Improving Marketing Campaigns with Optimization and Simulation Analysis

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I. INTRODUCTION

Optimization and simulation analysis can be incredibly useful when it comes to predicting and mitigating customer churn in the telecommunications industry. By utilizing data-driven insights, companies can identify patterns and trends that may indicate when a customer is at risk of leaving and take proactive steps to retain them. This can include targeted marketing campaigns, personalized offers and incentives, and improved customer service. Ultimately, optimization and simulation analysis can help telecommunications companies reduce customer churn, increase customer loyalty, and ultimately grow their business.

This paper describes a project that aimed to build upon the success of our prior work [1]. In that project, we utilized predictive modeling and prescriptive analysis to identify potential solutions to reduce customer churn for a telecommunications company in California. In this project, we used the final preprocessed customer dataset and the Random Forest top predictive model from Project 1's analysis to analyze a proposed promotional marketing campaign for the Telecommunications company. The campaign was aimed at reducing churn and growing the company's customer base in future quarters. To predict future customer growth over the next twelve quarters, given a proactive marketing campaign, we focused on optimization and simulation analysis of a net customer growth utility function. The analysis allowed us to determine the effectiveness of proposed service promotions to offer in a proposed marketing campaign.

Most of the heavy lifting for preprocessing the data was completed in Project 1. After importing the data, the remaining tasks were to normalize the features and split the data for model training and testing. In Project 1, we found that the Random Forest model had the best predictive performance with this dataset, so we imported it for use in this project for optimization and simulation analysis. To aid in this analysis, we developed a customer growth utility function that uses the Random Forest model's probability of churn output. We used a dual annealing optimization technique to minimize the Random Forest model's probability of churn in the utility function. The optimization analysis yielded feature attributes of an ideal customer. This information, along with detailed feature analysis, was used to develop marketing promotions aimed at encouraging existing customers to adopt behaviors similar to those of the ideal customer and to attract new customers who resemble the ideal customer.

To analyze the immediate impact of the marketing promotion, we used a Monte Carlo Simulation to generate a distribution of potential customer growth for the upcoming quarter and demonstrate the effectiveness of our promotional concept. To further study the impacts of our proposed changes over time, we implemented a Discrete Event Simulation to perform iterations on successive quarters while also comparing the impact with and without a marketing promotion. Finally, we conclude with a discussion of prescriptive recommendations for the marketing campaign.

This paper is organized as follows. In Section II, we provide details about the dataset composition. Section III covers the methodology used for data preprocessing, modeling, optimization, and simulation analysis. Section IV presents a detailed discussion of the results and recommendations. In Section V, we offer the conclusions of the project. Lastly, Section VI outlines the individual contributions of the project team's collaboration.

II. DATA DESCRIPTION

A. Data Overview

The dataset utilized in this project is the final preprocessed 11 top customer features dataset from Project 1 [1]. The original raw data was obtained from Maven Analytics and originally sourced from IBM Cognos Analytics [2]. The dataset pertains to customer churn data for a telecommunications company that provides phone and internet services to customers in California. It covers the reporting period of Q2 2022 and contains information on 7,043 customers. Through Project 1, the dataset was filtered down to the top 11 attributes that describe key customer demographics, subscription services, and billing information. The Target feature used for classification and analysis is *Customer Status*, which can have two possible values: Stayed or Churned. A status of Stayed indicates a retained customer, while a status of Churned indicates a customer who has left and terminated services with the company. The data dictionary for this dataset is shown in Table I.

TABLE I. DATA DICTIONARY.

Feature	Data Type	Values	Description
Customer_Status **(TARGET)**	Binary	Churned=1, Stayed=0	Status of the customer at the end of the quarter
Age	Int	Range 19 to 80	Customer's current age in years
Dependents	Binary	Yes=1, No=0	Customer has dependents living with them
Region_San_Diego	Binary	Yes=1, No=0	Customer resides in the San Diego region
Online_Security	Binary	Yes=1, No=0	Additional online security service subscriber
Premium_Tech_Support	Binary	Yes=1, No=0	Additional technical support plan subscriber
Streaming_Music	Binary	Yes=1, No=0	Customer streams music from a third-party provider at no additional fee
Contract_Month_to_Month	Binary	Yes=1, No=0	Month-to-Month contract type
Paperless_Billing	Binary	Yes=1, No=0	Customer utilizes paperless billing
Payment_Credit_Card	Binary	Yes=1, No=0	Customer pays bill w/ Credit Card
Monthly_Charge	Float	Sample 65.6	Total monthly charge for all services

B. Data Visualization and Exploration

Figure 1 displays the distributions of the 11 features categorized by Churn. All the features have skewed distributions, indicating that they are not normally distributed. The distributions suggest that senior citizen customers and those with no Dependents have a higher churn rate. Furthermore, customers residing in the San Diego Region seem to have a disproportionately high churn rate. Similarly, customers enrolled in a Month-to-Month Contract have an excessively high churn rate. Additionally, customers who are not subscribed to additional Online Security or the Technical Support Plan are more likely to churn. Customers using Paperless Billing have a higher churn rate. Furthermore, customers paying by other than Credit Card also have higher churn rates. Lastly, customers paying a higher monthly bill are more likely to churn, which is quite expected.

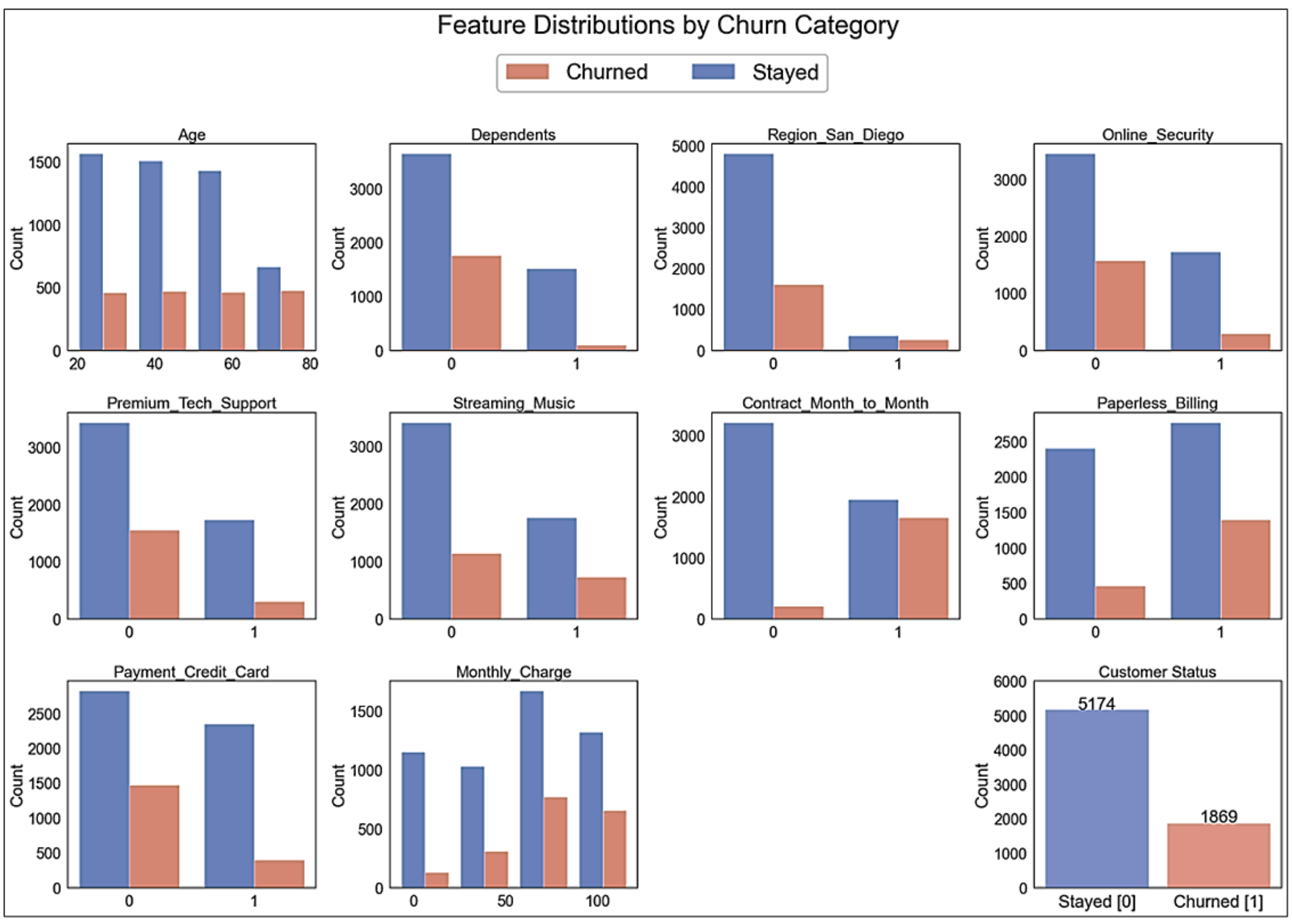

Fig. 1. Features Distributions by Churn Category.

To provide a comprehensive overview of the features, Table II presents a summary of the feature statistics, which is a helpful complement to the distribution charts shown in Figure 1. It is worth noting that there are a number of features that contain values of zero (0) or, as in the case of the Monthly Charge feature, a negative value. This poses a challenge in transforming these skewed features into a normal Gaussian distribution for modeling, since many standard transformation algorithms cannot handle such values.

TABLE II. FEATURE SUMMARY STATISTICS.

	Customer Status	**Age**	**Dependents**	**Region San Diego**	**Online Security**	**Premium Tech Support**	**Streaming Music**	**Contract Month-to-Month**	**Paperless Billing**	**Payment Credit Card**	**Monthly Charge**
Count	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043
Mean	0.3	46.5	0.2	0.1	0.3	0.3	0.4	0.5	0.6	0.4	63.60
Std	0.4	16.8	0.4	0.3	0.5	0.5	0.5	0.5	0.5	0.5	31.20
Min	0	19	0	0	0	0	0	0	0	0	-10.00
Q1 25%	0	32	0	0	0	0	0	0	0	0	30.40
Q2 50%	0	46	0	0	0	0	0	1	1	0	70.05
Q3 75%	1	60	0	0	1	1	1	1	1	1	89.75
Max	1	80	1	1	1	1	1	1	1	1	118.75

III. METHODOLOGY

For this project, Python's analytics and modeling capabilities were utilized for all data analysis and modeling. The coding was conducted in Jupyter Notebook, an open-source web application that allows for interactive data science and scientific computing using the Anaconda distribution [3,4]. A flowchart of the analytical process used is displayed in Figure 2.

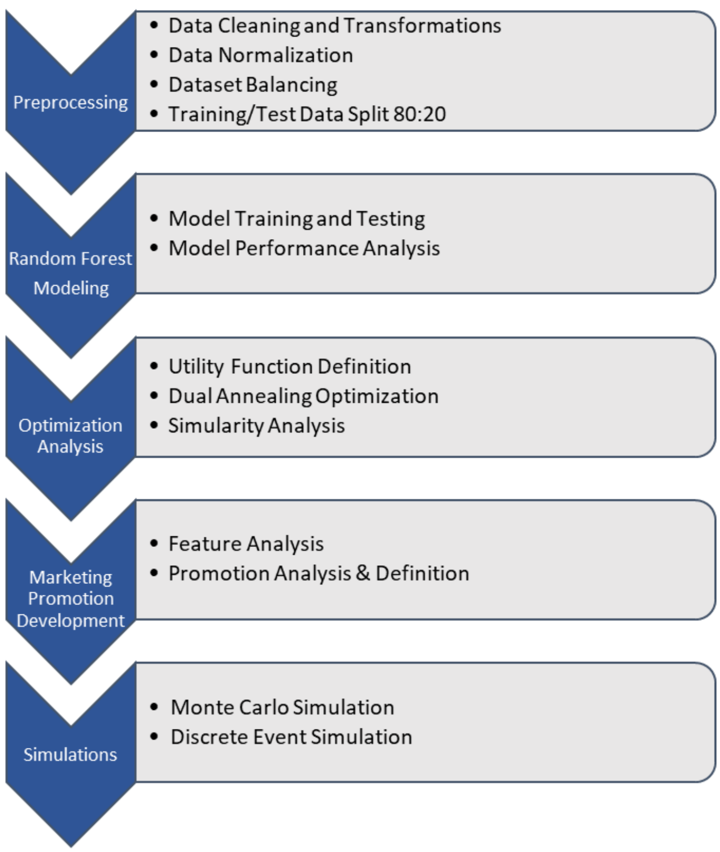

Fig. 2. Flowchart of Analytical Process.

A. Preprocessing

a) Importing Preprocessed Data

In Project 1, we conducted several preprocessing steps such as data cleaning, transformation/encoding, outlier treatment, correlation analysis, and feature selection with the original dataset of 38 features [1]. Feature selection identified 14 meaningful features that had a significant impact on prediction modeling. In this follow-up project, we imported and filtered this 14 feature dataset further, eliminating three interdependent features (subcategory types of customer charges). As a result, we had a final dataset of 11 features ready for final preprocessing, analysis, and modeling.

b) Data Normalization

In preparation for modeling, we used min-max scaling to normalize the features to a scale of [0,1]. The process of min-max scaling involves subtracting the minimum feature value from the feature value and then dividing by the range.

c) Dataset Balancing

In Figure 1, the distribution chart on the lower rights shows that our dataset has an imbalance with unequal observations in the target class. This can be a significant challenge for predictive modeling as many machine learning algorithms used for classification assume an equal number of examples for each class. Models trained on imbalanced data can have poor predictive performance, particularly for the minority class [5]. To tackle this issue, we used undersampling to balance our dataset, resulting in each class being equally represented with 1,869 records. Undersampling involves randomly sampling observations from the majority class to match the numbers with the minority class.

d) Training and Test Data Split 80:20

In order to prevent overfitting and underfitting, the dataset was divided into a training set and a test set using a ratio of 80:20. The training set was used to train the model, while the test set was used to evaluate the accuracy of the model.

B. Modeling

Previously, the Random Forest model demonstrated the best predictive performance with this dataset and hence was imported for use in this project [1]. The Random Forest model is an ensemble model that iteratively creates multiple decision trees with changing parameters to enhance predictive accuracy and control over-fitting. To refine the model and select the appropriate hyperparameters, a 10-fold cross-validation was performed. The resulting hyperparameters were: *criterion – entropy, maximum depth – 8, and number of estimators – 100.*

Now, the Random Forest model was refitted using our modified feature set. In Figure 3, the training and test performance metrics for the Random Forest model are presented. The test accuracy of the model is 0.81 and its recall is 0.84, which are comparable to the results achieved in Project 1. With the model's performance re-validated, it will now be utilized for the optimization and simulation stages of this project.

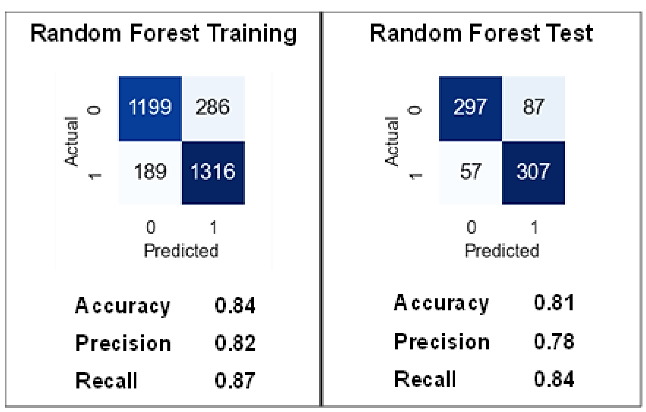

Fig. 3. Random Forest Model Classification Training & Test Results.

C. Optimization

a) Utility Function

A utility function is a useful mathematical tool for decision-making in uncertain situations. It lets individuals assign values or preferences to various outcomes, making it easier to make optimal choices based on those values. The central idea behind a utility function is to provide an objective to maximize/minimize so as to optimize the overall utility.

Equation (1) outlines our customer growth utility function. This utility function will be used in optimization and simulation analysis to assist in developing the best service promotions for the Telecommunications company's marketing campaign.

$$N_i = (N_{i-1} + new_{\ i})\ x\ (1 - P(Churned)) \qquad (1)$$

Where N_i is the total number of customers after the i'th quarter, N_{i-1} is the total number of customers from the preceding quarter, new_i is the total number of new customers in the i'th quarter, and *P(Churned)* is the probability of Churned generated by our Random Forest predictive model. Our goal is to increase the number of customers in future quarters, which means we need to reduce the probability of customers churning as predicted by the Random Forest model.

b) Dual Annealing Optimization

To minimize the utility of the *P(Churned)* probability output within the Random Forest model's domain, we employed the dual annealing optimization technique. This technique helped us determine the optimal/ideal values of our ten features. Dual annealing is a type of stochastic global optimization algorithm that's based on the simulated annealing optimization algorithm [6]. The latter is a variant of stochastic hill climbing.

Python's *dual_annealing()* function in the SciPy library was utilized to minimize *P(Churned)*. For this purpose, the function requires search bounds and a callable objective function. The search bounds were defined by specifying the max and min values of each feature. Our trained Random Forest model's probability predictor (*predict_prob( )*) was used as the objective function. The results of the dual annealing optimization are presented in section IV, Results and Discussion.

c) Similarity Analysis

Similarity analysis was performed to compare each of the current customers with the ideal customer attributes identified through dual annealing optimization and listed in Table III. There are several metrics available to find the similarity between two data points [7]. We elected to use Euclidean distance, which is the most common distance function, as our similarity measure. With distance similarity measures, the smaller the distance, the higher the similarity. The feature values of both the ideal customer and current customers were normalized before computing the Euclidean distances. The results of the similarity analysis are presented in section IV, Results and Discussion.

D. Marketing Promotion Development

a) Feature Analysis

Table III provides a composite summary of the various feature analysis techniques used. This side-by-side comparison of the Random Forest model's feature importances, sensitivity, distributions, and optimal values will be leveraged to aid in the development of promotional service offers for the marketing campaign. Feature importance denotes the contribution of each feature to the model's prediction, while sensitivity indicates how much variation in the model's *P(Churn)* output can be attributed to variations in the input features. Feature distributions can reveal customer churn trends based on feature value ranges. Optimization identified the feature attributes (values) of an ideal customer that has zero probability of churn.

TABLE III. FEATURE ANALYSIS COMPOSITE SUMMARY.

Feature	RF Model Feature Importances	Churn Sensitivity (Normalized)	Distribution Interpretaion	Optimal Ideal Value	
Contract_Month_to_Month	0.36	0.27	= 1 ⇨ Churns More	0.15	0 = No
Monthly_Charge	0.20	0.10	> 70 ⇨ Churns More	$40	
Age	0.13	0.15	> 60 ⇨ Churns More	21	
Dependents	0.12	0.09	= 0 ⇨ Churns More	0.69	1 = Yes
Payment_Credit_Card	0.04	0.12	= 0 ⇨ Churns More	1.00	1 = Yes
Online_Security	0.04	0.12	= 0 ⇨ Churns More	0.97	1 = Yes
Paperless_Billing	0.03	0.07	= 1 ⇨ Churns More	0.18	0 = No
Premium_Tech_Support	0.03	0.02	= 0 ⇨ Churns More	0.54	1 = Yes
Streaming_Music	0.03	0.02	= 1 ⇨ Churns More	0.78	1 = Yes
Region_San_Diego	0.02	0.04	= 1 ⇨ Churns More	0.30	0 = No

After analyzing the model feature importances, we found that the *Contract Month-to-Month* and *Monthly Charge* are the most significant features that we can influence. These two features, along with *Payment by Credit Card* and *Online Security*, are also the most sensitive features that can significantly drive a change in the model's prediction with a change in their values. *Age* is both sensitive and important, but neither within a given customer's direct control nor the company's, so there is less opportunity to drive results. The distribution interpretation column helps to identify the undesirable feature values, which are often the primary drivers of customer churn. In contrast, the last column highlights the desirable feature values of an ideal customer. It is worth noting that nine of the ten features behave as expected, with the optimal value pointing away from high churn likelihood.

b) *Promotion Analysis* & *Definition*

The goals of the promotion are to expand the customer base by encouraging existing customers to adopt behaviors similar to those of the ideal customer and to draw in new customers who resemble the ideal customer. From the optimization and feature analysis, it is evident that incentivizing customers to switch from a Month-to-Month Contract to a 1+ year contract plan should result in less customer churn. Additionally, incentivizing customers to use a Credit Card for payments should also result in less customer churn. Based on the disproportionately high churn rate in the San Diego area, there appear to be other factors in play outside our purview, so any promotion there may not be the best allocation of marketing dollars. Two of the ways to influence customer behavior are by offering them *Monthly Charge* discounts and incentivizing adoption of *Premium Tech Support* and *Online Security.* These features have the added benefit of also possibly reducing the customer churn rate. From this analysis, the following promotions were developed.

Promotions:

#1 10% monthly bill discount for switching away from Month-to-Month onto a 1+ year contract plan.

#2 Free Premium Tech Support & Online Security for customers who make their payments by Credit Card.

Timeframe/Parameters:

- For the MCS, the promotions are in effect during the simulated quarter.
- For the DES, the promotions are in effect for the first four quarters. Promotional benefits are permanent and survive after the promotion is no longer in effect.
- Customers in the San Diego area are not eligible for either promotion.
- During quarters when the promotion is in effect, the new customer count will be increased by 10%. All new customers are potentially subject to churn during the quarter in which they join or any quarter thereafter.

Promo 1 Application:

- Existing customers who are Month-to-Month have a 10% chance of switching to a contract plan (no longer being Month-to-Month) in any given quarter. If these are applied, then at that time, also apply the monthly discount permanently.
- New customers are 10% more likely to join on contract (not Month-to-Month). Apply a 10% discount to Monthly Charge after the monthly charge is determined stochastically.

Promo 2 Application:

- Existing customers who are not paying by Credit Card have a 10% chance of becoming Credit Card Payers in any given quarter. Apply Premium Tech Support & Online Security = TRUE to these customers.
- New customers are 15% more likely to sign up for Credit Card payment and receive free Tech Support & Online Security.

The Project team's conservative best estimate was used to come up with the probabilities of chance for the promotion modeling. Modular functions were created using the promotional modeling parameters to modify customer attributes and generate new customers (new_i - utility function parameter) which are generalized to be applied to both the Monte Carlo and Discrete Event simulations.

E. *Simulation*

a) *Model iteration*

Our team developed and implemented logic to simulate model activity within a quarter, paralleling the scope of the original dataset. We modeled new customer counts using a Gaussian distribution. As the single data point available showed 1051 customers with a tenure of 3 months or less, we posited that a range of 892 to 1210 customers per quarter (SD equal to 5% of mean) was a realistic estimate, giving us $\mathcal{N}(1051, 53)$. We also provided that during promotional quarters, we would see an added 10% factor to new customers.

For new customers, 10 features were assigned. 8 Boolean values were determined based on random number generation using the population likelihood for each feature. 2 numeric values (Age and Monthly Charge) were generated using random number generation to assign percentiles within the population data range. We considered that this approach does not allow for new data to provide outliers beyond the existing data range, but determined that such edge cases were either implausible (e.g., ages below 18, monthly charges below $0) or unlikely to provide additional probabilistic information beyond range min/max values.

b) *Monte Carlo Simulation*

To study the immediate outcomes of the suggested modifications, we conducted a Monte Carlo Simulation using the Monte Carlo Method. This method was initially developed by a group of researchers, including Nicholas Metropolis, John von Neumann, and Stanislaw Ulam, in the late 1940s and early 1950s [8]. The simulation was performed on the quarter that follows immediately after the quarter described in our dataset. In our MCS model, we ran 1,000 iterations of the following quarter, with each of the 1,000 iterations including a new set of customers, each with randomized feature values based on the original dataset, alongside the retained customers from the original dataset. Once the new customers signed up and joined the retained customers from the last quarter, the customer database is then scored via the Random Forest classification model, with the output directly corresponding to the probability that the customer churns in the next quarter.

c) *Discrete Event Simulation*

To further study the impacts of our proposed changes over time, we implemented a Discrete Event Simulation (DES) to perform iterations on successive quarters. DES was first developed by Geoffrey Gordon at IBM in the early 1950s for finite-state electronic circuit analysis [9]. The model utilized 1 business quarter as the discrete event to simulate, which parallels the original dataset. Two sets of simulations were performed; 100 cycles with promotions effective for quarters 1 through 4, and 100 cycles with no promotional effects. We conducted each cycle over a span of 12 quarters to assess the lasting effects of our promotions.

At each discrete event, stochastic changes were applied to the existing customer base, including promotion logic as applicable, and new customers generated with promotion logic as applicable. The updated customer database was then scored via the Random Forest classification model, with each customer assigned a current-quarter probability of churn. These probabilities were used to stochastically determine the composition of the Stayed/Churned target feature.

IV. Results and Discussion

a) *Results: Optimization*

During the optimization process, the dual annealing function performed 20,056 evaluations and successfully reached a minimum of zero (*0*) for *P(Churned)*. The optimized ideal values for the 10 features can be found in Table IV. It's worth noting that the real number decimal values for the binary features can be interpreted as a probability for the binary value 1 (yes). However, applying the definitive feature binary values [0,1] as indicated by these probabilities, mapping values < 0.50 to “no” and ≥ 0.50 to “yes,” still yields a minimized *P(Churned) = 0.*

TABLE IV. FEATURE VALUES FOR AN OPTIMAL IDEAL CUSTOMER.

Dual Annealing Minimized Probabilities P(Stayed) = 1.0, P(Churned) = 0.0		
Optimized / Ideal Value	**Definitive Binary Value**	**Feature**
26.26	–	Age
0.69	1 = Yes	Dependents
0.30	0 = No	Region_San_Diego
0.98	1 = Yes	Online_Security
0.54	1 = Yes	Premium_Tech_Support
0.78	1 = Yes	Streaming_Music
0.15	0 = No	Contract_Month_to_Month
0.18	0 = No	Paperless_Billing
1.00	1 = Yes	Payment_Credit_Card
$39.83	–	Monthly_Charge

The distribution of Euclidean distances from the similarity analysis of current customers to the ideal customer is shown in Figure 4. The distribution shows that there are very few current customers who precisely match the ideal customer. The distribution is negatively skewed, with a minimum distance of 0.17, a mean distance of 2.09, a maximum distance of 2.99, and a standard deviation of 0.39. Only 31 current customers were found to have a perfect match to all eight binary feature attributes of the ideal customer. These results could explain why the Telecom company experienced a high rate of customer churn in the previous quarter.

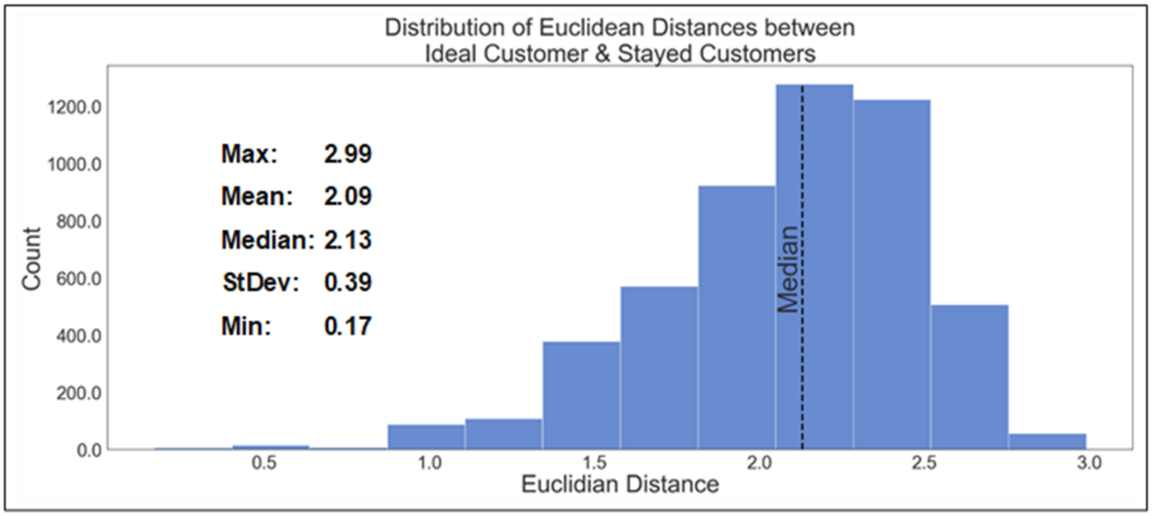

Fig. 4. Distribution of Euclidean Distances between Ideal Customer & Stayed Customers.

b) Results: Monte Carlo Simulation

Figure 5 presents the results of the Monte Carlo simulation, displaying two histograms that show the customer count forecast after a simulated quarter. The histogram on the left, shown in blue, represents the non-promotion simulation scenario, while the one on the right, shown in orange, represents the promotion simulation scenario. Both distributions closely resemble a normal Gaussian distribution. Upon examining the measures-of-center, it was observed that the promotion scenario distribution mean and median were identical, with a value of 4,450 customers, which further reinforces the normalcy of the distribution. The mean and median of the non-promotion distribution were also identical, with a slightly lower value of 4,320, indicating that the promotion did not have a major effect after only one quarter. It is worth noting that both distributions show a customer count that is lower than the initial count at the start of the simulation, which was 5,174. This equates to a 15% decline in total customers for this one forecast quarter. However, the customer loss trend is slowing down, as the previous quarter saw over a 26% decline in customers. This lack of significant improvement after only one quarter is why we elected to conduct a more detailed discrete event simulation forecasting out 12 quarters.

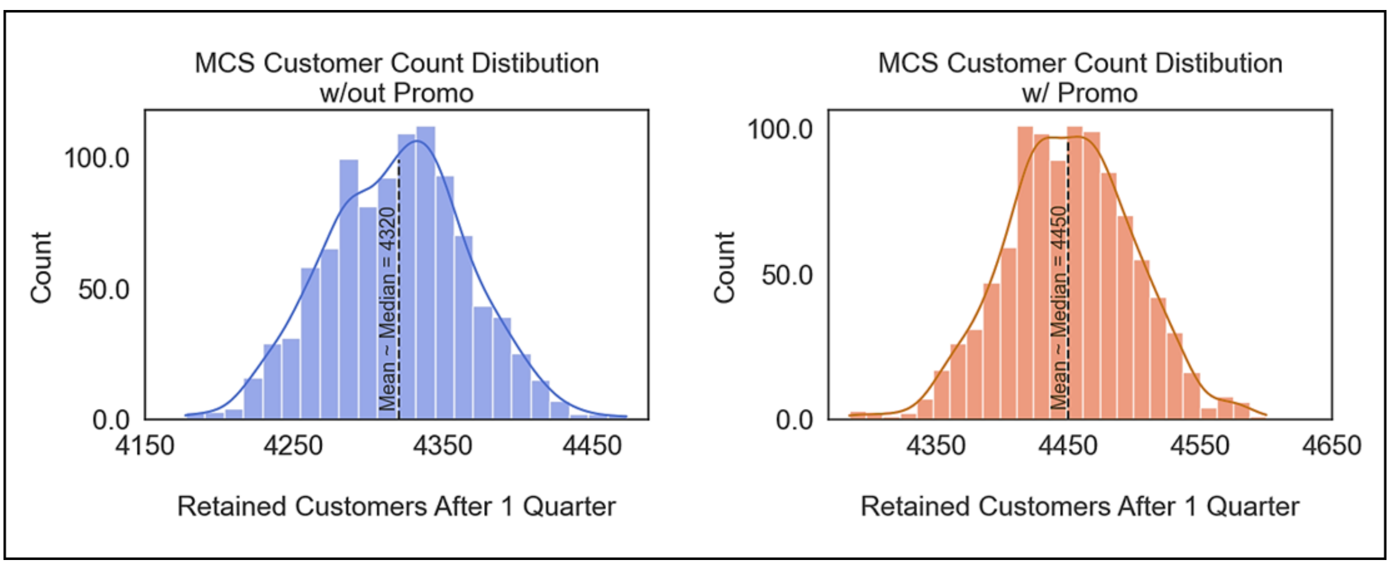

Fig. 5. Monte Carlo Simulation Results – Distributions of Customer Counts after 1 Quarter.

c) Results: Discrete Event Simulation

The outcomes obtained from the discrete event simulation are displayed in Figure 6. As seen in the trendlines, both the promotion and non-promotion scenarios experienced a dip in total customers through three quarters. This is reasonable to expect given the trends identified in earlier phases: the original dataset showed a single-quarter churn rate of 26% in dropping from 7,043 (N_{-1}) to 5,174 (N_0), and we recognized that our customer base was still poorly fit in many ways relative to the attributes most correlated with retention. To achieve a net positive effect, it was necessary to mitigate the losses while simultaneously acquiring new customers. This would lead to a steady-state equilibrium point between customer growth and churn rates that we would expect to be the same for both scenarios post-promotion phase. While both trend curves declined through three quarters, the promotional trendline outperformed by around 200 net customers, with the advantage persisting all the way out to quarter 12 with little sign of regression to the benchmark. This indicates that success with adding customers more suited to our model results in long-term retention.

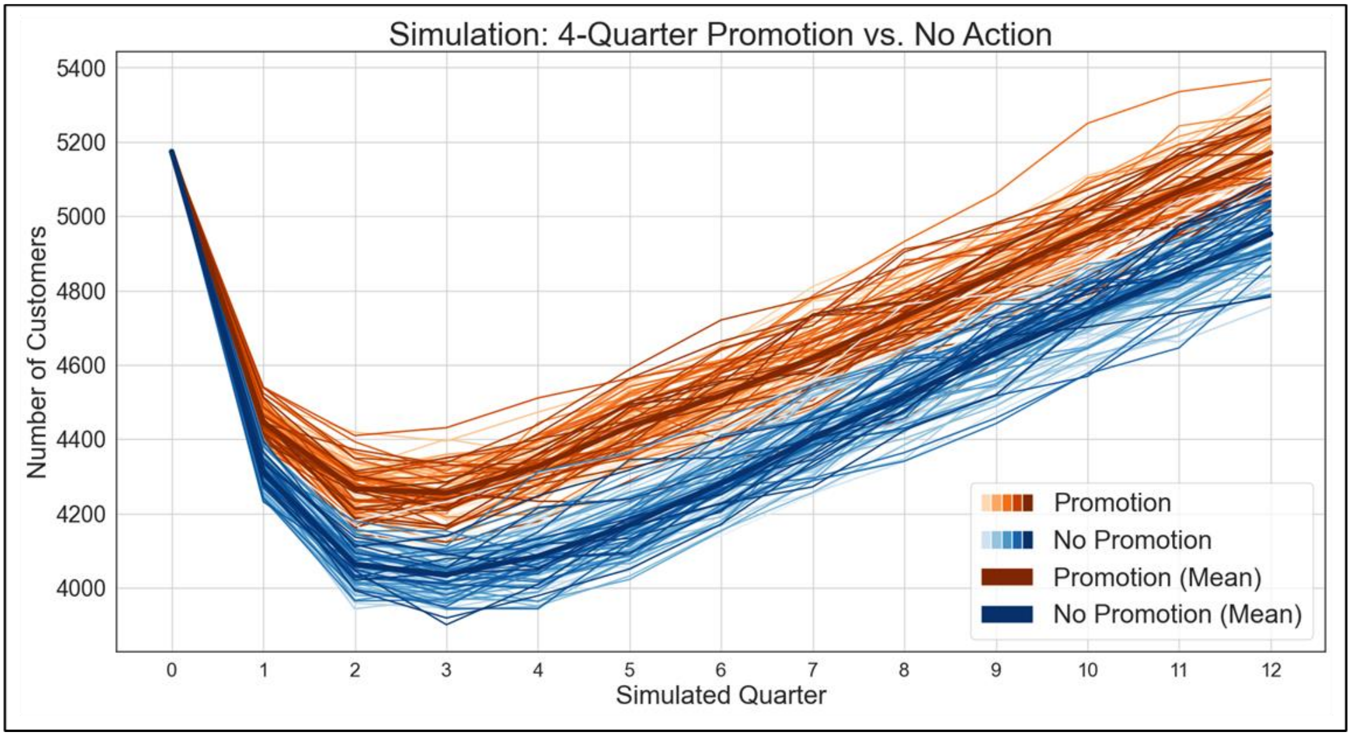

Fig. 6. Discrete Event Simulation Results

With this knowledge in hand, it is natural to seek to quantify the improvement in that aspect. Utilizing the dual-annealing optimization result from III(C), we compute the mean Euclidean distance from our customer base to the ideal on a quarterly basis. The results are presented in Figure 7. Both scenarios depict an asymptotic trend toward a steady state in this metric. This is expected, as the evolving conformity of the customer base toward retention characteristics is the chief input into reaching a steady-state value of total customers, and those optimal parameters are the same between the two scenarios, independent of the limited-time application of promotional factors. Interestingly, both "promo" and "non-promo" scenarios provide similar results in quarter 1, but promo swiftly outpaces non-promo from that point forward. Indeed, while the non-promo scenario continues to converge toward that steady-state value from above, the promo scenario appears to bypass it and gradually refract back toward it. This explains why the results did not taper off, but rather persisted after the promotion ended.

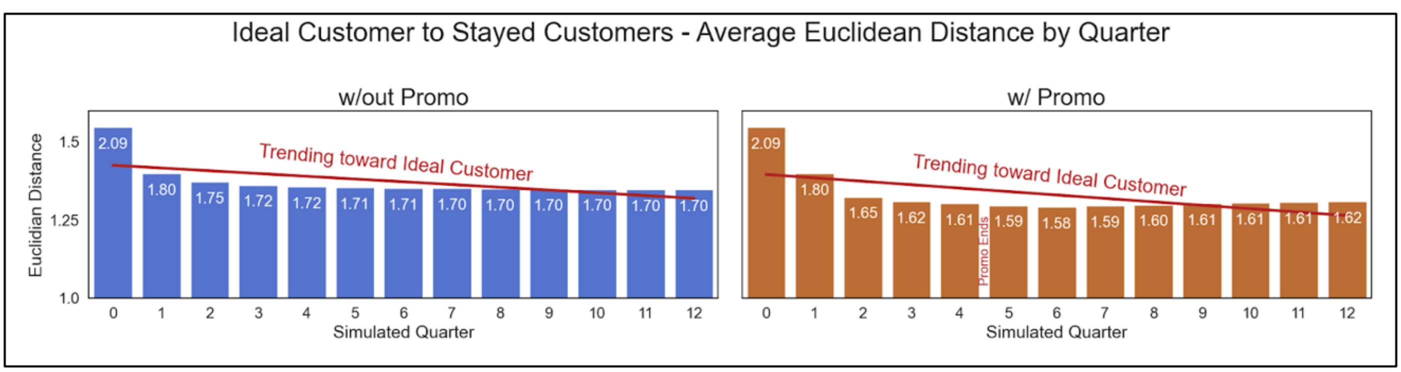

Fig. 7. Ideal Customer to Stayed Customers - Average Euclidean Distance by Quarter

V. Conclusions

As detailed above, our project team was successfully able to utilize dual annealing optimization to identify an "ideal" customer feature set tuned to maximize our utility function for total customer count. We calculated a mean population Euclidean distance from that ideal of 2.09, giving a benchmark to measure the trends achieved in future simulation steps. Inspection of that result, with modest interpretation into practical effects, allowed us to craft a tailored proposal to influence these parameters among the company's total customer population, resulting in greater retention (~ reduced churn) of both existing and new customers. Our promotions sought to increase feature prevalence in both new and existing customers, with stated goals to both gain/retain customers in the immediate term, and shift the population statistics in a more sustainable direction in the long term.

Through Monte Carlo Simulation, we were able to calculate a net effect and likelihood of impact from running the promotion as designed. We found that the retained count of customers increased by an average of 130 after one quarter, representing a 15.02% reduction in churn and a 3.01% improvement in overall customer count in a single quarter, which is both a statistically and operationally significant improvement. Analysis of the MCS histograms indicated a 97.75% likelihood that the promotion would outperform the default assumptions, but nevertheless continued decline in customer counts.

This marked, yet incomplete improvement spurred us to construct and complete a Discrete Event Simulation carrying these results into the future. For this, we hypothesized that running the promotion for 4 consecutive quarters would have some lasting impact beyond the duration of the promotion, so iterations were carried out for an additional 8 quarters (12 in total). This was compared once again to a null hypothesis simulation, and we found that the improvements did indeed persist. In terms of overall count, the net benefit averaged 202 additional customers, and we saw the statistical composition of those retained customers continued to match the optimized feature values more closely than the non-promotional benchmark (1.62 vs. 1.70 after 12 quarters).

Thus, our simulations showed, and we concluded, that the promotional proposal below is very likely to be successful.

Recommended promotional proposal based on prescriptive analysis:

#1 10% monthly bill discount for switching away from Month-to-Month onto a 1+ year contract plan.

#2 Free Premium Tech Support & Online Security for customers who make their payments by Credit Card.

VI. Collaboration Contributions

A. Mark Bronakowski

- Updated preprocessing of data from Project 1
- Contributed to the development of the utility function
- Contributed to the development of the marketing promotion parameters
- Performed the optimization analysis
- Performed the similarity analysis on the optimization results
- Performed the similarity analysis on results from DES simulation
- Authored report Intro, Data Description section and Methodology Preprocessing, Modeling and Optimization sections
- Authored optimization results and contributed to the conclusion narrative.

B. Chris Schneider

- Contributed to the development of the utility function
- Devised and programmed logic to implement promotions
- Formalized utility function and simulation loop logic
- Provided implementation for simulation loop
- Implemented and ran Discrete Event Simulation (DES)
- Constructed compound-line data visualization for DES results (Fig. 6)
- Authored simulation logic and DES methodology and contributed to results/conclusion narratives.

C. Evan Busman

- Contributed to the development of the utility function
- Provided implementation for randomized customer generation function
- Implemented and ran Monte Carlo Simulation (MCS)
- Constructed histogram data visualization for MCS results (Fig. 5)
- Authored Monte Carlo simulation methodology and results and contributed to the conclusion narrative.

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