GOOGLE CASE STUDY

Dynamic Agent Staffing Plan for Google Ads

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INTRODUCTION

Millions of businesses advertise on Google, with thousands of new advertisers joining daily. To support high-potential advertisers, Google provides 60-day personal onboarding through dedicated local agents. Each agent can support up to **10 advertisers**, but **fluctuating daily sign-ups** create challenges in matching supply (agents) with demand (eligible advertisers). Overstaffing leads to **idle costs**; understaffing reduces **incremental revenue** from delayed or missed onboarding. This project builds a **month-by-month dynamic staffing plan** to optimize cost and support quality across regions.

Figure 1. Similar sign-up trends across countries (2023, Exponential Moving Averages)

OBJECTIVE

The goal is to maximize net revenue by dynamically hiring and firing agents based on forecasted advertiser sign-ups.

Decision Variable: Number of agents to **hire/fire** each month per region, s.t:

- 1-month ramp-up period (hire)
- 1-month notice period + 40% salary penalty (fire)

Key Constraints:

- Each agent handles **≤ 10 advertisers**
- Advertisers stay for **60 days**
- Eligible advertisers only (budget above threshold)
- Agent support boosts revenue via probabilistic **incremental uplift** (13.5% avg)

MODEL DESIGN

AGENT POOL

- **Structure:** n × 10 matrix
  - n - number of agents
  - Row represents availability across 10 slots
  - Item - number (0 = available, 60 = fully booked)
- **Update:**
  - If assigned, slots are set to 60
  - Assigned slots reduce by 1 daily
  - When a slot reaches 0, the agent becomes available

ADVERTISER POOL

- **Structure:** m × 3 matrix
  - m - number of advertisers
  - Columns:
    - Budget (descending order)
    - Day Signed
    - Advertiser ID
- **Update:**
  - Top advertisers assigned upon agents' availability and removed
  - If not assigned, remove from the pool after 60 days

BASELINE STRATEGY

- **Hire** *(H)* or **Fire** *(F)* specific number of agents based on comparing:
  60-day forward average demand ⚖ Overall average demand
- **Daily Decision**:
  - 60-day average **exceeds** overall average ➡ Hire *H* agents
  - 60 days average **falls below** overall average ➡ Fire *F* agents

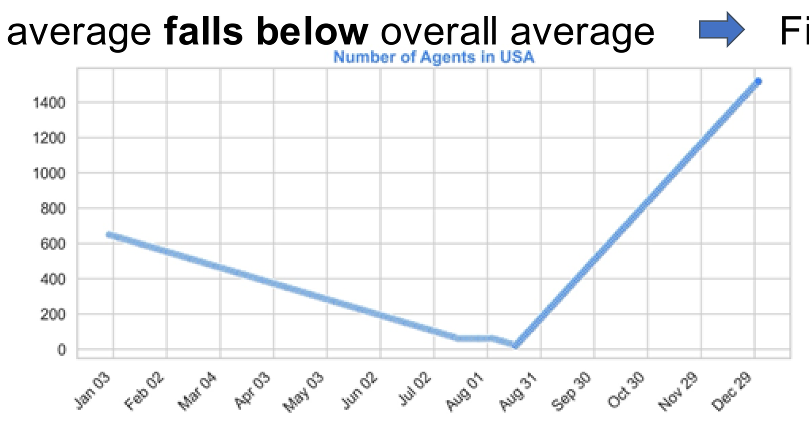

Figure 2. Agent Staffing Plan (Baseline Model)

- **Parameter tuning** (*H, F* from 1 to 20) ➡ **Optimal values:** *H* = 11, *F* = 3

✓ **Profit*: $207 million**

References

1. Zan, J., Hasenbein, J. J., & Morton, D. P. (2013). *Staffing large service systems under arrival-rate uncertainty*. arXiv: https://arxiv.org/abs/1304.6701
2. Project Source Code Link: https://github.com/Dynamic-Agent-Staffing-Plan-Google-Ads/

MAIN STRATEGY

Client friendly strategy with hiring/firing conditions based on penalty weighted predicted demand over the next 30-day period

- **Daily Decision:**
  30-day demand **exceeds** agents available after 30 days ➡ Hire ***H*** agents
  30-day demand **falls below** agents' avail. after 30 days ➡ Fire ***F*** agents

Objective function:

$$\text{Maximize} \quad \sum_{i=1}^{365} ((R_f - C_f)x_f + (R_h - C_h)x_h + (R_n - C_n)x_n)$$
$$x_f + x_h + x_n = 1, \quad x_i \in \{0,1\}$$

Parameters:

- A_{ij}: # of days after which Agent *j* 's slot *i* frees up
- S_{30}: 30-day pred. demand
- B_z: Budget of advertiser z
- *S* : Average annual salary

Decision variables:

- α: Penalty on firing
- β: Penalty on hiring
- *F*: Number of people fired
- *H*: Number of people hired

Hiring Condition	Firing Condition	No Change
When $S_{30} > \beta \sum_{i,j}(A_{ij} < 30)$ set $x_h = 1$ $H = \left\lceil \frac{S_{30} - \beta \sum_{i,j}(A_{ij} < 30)}{10} \right\rceil$ $R_h = \sum_{z \in \text{helped}} \frac{0.135 B_z}{365}$ $C_h = \frac{(\max(j) + H) \cdot S}{365}$	When $\sum_{i,j}(A_{ij} < 30) > \alpha S_{30}$ set $x_f = 1$ $F = \left\lfloor \frac{\sum_{i,j}(A_{ij} < 30) - \alpha S_{30}}{10} \right\rfloor$ $R_f = \sum_{z \in \text{helped}} \frac{0.135 B_z}{365}$ $C_f = \frac{(\max(j) - F) \cdot S}{365} + \frac{30FS}{365} + 0.4 \cdot FS$	Otherwise, set $x_n = 1$ $R_n = \sum_{z \in \text{helped}} \frac{0.135 B_z}{365}$ $C_n = \frac{\max(j) \cdot S}{365}$

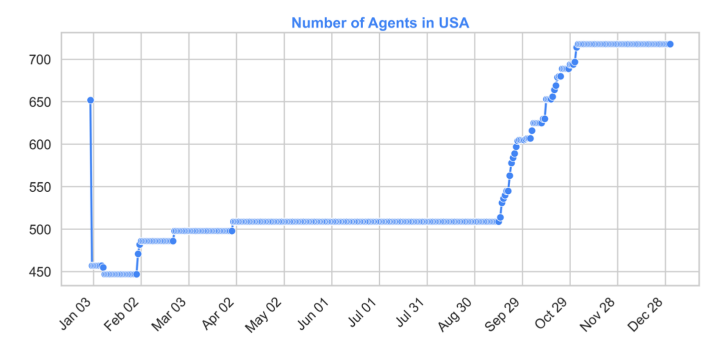

Figure 3. Agents Staffing Plan (Main Strategy)

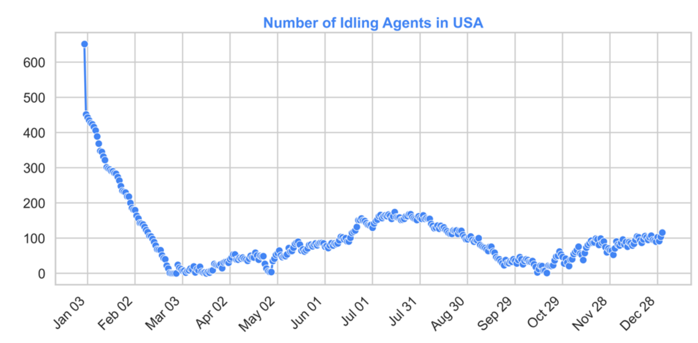

Figure 4. Agent Idling Estimates (Main Strategy)

- **Parameter tuning** (α,β from 0.5 to 20) ➡ **Optimal values:** α = 2.16 β = 1

✓ **Profit*: $295 million**

FORECASTING

Stepwise ARIMA model forecasted daily advertiser sign-ups in **2024**, based on historical patterns from **2023**. Automatically selected optimal *ARIMA(p,d,q)* using AIC. Forecasts updated daily using a **30-day rolling window** and adjusted for **assignment ratios** (dynamic feedback).

RESULTS & SENSITIVITY ANALYSIS

Strategy	Before ARIMA Forecasting	After ARIMA Forecasting
Baseline Strategy	$H = 11, \quad F = 3$ Profit: \$207M	➡ $H = 3, \quad F = 1$ ✓ Profit: \$292M
Main Strategy	$\alpha = 2.16, \quad \beta = 1$ Profit: \$295M	➡ $\alpha = 17.156, \quad \beta = 1$ ✓ Profit: \$295M

FUTURE WORK & SUGGESTIONS

The proposed implementation follows **a greedy assignment algorithm**, in which all eligible advertisers are immediately assigned to agents. While this ensures maximum coverage, it may not yield the optimal staffing plan under cost constraints. Future work should explore **wait pool and assignment delays** – within the allowed 60-day window – to reduce unnecessary hires during temporary demand peaks. Some advertisers may not need assignment if their expected uplift doesn't justify hiring/firing costs.

The original problem assumes agent assignment within their respective country. We propose exploring **cross-country agent assignments** between countries with overlapping **languages and time zones** (e.g., USA and Canada) to better balance capacity.

Integrating **seasonality** should also be considered. Demand surges during Q2 and Q4 suggest that **hiring ramps** and **firing cooldown periods of 4–6 months** would better reflect operational constraints and workforce morale.

*Net profit: Profit = 13.5% x Revenue - Costs

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