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Original Article

Optimization of the Energy Monitoring System for Continuous-Process Industrial Enterprises

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Abstract: In the context of growing demand for efficiency, resilience, and sustainability in industrial energy usage, optimizing monitoring systems has become a critical priority. This paper develops and tests a data-driven approach to enhance energy monitoring in continuous-process industries, with a case study of a large-scale water supply enterprise in the Khorezm region of Uzbekistan. The proposed methodology integrates statistical distribution analysis, correlation mapping, and logical process modeling to capture both quantitative relationships and the physical dynamics of operations. Unlike traditional systems that rely on isolated parameters or manual interpretation, the new model embeds process logic into digital platforms, thereby reducing human dependency, minimizing error, and improving response time. The results demonstrate that the modular framework enables more accurate identification of key parameter interdependencies, supports predictive forecasting of energy consumption, and allows for real-time adjustment through ensemble machine learning submodules. In the water supply case, the system successfully differentiated between operational and idle energy usage, optimized pump loads, and provided early detection of anomalies. These improvements translate into enhanced energy efficiency, reduced operational costs, and greater reliability of supply. The study concludes that integrating physical process logic with statistical modeling not only improves monitoring accuracy but also supports the deployment of digital twins and adaptive control systems aligned with Industry 4.0. Policy implications highlight the potential for broader adoption of such models across industrial sectors, particularly in contexts where energy sustainability and infrastructure resilience are national priorities. This approach offers a scalable pathway toward smarter, more sustainable industrial energy management.

Keywords: Energy Monitoring Systems; Continuous-Process Industries; Digital Twin Integration; Industrial Energy Efficiency.

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1. Introduction

In the era of Industry 4.0, energy monitoring systems have become indispensable tools for enhancing the operational efficiency and sustainability of industrial enterprises, particularly those operating under continuous production regimes (Alarcón et al., 2021; Meng et al., 2018; Nota et al., 2020). These systems enable real-time tracking of energy consumption, identification of inefficiencies, and decision-making support to ensure optimal performance. According to the International Energy Agency (IEA), industrial sectors account for nearly 38% of global final energy use, highlighting the critical importance of effective energy management systems in achieving energy efficiency goals (Tian et al., 2018). Despite their increasing deployment, conventional energy monitoring systems often suffer from several limitations. One of the most significant shortcomings lies in their inability to preserve the physical causality between observed parameters. Many monitoring frameworks primarily rely on statistical or empirical data analyses without integrating the underlying process logic, which can lead to the misinterpretation of system behavior (Van de Graaf, 2014). For example, energy consumption trends may appear stable even when production activities are halted, an issue that indicates a failure to capture the real-time operational context of the equipment or system being monitored.

Furthermore, many current implementations depend heavily on manual interpretation by human operators. While expert oversight is crucial, it introduces subjectivity and slows response times, especially in complex, high-throughput environments. Human-driven decision-making is also prone to error when confronting multivariate and nonlinear parameter relationships, which are often encountered in continuous-process industries such as petrochemicals, metallurgy, and water treatment facilities (Moreira et al., 2020). To overcome these limitations, there is a growing focus on data-driven digital models that incorporate both statistical analysis and domain-specific process knowledge. This hybrid modeling approach allows for more accurate diagnostics, fault detection, and system optimization by preserving physical meaning and logic in parameter interactions (Madakam et al., 2015). The integration of such models into energy monitoring systems is not only technologically feasible but is increasingly supported by advancements in machine learning, IoT (Internet of Things) devices, and edge computing, which together enable dynamic, intelligent energy management strategies (Rogge et al., 2018).

This paper contributes to the field by presenting a structured approach to modeling the physical and statistical interrelations of process parameters in an industrial setting. As a case study, we analyze the technological process of a large-scale water supply enterprise in the Khorezm region of Uzbekistan. The enterprise represents a critical infrastructure component, supplying water to both residential and industrial consumers, including the Navoi Mining and Metallurgical Combinat (NMMC). The model developed in this research aims to improve the accuracy, responsiveness, and interpretability of energy monitoring systems in such enterprises by integrating Gaussian distribution assessments, correlation analyses, and technological logic modeling into a unified framework.

2. Literature Review

Energy monitoring has become a critical component in improving operational efficiency and sustainability in industrial enterprises (Embergenov, 2023; Herce et al., 2021; Prashar, 2019). With growing global energy demands and the pressure to reduce carbon emissions, many industries have adopted digital monitoring systems to track consumption and identify inefficiencies in real time. However, the literature reveals that while many monitoring systems are widely implemented, they often lack analytical depth and contextual accuracy when applied to complex industrial processes. Several studies highlight the limitations of traditional energy monitoring systems. For example, Kampelis et al. (2020) reviewed decision support systems for industrial energy management and found that most existing models do not integrate the physical dynamics of the monitored processes, resulting in suboptimal decisions and missed efficiency gains (Tian et al., 2018). Similarly, Tian et al. (2018) emphasized that statistical prediction models such as artificial neural networks (ANNs) and support vector machines (SVMs) often lack interpretability, making them difficult to apply in real-time industrial settings where physical causality must be preserved (Van de Graaf, 2014).

Recent advances have aimed to bridge the gap between data-driven methods and process-level understanding. Hybrid models that combine statistical tools with domain-specific knowledge have been proposed to enhance prediction accuracy and system transparency. Tian et al. (2018) introduced a decision-making model for industrial energy systems that leverages both machine learning and physical process parameters, showing improved reliability and control (Moreira et al., 2020). This aligns with the approach presented in the current study, which uses a Gaussian distribution and correlation analysis in tandem with technological logic to model interdependencies among system variables. Moreover, the adoption of digital twins and SCADA-integrated architectures is gaining traction in the industrial automation domain. Digital twins provide real-time virtual representations of physical systems, allowing for continuous simulation, prediction, and optimization of operational states. Madakam et al. (2015) underscore the role of the Internet of Things (IoT) and digital infrastructure in enabling such intelligent frameworks. In this context, physical modeling becomes essential to ensure that the digital twin reflects the true behavior of the physical process (Bao et al., 2019; Jiang et al., 2021; Rasheed et al., 2020; Stary et al., 2022).

Another area of focus in the literature is the modularization of system architecture. Modular energy monitoring frameworks allow for component-level diagnostics and localized optimization, enabling scalable implementation across multiple sectors. The modular approach also supports ensemble learning techniques, which improve robustness by combining outputs from multiple predictive models. Despite these advancements, challenges remain, particularly in integrating laboratory and sensor-based data streams, managing noisy or incomplete datasets, and automating adaptive responses. This paper contributes to addressing these challenges by proposing a logically structured, physically grounded, and statistically verified model for real-time energy monitoring in a water supply enterprise, a model that can be generalized to other continuous-process industries.

3. Materials and Methods

This study was conducted using real-world operational data collected from a large-scale water supply enterprise located in the Khorezm region of Uzbekistan. The facility operates in a continuous mode and provides water to residential areas, Zarafshan city, and the Navoi Mining and Metallurgical Combinat (NMMC). The dataset includes both digital sensor readings and daily laboratory measurements related to raw water and treated water parameters such as temperature (T), turbidity (W1, W2), viscosity (K), flow volumes (V1, V2, V3), and reagent dosage (m), along with environmental conditions like ambient temperature. A Gaussian distribution analysis was initially performed to validate the reliability and distribution of the recorded parameters. Following this, a correlation matrix was developed to identify interdependencies among variables, which were then structured into a physically meaningful process model based on the enterprise's technological flow diagram. The logical structure of the process was reconstructed using flow analysis, highlighting how environmental and operational factors interact within the system. All statistical computations and visualizations were performed using Python libraries, including NumPy, pandas, and seaborn, ensuring reproducibility and transparency in model development.

4. Results

Currently, existing energy monitoring systems are widely used. Alongside their efficiency, these existing systems also reveal several shortcomings. In particular, the analysis of the interrelation between parameters is still carried out by humans based on their scientific experience, using the results provided by digital systems. Translating these processes into computer language requires a logical connection function of the identified parameters based on the existing technological process. These processes have been implemented using the example of a water supply enterprise, where the average annual electricity consumption of the enterprise amounts to 80,599,925 kWh. This enterprise is in the Khorezm region and supplies water from the Amu Darya River to the rural population of the area, the city of Zarafshan, and the Navoi Mining and Metallurgical Combined (NMMC).

Table 1. Descriptive Statistics of Key Process Parameters in Water Supply Enterprise

	Mean	Median	Mode	Sum
EE	220210.9743	210240.0	197144.0	58677259.0
m	142.3679	130.0	124.0	3787098.0
W2	30.0142	19.0	13.42	7973.76
T2	18.0556	18.0	18.0	4802.8
K	1.6487	1.64	1.64	438.56
V3	2697.6541	2260.0	2250.0	718572.0
t	1.6631	1.7	1.7	442.39
V2	217716.0376	208216.0	203824.0	57907469.0
V1	289812.7895	280812.0	280000.0	77190599.0
h	6.4746	6.423	6.18	1722.13

Table 1 presents the descriptive statistics of the key process parameters monitored in the water supply enterprise. Energy expenditure (EE) shows a high mean value of 220,210.97, with the median (210,240.0) and mode (197,144.0) indicating a slightly right-skewed distribution. This suggests that while most energy consumption values cluster around 200,000–210,000, occasional peaks elevate the average, reflecting periods of high demand or operational intensity. The water mass flow rate (m) has a mean of 142.37 and a median of 130.0, showing a moderate spread and alignment between central tendency measures, which indicates relatively stable flow dynamics across operations. Water parameter W2 records a mean of 30.01, with a much lower median (19.0) and mode (13.42), highlighting significant variability and the presence of higher-value outliers. By contrast, water temperature (T2) demonstrates remarkable stability, with mean, median, and mode values closely aligned at approximately 18.0, suggesting consistent environmental or operational control.

The coefficient K (mean 1.65) and time factor t (mean 1.66) also reflect consistency, with minimal variation between mean, median, and mode, implying stable operational cycles. Meanwhile, velocity-related parameters show distinct patterns: V3 has a mean of 2,697.65, higher than its median (2,260.0) and mode (2,250.0), pointing to occasional spikes in water velocity. Similarly, V2 and V1 register very large mean values of 217,716.04 and 289,812.79, respectively, with medians and modes slightly lower, reflecting the heavy-volume flows typical of large-scale water supply enterprises. Lastly, the water level (h) is relatively stable, with a mean of 6.47 and a median of 6.42, indicating minimal fluctuation. Overall, these descriptive statistics suggest that while most parameters remain stable and predictable, energy expenditure and certain flow parameters (W2, V3, V2, V1) exhibit variability that warrants closer monitoring and advanced predictive modeling to optimize efficiency.

Here, K – viscosity of the raw water [mg/l]; T – temperature of the raw water [^{0}C]; W1 – turbidity level of the raw water [mg/l]; W2 – turbidity level of the treated water [mg/l]; V1 – volume of incoming raw water [m³]; V2 – volume of treated water [m³]; V3 – volume of discharged sludge water [m³]; m – amount of reagent added to raw water [kg]; Ambient T – air temperature [^{0}C]. Based on the technological process of the enterprise, modeling is planned to use the data presented in Figure 1, with subsequent stages aimed at obtaining results. At the initial stage, the objective is to optimize the enterprise's monitoring system. Accordingly, we proceed with the analysis of the primary data. In this process, we assess the reliability of the data using the Gaussian distribution law (Figure 1).

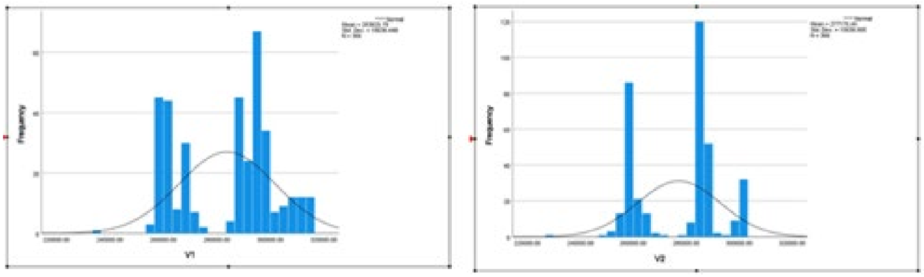

Figure 1. Gaussian distribution

The parameters derived from the Gaussian distribution suggest that meaningful results can be obtained from these data. Relying on this information, we examine the interaction characteristics among the variables. To perform this analysis, the correlation analysis method is applied, as shown in Table 2.

Table 2. Result of Correlation Analysis

	h	V1	V2	t	V3	K	m	W2	EE	tT0	W1
h	1.0	0.512	0.435	0.504	0.593	-0.556	0.257	-0.441	0.417	0.463	0.513
V1	0.512	1.0	0.982	0.762	0.578	-0.29	0.46	-0.239	0.93	0.711	0.46
V2	0.435	0.982	1.0	0.705	0.448	-0.253	0.404	-0.162	0.942	0.659	0.357
t	0.504	0.762	0.705	1.0	0.662	-0.135	0.42	-0.286	0.682	0.95	0.508
V3	0.593	0.578	0.448	0.662	1.0	-0.159	0.596	0.575	0.43	0.643	0.852
K	-0.556	-0.29	-0.253	-0.135	-0.159	1.0	0.121	0.575	-0.251	-0.071	-0.087
m	0.257	0.46	0.404	0.42	0.596	0.121	1.0	-0.003	0.424	0.417	0.638
W2	-0.441	-0.239	-0.162	-0.286	0.575	0.575	-0.003	1.0	-0.11	-0.237	-0.243
EE	0.417	0.93	0.942	0.682	0.43	-0.251	0.424	-0.11	1.0	0.64	0.327
tT0	0.463	0.711	0.659	0.95	0.643	-0.071	0.417	-0.237	0.64	1.0	0.496
W1	0.513	0.46	0.357	0.508	0.852	-0.087	0.638	-0.243	0.327	0.496	1.0

Table 2 presents the correlation coefficients among the principal process parameters in the water supply enterprise. Several strong and significant relationships emerge, particularly among the core operational variables. A near-perfect correlation is observed between V1 and V2 (r = 0.982), indicating that these two velocity parameters are almost directly proportional, and changes in one can be reliably used to predict changes in the other. Similarly, EE (energy expenditure) shows very strong positive correlations with both V1 (r = 0.93) and V2 (r = 0.942), suggesting that energy consumption is heavily dependent on flow velocity and load levels. This reinforces the operational understanding that higher pumping volumes directly drive energy use. Another notable relationship is between t (time factor) and tT0 (temperature-related time parameter), with an almost perfect correlation (r = 0.95). This reflects a high level of synchronization between temporal process variables, which is essential for predictive modeling and scheduling. Strong positive correlations are also observed between V3 and W1 (r = 0.852), indicating that variations in water velocity at point 3 are closely tied to water volume or pressure at point 1.

Additionally, V3 shows moderate-to-strong positive associations with h (r = 0.593), t (r = 0.662), and m (r = 0.596), highlighting its central role as a linking parameter across multiple process domains. On the other hand, the coefficient K exhibits negative correlations with key variables, particularly h (r = -0.556), V1 (r = -0.29), V2 (r = -0.253), and EE (r = -0.251). This suggests that higher K values may act as a balancing or constraining factor, potentially representing resistance or efficiency loss in the system. Similarly, W2 correlates negatively with h (r = -0.441) and several energy-related variables, which could imply that this parameter captures counteracting effects within the system's dynamics. Overall, the correlation matrix highlights three clusters of interdependent variables: (i) Energy–velocity cluster (EE, V1, V2), driving system efficiency and energy demand. (ii) Temporal cluster (t, tT0), governing synchronization and process stability. (iii) Velocity–pressure cluster (V3, W1, h, m), reflecting operational load dynamics. These relationships provide critical input for model development, enabling the design of monitoring frameworks that move beyond isolated parameters toward integrated, context-aware predictive systems.

Nowadays, direct analyses are carried out based on this method; however, in many cases, these analyses lose their physical significance. For example, the system may indicate electricity consumption like previous levels even when the enterprise is not producing any output. This suggests that the model has lost its physical meaning. Therefore, it is essential to incorporate physical significance into monitoring algorithms. To accurately reflect this physical aspect, it is advisable to separately examine the technological process. If we look at the technological process of the water supply enterprise under consideration, the enterprise receives water from the Amu Darya River through a natural flow into a 400 m^3 reservoir. The collected water is then pumped into four subsequent reservoirs using pumps. In these reservoirs, special reagents are added to the water, converting it into technical water, which is then supplied to Zarafshan city under high pressure (Figure 4). In this process, observation parameters are obtained directly from digital systems, while laboratory data—which are not available in digital form—are provided daily.

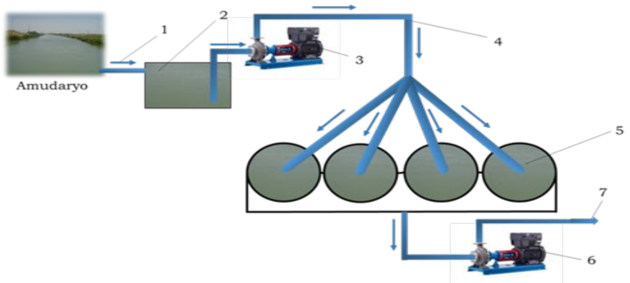

Figure 2. Technological Process of the Enterprise

Note: 1. Water flow; 2. Natural water intake reservoir; 3. Water intake pump; 4. Water pipeline; 5. Water treatment reservoir; 6. Water distribution pump; 7. Water distribution pipeline

The establishment of optimized digital systems within the process is carried out through the analysis of the interrelation between system parameters (Figure3). In this case, weather conditions influence the water level in the river, and the higher the water level, the lower the load on the pumps responsible for transferring water to the next stage, enabling a greater volume of water to be delivered. A certain portion of the incoming raw water is supplied to rural residents for seasonal irrigation (from March 15 to October 15) and drinking purposes. The remaining volume is directed to a special water treatment reservoir, where the water parameters are identified, and reagents are added accordingly. Following this, the water in the reservoir separates into two streams: sludge water and purified technical water. The sludge water is discharged into nearby ponds, while the purified technical water is delivered to the city of Zarafshan. During the delivery of the clean water, its turbidity level is also measured and monitored.

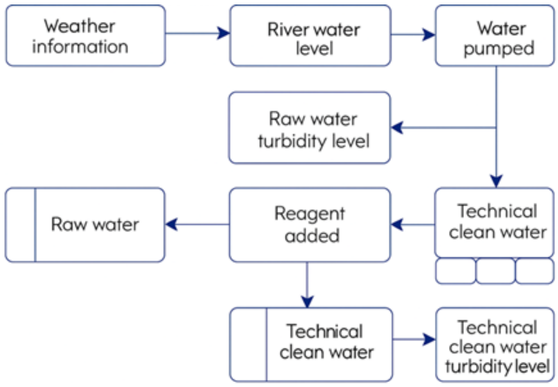

Figure 3. Process of Analyzing Interrelations

The modeling of interdependencies among the data based on the above-described technological process is carried out as shown in Figure 4. Specifically, weather information influences the variable h, with a correlation coefficient of 0.461. Additionally, h is affected by the raw water parameters: temperature (t), viscosity (K), and turbidity level (W1). In turn, h impacts the volume of incoming water (V1) with a coefficient of 0.512, while t and K also directly affect V1. The variable V1 influences V2 (clean water) and V3 (sludge water) with coefficients of 0.982 and 0.578, respectively. The amount of reagent added (m) for water purification is determined solely by the turbidity level W1 of the incoming water. The variable m subsequently affects V3 with a coefficient of 0.59. In addition, m is influenced by weather information, water level (h), and the raw water parameters: temperature (t), viscosity (K), and turbidity level (W1)—with respective coefficients of 0.643, 0.593, 0.662, -0.621, and 0.852. Furthermore, water parameters t and K impact the volume of purified technical water (V2) with correlation coefficients of 0.705 and -0.54, respectively. This entire process is modeled in a logically structured sequence.

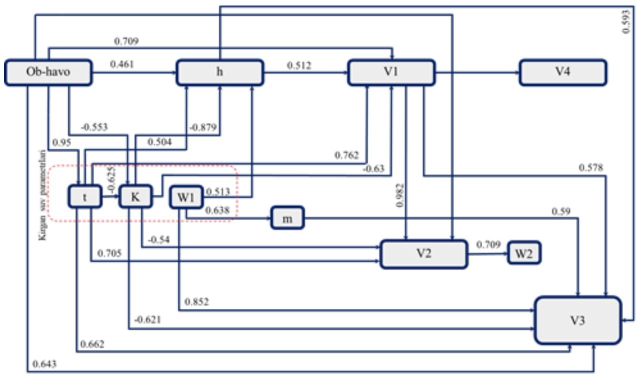

Figure 4. Modeling of Interrelations

In previous systems, either a unified model was created for all parameters or human intervention was required. This, in turn, led to excessive time consumption and additional costs. In contrast, our model establishes the interrelations of each parameter separately, in subsequent stages, particularly in modeling tasks based on ensemble methods, are significantly simplifies the process.

5. Discussion

The findings of this study highlight significant limitations in traditional energy monitoring models currently employed in continuous-process industrial enterprises. Most legacy systems adopt either a generic one-size-fits-all approach, which fails to accommodate the unique operational characteristics of different technological processes, or they rely on manual interpretation of data outputs. While such systems may provide baseline functionality, they often result in delayed response times, increased labor costs, and a higher potential for human error, especially in complex industrial settings with multivariable interdependencies. Moreover, these traditional models tend to treat each parameter in isolation or assume linear relationships that do not reflect the nonlinear dynamics and physical constraints of real industrial processes. For instance, in the water supply enterprise examined, traditional systems may continue to indicate high energy consumption levels regardless of whether water is being treated or transported, due to a lack of context-aware logic in the system's architecture. This disconnects between data interpretation and physical process behavior undermines the credibility and utility of the monitoring system.

The proposed model, by contrast, introduces a modular framework where parameter interrelations are established based on both statistical correlations (e.g., through Gaussian and correlation analysis) and their technological significance. This structure facilitates the development of models that are not only data-driven but also grounded in process logic, enabling the system to discern between meaningful operational changes and background noise or anomalies. This approach lays the foundation for scalable implementation of ensemble machine learning models, where different submodules can specialize in forecasting specific outcomes such as reagent usage, water turbidity levels, or pump load optimization. Such modularity allows for incremental training, real-time adjustment, and seamless integration with digital twin platforms—virtual replicas of physical systems that can simulate and predict system behavior under varying conditions.

Another key advantage of the proposed model is its readiness for integration into adaptive control systems, where machine learning algorithms or rule-based decision systems can autonomously adjust operational parameters to optimize performance. This not only improves energy efficiency and resource allocation but also enhances resilience and system adaptability in the face of changing environmental conditions or demand profiles. In addition, the modeling framework contributes to explainable AI (XAI) practices in industrial settings. Because the system retains a clear logic-based structure rooted in physical relationships, it enables operators and engineers to interpret and validate the model's outputs an increasingly important requirement in critical infrastructure monitoring and regulation compliance. In sum, the proposed modeling approach addresses several critical gaps in conventional systems by: Embedding physical process logic alongside statistical modeling; Enabling modular and ensemble learning capabilities; Supporting real-time optimization and predictive maintenance; and aligning with digital transformation goals in industrial sectors. These enhancements collectively contribute to building smarter, more sustainable, and more efficient energy monitoring infrastructures suited for the demands of Industry 4.0 and beyond.

6. Conclusions

This study demonstrates that integrating physical process logic with statistical and correlation-based analysis can significantly enhance the effectiveness of energy monitoring systems in continuous-process industries. Using a water supply enterprise as a case study, key parameter relationships were identified and modeled to reflect real operational dynamics. The approach enables more accurate monitoring, supports predictive and automated control, and lays the foundation for integration with advanced technologies like digital twins and machine learning. Future work will focus on real-time implementation and expansion to other industrial sectors.

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