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Improving Energy Efficiency In Food Production With Real-Time Data Management

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Abstract
Rising energy demand and prices are significant challenges for the energy-intensive food sector throughout the supply chain. Thus, improving energy efficiency has become an important priority for the food sector. However, most food businesses have limited awareness of the latest technological advances in real-time energy monitoring. The concept of "Internet of Things" (IoT) is used in production enterprises of developed countries around the world to obtain energy data in real time. The Internet of Things has been explored to increase visibility, transparency and awareness of different levels of energy use. This article provides analysis and suggestions for achieving energy efficiency through real-time data collection in food production and processing enterprises. An example of a beverage plant in food processing and processing enterprises is given, where energy consumption reduction measures have been developed by introducing sensor technology that supports the Internet of Things, based on the product energy model.
Key words. Food production, energy efficiency, energy saving, real time, intelligent devices, efficient lighting solutions, heating and cooling, energy saving, energy used per unit of product, improving the efficiency of equipment use, reducing waste.

Most of the current solutions available on the market are primarily designed for large enterprises. Due to their high costs and the need for customization by specialized personnel, they are considered inconvenient for small and medium-sized businesses and individual building owners. The main objective of this study is to eliminate these limitations by developing an IoT-based energy management platform that is comprehensive in functionality, economically viable, and user-friendly.
This research integrates sensors, software, hardware models, decision-making algorithms, actuators, and a structured knowledge base. It enables data exchange and system control via the Internet and cloud technologies. The system was tested in three real-life scenarios, aimed at shaping an advanced energy management model.
The first experiment focused on optimizing a ventilation system, where IoT sensors monitored temperature, pressure differences, and airflow. Artificial neural networks were employed to predict system behavior under various conditions. A genetic algorithm was used to identify optimal operational conditions. This approach reduced annual ventilation energy consumption by 20% and weekend energy use by 60% [1].
The second experiment involved optimizing the compressed air system pressure. Key energy efficiency issues such as air leaks, heat losses, and pressure drops were targeted. Real-time monitoring of pressure, flow, and energy consumption was conducted using IoT sensors and analyzed via machine learning models. As a result, reducing air pressure by just 1 bar led to a 7% energy saving.
The third experiment aimed at detecting unnecessary air usage. Here, the k-means clustering algorithm was used to differentiate between normal and abnormal operation modes. Unexpected air consumption during non-working hours was identified using histograms and heat maps. This optimization resulted in weekly savings of 393 kWh, equivalent to 10% of the compressor’s weekly energy usage.

The key innovation of this research lies in the integration of IoT systems with modeling intelligence, enabling real-time energy management, improving efficiency, and facilitating continuous optimization of operational processes. The findings show that advanced IoT platforms can offer energy-saving and economically feasible innovative solutions for small and medium enterprises.

Global electricity demand has grown steadily by approximately 4% annually over the last decade. Industrial and building infrastructures are the largest consumers. According to the International Energy Agency (IEA), the industrial sector accounts for 42.3% of global electricity consumption. Hence, improving energy efficiency is a global priority, and analyzing factors influencing energy use in production processes is of paramount importance [2,3].

The ISO 50001 international standard is tailored for industrial, commercial, and institutional users to enhance energy efficiency. It defines strategies for demand-based energy management. Traditional approaches like deploying energy-saving technologies, financial incentives, consumer education, and regulatory measures have yielded results. However, in recent years, the Demand Response (DR) concept has emerged. This system promotes the active integration of consumers into the power supply, real-time control of energy use, and load reduction in power grids.

Originally, DR programs were introduced for large industrial and commercial enterprises due to their high energy usage and availability of remote-control infrastructure. Now, with the development of smart grids, these programs are extending to private consumers as well. For DR strategies to be effective, all consumers must have well-functioning energy management systems. Managing energy use in manufacturing facilities is complex and influenced by weather, work schedules, equipment conditions, malfunctions, and planning factors [4].

Currently available commercial energy management systems are primarily tailored for large organizations with greater financial capacity and dedicated energy managers. Thus, developing simple and efficient energy management systems for SMEs is crucial.

Low energy efficiency remains a pressing issue for small and medium-sized enterprises (SMEs), which face several barriers:

1. Lack of appropriate tools to identify energy-saving opportunities:
   - ✓ Energy losses often stem from malfunctioning or inefficient equipment,
   - ✓ Improperly loaded systems,
   - ✓ Poor equipment planning, which causes excessive demand,
   - ✓ System faults and leaks causing major energy losses. Often these issues are hidden and difficult to detect.
2. Lack of sufficient evidence to address identified issues:
   - ✓ Even when problems are found, they may not be prioritized,
   - ✓ Enterprise managers often focus on production processes and lack clear insight into the financial benefits of energy-saving measures,
   - ✓ Therefore, such issues are postponed or neglected.
3. Ineffective analysis of data collected from sensors:
   - ✓ While many enterprises have sensors, the collected data is underutilized in decision-making,
   - ✓ Such valuable data, if analyzed properly, could guide energy-saving decisions.

Several commercial energy management tools have been developed by companies such as SAP, Schneider Electric, EnergyCAP, CA Technologies, and JouleX. However, these tools are complex, require substantial customization, and necessitate specialized training. Local monitoring tools like ABB's motor monitoring system or Air Technologies' MonitAIR® also exist, but are not integrated into the overall factory energy management strategy [5,7].

Key obstacles include:

✓ Sensors and energy management tools are not interconnected, requiring manual data collection and input,
✓ Forecast models exist for specific energy consumers, but they are not aligned with the overall plant strategy,
✓ Current cloud-based management strategies lack decision-making mechanisms,
✓ Demand-based energy management (DR) is ineffective due to unaccounted real-time and random factors (e.g., weather),
✓ Reliable investment proposals for energy efficiency improvements are lacking, and SMEs lack specialized personnel to develop such solutions,
✓ There is no clear roadmap for future energy efficiency improvements.

Modern technologies—IoT, SCADA, MATLAB, PLC, and AI—enable real-time monitoring, remote control, optimal load forecasting, automatic reactive power management, and efficient energy distribution. These can reduce energy consumption by 15–25% [6,9].

IoT technologies continuously monitor real-time parameters like temperature, pressure, load, and operational time for each device. SCADA systems enable centralized control of energy flows, allowing real-time visualization, signaling, and historical analysis of technological blocks. MATLAB/Simulink provides a robust scientific platform for multi-parameter mathematical modeling and optimization, including energy balances, load variations, and predictive models for temperature-pressure coefficients. PLC (Programmable Logic Controller) technology automates energy control in production lines, optimizing device operation stages and load balancing. AI algorithms enable forecasting of energy consumption, fault prediction, and continuous system operation [10].

This study is being conducted at "Qo‘qon Oziq-Ovqat Invest" LLC. Based on the energy audit carried out in January 2025, the enterprise's energy consumption is as follows:

✓ Annual average electricity consumption – 617,284 kWh
✓ Major consumption zones – pumps, steam boilers, compressors
✓ Energy efficiency index – 62%
✓ Energy loss rate – 38%

According to 2024 studies of Uzbekistan's food industry, 65–75% of facilities experience thermal energy losses, especially from outdated boilers and steam lines. Electrical losses stem from high reactive power ($\cos\varphi < 0.85$) and worn-out motors.

At "Qo‘qon Oziq-Ovqat Invest" LLC, the 2023 audit showed that discrepancies between temperature, pressure, load, and electrical power led to a 37% decrease in energy efficiency.

The major types of energy losses in the food industry are listed in Table 1.

Table 1

Loss Type	Definition	Main Causes
Heat Loss	Heat escaping into the environment during boiler, drying, or cooking processes.	Poor insulation; outdated equipment
Electrical Loss	Active and reactive energy losses in electrical networks.	High resistance; low power factor ($\cos\varphi$)
Mechanical Loss	Frictional losses in pumps, compressors, and motors.	Lack of proper lubrication; operational errors
Pneumatic Loss	Loss due to air leakage or incorrect distribution in compressed-air systems.	Air leakage; excessive pressure
Hydraulic Loss	Pressure drops in water and steam pipes.	Unbalanced networks; bottlenecks
Idle Running	Equipment operating without load.	Lack of automation

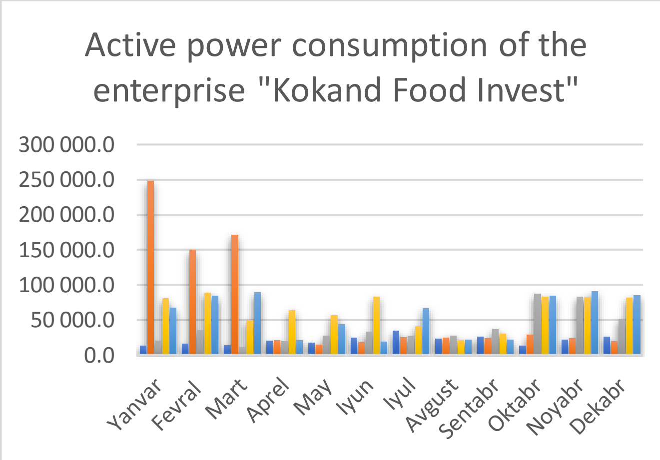

Figure 1. Dynamics of active power consumption of the enterprise

From the dynamics of the enterprise's active power consumption during 2020-2024, the highest energy consumption was observed in January 2021, which indicates a 32% increase compared to the lowest 5-year energy consumption indicator (770,420 kWh).

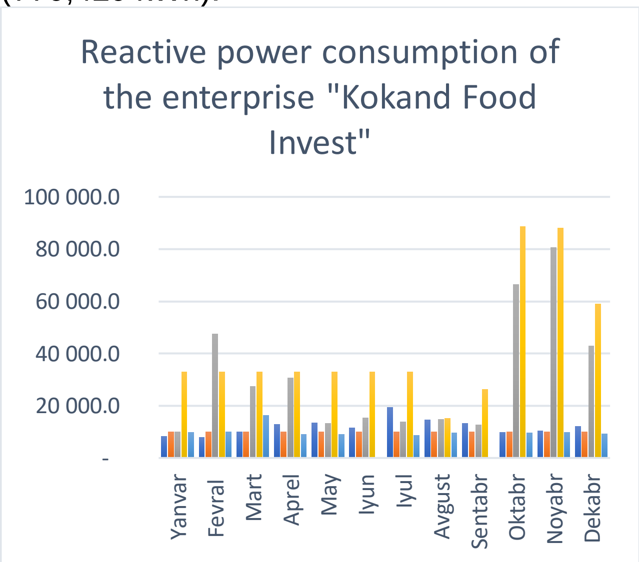

Figure 2. Dynamics of reactive power consumption of the enterprise

The diagram above shows that the largest amount of reactive power was consumed by month in 2023 at the production plant of the "Kokand Ozgot-Ovqat Invest".

Percentage expression of energy consumption by production stage at the Kokand Ozgot-Ovqat Invest LLC oil and fat plant.

1. Pressing – 29.7%. The highest energy consumption occurs during the pressing stage. The oil extraction process from cottonseed is carried out under high pressure, which requires the use of powerful electromechanical presses, hydraulic systems, and motors. This stage can be optimized through real-time load monitoring via SCADA, detection of pressing vibrations, and optimization through PID regulators.

2. Roasting – 22.8%. A large amount of thermal energy is required to raise the temperature to 100–140°C. Gas or electric boilers are used; therefore, thermographic control of heat losses is essential. IoT temperature sensors and an AI model for controlling steam consumption should be implemented.

3. Extraction – 20.2%. The process of extracting the remaining oil from cottonseed using a solvent (hexane) is energy-intensive. The cooling and evaporation processes consume a large amount of steam and electricity. An AI-based model that forecasts steam consumption should be developed to optimize the energy balance.

4. Refining – 9.1%. At this stage, insoluble impurities and acidic compounds are removed from the oil. Heating, mixing, and operation of pumps. Monitor pump loads and automatically manage load balancing through inverters.

5. Deodorization – 6.1%. Odors are removed using heat. A constant temperature of 180–220°C must be maintained, indicating high energy consumption. PID control, temperature sensors, and a steam distribution algorithm.

6. Separation – 3.7%. Solids are separated from the oil. Pumps and separators consume energy. Pump load can be optimized through vibration sensors.

7–10. Packaging, Auxiliary Equipment, Receiving (3.4%, 3.4%, 1.7%). These are relatively low-energy consumption stages. Their combined energy consumption is approximately 8.5%, resulting from lighting, motion sensors, and air compressors. In lighting systems, use LED lamps, motion sensors, and control ventilation loads via SCADA.

The energy performance indicators of food production enterprises are described based on mathematical modeling using the example of "Qo'qon Oziq-Ovqat Invest" LLC.

The purpose of the modeling is to develop mathematical formulas that express the relationship between energy consumption, losses, and production efficiency. This, in turn, creates opportunities for real-time monitoring and optimization.

1. Main energy indicators:

✓ W – Annual electricity consumption (kWh)

✓ Q – Annual thermal energy consumption (Gcal)

✓ P_{inst} – Total installed capacity (kW)

✓ P_{avg} –Average loaded capacity (kW)

✓ η – Efficiency coefficient

✓ $k_z = \frac{P_{\text{avg}}}{P_{\text{inst}}}$ – Load factor

✓ $C_{\text{sp}} = \frac{W}{V_{\text{prod}}}$ – Specific energy consumption per unit of production

2. General Mathematical Representation of the Energy Balance:

The energy balance can be expressed with the following equation:

$$W_{\text{input}} = W_{\text{prod}} + W_{\text{loss}} + W_{\text{aux}}$$

(1)

Where:

✓ W_{input}– Total incoming energy (kWh or Gcal);

✓ W_{prod} – Energy directly used for production;

✓ W_{loss} – Energy losses (thermal and electrical), such as insulation, transformation, and motor efficiency losses;

✓ W_{aux} – Energy for auxiliary systems (lighting, ventilation, compressed air, pumps).

Losses are calculated as follows:

$$W_{\text{loss}} = W_{\text{elecloss}} + W_{\text{heatloss}} + W_{\text{mechloss}}$$

(2)

3.Mathematical Model of Load Fluctuations:

To forecast load fluctuations using AI, the following model is applied:

$$P(t) = a_0 + a_1 \cdot \sin(\omega t) + a_2 \cdot \cos(\omega t) + a_3 \cdot T(t) + a_4 \cdot \Delta p(t) + \varepsilon(t) \qquad (3)$$

Where:

✓ $P(t)$ – Power consumption at time t;

✓ T –Temperature;

✓ $\Delta p(t)$– Pressure fluctuation;

✓ ω– Frequency of load fluctuation;

✓ $\varepsilon(t)$ – Prediction error in the AI model.

This model operates based on real-time sensor data built on the MATLAB/Simulink platform.

4. Energy Consumption and Efficiency Index per Product Unit:

The energy efficiency indicators relative to the volume of produced goods are described as follows:

$$ESI = \frac{W}{V_{\text{prod}}} \cdot \frac{1}{\eta}$$

(4)

This index reflects the energy consumption per unit of product and technological efficiency. A separate ESI value is calculated for each technological stage.

5. Heat Loss Calculation Formula (through pipelines):

$$q = \lambda \cdot \frac{T_{\text{int}} - T_{\text{ext}}}{\delta} \cdot A \cdot t$$

(5)

Where:

✓ λ – Thermal conductivity coefficient (material-dependent);

✓ $T_{\text{int}} - T_{\text{ext}}$ –Internal and external temperatures (°C);

✓ δ – Insulation thickness (m);

✓ A – Surface area (m²);

✓ t – Time (hours).

This formula is used to determine heat losses in thermal pipelines, and to optimize them, an AI-based insulation control algorithm integrated with a PID controller is developed.

6. AI-Based Automatic Control Model:The automatic control model using Artificial Intelligence operates in the following sequence:

1. Real-time data is collected via sensors.
2. The AI module forecasts load and efficiency using regression or neural network models.
3. A continuous control signal is sent via the PLC/SCADA system.
4. Each device (pump, motor, boiler) operates in accordance with its optimal mode.

7. Complex Integrated Mathematical Model:The generalized model representing energy efficiency is proposed as:

$$EFF_{\text{total}} = \frac{\sum_{i=1}^{n}(\eta_i \cdot P_{\text{useful}_i})}{\sum_{i=1}^{n} P_{\text{input}_i}}$$

(6)

This model calculates energy efficiency based on the useful power (P_{useful}) and the total input energy (P_{input}) for each technological stage. Using this model, the overall efficiency of the production process is evaluated in a mathematically grounded manner.

The plant's electrical, thermal, compressed air, and auxiliary energy systems are interconnected and form a complex structure. The main load is represented by technological lines that cover the stages of oil and fat production: pressing, roasting, extraction, refining, deodorization, separation, and packaging.

Model algorithms are developed based on the Newton-Raphson iterative method and Taylor series**.** In real-time, the following parameters are transmitted by IoT devices:

✓ Electric current and voltage: I(t),U(t)
✓ Load and rotational speed: E(t),n(t)
✓ Temperature: T(t)
✓ Pressure and steam flow rate: p(t),q(t)

The total energy flow is calculated as:

$$E(t) = U(t) \cdot I(t)$$

(7)

Mathematical Model – Newton-Raphson Iteration Structure:

Assume the energy balance equation in its initial state is given by:

$$f(E) = E(t) - \eta \cdot E_{\text{max}} = 0$$

(8)

Where η is the efficiency coefficient. This equation is solved by the Newton-Raphson method using the following iteration:

$$E_{n+1} = E_n - \frac{f(E_n)}{f'(E_n)}$$

(9)

If, $f(E) = E - \eta \cdot E_{\text{max}}$, than $f'(E) = 1$, thus:

$$E_{n+1} = \eta \cdot E_{\text{max}}$$

(10)

This means that with each iteration, the system approaches optimal power.

Prediction Based on Taylor Series for Temperature, Pressure, and Load: The forecast model for energy consumption in relation to temperature and pressure, based on Taylor series, is given by:

$$(t + \Delta t) = E(t) + \frac{dE}{dT} \cdot \Delta T + \frac{dE}{dp} \cdot \Delta p + \frac{dE}{dL} \cdot \Delta L$$

(11)

Using this model, the system is updated every 1–5 seconds, and the control algorithm adapts the system in an energy-efficient direction.

Comprehensive Energy Efficiency:

$$EFF_{\text{total}} = \frac{\sum_{i=1}^{n}(\eta_i \cdot P_{\text{useful}_i})}{\sum_{i=1}^{n} P_{\text{input}_i}}$$

(12)

This model offers the following advantages:

✓ Control based on new data every 1 second
✓ Automatic optimization of both reactive and active power
✓ Energy efficiency improvement of up to 20–30%
✓ Real load balancing in pumps, steam systems, fans, and motors

This mathematical model, developed based on Newton-Raphson and Taylor methods, enables forecasting, optimization, and real-time control of energy flows using real-time data collected through IoT sensors. The model is practically implemented by integrating it into MATLAB/Simulink, PLC, and SCADA systems. For "Qo'qon Invest" LLC, this approach allows for the development of a highly efficient AI-predictive control mechanism.

Conclusion:In general, real-time energy data collection enables enterprises to make data-driven decisions, increase operational efficiency, reduce costs, minimize risks, and contribute to sustainability goals. Given the increasing demand and cost of energy, this is a pressing issue for the food sector, which consumes large amounts of energy throughout the energy supply chain. Therefore, improving energy efficiency has become a crucial priority for the food industry.

In real-time data collection, the Internet of Things (IoT) is studied as a tool to enhance visibility, transparency, and awareness regarding various levels of energy consumption.

The proposed “General Model of Food Production and Processing Enterprises Based on the Internet of Things (IoT)” mainly consists of energy-consuming equipment (motors, heating, cooling, freezing devices, electrotechnical devices, lighting, storage, transport systems, etc.) and intelligent devices (microcontrollers, sensors, smart devices, automation equipment, smart monitoring boxes, relays, etc.). Its key distinction from similar existing models lies in the use of individually integrated intelligent modern devices that enable real-time data collection for energy consumption, control, and monitoring.

The model developed above presents the infrastructure of the Unified Energy System (UES) of food production and processing enterprises. It describes the energy consumption at various departments and equipment levels until the food product reaches its final form. The stages that involve converting raw materials into finished products (e.g., motors, compressors, and heaters) are the most energy-intensive.

Applying correct technologies for management and monitoring to reduce and optimize energy consumption at the above stages has a significant impact on improving the energy efficiency of the process.

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