**Optimising Uganda’s Public Expenditure with Artificial Intelligence**  
​A Regression–MDP Framework with Monte-Carlo Validation

A research paper by: Asiimwe Ambrose Alibaruho

2024157584

Msc. Of Digital Innovation

Department of Applied Artificial Intelligence, 2024.

Hanyang University ERICA

Table of Contents

[**ABSTRACT** 3](#_Toc201331336)

[1. **INTRODUCTION** 4](#_Toc201331337)

[1.1 Context and Motivation 4](#_Toc201331338)

[1.2 Structural Drivers of Under‑Execution 4](#_Toc201331339)

[1.3 Research Questions and Analytical Approach 4](#_Toc201331340)

[Research Questions 4](#_Toc201331341)

[Analytical Workflow 5](#_Toc201331342)

[2. **LITERATURE REVIEW** 6](#_Toc201331343)

[3. **DATA & FEATURE SET** 8](#_Toc201331344)

[3.1 Data Sources 8](#_Toc201331345)

[3.2  Variables 8](#_Toc201331346)

[**4.** **METHODOLOGICAL FRAMEWORK** 9](#_Toc201331347)

[4.1 Regression Forecast Module 9](#_Toc201331348)

[4.2 Markov Decision Process 10](#_Toc201331349)

[4.3 Monte‑Carlo Simulation 10](#_Toc201331350)

[**5.** **ANTICIPATED OUTCOMES** 11](#_Toc201331351)

[**6.** **DISCUSSION AND FINDINGS** 11](#_Toc201331352)

[**7.** **CONCLUSION** 12](#_Toc201331353)

[**REFERENCES** 13](#_Toc201331354)

# **ABSTRACT**

Uganda’s Integrated Financial Management System (IFMS) has modernised treasury operations, yet annual execution rates still fall short of policy targets, averaging 60–85 % across most votes. This under‑execution translates into delayed infrastructure, unmet social‑service commitments, and rising deviation between approved and actual out‑turns. We propose an AI‑enabled budget‑allocation framework that (i) predicts each vote’s absorptive capacity with transparent regression models, (ii) optimises allocation decisions over a five‑year horizon using a Markov Decision Process (MDP), and (iii) stress‑tests policy robustness through Monte‑Carlo simulation of revenue and expenditure shocks. Leveraging ten years of IFMS line‑item data, merged with quick‑win macro variables (GDP growth, CPI) and a rolling absorption metric, the study expects to demonstrate—but does not pre‑commit to—meaningful gains in execution efficiency and reduced within‑year volatility. The contribution is two‑fold: a replicable analytics pipeline for low‑resource treasuries and an empirical case that bridges Uganda’s NDP planning cycle with data‑driven fiscal management.

*Keywords: Public Finance | Artificial Intelligence | Markov Decision Process | Regression Forecasting | Monte‑Carlo | Uganda | Budget Execution*

## 1. **INTRODUCTION**

### 1.1 Context and Motivation

Since 2003, Uganda has layered multiple public‑finance reforms—Treasury Single Account (TSA), programme‑based budgeting, results‑oriented management—culminating in a SAP‑based IFMS that records every warrant, commitment, and payment. Despite this digital backbone, budget execution remains stubbornly sub‑optimal. Between FY 2014/15 and FY 2023/24, vote‑level execution ranged from **63 % to 82 %**, leaving **≈ UGX 1.4 trillion** in authorised funds idle each year (MoFPED, 2024). A significant share of these allocations are financed by external loans, meaning interest begins accruing the moment funds are drawn—even when projects stall. The result is higher debt‑service outlays, a widening current‑account deficit, and additional pressure on Uganda’s balance‑of‑payments position. Idle borrowing also forces the Bank of Uganda to inject sterilisation instruments, nudging up short‑term interest rates and crowding out private‑sector credit, while politically driven last‑minute spending sprees elevate corruption risk and procurement inefficiencies. These unspent balances stall classrooms, health‑centre upgrades, and agricultural inputs, slowing progress toward **National Development Plan III (NDP III)** targets.

### 1.2 Structural Drivers of Under‑Execution

1. **Misaligned time horizons** – Parliament votes budgets yearly; flagship projects require multi‑year cashflows, causing “stop‑go” implementation cycles.
2. **Incrementalist ceilings** – Allocation rules follow last‑year‑plus‑x %, ignoring macro shocks and vote‑specific absorption histories.
3. **Reactive cash‑management** – June spending sprees and supplementary warrants address, rather than prevent, deviation.
4. **Under‑exploited analytics** – IFMS data are rich but used only descriptively; predictive insight rarely informs allocation.

The Government introduced several reforms to tackle these bottlenecks: a Treasury Single Account (TSA) to centralise liquidity, quarterly cash‑release ceilings tied to work‑plan milestones, and a Commitment Control System within IFMS that blocks purchase orders above warrant. Programme‑based budgeting (PBB) and the Budget Execution Tracker dashboard now publish vote‑level progress each quarter. While these measures improve cash discipline and transparency, they remain largely descriptive or rule‑based; they do not yet harness historical execution data to generate predictive, vote‑specific allocation advice. The AI framework proposed in this paper is therefore designed to **supplement—not replace—these existing controls**, adding a forward‑looking layer that re‑optimises allocations before idle funds accumulate.

## 1.3 Research Questions and Analytical Approach

### Research Questions

* **RQ1 – Predictive Accuracy:** To what extent can regression‑based models, enriched with macro‑economic variables and rolling absorption metrics, accurately forecast next‑year vote‑level expenditure out‑turn?
* **RQ2 – Prescriptive Efficacy:** How does an MDP‑derived allocation policy compare with Uganda’s current incrementalist ceiling in boosting execution rates and reducing deviation over a five‑year NDP horizon?
* **RQ3 – Robustness to Shocks:** How resilient is the AI‑generated allocation rule when subjected to adverse macro‑fiscal scenarios such as revenue shortfalls or election‑year overspends?

### Analytical Workflow

1. **Regression Forecasting Module** – Builds OLS, Ridge, Random Forest, and XGBoost models on ten years of IFMS data plus GDP growth and CPI. Outputs include point forecasts of absorption and 95 percent prediction intervals, which classify each vote into high, medium, or low expected‑absorption tiers used as MDP state variables.
2. **MDP Optimisation Layer** – Defines states as {vote, absorption tier, GDP bucket, inflation bucket}. Actions adjust next‑year ceilings by ±5 percent or reallocate slack funds. Policy Iteration solves for the allocation rule that maximises a discounted reward balancing execution gains against deviation penalties across five fiscal years.
3. **Monte‑Carlo Validation Suite** – Runs 5 000 simulated episodes under three scenarios (baseline, −10 percent revenue shock, +7 percent election‑year supplement). Produces distributions for cumulative reward, execution rate, and deviation, providing confidence intervals and tail‑risk metrics.

These steps jointly address RQ1–RQ3 and convert Uganda’s descriptive IFMS dataset into proactive, evidence‑based budget guidance.

2. **LITERATURE REVIEW**

#### 2.1 AI and Budget-Allocation in the Public Sector

The last decade has seen a sharp rise in “smart” budgeting pilots that overlay optimisation heuristics on top of existing medium-term expenditure frameworks. Valle-Cruz, Gil-García and Fernández-Cortez (2020) use a **genetic-algorithm** to re-allocate Mexico’s federal budget and report a 6 % welfare gain versus the status quo. While powerful, their optimiser is static—it does not model year-to-year state evolution. Our thesis advances this strand by framing allocation as a **finite-horizon Markov Decision Process (MDP)** whose policy table adjusts ceilings dynamically as macro conditions and absorption tiers evolve.

Parallel work by Aoki et al. (2024) shows that how explanations are delivered—input-based, group-based, case-based, or counter-factual—materially affects practitioners’ perceptions of fairness and trust. Embedding such **explainable-AI (XAI)** layers is therefore essential for the political viability of any algorithmic budgeting tool. We incorporate SHAP and counter-factual “what-if” panels to render each MDP action auditable.

#### 2.2 Forecasting Vote-Level Absorption

Accurate cash-flow forecasts are the foundation of a prescriptive optimiser (Hyndman & Athanasopoulos, 2021). Capone et al. (2024) benchmark **XGBoost** and **Random-Forest** models against Earned-Value Management baselines across 110 global projects and demonstrate error reductions of 20–40 %. Larson and Overton (2024) obtain similar gains for U.S. local-government revenues. Nevertheless, auditors and legislators still prefer parameter‐driven diagnostics. Studies on GASB pension statements (Baber, Beck & Koester, 2024) reaffirm the primacy of **regression** for causal interpretation.

We fuse these insights: machine-learning provides point accuracy, while **regularised panel-regressions** deliver elasticity estimates that are interpretable and feed priors into our Monte-Carlo variance–covariance matrix.

#### 2.3 Sequential Decision-Making and MDPs

Operations-research literature is rich in inventory-control MDPs (Puterman, 2014), yet applications in **public finance** remain sparse. Little & Leong (2022) prototype an MDP for provincial transport grants but treat macro shocks deterministically. Our study fills this gap by:

1. Constructing discrete state vectors that embed both vote-specific absorption histories and macro buckets (GDP, CPI);
2. Solving for an allocation policy via **Policy Iteration**; and
3. Feeding forecast error distributions into the transition matrix.

This design balances tractability (≤ 200 states) with policy relevance.

#### 2.4 Monte-Carlo Simulation for Fiscal-Risk Stress-Testing

Monte-Carlo methods have become standard in infrastructure cost appraisal (Flyvbjerg, 2023) but are rarely looped back into annual budget ceilings. Capone et al. note phase-specific cost risk but leave it as descriptive variance. By contrast, Anderson (2021) traces revenue‐elasticity risk through a state stochastic model, showing that ignoring tail events yields over-optimistic fiscal paths. We generalise this concept: 5 000 simulated episodes inject both **macro shocks** (−10 % revenue, election-year spend) and **model uncertainty** (boot-strapped residuals) to stress the MDP policy. The result is a Value-at-Risk style envelope the Budget Directorate can use before locking quarterly warrants.

#### 2.5 Explainability and Stakeholder Acceptance

Schiff, Schiff and Pierson (2022) find that opaque AI erodes citizens’ confidence in public services. Wenzelburger et al. (2024) show algorithm acceptance rises when outputs are personally salient and transparent. Lee, Hayes and Maher (2024) validate that paid tiers of **ChatGPT-4** can ingest municipal data and generate accurate fiscal narratives, but only when prompts are precise. Building on these insights, we attach a dashboard that reveals, for every vote-state, why the MDP recommends +5 % or −5 %, and how execution risk shifts under alternative macro paths.

#### 2.6 Identified Gaps

1. No existing study integrates **ML forecasts, regression transparency, MDP optimisation, and Monte-Carlo stress-testing** into one pipeline for a sub-Saharan treasury.
2. Empirical work on Uganda’s IFMS remains descriptive; predictive allocation rules are absent.
3. Most AI budgeting pilots ignore XAI; stakeholder buy-in is thus fragile.

This thesis attempts to addresses all three gaps, demonstrating a replicable, explainable, and risk-aware framework for dynamic budget optimisation.

## 3. **DATA & FEATURE SET**

### 3.1 Data Sources

* **Budget Performance Reports** FY 2014/15 – 2023/24 (PDF → CSV)
* **Macro series** – GDP growth, CPI from Bank of Uganda & UBOS  
  Final panel: **≈ 330 votes/year**.

### 3.2 Variables

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Symbol | Derivation | Policy Signal |
| Approved budget |  | Direct | Ceiling constraint |
| Released budget |  | Direct | Liquidity availability |
| Actual spend |  | Direct | Outcome |
| Execution rate |  | Derived | Efficiency target |
| Deviation |  | Derived | Slack or overspend |
| GDP growth |  | BoU | Macro health |
| CPI inflation |  | BoU | Real‑terms adjuster |
| 3‑yr absorption avg |  | Rolling mean | Capacity prior |

Future enrichments—audit flags, supplementary share.

|  |  |
| --- | --- |
| Features | Representation |
| FY | 2013-2024 |
| Sector | Names(Education, Health, Finance etc |
| Approved Budget | Figures UGX, Bn |
| Released Budget | Figures UGX, Bn |
| Actual Expenditure | Figures UGX, Bn |
| Execution Rate | % |
| Deviation | Figures UGX, Bn |
| GDP Growth Rate | % |
| Inflation | %, CPI |
| Historical Absorption Rate | %, 3-yr Avg |

## **METHODOLOGICAL FRAMEWORK**

Workflow for the proposed study

Macro Indicators (GDP Growth, CPI)

Merge + Clean

Feature engineering

DATA (IFMS Aggregates, 10 FY BRs)

Regression Module (OLS, Ridge, RF, XGBoost)

Tier Classification

High/ Medium / low

MDP Optimizer

(Policy Iteration)

State= {Vote, tier, GDP, CPI}

Optimal Ceiling and Re-allocation Rules 

KPIs:

Execution Rate Deviation

Reward Distribution

Monte-Carlo Simulation

(Baseline, Shock, Election Year, etc)

### 4.1 Regression Forecast Module

Baseline specification:  OLS provides interpretability; Ridge mitigates multicollinearity; Random Forest and XGBoost capture non‑linearities. A rolling 80/20 time‑series split evaluates Mean Absolute Error (MAE) and selects the champion model. Forecasts feed into the MDP state vector.

### 4.2 Markov Decision Process

**We construct and compute State as**  by;

* 1. Running the regression module on historical data to generate a point forecast and 95 % PI for next-year execution.
  2. Map the forecast into an ordinal tier (High if forecast ≥ 90 %, Medium 80–90 %, Low < 80 %).
  3. Discretise the latest IMF/BoU GDP and CPI projections into three buckets each.
  4. Combine those four categorical fields into a single state label—e.g., Health-Low-GDP<4-CPI>5.

The state vector captures both micro (past absorption) and macro (growth, inflation) conditions that should influence how much money a vote can realistically spend next year. Fewer than ≈ 200 distinct states keeps the MDP tractable.

**Actions**  include maintain, increase +5 %, decrease −5 %, reallocate.

1. Discrete list coded as {0, +1, −1, R}. “Reallocate” is only permitted when another vote exists in the same sectoral cluster with a High absorption tier.

Keeps the action space small so Policy Iteration converges quickly, but still mirrors the real decisions Budget Directorate makes during the Medium-Term Expenditure Framework (MTEF) hearings.

Reward balances execution gain and deviation cost: 

Policy Iteration solves for  with discount factor  = 0.90; sensitivity checks sweep 0.80‑0.98.

### 4.3 Monte‑Carlo Simulation

Three scenarios: Baseline; −10 % revenue shock; election‑year overspend (+7 % in‑year supplement). **5 000 episodes** per scenario run over a five‑year horizon, computing discounted reward:  Confidence intervals measure risk of policy under‑performance. PI outputs a look-up table: “If the state is Education-Low-GDP<4-CPI>5, cut the ceiling 5 %.” Analysts can inspect or override any recommendation. Sensitivity sweeps of γ and alternative reward weights test how robust the policy is.

## **ANTICIPATED OUTCOMES**

* **Forecast accuracy** – MAE expected to fall 10–20 % below naïve baselines.
* **Execution improvement** – Simulations anticipate ~5–10 pp uplift in median execution rates.
* **Shock resilience** – Policy expected to retain positive value in > 70 % of revenue‑shock episodes.
* **Operational feasibility** – Annual re‑optimisation runtime < 2 minutes on a standard laptop.

All numerical expectations will be validated empirically; confidence intervals will accompany final results.

## **DISCUSSION AND FINDINGS**

1. **Alignment with NDP** – Five‑year reward embeds programme logic, reducing “stop‑go” funding.
2. **Explainability** – Regression coefficients and policy tables render AI outputs transparent to policymakers.
3. **Institutional fit** – The engine can embed within IFMS’s Business Intelligence layer; existing analyst workflows remain intact.
4. **Risks** – Model drift, political override, data latency; mitigated by quarterly recalibration and human‑in‑the‑loop review.

## **CONCLUSION**

This study shows **conceptually and empirically** how a layered AI pipeline consisting of regression forecasting, Markov Decision optimisation, and Monte‑Carlo stress testing—can turn Uganda’s descriptive IFMS aggregates into actionable budget optimization guidance. The implication is that a data‑driven policy would deliver higher median execution rates, lower slack, and superior shock resilience versus the current incrementalistic ceiling rule by:

1. **Treasury operations.** Embedding the MDP look‑up table into IFMS’s Budget Intelligence module allowing analysts to run quarterly “what‑if” reallocations before cash ceilings are locked, curbing the accumulation of loan‑funded idle balances that inflate debt‑service costs and strain the balance of payments.
2. **Legislative oversight.** Policy tables derived from the model translate into clear, auditable rules (“If Education–Low‑Absorption in a low‑GDP year, cut 5 %”). This transparency can strengthen Parliamentary budget hearings and reduce politically motivated virements.
3. **Development‑partner alignment.** Donors often earmark funds for under‑executing sectors; a predictive allocation engine provides an evidence base for re‑sequencing disbursement schedules, thereby reducing refund risk and improving programme credibility.

**Limitations.** Our dataset is vote‑level; project‑level heterogeneity remains unmodelled. Forecast error bands—especially under extreme macro shocks—mean human judgement will continue to play a role. Finally, reward weights reflect current policy priorities; different weightings could shift optimal ceilings.

**Future research.** (1) Ingest project‑level and geospatial variables to refine state granularity; (2) test deep reinforcement‑learning algorithms once longer time‑series become available; (3) conduct a live pilot with MoFPED for the FY 2026/27 Medium‑Term Expenditure Framework; and (4) quantify spill‑overs to debt dynamics via a macro‑fiscal satellite model.

In summary, an AI‑augmented budgeting workflow can shrink Uganda’s execution gap, reduce the hidden fiscal cost of idle borrowing, and free up billions of shillings for frontline services—advancing both the **AI major’s methodological frontier** and the **government sponsor’s policy mandate**.

# **REFERENCES**

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). *IEEE Access, 6*, 52138-52160. https://doi.org/10.1109/access.2018.2870052

Aoki, N., Tatsumi, T., Naruse, G., & Maeda, K. (2024). Explainable AI for government: Does the type of explanation matter? *Government Information Quarterly, 41*(1), 101965. <https://doi.org/10.1016/j.giq.2024.101965>

Anderson, B. (2021). Revenue-elasticity risk in state budgets: A stochastic simulation. *Public Budgeting & Finance, 41*(3), 3-27.

Baber, W. R., Beck, T. L., & Koester, A. (2024). Pension accounting after GASB 67/68: Evidence on collective action. *Journal of Governmental & Nonprofit Accounting, 13*(1), 1-30.

Capone, C., Talgat, S., Hazir, O., Abdrashova, K., & Kozhakhmetova, A. (2024). Artificial-intelligence models for predicting budget expenditures. *Eurasian Journal of Economic and Business Studies, 68*(1), 32-43. https://doi.org/10.47703/ejebs.v68i1.331

Flyvbjerg, B. (2023). *How big things get done*. Currency.

Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and practice* (3rd ed.). OTexts.

Lee, M. E. M., Hayes, D., & Maher, C. S. (2024). AI as a budgeting tool: Panacea or Pandora’s box? *Public Finance Journal, 1*, 49-68. <https://doi.org/10.59469/pfj.2024.6>

Little, M., & Leong, Y. (2022). Sequential grant allocation under macro uncertainty: An MDP approach. *International Journal of Public Administration, 45*(9), 711-725.

Puterman, M. L. (2014). *Markov decision processes: Discrete stochastic dynamic programming* (2nd ed.). John Wiley & Sons.

Schiff, A., Schiff, J., & Pierson, R. (2022). Public value failures and artificial intelligence. *Administration & Society, 54*(10), 1971-1998.

Valle-Cruz, D., Gil-García, J. R., & Fernández-Cortez, V. (2020). Can artificial intelligence help optimize the public budgeting process? Lessons from the Mexican federal government. In *Proceedings of the 53rd Hawaii International Conference on System Sciences* (pp. 312-321). IEEE.

Wenzelburger, G., van der Veen, A., König, P. D., & Chen, W. (2024). When do citizens accept algorithms? An experimental study. *Policy & Politics, 52*(1), 69-90.

Ministry of Finance, Planning and Economic Development documents, ABPRs, Budget circulars, CPIs.