Details of Ad Revenue Sharing (adrev_opti.py)

Team DeepSeekers

August 30, 2025

Contents

---

1 Current Problem TikTok Faces

Most ad revenue on short-form content is concentrated in a very small slice of videos (e.g. Pulse-eligible inventory), while the vast majority of creators receive no share. Concretely:

- **Pulse videos** (roughly the top few percent by quality/brand-safety) can share in ad revenue placed adjacent to their videos.
- **Non-Pulse videos** (the vast majority) still have ads shown between them, but creators typically receive no share; TikTok retains 100% of that revenue.
- The outcome is **low monetization coverage** for small and mid-size creators and weaker long-term incentives to invest in quality, safe, and engaging content.

Proposal (high level). Keep Pulse as premium inventory. For *non-Pulse* ads, TikTok chooses a platform cut and places the remainder into a creator pool P, then *fairly allocates* P across eligible videos using a quality- and engagement-aware optimization.

2 Business Interpretation and Visualization of the Model

For detailed formulation of the Multi-Objective Optimisation Model, refer to **Section 3**.

How TikTok Can Use This Model

The goal of this optimization is to decide how to split a fixed ad revenue pool P across millions of videos. Instead of splitting purely by views (which favors very large creators) or splitting evenly (which ignores quality), this model balances two goals:

1. **Fairness:** smaller or niche creators still get rewarded, through the $\log(p_v)$ term.
2. **Efficiency:** high-quality, high-engagement videos are rewarded proportionally to their impact.

By tuning the weights λ_{fair} and λ_{eff}, TikTok can directly control this balance. For example:

- Increasing λ_{eff} makes the system favor top-performing viral videos (platform growth focus).
- Increasing λ_{fair} spreads earnings more evenly, supporting smaller creators (ecosystem health focus).

Visual Intuition

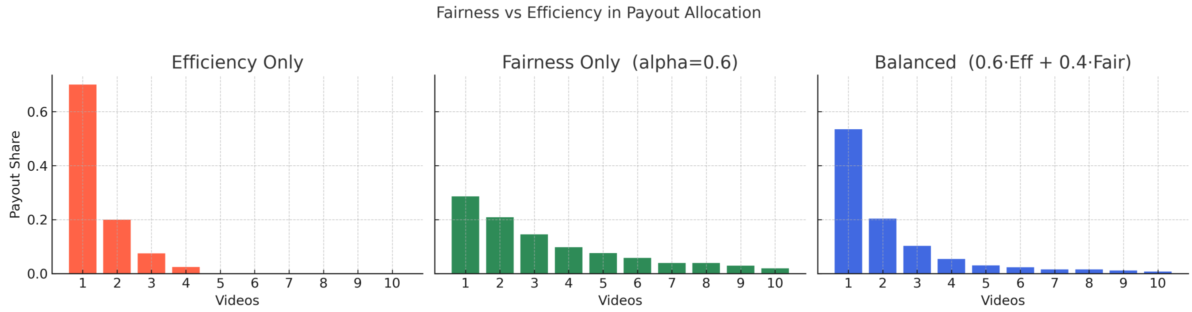

Illustration: On the left, payouts are concentrated in the largest videos (efficiency only). In the middle, payouts are more spread out (fairness only). The optimization model finds a balance point in between.

Quality Score in Practice

The quality score Q_v acts like a multiplier that boosts videos with:

- Higher watch completion (viewers finish the video).
- Richer engagement (not just likes, but also comments, shares, follows).
- Diversity of engagement types (not spammy likes).
- Rewatching (sticky content).
- Low toxicity and safe/positive content.

Thus, even if two videos have the same number of views, the one with higher Q_v will earn more. This discourages low-quality or botted content from gaming the system. For detailed formulation of quality score, refer to **Section 4: Quality Score Mathematical Formulation**.

Concrete Example

Suppose TikTok allocates $1,000,000 of ad revenue:

- A viral but low-quality spam video (many views, $Q_v = 0.2$) may get only $20,000.
- A smaller but high-quality educational video (fewer views, $Q_v = 0.9$) may get $50,000.
- A very large, high-quality creator (millions of views, $Q_v = 0.8$) still earns the bulk, say $600,000.

The key is that the system **balances fairness and performance**, sustaining TikTok's ecosystem: creators are motivated to produce engaging, safe, and high-quality content, while TikTok avoids concentrating all rewards at the top.

Why This Matters for TikTok

- Encourages more creators to join and stay active (healthy supply of content).
- Prevents over-reliance on a few mega-creators.
- Ensures advertisers' money is linked to genuine, high-quality engagement.

This mechanism strengthens TikTok's long-term ecosystem by aligning platform incentives, advertiser trust, and creator motivation.

Extension: Category-Specific Ad Pools

In the baseline model, we assumed that all ads are aggregated into a single homogenous pool of size P, which is then allocated across eligible videos. However, in practice, TikTok's advertising ecosystem is highly heterogeneous: ads belong to different verticals (e.g. gaming, music, commerce), and advertisers in these verticals bid differently for impressions.

Splitting the Ad Pool

To capture this reality, TikTok can divide the total ad revenue pool into category-specific sub-pools:

$$P = P^{\text{gaming}} + P^{\text{music}} + P^{\text{commerce}} + \dots$$

Each pool P^c corresponds to a category c of ads. Only videos that are relevant to category c compete for payouts from P^c. For instance, gaming ads would primarily be allocated across gaming-related videos, while commerce ads would be allocated across shopping- or product-related content.

Applying the Model per Category

For each category c:

- Define the set of eligible videos $V^c \subseteq V$ that belong to or are classified under category c.
- Run the same optimization model using P^c as the pool size and V^c as the competing videos.
- Compute payouts $p_v^{(c)}$ for each $v \in V^c$.

Final Payouts

The final projected earnings of each video are then aggregated across all categories:

$$\text{ProjEarnings}(v) \;=\; \sum_c p_v^{(c)}.$$

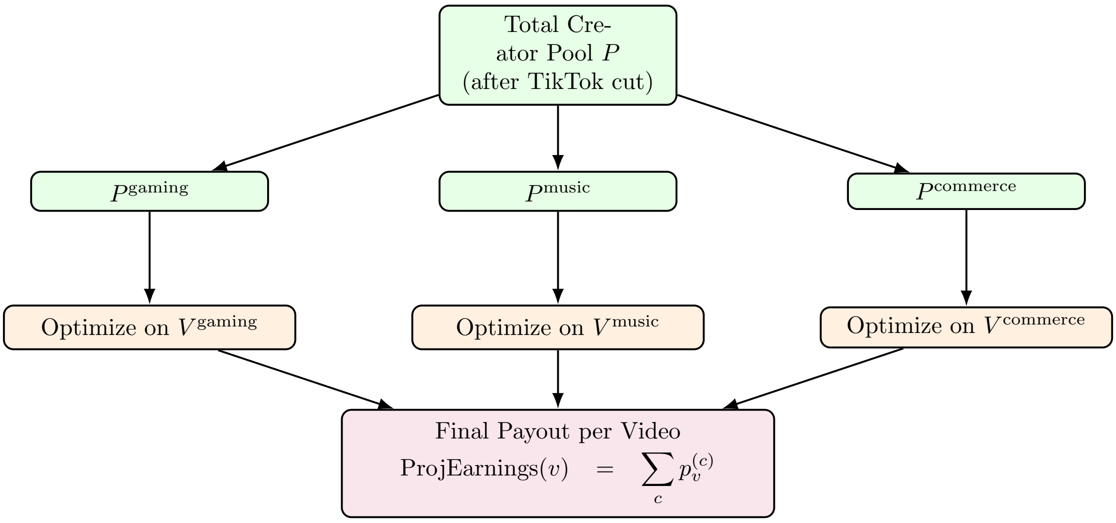

Figure 1: Category-specific sub-pools: split P into vertical pools, optimize per category, then aggregate payouts per video.

Business Interpretation

This extension makes the optimization more realistic and useful for TikTok's monetization strategy:

- **Fairness across verticals:** Gaming ads reward gaming creators, commerce ads reward commerce creators, etc.
- **Market-reflective:** Different ad verticals naturally have different CPMs (cost per mille impressions). By separating pools, creators benefit proportionally from higher-value ad markets.
- **Flexibility:** TikTok can dynamically adjust the relative sizes of P^c based on advertiser demand, seasonality, or strategic priorities.

In essence, this approach runs the optimization model multiple times (once per ad pool), then aggregates results to produce fair, category-sensitive payouts for each creator.

Relation to TikTok's Current Model

As discussed in **Section 1**, TikTok's current monetization heavily favors Pulse videos (top ∼4% of content, eligible for a 50/50 split), while the vast majority of non-Pulse videos generate ad revenue that is fully retained by TikTok.

Proposal. Instead of excluding non-Pulse creators entirely, TikTok could retain a fixed platform share of non-Pulse ad revenue, while allocating the remainder into the creator pool P. This pool would then be distributed across all eligible videos using the fairness–efficiency optimization.

Business Advantage.

- TikTok keeps strategic control by deciding what fraction of non-Pulse ad revenue enters P.
- Non-Pulse creators gain a new revenue stream, increasing loyalty and content supply.
- Advertisers benefit as their spend links more directly to genuine, quality engagement, not just the top few percent of videos.

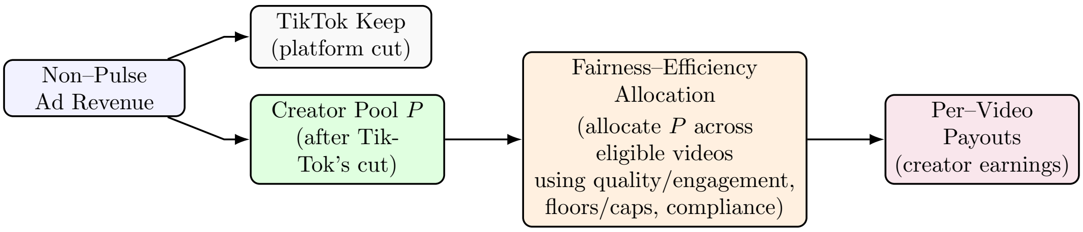

Figure 2: Proposed treatment for non–Pulse ads: TikTok retains a platform share; the remainder becomes P and is allocated fairly across eligible videos.

3 Quality-Weighted Ad Revenue Allocation (Optimization Formulation)

Setup

Let:

- P: total ad revenue pool available to creators (after TikTok's platform cut).
- V: set of eligible videos (with compliance gate $C_v = 1$).
- $Q_v \in [0, 1]$: quality score of video v.
- Views_v: number of qualified views of video v.
- $M_v := \text{Views}_v \cdot Q_v$: effective impressions for v.
- $s_v := \dfrac{M_v}{\sum_{u \in V} M_u}$: baseline share for v (quality × views).
- $w_v := s_v^{\alpha}$: fairness weight, with parameter $0 < \alpha \leq 1$.
- $p_v \geq 0$: payout allocated to video v (decision variable).

Optimization Problem

We maximize a convex combination of fairness and efficiency objectives:

$$\begin{aligned}
\max_{\{p_v\}_{v\in V}} \quad & \lambda_{\text{fair}} \sum_{v\in V} w_v \, \log(p_v) \; + \; \lambda_{\text{eff}} \sum_{v\in V} s_v \, \frac{p_v}{P} \\
\text{s.t.} \quad & \sum_{v\in V} p_v = P, \\
& p_v \geq \underline{p}_v \quad \text{(optional floor)}, \\
& p_v \leq \overline{p}_v \quad \text{(optional cap)}, \\
& p_v = 0 \quad \text{if } C_v = 0 \quad \text{(policy non-compliant)}.
\end{aligned}$$

Interpretation

- λ_{fair}: weight on fairness (via $\log(p_v)$, which enforces diminishing returns).
- λ_{eff}: weight on efficiency (pushing payouts toward quality $\times$ views baseline).
- α: fairness shaping parameter ($\alpha < 1$ makes w_v flatter, benefitting small creators).

Special cases:

- $\lambda_{\text{eff}} = 1$: reduces to $p_v = P \cdot s_v$ (pure proportional split).
- $\lambda_{\text{fair}} = 1$: reduces to $p_v \propto w_v$ (pure proportional fairness).

4 Quality Score Mathematical Formulation (Per Video v)

Viewer trust weights (two tiers). Each viewer i is assigned a trust weight:

$$w_i = \begin{cases} \alpha_{\text{ver}}, & \text{if viewer } i \text{ is verified}, \\ \alpha_{\text{unver}}, & \text{if viewer } i \text{ is unverified}, \end{cases} \qquad \alpha_{\text{ver}} > \alpha_{\text{unver}} > 0.$$

Weights are normalized:

$$\tilde{w}_i = \frac{w_i}{\sum_j w_j}, \qquad \sum_i \tilde{w}_i = 1.$$

—

Per-signal engagement components (all in $[0, 1]$). Let L_v be the video length and t_i the watch time of viewer i. Let $\ell_i, c_i, s_i, f_i \in \{0, 1\}$ indicate whether viewer i liked, commented, shared, or followed.

- **Watch completion:**
$$W_v = \sum_i \tilde{w}_i \cdot \min\Big(1, \frac{t_i}{L_v}\Big).$$
- **Engagement rate:**
$$E_v = \min\left(1, \sum_i \tilde{w}_i \big(\beta_\ell \ell_i + \beta_c c_i + \beta_s s_i + \beta_f f_i\big)\right),$$
where $\beta_\ell, \beta_c, \beta_s, \beta_f \geq 0$ and $\beta_\ell + \beta_c + \beta_s + \beta_f = 1$.
- **Engagement diversity:**
$$D_v = \frac{-\sum_{a\in\{\ell,c,s,f\}} p_a \log p_a}{\log 4}, \qquad p_a = \frac{\sum_i \tilde{w}_i \cdot \mathbf{1}\{a \text{ taken by } i\}}{\sum_b \sum_i \tilde{w}_i \cdot \mathbf{1}\{b \text{ taken by } i\}}.$$

- **Rewatch / retention:**

$$R_v = \min\Big(1, \sum_i \tilde{w}_i \cdot r_i\Big), \qquad r_i = \mathbf{1}\{\text{viewer } i \text{ watched} > 1 \text{ loop}\}.$$

- **NLP quality / safety:**

$$S_v = \max\big(0,\ s_v^{(+)} - \tau\, s_v^{(\text{tox})}\big),$$

  where $s_v^{(+)} \in [0,1]$ is a positive/educational score and $s_v^{(\text{tox})} \in [0,1]$ is a toxicity/violation score. The parameter $\tau \in [0,1]$ controls the penalty for toxic content.

Compliance gate:

$$C_v \in \{0,1\} \quad (1 \text{ if policy-compliant, else } 0).$$

—

Geometric aggregation (robust, hard to game). Choose nonnegative weights $\phi_W, \phi_E, \phi_D, \phi_R, \phi_S$ with $\sum \phi_\cdot = 1$. The raw score is:

$$q_v = W_v^{\phi_W}\, E_v^{\phi_E}\, D_v^{\phi_D}\, R_v^{\phi_R}\, S_v^{\phi_S}.$$

Apply compliance and clamp to $[0,1]$:

$$Q_v = C_v \cdot \min\big(1, q_v\big).$$

—

Suggested default parameters.

$$\alpha_{\text{unver}} = 0.8, \quad \alpha_{\text{ver}} = 1.0; \qquad \beta_\ell = 0.1,\ \beta_c = 0.2,\ \beta_s = 0.4,\ \beta_f = 0.3;$$

$$\phi_W = 0.35,\ \phi_E = 0.25,\ \phi_D = 0.15,\ \phi_R = 0.10,\ \phi_S = 0.15; \qquad \tau = 0.5.$$

—

Overall interpretation. The final content quality score $Q_v \in [0,1]$ reflects how engaging and trustworthy video v is. It blends:

- **Watch completion** (W_v) — do viewers finish the video?
- **Engagement rate** (E_v) — how many meaningful actions are taken?
- **Engagement diversity** (D_v) — are actions balanced across likes, comments, shares, follows?
- **Rewatch** (R_v) — do viewers return for multiple views?
- **NLP quality** (S_v) — does the content have positive value and low toxicity?

All components are *trust-weighted*: verified viewers have higher impact than unverified viewers. This ensures that creators are rewarded not just for raw engagement, but for *genuine, diverse, and safe* engagement from trusted users.