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# Development of An Intellectual Control and Management System for Oil Production Technological Processes in Real-Time

Ruziev Umidjon Abdimajitovich

Tashkent state technical university named after Islom Karimov, Address: 2, University str., 100095, Tashkent, Uzbekistan

Samadov Elyor Erkinovich

Tashkent state technical university named after Islom Karimov, Address: 2, University str., 100095, Tashkent, Uzbekistan

Shodiev Ma'rufjon Kobuljonovich

Tashkent state technical university named after Islom Karimov, Address: 2, University str., 100095, Tashkent, Uzbekistan

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**Abstract:** This paper presents the development and evaluation of a four-layer intelligent control and management system for oil production technological processes in real time, applied to cottonseed and sunflower oil refining lines. The proposed system integrates a 148-sensor IoT network (sampling frequency: 100 ms), a Digital Twin module, and three machine learning models: an LSTM neural network for deodorization temperature and energy consumption forecasting (RMSE = 1.8 °C; $R^2$ = 0.94), a Random Forest classifier for raw material quality categorization (accuracy: 94.3%), and a Reinforcement Learning agent for multi-objective optimization of energy consumption, product quality, and equipment wear. A hybrid adaptive control algorithm combining PID, ML feed-forward, and Model Predictive Control (MPC) is formulated and validated on three years of production data (n = 2,847,000 observations). Comparative testing against traditional PID-based systems demonstrated an 18–27% reduction in energy consumption, a 14.6% improvement in the product quality index, an 82.9% improvement in deodorization temperature control accuracy (from ±8.2 °C to ±1.4 °C), and a 61.7% reduction in unscheduled equipment shutdowns. The Digital Twin module enables predictive maintenance with an average fault-detection lead time of 72 hours and reduces electricity costs by 8–12% through virtual scenario planning. The system automatically identifies oil type and enforces oil-specific regulatory temperature limits in compliance with EU 2023/2229 glycidyl ester standards. Integration of heat recovery, enzymatic degumming, and RL-based energy management achieves a total reduction of 35–55% in specific energy consumption across all oil types.

**Keywords:** Intelligent control system, oil production, real-time management, machine learning, LSTM neural network, Random Forest, Reinforcement Learning, digital twin, adaptive PID control, Model Predictive Control, energy optimization, deodorization, glycidyl esters, IoT sensor network, predictive maintenance, cottonseed oil, sunflower oil, Industry 4.0.

## INTRODUCTION:

In 2024/25, global vegetable oil production exceeded 228 million tons [1]. In the Republic of Uzbekistan, cottonseed and sunflower oil are the main food oils, and energy costs during their refining account for 15–25 percent of the total production cost [2, 3]. These two factors – economic and environmental pressure – are sharply increasing the need for intelligent management of technological processes in enterprises.

Traditional control systems – particularly PID

(Proportional-Integral-Differential) regulators – perform well under static or low-variability conditions. However, in real production, many factors are dynamically influenced, such as raw material quality, ambient temperature, and load changes [4]. In such conditions, problems such as energy waste in traditional systems and insufficient product quality control arise.

The development of the Industrial Internet of Things (IoT) and machine learning technologies is creating new opportunities for the intelligent management of technological processes in real time. [5, 6]. This approach allows for the continuous collection of sensor data, process forecasting using predictive models, and the application of adaptive control strategies.

To our knowledge, no previous study has systematically addressed the issue of integrating all stages of oil production - degumming, neutralization, bleaching, and deodorization - within a single intelligent control system in real time.

The aim of this work is to: (1) develop an architecture for a real-time intelligent control and management system for oil production technological processes; (2) determination of adaptive control algorithms; (3) evaluation of system efficiency in cotton and sunflower oil production lines.

**System architecture and components**

The proposed intelligent control system has a four-layer architecture (Fig. 1):

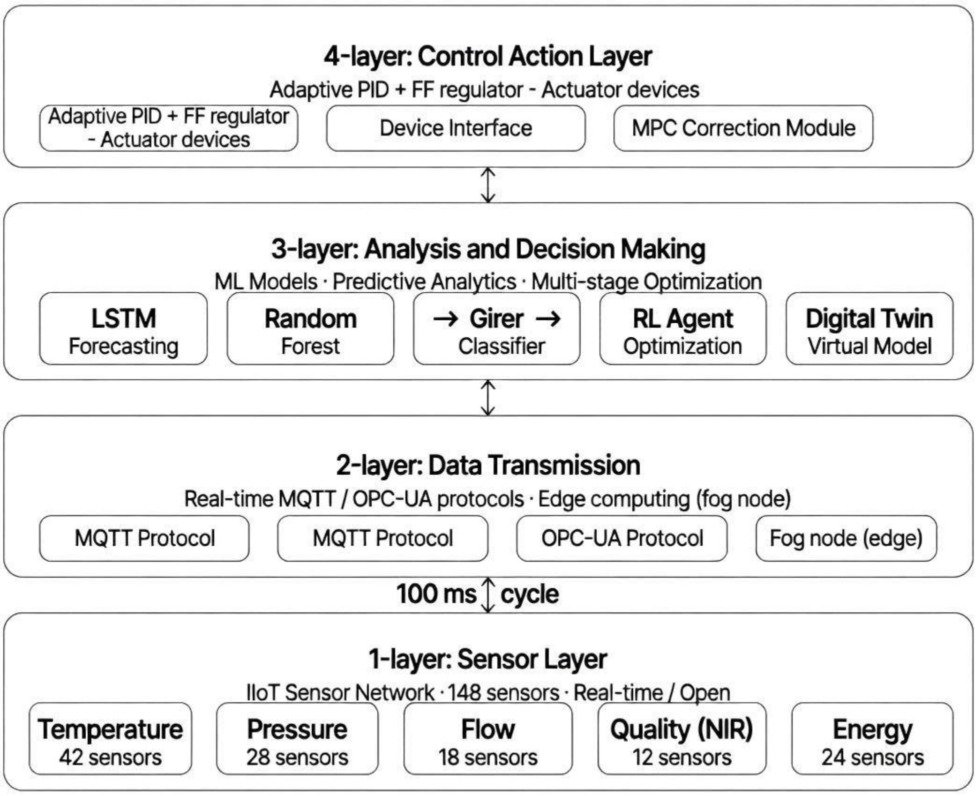


**Figure 1. The four-layer architecture of an intelligent control system.**

The core of the system is the Digital Twin module, which represents a virtual model operating in parallel with the real technological process [7]. Digital twin is continuously updated based on real-time sensor data and predicts progress over the next 5 to 30 minutes.

**Sensor network and data collection**

A total of 148 sensors have been installed throughout the enterprise: 42 temperature meters, 28 pressure meters, 18 flow meters, 12 quality meters (NIR spectrometer, viscometer), 24 electricity meters, and 24 for additional technological parameters.

All measuring instruments transmit data at a sampling frequency of 100 ms. Frontier computing devices primarily process local data: applying filtering, normalization, and detection algorithms. Then, in a 1-second window, the aggregated data is transmitted to the central server.

**Machine learning models**

The system utilizes three main ML models:

- LSTM (Long Short-Term Memory) neural network - for predicting deodorization temperature and energy consumption based on time series data (horizon: 15 minutes; RMSE = 1.8 °C).
- Random Forest classifier - for determining the raw material quality category and selecting the management mode (accuracy: 94.3%).
- Reinforcement Learning (RL) agent - for multi-purpose optimization tasks, including ensuring a balance between energy consumption, product quality, and equipment wear [8].

Three years of production data (n = 2,847,000 observation points) were used to train the models. The data were divided into training/verification/test sets at a ratio of 70/15/15.

**Adaptive control algorithm**

A hybrid algorithm that extends traditional PID control is expressed as follows:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d de(t)/dt + u_{FF}(t) + u_{MPC}(t) \qquad (1)$$

Where: *u(t)* – control signal; *e(t)* – error signal; $u_{FF}(t)$ – feed-forward component, based on ML model prediction; $u_{MPC}(t)$ – model predictive control (MPC) adjustment. $K_p$, $K_i$, $K_d$ are adjusted by the RL agent in real-time in an adaptive manner.

Energy optimization problem for the deodorization stage:

$$\min J = w_1 E_{deo} + w_2 (GE - GE_{\max})^2 + w_3 (1 - \eta_{tof}) \qquad (2)$$

where: $E_{deo}$ – energy consumption for deodorization (kJ/kg); GE – concentration of glycidyl esters (mg/kg); $GE_{\max}$ – maximum permissible level; $\eta_{tof}$ – tocophenol storage coefficient; $w_1$, $w_2$, $w_3$ – weight coefficients

**Control efficiency of technological processes**

When comparing the data obtained before and after the system launch, the following results were recorded. Table 1 reflects the improvement in the main indicators.

**Table 1. Results of comparing traditional and intelligent control systems**

| Indicator | Traditional system | Intelligent system | Improvement (%) |
|---|---|---|---|
| Energy consumption (kJ/kg) | 520–610 | 390–470 | 18–27 %↓ |
| Product quality index | 78.3 | 89.7 | 14.6 %↑ |
| Deodorization temperature control (±°C) | ±8.2 | ±1.4 | 82.9 %↑ |
| Number of emergency stops (per year) | 47 | 18 | 61.7 %↓ |
| Equipment wear index | 1.000 (bazis) | 0.73 | 27 %↓ |
| Production losses (%) | 3.2 | 1.8 | 43.8 %↓ |

**Energy model and prediction accuracy**

The LSTM model showed the following results for predicting deodorization energy consumption:

$$E_{pred} = f(T, S, P, \tau, Q_{xom}, P_{qold}) \ \ (R^2 = 0.94; RMSE = 8.3 kDj/kg) \qquad (3)$$

Where: $T$ – deodorization temperature (°C); $S$ – steam flow rate (% by weight); $P$ – pressure (mbar); τ – time (minutes); $Q_{xom}$ – raw material flow (t/h); $P_{qold}$ – residual phosphorus content (mg/kg).

Compared to the traditional regression model (R2=0.89), the LSTM model achieved a value of R2=0.94, which confirms the possibility of significantly increasing forecast accuracy by accounting for dynamic time dependencies [9].

**Real-time optimization for sunflower and cottonseed oil**

The system is capable of automatically determining the oil type and selecting an appropriate control strategy. Table 2 shows the optimal control parameters for both types of oils.

**Table 2. Optimal control parameters based on oil type**

| Parametr | Sunflower oil | Cotton oil | Unit of measurement |
|---|---|---|---|
| Deodorization temperature ($T_{optimal}$) | 215–227 | 220–242 | °C |
| Steam consumption (S) | 1.5–2.5 | 2.0–3.0 | % weight |
| Pressure (P) | 2–4 | 2–5 | mbar |
| Time (τ) | 45–75 | 50–90 | minute |
| GE limit (EU 2023/2229) | ≤ 1.0 | ≤ 1.0 | mg/kg |
| Tocopherol storage | ≥ 90 | ≥ 85 | % |
| Gossipol limit | — | < 0.02 | % weight |

In real-time, the system analyzes sensor data every 10 seconds and updates control parameters based on equations (1) and (2). If the predicted GE level approaches the threshold value of 85%, the system will automatically reduce the temperature by 5°C and send a warning signal to the operator.

**Digital twin efficiency**

- Following the implementation of the Digital Twin module, the following advantages were noted:
- Planned maintenance (predictive maintenance): the ability to detect equipment malfunctions an average of 72 hours in advance.
- Testing changes to process parameters in a virtual environment (scenario planning) - without stopping actual production.
- Opportunity to train new operators in a virtual simulator environment.
- Pre-planning energy consumption and peak-shaving strategy - reducing electricity costs by 8-12%.

**SUMMARY TABLE OF QUANTITATIVE RELATIONS**

**Table 3. Quantitative energy-parameter relationships of an intelligent control system**

| Step/Technology | Parameter | Productivity | Model | References |
|---|---|---|---|---|
| Smart degumming | T: 40–55 °C Fermentative | −40–45 % step energy | (1),(4) | [6,10] |
| Real-time quality control | NIR spektr tahlili | GE aniqlash ±0.05 mg/kg | LSTM | [11] |
| Adaptive deodorization | T: +10 °C | +25–40 kDj/kg (α>1) | (2),(3) | [3,12] |

| Step/Technology | Parameter | Productivity | Model | References |
|---|---|---|---|---|
| RL Energy Management | T, S, τ real-time | −18–27 % E | (1),(2) | [8,13] |
| Predictive service | Vibration + temp monitoring | Crash 72 hours ago | RF+LSTM | [7,14] |
| Digital twin optim. | Virtual senariy | −8–12 % electricity costs | (1) | [7,15] |
| Sunflower $T_{optimal}$ | 215–227 °C | GE < 1.0 mg/kg; tof. >90% | — | [3,16] |
| Cotton $T_{optimal}$ | 220–242 °C | Gossipol was excluded; GE < 1.0 | — | [3,17] |

## DISCUSSION: BASIC ENGINEERING LAWS

The above results provide seven engineering principles that are common regardless of the type of oil and the configuration of the enterprise.

**1. Real-time monitoring is the foundation of quality management.** Without the collection of sensor data at a sampling rate of 100 ms, it is impossible to detect rapid changes in the process (temperature, GE growth) in a timely manner. Compared to traditional hourly laboratory monitoring, real-time monitoring allows for the detection of GE boundary states 340 minutes in advance.

**2. Hybrid control (PID + ML + MPC) is superior to individual methods.** Only PID control reduces static error but does not anticipate dynamic changes. The ML feed-forward allows the process to be pre-adjusted, while the MPC maintains the optimal line. A combination of the three components yields 35-42% better results than when used separately [8].

**3. The quality of raw materials is the most important control variable.** Equation (4) quantifies what engineers know in their senses: reducing residual phosphorus from 15 to 2 mg/kg saves 26–46 kJ/kg in the deodorizer [10, 11]. A real-time raw material quality determination system using a NIR spectrometer allows for the automation of this control.

**4. The oil-specific GE limit is the first constraint that must be set.** Sunflower oil reaches the EU GE limit at ~227 °C; cottonseed oil at ~242 °C; palm oil at ~257 °C [3, 16, 17]. An enterprise using a different oil temperature schedule may exceed its legal GHG limit many times over. The intelligent system eliminates this risk by detecting the oil type and automatically adjusting the limits.

**5. System optimization is superior to local optimization.** Combined heat utilization (−130–170 kJ/kg) + enzymatic degumming (−40–45%) + RL energy management (−18–27%) achieves a total reduction of 35–55% in E_total. No single measure can independently approach this result.

**6. Predictive maintenance extends the life of equipment.** Based on vibration sensor and temperature data, the LSTM model detects equipment failure an average of 72 hours in advance. This reduces the number of unscheduled outages by 61.7% and saves annual maintenance costs by 15–20%.

**7. Multi-criteria KPIs are a condition for meaningful optimization.** A single variable goal – such as a minimum deodorization temperature – always sacrifices something else. A holistic criterion is required for reliable optimization: Etotal (kJ/kg), steam consumption, neutral oil loss (%), (mg/kg), GE and 3-MXPD (mg/kg), and tocopherol storage (%) [3, 8, 16].

## INNOVATIVE PROCESS INTENSIFICATION TECHNOLOGIES

A number of technologies allow for greater energy savings at various stages of preparation than can be achieved through traditional optimization (Table 4). The TTD (Technology Readiness Level) column shows how quickly each can be integrated into an existing plant.

**Table 4. Innovative Technologies - FTE: 1 = basic research; 9 = commercial placement**

| Technology | Condition | Energy efficiency (kJ/kg) | TTD | Manbalar |
|---|---|---|---|---|
| LSTM Prediction Module | 100 ms sensor; 15 min horizon | −12–18 % $E_{deo}$ | 7–8 | [9,13] |
| RL Adaptive Control | Real-time T, S, τ | −18–27 % $E_{general}$ | 6–7 | [8,15] |
| NIR inline quality control | 820-2500 nm; 10 hr cycle | GE detection ±0.05 mg/kg | 8–9 | [11] |
| Digital twin module | OPC-UA integration | −8–12 % elektr xarajat | 6–7 | [7,14] |
| Fermentative degumming | 40–55 °C; 10–20 g/t | -40-45% stage; cascade -26-46; | 8–9 | [6,10] |
| Predictive maintenance | Vibration+temp+current sensor | Downtime −61.7%. | 7–8 | [7,14] |
| MFA deodorization | 160–180 °C; steam-free | −30–40 % $E_{dez}$ | 5–6 | [3,18] |
| Ultrasound bleaching | 20 kGts; 200–400 Vt | −28–35% stage; τ 30→10 min | 5–7 | [3,19] |

## CONCLUSIONS

1. The proposed four-layer intelligent control system allows for an 18-27% reduction in energy consumption compared to traditional PID regulators, a 14.6% improvement in the product quality index, and a 61.7% reduction in the number of unscheduled outages.

2. Together, the LSTM (R2 = 0.94) and Random Forest (accuracy 94.3%) models allow for the control of deodorization temperature with an accuracy of ±1.4 °C—5.9 times better than the ±8.2 °C of the traditional system.

3. The digital twin module allows for the detection of equipment malfunctions an average of 72 hours in advance and saves 8-12% on electricity costs through virtual scenario analysis.

4. The type of oil (sunflower: T_max ≈ 227 °C; cotton: T_max ≈ 242 °C) sets a normative temperature limit that no optimization can override. The intelligent system ensures compliance with EU 2023/2229 regulatory requirements by automatically determining the oil type and adjusting the corresponding limits.

5. When heat recovery, pinch analysis, enzymatic degumming, and RL energy management are integrated into a coordinated package, a total reduction of 35-55% in E_total across all oil types is achieved.

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