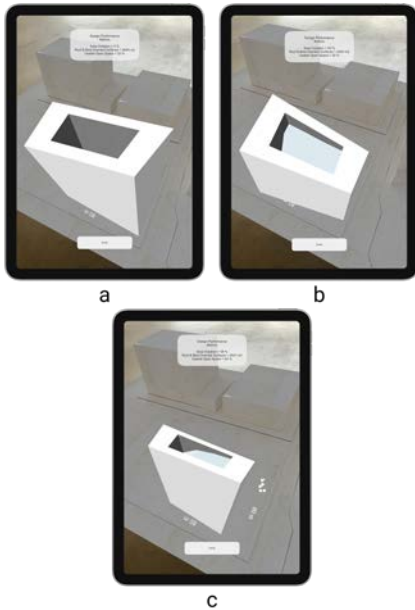


Figure 12. Generation 5 solutions. A. Case 1, b. Case 2, c. Case 3.

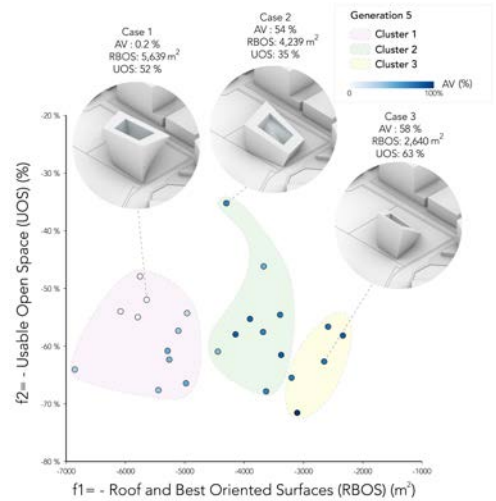


Figure 13. Generation 5 solutions. AV is represented using color. Darker color represents higher values.

5. Discussion

Design solutions in each generation were successfully clustered into three groups, where each cluster had distinct behaviors in terms of all three objective functions of RBOS, UOS, and AV. In all 5 generations, cluster 1 included design solutions with lower AV values and higher RBOS values, which is due to design options that provide larger floor plates. As the generations progressed, design options in cluster 1 provided an improved RBOS value compared to previous generations. Cluster 1 in generations 4 and 5 had selected cases with only carving as the design operation. Cluster 3 in all generations included solutions with the lowest RBOS and highest AV values. Case 3 in most generations was a hybrid solution (except for generation 1, where Case 3 is an expansion operation result). Cluster 2 in all generations provides a compromise between RBOS and AV values, where the selected Case 2

solution from each generation was a hybrid option. The algorithm was able to successfully cluster each generation's solutions and select a representative case among the solutions to be viewed by the users in InsightXR. In addition, InsightXR's application was able to view each generation's selected design solutions in real-time successfully. The proposed generative design process can also be asynchronous to allow users to visualize design alternatives. In the case study, even though the goal is to maximize RBOS and minimize AV, it is essential to note that creating design options with smaller courtyards while having a deep floor plate (e.g., case 1 in generation 4) can reduce the access to daylighting and natural ventilation, which is not desirable. It is ultimately the designer's role to evaluate the proposed non-dominated solutions provided by InsightXR to choose the most applicable design for the design at hand.

Future research can investigate the inclusion of user feedback in the optimization process using an interactive NSGA-II algorithm in InsightXR. In addition, research needs to be conducted to understand the perception of users regarding InsightXR and understand the opportunities and pain points of using InsightXR. In addition, this paper selected five generations as the termination criterion for the algorithm, which can also be tuned or defined with respect to other criteria in future research.

6. Conclusion

InsightXR enables designers and non-designers to participate in an Operative Generative design process using NSGA-II algorithm in real-time or asynchronously [1]. This paper introduced a clustering method based on

k-means clustering using the Scikit-learn Python module. This was combined with a shape similarity algorithm that allowed for selecting representative design solutions to be presented to the users for further investigation, reducing user fatigue caused by the presentation of all solutions per generation [13]. A case study experiment was conducted using three objective functions, RBOS, UOS, and AV, to generate early-stage massing design options on a site in San Francisco, USA. Each cluster per generation successfully created a set of unique options with respect to the objective functions. At each generation, the three presented options spanned the spectrum of the different objectives, presenting one at each extreme as well as a trade-off option.

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