Decision Analytics

MGSC 662

Final Team Project Report

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Linear Optimization for Improved Decision-Making in a Modeling Agency

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1. Executive Summary

In navigating the intricate landscape of modeling agencies, which grapple with multifaceted challenges involving profitability, ethical considerations, societal expectations, and model success, a complex decision-making challenge arises. To address these intricacies in model assignments, resource allocation, and event scheduling while concurrently minimizing environmental impact, a systematic quantitative approach becomes paramount.

This report unveils an innovative mathematical model, leveraging the robust framework of Linear Programming (LP), to tackle the complexities inherent in the modeling agency domain. Grounded in the broader context of linear optimization, our approach strategically defines decision variables and constraints to achieve a delicate equilibrium between maximizing profitability, ensuring fair model compensation, and adhering to sustainability goals.

This comprehensive methodology aligns seamlessly with the modeling agency's objectives, providing a data-driven foundation for informed decision-making within this dynamic and multifaceted industry. The subsequent numerical implementation on Gurobi not only validates the efficacy of our LP-based optimization model but also furnishes critical insights for strategic decision-making, showcasing its potential to revolutionize the operational landscape of modeling agencies.

2. Introduction

In the fast-paced and highly competitive world of fashion and modeling, agencies are at the forefront of a complex decision-making landscape. They are tasked with not only maximizing profitability but also navigating the nuanced realms of ethics, societal expectations, and the success of their models. This intricate balancing act involves critical decisions in model assignments, resource allocation, and event scheduling, all while being increasingly scrutinized for their environmental impact. Our project aims to address these multifaceted challenges through the lens of linear optimization, providing a structured and quantitative approach to streamline decision-making processes in modeling agencies.

The goal of this project is to develop a comprehensive optimization model that can effectively balance these diverse objectives. By integrating factors such as profitability, ethical standards, diversity, and environmental sustainability, the model aims to offer a holistic solution to the complex problem of talent placement and resource management in the modeling industry. This approach is not only innovative but also highly relevant in today's context, where businesses are expected to operate with a greater sense of social and environmental responsibility.

The choice of this problem is particularly interesting and relevant for several reasons. Firstly, the modeling industry, with its global reach and high visibility, has a significant influence on societal norms and trends. Decisions made by modeling agencies can have far-reaching implications, from shaping beauty standards to influencing fashion trends. Secondly, the industry is under increasing pressure to promote diversity and inclusivity, reflecting a broader societal shift towards equality and representation. Lastly, the environmental impact of the industry, particularly in terms of travel and events, is a growing concern. This project, therefore, not only addresses a current business challenge but also contributes to the discourse on ethical and sustainable practices in the modeling industry.

The complexities in this domain arise from the need to balance often conflicting objectives. Minimizing environmental impact, especially in terms of CO_2 emissions related to travel, must be weighed against the logistical and financial realities of the industry. These complexities make the modeling agency's talent placement problem not only challenging but also a perfect candidate for the application of a linear optimization model. By leveraging this approach, we aim to provide insights and solutions that are not only economically viable but also socially and environmentally responsible.

3. Problem Description: Overview

In formulating our mathematical model, we undertake the definition of key variables that encapsulate fundamental aspects such as model assignments and event scheduling within the modeling agency domain. The objective functions are meticulously crafted to address a range of goals, including the maximization of profitability, and mitigation of environmental impact. Imposing constraints is vital to guarantee the model's applicability within the ever-changing dynamics of the industry. Our approach integrates objectives into a comprehensive optimization model, aimed at enhancing the efficiency of decision-making processes within the specific context of the modeling agency under examination.

Data Collection and Integration Process: The data utilized in our modeling endeavors consists of information sourced from the Elite Model Look website [**website link**], primarily focusing on model demographics. Additionally, we augmented our dataset by incorporating synthetic data, with a significant portion being internally generated. In order to ensure consistency and alignment with industry practices, and to enhance the realism of our models, we also incorporated data from various verified sources. Notably, Google Flights data was employed for assessing CO_2 emissions (refer to *Appendix - Figure 2* for details)., and previous real communications data was obtained for job-related information - *leveraging the expertise of a team member who is a former Elite Model*. The culmination of these efforts resulted in the development of a robust master dataset, thoroughly documented in a comprehensive data dictionary (refer to *Appendix - Figure 1* for details).

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In this section, we delve into a comprehensive mathematical formulation. Our optimization objectives are centered on achieving efficiency in casting, implementing strategic scheduling, and reducing emissions. These objectives are navigated within the intricate landscape of the industry, considering real-world constraints. This mathematical framework, operating under the assumptions of reliable data and relevant variables, establishes the bedrock for precise and informed decision-making within the agency. It ensures the optimization of resources and a strategic approach to the management of models.

a. Decision Variables

Our problem entails three distinct data categories: Model Data (1), Location & CO2 Emissions (2), and Jobs Data (3). The first category centers around our model, specifically concentrating on male models affiliated with the Elite Model Toronto Men's Division. This category encompasses variables such as age, height, location, rates, and more. Noteworthy factors within location & jobs categories involve aspects like model's location/job destination, availability, the consideration of previous work incorporating non-compete agreements, an assessment of previous bookings, type of shoot requested by specific clients, etc.

i. Variables Description

The decision variables in our optimization model are binary entities denoted by x_{ij}, which play a pivotal role in determining the assignment of models to specific jobs. Each binary variable x_{ij} is associated with a unique combination of a model (i) and a job (j). When x_{ij} takes the value of 1, it indicates the affirmative assignment of model i to job j, signifying that the model is selected for that particular job. Conversely, when x_{ij} is set to 0, it denotes that the model is not assigned to the job. In essence, these binary decision variables serve as the "switches" that dynamically control the assignment of models to jobs within the optimization framework. This binary nature simplifies the decision-making process, allowing for clear and unambiguous representations of model-job assignments, contributing to the effectiveness and interpretability of the optimization model.

ii. Underlying Assumptions

Our underlying assumptions are grounded in the diverse features of our datasets. The dataset, identified by unique identifiers, integrates diverse attributes and considerations, providing essential geographical and client-specific insights for well-considered decision-making within the dynamic modeling sector.

The **Model Category Data** is a comprehensive dataset uniquely identified by Model Numbers. It covers diverse model attributes from physical features to professional metrics, including Instagram followers and years of experience. The dataset extends to model availability, optimizing scheduling. This nuanced approach enables informed and strategic decision-making aligned with industry standards, promoting diversity and operational efficiency. Integration into a Linear Optimization framework enhances adaptability in the dynamic industry landscape (refer to *Appendix* - *Figure 3.1.* for details).

The **Location Data** in our dataset is pivotal for providing essential geographical insights for each model. It encompasses the model's general location, specified city coordinates (X and Y), and associated carbon dioxide (CO_2) emissions costs per unit area, particularly in major urban centers like Montreal, Toronto, and Vancouver. The X and Y coordinates precisely map the model's location on a coordinate system, while CO_2 cost variables co5ntribute to understanding the environmental impact concerning specific cities. This dataset facilitates spatial analysis and integrates environmental considerations, aligning with our agency's commitment to informed and sustainable decision-making (refer to *Appendix* - *Figure 3.3.* for details).

The **Jobs Data** category offers a comprehensive overview of client-specific job requirements, crucial for modeling agencies and professionals. It includes key details such as the client's name, job location, nature of the shoot, preferred age range, ethnicity of models, and financial aspects indicated by payment range limits. Additional insights into job packages, shoot duration, job priority, client type, and the presence of non-compete agreements contribute to a holistic understanding of each opportunity. The model's weekly availability aids in strategic scheduling. This dataset facilitates informed decision-making, allowing agencies to align models with suitable job opportunities based on specific client criteria, promoting successful collaborations, and optimizing resource utilization in the dynamic modeling industry (refer to *Appendix* - *Figure 3.2.* for details).

iii. Mathematical Formulation

The decision variables are defined as binary entities, denoted by x_{ij}, where $x_{ij} = 1$ signifies the assignment of model i to job j, and $x_{ij} = 0$ denotes otherwise.

Let x_{ij} be a binary variable where $x_{ij} = 1$ if model i is assigned to job j, and $x_{ij} = 0$ otherwise.

b. Objective Function

i. Objective Functions Description

Our project centers on crafting a sophisticated linear optimization model using Linear Programming (LP) for a modeling agency. The model merges critical operational facets into one encompassing objective function, balancing financial gains with sustainable practices.

The core of the model lies in optimizing the assignment of models to jobs, aiming to maximize the agency's revenue while judiciously managing operational costs such as travel and accommodation. Alongside this, the model places significant emphasis on minimizing CO_2 emissions from model assignments, considering the travel distances and promoting environmentally friendly travel solutions.

A unique feature of our model is its ability to factor in the personal attributes of models, such as their reputation, years of experience in the industry, and their social media following. Each of these attributes is assigned a specific weight within the objective function, reflecting their relative importance in decision-making. The reputation factor, gauged from the model's previous work, carries a weight emphasizing the quality and prestige (refer to *Appendix - Figure 5.* for details) associated with the model. The experience metric, based on the duration of their career, underscores the reliability and expertise the model brings. The social media following, indicative of the model's public reach and influence, is also integrated into the model with a designated weight.

By weaving these personal attributes into the objective function, the model not only targets optimal financial performance but also ensures the promotion of models who bring a blend of professional excellence and social influence. This comprehensive approach aligns with the agency's overarching objectives of maximizing profitability and adhering to environmental sustainability goals.

ii. Underlying Assumptions

Our objective functions are contingent upon several assumptions. The model's benefit is a combined measure of payments, reputation, experience, following scores, and minimized CO_2 emissions. Weighting factors $(\alpha, \beta, \gamma, \delta)$ are applied to reputation, experience, following scores, and CO_2 emissions, respectively, reflecting their relative importance.

iii. Mathematical Formulation

The structure of our mathematical formulation can be expressed as follows:

Maximize

$$\sum_{i,j}\left[\boldsymbol{B_{ij}} + \frac{\boldsymbol{R_{ij}}}{\mathbf{10}} \cdot (\boldsymbol{\alpha R_i} + \boldsymbol{\beta E_i} + \boldsymbol{\gamma F_i}) - \boldsymbol{\delta C_{ij}}\right] \cdot \boldsymbol{x_{ij}}$$

Where:

$\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, ***and*** $\boldsymbol{\gamma}$, are weight factors for reputation (0.7), experience (0.25), and following scores (0.05) respectively.

$\boldsymbol{\delta}$ is the penalty factor for CO_2 emissions, decided by the management of Elite Model Look Toronto.

Note: The reputation, experience, and following scores are scaled to be between 0 and 10. **For more information, see Appendix V.**

This mathematical formulation incorporates several critical parameters:

- Base Payment: $\boldsymbol{B_{ij}}$ representing the base payment for assigning model i to job j.
- Payment Range: $\boldsymbol{R_{ij}}$ representing the range of payment for assigning model i to job j. This is calculated as 'Pay Range Upper' minus 'Pay Range Lower' in the jobs dataset.
- Reputation Score: $\boldsymbol{R_i}$ denoting the reputation score for model i, based on the previous work of the model.
- Experience Score: $\boldsymbol{E_i}$ for model i, based on the number of years worked in the industry.
- Following Score: $\boldsymbol{F_i}$ for model i, based on the number of Instagram followers a model has.
- CO2 Emissions: $\boldsymbol{C_{ij}}$ for assigning model i to job j.

In brief, the optimization objective aims to maximize overall utility, taking into consideration payment, reputation, and social media following, while respecting constraints such as budget limitations and CO_2 emission thresholds. Our underlying assumptions include the dependability of reputation, experience, and following scores as accurate reflections of a model's qualifications. Moreover, the assumption is made that job requirements are binary, indicating a straightforward match or mismatch. This mathematical framework establishes the groundwork for precise and informed decision-making within our modeling agency, aligning seamlessly with our strategic objectives of optimization and sustainability.

c. Constraints

In navigating a complex landscape of considerations, our approach to constraints involves a comprehensive framework, addressing budget limitations, client requirements, model availability, and CO2 emissions. We prioritize staying within budget limits to safeguard financial resources. Model availability, considering both availability and willingness, is crucial. Simultaneously, we adhere to emission caps for sustainability. Meeting client requirements involves aligning with preferences and specifications. This holistic approach is the bedrock of our strategy, allowing effective constraint navigation for optimal outcomes.

- **Non-Conflicting Assignments Constraint**

For each model and each day of the week, the model can be assigned to at most one job that requires availability on that day.

$$\sum_{j \in \text{Jobs}_{\text{day}}} x_{ij} \leq 1, \quad \forall i \in \text{Models}, \text{day} \in \text{Week}$$

- **One Model Per Job Constraint**

Each job can be assigned to at most one model.

$$\sum_{i \in \text{Models}} x_{ij} \leq 1, \quad \forall j \in \text{Jobs}$$

- **One Job Per Model Constraint**

Each model can be assigned to at most one job.

$$\sum_{j \in \text{Jobs}} x_{ij} \leq 1, \quad \forall i \in \text{Models}$$

- **Ethnicity Constraints**

Let (e_{ij}) be a binary parameter that is 1 if the ethnicity of model i matches the ethnicity preference of job *j* or if the job preference is 'open', and 0 otherwise. For all models *i* and all jobs *j*:

$$x_{ij} \leq e_{ij} \quad \forall i \in \text{Models}, \forall j \in \text{Jobs}$$

- **Age Category Preference Constraints**

Let (a_{ij}) be a binary parameter that is 1 if the age category of model i matches the age category preference of job *j* or if the job preference is 'open', and 0 otherwise. For all models *i* and all jobs *j*:

$$x_{ij} \leq a_{ij} \quad \forall i \in \text{Models}, \forall j \in \text{Jobs}$$

- **Non-Compete Agreement (Project Extension #1)**

If a model has a non-compete agreement with a client type, the model cannot be assigned to any other job with the same client type.

For each model *i* and each unique client type *c* in the set of all client types *C*, the non-compete constraint is:

$$\sum_{j \in \text{Jobs} | c_j = c} x_{ij} \leq n_{ic} \quad \forall i \in \text{Models}, \forall c \in C$$

where c_j is the client type of job *j*, and n_{ic} is a binary variable which is 1 if model *i* does not have a non-compete agreement for client type *c*, and 0 otherwise.

- **Job Package (Project Extension #2)**

In reality, some jobs do not pay for the model's travel and accommodation. The revised objective function to incorporate the job-package costs would be:

Maximize

$$\sum_{i,j}\left[B_{ij}+\frac{R_{ij}}{10}\cdot(\alpha R_i+\beta E_i+\gamma F_i)-\left(\boldsymbol{1}-\boldsymbol{k_j}\right)\cdot\left(\boldsymbol{D_j R_j}+\boldsymbol{T_{ij}}\right)-\delta C_{ij}\right]\cdot x_{ij}$$

Where:

- $\boldsymbol{k_j}$ is a binary variable which is 1 if the job *j* pays for the model's travel and accommodation, and 0 otherwise.
- $\boldsymbol{D_j}$ is the duration of the shoot for job *j* (in days).
- $\boldsymbol{R_j}$ is the average cost of accommodation per night in the city of job *j*.
- $\boldsymbol{T_{ij}}$ is the air travel cost from the model *i*'s home city to job *j*'s location.

4. Numerical Implementation on Gurobi

Analyzing the outcomes of our optimization model reveals a harmonious blend of objectives, showcasing an adept equilibrium in maximizing agency profits, ensuring equitable model compensation, and adhering to sustainability goals. The observations gleaned from unassigned jobs and operational efficiency metrics serve as invaluable inputs for strategic decision-making, offering nuanced insights and identifying potential avenues for future enhancements to the model.

Model Allocation Efficiency:

- **High Utilization Rate:** The model successfully assigned models to 20 out of 21 listed jobs, demonstrating an effective utilization of the agency's talent pool.
- **Unassigned Job Insight:** The unassigned job ('Moose Knuckles' in Vancouver) indicates a potential gap in the agency's model roster or possibly restrictive job requirements. This gap offers an opportunity for targeted talent acquisition or renegotiation of job terms.

Financial Performance:

- **Profit Maximization:** The model efficiently maximized agency profits, as seen in the substantial agency profit margins for each assignment.
- **Model Net Income:** The distribution of net income among models suggests a balanced approach, ensuring fair compensation while considering individual model attributes like reputation, experience, and social media following.

Operational Costs and Sustainability:

- **CO_2 Emissions:** The model's focus on reducing CO2 emissions is evident in the varying emissions data. Assignments like 'Mackage' in Montreal (40 kg CO2) versus 'Arc'teryx' in Montreal (205 kg CO2) demonstrate the model's capacity to balance profitability with environmental considerations.

Geographical and Job Package Distribution:

- **Strategic Job Assignments:** The model showcased a strategic distribution of models across various locations. Assigning local models like Dwight Ireland to Toronto-based jobs minimizes travel costs and emissions.
- **Job Package Preferences:** The distinction between jobs with and without a package ('Yes' or 'No' in 'Job Package') highlights the model's ability to account for varying job attributes while optimizing for agency profit and model welfare.
- **Diverse Model Representation:** The diverse origins of models (e.g., Tokyo, Paris, Stockholm) reflect the agency's global reach and the model's capability to harness this diversity effectively.

Career Advancement Opportunities:

- **Balancing High- & Low-Profile Jobs:** The model does not solely assign top models to high-profile jobs, indicating a balanced approach that potentially allows career progression opportunities for models across different tiers.

Future Considerations:

- **Addressing Unassigned Jobs:** Exploring why certain jobs remain unassigned could lead to enhancements in the model or adjustments in job requirements.
- **Sustainability Focus:** Further refining the model to enhance its focus on sustainability could align more closely with environmental goals, such as targeting zero-emission assignments where feasible.

Gurobi Optimization Results Summary

Model Name	Model Location	Job Name	Job Location	Job Package	Total Job Pay	Total Travel Cost	Model Net Income	Agency Profit	CO2 Emissions
Brodie Scott	Tokyo	Frank And Oak	Vancouver	Yes	5149.35	0	4119.48	1029.87	639
Dwight Ireland	Toronto	Maple Leaf Diamonds	Toronto	Yes	6192.55	0	4954.04	1238.51	0
Hector Raptis	Toronto	Herschel Supply Co.	Vancouver	Yes	6472.43	0	5177.95	1294.49	229
Jacob Cheng	Toronto	Lululemon	Vancouver	Yes	6124.68	0	4899.75	1224.94	229
Justin Lyons	Toronto	Flare Magazine	Toronto	Yes	4523.09	0	3618.47	904.62	0
Malik Lindo Ireland	New York	Canadian Tire	Toronto	No	6883.33	762	4897.07	1224.27	54
Steven Smith	Los Angeles	Holt Renfrew	Toronto	No	7189.56	1016	4938.85	1234.71	244
Michael Gonzalez	Los Angeles	Canada Goose	Vancouver	No	6168.7	615	4442.96	1110.74	117
Steven Lee	Paris	Blue Ruby	Toronto	No	5488.38	799	3751.51	937.88	397
Robert Smith	Paris	Bombardier	Montreal	No	8122.32	1495	5301.86	1325.46	376
Michael Lopez	Tokyo	Aldo	Montreal	No	8182.86	2556	4501.49	1125.37	929
Joshua White	Montreal	Lincoln	Vancouver	No	8937	963	6379.2	1594.8	252
Daniel Jones	Tokyo	Rudsak	Montreal	No	5120.73	2412	2166.98	541.75	929
Ronald Harris	Tokyo	Peace Collective	Toronto	Yes	5953.64	0	4762.91	1190.73	782
Andrew Jackson	Paris	Smythe	Toronto	Yes	5240.41	0	4192.33	1048.08	397
Richard Jones	Paris	Roots Canada	Vancouver	Yes	6547.5	0	5238	1309.5	579
Michael Smith	Miami	Arc’teryx	Montreal	Yes	7400.05	0	5920.04	1480.01	205
David Smith	Stockholm	Magazine "Elle Canada"	Toronto	Yes	4843.3	0	3874.64	968.66	455
Kevin Moore	Madrid	Birks	Montreal	Yes	7330.65	0	5864.52	1466.13	445
David Thomas	Toronto	Mackage	Montreal	No	7615.77	732	5507.02	1376.75	40
Unassigned	N/A	Moose Knuckles	Vancouver	No	3500 - 6900	N/A	0	0	N/A

Cf. MGSC662_Final_Results_ModelingAgency_Group1.xlsx

5. Strategic Recommendations

a. Key Suggestions

i. Recommendation #1

The application of the optimization model has revealed a critical insight into the current capabilities and limitations of Elite's talent pool as some modeling jobs remain unassigned. This outcome underscores the presence of gaps within our agency's offerings. Specifically, it indicates that for certain job requirements, we currently lack models who meet the criteria, or that our models may be over-committed due to scheduling conflicts or non-compete clauses.

This gap in Elite's portfolio could be attributed to various factors such as a shortfall in diversity of skills, experience levels, or specific client-demanded attributes among its models. The insight drawn from the optimization model is pivotal, as it directs us to consider strategic initiatives such as expanding our recruitment efforts to diversify the talent pool, providing additional training to existing models to enhance their skills, or revising our job acceptance criteria to ensure a better match bet*ween model availability and job requirements. The model's output serves as a quantitative backing for these strategic decisions, enabling us to move forward with data-driven confidence in our talent development and acquisition strategies.*

ii. Recommendation #2

The project's focus on incorporating travel and accommodation expenses into the optimization model offers a nuanced view of cost-efficiency. By doing so, it allows the agency to strategically select model assignments that not only meet the job's requirements but also minimize the financial outlay. This approach ensures that the agency can allocate its resources more effectively, reducing unnecessary expenses and optimizing the return on investment for each project. Enhanced cost-efficiency through such meti*culous planning could lead to more competitive pricing strategies and improved profitability.*

iii. Recommendation #3

The incorporation of CO_2 emissions into the optimization model's criteria is a forward-thinking approach that aligns the agency's operational decisions with broader environmental sustainability goals. By quantifying and minimizing the carbon footprint associated with each model assignment, the agency can make more environmentally responsible choices. This could involve selecting local models to reduce travel-related emissions or prioritizing jobs with clients who share a commitment to sustainability.

Such practices not only reduce the ecological impact but also resonate with increasingly eco-conscious clients and the public. This alignment can enhance the agency's brand as a leader in sustainability within the industry, potentially attracting new business and talent who value ecological responsibility. Furthermore, it can lead to long-term cost savings through efficient resource use and positioning the agency favorably for future regulations and industry standards focused on environmental impact.

b. Future Scope

i. Scope #1

A potential extension for our modelling agency's optimization model is the incorporation of fair opportunity allocation strategies, ensuring equitable career advancement for all models. One method to incorporate fair opportunity allocation into the model could involve implementing a tier-based job distribution mechanism. The tier-based distribution would categorize models into various levels based on their experience and past performances. Jobs could then be allocated proportionally across these tiers, ensuring that newer models receive adequate opportunities alongside established ones. This approach would not only maintain a balance in job assignments but would also nurture emerging talent, fostering a diverse and dynamic modeling workforce.

ii. Scope #2

Incorporating emergency backup options into our optimization model can enhance its practicality and robustness in real-world scenarios. This suggested extension would involve creating a pool of standby models who can be swiftly assigned to jobs in case of unforeseen circumstances, such as last-minute cancellations or unavailability of the initially assigned model. To implement this, the model could designate a subset of models as potential backups for each job, based on their compatibility and availability. These backups would be selected considering factors such as proximity to the job location, relevant experience, and minimal adjustment costs. The model would thus maintain a dynamic list of backup models for each job, ensuring a quick and efficient response to any sudden changes. Moreover, this extension could include a mechanism for regularly updating the backup pool, taking into account any changes in models' availability or job requirements. By doing so, the agency ensures continuity in its operations, minimizes disruptions, and maintains a high level of client satisfaction.

6. References

Research papers and pertinent resources that were explored

Nesi, G., Rialti, R., Zollo, L., & Ciappei, C. (2019). Community Based Social Media Fashion Branding: Do Fashion Brands Heritage and Prestige Affect Consumers' Brand Loyalty Intention? *Business Models and ICT Technologies for the Fashion Supply Chain* (pp. 53-65).

Prabowo, A. R., Yu, Y., Tu, J., Shi, K., Liu, M., & Chen, J. (2021). Flexible Optimization of International Shipping Routes considering Carbon Emission Cost. *Mathematical Problems in Engineering*, 2021, 6678473.

Su, J., & Hao, L. (2022). Optimal Allocation of Human Resource Structure Based on Capability Maturity Model Integration. *Security and Communication Networks*, 2022, 3162328.

Nobil, A. H., Sharifnia, S. M. E., & Cárdenas-Barrón, L. E. (2021). Mixed integer linear programming problem for personnel multi-day shift scheduling: A case study in an Iran hospital. *Alexandria Engineering Journal.*

Wen, X., Choi, T. M., & Chung, S. H. (2018). Fashion Retail Supply Chain Management: A Review of Operational Models. *Fashion Retail Supply Chain Management: A Review of Operational Models*.

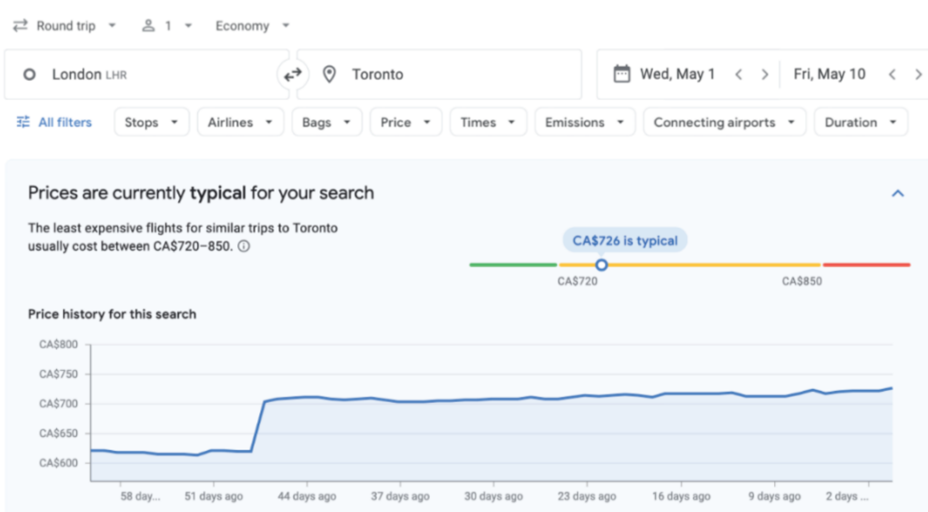
7. Appendix

Figure 1. Data Dictionary

Data Dictionary			
Data Category	**Data**	**Data Description**	**Data Type**
Model Data	Model Number	An identifier assigned to each model for unique identification.	*Numerical*
	Name	The full name of the model.	*Text*
	Location	The current geographical location of the model.	*Text*
	Longitude/Latitude	The precise geographical coordinates of the model's location.	*Numerical*
	Age Category	The category or range that represents the model's age.	*Text - Multiple Categories*
	Body Type	Describes the physique or build of the model (athletic, slim, etc.).	*Text - Multiple Categories*
	Height	The height of the model (measured in inches).	*Numerical*
	Waist	The circumference of the model's waist (measured in inches).	*Numerical*
	Suit	The model's suit size.	*Text - Multiple Categories*
	Pants Inseam	The inseam length of the model's pants (measured in inches).	*Numerical*
	Shoe	The model's shoe size.	*Numerical*
	Hair Color	The color of the model's hair.	*Text*
	Eye Color	The color of the model's eyes.	*Text*
	Instagram Followers	The number of followers the model has on Instagram.	*Numerical*
	Years of Experience	The number of years the model has been working in the industry.	*Numerical*
	Follower Score	A calculated score representing the model's online presence taking into account multiple factors such followers number.	*Numerical*
	Race	The ethnic background or heritage of the model (e.g., Hispanic, etc.)	*Text - Multiple Categories*
	Previous Work	Indicates the previous work importance rank (S, A, B,C).	*Text - Multiple Categories*
	Number of Languages Spoke	The total number of languages the model is proficient in.	*Numerical*
	Diversity Score Calculation	A calculated score representing the model's diversity based on various factors - body type, ethnicity, language proficiency.	*Numerical*
	Monday	Model's availability for work on Monday.	*Binary*
	Tuesday	Model's availability for work on Tuesday.	*Binary*
	Wednesday	Model's availability for work on Wednesday.	*Binary*
	Thursday	Model's availability for work on Thursday.	*Binary*
	Friday	Model's availability for work on Friday.	*Binary*
	Saturday	Model's availability for work on Saturday.	*Binary*
	Sunday	Model's availability for work on Sunday.	*Binary*
Location & CO2 Data - Airplane	Location	Describes the general location associated with the model (current or destination), which could be a city.	*Text*
	Location X Cordinate	The X coordinate (horizontal position i.e., longitude) of the location on a coordinate system.	*Numerical*
	Location Y Cordinate	The Y coordinate (vertical position i.e., latitude) of the location on a coordinate system.	*Numerical*
	CO2 Cost to Montreal (kg2)	The carbon dioxide (CO2) emissions cost associated with the location, measured in kilograms per unit area (e.g., square kilometer), specifically in relation to Montreal.	*Numerical*
	CO2 Cost to Toronto (kg2)	The carbon dioxide (CO2) emissions cost associated with the location, measured in kilograms per unit area (e.g., square kilometer), specifically in relation to Toronto.	*Numerical*
	CO2 Cost to Vancouver (kg2)	The carbon dioxide (CO2) emissions cost associated with the location, measured in kilograms per unit area (e.g., square kilometer), specifically in relation to Vancouver.	*Numerical*
	Client Name	The name of the organization requesting models for a job.	*Text*
	Location of Job	The geographical location or address where the job or shoot is taking place.	*Text*
	Type of Shoot	Specifies the nature or purpose of the photo shoot or job (e.g., fashion, commercial, lifestyle).	*Text - Multiple Categories*
	Age Category	The preferred age range or category for models specified by the client.	*Text - Multiple Categories*
	Ethnicity	The desired ethnic background or appearance of the models requested by the client.	*Text*
	Pay Range Lower	The lower limit of the payment range offered for the job (in $).	*Numerical*
	Pay Range Upper	The upper limit of the payment range offered for the job (in $).	*Numerical*

The data dictionary, encapsulating model data, jobs data, and locations data, serves as a comprehensive guide detailing the diverse attributes, requirements, and geographical insights**.**

Figure 2. Travel Cost Estimation



Travel costs were estimated using the average cost of specified flights between May 1st to May 10th.

Figure 3.1. Model Data Overview

Model Number (ID)	Name	Location	Longitude/Latitude	Age Category	Body Type	Height	Waist	Suit	Pants Inseam	Shoe
1	Adam Berg	Stockholm	59.64871, 17.934498	Adult	Athletic	73	33	38R	32	10
2	Alec Lalli	Toronto	43.645532, 79.381236	Young Adult	Slim	75	30	38R	34	10
3	Alex Cazemiro	Montreal	45.454949, -73.751445	Young Adult	Athletic	72.5	29	36S	33	10.5
4	Ali El Zeir	Toronto	43.645532, -79.381236	Senior Adult	Slim	72	32	40R	31	10
5	Ben Tsuruda	Toronto	43.645532, 79.381236	Young Adult	Athletic	74	31.5	38R	34	10.5
6	Brandon Soon Shiong	New York	40.777333, -73.872786	Adult	Slim	74.5	31	38R	32	11
7	Brodie Scott	Tokyo	35.548305, 139.778175	Young Adult	Petite	74	31	40R	34	12
8	Bryce Mason	Vancouver	49.19465, 123.178985	Adult	Slim	74	32	40R	32	11
9	Callum Murphy	Toronto	43.645532, -79.381236	Young Adult	Slim	72	30	38R	32	11.5
10	Cedric Dauberton	Toronto	43.645532, -79.381236	Adult	Slim	73.5	31	38R	30	11.5
11	Clark Coombs	New York	40.777333, -73.872786	Young Adult	Slim	74.5	31	38R	34	12
12	Dane Christensen	Milan	45.629822, 8.725273	Adult	Athletic	74	32.5	38R	34	11.5
13	Dwight Ireland	Toronto	43.645532, -79.381236	Mature Adult	Slim	71	32	38R	32	11
14	Ethan Moretta	Toronto	43.645532, 79.381236	Young Adult	Slim	72	31	40R	32.5	13
15	Finn O'Farrel	Montreal	45.454949, -73.751445	Young Adult	Slim	75	28.5	36R	32.5	11
16	Franco Lo Presti	Toronto	43.645532, -79.381236	Mature Adult	Athletic	75	34	40L	32	12
17	Gabe Chrsitensen	Toronto	43.645532, -79.381236	Young Adult	Curvy	72	29	38R	33	10.5
18	Gary Goba	Toronto	43.645532, -79.381236	Mature Adult	Athletic	73	32	40R	33	10.5
19	Giacomo Manchisi	Toronto	43.645532, -79.381236	Young Adult	Slim	75	30.5	40L	32	11
20	Griffen Thuss Conkie	Toronto	43.645532, 79.381236	Young Adult	Slim	74.5	30	38R	34	12
21	Hani Mazloum	Paris	49.00819, 2.549924	Young Adult	Slim	73	30	38R	32	11
22	Hector Raptis	Toronto	43.645532, -79.381236	Adult	Athletic	72	32	38R	29	10
23	Jacob Cheng	Toronto	43.645532, 79.381236	Young Adult	Curvy	73	31	38L	32	11
24	Jarret Kennedy	Toronto	43.645532, -79.381236	Adult	Athletic	74	32	39R	24	12.5
25	John Nightingale	Toronto	43.645532, -79.381236	Senior Adult	Slim	72	33	40R	33	10
26	Jonathan Azar	New York	40.777333, -73.872786	Young Adult	Slim	73	30	38R	34	11.5
27	Jordan Alex	Toronto	43.645532, -79.381236	Young Adult	Slim	74	32	38L	33	12
28	Justin Lyons	Toronto	43.645532, -79.381236	Adult	Slim	72.5	32	40R	31	11

Figure 3.2. Model Data Overview

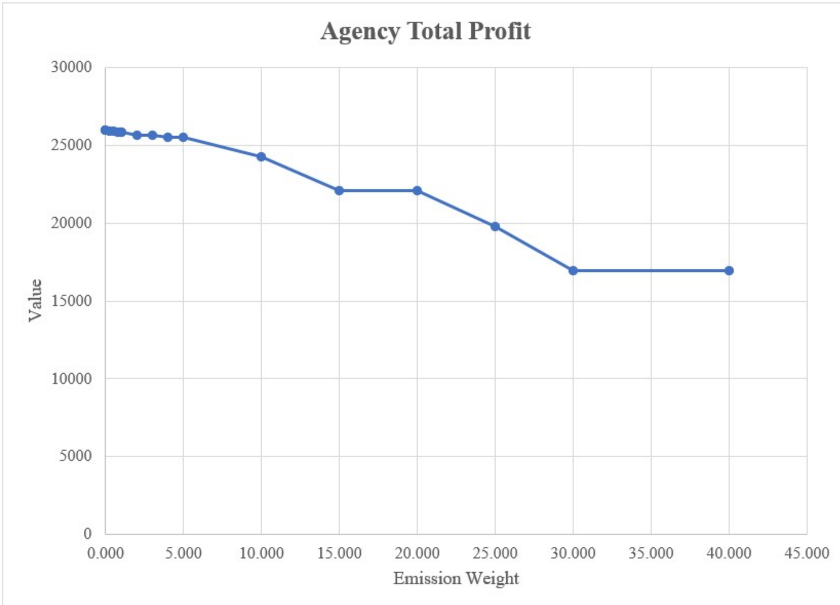
Client Name	Location of Job	Type of Shoot	Age Category Preference	Race Preference	Pay Range Lower	Pay Range Upper	Job Package
Lululemon	Vancouver	Open	Young Adult	Open	3500	7000	Yes
Birks	Montreal	Commercial	Young Adult	Open	3000	8200	Yes
Canadian Tire	Toronto	Lifestyle	Adult	African-American	2500	7500	No
Roots Canada	Vancouver	Fashion	Senior Adult	Asian	4500	7000	Yes
Aldo	Montreal	Editorial	Adult	Hispanic	4000	9600	No
Maple Leaf Diamonds	Toronto	Lifestyle	Mature Adult	Asian	4800	6800	Yes
Moose Knuckles	Vancouver	Streetwear	Young Adult	Mixed	3500	6900	No
Flare Magazine	Toronto	Editorial	Adult	Hispanic	3200	5100	Yes
Bombardier	Montreal	Commercial	Senior Adult	Caucasian	5000	9000	No
Frank And Oak	Vancouver	Fashion	Young Adult	Asian	4200	5500	Yes
Holt Renfrew	Toronto	Luxury	Mature Adult	African-American	4800	8000	No
Smythe	Toronto	Editorial	Adult	Caucasian	3200	5800	Yes
Canada Goose	Vancouver	Commercial	Young Adult	Open	3500	7000	No
Arc'teryx	Montreal	Fashion	Senior Adult	African-American	4600	8000	Yes
Blue Ruby	Toronto	Lifestyle	Mature Adult	Asian	2800	6400	No
Herschel Supply Co.	Vancouver	Streetwear	Adult	Hispanic	4000	7500	Yes
Mackage	Montreal	Luxury	Young Adult	Open	5000	8500	No
Magazine "Elle Canada"	Toronto	Editorial	Adult	Caucasian	3000	5500	Yes
Lincoln	Vancouver	Commercial	Senior Adult	Asian	5500	9000	No
Peace Collective	Toronto	Fashion	Mature Adult	African-American	3300	6800	Yes
Rudsak	Montreal	Streetwear	Young Adult	Open	2900	6000	No

Figure 3.3. Locations & Emissions Data Overview

Location	Location - X Cordinate	Location - Y Cordinate	CO2 Cost to Montreal (kg2)	CO2 Cost to Toronto (kg2)	CO2 Cost to Vancouver (kg2)
Toronto	43.645532	-79.38124	40	0	229
Paris	49.00819	2.549924	376	397	579
New York	40.777333	-73.872786	83	54	257
London	51.469601	-0.454072	421	366	497
Montreal	45.454949	-73.751445	0	40	252
Los Angeles	33.943411	-118.412315	311	244	117
Miami	25.794508	-80.279839	205	167	342
Vancouver	49.19465	-123.178985	243	229	0
Madrid	40.48998	-3.56581	445	437	624
Milan	45.629822	8.725273	427	468	541
Berlin	52.364414	13.500843	411	430	540
Stockholm	59.64871	17.934498	485	455	603
Tokyo	35.548305	139.778175	929	782	639

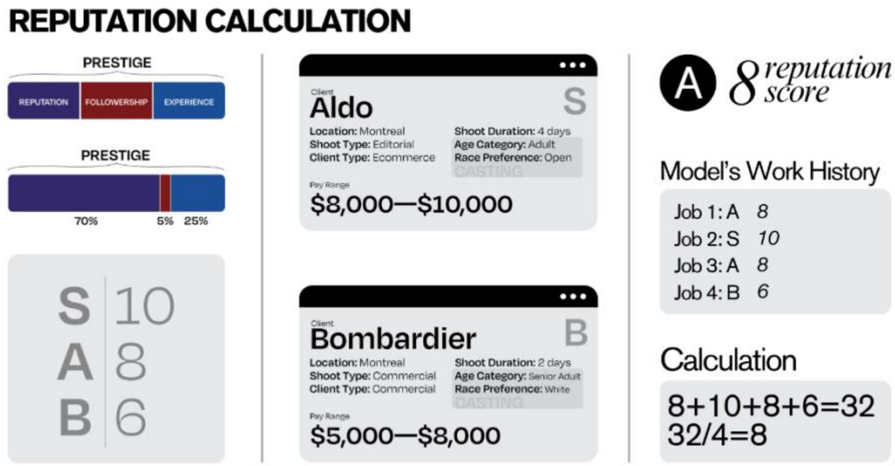
*The **final_data.xlsx** file contains the comprehensive versions of these datasets and can be accessed accordingly.*

Figure 4. Total Profit Vs. Emission Weight ($\boldsymbol{\delta}$)



Agency Total Profit and Emissions Based on Varying Emission Weights Accounting for Travel and Lodging Costs		
Emission Weight	Agency Total Profit	Agency Total Emissions
0.000	23627.27	7298
0.500	24389.01	4400
1.000	24296.43	3563
15.000	21009.77	1448
30.000	14991.4	237

Figure 5. Prestige Score & Model Reputation



In our optimization model, a model's compensation is intricately linked to their Prestige Score, a composite measure that encapsulates their reputation, years of experience, and social media following. This Prestige Score is a crucial component in determining the pay for each model and is directly embedded within our objective function. Here's an in-depth explanation:

Components of the Prestige Score:

Reputation (70% Weight): The reputation score is derived from the categories of jobs a model has previously undertaken, classified as S, A, and B. 'S' represents the highest-tier jobs, followed by 'A' and 'B'. This score is the most heavily weighted, reflecting the importance of a model's professional accomplishments and industry recognition.

Years of Experience (25% Weight): This aspect of the score is based on the duration of a model's career, emphasizing the value of industry experience and expertise.

Social Media Following (5% Weight): The number of followers a model has on platforms like Instagram contributes to this score, albeit with a lower weight. This reflects the growing importance of social media presence in the modeling industry.

Calculation of the Prestige Score:

The Prestige Score is a weighted sum of these three components, each scaled to be out of 10. This ensures a uniform scoring system across different metrics.

The model's pay is determined by applying their Prestige Score to the payment range of the job. The pay range is divided into 10 bins, and the model's Prestige Score (out of 10) is used to select the corresponding pay bin.

Influence on Model's Pay:

The higher a model's Prestige Score, the higher their position within the payment range for a job. This system rewards models with higher reputation, more experience, and significant social media presence, aligning their compensation with their market value and industry standing.

Figure 6. Model to Job Assignment with Varying Emission Weights

(visualized weights: 0; 0.5; 1; 15; 30)