Composite Alternative Pareto Optimal Recommendation System with Individual Utility Extraction (CAPORS-IUX)

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Abstract: We propose a methodology and develop a system for generating composite alternative recommendations combining user-guided continuous improvement with Pareto optimal trade-off considerations and for extracting individual utility. The methodology describes a way to (1) construct a set of Pareto optimal recommendations given a selected metric and the user's current utility, (2) explore the feasibility space by relaxing the Pareto optimal constraint in a given dimension, and (3) extract the utility for an individual user by capturing the interactions between the user and the system. The system itself consists of (1) a mechanism for generating feasible recommendations, (2) implementation of the key algorithms of the methodology, and (3) user interface for enabling interaction with the user.

1 INTRODUCTION

Composite alternative recommender systems recommend a combination of products and services, based on multiple criteria such as price, availability, and user ratings. They include recommenders for vacation packages, investment portfolios, healthcare plans, product bundles, and more.

Consider an example of a sourcing recommender. In this case, a recommendation is a set of orders, where an order contains a set of item quantities to be purchased from a particular supplier. Sourcing recommendations are associated with multiple criteria such as cost, carbon emissions, and fulfillment time. These recommendations are composite since they contain multiple suppliers with multiple items, and they are multi-criteria because of the three metrics mentioned previously. The result of generated recommendations must be Pareto-optimal.

There has been extensive research conducted on composite alternative recommenders in recent years. This research comprises proposed methods and presented systems, addressing both domain specific and domain-independent recommenders.Interdonato et al (2013) propose a graph-based framework that uses Page Rank-style algorithm to learn packages that conform to a user preference model. The framework is ultimately based on user rankings and identifies domain-independence as its key feature. CARD (Brodsky, Henshaw and Whittle, 2008) is a proposed framework for generating optimal composite alternative recommendations. CARD utilizes a SQL-based data model for generating the recommendation space. It also extends the SQL language in order to provide diverse recommendations and to provide a mechanism for learning user preferences. CARD is a generic framework capable of being applied across domains. There is no current implementation of the CARD framework. FlexRecs (Koutrika, Bercovitz and Garcia-Molina, 2009) is a proposed framework for providing domain-independent recommendations. The recommendation space in FlexRecs is generated using workflows designed by system implementers. As with CARD, the FlexRecs framework is built on top of relational data models and extended relational operators.

These three frameworks address composite recommendations, but do not offer a system that implements the framework, nor use methodology on which the system functionality can be based.

Xie, Lakshmanan and Wood (2010) present a generic package recommender system that uses a variation of the knapsack problem to generate optimal top-k recommendations. The recommendation space in their system is generated using individual component recommenders. Furthermore, ratings are the only metric used to calculate recommendations. TopRecs+ (Khabbaz,

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Xie and Lakshmanan, 2011) is another generic package recommender that uses a variation of the knapsack problem to find optimal top-k package recommendations. As with Xie et al above, TopRecs+ leverages individual item recommenders to generate the composite alternative recommender space. CompRec-Trip (Xie, Lakshmanan and Wood, 2011) is a system for recommending travel packages by finding the optimal alternatives using user-supplied preferences and constraints. As Xie et al's other work mentioned above, the system uses component recommender systems for generating the recommendation space. The system is narrowly focused, but allows flexibility through interaction with the user.

These three systems generate composite recommendations by aggregating single-item recommenders. However, this aggregation does not take into account interaction among the components of the composite recommendation. Therefore, neither offers an integrated composite alternative methodology, which is often required when components have a non-trivial interaction among them. Also, in the case of CompRec-Trip, the system is domain-specific and not designed to accommodate general recommendation problems.

Ribeiro, et al (2015) propose two Pareto-efficient approaches for recommender systems. In both approaches, they propose using recommendation accuracy, novelty, and diversity as the objectives to consider when generating a Pareto-efficient list of recommendations. One approach creates a Pareto-efficient ranked list from multiple competing recommendation algorithms. Their second approach creates Pareto-efficient hybrid recommenders built from individual recommender algorithms. While both approaches apply Pareto-efficiency to their recommendations, it is limited to the criteria of accuracy, diversity, and novelty. However, many package recommendations require diverse user-defined criteria, such as cost, risk, benefit, etc., which is outside the scope of (Ribeiro et al, 2015). Neither approach considers continuous user feedback. Furthermore, both approaches are proposed algorithms that do not include a system to implement their methodology.

To the best of our knowledge, there are no proposed recommender systems that combined Pareto optimal solutions for arbitrary user-defined criteria with continuous user guidance. Nor is there a system with this combination of features designed for composite alternatives that have complex interactions between them.

To address these limitations, CAPORS (Jeffries and Brodsky) was developed. CAPORS introduced a methodology and system for recommending Pareto-optimal composite alternatives based on (1) multi-criteria optimization and (2) continuous user-guided feedback.

In CAPORS, the trade-off consideration is explicitly expressed between designated cost and benefit metrics, but not with arbitrary metrics. And, while CAPORS allows a user to explore the feasibility space to find an optimal recommendation, CAPORS was not designed to learn the user's utility.

Addressing these two limitations of CAPORS is the exact focus of this paper.

First, we propose a methodology for (1) generating Pareto optimal recommendations using arbitrary metrics and (2) extracting the utility of an individual user. The methodology first generates an initial set of recommendations based on Pareto-optimal curve by comparing one of the metrics (the default metric) against the default user utility. Then, the user iteratively improves the alternatives through critique of additional metrics and re-optimizations to iteratively discover a feasible recommendation closest to that user's utility. Finally, the user accepts the most desired recommendation and a final utility for that user is extracted.

Second, we develop Composite Alternative Pareto Optimal Recommender System with Individual Utility Extraction (CAPORS-IUX) to implement this methodology. CAPORS-IUX is implemented using Unity Decision Guidance Management System (DGMS) (Brodsky, Luo, and Nachawati). CAPORS-IUX also uses the same notion of an Analytic Model as CAPORS. An analytical model formally describes feasibility constraints and metrics of interest as a function of parameter and control variables. With the help of Unity DGMS, CAPORS-IUX manages the workflow of recommendations improvement based on three key algorithms.

Third we have developed algorithms for (1) generation of Pareto-optimal curve for the recommendation Analytic Model along a selected metric and the current user utility, (2) generation of Pareto-optimal improvement along a different metric and the updated user utility, and (3) calculation of the updated user utility.

Finally, we conduct an experiment using synthetic users to demonstrate the ability of CAPORS-IUX to find a recommendation that is optimal, or very close to optimal, for a given user utility.

This paper is organized into the following sections. Section 2 demonstrates composite alternative recommendation using a supply chain sourcing example. Section 3 describes the core algorithms of the system. Section 4 illustrates the system architecture. Section 5 details an experimental study conducted to demonstrate utility convergence. Section 6 concludes and offers ideas for future extensions.

2 UTILITY EXTRACTION BY SOURCING EXAMPLE

We return to the sourcing example from the original paper in order to explain the utility extraction methodology. Supply chain sourcing is the process of constructing orders for goods to be purchased from some universe of suppliers such that constraints such as demand are met. For a more detailed explanation on supply chain sourcing, please refer to Section 2 of the original paper.

In this scenario, CAPORS-IUX is used to generate an order configuration stipulating which items are to be ordered from which suppliers and at what quantities. As with any recommender system, the goal is to generate recommendations with the highest predicted utility to the individual user.

The methodology used by CAPORS-IUX to generate the optimal recommended order configuration is shown in Figure 1.

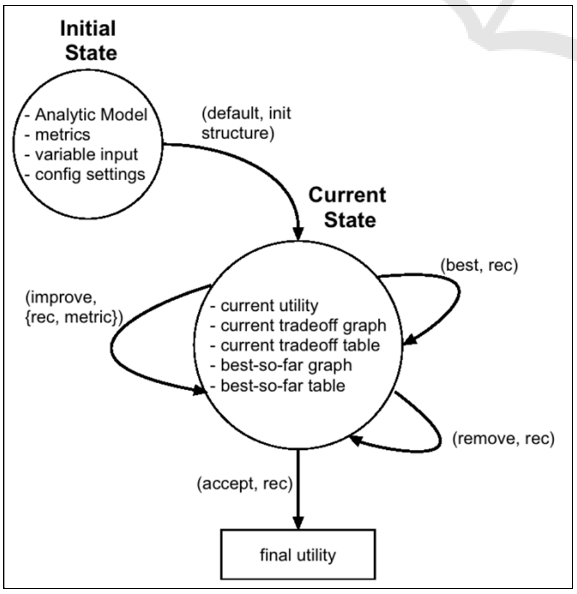
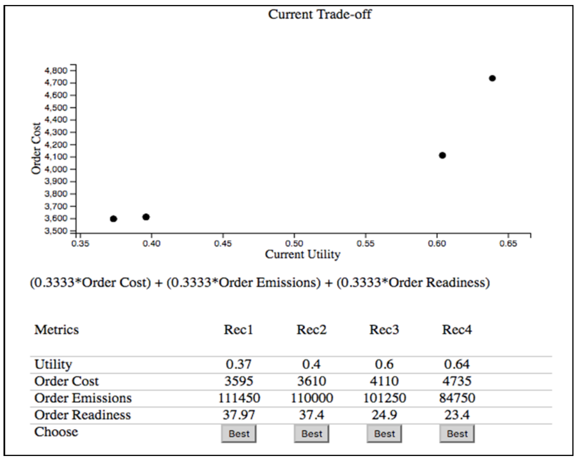


Figure 1: State Diagram.

To generate an initial set of recommendations, an initial data structure is used. This data structure includes (1) metrics definitions used to evaluate each recommendation, (2) an analytic model for computing metrics and constraints of a given recommendation, (3) variable input for exploring the feasible space of composite alternatives, (4) configuration setting for maximum number of recommendations to generate, (5) configuration setting for default metric for user to consider, and (6) configuration setting for default utility weights (e.g. equal weights for all metrics).

The system generates an initial set of recommendations and displays to the user. The user is presented with four main user interface sections (explained in greater detail below and shown in Appendix A): (1) a graph, called the Current Trade-off Graph of recommendations with current utility along the x-axis and the metric to consider along the y-axis, (2) a table of all current recommendations to consider with each of the computed metrics and a mechanism for choosing the best recommendation in the set, (3) a graph, called the Best-So-Far Graph displaying all of the recommendations chosen by the user as best in each iterative Current Trade-off Graph, and (4) a table of all the best recommendations so far chosen by the user.

The Current Trade-off Graph allows the user to consider recommendations by comparing a set of recommendations projected onto the Pareto front of the feasibility space against a single metric of interest. That is, there does not exist a recommendation that improves on one metric without sacrificing another. Initially, the current utility is computed using equal weights for each metric and the metric of interest is defined in the configuration setting of the initial data structure.

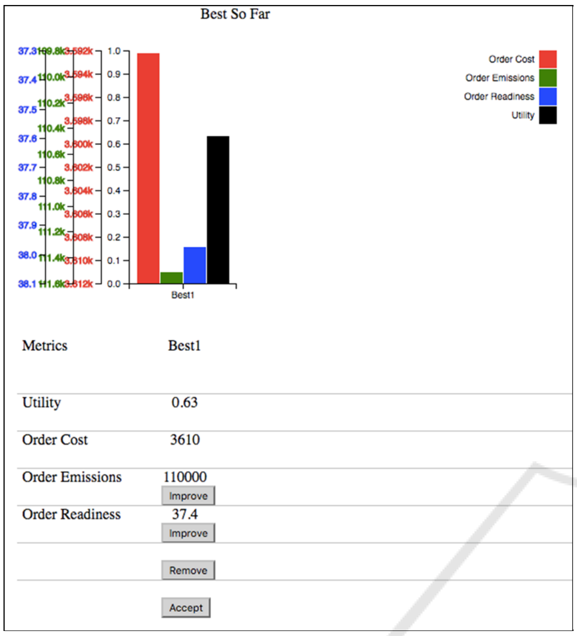


(0.3333*Order Cost) + (0.3333*Order Emissions) + (0.3333*Order Readiness)

Metrics	Rec1	Rec2	Rec3	Rec4
Utility	0.37	0.4	0.6	0.64
Order Cost	3595	3610	4110	4735
Order Emissions	111450	110000	101250	84750
Order Readiness	37.97	37.4	24.9	23.4
Choose	Best	Best	Best	Best

Figure 2: Current Trade-off Graph and Table.

For example, the user selects "Rec 2" as the best of the currently displayed set of recommendations. Upon selection the preferred recommendation is added to the Best Recs Graph and Best Recs Table.



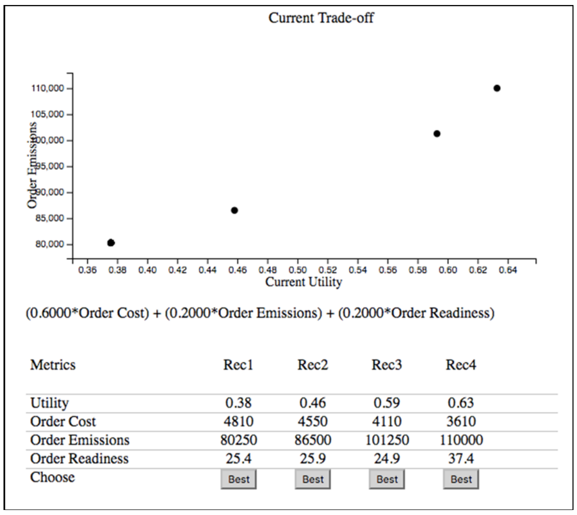
Metrics	Best1
Utility	0.63
Order Cost	3610
Order Emissions	110000
Order Readiness	37.4

Figure 3: Best-So-Far Graph.

Also, the current utility is updated based on the selection, and the Current Trade-off Graph and Current Trade-off Table are updated to reflect the new utility calculations.

Next, the user can (1) generate a new set of recommendations by improving upon one of the metrics for the recommendation, (2) remove the recommendation from the list, or (3) accept the final, best overall recommendation.

In our example, the user selects the column containing the recommendation and then the row containing the Order Emissions metric. The Improve button is pressed and the Current Trade-off Graph and Table are updated with a new set of recommendations. The y-axis of the Current Trade-off Graph will be the selected metric to improve, and the x-axis will be the current utility that was calculated the last time the user selected a Best recommendation.

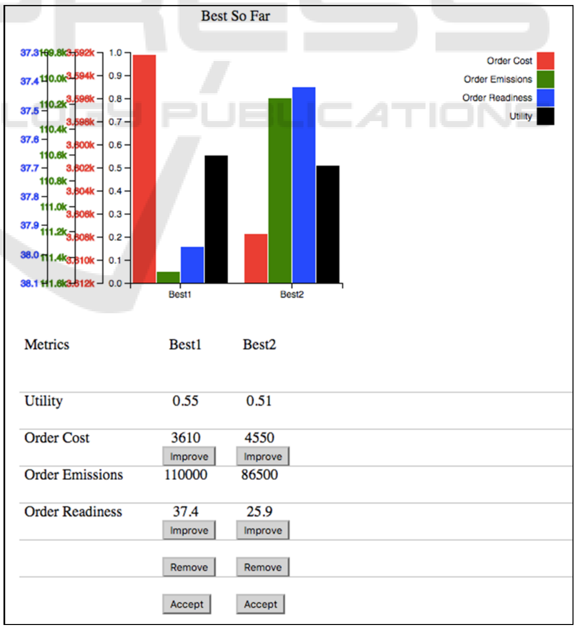


(0.6000*Order Cost) + (0.2000*Order Emissions) + (0.2000*Order Readiness)

Metrics	Rec1	Rec2	Rec3	Rec4
Utility	0.38	0.46	0.59	0.63
Order Cost	4810	4550	4110	3610
Order Emissions	80250	86500	101250	110000
Order Readiness	25.4	25.9	24.9	37.4
Choose	Best	Best	Best	Best

Figure 4: Updated Current Trade-off.

Now, the user selects new Rec 2 as the new best recommendation so far. The recommendation is added to the Best So Far graph and table, and the utilities are all recalculated and updated in the graphs and tables. The Best So Far graph always displays recommendations from highest utility to lowest utility, left to right.



Metrics	Best1	Best2
Utility	0.55	0.51
Order Cost	3610	4550
Order Emissions	110000	86500
Order Readiness	37.4	25.9

Figure 5: Updated Best-So-Far.

To finalize the process this example, the user chooses Best 1 as the most optimal recommendation by selecting the Best 1 column and pressing the Accept button. A final user utility is then calculated.

3 KEY ALGORITHMS

CAPORS-IUX is implemented using three main algorithms. These algorithms are responsible for generating a set of recommendations for consideration and for updating the user-specific utility.

The first algorithm is the **paretoOptimal** algorithm for generating recommendations. This algorithm takes as input (1) an analytic model *am*, (2) variable input *vi*, (3) metrics definitions *m*, (4) metric weights for y-dimension *y-dim*, (5) metric weights for x-dimension *x-dim*, (6) number of points to generate *L*, and (7) epsilon *e*.

A two-dimensional space is created using a linear combination of metrics in the y direction and a linear combination of metrics in the x direction. These linear combinations are determined by the weights passed in for each dimension. Both dimensions are normalized to [0, 1].

L unit vectors are then generated for the space. The directions of the vectors are evenly spaced from the x-axis to the y-axis.

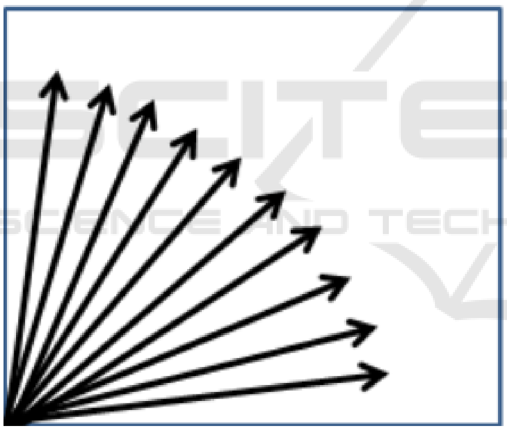


Figure 6: Candidate Utility Vectors.

A point on each vector is then produced by using the linear combination of the weighted x-axis metrics for the x component of the point, and a linear combination of the weighted y-axis metrics for the y component of the point. This point captures the preferred recommendation by the user for the associated vector direction.

However, this point might not represent a point in the space of feasible recommendations. Therefore, a final step is performed that projects this point onto the Pareto-front.

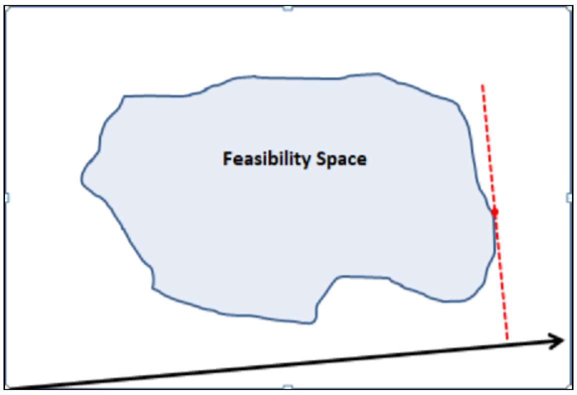


Figure 7: Projection onto Utility Vector.

paretoOptimal(am, vi, m, y-dim, x-dim, L, e)

```
recs ← []
for i=0 to L-1 do {
  alpha_i ← e + [((π/2 – 2e) / L) * i]
  w_xi ←cos(alpha_i)
  w_yi ←sin(alpha_i)
  rec_i ← max_utility(am, vi, m, w_xi, w_yi, x-dim, y-dim, e)
  recs ← recs + {w_xi, w_yi, rec_i}
}
return recs

function max_utility(am, vi, m, w_x, w_y, x-dim, y-dim, e)
  optimal_rec ← argmax{rec_utility}(compute_rec)
  return optimal_rec

function compute_rec(am, vi, m, w_x, w_y, x-dim, y-dim, e)
  model_output ← am(vi)
  model_constraints ← model_output.constraints
  num_metrics ← m.length
  sum_x ←0
  sum_y ←0
  for i in num_metrics do {
   weight_i ← x-dim[i]
   value_i ← model_output.metrics[i]
   sum_x ← sum_x + (weight_i * value_i)
  for i in num_metrics do {
   weight_i ← y-dim[i]
   value_i ← model_output.metrics[i]
   sum_y ← sum_y + (weight_i * value_i)
  rec_utility ← (w_x * sum_x) + (w_y * sum_y)
  return {model_output, rec_utility}
```

The second algorithm, **improveMetric**, is used to generate a new set of recommendations based on improving one metric while relaxing the Pareto-optimal constraints of the others. This algorithm takes as input (1) an analytic model *am*, (2) variable input *vi*, (3) metrics *m*, (4) current utility *cu*, (5) metric to improve *mp*, (6) number of points to generate *L*, and (7) epsilon *e*.

This algorithm simply leverages the paretoOptimal algorithm by setting the y-dim to 1 for the metric corresponding to *mp*, and the x-dim to the weight of current utility for all metrics not *mp*.

```
improveMetric(am, vi, m, cu, mp, L, e)
  num_metrics ← m.length
  x-dim[1,…,num_metrics] ←0
  y-dim[1,…,num_metrics] ←0
  y-dim[mp] ← 1
  for i=0 to num_metrics-1 do{
   x-dim[i] = cu[i]
  return paretoOptimal(am, vi, m, y-dim, x-dim, L, e)
```

Finally, the **extractUtility** algorithm, calculates the user's utility using the x and y components of the underlying vector for the user's preferred recommendation point. This algorithm takes as input (1) selected recommendation *srec* and (2) the current utility *cu*. The output is the normalized user utility.

The mechanism for extracting the utility involves recovering the underlying vector that was projected onto the Pareto-front by the **paretoOptimal** algorithm. This algorithm takes as input (1) selected recommendation *srec*, (2) current utility *cu*, (3) metrics *m*, and (4) current metric-to-consider *mp*.

```
extractUtility(srec, cu, m, mp)
axis ← srec.axis
w_x ← axis.x
w_y ← axis.y
y_weight ← 1
num_metrics ← m.length
user_utility ← []
sum_utility ← 0
for i=0 to num_metrics do {
  if i==mp then {
   user_utility ← user_utility + w_yi
   sum_utility ← sum_utility + w_yi
  }
  else {
   x_weight = cu[i]
   user_utility ← user_utility + (x_weight * w_xi)
   sum_utility ← sum_utility + (x_weight * w_xi)
  }
normalized_utility ← []
for i=0 to num_metrics-1 do {
  normalized_utility ← user_utility[i] / sum_utility
}
return normalized_utility
```

4 SYSTEM ARCHITECTURE

The system consists of two core internal components: (1) Recommendation Engine, which implements **paretoOptimal**, **improveRec**, and **extractUtility** algorithms, and (2) Recommendation User Interface for displaying results and enabling user-guided improvement of recommendations. The Recommendation Engine is further integrated with Unity DGMS for: (1) generating recommendation space and computing metrics, and (2) executing argmin and argmax functions.

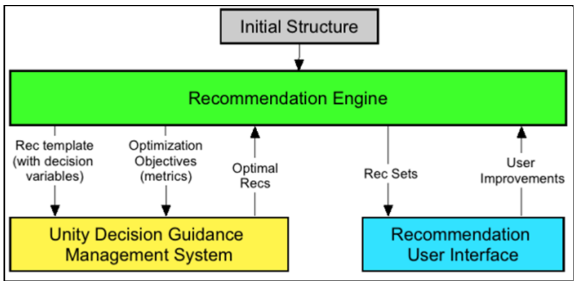

Initial Structure
Recommendation Engine
Rec template (with decision variables)
Optimization Objectives (metrics)
Optimal Recs
Rec Sets
User Improvements
Unity Decision Guidance Management System
Recommendation User Interface

Figure 8: System Architecture.

The Recommendation Engine must be initialized with a data structure that contains (1) metrics definitions used to evaluate each recommendation, (2) an analytic model for computing metrics and constraints of a given recommendation, (3) variable input for exploring the feasible space of composite alternatives, (4) configuration setting for maximum number of recommendations to generate and (5) configuration setting for default metric for user to consider, and (6) configuration setting for default utility weights (e.g. equal weights for all metrics).

The Recommendation Engine integrates with Unity DGMS in order to generate the domain-specific recommendations based on the input model. Furthermore, Unity DGMS provides the capability of calculating metrics on each recommendation.

The JSON output of the recommendation engine is fed directly to the user interface. The user interface is written in HTML and JavaScript. The JavaScript functions of the user interface perform the following: (1) load the recommendation JSON records; (2) bind JSON data to D3JS (Data Driven Documents, 2016) charting library; (3) format the Current Tradeoff Graph; (4) display Current Tradeoff Table; (5) format the Best So Far Graph; (6) display Best So Far Table; (7) load improved recommendations from Unity DGMS; (8) handle all user interactions (best, remove, improve, accept).

5 EXPERIMENTAL STUDY

We conduct an experimental study using synthetic users, in order to measure the performance of the system. Performance is measured by how fast, and to what degree, the system converges in presenting the user with the most optimal recommendation, based on the user's known utility. For this experiment, we use the sourcing example from Section 2.

To initialize the experiment, a set of ten synthetic users is created by generating a random utility for each user. The random utility is an array of random weights, one for each metric.

User 1	[0.54636, 0.1495, 0.3041]
User 2	[0.3393, 0.0763, 0.5844]
User 3	[0.2262, 0.0862, 0.6876]
User 4	[0.1378, 0.3556, 0.5066]
User 5	[0.7261, 0.2243, 0.0495]

Figure 9: First 5 Synthetic User Utilities.

The experiment is run by iterating through each synthetic user and executing the system's algorithms until convergence between the system recommended alternative and the preferred user alternative is reached. Convergence is defined as when the distance between the system recommended alternative and the preferred user alternative stops improving.

At the start of a user iteration, the optimal recommendation is calculated using DGMS, given the assigned user utility. This recommendation serves as ground truth when measuring convergence.

Next, a first set of Pareto-optimal recommendations are generated using default utility of [0.33, 0.33, 0.33] with the cost metric as the first metric to consider. A utility gap is then generated. We define utility gap *UG* by

$$UG = \frac{BUU - UU(srec)}{BUU}$$

BUU=best user utility and *UU(srec)* is the user utility of the system recommendation. If the utility gap is zero, indicating that the system found the optimal recommendation, the user iteration is complete.

Otherwise, the best-so-far recommendation is chosen based on the assigned user utility. This causes the system to extract an updated system utility for the user. The next metric to consider is then determined by computing the gap between the system utility and user utility for each metric. The metric with the largest gap is chosen as the next metric to consider.

The **improveMetric** algorithm is then called with the new metric to consider and the updated system utility, to generate a new set of recommendations. A new utility gap is calculated and the experiment checks for convergence. If convergence is not reached, another cycle of recommendations begins.

runExperiment(num_users, num_metrics)

```
convergences = []
for i=1 to num_users do {
  utility_gap ← Inf
  last_utility_gap ← Inf
  done ← false
  step ← 1
  user_convergence = {}
  user_utility ← randomizeWeights(num_metrics)
  system_utility ← [0.33, 0.33, 0.33]
  bestUserUtility ← findBestRecommendation(user_utility)
  recs ← paretoOptimal(…)
  while done == false do {
    bestSystemUtility ← max(recs.utility)
    utility_gap ← abs(bestUserUtility – bestSystemUtility) /
                        bestUserUtility
    user_convergence[step] = utility_gap
    if (utility_gap == 0) or (utility_gap >= last_utility_gap) {
      done ← true
      convergences ←convergences + user_convergence
    }
    else {
      best_so_far ← findBestSoFar(recs, user_utility)
      system_utility ← extractUtility(best_so_far, …)
      next_metric ← findNextMetric(best_so_far, user_utility
                        system_utility)
      recs ← improveMetric(next_metric, system_utility, …)
    }
    step ← step + 1
    last_utility_gap ← utility_gap
  }
}
return convergences
```

The utility gaps and rates of convergence across all of the users in the experiment are collected and plotted. As seen in Figure 10, the system converges to the optimal recommendation within 3 steps, or the number of metrics.

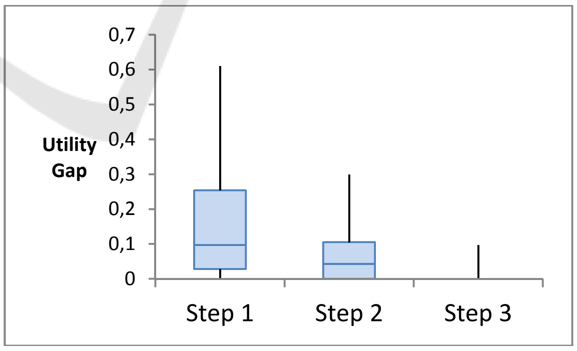


Figure 10: Convergence Results.

6 CONCLUSIONS

In this paper we proposed a methodology and presented a system for generating composite alternative recommendations combining user-guided continuous improvement with Pareto optimal trade-off considerations and for extracting individual utility.

This methodology improves upon earlier research by providing a way to iteratively construct Pareto-optimal recommendations such that the individual user's utility can be extracted.

Furthermore, we developed a system, CAPORS-IUX, to implement the methodology. We also provided experimental results that prove the ability of CAPORS-IUX to converge on the true utility of the individual user.

In future work, we will extend the concept of utility extraction beyond the individual to the group level.

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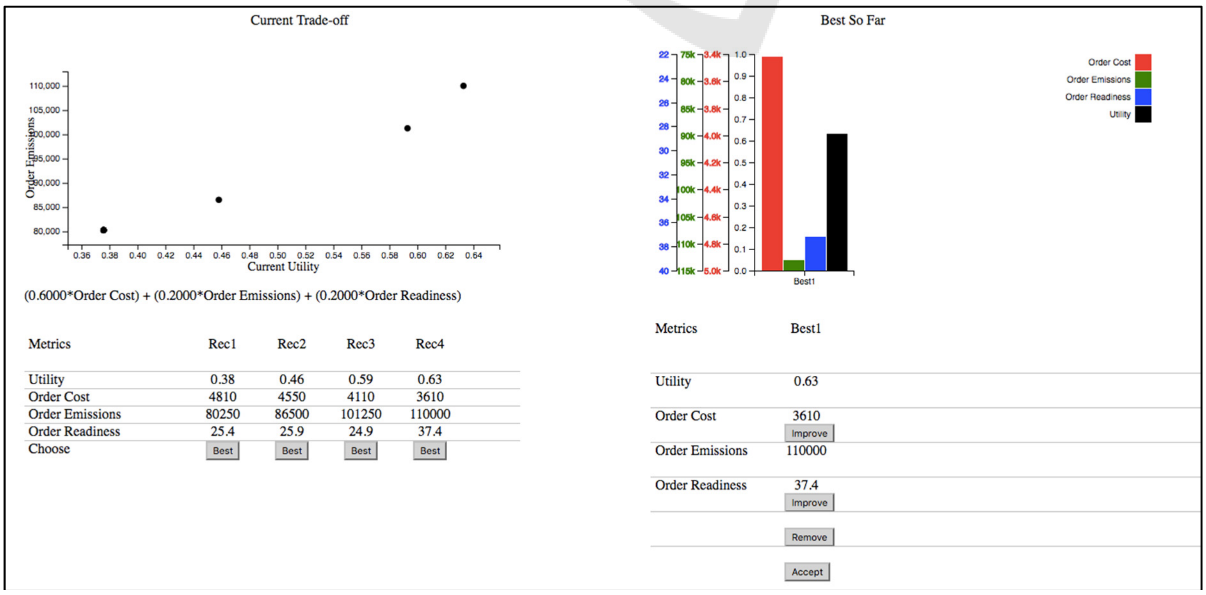
APPENDIX A: USER INTERFACE



(0.6000*Order Cost) + (0.2000*Order Emissions) + (0.2000*Order Readiness)

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Order Emissions	80250	86500	101250	110000
Order Readiness	25.4	25.9	24.9	37.4
Choose	Best	Best	Best	Best

Metrics	Best1
Utility	0.63
Order Cost	3610 Improve
Order Emissions	110000
Order Readiness	37.4 Improve
	Remove
	Accept