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Research Article

Real-Time IoT-Based Energy Consumption Management for Improving Energy Efficiency in Cottonseed Oil Production

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Abstract

Cottonseed oil mills are electricity-intensive, and most of their demand comes from motor-driven hulling, conditioning and screw-pressing units whose specific energy consumption (SEC) depends strongly on raw-material properties that vary from batch to batch. Conventional energy accounting in such plants relies on monthly meter readings and cannot respond to these variations. This study develops and evaluates a real-time energy management approach for a cottonseed oil mill in Kokand, Uzbekistan, that links Internet of Things (IoT) sensing with process-level control. A five-layer IoT–edge–PLC–SCADA–cloud architecture samples electrical and technological variables at 1 s intervals. Energy characteristics of the main aggregates were identified by regression: the SEC of the MP-3000 screw press has a minimum of 19.1 kWh/t at a cake output of 0.68 t/h, and the residual oil in hulls reaches its minimum at seed moistures of 12.1%, 11.3% and 12.5% for grades I–II, III and IV. These relations are embedded in a moisture-aware SEC model that normalises throughput to conditioned mass and accounts for seed oil content, whose variation between 15% and 23% changes the SEC per tonne of oil by 53% at the press and by 36% at plant level. A damped Newton–Raphson optimiser computes the moisture and press-torque set-points in real time from a model re-identified on line, and the PLC enforces them through the seed conditioner and variable-frequency drives. In MATLAB/Simulink simulations parameterised with plant data, the closed loop narrowed moisture variability from ±2.4% to ±0.3%, press-torque fluctuation from ±18% to ±4% and load dispersion

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from ±15% to ±5%, and reduced the SEC of the pressing line from 53.1 to 49.2 kWh/t (7.3%). At plant level the implementation is credited with saving 142.2 MWh of electricity per year (128 million UZS) for an investment of 405 million UZS, giving a simple payback of 3.2 years and an internal rate of return of 29%. The results show that coupling IoT data with raw-material-aware process models turns energy monitoring into an active control variable in oilseed processing.

KEYWORDS

Energy efficiency, Internet of Things, real-time energy management, cottonseed oil, specific energy consumption, Newton–Raphson optimization, SCADA, seed moisture.

Highlights

- A five-layer IoT–edge–PLC–SCADA–cloud architecture for real-time energy control in a cottonseed oil mill.
- Energy characteristics of the screw press and disc hullers identified from monitoring data.
- Grade-specific optimal seed moisture (11.3–12.5%) derived from residual-oil-in-hull models.
- A Newton–Raphson optimiser sets moisture and press-torque targets from an on-line re-identified model.
- Simulated SEC reduction of 7.3% in the pressing line; payback of 3.2 years.

1. INTRODUCTION

Industry remains the largest final consumer of energy, and electric motor-driven systems account for the largest share of its electricity use [1–4]. Reviews of industrial energy-saving strategies agree that high-efficiency motors, variable-speed drives and power-factor correction are among the cheapest measures available, with typical payback periods of one to four years [1,2]. Yet many plants still operate motors far from their efficient load range because they lack information on how the load actually varies with production [3,4].

Food manufacturing is a characteristic case. Its energy use is distributed over many small and medium-sized units, and product-level specific energy consumption (SEC) differs by an order of magnitude between product groups [5,6]. Vegetable-oil extraction combines mechanical operations (cleaning, hulling, flaking, screw pressing) with thermal ones (conditioning, solvent extraction, desolventising, refining) [7]. In cottonseed processing the mechanical stages are driven by induction motors whose load depends on seed moisture, grade, hull content and oil content. These properties change from batch to batch, so a fixed set of operating set-points cannot keep the process at its energy optimum.

The Internet of Things (IoT) makes it possible to measure energy at machine and line level rather than from monthly bills. Shrouf and Miragliotta [8] showed how IoT-based energy data enable

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energy-aware production management practices. Wei et al. [9] built an IoT energy-management platform for industrial facilities. Chen et al. [10] implemented an IoT system for monitoring the energy efficiency of a machining workshop. Mohamed et al. [11] analysed how Industry 4.0 technologies reduce energy use in smart factories. In a study of 72 integration projects, Arana-Landín et al. [12] found that IoT, analytics and artificial-intelligence technologies improved energy efficiency by 15–25% on average in the processes where they were deployed. Haddouche and Ilinca [13] reached similar conclusions for process industries. In food manufacturing, Jagtap et al. [14] showed that real-time data collection reveals energy waste that monthly accounting hides. In earlier work on the same plant, we showed that managing energy data in real time can reduce energy use in food production [17].

Most of these studies, however, treat IoT as a monitoring layer: they measure and visualise energy and leave decisions to operators or schedulers. Three gaps are evident for oilseed processing:

1. Energy characteristics of oil-mill aggregates are rarely identified from high-frequency plant data and linked to raw-material properties such as moisture and oil content.
2. Optimal technological set-points (seed moisture, press torque) are usually fixed values taken from handbooks, even though the energy optimum shifts with seed grade and condition.
3. Few studies close the loop: optimisation results are not passed back to programmable logic controllers (PLCs) and drives in real time.

This paper addresses these gaps using a cottonseed oil mill in Kokand, Uzbekistan, as a case study. Energy efficiency is a national priority in Uzbekistan: Presidential Resolution PQ-4422 of 22 August 2019 set accelerated measures for energy efficiency in the economy [15], and the 2024 Law on energy saving, rational use and improvement of energy efficiency requires regular energy audits and monitoring in energy-intensive enterprises [16].

The contributions of the study are as follows:

a) a five-layer IoT–edge–PLC–SCADA–cloud architecture that samples electrical and technological variables at 1 s and returns optimised set-points to the process;

b) energy characteristics of the screw press and two-stage disc hullers, identified by regression, with analytically derived optimal loads;

c) a moisture- and oil-content-aware SEC model, including grade-specific optimal seed moisture derived from residual-oil-in-hull models;

d) a damped Newton–Raphson optimiser that computes moisture and torque set-points from an on-line re-identified surrogate model, evaluated in closed-loop simulation and by a techno-economic assessment.

The rest of the paper is organised as follows. Section 2 describes the plant, the architecture and the models. Section 3 presents the results. Section 4 discusses them against the literature and states the limitations. Section 5 concludes.

2. METHODS

2.1. Case-study plant and process.

The study was carried out at the “Qo’qon Oziq-Ovqat Invest” LLC oil mill (Kokand, Fergana region, Uzbekistan) under a research contract between Fergana State Technical University and the company. The mill processes technical cottonseed in continuous two-shift operation and produces crude, refined and deodorised cottonseed oil, meal, hulls and soap. The process chain comprises seed reception and storage,

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cleaning (removal of mineral and metallic impurities), two-stage disc hulling and kernel separation, moisture conditioning, flaking, cooking, pre-pressing, solvent extraction of the press cake, solvent recovery, refining, deodorisation and packaging [7].

The mill is supplied at 6 kV through a 6/0.4 kV package substation with 630 kVA transformers. Most drives are three-phase squirrel-cage induction motors rated 15–90 kW. Field measurements showed that more than 60% of the motors in the pressing and extraction sections operate at 70–90% of rated load. The key unit is the MP-3000 screw press, driven by a 45 kW 5A200L4 induction motor through a gearbox and belt drive, with worm-shaft speeds of 18, 24 and 37 rpm and a capacity above 3 t/h of seed. Before the project, the press motor was started direct-on-line at 380 V and ran at fixed speed.

2.2. Energy baseline and measurement. The baseline was established from the plant's 2024 metering records and from instrumental measurements taken with a C.A 8331 power-quality analyser. Active power, current, voltage and power factor were logged for each major consumer, and annual consumption was obtained from the logged power and the annual operating hours. The system boundary of the analysis is the crude-oil production chain (seed storage and handling, preparation and separation, conditioning, pressing and extraction). This chain consumed 2,218,800 kWh of electricity in 2024 and produced 3,857 t of crude oil, giving an SEC of 575 kWh per tonne of crude oil. Downstream operations were analysed separately (Section 3.1).

The SEC of a unit or line over a time window is defined as

$$d(t) = \frac{E(t)}{A_{kon}(t)} = \frac{\int_{t-\Delta}^{t} P_{\Sigma}(\tau)\, d\tau}{A_{kon}(t)},$$

$$P_{\Sigma}(t) = \sum_{j=1}^{m} \sqrt{3}\, U_j(t)\, I_j(t) \cos\varphi_j(t) \qquad (1)$$

where E is the electricity consumed in the window, PΣ the total active power of the m metered drives and A_kon the processed mass reduced to standard (conditioned) moisture.

Because wet seed carries extra water, SEC computed on actual mass would favour wet batches. The conditioned mass is therefore used:

$$A_{kon} = A_h \frac{100 - w_h}{100 - w_m} \qquad (2)$$

where A_h is the actual mass, w_h the measured moisture and w_m the standard moisture for the seed grade (8–13% according to O'zDSt 596:2014 [18]).

2.3. IoT–edge–PLC–SCADA architecture. The proposed system has five layers (Fig. 1).

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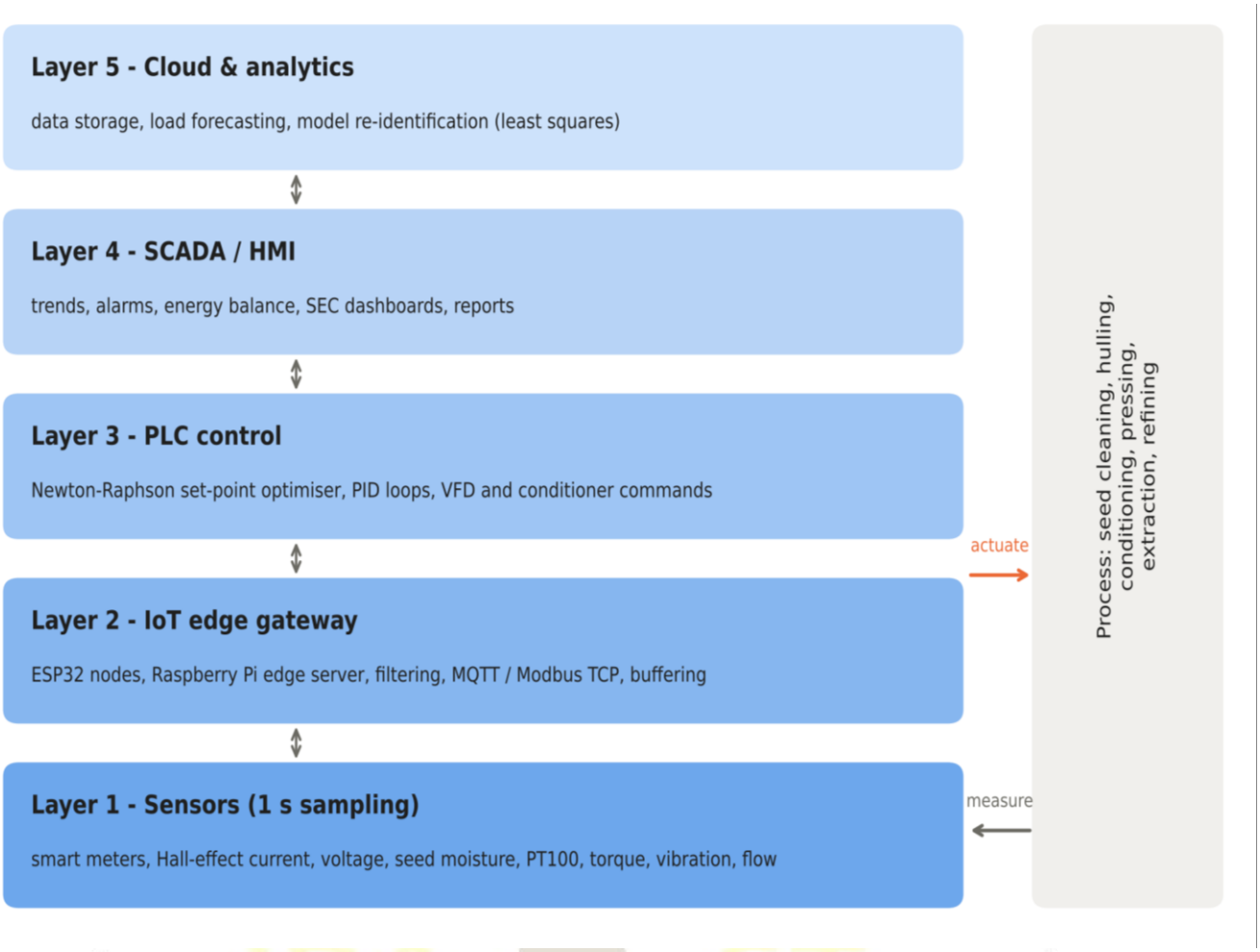


Fig. 1. Five-layer architecture of the real-time energy management system.

1. **Sensor layer.** Smart energy meters, Hall-effect current sensors, voltage transducers, capacitive seed-moisture sensors, PT100 temperature sensors, a torque sensor on the press shaft, accelerometers and flow meters sample at 1 s (Table 1).

2. **Edge layer.** ESP32 nodes and a Raspberry Pi edge server filter the signals, time-stamp them and publish packets M(t) = {ID, timestamp, x(t)} over MQTT and Modbus TCP, with local buffering for network outages. Measurement noise is attenuated with a first-order exponential filter, $x_f(k) = \alpha x(k) + (1 - \alpha)x_f(k - 1)$.

3. **Control layer.** PLCs run PID loops for drives and the seed conditioner and execute the set-point optimiser of Section 2.6.

4. **Supervisory layer.** SCADA/HMI computes P, Q, S, cosφ, E and d on line, archives trends and raises alarms.

5. **Cloud layer.** Stores historical data, re-identifies model parameters and produces short-term load forecasts.

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Table 1. Measured variables and sensors.

Variable	Sensor	Stated accuracy
Active/reactive power, energy	Smart energy meter	—
Motor current	Hall-effect sensor	±0.5%
Voltage	Voltage transducer	—
Seed moisture	Capacitive moisture sensor	±0.2% (abs.)
Temperature	PT100 (RTD)	±0.1 °C
Press-shaft torque	Torque sensor	±1%
Steam and pressure	Pressure transmitter	±0.25%
Vibration	Accelerometer	—

The state, output and control vectors used by the optimiser are

$$X(t) = [W,\ N,\ P_{\Sigma},\ M,\ T,\ A]^{T}, \qquad Y(t) = [d,\ \eta,\ K_y]^{T},$$
$$U(t) = [f_{VFD},\ Q_w,\ T_q]^{T} \qquad (3)$$

where W is seed moisture, N seed grade, M press torque, T process temperature, A throughput, η drive efficiency, K_y = PΣ/P_nom the drive load factor, f_VFD the drive frequency, Q_w the conditioning water (or steam) rate and T_q the drying temperature.

2.4. Energy characteristics of the main aggregates. The dependence of active power on throughput, P = f(A), and of SEC on throughput, d = f(A) = P/A, was identified for the press and the hullers by least squares from the monitoring data. Linear, quadratic and cubic models were compared using the coefficient of determination, RMSE and MAPE, and the lowest-order adequate model was retained. For a quadratic power characteristic

$$P(A) = c_0 + c_1 A + c_2 A^2 \ \Rightarrow\ d(A) = \frac{c_0}{A} + c_1 + c_2 A,$$
$$A^{*} = \sqrt{\frac{c_0}{c_2}},$$
$$d^{*} = c_1 + 2\sqrt{c_0 c_2} \qquad (4)$$

The constant term c_0 represents the throughput-independent (no-load) power. At low throughput it dominates the SEC; the quadratic term reflects the growth of compression torque at high throughput. A finite optimum A* exists only when $c_2 > 0$. For linear characteristics, or when $c_2 < 0$, the SEC decreases monotonically and the best operating point is the highest throughput allowed by quality constraints.

2.5. Moisture- and oil-content-aware SEC model. Seed moisture affects energy use through two mechanisms. Below the optimum, kernels become brittle, fines increase and more oil leaves with the hulls. Above it, the material becomes sticky, friction and screw resistance rise, and drive current increases. The residual oil in hulls m_sh was modelled for each grade N as

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$$m_{sh}^{N}(W) = a_N + b_N W + c_N W^2, \qquad W_N^{*} = -\frac{b_N}{2c_N} \quad (c_N > 0) \qquad (5)$$

and the SEC model was extended with grade dummies and interaction terms (grade I–II as the base level):

$$d(t) = \beta_0 + \beta_1 W + \beta_2 W^2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 W D_3 + \beta_6 W D_4 + \beta_7 W^2 D_3 + \beta_8 W^2 D_4 + \beta_9 m_{sh}^{N}(W) + \beta_{10} P_{\Sigma} + \beta_{11} K_y + \beta_{12} A + \varepsilon(t) \qquad (6)$$

where D_3 and D_4 equal 1 for grades III and IV respectively and 0 otherwise. Treating grade as a categorical rather than an ordinal variable avoids imposing an artificial linear ordering between grades.

Seed oil content m_ch, which varies between 15% and 23% in delivered cottonseed, changes the oil yield without changing the electricity needed to process a tonne of seed. From the oil balance of the pressing stage, the SEC per tonne of press oil is

$$d_{pch} = \frac{d_p}{m_{ch} - m_{sh}K_{sh} - m_k K_k} = \frac{d_p}{m_{ch} - \alpha} \qquad (7)$$

where d_p is the electricity per tonne of seed in pressing, K_sh and K_k the hull and cake yield coefficients, m_sh and m_k their oil contents, and α = m_sh K_sh + m_k K_k is nearly constant within a campaign. With the plant values (A_ch = 9 t/h, d_p = 48.2 kWh/t, α = 0.0786):

$$d_{pch} = \frac{48.2}{m_{ch} - 0.0786} \qquad (8)$$

At plant level, for refined oil with refining yield K_rm = 0.86 and the integral loss coefficient β = m_sh K_sh + m_shr K_shr = 0.012 (A_ch = 8 t/h, d_mz = 62.4 kWh/t):

$$d_{zch} = \frac{d_{mz}}{m_{ch} - \beta K_{rm}} = \frac{62.4}{m_{ch} - 0.012 \cdot 0.86} \qquad (9)$$

The deviation of Eq. (9) from the plant's production records did not exceed 1.8%.

2.6. Real-time set-point optimisation by the Newton–Raphson method. Because W, M and the seed grade change continuously, the energy-optimal operating point also moves. The optimiser therefore recomputes it at every control cycle from a surrogate model whose parameters θ are re-identified by least squares over a moving window of IoT data:

$$d(\mathbf{x};\boldsymbol{\theta}) = \theta_0 + \theta_1 W + \theta_2 W^2 + \theta_3 M + \theta_4 M^2 + \theta_5 M^3 + \theta_6 W M + \theta_7 A + \theta_8 T, \qquad \hat{\boldsymbol{\theta}} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{y} \qquad (10)$$

with $\mathbf{x} = [W, M]^{\mathrm{T}}$. Product quality is protected by a penalty that keeps moisture near the grade-specific minimum of hull-oil loss W*_N from Eq. (5):

$$J(\mathbf{x}) = d\left(\mathbf{x};\hat{\boldsymbol{\theta}}\right) + \rho\,(W - W_N^{*})^2, \qquad W_{min} \le W \le W_{max},\ M_{min} \le M \le M_{max} \qquad (11)$$

The stationary point ∇J = 0 is found by the damped Newton–Raphson iteration [19]

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$$\mathbf{x}_{k+1} = \Pi[\mathbf{x}_k - \gamma_k \mathbf{H}^{-1}(\mathbf{x}_k)\,\nabla J(\mathbf{x}_k)], \qquad \mathbf{H} = \begin{bmatrix} \partial^2 J/\partial W^2 & \partial^2 J/\partial W\,\partial M \\ \partial^2 J/\partial M\,\partial W & \partial^2 J/\partial M^2 \end{bmatrix} \qquad (12)$$

where Π projects onto the admissible box and the step length γ_k ∈ (0, 1] is halved until J decreases (Armijo backtracking). If H is not positive definite, a multiple of the identity is added to it. Iteration stops when ‖∇J‖ falls below a tolerance or after a fixed number of iterations. For a purely quadratic surrogate the Newton step is exact and converges in a single iteration; the cubic torque term and the W–M coupling make iteration necessary in general. Warm-starting from the previous cycle's solution keeps the number of iterations small.

The PLC converts the optimal set-points into actuator commands:

$$f_{VFD} = f_0 + K_f\,(M^* - M), \qquad Q_w = K_n\,(W^* - W) \;\; (W < W^*), \qquad T_q = T_0 + K_q\,(W - W^*) \;\; (W > W^*) \qquad (13)$$

The press drive is thus moved from fixed-speed direct-on-line operation to variable-frequency operation, and the conditioner either adds moisture or activates drying.

2.7. Simulation set-up and techno-economic assessment. The closed loop (sensors, filter, optimiser, PID controllers, VFD, conditioner and process models of Sections 2.4–2.5) was implemented in MATLAB/Simulink with process parameters taken from the plant. It was compared with conventional operation (fixed press speed, manual moisture adjustment) using the same moisture and throughput disturbances. A short-term load forecast based on a second-order Taylor extrapolation of the measured load, $L(t + \Delta t) = L + L'\Delta t + \tfrac{1}{2}L''\Delta t^2$, was used to anticipate peaks [20].

The economic assessment used the annual electricity saving ΔW, the tariff c = 900 UZS/kWh (mid-peak rate, appropriate for continuous operation), the investment I, and a 10-year horizon:

$$\Delta C = \Delta W \cdot c, \qquad T_{sp} = \frac{I}{\Delta C}, \qquad NPV = -I + \sum_{t=1}^{10} \frac{\Delta C}{(1 + r)^t} \qquad (14)$$

The internal rate of return (IRR) is the discount rate r at which NPV = 0. Operating and maintenance costs of the IoT system and tariff escalation were not included; their effect is discussed in Section 4.

3. RESULTS

3.1. Baseline energy structure. Pressing and extraction together account for 60% of the electricity of the crude-oil production chain (Fig. 2). Pressing alone takes 709.7 MWh per year (32.0%), followed by extraction (622.0 MWh, 28.0%), seed preparation and separation (399.2 MWh, 18.0%), seed storage and handling (266.1 MWh, 12.0%) and the conditioning chamber (221.8 MWh, 10.0%). Ventilation and lighting are included in the consumption of each unit. The concentration of demand in a few motor-driven units makes the pressing section the first target for real-time control.

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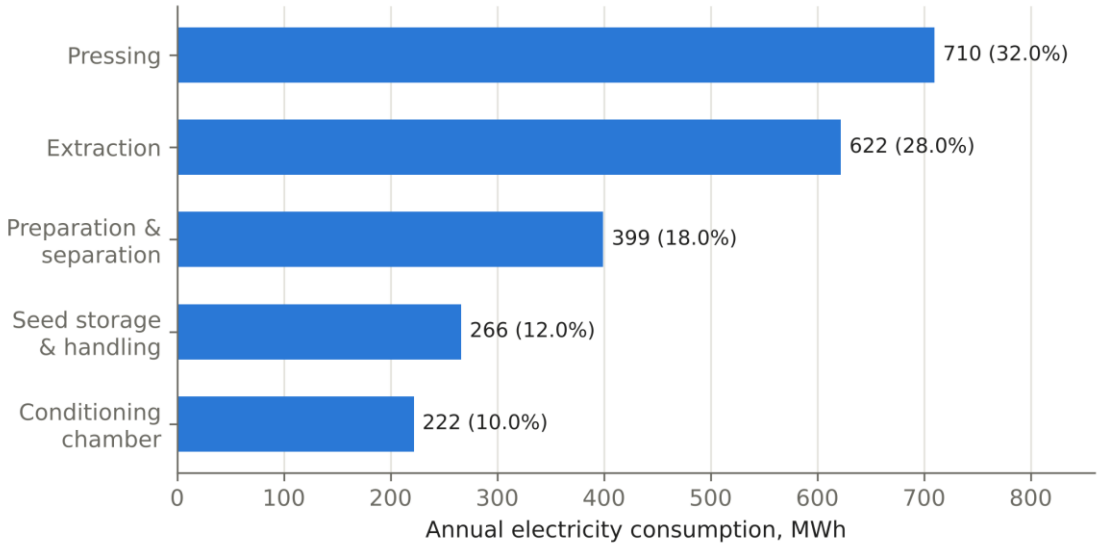


Fig. 2. Annual electricity consumption of the crude-oil production chain by unit, 2024 (total 2,218.8 MWh; 3,857 t of crude oil).

The SEC of the downstream operations, computed from their annual consumption and 2024 output, is given in Table 2. Crude oil production is by far the most electricity-intensive step per tonne of product. Downstream operations are an order of magnitude less intensive.

Table 2. Specific electricity consumption of production stages, 2024.

Stage	Electricity, kWh/yr	Output, t/yr	SEC, kWh/t
Crude oil production (chain of Fig. 2)	2,218,800	3,857 (crude oil)	575
Packaging of oil	158,096	1,928	82
Deodorisation	150,384	1,928	78
Soap production	217,880	2,944	74
Refining	115,710	3,857	30
Meal packing and transport	144,638	9,643	15
Hull handling	68,944	5,303	13

3.2. Energy characteristics of the press and hullers. The identified power characteristics and the corresponding SEC curves are

$$P_p = 7.18 - 1.94A_k + 15.42A_k^2, \qquad d_p = \frac{7.18}{A_k} - 1.94 + 15.42A_k \qquad (15)$$

$$P_{h1} = 5.14 + 2.86A_{ch}, \qquad d_{h1} = 2.86 + \frac{5.14}{A_{ch}} \qquad (16)$$

$$P_{h2} = 9.04 + 5.72A_{ch} - 0.39A_{ch}^2, \qquad d_{h2} = \frac{9.04}{A_{ch}} + 5.72 - 0.39A_{ch} \qquad (17)$$

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where P is in kW, A_k is the cake output and A_{ch} the seed flow (t/h), and d is in kWh/t.

The press characteristic is convex. By Eq. (4) its SEC has a minimum of 19.1 kWh/t at A_k = √(7.18/15.42) = 0.68 t/h (Fig. 3a). Below this load the no-load power of the 45 kW drive dominates; above it the compression torque grows faster than throughput. The first-stage huller has a linear characteristic, so its SEC falls monotonically with throughput and reaches 3.89 kWh/t at the rated 5.0 t/h. The second-stage huller has $c_2 < 0$, so its SEC also decreases over the whole admissible range; the best operating point is the quality-limited maximum of 4.0 t/h, where d = 6.42 kWh/t (Fig. 3b). At higher feed rates hulling quality deteriorates and drive torque rises sharply, which is why the optimiser treats 4.0 t/h as a constraint rather than an optimum.

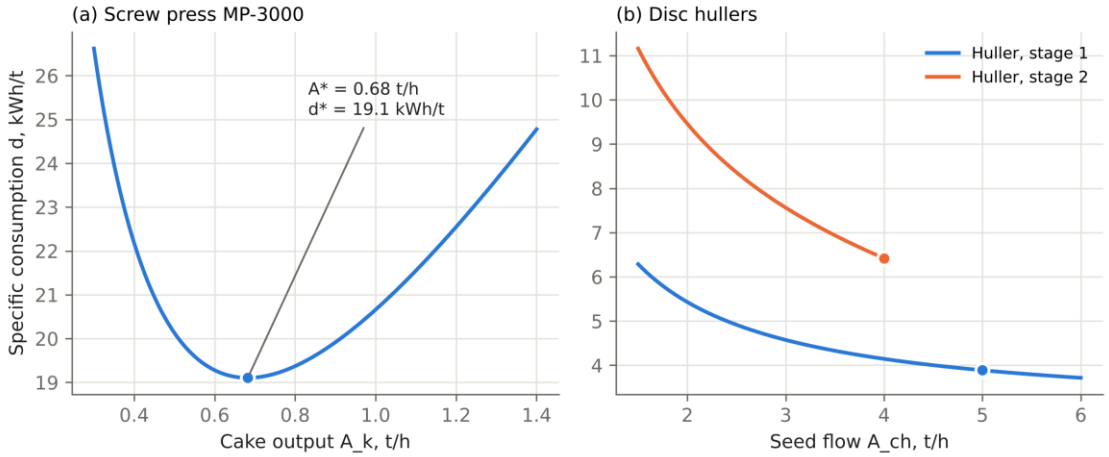


Fig. 3. Energy characteristics: (a) SEC of the MP-3000 screw press; (b) SEC of the first- and second-stage disc hullers. Markers show the optimal (a) or quality-limited (b) operating points.

3.3. Grade-specific optimal seed moisture. The residual oil in hulls was identified for three seed grades:

$$m_{sh}^{I-II} = 6.022 - 0.705W + 0.0291W^2, \quad m_{sh}^{III} = 8.027 - 1.104W + 0.0487W^2,$$
$$m_{sh}^{IV} = 3.942 - 0.352W + 0.0141W^2 \qquad (18)$$

All three curves are convex, and their minima give the grade-specific optimal moisture (Table 3, Fig. 4). The minima lie in a narrow band of 1.75–1.77% hull oil, but they occur at different moistures. Grade III, with the highest hull content, is the most sensitive: moving from 11.3% to 15% moisture raises its hull-oil loss by 37%. A single fixed moisture set-point for all grades therefore always leaves some batches away from their optimum.

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Table 3. Optimal seed moisture by grade, from Eq. (18).

Grade	Optimal moisture W*, %	Minimum hull oil, %	Hull oil at 15% moisture, %
I–II	12.1	1.75	2.00
III	11.3	1.77	2.43
IV	12.5	1.75	1.84

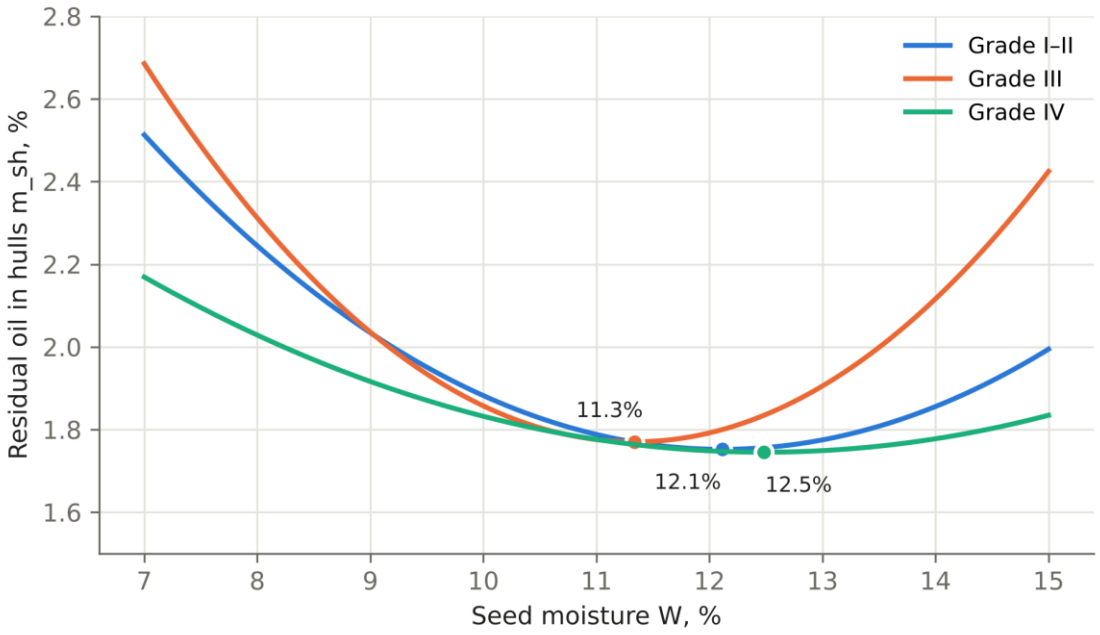


Fig. 4. Residual oil in hulls as a function of seed moisture for three cottonseed grades; markers show the minima.

Plant observations agree with this picture. When moisture exceeded 11%, the throughput of the disc hullers and roller mills at equal power fell by 10–15% because of sticking, and each percentage point of deviation from the optimum increased electricity use by about 1.6%.

3.4. Sensitivity to seed oil content. Eq. (8) and Eq. (9) show that the electricity required per tonne of oil is strongly non-linear in seed oil content (Fig. 5). When m_ch rises from 15% to 23%, the SEC of press oil falls from 675 to 318 kWh/t (−53%), and the plant-level SEC of refined oil falls from 447 to 284 kWh/t (−36%). The press stage is more sensitive because $\alpha = 0.0786$ removes a larger part of the oil than the plant-level loss term $\beta K_{rm} = 0.0103$. In practice, an apparent rise in SEC per tonne of oil may simply reflect lower-oil seed rather than less efficient

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equipment. Real-time measurement of oil content and moisture is therefore needed to separate raw-material effects from genuine inefficiency when SEC norms are set or audited.

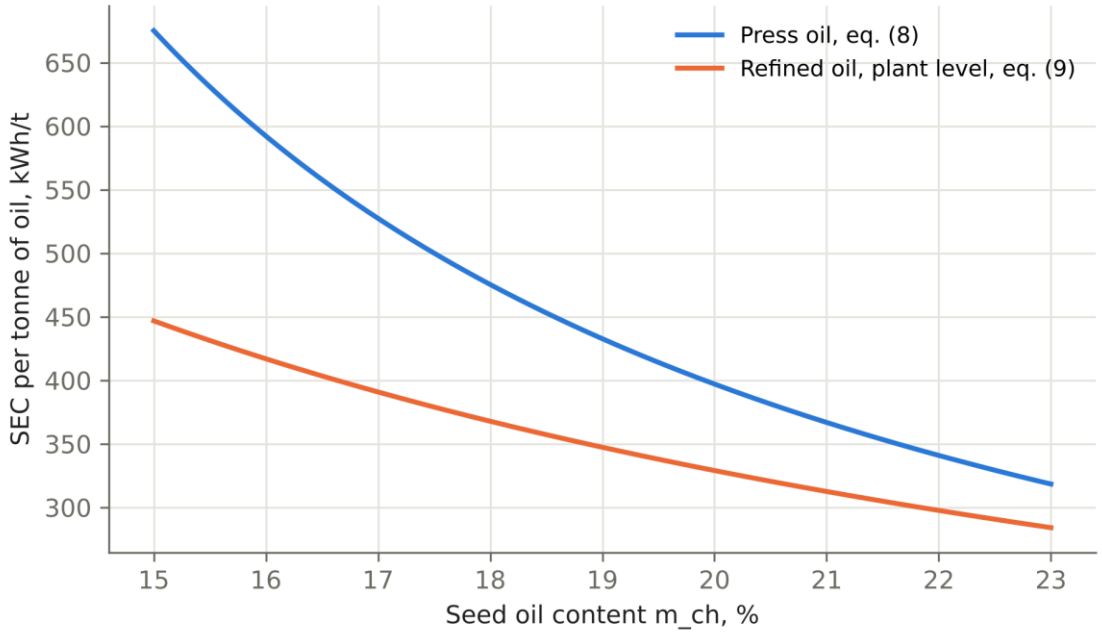


Fig. 5. Specific electricity consumption per tonne of oil versus seed oil content: press oil, Eq. (8), and refined oil at plant level, Eq. (9).

3.5. Closed-loop performance (simulation). Table 4 compares conventional operation with the proposed control in the MATLAB/Simulink model. With the Newton–Raphson optimiser updating moisture and torque set-points, moisture variability narrowed from ±2.4% to ±0.3% and press-torque fluctuation from ±18% to ±4% (Fig. 6). Load dispersion of the pressing section fell from ±15% to ±5%, and the average drive load factor decreased from 0.94 to 0.82. This moved the press motor out of its high-loss region near rated load. The SEC of the pressing line fell from 53.1 to 49.2 kWh per tonne of seed, a reduction of 7.3%.

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Table 4. Conventional versus proposed control of the pressing line (simulation).

Indicator	Conventional	Proposed	Change
Seed moisture variability	±2.4%	±0.3%	−8×
Press-torque fluctuation	±18%	±4%	−4.5×
Load dispersion	±15%	±5%	−3×
Drive load factor K_y	0.94	0.82	−0.12
SEC of pressing line, kWh/t seed	53.1	49.2	−7.3%
Power factor with automatic compensation	0.72	0.96	+0.24

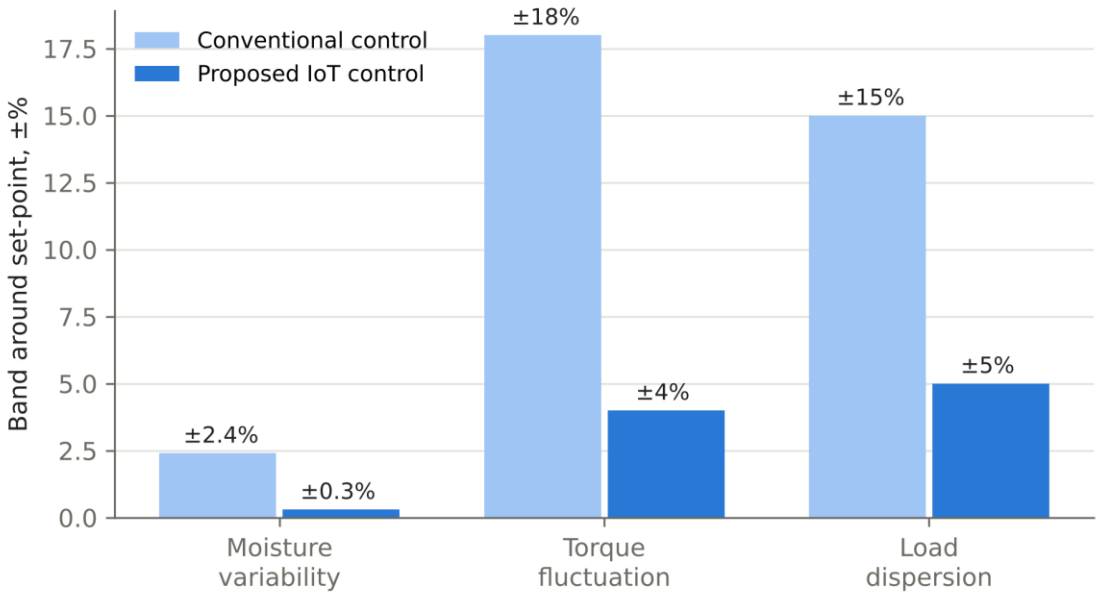


Fig. 6. Variability of the controlled variables under conventional and proposed control (simulation).

The short-term load forecaster used by the supervisory layer reproduced the pressing-section load with RMSE = 1.92 kWh, MAE = 1.38 kWh, MAPE = 2.41% and R^2 = 0.964 (n = [__] intervals; [period]). This accuracy is sufficient to anticipate load peaks one control horizon ahead.

3.6. Techno-economic assessment. The hardware and software required for the system are listed in Table 5; the total investment is 405 million UZS. Variable-frequency drives and IoT sensors make up almost half of it.

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Table 5. Investment in the IoT energy management system.

Item	Quantity	Cost, million UZS
Variable-frequency drives	8	96
IoT sensors	48	84
PLC modules	6	58
SCADA server	1	42
Software	—	37
Smart energy meters	12	36
IoT gateways	4	28
Installation and commissioning	—	24
Total		**405**

The implementation at the plant is credited with an annual electricity saving of 142,222 kWh, about 6.4% of the electricity of the crude-oil production chain. At 900 UZS/kWh this is worth 128.0 million UZS per year. Table 6 summarises the resulting indicators.

Table 6. Economic indicators (10-year horizon, constant savings).

Indicator	Value
Annual saving	142.2 MWh; 128.0 million UZS
Simple payback period	3.2 years
Discounted payback period (r = 14%)	4.5 years
NPV at r = 10% / 14% / 18% / 22%	381.5 / 262.7 / 170.2 / 97.2 million UZS
Internal rate of return	29.2%

NPV remains positive for discount rates up to 29%, so the investment is robust to the high cost of capital typical for the region.

4. Discussion

4.1. Comparison with previous studies. The simulated 7.3% reduction in the SEC of the pressing line, and the 6.4% plant-chain saving credited to the implementation, are at the lower end of the 10–30% range often reported for industrial energy management systems [1,12]. The difference is expected. Large reported savings usually combine monitoring with equipment replacement (high-efficiency motors, new boilers), while the present results come almost entirely from operating the existing equipment closer to its optimum. In this respect they are closer to the savings that Jagtap et al. [14] attributed to real-time data collection in a food factory, and to the efficiency gains of IoT monitoring reported by Chen et al. [10] for machining.

The main difference from earlier IoT energy-management frameworks [8–11] is that energy data are combined with raw-material variables

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(moisture, grade, oil content) in a process model, and the model's optimum is fed back to the actuators. Monitoring-only systems can show that SEC rose; they cannot tell whether the rise came from wet seed, low-oil seed or a drifting drive. The oil-content analysis in Section 3.4 shows why this matters. A 53% change in SEC per tonne of press oil can come purely from seed quality, which is far larger than any plausible equipment-related effect. Energy norms expressed per tonne of oil, as used in national reporting, should therefore be corrected for oil content and moisture before plants are compared or penalised.

The press characteristic illustrates a common motor-system problem [2,3]. At low throughput the fixed no-load power of the 45 kW drive inflates the SEC, while at high throughput the torque rises faster than output. Variable-frequency operation allows the drive speed to follow the optimum computed by the Newton–Raphson step instead of running at a single fixed speed. The reduction of the load factor from 0.94 to 0.82 also lowers copper losses and thermal stress on the windings, which supports equipment life.

4.2. Practical implications. Three findings are directly usable by oil mills:

1. **Grade-specific moisture set-points.** Seed conditioning should target 12.1% for grades I–II, 11.3% for grade III and 12.5% for grade IV rather than a single value. Grade III is the most sensitive to over-wetting.
2. **Raw-material-corrected energy norms.** SEC norms per tonne of oil should be corrected using Eqs. (2), (8) and (9); otherwise audits confuse seed quality with energy performance.
3. **Staged deployment.** The pressing and extraction sections, which take 60% of chain electricity, should be instrumented first. Sensors, PLC–SCADA integration and the optimiser can then be extended to auxiliary systems.

With a simple payback of 3.2 years and an IRR of 29%, the system is economically attractive even at the high discount rates typical for the region. In Uzbekistan, such projects are also eligible for the support mechanisms introduced by PQ-4422 [15], and the measured SEC indicators fit directly into an ISO 50001 energy management system [21].

4.3. Limitations. The study has several limitations that should be addressed in further work.

1) **Single plant.** All models were identified at one mill. The coefficients of Eqs. (15)–(18) are plant- and equipment-specific, although the model structure is transferable.

2) **Simulation-based control results.** The closed-loop indicators in Table 4 come from a MATLAB/Simulink model parameterised with plant data, not from a long-term field trial with a control group. A measurement and verification campaign following the IPMVP [22] or ISO 50015 [23] approach, with weather- and production-normalised baselines, is needed to confirm them in operation.

3) **Economic scope.** The economic assessment assumes constant savings and tariff and excludes the operating and maintenance costs of the IoT system, which would lengthen the payback. Tariff increases, by contrast, would shorten it.

4) **Thermal energy.** Natural gas and steam, which are significant in cooking, extraction and deodorisation, were analysed only qualitatively. Extending the optimiser to steam-condensate balance is a natural next step.

5) **Data and cybersecurity.** Sensor drift, especially of moisture sensors, and the cybersecurity of the PLC–SCADA link were not

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studied, although both affect long-term performance.

5. Conclusions

This study developed a real-time, IoT-based energy management approach for cottonseed oil production and evaluated it at a mill in Kokand, Uzbekistan. The main conclusions are as follows.

1. Pressing and extraction account for 60% of the electricity of the crude-oil production chain (2,218.8 MWh/yr; SEC 575 kWh per tonne of crude oil), which makes the pressing section the priority for real-time control.
2. The SEC of the MP-3000 screw press has a minimum of 19.1 kWh/t at a cake output of 0.68 t/h. The disc hullers have no interior optimum, and their best operating points are the quality-limited maximum throughputs.
3. Optimal seed moisture depends on grade: 12.1% for grades I–II, 11.3% for grade III and 12.5% for grade IV. A variation of seed oil content from 15% to 23% changes the SEC per tonne of oil by 53% at the press and by 36% at plant level, so energy norms must be corrected for raw-material properties.
4. A damped Newton–Raphson optimiser working on an on-line re-identified surrogate model, integrated into a five-layer IoT–edge–PLC–SCADA–cloud architecture, reduced moisture variability from ±2.4% to ±0.3%, torque fluctuation from ±18% to ±4% and load dispersion from ±15% to ±5% in simulation. It lowered the SEC of the pressing line by 7.3%.
5. The implementation is credited with saving 142.2 MWh (128 million UZS) per year for an investment of 405 million UZS: a simple payback of 3.2 years, an NPV of 263 million UZS at 14% over 10 years and an IRR of 29%.

Future work will verify the closed-loop savings in a long-term field measurement campaign, extend the optimiser to steam and natural-gas consumption, and test the transferability of the models to other oilseed plants.

Declarations

CRediT authorship contribution statement. Usmonov Shukurillo Yulbarsovich: conceptualisation, methodology, supervision, writing – review and editing. Sobirov Murodiljon Nusrotillo ugli: investigation, data curation, formal analysis, software, visualisation, writing – original draft.

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Implementation. The results were implemented at “Qo’qon Oziq-Ovqat Invest” LLC (certificate of the Ministry of Energy of the Republic of Uzbekistan No. 04-13-5790, 28 November 2025).

Data availability. The data supporting the findings of this study are available from the corresponding author on reasonable request, subject to the consent of the company.

Declaration of competing interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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