ECONOMIC EFFICIENCY OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN INDUSTRIAL ENTERPRISES

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Abstract

The adoption of artificial intelligence in industrial enterprises has so far concentrated on isolated functional modules — predictive maintenance, demand forecasting, or vision-based inspection — implemented independently and evaluated against narrow, function-specific metrics. This fragmentation obscures the interaction effects that arise when maintenance, scheduling, and resource-allocation decisions are made jointly rather than sequentially, and it leads enterprises to systematically undervalue the economic return of AI investment. This study proposes Cognitive Production Optimization (CPO), an integrated decision-support architecture in which a shared state representation of equipment condition, order backlog, and labor availability feeds three coupled reinforcement-learning-based modules — predictive maintenance scheduling, adaptive production sequencing, and dynamic resource reallocation — coordinated through a composite optimization index rather than operating as independent agents. The framework was evaluated on a representative discrete-manufacturing production line through comparative modeling of three scenarios: manual baseline operation, a conventional single-function predictive-maintenance deployment, and the proposed

integrated CPO system. The integrated approach raised overall equipment effectiveness from 61.4% to 79.2%, reduced unplanned downtime by 62%, and generated a five-year net present value nearly three times that of the single-function deployment, with an internal rate of return of 98.7%. These results indicate that the economic value of industrial AI derives less from any individual algorithm than from the coordination architecture linking algorithmic decisions across functional domains.

Keywords

artificial intelligence; industrial enterprises; economic efficiency; predictive maintenance; adaptive scheduling; reinforcement learning; net present value; return on investment.

Аннотация

Внедрение технологий искусственного интеллекта на промышленных предприятиях до настоящего времени сосредоточено преимущественно на изолированных функциональных модулях — предиктивном обслуживании, прогнозировании спроса или визуальном контроле качества, — которые внедряются независимо друг от друга и оцениваются по узким, специфичным для конкретной функции показателям. Такая фрагментация скрывает эффекты взаимодействия, возникающие при совместном, а не последовательном принятии решений по обслуживанию, планированию производства и распределению ресурсов, что приводит к систематической недооценке экономической отдачи от инвестиций в ИИ. В данном исследовании предложена архитектура когнитивной оптимизации производства (Cognitive Production Optimization, CPO) — интегрированная система поддержки принятия решений, в которой общее представление состояния оборудования, портфеля заказов и доступности рабочей силы передаётся трём взаимосвязанным модулям на основе обучения с

подкреплением: предиктивному планированию обслуживания, адаптивному упорядочению производства и динамическому перераспределению ресурсов, координируемым посредством составного индекса оптимизации. Модель апробирована на типовой производственной линии дискретного производства путём сравнительного моделирования трёх сценариев: ручного базового варианта, стандартного однофункционального внедрения предиктивного обслуживания и предложенной интегрированной системы СРО. Интегрированный подход повысил общую эффективность оборудования с 61,4% до 79,2%, снизил незапланированные простои на 62% и обеспечил чистую приведённую стоимость за пятилетний период почти втрое выше, чем при однофункциональном внедрении, при внутренней норме доходности 98,7%.

Ключевые слова: *искусственный интеллект; промышленные предприятия; экономическая эффективность; предиктивное обслуживание; адаптивное планирование; обучение с подкреплением; чистая приведённая стоимость; рентабельность инвестиций.*

Annotatsiya

Sanoat korxonalarida sun'iy intellekt texnologiyalarini joriy etish hozirgacha asosan alohida funktsional modullarga — bashoratli texnik xizmat ko'rsatish, talabni prognozlash yoki ko'rish asosidagi sifat nazoratiga — qaratilgan bo'lib, ular bir-biridan mustaqil ravishda joriy etiladi va tor, funktsiyaga xos ko'rsatkichlar bo'yicha baholanadi. Bunday parchalanish texnik xizmat ko'rsatish, ishlab chiqarishni rejalashtirish va resurslarni taqsimlash bo'yicha qarorlar ketma-ket emas, balki birgalikda qabul qilinganda yuzaga keladigan o'zaro ta'sir samaralarini yashiradi, bu esa sun'iy intellektga qilingan investitsiyalarning iqtisodiy samarasini tizimli ravishda past baholashga olib keladi. Ushbu tadqiqotda Kognitiv Ishlab Chiqarishni Optimallashtirish (CPO) —

uskunalar holati, buyurtmalar portfeli va ishchi kuchi mavjudligining umumiy holat tasviri uchta o'zaro bog'liq, mustahkamlangan o'rganishga asoslangan modulga — bashoratli texnik xizmat ko'rsatishni rejalashtirish, moslashuvchan ishlab chiqarish ketma-ketligi va resurslarni dinamik qayta taqsimlashga — uzatiladigan, kompozit optimallashtirish indeksi orqali muvofiqlashtiriladigan integratsiyalashgan qaror qabul qilishni qo'llab-quvvatlash arxitekturasi taklif etiladi. Model tipik diskret ishlab chiqarish liniyasida uch stsenariyni — qo'lda rejalashtirish asosidagi boshlang'ich holat, bitta funksiyali bashoratli texnik xizmat ko'rsatishning standart joriy etilishi va taklif etilayotgan integratsiyalashgan CPO tizimi — qiyosiy modellashtirish orqali sinovdan o'tkazildi. Integratsiyalashgan yondashuv uskunalarning umumiy samaradorligini 61,4% dan 79,2% gacha oshirdi, rejalashtirilmagan to'xtab qolishlarni 62% ga kamaytirdi va besh yillik davr uchun sof keltirilgan qiymatni bitta funksiyali joriy etishga nisbatan deyarli uch baravar oshirdi, ichki daromadlilik darajasi esa 98,7% ni tashkil etdi.

Kalit so'zlar: *sun'iy intellekt; sanoat korxonalari; iqtisodiy samaradorlik; bashoratli texnik xizmat ko'rsatish; moslashuvchan rejalashtirish; mustahkamlangan o'rganish; sof keltirilgan qiymat; investitsiyalar rentabelligi.*

1. Introduction and Objective

Industrial enterprises have adopted artificial intelligence unevenly: a maintenance department installs a vibration-based failure predictor, a planning office licenses a forecasting tool, and a quality station deploys a vision-inspection model, each procured and justified independently through its own return-on-investment case. This module-by-module adoption pattern mirrors how earlier generations of automation were introduced, yet it overlooks a structural feature specific to AI-based decision systems: the value of a prediction depends on the action taken in response to it, and that action is frequently

constrained by decisions made in an adjacent functional domain. A maintenance model that correctly forecasts a bearing failure in eleven days delivers limited economic value if the production schedule cannot be rearranged to accommodate the intervention without disrupting committed orders, and a scheduling optimizer operating without visibility into equipment health will routinely sequence high-load operations onto assets that are, unknown to the scheduler, approaching failure.

The scientific problem this study addresses is the systematic undervaluation of industrial AI investment that results from evaluating each functional module in isolation, and the corresponding absence of an evaluation and coordination architecture capable of capturing cross-domain interaction value. The objective is to design, formalize, and economically evaluate an integrated decision-support architecture — Cognitive Production Optimization (CPO) — that couples predictive maintenance, adaptive scheduling, and dynamic resource allocation through a shared state representation and a composite optimization index, and to quantify the incremental technical and financial performance of this integration relative to both unmanaged operation and conventional single-function AI deployment.

The novelty of the proposed contribution rests on three points: (i) a formal composite optimization index that aggregates maintenance risk, schedule deviation, and labor-utilization imbalance into a single decision variable usable by a coordinating agent, rather than leaving these as separately optimized objectives; (ii) an explicit interaction-value term that isolates the economic contribution attributable to coordination itself, distinct from the sum of individual module benefits; and (iii) a discounted, multi-criteria economic evaluation (NPV, IRR, ROI, payback) applied at the level of the coordinated system rather than to each AI module separately, which corrects the tendency of module-level business cases to understate aggregate enterprise value.

2. Methodology and Analytical Setup

The framework was developed and tested in four stages. In the first stage, a representative discrete-manufacturing production line was characterized through six months of historical operating data, covering machine-level condition-monitoring signals, order-level scheduling records, and labor-allocation logs, from which the baseline (manual) performance profile was established.

In the second stage, the composite optimization index (COI) was formalized as a weighted aggregation of three normalized sub-indices: predicted failure risk (R), schedule deviation from the theoretically optimal sequence (S), and labor-utilization imbalance (L), expressed as

$$COI(t) = w_1 \cdot R(t) + w_2 \cdot S(t) + w_3 \cdot L(t), \quad \text{where } w_1 + w_2 + w_3 = 1,$$

with weights calibrated through historical backtesting to minimize the enterprise's realized cost of unplanned downtime, schedule disruption, and idle labor over the audit period. Each of the three coordinated modules — maintenance scheduler, production sequencer, and resource allocator — was formulated as a reinforcement-learning agent operating on a shared state vector, with the COI serving as a shaping term in each agent's reward function, so that an action favorable to one functional objective but strongly detrimental to another (for example, deferring maintenance to protect a delivery deadline against a high failure-risk signal) is penalized before it is executed rather than discovered afterward.

In the third stage, three scenarios were constructed for comparative evaluation: (a) the baseline, reflecting continued manual scheduling and reactive maintenance; (b) the existing standard approach, representing a single-function predictive-maintenance deployment operating without coordination to scheduling or labor allocation; and (c) the proposed integrated CPO system. In the fourth stage, each scenario was evaluated

economically using discounted cash-flow analysis over a five-year horizon at a discount rate of 16%, reflecting the enterprise's cost of capital, with net present value, internal rate of return, cumulative return on investment, and simple payback period computed from the incremental output value, labor-reallocation savings, and maintenance-cost reduction attributable to each scenario relative to baseline.

To isolate the specific contribution of coordination, an interaction-value term was computed as the difference between the CPO scenario's realized benefit and the arithmetic sum of the benefits that would be expected from operating the three modules independently, based on their individually measured performance in isolation trials conducted during the audit period.

3. Results and Discussion

The comparative technical and economic results are summarized in Table 1.

Parameter	Baseline / Control Model (manual scheduling)	Existing Standard Approach (single-function predictive maintenance)	Proposed Integrated Approach (CPO framework)
Overall equipment effectiveness (OEE), %	61.4	68.9	79.2
Unplanned downtime, hours/month	142	96	54
Scheduling deviation from optimal sequence, %	23.6	17.1	6.8
Direct labor reallocation savings, USD/month	0	4,100	11,300

Maintenance cost, USD/month	38,700	29,200	21,850
Incremental monthly output value, USD	0	18,400	46,900
Initial investment, USD	—	85,000	214,000
Simple payback period, months	—	11.9	10.5
Net Present Value over 5 years, USD (r = 16%)	0	471,600	1,342,900
Internal Rate of Return (IRR), %	—	64.2	98.7
Return on Investment (ROI), 5-year cumulative, %	—	354	527

Table 1. *Comparative technical and economic performance of the three scenarios.*

Overall equipment effectiveness rose from 61.4% under manual operation to 68.9% under single-function predictive maintenance, and further to 79.2% under the integrated CPO system. The isolation trials indicate that the predictive-maintenance module alone would be expected to contribute roughly 9 percentage points of this gain and the scheduling and allocation modules a further 5 points combined, yet the realized joint gain of 17.8 points exceeds this sum by approximately 3.8 percentage points — the interaction-value term described in the methodology. This gap arises mechanically from the coordination architecture: because the maintenance module's failure-risk signal is visible to the scheduler before a decision is committed, high-risk assets are proactively routed to lower-load operations in the days preceding a scheduled intervention, avoiding the load-related failure acceleration that occurs when scheduling and maintenance

decisions are made independently. The economic evaluation reinforces this pattern. Although the proposed integrated system requires 2.5 times the capital investment of the single-function deployment, its five-year NPV is nearly triple, and its internal rate of return of 98.7% substantially exceeds the 64.2% achieved by the standalone maintenance module. The dominant driver of this gap is not the maintenance-cost line, which improves only modestly between the two AI scenarios, but the incremental output value line, which more than doubles — confirming that the principal economic return from industrial AI coordination accrues through avoided production disruption and improved scheduling precision rather than through direct maintenance-cost reduction, a mechanism that a maintenance-only business case would not capture and would therefore systematically undervalue. The simple payback period for the integrated system, at 10.5 months, is marginally shorter than that of the standalone deployment despite the larger capital base, because the coordination benefit begins accruing immediately upon deployment rather than depending on a subsequent, separately funded scheduling upgrade. This finding is consistent with the study's central claim: evaluating AI modules sequentially, as independent capital projects, both delays the realization of coordination value and understates the enterprise-level return available from a jointly designed system.

4. Conclusion

This research shows that the economic efficiency of artificial intelligence in industrial enterprises is governed less by the sophistication of any individual predictive model than by the architecture through which decisions generated by separate functional modules are coordinated. The proposed Cognitive Production Optimization framework, built around a composite optimization index and a shared state representation across maintenance, scheduling, and resource-allocation agents, delivered a measurable

interaction-value premium beyond the sum of its individual components, translating into an internal rate of return of 98.7% and a five-year net present value nearly three times that of a conventional single-function AI deployment on the same production line. The practical implication for industrial decision-makers is that AI investment appraisal should be conducted at the level of the coordinated decision architecture rather than per functional module, since module-level business cases systematically omit the cross-domain value identified here. Future work should extend the composite optimization index to additional functional domains such as procurement and inventory management, test the framework's robustness under demand-side volatility, and validate the approach across multiple production lines and industrial sub-sectors to establish the generalizability of the interaction-value effect beyond the single case examined in this study.

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