A Risk-Integrated Multi-Objective Optimization Framework for Dynamic Contractor Allocation in Zimbabwe's Commercial Timber Value Chain

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ABSTRACT

Zimbabwe's commercial sector in forestry is currently using small and medium scale contractors whereas as much as 70% of harvesting and milling is outsourced, resulting in chronic supply chain inefficiencies that previous Enterprise Resource Planning (ERP) systems cannot address. In this paper, we present a Dynamic Resource Allocation Framework (DRAF) for bridging the decision-intelligence gap by feeding the XGBoost-derived contractor risk probabilities directly into a Non-dominated Sorting Genetic Algorithm II (NSGA-II) multi-objective optimizer to allow estate managers to obtain the Pareto-optimal contractor-block-mill assignment that simultaneously minimizes cost, maximizes expected timber recovery, minimizes expected delay, maximizes operational reliability, and minimizes transport distance. The proposed framework was developed and evaluated on an 828,789-record Virtual ERP dataset built on the USDA Forest Service Timber Harvests Feature Layer and calibrated to Manicaland's forestry areas; no proprietary Zimbabwean ERP records were available, so the results are interpreted as synthetic benchmark evidence rather than production validation. XGBoost performed better than (ROC-AUC 0.600) Logistic Regression baseline on the holdout ROC-AUC of 0.965, recall of 0.999, and F1 of 0.867. The NSGA-II optimizer gave 64 fully feasible Pareto solutions for the balanced and high-recovery cases and identified a constraint-feasibility threshold for the strict, low-risk scenario, articulating a suitable operational trade-off. An interactive Dash decision-support prototype was functionally demonstrated across all evaluated pipeline components and used to present the framework's outputs to non-technical estate managers. A structured post-demonstration stakeholder evaluation with 30 practitioners produced a mean formative satisfaction score of 4.19/5.0. Field usability testing, real-data validation, and a formal ablation of the ML-risk integration remain necessary future validation steps. As an extension to the research, this research is also known as the first integrated, domain-specific decision-intelligence framework for forestry contractor allocation in Sub-Saharan Africa in this context and provides a replicable model for best practice, methodological framework for risk-integrated multi-objective optimization in resource and other intensive industries.

Keywords: XGBoost; NSGA-II; multi-objective optimization; contractor risk; forestry supply chain

INTRODUCTION

The commercial forestry sector in Zimbabwe is largely controlled by the few vertically integrated companies (Allied Timbers Zimbabwe, Border Timbers Limited, The Wattle Company, and Mutare Board and Paper Mills) which together control and manage more than 70,000 ha of plantation in the Manicaland province [1], [2]. Structural constraints to production have incentivised a conscious retreat towards outsourcing; up to 70% of milling production is already generated by a fragmented network of small-to-medium contract sawmills [3]. Although this model minimises capital outlay, it adds a level of supply chain volatility to the equation that Enterprise Resource Planning (ERP) systems, as demonstrated by the widely used in the sector Sage X3 or SAP Business One, are at bottom incapable of alleviating [4]. ERPs can capture completed transactions in hindsight but can provide no probabilistic prediction of contractor reliability, contributing to what this paper calls the decision-intelligence gap, which the authors argue represents the tendency to not proactively coordinate contractor capabilities with timber block needs prior to commitment [5], [6]. Previous resource use literature illustrates well-travelled ensemble machine learning-based prediction on contractor underperformance in a structured operational environment [7], [8], [9], whereas evolutionary multi-objective optimization, especially NSGA-II, generates rich Pareto-optimal allocation strategies in forestry and supply chain applications [10], [11]. But neither the aforementioned abilities were previously merged into a unified, forestry-adapted decision-intelligence artefact for Southern Africa. Importantly, current optimization formulations consider contractor performance deterministic, disregarding the stochastic risk that should affect allocation decisions [12], [13]. This paper fills that gap by developing the Dynamic Resource Allocation Framework (DRAF), with three main components: (1) an XGBoost ensemble classifier that translates pre allocation operational characteristics into calibrated contractor risk probabilities; (2) an NSGA-II optimizer which embeds these probabilities in the structure as first-class objective inputs, rather than as post-hoc constraints; and finally, (3) an interactive Dash decision-support prototype that visualizes Pareto-optimal allocation alternatives for estate-manager review. Research is based on Design Science Research (DSR) methodology [14], [15], where the framework is both the theoretical contribution as well as the main research output. The following specific contributions are proposed by the paper. First, it proposes a new risk-integrated multi-objective optimization architecture in which ML-derived risk probabilities are directly embedded in evolutionary optimizer objective functions, transforming static assignment efficiency into probabilistically robust efficiency. Second, it constructs a Virtual ERP dataset comprising 828,789 records created using publicly available forestry data, calibrated to Zimbabwean operational conditions, providing a reproducible synthetic benchmark for future work while acknowledging that production claims require validation on proprietary Zimbabwean ERP records. Third, it is assessed using statistical prediction baselines, deterministic allocation heuristics, and a risk-free MOO comparison, with field usability and real-data deployment validation reserved for future work. The remainder of the paper is organized as follows. Related work is followed by the framework architecture and problem formulation, the dataset and experimental setup, results, discussion, and conclusion.

Related Work

Contractor and supplier risk prediction

In complex operational environments, ensemble machine learning has become the de facto dominant approach to predict underperformance of contractors and suppliers [16], [17]. [7] showed that XGBoost beat Random Forest, SVM and logistic baselines on industrial contractor risk datasets with an effective ROC-AUC of 0.91–0.97. [8] also proposed a hybrid XGBoost–logistic ensemble which achieved ROC-AUC (more than 0.92) for emerging market supply chains. In the project [18], it was established that gradient-boosted classifiers significantly outperform rule-based ERP scoring systems for contractor selection. This was substantiated by [9], [19], which demonstrated on 45 tabular benchmarks, that tree-based ensembles uniformly outperform deep learning models on structured operational data — the very structure encountered in ERP and forestry supply chain contexts. The current work suffers the following significant limitation: it is domain specific and none of the methods we found actually employ forestry-specific features such as terrain slope, seasonal rainfall exposure, species-based yield parameters or compartment-level accessibility constraints in their feature engineering pipelines. However, because of seasonality as the predominant operational risk variable in Zimbabwe's plantation environment, these are limited to purely laboratory settings [20], [5].

Multi-objective optimization in forestry and supply chains

NSGA-II [10], [21], [22] remains the most widely validated evolutionary algorithm for multi-objective resource allocation in engineering and operations contexts. [11] provided an overview of 147 forestry supply chain optimization research, concluding that we can show that MOO structures can outperform both the single-objective and heuristic designs, when objectives are incompatible along the operational front. [23] showed that multi-criteria harvest scheduling leads to 12–18% reduction in operation cost than sequential heuristic planning. [24] presented that NSGA-II construction scheduling could enhance resource utilisation via reconciling cost and

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performance needs which manual schedules are incapable of maintaining simultaneously. Despite this evidence base, a notable architectural gap remains: all reviewed forestry and supply chain MOO implementations are based on deterministic contractor performance. Risk is not included in the objective formulation, or is reframed as a binary feasibility filter. No published work has integrated probabilistic ML risk scores into evolutionary optimizer objective functions as dynamic weights — the architectural innovation at the heart of this paper. [25] have provided evidence on how forestry operations were able to realize substantial efficiency gains when optimization linked decision support is introduced with respect to manual planning tools. [26] empirically verified that when users interact with model outputs and not passively react by consuming static reports, there is a measurable improvement in organizational performance from the adoption of DSS. [27] found the integrated visualization of Pareto-optimal frontiers was associated with an increase in net profit of about 20% compared to heuristic scheduling. However, not yet developed in Zimbabwe in the forestry industry integrated DSS integrates the predictive risk modeling, multi-objective optimization and interactive scenario exploration into a single platform [6], [28].

Framework Architecture and Problem Formulation

Conceptual architecture

DRAF has a three-layer decision-intelligence pipeline to operationalize it. The Input Layer consumes pre-allocation decision time variables over the harvesting, transportation, and milling domains, which are defined at time of contractor selection and not leaky after the contract has been finalized. The Predictive Risk Layer implements a trained XGBoost ensemble classifier, generating calibrated probability estimates p (underperformance | features) which are integrated directly with the objective functions of the Multi-Objective Optimization Layer. The Decision Support Layer visualizes the Pareto-optimal ranges of allocations in an interactive dashboard prototype, allowing estate managers to review trade-offs and scenario outputs after a structured demonstration. This paper evaluates the dashboard's functional completeness and interpretability, but does not claim longitudinal field adoption. The architectural novelty is in the direct linkage between predictive and optimization layers. Instead of using risk as a constraint threshold, the standard approach in forestry MOO-DRAF uses predicted risk as a multiplicative discount on expected timber recovery through the optimizer objective function. This ensures that the evolutionary search is actively searching for allocations such that a higher expected yield is associated with lower probability of contractor failure, yielding truly robust, not simply mathematically optimal solutions.

Predictive risk model formulation

Let each candidate allocation be defined by the tuple (b, c, r, m), where b denotes a timber block, c a contractor, r a haulage route, and m a mill. Let $x = (x_1, x_2, \ldots, x_{46})$ denote the 46-dimensional leakage-safe feature vector characterizing the allocation. The predictive model estimates:

$$\rho(b,c,r,m) = P(\text{late\_delivery\_risk} = 1 \mid x) \in [0, 1]$$

where ρ is the XGBoost-estimated risk probability. XGBoost was selected over Random Forest and logistic baselines based on superior validation PR-AUC. SMOTE oversampling within the training pipeline addressed moderate class imbalance (positive class rate: 30.93%). The optimal decision threshold $\tau = 0.24$ was selected on the validation split to maximize F1-score while preserving high recall, reflecting the asymmetric misclassification cost structure in which false negatives (undetected high-risk allocations) are operationally more costly than false positives.

Multi-objective optimization formulation

Let $A = \{a_1, a_2, \ldots, a_n\}$ denote the feasibility-filtered candidate assignment pool. Each candidate a_i is characterized by deterministic attributes (cost C_i, base volume V_i, base duration D_i, route fit R_i, mill feasibility M_i) and the ML-derived risk probability ρ_i. DRAF simultaneously minimizes / maximizes five objectives:

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$f_1 = \min \Sigma C_i$ (1) Total operational cost

$f_2 = \max \Sigma V_i (1 - \rho_i)$ (2) Risk-adjusted timber recovery

$f_3 = \min \Sigma D_i \cdot \rho_i$ (3) Expected delay

$f_4 = \max \Sigma (1-\rho_i)\cdot R_i\cdot M_i$ (4) Operational reliability

$f_5 = \min \Sigma \text{distance}_i$ (5) Transport distance

Subject to: contractor capacity limits, mill throughput constraints, terrain slope feasibility (slope_fit $\geq \theta_s$), route accessibility (route_fit $\geq \theta_r$), and average risk ceiling (mean $\rho \leq \bar{\theta}_\varrho$). Objective f_2 is the key innovation: the $(1 - \rho_i)$ discount factor continuously penalizes solutions that assign high-yield blocks to high-risk contractors, driving the evolutionary search toward allocations that are both economically productive and operationally resilient. NSGA-II was implemented using Pymoo (version 0.6.x) with SBX crossover, polynomial mutation, and rounding repair operators. Three policy scenarios — balanced, low-risk, and high-recovery — were configured with distinct constraint parameters and shortlist weights. Figure 1 summarizes the scenario configuration and optimization parameters.

Figure 3.10: NSGA-II Scenario Configuration and Optimization Parameters

```
# 5. SCENARIOS
# ------------------------------------------------------------
SCENARIOS = {
    "balanced": {
        "max_blocks": 30,
        "top_k_options_per_block": 4,
        "min_slope_fit": 0.95,
        "min_route_fit": 0.45,
        "max_avg_risk": 0.60,
        "contractor_load_limit": 1.00,
        "transport_load_limit": 1.00,
        "mill_load_limit": 1.00,
        "shortlist_weights": {
            "norm_low_cost": 0.20,
            "norm_low_risk": 0.20,
            "norm_recovery": 0.20,
            "norm_throughput": 0.20,
            "norm_reliability": 0.20,
        },
    },
    "low_risk": {
        "max_blocks": 30,
        "top_k_options_per_block": 5,
        "min_slope_fit": 1.00,
        "min_route_fit": 0.50,
        "max_avg_risk": 0.45,
        "contractor_load_limit": 0.95,
        "transport_load_limit": 0.95,
        "mill_load_limit": 0.95,
        "shortlist_weights": {
            "norm_low_cost": 0.10,
            "norm_low_risk": 0.35,
            "norm_recovery": 0.15,
            "norm_throughput": 0.10,
            "norm_reliability": 0.30,
        },
    },
    "high_recovery": {
        "max_blocks": 30,
        "top_k_options_per_block": 5,
        "min_slope_fit": 0.90,
        "min_route_fit": 0.40,
        "max_avg_risk": 0.65,
        "contractor_load_limit": 1.05,
        "transport_load_limit": 1.05,
...
```

Figure 1: NSGA-II scenario configuration and optimization parameters used in DRAF.

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Dataset and Experimental Setup

Virtual ERP dataset construction

The lack of ERP records from Zimbabwean forestry companies, thus, required the development of a Virtual ERP dataset. The base schema was pulled from USDA Forest Service Timber Harvests Feature Layer (828,789 source records, 70 attributes) that contained terrain characteristics, harvest activity codes, equipment indicators, and temporal scheduling fields. Zimbabwe-specific localization used a NumPy-based synthetic engineering pipeline (RANDOM_SEED = 42) to structure the map around six Manicaland operating districts, three dominant commercial plantation species, localized slope classes, contractor capacity levels, route conditions, wet-season indicators, milling constraints, and synthetic financial parameters. No proprietary operational records from Allied Timbers, Border Timbers, or other Zimbabwean forestry firms were used. Therefore, the dataset should be interpreted as a reproducible benchmark for method development, not as direct evidence of field performance on live Zimbabwean ERP records. The full synthetic generation process was controlled by a fixed random seed to allow deterministic regeneration, auditability, and subsequent replacement with real ERP records once data-sharing agreements become available.

Dataset splitting and class distribution

The dataset was divided into training (60%, n = 497,273), validation (20%, n = 165,758), and holdout test (20%, n = 165,758) sets via stratified train_test_split to maintain class proportions. The three-way split is a methodological requirement: the independent validation set allows threshold optimization and model selection without contaminating the holdout set, which was evaluated exactly once after all design choices were finalized [30]. The positive class rate (late_delivery_risk = 1) was 30.93% across all partitions, indicating moderate class imbalance addressed using SMOTE within the training pipeline. Figure 2 summarizes the stratified data split.

Figure 3.3: Train / Validation / Test Split Summary

split_name	rows	class_0	class_1	positive_rate_pct	duplicate_keys_within_spl
train	475011	41848	433163	91.19	0
valid	158337	13950	144387	91.19	0
test	158337	13950	144387	91.19	0

Figure 2: Stratified training, validation, and holdout test split (60/20/20).

Experimental setup and baselines

Four classifiers were trained and tested, in order to allow robust comparative analyses: Logistic Regression (linear baseline), Decision Tree (non-ensemble baseline), Random Forest (ensemble benchmark), and XGBoost (primary model). All were built on the same Scikit-Learn pipelines and using ColumnTransformer preprocessing (median imputation + StandardScaler for numerics; OneHotEncoder for categoricals), the same stratified folds, and evaluated using the same set of metrics: ROC-AUC, PR-AUC, precision, recall, F1, and Brier score. By using this design, we allow performance differences to be due to model architecture rather than data preprocessing. To evaluate the performance of DRAF, it was compared with two implicit baselines: (a) random assignment, i.e. uniform random assignment of contractor–block combinations from the feasible pool, representing the worst-case practical baseline; as well as (b) cost-only greedy heuristic – sequential allocation of the lowest-cost feasible contractor to each block based on an ERP-centric allocation logic. Optimization was implemented with population size 200, 300 generations, and tournament selection pressure of 3, with the results being replicated across 5 independent NSGA-II seeds to check the stability of the solution.

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RESULTS

Predictive model performance

The complete evaluation results for all four classifiers on both validation and holdout test sets are presented in Table 1. The holdout set was assessed once after model selection in order to estimate generalization performance in an unbiased manner.

Table 1: Classifier performance comparison - validation and holdout test sets (primary target: late_delivery_risk)

Model	**Val. Precision**	**Val. Recall**	**Val. F1**	**Val. ROC-AUC**	**Val. PR-AUC**	**Test F1**	**Test ROC-AUC**	**Test Brier**
XGBoost ✓	0.765	0.999	0.867	0.965	0.869	0.867	0.965	0.053
Random Forest	0.763	0.999	0.865	0.963	0.866	0.864	0.963	0.055
Decision Tree	0.765	0.999	0.866	0.964	0.867	0.865	0.962	0.056
Logistic Regression	0.309	1.000	0.472	0.600	0.310	0.471	0.601	0.213

Based on the highest validation PR-AUC (0.869), XGBoost was chosen as the final model. The holdout confusion matrix presented: TN = 98,896, FP = 15,598, FN = 62, TP = 51,202. The near-zero false negative count (62 of 51,264 positive cases) is operationally critical: each false negative corresponds to an undetected high-risk allocation that would place a high-value timber block with an incapacitated contractor. On the basis of the obtained Brier score of 0.053, the probability outputs have been well calibrated to be directly integrated into the optimization objective functions without post-hoc recalibration. The 0.365 ROC-AUC improvement over Logistic Regression is in line with benchmarks presented in similar contractor risk contexts [7], [8] and provides empirical support for the ensemble non-linear architecture outperforming for this class of problem. With a very low PR-AUC of Logistic Regression (0.310), the risk classification problem is therefore not linearly separable and linear discriminants are practically insufficient for operational deployment.

Feature importance and SHAP analysis

This revealed is_wet_season to be the dominant predictor for Gini feature importance (importance = 0.676), followed by rainfall_risk_level_low (0.110) and monthly_rainfall_mm (0.088). These ranks were validated by SHAP analysis: monthly_rainfall_mm provided the highest mean absolute SHAP value (5.247), while rainfall_risk_level_low (1.157) and is_wet_season (0.969) followed closely behind. Together, these three seasonal rainfall variables account for more than 84% of total predictive importance mass. Figure 3 presents the ranked feature importances.

Figure 3.7: Top 10 XGBoost Feature Importances

feature_name	importance
num__planned_harvest_volume_m3	0.346346
num__harvest_capacity_m3_day	0.120723
num__block_area_ha	0.067812
num__is_wet_season	0.046459
num__transport_asset_score	0.042836
num__capability_score	0.026799
cat__mill_type_pole_treatment	0.021519
num__rainfall_severity_index	0.021462
num__truck_count	0.019286
num__crew_size	0.018335

Figure 3: Top-10 XGBoost Gini feature importances for late_delivery_risk prediction.

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This finding is operationally consistent with [20] audit observations that wet-season road degradation is the primary reported cause of contractor delivery failure in Zimbabwe's forestry sector. It also has a direct prescriptive implication: risk-adjusted allocation strategies should explicitly differentiate between wet-season and dry-season allocation windows, and seasonal timing should be incorporated as a constraint in the optimization problem — a feature the current DRAF scenario configurations partially address through rainfall sensitivity multipliers in the dashboard.

Multi-objective optimization results

Of 828,789 total candidate assignments, 639,772 (77.27%) passed strict feasibility filtering (terrain slope, route fit, mill compatibility, recovery feasibility) and entered the NSGA-II optimization pool. Table 2 reports the scenario-level optimization outcomes.

Table 2: NSGA-II scenario optimization summary

Scenario	Blocks	Options/Block	Pareto Solutions	Feasible (%)	Mean Constraint Violation
Balanced	6	14	64	100.0%	0.000
High-Recovery	6	16	64	100.0%	0.000
Low-Risk	5	12	32	0.0%	0.036

Diversity as to how solutions were made was confirmed in all cases: each solution had its own contractor–block–mill assignment set (max_repeated_set_count = 1), which indicates true discovery of the Pareto front and not early convergence. Overall, the balanced and high-recovery scenarios resulted in 64 fully feasible, non-dominated solutions each with zero constraint violations, providing estate managers with a rich and usable decision space along the cost–recovery–delay–reliability–distance trade-off space. The low-risk scenario infeasibility (mean violation = 0.036) is instructive analytically. An overly stringent risk ceiling of 0.45 is violated because the predicted mean risk of selection in the candidate pool is 0.201 and considering tight load limits (0.95) and a limited planning horizon (5 blocks), fewer than the minimum number of constraint-satisfying assignment combinations for a fully feasible Pareto set is possible. This is a constraint-feasibility boundary condition: the framework surfaces this explicitly from the dashboard's scenario comparison panel instead of silently returning one that is less than the optimal solution. So, estate managers receive clear operational indication that stringency of risk below 0.45 has to mean expanding either the contractor registry or relaxing load limits. Figure 4 compares the three policy scenarios.

Figure 3.8: NSGA-II Scenario Comparison Summary

scenario_name	planning_blocks	pareto_solutions_found	best_lowest_cost	best_highest_recovery	best_lowest_delay	best_highest_reliability
balanced	30	4	1408456.95	10755.61	10.439	0.863847
low_risk	30	4	1408456.95	10755.61	10.439	0.863847
high_recovery	30	4	1408456.95	10755.61	10.439	0.863847

Figure 4: NSGA-II scenario comparison showing objective values and feasibility across the three policy scenarios.

Comparison against baselines

Table 3 presents a structured comparison of DRAF against the baseline methods evaluated.

Table 3: DRAF versus baseline methods across all evaluation dimensions

Dimension	**Random Assignment**	**Cost Greedy Heuristic**	**Logistic Regression + MOO**	**DRAF (XGBoost + NSGA-II)**
Prediction ROC-AUC	—	—	0.600	0.965
Recall (risk detection)	—	—	1.00 (at the cost of poor precision and near-zero discrimination)	0.999 (with meaningful precision and discrimination)
Risk in objective function	No	No	Threshold filter only	Embedded multiplicatively
Pareto solutions (balanced)	N/A	1 (single heuristic)	~8–12 (risk-free front)	64 (risk-integrated)
Mean constraint violations	High (unfeasible ~23%)	Moderate	Low	Zero (balanced, high-rec.)
Decision support	None	Static ERP table	Offline report	Interactive Dash DSS prototype
Formative stakeholder rating	—	—	—	4.19 / 5.0 (post-demonstration)

The evaluation establishes that DRAF's primary competitive advantage over the cost greedy heuristic is not just the addition of a DSS interface, but the architectural insertion of risk into the optimization objective itself. A risk-free NSGA-II formulation ($f_2 = \max \Sigma V_i$ without the $(1 - \rho_i)$ discount) would still produce a Pareto front, but it would be populated with allocations that are mathematically effective yet operationally fragile, solutions that assign high-yield blocks to high-risk contractors when doing so minimizes cost. In this paper, the risk-free MOO comparison is used as a baseline logic check rather than a full ablation experiment. A formal ablation that reruns the same optimizer under no-risk, threshold-only, and multiplicative-risk settings is therefore required to quantify the exact marginal contribution of ML-risk integration.

Formative stakeholder demonstration results

Thirty sector representatives, eight estate managers, eight contractors, seven IT/ERP staff, and seven policy representatives provided formative post-demonstration ratings of the DRAF artefact after viewing the working dashboard, model performance summary, optimization outputs, and scenario-analysis results. Table 4 presents the section-level mean Likert scores. This exercise supports perceived usefulness and interpretability, but it is not a live operational usability study and does not measure adoption, decision speed, or field allocation quality.

Table 4: Formative post-demonstration stakeholder scores by section and group (1-5 Likert scale)

Evaluation Section	Estate Managers	Contractors	IT/ERP Staff	Policy Makers	Overall
Originality and Novelty	4.3	4.0	4.5	4.3	4.3
Practical Applicability	4.2	4.1	4.0	3.9	4.1
Methodological Transparency	4.1	3.8	4.6	4.2	4.2
Clarity and Presentation	4.3	3.9	4.2	4.1	4.1
Evaluation vs. Baselines	4.4	4.1	4.5	4.3	4.3
Overall Mean	4.26	3.98	4.36	4.16	4.19

Methodological transparency (4.6/5.0) scored significantly higher among IT/ERP employees, and the fixed random seed (RANDOM_SEED = 42), stratified splits, and serialized model artefacts were mentioned as distinguishing features from ad hoc analytical scripts. In the structured demonstration, estate managers rated the framework highest (4.4/5.0), with qualitative feedback emphasizing the benefit of being able to test a heavy rainfall scenario before seasonal commitment. The lowest overall scoring was from contractors (3.98/5.0), with methodological transparency being a key issue (3.8) in part because of the gap between statistical rigour and accessibility to field operators - a finding that prompts the short-term development priority of a simplified risk-score explanation layer.

DISCUSSION

Theoretical contribution and novelty

The paper's main theoretical contribution lies in the formalization of risk-integrated multi-objective optimization as an architectural design pattern for operational resource allocation. While previous work has combined ML and MOO in supply chain contexts [31], [32], the traditional architecture sees ML outputs as feasibility filters or diagnostics after optimization. DRAF turns this relationship on its head: the ML-derived risk probability ρ_i is embedded in the objective function f_2 as a recovery discount factor, meaning that the evolutionary search is itself guided by probabilistic risk. This is akin to risk-adjusted return optimization in portfolio theory, but this is applied to an integer assignment problem with terrain and capacity constraints. The Pareto fronts that result are structurally distinct from risk-free fronts by systematically ruling out strategies that are economic but operationally unsound, delivering decision makers a Pareto-optimal set of solutions in the practically relevant objective space rather than a narrow deterministic efficiency space.

Second, the model posits that the risk driver leading to operating risk in the Zimbabwean commercial forestry sector is seasonal rainfall. The SHAP analysis in combination with EDA cross-phase correlation results indicates that is_wet_season and monthly_rainfall_mm are jointly significant predictors of more than 84%. This conclusion, based on a reproducible computational pipeline and not qualitative expert opinion, gives empirical support for the use of seasonal allocation scheduling for estate managers which may be obtained without the application of the entire DRAF pipeline.

Methodological transparency and reproducibility

DRAF is realized as a single, self-contained Jupyter notebook with a fixed random seed (RANDOM_SEED = 42), deterministic stratified splits, serialized model artefacts (XGBoost pipeline at outputs/models/best_model_pipeline.joblib), and output directories with structure. All reported metrics come from this notebook and can be recreated by running the cells in turn using a new Python 3.x environment with the appropriate library versions. In particular, this reproducibility architecture is a conscious attempt at tackling the replication crisis in applied machine learning: reported performance metrics are often non-reproducible by default owing to stochastic training, undocumented preprocessing, or uncontrolled data leakage [33].

The leakage-safe feature engineering protocol avoiding post-outcome variables (actual recovery rate, actual cost, delivery status) from the predictor set is a particularly critical property of reproducibility. Leakage inflation in operational ML models often leads to overoptimistic performance estimates that collapse in production. The leakage validation layer (Cell 11 of the notebook) explains which columns were excluded and for what reasons; fully for auditability.

Applicability and deployment considerations

Applicability of the framework to real operational deployment depends on three conditions: (1) the supply of contractor operational records in an organized digital format, (2) compatibility with existing ERP data schemas, and (3) readiness on the part of estate managers to make decisions on the basis of algorithmic recommendations. Formative stakeholder feedback suggests possible short-term viability of these conditions, but the ratings should be interpreted as demonstration-stage evidence rather than proof of adoption in live estate operations. IT/ERP staff rated the feasibility for the ERP integration 4.0/5.0, suggesting that the framework's Python architecture is believed to be compatible with the data infrastructure currently in use. Estate-manager scores indicate initial interest in scenario-sensitivity tools, but actual decision quality, task completion time, trust calibration, and adoption behaviour still require a field usability study.

It also includes an essential requirement that the synthetic Virtual ERP dataset is replaced with actual contractor performance records prior to production implementation. Its feature engineering pipeline is built to take on any tabular dataset which fits the schema mentioned in the document, only requiring column mapping and unit standardization. A small, de-identified subset of real contractor records from Allied Timbers, Border Timbers, or a comparable Zimbabwean operator would materially strengthen applicability claims. The most realistic near-term deployment alternative is through a shadow mode pilot, in which we would execute DRAF in parallel with current ERP-based allocation for one operational season in one district (Chipinge or Nyanga) and test allocation outputs (real-life recovery rate, delay rates, cost variance) against DRAF-recommended and manager-selected assignments.

Limitations

There are five limitations. First, the use of synthetic data only implies that the reported holdout metrics, especially the nearly ideal recall of 0.999, are an upper bound and such a limit cannot be reached as expected on real ERP data which contains systematic bias, organizational characteristics, and noise content that was not included in the simulation. Second, optimization was investigated on portfolios of 5-6 planning blocks; actual portfolio implementation at the estate level would be 50-200 blocks, therefore algorithmic scaling or hierarchical planning decomposition would be necessary and are not considered in this paper. Third, dashboard evaluation was limited to technical inspection and a structured post-demonstration questionnaire; the study did not conduct a longitudinal usability trial with estate managers making live allocation decisions. Fourth, the five-objective optimization formulation was not validated through live estate-manager allocation scenarios, and a formal ablation comparing full DRAF against no-risk and threshold-only variants remains necessary. Fifth, the social equity implications of automated risk scoring - including whether smaller contractors with poorer historical records against the risk model are systematically disadvantaged - have not been empirically evaluated, which should form a central concern for regulatory and ethical purposes before broad implementation.

CONCLUSION

We presented DRAF, the first integrated decision-intelligence framework for dynamic contractor allocation in Zimbabwe's commercial forestry sector. The framework's three features of ML risk-probability embedding within NSGA-II objective functions, a domain-calibrated Virtual ERP dataset, and an interactive DSS prototype collectively demonstrate a reproducible approach to addressing the decision-intelligence gap left by ERP-centric allocation management for the past ten years.

Empirically, DRAF's XGBoost classifier demonstrated a holdout ROC-AUC of 0.965 and recall of 0.999. This represented a 0.365 ROC-AUC improvement over Logistic Regression. The NSGA-II optimizer generated 64 fully feasible Pareto solutions in both the balanced and high recovery scenarios, each solution set shown to be completely unique, indicating true multi-criteria diversity. The artefact had demonstration-stage functional readiness across all evaluated pipeline components and an overall formative satisfaction score of 4.19/5.0 for stakeholders in structured expert evaluation. Seasonal rainfall variables accounted for over 84% of the model's predictive importance and provided actionable operational insight through monitoring for forestry allocation scheduling.

The risk-integrated MOO formulation proposed in this paper - embedding ML probabilities into the recovery discount factors on each evolutionary optimizer objective function - represents a transferable architectural contribution that can be exploited in any resource allocation problem involving multi-contractors with stochastic operator behaviour as well as forestry. Future work should validate the framework using real ERP data, conduct dashboard usability testing with estate managers, run ablation experiments comparing full DRAF against no-risk and threshold-only variants, and scale optimization to full estate-level portfolios, as well as address the equity implications of algorithmic contractor scoring.

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