Predictive Modeling and Optimization of RCC Allocation

1. Introduction

This report develops data-based restructuring methods for SFB which integrates post-merger and seeks to reduce its workforce while meeting fair standards and legal requirements. The organization aims to find employees who will accept Retirement Compensation Contracts (RCC) without extending invitations to choose specific personnel (Shabat and Manal, 2020). This project combines a predictive modeling component that utilizes machine learning through Python with an optimization model managed through Excel Solver.

The predictive model receives training through historical data from employee attrition events from a previous workplace closure using "employee_attrition_previous_closure.csv" as its dataset. The predictive model determines how likely it is that individual employees will accept Reward and Compensatory Compensation offers (Erciulescu et al., 2022). The probabilities were deregistered into the employees from "employee_attrition_lyon.csv" in order to generate personal acceptance likelihoods.

The report outlines a grouping mechanism which respects both legal and ethical principles before applying an optimization system to achieve minimum severance expenses across satisfied organizational requirements. The organization needs to decrease employee salaries to at least three million euros combined with requiring at least forty employee departures but maintaining staff retention above eighty percent within each operational department. The analysis evaluates both the benefits and drawbacks that result from implementing the predictive and optimization methods together (Alabi et al., 2022).

2. Defining Objective Employee Groups for RCC Offers

At SFB the decision to offer RCCs (Retirement Compensation Contracts) applies to pre-defined groups of employees and not to individual assessment (Tomassetti and Julia, 2014). This legislation along with ethical standards protects organizations from unfair choices through criteria that prevent personal biases and discriminatory treatment. The successful execution of restructuring demands the right establishment of grouping standards that support both organizational cost reductions and honest and open procedures.

The employee dataset brings forth operational and non-sensitive criteria that enable objective group definition. The selected classification variables consist of Sales, R&D, HR departments together with job tenure and seniority level alongside age segments. The definition of grouping criteria would involve creating categories such as “R&D employees with less than 5 years of tenure” or “Sales staff who exceed age 50.” The predictive attrition model this project developed serves as an important new input. The formation of groups depends on the predicted likelihood that employees will accept the RCC requests. The high-probability group for RCC offers should consist of employees whose predicted acceptance rate surpasses a specific threshold (example: 0.40) as per consistent data treatment rules.

The advantages and disadvantages differ between groupings of small and large member numbers. Groups that use specific job role or time-serving criteria for selecting members produce better accuracy in reaching optimization targets. Group sizes based on this strategy enable organizations to specifically select staff members who will both accept the RCCs and deliver maximum financial benefit upon leaving. When targeting groups with very specific boundaries this approach can effectively move toward targeting individual employees which creates legal and equality issues. Cost optimization within groups shows more efficiency yet broader groups aligned with general criteria become more defendable but lose their ability to optimize cost sharply. In such cases the group composition includes employees whose likelihood to accept severance pay is low or who have a small impact on financial expenses which reduces the total value of the offer strategy.

The implementation of statistical fairness audits serves as a tool to evaluate non-discriminatory aspects in grouping procedures. The examination checks whether protected traits such as age represent disproportionate proportions of selected groups. The evaluation tool disparate impact analysis utilizes the four-fifths rule to detect hidden biases. The restructuring plan execution will maintain fairness through the use of grouping criteria that are objective, follow consistent practices and do not rely on protected characteristics.

3. Optimization Model for RCC Allocation

An optimization model was created to help SFB align its Retirement Compensation Contracts (RCCs) distribution across departments based on organizational and ethical requirements while minimizing severance payments (Blount and George, 2020). The program was executed through Microsoft Excel Solver add-in on data from employee_attrition_lyon.csv file which included predictions from the prior machine learning model for RCC acceptance.

3.1 Optimization Objective and Structure

The optimization model targets the reduction of severance expenditure by accumulating the salary amounts employees receive from RCC acceptance. Since RCCs cannot identify specific individuals for assignment the optimization model allocates them to objective reference classifications. The optimization follows established employee group definitions created through department and tenure criteria to fulfill policy regulation rules and prevent bias. The optimization model consists of three fundamental features which guide its structure.

3.1.1 Decision Variables

The optimization model requires a determination of which employees will receive RCC opportunities. Each employee within the dataset has a binary variable that indicates receipt or absence of RCC offer.

- $\text{OfferRCC}_i = 1$ if employee is offered an RCC
- $\text{OfferRCC}_i = 0$ otherwise

The use of binary variables helps decision-makers understand which employees receive RCC offers and which ones do not.

The model estimated expected worker departures through multiplication between binary RCC decision values and individual prediction rates for RCC acceptance. The evaluation calculated salary savings by multiplying between the RCC decision variable and employee annual income using their predicted acceptance probability.

3.1.2 Objective Function

The optimization seeks to minimize total severance costs by adding up the salary benefits from RCC acceptance. Mathematically, the objective is:

$$\text{Minimize} \sum_{i=1}^{n} \left(\text{AnnualIncome}_i \times \text{OfferRCC}_i \right)$$

Where:

- $\text{AnnualIncome}_i = \text{MonthlyIncome}_i \times 12$

- $\text{OfferRCC}_i \in \{0,1\}$ is the binary decision variable for each employee

This optimization approach determines RCC offers for workers who have a strong acceptance likelihood and generate significant cost reductions.

3.1.3 Constraints

1. **Binary Constraints:**

   The model requires all decision variables OfferRCC_i to use binary values 0 or 1 to establish either yes or no decisions regarding RCC offers.

$$\text{OfferRCC}_i \in \{0,1\}$$

2. **Minimum Salary Reduction**

   At least 3 million euros should be saved through RCC offer salary cuts every year.

$$\sum (\text{AnnualIncome}_i \times \text{OfferRCC}_i) \geq 3{,}000{,}000$$

3. **Minimum Number of Leavers**

   The expected number of workers who will accept RCCs needs to reach at least 40 employees.

$$\sum (\text{Probability}_i \times \text{OfferRCC}_i) \geq 40$$

4. **Department-Level Staffing Constraints**

   The model utilizes a strategy to safeguard departments from substantial workforce reduction by maintaining a minimum retention rate of 80% for all departments. For each department (HR, Sales, R&D). This was calculated by tracking:

   1. The original number of employees in each department

2. The model tracks how many workers in each department accepted RCCs
3. The simulation predicts how many workers would depart their positions according to RCC promotions combined with acceptance chances.

For each department:

$$\text{Remaining Employees} \geq 80\% \times \text{Original Employees}$$

Excel Solver used reference logic with cell formulas to implement binary constraints on the variables.

3.2 Solver Configuration and Results

The Excel Solver was configured as follows:

- **Set Objective**: Minimize total salary saved
- **By Changing Variable Cells**: Offer RCC column (binary decision variables)
- **Subject to Constraints**: Implemented via reference cells for leavers, cost, and department thresholds
- **Solving Method**: Evolutionary was used because the variables were non-linear.

Excel Solver has a restriction on variable cells so we divided the 441-employee dataset into three manageable sections with each part containing 147 employees. A consistent methodology together with constraints and segment grouping techniques was used separately on each segment of the model. The individual parts' solutions were consolidated to verify that the target objectives consisting of a €3 million salary cut and minimum 40 leavers and 80% staff retention were met.

3.3 Expected Acceptance Rates and Model Validity

The optimization model relies on this fundamental principle from probability that multiple independent trials with identical success probabilities produce success frequencies based on product of trials and probability. Mathematically, for N employees each with acceptance probability p:

$$E[\text{Acceptances}] = \Sigma\ (\text{Offer RCC}_i \times p\_i), \text{ for } i = 1 \text{ to } N$$

Where:

- offer $\text{RCC}_i \in \{0,1\}$ is the decision to offer RCC (1) or not (0)
- p_i is the individual acceptance probability
- E[.] denotes the expected value

The model enables accurate prediction that providing RCCs to 10 employees who each have p=0.5 should produce 5 expected acceptances. The linearity assumption holds because:

1. The model depicts employee acceptance or rejection as randomized outcomes structuring as independent Bernoulli trials
2. The total expectations within the population follow an addition pattern
3. Large population samples benefit from the law of large numbers to achieve convergence.

The model addresses the probabilistic nature of employee decisions by mathematically incorporating the acceptance probability through this multiplicative method.

4. Evaluation of the Prediction-and-Optimization Approach

This assessment implements prediction-and-optimization as a method to provide structured data-driven support in making complex workforce restructuring choices (Hemachandran et al., 2024). The technique demonstrates great power but carries multiple assumptions which impact its suitable utilization for real-world applications.

The approach shows effectiveness by distributing RCC proposals to staff members who accept them efficiently to achieve maximum cost efficiency. The system lets decision-makers check various constraints that include departmental requirements and budget limits at once. The approach delivers transparent results that can be defensively defended during critical situations where meeting fairness standards and adherence to regulations matter.

The method contains various assumptions together with restrictions which need consideration. The predictive model bases its forecast on previous employee attrition patterns during the previous facility closure to project RCC acceptance in the Lyon branch. This supposition might not maintain its strength since distinct work environments together with employee emotional states could change employee choice. The optimization model requires independence between employee acceptance of RCCs while treating each decision through a fixed probability estimation (Talebi et al., 2024). Real-life decision-making processes that shape acceptance of relocation and change control seem to stem from social interactions and workplace atmosphere as well as communication approaches despite lacking representation in recorded data.

The model runs under an assumption that both cost requirements and staffing limitations stay fixed and completely known prior to implementation. Organizational priorities tend to change practical implementation of cost and headcount constraints. The model has a weakness in its exclusion of important softer factors which include employee satisfaction levels and team dynamics interactions with quantifiable metrics.

The prediction-optimization framework maintains its importance for strategic planning when managers integrate contextual knowledge and their professional insights during its implementation (Bui et al., 2017).

5. Conclusion

The report proves how strategic workforce restructuring at SFB can benefit from combining predictive modeling and optimization techniques (Rahaman et al., 2024). The application of a machine learning model utilizing past attrition data enabled the assessment of each employee in Lyon branch for RCC acceptance likelihood (Ho-Peltonen and Mai, 2024). Once the predictions concluded their analysis an optimization model based on Excel framework distributed RCC positions to achieve minimum severance expenses within budget guidelines and headcount limits and departmental requirements.

The method combines clear business practices along with data-based decisions which preserve equal treatment through group-level offers while adhering to company regulations. The model depends on certain assumptions which do not accurately portray human behavior but still provides effective analytical principles to guide essential restructuring choices. When organizations implement this methodology through proper ethical monitoring and interpretation SFB will experience transparent changes that maintain accountability throughout the process of transformation.

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