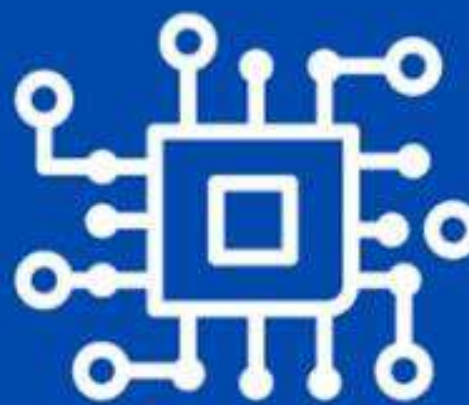




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Ochilov Abduraxim Abdurasulovich – Texnika fanlari bo'yicha falsafa doktori (PhD), Buxoro, O'zbekiston.

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TAHRIRIYAT MANZILI:

Toshkent shahri, Yakkasaroy tumani, Kichik
Beshyog'och ko'chasi, 70/10-uy.

Elektron manzil:

scienceproblems.uz@gmail.com

Barcha huquqlar himoyalangan.

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MUNDARIJA

Ataboyeva Shaxrizoda

EMPIRIK TAHLILLAR ASOSIDA OLIY TA'LIM BOSHQARUVI VA INDIVIDUAL
TA'LIM JARAYONLARINI TAKOMILLASHTIRISHDA SUN'IY INTELLEKTGA
ASOSLANGAN OPTIMALLASHTIRISH ALGORITMLARI 4-11

Turgunbaev Rashid

METAEXTRACT - KO'P TILLI ILMIY JURNALLARDAN BIBLIOGRAFIK
METAMA'LUMOTLARNI QOIDALARGA ASOSLANGAN EKSTRAKSIYA QILISH TIZIMI 12-18

Muqimova Anaxon

ADVANCED REAL-TIME TRAFFIC SIGN SEGMENTATION AND CLASSIFICATION USING
HYBRID DEEP CONVOLUTIONAL ARCHITECTURES ON GTSDB AND BENCHMARK
DATASETS 19-24

Pulatov G'iyos, Kabildjanov Aleksandr, Pulatova Gulxayo

SUST SHAKLLANGAN JARAYONLARNI BASHORATLASHDA INTELLEKTUAL
ALGORITMLARNI QIYOSIY TAHLILI 25-33

Usarkulova Feruza

AN INTEGRATED MODEL FOR AI-BASED FORECASTING OF TECHNICAL SERVICE
DEMAND AND OPTIMAL RESOURCE ALLOCATION IN AGRO-INDUSTRIAL
COMPLEXES 34-43

Botirov Munisbek

NUMERICAL MODELING AND OPTIMIZATION OF GROUNDWATER FILTRATION
PROCESSES USING COMPUTATIONAL ALGORITHMS 44-53

Гулямов Шухрат, Зайниддинова Зебинисо, Караханова Алсу

РАЗРАБОТКА МЕТОДОВ ПОСТРОЕНИЯ ВИРТУАЛЬНЫХ ПРИБОРОВ
ЭКОЛОГИЧЕСКОГО КОНТРОЛЯ КАЧЕСТВА ПРОМЫШЛЕННОЙ ПРОДУКЦИИ 54-61

Каршиев Хумоюн, Хасанов Абдирашид

ПЕРСПЕКТИВНЫЕ СПОСОБЫ ПЕРЕРАБОТКИ КОБАЛЬТСОДЕРЖАЩИХ
ОТХОДОВ ЦИНКОВОГО ПРОИЗВОДСТВА 62-73

Xaytbayev Aybek

TAKOMILLASHTIRILGAN KUZATUVCHI QIDIRUV ALGORITMI ASOSIDA SIMSIZ SENSOR
TARMOQLARIDA ENERGIYA SAMARADOR KLASTER BOSH TUGUNINI TANLASH 74-88

Zokirov Islomjon, Nurillaev Ahadullo, Abdullaev Shavkat

INTEGRATED MATLAB/SIMULINK–SIMSCAPE MODELING AND PI-BASED CLOSED-LOOP
CONTROL OF A MICRO-HYDROPOWER PLANT 89-101

Qarshiboyev Asqar, Tursunov Ilhom

KOMPRESSOR USKUNALARINING OPTIMAL ISH REJIMINI ANIQLASH VA ELEKTR ENERGIYASI
ISTE'MOLI SAMARADORLIGINI BAHOLASH 102-112

AN INTEGRATED MODEL FOR AI-BASED FORECASTING OF TECHNICAL SERVICE DEMAND AND OPTIMAL RESOURCE ALLOCATION IN AGRO-INDUSTRIAL COMPLEXES

Usarkulova Feruza

Master's student, Karshi State Technical University,

Email: usarkulovaferuza@gmail.com

ORCID: 0009-0009-2707-7116

Karshi, Uzbekistan

Annotation. This paper proposes an integrated decision model for forecasting technical-service demand and allocating limited maintenance resources in agro-industrial complexes. The forecasting layer represents daily, intermittent service requests by zone and service category through a Poisson gradient-boosting model with calendar, weather, fleet, workload and lagged-demand features. A split-conformal procedure converts point predictions into empirical uncertainty margins. The prescriptive layer is formulated as a mixed-integer linear program that assigns team-days and service jobs subject to skill compatibility, regular and overtime capacity, spare-parts availability and shortage penalties. A reproducible controlled experiment with 21,600 zone-category-day observations is used to test the computational procedure. The HGB-Poisson model reduces MAE and RMSE relative to seasonal-naïve and Croston-SBA benchmarks. In a calendar-defined 14-day workload window, budgeted-robust AI planning improves realized service continuity compared with a historical seasonal plan. The results support a rolling-horizon software architecture in which forecasts and allocation decisions are updated from completed work orders.

Keywords: agro-industrial complex; technical service; intermittent demand; artificial intelligence; mathematical modeling; mixed-integer programming; robust allocation; software complex.

AGROSANOAT MAJMUALARIDA TEXNIK XIZMAT KO'RSATISHGA BO'LGAN TALABNI SUN'IY INTELLEKT ASOSIDA PROGNOZLASH VA RESURLARNI MAQBUL TAQSIMLASHNING INTEGRATSIYALASHGAN MODELII

Usarkulova Feruza

Magistrant, Qarshi davlat texnika universiteti

Qarshi, O'zbekiston

Annotatsiya. Maqolada agrosanoat majmualarida texnik servis xizmatlariga bo'lgan talabni prognozlash va cheklangan resurslarni taqsimlash uchun integratsiyalashgan qaror modeli taklif etilgan. Prognozlash qatlamida hudud va xizmat turi kesimidagi uzlukli kunlik talab kalendar omillari, ob-havo, mashina-traktor parkining holati, mavsumiy ish yuklamasi hamda kechikkan talab belgilaridan foydalanuvchi Puasson yo'qotish funksiyali gradient boosting modeli orqali ifodalanadi. Nuqtaviy prognozlar split-konformal kalibrlash yordamida noaniqlik chegaralari bilan to'ldiriladi. Resurslarni taqsimlash masalasi brigadalarining malaka mosligi, me'yoriy va qo'shimcha ish vaqti, ehtiyot qismlar zaxirasi hamda bajarilmagan buyurtmalar jarimasini hisobga oluvchi aralash butun sonli chiziqli dasturlash modeli sifatida tuzilgan. 21 600 ta "hudud-xizmat turi-kun" kuzatuvidan iborat nazoratli hisoblash tajribasi modelning sonli xususiyatlarini tekshirish uchun qo'llanildi. Natijalar integratsiyalashgan yondashuv prognoz xatosini kamaytirishi va tig'iz davrda servis uzluksizligini yaxshilashini ko'rsatdi.

Kalit so'zlar: agrosanoat majmuasi; texnik servis; uzlukli talab; sun'iy intellekt; matematik modellashtirish; aralash butun sonli dasturlash; robust taqsimlash; dasturlar majmui.

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INTRODUCTION

The technical-service system of an agro-industrial complex operates under a distinctive combination of intermittency and urgency. A tractor may require no repair for several weeks, yet a failure during sowing or harvesting can stop several linked operations at once. Service demand therefore arrives unevenly across time, territory and machine type. The same request also consumes a specific combination of technician hours, diagnostic equipment, transport and spare parts. If these components are planned independently, a forecast may be statistically accurate but operationally unusable, or a mathematically efficient schedule may be built on the wrong demand signal.

Predictive-maintenance studies usually focus on the probability or remaining time of component failure [1]. This is necessary but not sufficient for a service organization that must decide where to place mobile teams, which skills must be available and what volume of requests can be accepted. The practical decision is prescriptive: an expected flow of work orders must be converted into a feasible resource plan. Predictive and prescriptive analytics should therefore be coupled through common data definitions, horizons and uncertainty measures [2].

The research problem is formulated as follows. For each service zone and category, daily requests are forecast from operational and exogenous variables. Forecast errors are then transformed into a controlled uncertainty margin, after which a mixed-integer allocation model selects team-days, job assignments and overtime. The formulation must preserve interpretability because planners need to understand why capacity has been moved between zones. It must also be computationally light enough for repeated rolling-horizon use rather than a one-off retrospective calculation.

The aim of the study is to develop and numerically evaluate an integrated mathematical model that connects AI-based demand forecasting with optimal allocation of technical-service resources in agro-industrial complexes. The objectives are: to formalize intermittent service demand; to construct a feature-based forecasting function; to calibrate uncertainty without imposing a restrictive error distribution; to formulate resource allocation with skill, capacity and inventory constraints; and to define a modular software complex for data preparation, numerical solution and decision reporting.

The contribution is not a claim of field implementation. The empirical section is a controlled computational experiment with a fixed random seed and explicitly stated assumptions. Its role is to test model logic, numerical behavior and the direction of operational effects before deployment on enterprise data. This distinction is important: synthetic evidence can validate an algorithmic mechanism, but only a later prospective study can establish the economic effect for a particular service enterprise.

LITERATURE REVIEW

Technical-service demand inherits the intermittent structure of spare-parts consumption. Croston's method separates non-zero demand size from the interval between demand occurrences [3]. The Syntetos-Boylan adjustment corrects part of the bias in the original estimator [4]. These methods remain useful benchmarks because they require little data and their calculations are easy to audit. Their limitation is equally clear: they do not naturally incorporate rainfall, field-work intensity, fleet age or cross-sectional information shared by zones and service categories.

Agricultural machinery research increasingly treats service and spare-parts demand as a data-classification and prediction problem. Qiu et al. [5] show that agricultural spare-parts records can be classified and predicted when labeled observations are limited. More generally, ensemble trees can model nonlinear interactions, missing thresholds and mixed scales without assuming a linear response surface. Random forests [6] and gradient boosting [7] are established representatives of this family, while LightGBM and XGBoost provide computationally efficient implementations for large tabular data sets [8, 9].

For multi-horizon problems, attention-based architectures such as the Temporal Fusion Transformer can combine static attributes, known future inputs and observed covariates [10]. Such models are attractive when long sequences and sufficiently large enterprise histories are available. They are not automatically superior for a modest tabular service database. A simpler boosted-tree model can be preferable when retraining time, auditability and stable numerical operation are primary requirements. The choice should therefore follow data scale and decision use rather than model fashion.

Forecast evaluation also requires care. Percentage errors are unstable when the actual demand is zero, which is common in service-category series. MAE and RMSE describe absolute error, WAPE provides a portfolio-level relative measure, and MASE compares error with an in-sample naive scale [11]. No single metric is sufficient: RMSE penalizes large misses, whereas MAE better represents a typical record. Coverage of uncertainty intervals should be reported separately from point accuracy.

The allocation layer is related to robust optimization and vehicle-routing or workforce-scheduling models. Bertsimas and Sim [12] introduced a budgeted treatment of uncertainty that allows a planner to control conservatism. Solomon's time-window routing formulation [13] remains a foundation for detailed daily dispatching. The present study operates one level above routing: it allocates team-days and service capacity over a 14-day horizon. Routes can subsequently be built inside each allocated zone, but embedding both decisions in the first model would obscure the central forecast-allocation linkage.

The literature review reveals a methodological gap relevant to 05.01.07. Forecasting studies often stop at an accuracy table, while optimization studies treat demand as known. A complete software-oriented model requires a formal interface between the two: identical zone-category indices, a calibrated uncertainty object, a deterministic numerical solver and diagnostics that trace every plan back to input data and model version. The integrated formulation below is designed around this interface.

RESEARCH METHODOLOGY

Problem statement and notation

Let $t=1,...,T$ denote days, $z \in Z$ service zones, and $c \in C$ service categories. The observed number of requests is $y_{tzc} \in \mathbb{Z}_+$. The feature vector x_{tzc} contains zone and category codes, planned agricultural workload, temperature, rainfall, fleet size, mean machine age, one- and seven-day lags, and cyclical calendar coordinates. At forecast origin τ , the model produces a non-negative conditional mean for each future record:

$$\hat{y}_{tzc} = f\theta(x_{tzc}), \quad \hat{y}_{tzc} \geq 0 \quad (1)$$

The mapping $f\theta$ is estimated by histogram-based gradient boosting with a Poisson deviance objective. For observation i , the empirical objective is

$$L(\theta) = \sum_i [\hat{y}_i(\theta) - y_i \ln(\hat{y}_i(\theta) + \varepsilon)] + \lambda \Omega(\theta) \quad (2)$$

where ε is a small numerical constant and $\Omega(\theta)$ denotes tree-complexity regularization. The log-link implicit in the Poisson loss prevents negative forecasts while allowing nonlinear interactions. This distributional choice is used as a loss function, not as a claim that the zero-inflated service process is exactly Poisson.

Forecast uncertainty and rolling-horizon demand

A proper training set and a chronologically later calibration set are separated to avoid information leakage. For each service category, the 0.90 quantile of absolute calibration residuals is calculated. The resulting split-conformal interval is

$$I_{tzc} = [\max(0, \hat{y}_{tzc} - \hat{q}_c), \hat{y}_{tzc} + \hat{q}_c] \quad (3)$$

For tactical planning, record-level forecasts are summed over a horizon H . Because directly summing pointwise interval radii is excessively conservative, aggregate residuals are recalculated in rolling H -day calibration windows. Let mzc be the empirical 0.90 quantile of these one-sided aggregate residuals. The demand passed to the optimization layer is

$$\tilde{d}_{zc} = \sum_{t=1}^H \hat{y}_{tzc} + \delta_{zc} mzc, \quad \sum_{z,c} \delta_{zc} \leq \Gamma, \quad \delta_{zc} \in \{0,1\} \quad (4)$$

The integer budget Γ specifies how many of the 24 zone-category cells receive their calibrated upper margin. $\Gamma=0$ gives a point-forecast plan. For $\Gamma>0$, cells are ranked by $\pi_c \cdot mzc$ so that protection is directed first to combinations with both high underprediction exposure and a high interruption penalty. This transparent risk-priority implementation approximates the budgeted robust counterpart and prevents every demand component from reaching its upper value simultaneously. The parameter changes the protection built into the resource plan, not the statistical point forecast.

Mixed-integer resource-allocation model

Let $k \in K$ index team types. Decision x_{kz} is the integer number of team-days assigned to zone z ; q_{zck} is the integer number of category- c jobs completed by team type k ; ok_z is overtime in hours; and uz_c is unmet demand. Parameters include the category labor requirement h_c , skill indicator ak_c , available teams N_k , regular shift length B , overtime limit B^o , travel-deployment cost g_{kz} , service cost v_{ck} , shortage penalty π_c , part requirement r_{pc} and inventory I_p . The tactical model minimizes

$$\min J = \sum_{k,z} g_{kz} x_{kz} + \sum_{z,c,k} v_{ck} q_{zck} + \sum_{k,z} p_{okz} + \sum_{z,c} \pi_c uz_c \quad (5)$$

subject to the following availability, capacity, overtime, demand-balance and inventory constraints:

$$\sum_z x_{kz} \leq HN_k, \quad \forall k \quad (6)$$

$$\sum_c h_c q_{zck} \leq Bx_{kz} + ok_z, \quad q_{zck} \leq M ak_c, \quad \forall z,k,c \quad (7)$$

$$0 \leq ok_z \leq B^o x_{kz}, \quad \forall z,k \quad (8)$$

$$\sum_k q_{zck} + uz_c \geq \tilde{d}_{zc}(\Gamma), \quad \forall z,c \quad (9)$$

$$\sum_{z,c,k} r_{pc} q_{zck} \leq I_p, \quad \forall p \quad (10)$$

All team-day and completed-job variables are integer; overtime and unmet demand are continuous non-negative variables. The big- M upper bound is used only to eliminate skill-incompatible assignments and may be replaced by explicit variable removal in a production implementation. Large but finite shortage penalties preserve feasibility and reveal where capacity or inventory prevents full coverage.

Numerical algorithm and software complex

The solution procedure has four modules. The data module validates timestamps, zone and category dictionaries, missing values and lag construction. The forecasting module fits the

HGB-Poisson model and stores point predictions with model and feature versions. The calibration module estimates category-level record intervals and horizon-level residual margins. The optimization module constructs the sparse constraint matrix, calls a mixed-integer solver and exports team-day, overtime, parts and unmet-demand diagnostics. Completed work orders return to the data layer, creating a controlled feedback loop.

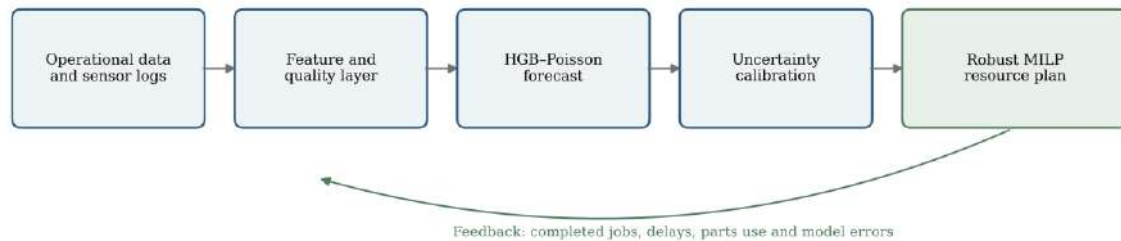


Figure 1. Functional scheme of the integrated forecasting and allocation model

Algorithmically, a planning run consists of: data cutoff at forecast origin; deterministic feature generation; model inference; aggregation to the planning horizon; uncertainty-margin selection; sparse MILP construction; numerical solution; and validation of balance constraints. Each run is identified by the data cutoff, random seed, feature schema, model parameters, Γ and solver tolerance. This metadata is part of the proposed programs complex because a decision that cannot be reproduced is unsuitable for operational audit.

Controlled computational experiment

The experiment contains six zones, four service categories and 900 consecutive days, giving 21,600 zone-category-day records. Demand is generated from a zero-inflated, nonlinear count process with two agricultural workload peaks, weather variation, heterogeneous fleet age and lag dependence. The first 630 days form the proper training set, days 631–720 form the calibration set, and the last 180 days form the test set. All test features use only information that would be available at the relevant day. The random seed is fixed at 20260831.

Table 1.

Main parameters of the numerical experiment

Parameter	Value	Role in the experiment
Observation unit	Zone–category–day	Forecasting index
Data volume	$900 \times 6 \times 4 = 21,600$	Controlled panel
Split	630 / 90 / 180 days	Train / calibration / test
Service categories	4	Inspection, mechanical, hydraulic/electrical, emergency
Team types	4; 9 teams/day	Skill-compatible capacity
Planning horizon	14 days	Rolling tactical allocation
Regular / overtime cap	8 / 2 h per team-day	Labor constraints

Parameter	Value	Role in the experiment
Random seed	20260831	Reproducibility

Three point-forecast methods are compared: a seven-day seasonal naive benchmark, Croston–SBA with smoothing coefficient 0.15, and HGB–Poisson. Accuracy is measured by MAE, RMSE, WAPE and MASE. For N test observations,

$$MAE = N^{-1} \sum |y_i - \hat{y}_i|, \quad RMSE = [N^{-1} \sum (y_i - \hat{y}_i)^2]^{1/2} \quad (11)$$

$$WAPE = 100 \cdot \sum |y_i - \hat{y}_i| / \sum y_i, \quad MASE = MAE / Q \quad (12)$$

where Q is the mean in-sample absolute seven-day difference, averaged across zone-category series. The allocation experiment evaluates three ex-ante plans in a calendar-fixed spring workload window: a seasonal historical plan, an AI point-forecast plan and a budgeted-robust AI plan with $\Gamma=3$. Team-day assignments are fixed before realized demand is evaluated; jobs may then be assigned within the reserved capacity. This prevents the comparison from benefiting from perfect hindsight.

Analysis and results

The simulated panel has a mean demand of 0.638 requests per zone-category-day, while 37.5% of records are non-zero. This level of intermittency is sufficient to challenge conventional percentage errors without making the aggregate workload trivial. The chronological split also exposes the models to a later seasonal phase rather than a random sample of familiar days.

Table 2.

Out-of-sample forecasting accuracy

Model	MAE	RMSE	WAPE, %	MASE
Seasonal naive (t-7)	0.788	1.261	131.37	0.947
Croston–SBA	0.692	0.930	115.37	0.832
HGB–Poisson	0.692	0.918	115.34	0.831

HGB–Poisson produces the lowest MAE and RMSE. Relative to the seasonal-naive benchmark, MAE falls by 12.2% and RMSE by 27.2%. Croston–SBA remains competitive on MAE, confirming the importance of intermittent-demand structure, but it cannot respond directly to the simulated workload and weather covariates. WAPE exceeds 100% because the denominator contains many zero or small observations; it should therefore be read as a portfolio error ratio rather than an observation-level percentage.

The category-calibrated 90% split-conformal interval covers 91.8% of test observations with a mean width of 2.09 requests. Coverage is close to, but not guaranteed to equal, the nominal level under time dependence. The interval is used as a diagnostic, whereas allocation employs horizon-level residual margins that better reflect error cancellation across 14 days.

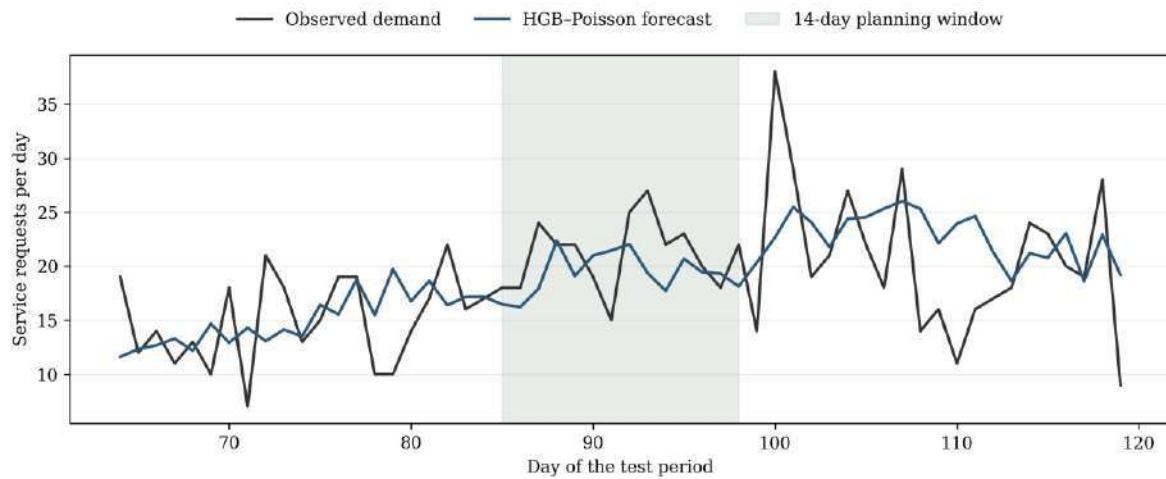


Figure 2. Aggregate observed and forecast service demand around the planning window

The selected window spans simulated days 805–818. It is fixed from the experiment calendar as the beginning of the spring workload peak, before realized service counts are inspected. Actual demand equals 295 jobs, compared with 271.1 HGB point-predicted jobs and 291 jobs in the calendar-matched historical plan. Protecting the three highest-risk cells raises the planning quantity to 298.0 jobs. These totals are not direct capacity decisions: category hours, team skills and parts determine how much of each plan can be served.

Table 3.

Realized performance of alternative allocation policies

Policy	Team-days	Overtime, h	Unserviced	Service, %	Cost	Use, %
Historical seasonal	116	11.0	66.0	77.6	30879	93.9
AI point forecast	114	10.0	59.0	80.0	29373	98.4
AI budgeted-robust forecast	116	6.0	60.0	79.7	31893	93.5

The budgeted-robust AI plan increases realized service level by 2.0 percentage points relative to the historical seasonal plan. Its additional protection is concentrated in zones and skills where the forecast margin interacts with high shortage penalties. Overtime is used only when the avoided shortage penalty exceeds its marginal cost. The realized objective includes deployment, job-processing, overtime and shortage terms; it is an analytical cost index in the controlled experiment, not a monetary estimate for a specific enterprise.

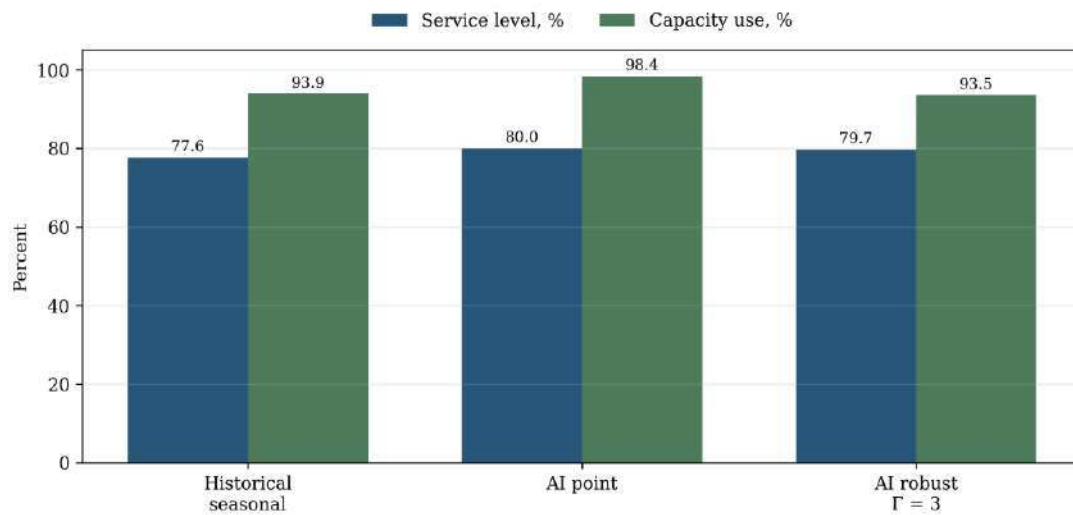


Figure 3. Service level and regular-capacity use by allocation policy

Higher service level does not necessarily imply maximum utilization. A historical plan can appear highly utilized because too little or incorrectly located capacity was reserved; the resulting queues are recorded as unserved demand. The budgeted plan protects selected skill groups, so utilization must be considered together with service continuity and cost. This is a central advantage of the integrated model: forecast uncertainty is converted into an explicit operational trade-off rather than hidden in a manual safety factor.

Table 4.

Sensitivity of the rolling-horizon plan to the uncertainty budget Γ

Γ	Planned jobs	Team-days	Unserved	Service, %	Realized cost
0	271.1	114	59.0	80.0	29373
3	298.0	116	60.0	79.7	31893
6	323.3	116	67.0	77.3	32146
9	345.1	116	69.0	76.6	33270

The sensitivity calculation shows whether protecting additional zone-category cells still changes the integer team-day plan. Flat and non-monotone segments are possible because capacity is indivisible and a team reassigned to one protected cell is no longer available elsewhere. A manager should not select Γ solely from the lowest simulated cost. A practical rule is to define the minimum acceptable service level first, then choose the smallest Γ that meets it under rolling backtests. The result also warns against indiscriminate buffering: excessive protection can misplace scarce skills.

Several limitations constrain interpretation. First, the data-generating mechanism is synthetic and cannot reproduce all institutional causes of service demand, including operator reporting behavior and supplier lead-time shocks. Second, the tactical MILP aggregates routes into team-days; a daily routing submodel is required when travel time windows are binding. Third, model drift is represented only through chronological testing. A deployment should monitor residuals, interval coverage, data latency and solver feasibility, and it should revert to an auditable baseline when quality checks fail.

From a numerical perspective, the formulation is deliberately compact. The sparse MILP contains a small number of integer team-day and job variables for each rolling horizon, and the

experiment is solved with a relative mixed-integer gap of 0.1%. Scientific Python provides the forecasting, sparse-matrix and optimization components used in the prototype [14]. For a larger enterprise, zone decomposition or a two-stage stochastic extension may be introduced without changing the forecast interface.

Conclusion and recommendations

An integrated model has been developed for AI-based forecasting of technical-service demand and optimal allocation of resources in agro-industrial complexes. The model links a non-negative gradient-boosting forecast, empirical uncertainty calibration and a skill-constrained mixed-integer allocation problem. Its indices, variables and constraints provide the mathematical-modeling component of specialty 05.01.07; the chronological estimation, conformal calibration and MILP solution constitute the numerical methods; and the modular data-forecast-calibration-optimization pipeline defines the programs complex.

In the controlled experiment, HGB-Poisson reduced MAE by 12.2% and RMSE by 27.2% relative to a seven-day seasonal naive model. The 90% split-conformal interval achieved 91.8% test coverage. In the calendar-defined workload period, feeding a limited number of calibrated margins into the allocation model improved the realized service level relative to historical seasonal planning. These results support the internal consistency of the proposed linkage, but they do not replace field validation.

For implementation, four actions are recommended. First, an enterprise should establish a single work-order dictionary for zones, service categories, completion status and parts use. Second, rolling backtests should be performed by season and machine class before selecting a model. Third, Γ and shortage penalties should be approved as service-policy parameters rather than hidden technical constants. Fourth, the optimizer should publish both the recommended plan and diagnostic reasons for any unmet demand. A prospective pilot can then compare the integrated plan with the existing dispatch procedure over at least one complete agricultural season.

Further research should combine the tactical model with daily vehicle routing, supplier lead-time uncertainty and component-level condition monitoring. A multiobjective extension may also balance service continuity, travel emissions and technician workload equity. Once operational records become available, the same architecture can be recalibrated without changing its mathematical interface, allowing controlled comparison between synthetic verification and field performance.

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**TEXNIKA FANLARINING DOLZARB
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TOPICAL ISSUES OF TECHNICAL SCIENCES

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scienceproblems.uz@gmail.com