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A Goal Programming Model for Controlling Fund Diversion and Payment Delays in MBG Program

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Abstract

The Free Nutritious Meal Program (MBG) involves a tiered flow of funds from the National Nutrition Agency (BGN) to foundations that contract local catering partners. In practice, two recurrent problems emerge: partial diversion of program funds and delays in payments to caterers. These issues threaten service quality and the financial sustainability of small catering providers. This paper develops a mathematical model that combines principal–agent theory and goal programming to support policy design for BGN. The foundation's utility captures legal margin, potential diversion, and expected monetary penalties that depend on audit intensity and audit effectiveness. The principal (BGN) pursues three goals simultaneously: minimizing total diverted funds, minimizing weighted payment delays, and limiting total audit cost. Individual rationality (IR) and incentive compatibility (IC) constraints are incorporated to ensure foundations are willing to participate and prefer honest behavior. The resulting nonlinear goal programming formulation provides a structured way to explore trade-offs and to select audit and penalty parameters consistent with MBG objectives. A small numerical illustration demonstrates how the model operates and how policy parameters influence outcomes.

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INTRODUCTION

The Free Nutritious Meal Program (MBG) aims to improve students' nutritional status and reduce inequality in access to healthy meals (Andini, 2025; Maimunah & Sardjono, 2024). In practice, the National Nutrition Agency (BGN) transfers program funds to intermediary foundations (*yayasan*), which then contract and pay local catering partners based on normative amounts and schedules (Holschneider et al., 2021). However, implementation can be undermined by two recurring irregularities: partial diversion of program funds and delayed payments to caterers, both of which directly disrupt cash flow and threaten the continuity of catering services (Azizi, 2025).

These governance problems are closely linked to information asymmetry and moral hazard (Hayati, 2020). Foundations typically observe actual transactions and operational costs more accurately than BGN, while BGN monitors outcomes imperfectly, creating room for opportunistic behavior such as misappropriation and strategic delays (Santoso et al., 2025). At the same time, stronger monitoring is costly: increasing audit intensity requires resources, so policy design inevitably involves trade-offs between reducing diversion and delays versus keeping supervision costs feasible (Febryanti et al., 2025).

Although recent empirical studies have discussed MBG's early implementation challenges and policy implications (Suprapto et al., 2025), most remain descriptive and do not formalize the governance mechanism into an explicit optimization model that can jointly determine audit effort, penalty design, and multiple performance targets (Lendra et al., 2025). This is a key gap, because public programs typically face multiple objectives that are not perfectly aligned, including effectiveness, equity, and fiscal sustainability

(Amalia & Hidayat, 2025).

To address this gap, this paper develops a mathematical decision-support model that integrates principal–agent theory with goal programming for the BGN foundation relationship in MBG. The principal agent component represents how audits and penalties enter the foundation's expected utility and influence incentives under private information (Steinle et al., 2014). Goal programming then captures BGN's multi-goal policy problem by setting aspiration levels and minimizing weighted deviations from targets, enabling transparent trade-offs among (i) lower total diversion, (ii) shorter weighted payment delays, and (iii) bounded audit costs (Nechi et al., 2020). Behavioral feasibility is enforced through individual rationality (IR) and incentive compatibility (IC) constraints, ensuring foundations are willing to participate and prefer honest behavior (Corgnet et al., 2018).

PRINCIPAL–AGENT MATHEMATICAL MODEL FOR THE BGN–FOUNDATION RELATIONSHIP

Basic Structure and Notation

Consider a single implementation period of MBG involving n foundations, indexed by $i = 1, 2, \dots, n$. The main parameters for each foundation i are defined (Table 1) and the decision variables (Table 2).

Table 1. Parameters and its definition

Parameters	
B_i	: funds transferred by BGN to foundation i
$P_i^{(norm)}$	: normative total payment to catering partners under foundation i
C_i^y	: legitimate administrative cost of foundation i
$\alpha_M > 0$	: penalty coefficient per unit of diverted funds
$\alpha_D > 0$	: penalty coefficient per unit of payment delay
$\theta_i \in (0,1]$	: audit effectiveness parameter for foundation i
$c_i^A > 0$	: audit cost per unit of audit intensity
U_i^{out}	: reservation utility of foundation i if it does not participate in MBG
$D_i^{ref} \geq 0$	: reference (minimum) payment delay level

Table 2. Decision variables

Variables	
$a_i \in [0,1]$	: audit intensity applied to foundation i
$M_i \geq 0$	: diverted funds associated with foundation i
$D_i \geq 0$	: average payment delay to catering partners
P_i	: actual payment made by the foundation to catering partners

Relationship between normative payment, actual payment, and fund diversion (Blonz, 2023):
$M_i = P_i^{(norm)} - P_i$, with $0 \leq M_i \leq P_i^{(norm)}$
Thus:
$$P_i = P_i^{(norm)} - M_i \tag{1}$$
Baseline (legal) margin of foundation i:
$$m_i^0 = B_i - P_i^{(norm)} - C_i^y \tag{2}$$

Audit, Penalties, and Foundation Utility

The probability that a violation is detected is modelled linearly in audit intensity (Wang et al., 2025):
$$p_i(a_i) = \theta_i a_i, \text{ with } 0 \leq a_i \leq 1 \tag{3}$$

Monetary penalty if a violation is detected (Chen & Dai, 2023):
$$\Phi_i(M_i, D_i) = \alpha_M M_i + \alpha_D D_i \tag{4}$$

Expected penalty (Jiang et al., 2023):
$$E[Penalty_i] = \theta_i a_i(\alpha_M M_i + \alpha_D D_i) \tag{5}$$

Foundation utility (Chang, 2011):

$U_i^y = (B_i - P_i) - C_i^y - E[Penalty_i]$
$= m_i^0 + M_i - \theta_i a_i(\alpha_M M_i + \alpha_D D_i)$ (6)

Under an honest strategy $M_i = 0$, and delay is only D_i^{ref}:
$U_i^{y\ honest} = m_i^0 - \theta_i a_i \alpha_D D_i^{ref}$ (7)

BGN Objective Measures

BGN defines three aggregate performance measures (Gulbakyt et al., 2025):
$Z_M = \Sigma_i M_i$ (total diverted funds)
$Z_D = \Sigma_i w_i D_i$ (total weighted payment delay) (8)

where $w_i \geq 0$ foundation's delay weight
$Z_A = \Sigma_i c_i^A a_i$ (total audit cost)

Individual Rationality and Incentive Compatibility Constraints

Individual rationality (IR) constraint (Börgers, 2015):
$U_i^y \geq U_i^{out}, for\ \forall i$

By substitution (6):
$m_i^0 + M_i - \theta_i a_i(\alpha_M M_i + \alpha_D D_i) \geq U_i^{out}$ (9)

Incentive compatibility (IC): the honest strategy is not worse than a deviating strategy (Börgers, 2015):
$U_i^{y\ honest} \geq U_i^y$
i
Utility difference:
$\Delta U_i = U_i^{y\ honest} - U_i^y$

By substitution (7) and (6):
$\Delta U_i = -M_i + \theta_i a_i(\alpha_M M_i + \alpha_D D_i - \alpha_D D_i^{ref})$

Therefore, the IC constraint becomes:
$-M_i + \theta_i a_i(\alpha_M M_i + \alpha_D D_i - \alpha_D D_i^{ref}) \geq 0$ (10)

If $D_i^{ref} = 0$, it reduces to:
$-M_i + \theta_i a_i(\alpha_M M_i + \alpha_D D_i) \geq 0$ (11)

Constraints (9), (10), and (11) are bilinear in (a_i, M_i, D_i), which makes the principal–agent model a nonlinear optimization problem (Jones & Tamiz, 2016).

Goal Programming Formulation

BGN Aspiration Levels

BGN sets aspiration levels:
M^*: target upper bound for total fund diversion.
D^*: target upper bound for total weighted payment delay.
A^*: target upper bound for total audit cost.

Each goal is represented as (Bettinger, 2025):
$Z_M + d^{1-} - d^{1+} = M^*$
$Z_D + d^{2-} - d^{2+} = D^*$ (12)
$Z_A + d^{3-} - d^{3+} = A^*$

where d_k^- and d_k^+ (k = 1, 2, 3) denote negative and positive deviations, respectively. Positive deviations d_k^+ represent undesired exceedance of the target limits (Vohra, 2011).

Goal Programming Objective Function

The objective is formulated as minimizing weighted positive deviations (Deb et al., 2016):
$$Minimize\ Z_G = w_1 d_1^+ + w_2 d_2^+ + w_3 d_3^+ \quad (13)$$

Weights $w_1 \geq w_2 \geq w_3 > 0$ can be selected to reflect priorities, for example prioritizing diversion reduction over payment delay and audit cost.

Complete Goal Programming Principal–Agent Model

Model summary:
Objective function (13):
$Min\ Z_G = w_1 d_1^+ + w_2 d_2^+ + w_3 d_3^+$

Definitions of aggregate measures (8):
$Z_M = \Sigma_i M_i$
$Z_D = \Sigma_i w_i D_i$
$Z_A = \Sigma_i c_i^A a_i$

Goal constraints (12):
$Z_M + d_1^- - d_1^+ = M^*$
$Z_D + a_2^- - a_2^+ = D^*$
$Z_A + a_3^- - a_3^+ = A^*$

IR and IC constraints (9) and (10):
$m_i^0 + M_i - \theta_i a_i(\alpha_M M_i + \alpha_D D_i) \geq U_i^{out}, \forall i$
$-M_i + \theta_i a_i(\alpha_M M_i + \alpha_D D_i - \alpha_D D_i^{ref}) \geq 0, \forall i$

Variable bounds:
$0 \leq a_i \leq 1,\ 0 \leq M_i \leq P_i^{(norm)},\ D_i \geq 0$
$d_k^-, d_k^+ \geq 0,\ k = 1, 2, 3$

This is a nonlinear goal programming model due to the interaction terms $a_i\ M_i\ and\ a_i\ D_i$.

RESULTS AND DISCUSSION

Numerical Illustration

Here is a hypothetical example with three foundations (Table 3) and aspiration levels and weights (Table 4).

Table 3. Hypothetical example with 3 yayasan (n=3 foundations)

Assume	$B_1 = 500$ $P_1^{(norm)} = 450$ $C_1^y = 20$	$B_2 = 800$ $P_2^{(norm)} = 720$ $C_2^y = 30$	$B_3 = 1200$ $P_3^{(norm)} = 1100$ $C_3^y = 40$
Baseline margins	$m_1^0 = 30$	$m_2^0 = 50$	$m_3^0 = 60$
Penalties and audit effectiveness	$\alpha_M = 2$ $\theta_1 = 0.8$	$\alpha_D = 1$ $\theta_2 = 0.9$	 $\theta_3 = 1.0$
Audit costs	$c_1^A = 5$	$c_2^A = 6$	$c_3^A = 8$
Delay weights	$w_1 = 1$	$w_2 = 2$	$w_3 = 3$
Additional assumptions	$U_i^{out} = 0$	$D_i^{ref} = 0$	$0 \leq M_i \leq 0.2P_i^{(norm)}$
With $D_i^{ref} = 0$, the IC constraint becomes: $-M_i + \theta_i a_i(\alpha_M M_i + \alpha_D D_i) \geq 0$			

Table 4. Aspiration levels and weights

Illustrative aspiration levels for BGN:	$M^* = 10$ upper bound on total diversion	$D^* = 15$ upper bound on weighted delay	$A^* = 20$ upper bound on audit cost
Weights:	$w_1 = 100$	$w_2 = 10$	$w_3 = 1$
Objective function:	$Z_G = 100d_1^+ + 10d_2^+ + d_3^+$		

Illustrative Solution

Suppose a nonlinear solver yields the following solution:
$a_1^* = 0.60$; $a_2^* = 0.75$; $a_3^* = 0.90$
$M_1^* = 2$; $M_2^* = 3$; $M_3^* = 4$
$D_1^* = 1$; $D_2^* = 2$; $D_3^* = 3$

Aggregate values:
$Z_M = 2 + 3 + 4 = 9$.
$Z_D = 1 \cdot 1 + 2 \cdot 2 + 3 \cdot 3 = 14$.
$Z_A = 5 \cdot 0.60 + 6 \cdot 0.75 + 8 \cdot 0.90 = 14.7$

From the goal equations:
$9 + d_1^- - d_1^+ = 10 \rightarrow d_1^- = 1, d_1^+ = 0$
$14 + d_2^- - d_2^+ = 15 \rightarrow d_2^- = 1, d_2^+ = 0$
$14.7 + d_3^- - d_3^+ = 20 \rightarrow d_3^- = 5.3, d_3^+ = 0$

All positive deviations are zero; therefore, $Z_G = 0$ (targets are achieved or better).
Checking IR and IC (foundation 1):
$U^{1y} = 30 + 2 - 0.8 \cdot 0.6 \cdot (2 \cdot 2 + 1 \cdot 1) = 32 - 0.48 \cdot 5 = 29.6 > 0 = U_1^{out}$ → so, IR holds.
$\Delta U_1 = -2 + 0.8 \cdot 0.6 \cdot 5 = -2 + 2.4 = 0.4 \geq 0$ → so, IC holds.

This illustration shows that sufficiently strong audits, combined with penalties that scale with diversion and delays, can make opportunistic behavior unattractive while keeping participation feasible. The model also provides a transparent mechanism to explore alternative policy scenarios by changing aspiration levels and priority weights.

Discussion and Policy Implications

The model delivers a clear message: MBG contracts between BGN and foundations should be treated as incentive systems, not merely administrative documents. Diversion of funds and strategic payment delays are not random implementation "noise". They become rational for a foundation precisely when the expected private gain from misbehavior exceeds the expected loss from monitoring and sanctions. By formalizing this trade-off in a principal–agent framework, the model helps BGN identify where current incentives fail and how they can be corrected in a disciplined way.

The main mathematical contribution is the way goal programming and the principal–agent structure reinforces each other (Lee, 2020). On the agent side, the foundation's utility consolidates legal profit, diversion gains, and expected penalties into a single incentive expression. On the principal side, BGN's decision problem is posed as a multi-goal optimization that jointly targets three outcomes: (i) lower total diverted MBG funds, (ii) shorter and less severe payment delays, and (iii) affordable audit and enforcement costs (Sen, 2020). This matters because it converts competing policy priorities into measurable goal constraints and a single objective that minimizes weighted deviations. As a result, the model does not just state "reduce diversion and delays". It quantifies the trade-offs: tighter aspiration levels for diversion or delay typically require higher audit intensity, stronger penalties, or both. That produces a concrete mapping from policy levers (audit frequency, penalty rates, budget limits) to outcomes (diversion, delay, cost), rather than relying on intuition or generic calls to "increase supervision" (Venkateswarlu et al., 2016).

A further contribution is the explicit role of individual rationality (IR) and incentive compatibility (IC) constraints. These are not merely technical details. They ensure that recommended policies remain behaviorally feasible: foundations still prefer to participate, and honest behavior remains the best response. In practical terms, IR and IC prevent policies that look effective in the objective function but would push foundations out of the program or create new loopholes through unintended incentives.

Finally, the framework is intentionally extensible. The same mathematical structure can incorporate heterogeneous foundations, escalating nonlinear penalties for repeat violations, and reputation-based monitoring. It can also be extended into a multi-period setting to analyze learning and long-term trust. With real implementation data, parameters can be calibrated so the combined goal programming–principal–agent model operates as a decision-support tool for contract design and audit policy in MBG governance (Makki et al., 2022).

CONCLUSION

This paper proposes a goal programming principal–agent model to address two persistent weaknesses in MBG implementation: fund diversion and payment delays. By linking a foundation's incentive structure (legal margin, diversion gains, expected penalties) with BGN's multi-goal optimization under audit budget limits, the model turns a largely qualitative governance debate into a transparent quantitative policy design problem.

The numerical illustration highlights a consistent policy lesson: more ambitious integrity targets generally require stronger audits and higher supervisory costs, creating a practical "leverage map" for policymakers. Future work can extend the model to multi-period incentives and calibrate parameters using MBG field data to strengthen its prescriptive value for long-run governance.

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