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Feedstock-Aware Real-Time Energy Management in Cottonseed Oil Processing: Linking Seed Oil Content and Moisture to Specific Electricity Consumption

Usmonov Shukurillo Yulbarsovich
Department of Electrical Engineering, Fergana State Technical University, Fergana, Uzbekistan

Sobirov Murodiljon Nusrotillo ugli
Department of Electrical Engineering, Fergana State Technical University, Fergana, Uzbekistan

Akbarov Asadbek Haydarali ugli
Department of Electrical Engineering, Fergana State Technical University, Fergana, Uzbekistan

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Abstract: Energy management in small and medium-sized food plants is usually based on monthly utility bills, which conceal the link between raw-material quality and energy use. This study quantifies that link for a cottonseed oil plant in Uzbekistan processing about 50.9 kt of seed per year and embeds it in a real-time monitoring and control system. Five years of monthly metering (2020–2024), product-level energy accounts and on-site measurements were used to derive product-specific electricity consumption (SEC), an oil-balance model giving SEC per tonne of oil as a function of seed oil content, and grade-specific regressions of hull oil loss on seed moisture. Pressing, roasting and extraction account for 72.7% of plant energy use, and crude oil requires 575 kWh t−1. Over the observed range of seed oil content (15–23%), pressing-shop SEC changes by 53% and plant-level SEC by 36%, with elasticities of −1.71 and −1.06 at 19% oil content. Hull oil loss is minimised at 11.4–12.5% seed moisture, and moisture normalisation offers a saving potential of 167.8 MWh yr−1. A four-layer IoT–SCADA–PLC system reduced load fluctuation in the pressing shop from ±15% to ±5%, raised the power factor from 0.72 to 0.96 and achieved a certified 7% energy saving with a 3.3-year payback. Treating feedstock properties as measured state variables makes energy monitoring actionable in oilseed processing.

Keywords: Specific energy consumption; cottonseed oil; food processing; Internet of Things; real-time energy management; energy efficiency.

1. INTRODUCTION:

Agri-food systems use about 30% of the world's energy [1], and global food demand is expected to rise by roughly 50% between 2012 and 2050 [2]. Industry already accounts for around 42% of global electricity consumption [3], so the energy performance of food factories matters both for production costs and for emissions [4]. In food processing, demand is spread over many medium-sized drives, heat exchangers and auxiliaries whose consumption depends on product mix and raw-material properties [5–7].

Most small and medium-sized food manufacturers still monitor energy only through monthly invoices [8]. This information deficit is a recognised cause of the energy efficiency gap: cost-effective measures are not implemented because their benefits cannot be quantified at line or machine level [9,10]. Energy management systems based on ISO 50001 [11] close

the gap only when they receive granular and interpretable data. Industrial IoT, wireless sensor networks and smart metering now make such data inexpensive [12–14], and cyber-physical architectures and big-data analytics connect measurement with decisions [15,16]. IoT platforms have been used to forecast daily peak demand in manufacturing [17], to predict compressor load with neural networks [18] and to optimise industrial ventilation [19]; in food processing, real-time energy data saved about 163 MWh in one year at a beverage plant [8].

These approaches model energy demand as a function of time, schedule and equipment state. In oilseed processing, however, much of the variation in energy intensity originates in the raw material: a tonne of seed needs nearly the same electricity whatever its oil content, but the electricity per tonne of oil—the figure used for costing and benchmarking—does not. Seed moisture further affects friction, adhesion and oil loss with hulls. No study known to the authors has quantified this feedstock–energy coupling from plant data or used it inside a real-time energy management loop.

This paper addresses that gap for a cottonseed oil plant in Uzbekistan, where national policy targets a 20% gain in the energy efficiency of the economy [20,21]. The objectives are to (i) establish product-specific SEC for an integrated oil, refining and soap plant; (ii) derive an oil-balance model and a closed-form elasticity of SEC with respect to seed oil content; (iii) identify energy-optimal seed moisture by grade and the associated saving potential; and (iv) evaluate an IoT–SCADA–PLC system that uses these models online. Partial results were reported earlier [22–24].

2. METHODS

2.1. Plant and data

The plant ("Qo'qon Oziq-Ovqat Invest" LLC, Kokand) operates in three shifts and processes cottonseed by cleaning, dehulling, conditioning and flaking, roasting, prepressing in MP-3000 screw presses (45 kW drives), hexane extraction, refining, deodorisation and packaging, with soap and fatty-acid production as by-product lines. In 2024 it processed 50,850 t of seed and produced 8381.7 t of crude oil, 6964.9 t of refined oil, 4070.5 t of deodorised oil, 18,069.4 t of meal and 11,359 t of hulls. Three data sources were used: monthly active-energy readings of the revenue meter for 2020–2024 (60 values); an equipment-level electrical inventory with departmental energy accounts for 2024; and on-site measurements with an MQ31 power-quality analyser, thermography of switchgear, and laboratory analyses of seed moisture and hull oil content by seed grade. Normative moisture follows O'zDSt 596:2014 [25]. Monthly series were described by annual totals, the coefficient of variation (CV) and a seasonal index.

2.2. Specific consumption and oil-balance model

For product j, SEC is the electricity W_j attributed to its production chain divided by output M_j:

$$e_j = \frac{W_j}{M_j} \tag{1}$$

The oil obtained in pressing equals the oil in the seed minus the oil leaving with hulls and press cake. Dividing pressing-shop electricity by this quantity and introducing yield coefficients $K_{sh} = G_{sh}/G_{ch}$ and $K_k = G_k/G_{ch}$ gives SEC per tonne of press oil in terms of SEC per tonne of seed, $e_{p,s}$:

$$e_p = \frac{e_{p,s}}{m_{ch} - m_{sh}K_{sh} - m_kK_k} = \frac{e_{p,s}}{m_{ch} - \alpha} \tag{2}$$

where m denotes oil mass fractions and the losses with hulls and cake, which vary little over a production period, are lumped into α; unaccounted losses (≈0.01%) are neglected. At plant level, with hull and meal losses lumped into β and refining yield K_{rm}, SEC per tonne of refined oil is

$$e_z = \frac{e_{z,s}}{m_{ch} - \beta K_{rm}} \tag{3}$$

In the extraction shop the oil input is the residual oil of the cake, so its SEC does not depend explicitly on m_{ch}. Because Eqs. (2) and (3) have the form $e = c/(m_{ch} - a)$, the elasticity of SEC with respect to seed oil content is

$$\varepsilon = \frac{\partial e}{\partial m_{ch}} \cdot \frac{m_{ch}}{e} = -\frac{m_{ch}}{m_{ch} - a} \tag{4}$$

Parameters were estimated from the 2024 production and energy accounts, and plant-level predictions were compared with metered SEC.

2.3. Moisture model

Moisture acts through the mass basis—seed at actual moisture w_h is converted to conditioned mass $G_{kon} = \xi G_h$, $\xi = (100 - w_h)/(100 - w_m)$—and through oil loss with hulls, since dry kernels are crushed into oil-bearing dust while wet kernels adhere to hulls [23].

Hull oil content by seed grade was fitted with second-order polynomials,

$$m_{sh} = a_0 + a_1 w_{ch} + a_2 {w_{ch}}^2, \quad {w_{ch}}^* = -\frac{a_1}{2a_2} \qquad (5)$$

and inserted into the plant oil balance. The annual saving from moisture normalisation is $\Delta W = \Delta e \cdot G_{ch} \cdot s$, where Δe is the SEC change between actual and target moisture and s is the share of seed processed at that moisture.

2.4. Real-time management system and economic evaluation

The models were deployed in a four-layer architecture (Fig. 1). IoT meters and process sensors sample at 1–5 s; outliers are removed with a Hampel filter [26] and gaps are filled with a Kalman estimator [27]. The oil-balance and moisture coefficients are updated recursively, and short-horizon demand is predicted by a first-order Taylor expansion, $P(t+\Delta t) \approx P(t) + (\partial P/\partial T)\Delta T + (\partial P/\partial p)\Delta p + (\partial P/\partial L)\Delta L$, with sensitivities identified online. The decision layer sets load balancing among parallel drives, rate-of-change peak warnings [17], moisture targets and capacitor-bank stages; PLCs and variable-frequency drives execute them and SCADA provides visualisation and archiving [28,29]. Payback and return on investment were computed as I/S and S/I, with I the investment and S the certified annual saving; electricity was valued at 900 UZS kWh^{-1} [30].

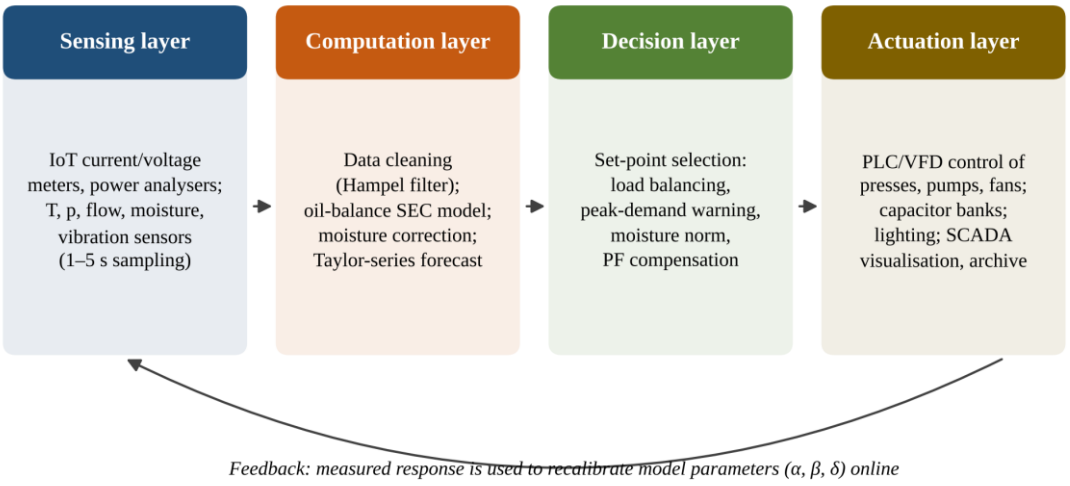


Fig. 1. Four-layer IoT–SCADA–PLC architecture used for real-time energy management in the plant.

3. RESULTS

3.1. Consumption pattern and energy structure

Annual consumption rose from 2.47 GWh in 2020 to 4.83 GWh in 2024 (compound growth 18.3% yr^{-1}), and monthly values ranged from 110.3 MWh (March 2022) to 448.0 MWh (May 2024) (Fig. 2). The CV of monthly consumption was 20–31% in 2020–2023 but only 7.1% in 2024; the seasonal index peaked in July–September (1.09–1.18), following the seed-supply campaign. Pressing (29.7%), roasting (22.8%) and extraction (20.2%) consume 72.7% of plant energy, followed by refining (9.1%) and deodorisation (6.1%). Product-specific SEC values are given in Table 1: crude oil is by far the most electricity-intensive chain, whereas downstream refining, deodorisation and packaging add 30–82 kWh t^{-1}.

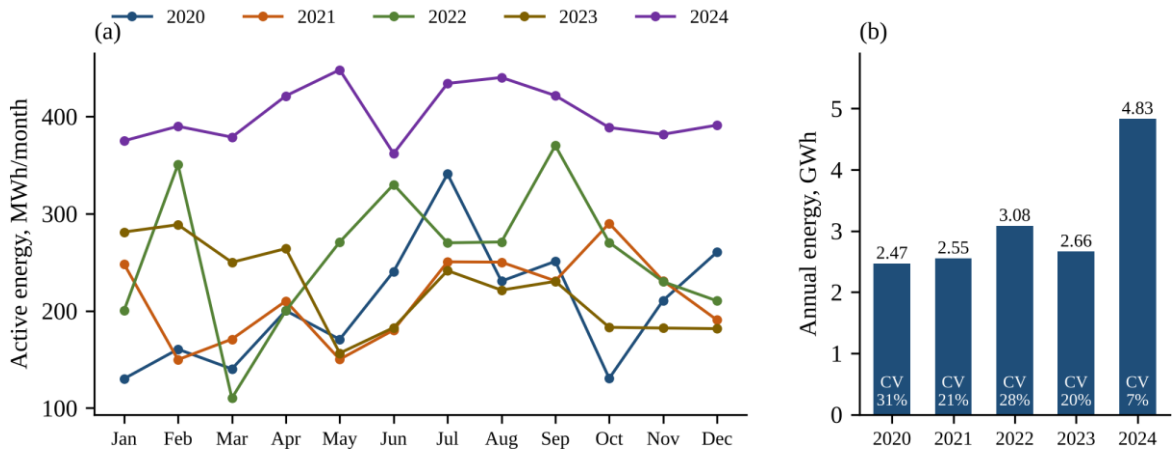


Fig. 2. (a) Monthly active-energy consumption, 2020–2024; (b) annual totals and coefficient of variation (CV) of monthly values.

Table 1. Product-specific electricity consumption (2024 accounting period).

Product / service	SEC	Product / service	SEC
Crude oil, kWh t^{-1}	575	Laundry soap[a], kWh t^{-1}	74
Refining, kWh t^{-1}	30	Meal handling, kWh t^{-1}	15
Deodorisation, kWh t^{-1}	78	Hull handling, kWh t^{-1}	13
Packaging (1 L, 5 L), kWh t^{-1}	82	Steam generation, kWh $Gcal^{-1}$	18
Distilled fatty acids (DFA), kWh t^{-1}	510	Refrigeration, kWh $Gcal^{-1}$	580
Distilled fatty acids (FFA), kWh t^{-1}	90	Well water, kWh $(1000\ m^3)^{-1}$	320

[a] Output of 2023. Electricity only; boiler fuel is excluded.

3.2. Effect of seed oil content

With the estimated parameters (Table 2), Eq. (2) becomes $e_p = 48.2/(m_{ch} - 0.0786)$ and Eq. (3) becomes $e_z = 62.4/(m_{ch} - 0.0103)$. Between 15% and 23% oil content, pressing SEC falls from 675 to 318 kWh per tonne of oil (−53%) and plant SEC from 447 to 284 kWh per tonne of refined oil (−36%) (Fig. 3a). At 19% oil content the elasticities from Eq. (4) are −1.71 and −1.06, so each additional percentage point of oil lowers SEC by about 8.3% in pressing and 5.3% at plant level. Plant-level predictions deviated from metered SEC by no more than 1.8%.

Table 2. Oil-balance model parameters and predicted SEC (kWh per tonne of oil).

Quantity	Pressing shop	Whole plant
SEC per tonne of seed e_s, kWh t^{-1}	48.2	62.4
Loss coefficient	$\alpha = 0.0786$	$\beta K_{rm} = 0.012 \times 0.86$
SEC at m_{ch} = 15 / 19 / 23%	675 / 433 / 318	447 / 347 / 284
Change over 15–23%	−53%	−36%
Elasticity ε at 19%	−1.71	−1.06

3.3. Effect of seed moisture

Hull oil content is a convex function of moisture for all grades (Table 3, Fig. 3b). Losses are lowest at 12.2% (grades I–II), 11.4% (grade III) and 12.5% (grade IV) and rise steeply below about 10%: drying grade-III seed from 11% to 8% raises hull oil content from 1.65% to 2.22%. Including the conditioned-mass

correction, the SEC-optimal moisture is 12.5, 11.0 and 12.0%, respectively; each percentage point of deviation increases electricity use by about 1.6%, and above 11% moisture the throughput of hullers and roller mills falls by 40–50% at unchanged power.

Table 3. Regression coefficients of hull oil content on seed moisture and resulting optima.

Seed grade	a_0	a_1	a_2	w^*, %	$m_{sh,min}$, %	SEC-optimal w, %
I–II	6.13	−0.730	0.030	12.2	1.69	12.5
III	8.14	−1.140	0.050	11.4	1.64	11.0
IV	3.81	−0.324	0.013	12.5	1.79	12.0

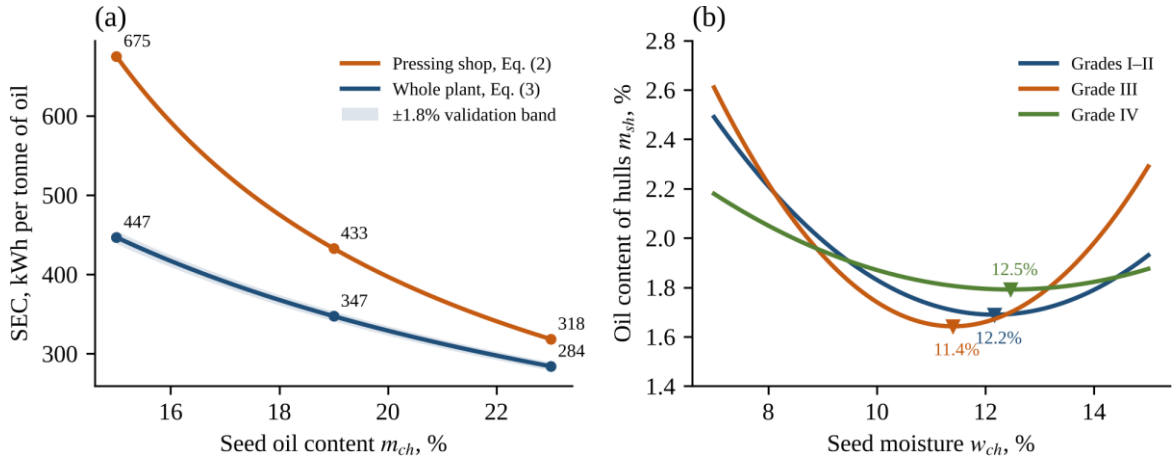


Fig. 3. (a) SEC per tonne of oil versus seed oil content for the pressing shop and the whole plant; (b) hull oil content versus seed moisture by grade (triangles: minima).

In 2024, 25% of the seed arrived at about 14% moisture and 12% at about 8%. Drying the wet fraction to 11% saves 82.6 MWh yr^{-1}, conditioning the dry fraction costs 14.0 MWh yr^{-1}, and restoring huller and roller-mill throughput saves a further 99.2 MWh yr^{-1}. The net technical potential is 167.8 MWh yr^{-1}, about 3.5% of 2024 consumption (Fig. 4).

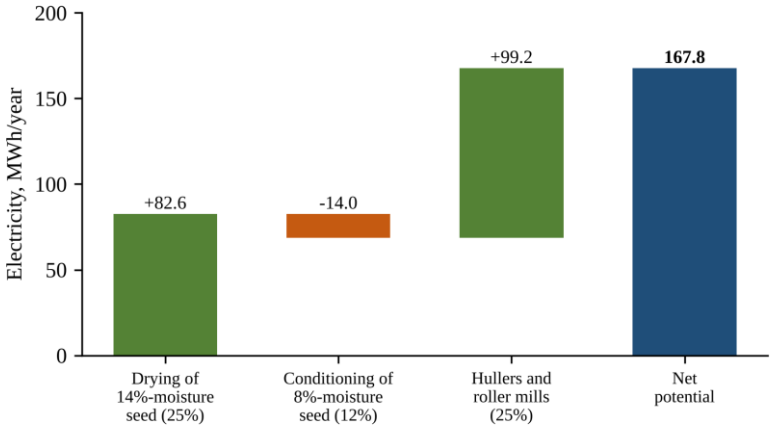


Fig. 4. Components of the annual saving potential from normalising seed moisture (G_{ch} = 50,850 t yr^{-1}).

3.4. Implementation and economics

After commissioning, load fluctuation in the pressing shop narrowed from ±15% to ±5%, steam monitoring revealed and removed 11.2% excess steam use in extraction, the power factor rose from 0.72 to 0.96 with about 106.7 MWh yr^{-1} lower network losses, and

lighting energy fell by up to 21% (Table 4). The plant-level saving certified by the Ministry of Energy of Uzbekistan (No. 04-13-5790, 28 November 2025) is 7% of energy use, or 128 million UZS yr^{-1}. With an investment of 425 million UZS, the payback period is 3.3 years and the annual return 30.1%; the production cost of finished oil fell from 8500 to 7390 UZS kg^{-1} (−13.1%).

Table 4. Outcomes of the IoT–SCADA–PLC deployment and economic indicators.

Indicator	Before	After
Load fluctuation, pressing shop	±15%	±5%
Power factor, cos ϕ	0.72	0.96
Excess steam use, extraction	11.2%	eliminated
Lighting energy	100%	≤79%
Certified energy saving / annual savings	–	7% / 128 million UZS
Investment / payback / annual ROI	–	425 million UZS / 3.3 yr / 30.1%
Cost of finished oil, UZS kg^{-1}	8500	7390

4. DISCUSSION

The results show that in cottonseed processing the energy intensity of the product depends more on feedstock composition than on machine efficiency. Because crushing and pressing work scales with seed mass while output scales with oil content, the elasticity of pressing SEC exceeds unity: a change of two percentage points in average oil content moves pressing SEC by about 17%, comparable to a major equipment retrofit. Energy benchmarks for oilseed plants should therefore be normalised to oil content, which existing maps of food-manufacturing energy use, reporting SEC per unit of product, do not do [5,6].

Moisture behaves differently, with an interior, grade-dependent optimum. Since it can be measured inline and controlled during conditioning, it is the feedstock variable best suited to closed-loop control, and its saving potential requires little more than instrumentation—consistent with evidence that information and organisational measures dominate the cost-effective part of the industrial efficiency gap [9,10]. Compared with IoT platforms that forecast demand from load and schedule alone [17–19], the oil-balance and moisture models act as soft sensors: a rise in SEC explained by lower oil content calls for a procurement or blending response, whereas an unexplained rise points to faults or mis-set equipment. The electrical outcomes agree with known effects of drive control and compensation [10]; raising cos ϕ from 0.72 to 0.96 cuts current-dependent network losses by about 44% at unchanged active power.

Eqs. (2)–(4) rest only on mass and oil balances and apply to any prepress–extraction plant once e_s, α and β are identified locally; the moisture regressions are specific to cottonseed and the hulling equipment. The study has limitations: it covers one plant and one accounting year for the model parameters; monthly metering cannot separate the effects of throughput growth and of the monitoring system on 2024 variability; shared loads were allocated by proportional rules; goodness-of-fit statistics of the moisture regressions were not available at sample level; and the moisture saving is a modelled potential, whereas the certified 7% reflects all measures combined. High-resolution IoT data will allow batch-level estimation, uncertainty quantification and model-predictive control of conditioning.

5. CONCLUSIONS

An oil-balance model linking seed oil content to specific electricity consumption, $e = e_s/(m_{ch} - a)$, with elasticity $\varepsilon = -m_{ch}/(m_{ch} - a)$, was developed and validated (error ≤1.8%) for a cottonseed oil plant. Between 15% and 23% oil content, pressing SEC changes by 53% and plant SEC by 36%. Hull oil loss is minimised at 11.4–12.5% seed moisture, and moisture normalisation offers 167.8 MWh yr^{-1} of savings. Embedded in an IoT–SCADA–PLC system,

these models supported a certified 7% energy saving, a rise in power factor from 0.72 to 0.96 and a 3.3-year payback. Treating feedstock oil content and moisture as measured state variables makes real-time energy management in oilseed processing both explainable and actionable.

CRediT authorship contribution statement. M.N. Sobirov: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Visualization, Writing – original draft. Sh.Yu. Usmonov: Supervision, Validation, Writing – review & editing.

Declaration of competing interest. The authors declare no competing interests.

Data availability. Aggregated data are given in the paper; raw plant data are available from the corresponding author on reasonable request, subject to the operator's consent.

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