Automation of Water Treatment Facilities with Adaptive KPI Integration within a Sustainable Development Strategy

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Abstract: This paper is devoted to the development of engineering methods for integrating a Sustainable Development strategy into automated process control systems of industrial enterprises. The relevance of the study is driven by the need to shift from conventional variables stabilization systems to adaptive control models capable of dynamically responding to environmental and energy-related challenges. An original approach is proposed in which Key Performance Indicators (KPIs) are transformed from reporting tools into dynamic setpoints for local control loops. The authors develop a dynamic model for KPI selection and adjustment based on an integral sustainability compliance index, enabling real-time balancing between environmental requirements – such as wastewater treatment quality indicators – and economic efficiency. The adaptive behavior of the model is achieved through time-dependent weighting coefficients, which are automatically adjusted according to the proximity of monitored process variables to regulatory discharge limits, thereby prioritizing environmental safety under critical operating conditions. Special attention is given to an object-oriented approach that ensures the adaptation of strategic sustainability goals to specific technological units of wastewater treatment facilities. The paper also analyzes the impact of an enterprise's digital maturity level on the reliability of KPI calculation and proposes the use of soft sensors for forecasting complex environmental variables under conditions of limited instrumentation. The effectiveness of the proposed solutions is validated through simulation modeling of wastewater treatment processes at a dairy processing plant. The results demonstrate that the implementation of the dynamic control model reduces specific energy consumption by 28.1% while fully complying with established environmental regulations. The practical significance of the study lies in the creation of an algorithmic foundation for modernizing industrial process automation systems, enabling the integration of technological reliability with the requirements of the global green transition.

1 INTRODUCTION

The current stage of industrial automation development is characterized by a transition from conventional systems focused on stabilizing technological variables to intelligent control systems based on global Sustainable Development strategies [1]. Under conditions of the ongoing energy crisis and the tightening of environmental regulations – particularly ESG requirements – industrial facilities such as wastewater treatment systems require not only the maintenance of predefined operating regimes but also real-time dynamic process optimization [2].

KPIs serve as a fundamental tool for assessing the efficiency of such systems. However, from the perspective of automation engineering, KPIs can no longer be regarded solely as reporting metrics. Instead, they must be transformed into state variables and dynamic setpoints that directly influence the control logic of Programmable Logic Controllers (PLCs) and Supervisory Control and Data Acquisition (SCADA) systems.

Traditional automated process control systems (APCS) are primarily focused on technical reliability and compliance with maximum permissible concentrations (MPC) of pollutants. However, they often lack the flexibility required for instantaneous adaptation to changes in an enterprise's strategic priorities, such as switching to a maximum energy-saving mode under low-load conditions or prioritizing treatment quality during shock discharges. The absence of mechanisms enabling a dynamic linkage between sustainable development objectives and automatic control algorithms creates a gap between business-level planning and the actual technological process.

Industrial wastewater treatment in the food industry is a complex, nonlinear, and high-inertia process with variable influent loads. Key stages – mechanical sedimentation, reagent treatment, and biological degradation – require precise coordination of blowers, pumps, and dosing systems. Maintaining the balance between aeration and pollutant concentration is critical. Consequently, modern facilities demand predictive control, where automation decisions directly align with resource efficiency and environmental safety targets.

The aim of this study is to develop an engineering approach to the design of automation systems that employ a dynamic model for KPI selection and adjustment as the primary factor in shaping control actions. This approach enables the implementation of a "green" development trajectory directly at the level of actuating mechanisms. The object of the research comprises automated control processes of water treatment facilities (with dairy processing plants used as a case study) operating under conditions of variable influent flows and environmental constraints. The subject of the research includes methods and algorithms for integrating dynamic KPIs into automatic control loops in order to realize a sustainable development strategy.

2 LITERATURE REVIEW

Sustainable automation involves the implementation of automated solutions aimed at minimizing environmental impact, ensuring efficient resource utilization, and maintaining long-term ecological stability. In the field of water treatment, this approach is realized through the integration of environmental and energy-related KPIs [3] – in particular, treatment quality indicators and energy intensity metrics [4] – with technological process variables [5]. Given the complexity and nonlinearity of wastewater treatment processes [6], control systems must be based on dynamic models capable of adapting to changing operating conditions and fluctuating load regimes.

Modern computational and intelligent models in water treatment enable KPI monitoring [7], KPI forecasting [8],[9], and effective fault detection both related and unrelated to key performance indicators, thereby transforming raw process data into strategic decision-making tools for improving energy efficiency and process stability. Recent studies focus on control system architectures for wastewater treatment plants that emphasize multi-objective optimization of treatment quality and operational costs. In particular, works [10]–[12] propose multilevel and multi-objective architectures combining benchmarking models, metaheuristic optimization algorithms, and intelligent predictive models to adapt to variable loading conditions. A separate research direction is represented by economically oriented control architectures [13], which integrate predictive control with economic performance criteria to minimize energy consumption while ensuring compliance with regulatory wastewater quality standards.

In wastewater treatment facilities, actual KPIs are typically calculated based on direct measurements, while accurate estimation of complex indicators relies on soft-sensor models [14], [15]. Adaptive soft-sensor architectures enable the simultaneous prediction of multiple hard-to-measure variables, assessment of their reliability, and enhancement of the digital maturity of wastewater treatment control systems. A general review indicates that the evolution of soft sensors from mechanistic models to modern machine learning–based approaches reduces dependence on physical instrumentation and improves the reliability and efficiency of online monitoring [16].

Simulation scenarios demonstrate stable operation under nominal conditions and energy consumption optimization when dynamic KPIs are employed [13], [17]. The application of KPIs as control variables confirms their effectiveness in supporting sustainable development objectives, while the integration of digital twins and soft sensors enhances system adaptability. At the same time, international case studies report significant economic and environmental benefits associated with such approaches [17], [18].

3 METHODS

To address the problem of efficient control of water treatment facilities within a sustainable development strategy, an approach based on the decomposition of a complex technological process into individual software objects is proposed. The complexity of such facilities lies in their high degree of heterogeneity; therefore, an object-oriented approach enables the adaptation of a global KPI strategy to the specific characteristics of each technological unit [19].

Within the proposed architecture, each unit of the wastewater treatment plant is considered an autonomous software object with its own set of local KPIs, which are integrated into a unified enterprise-level hierarchy:

1) Primary sedimentation unit: this object is oriented toward the KPIs Throughput capacity and Suspended solids removal efficiency, where the control algorithm adapts the influent flow rate according to the current hydraulic load;
2) An eration tank unit: the key performance metrics include Nitrification level and Aeration energy intensity; at this stage, the control algorithm operates with the most dynamic setpoints;
3) Sludge dewatering unit: control is focused on the KPI Minimum flocculant consumption while achieving the specified sludge cake moisture content.

Such decomposition enables the development of flexible control systems: when a single unit is modernized (for example, through the installation of a more accurate ammonium sensor), only the corresponding local object-oriented module requires adjustment, while the overall structure of strategic control remains unchanged. The engineering advantage of this approach lies in the simplification of PLC programming, allowing validated code blocks to be replicated across different process units while preserving a unified sustainable development trajectory for the entire facility.

3.1 KPIs as Dynamic Setpoints in Automated Control Loops

In classical automation systems, the setpoints of local controllers are static or change according to a rigid predefined schedule. However, a sustainable development strategy requires flexibility: the system must be capable of autonomously determining target variable values based on current priorities (environmental performance versus energy efficiency). In this context, KPIs function as dynamic external reference signals for automated process control systems.

To transition from the conceptual foundations of sustainable development to practical automation algorithms, it is necessary to systematize the measurable variables of the technological process. Table 1 presents an extended classification of KPIs, in which each indicator is treated not as a static reporting metric but as an active variable within the control loop of wastewater treatment automation systems.

Table 1: Classification of KPIs as control variables for water treatment automation systems.

Category	KPI (Source, Unit)	Variable Type in APCS	Role in Dynamic Model
1. Technical (Operational)	Flow rate (Flowmeter, m^3/h)	Input variable	System load definition
	System pressure (Pressure sensor, Pa)	Controll variable	Hydraulic regime maintenance
	Tank level (Level sensor, m)	Constraint	Emergency prevention
2. Environmental (Sustainable)	Chemical or biochemical oxygen demand – COD, BOD (Analyzer or Soft sensor, mg/dm^3)	Target setpoint	Effluent quality indicator
	Dissolved oxygen concentration (Oximeter, mg/L)	Intermedi-ate setpoint	Control of aeration intensity
	pH value (pH meter)	Hard constraint	Reagent dosage correction
3. Energy (Economic)	Specific energy consumption (Power-analyzer kWh/m^3)	Objective function	Cost minimization
	Reagent consumption (Dosing pump L/m^3)	Cost variable	Operational optimization

The analysis of Table 1 indicates that the effectiveness of implementing a Sustainable Development strategy directly depends on the ability of automated process control systems to integrate heterogeneous metrics into a unified decision-making framework. In contrast to traditional control approaches, where priority is given exclusively to technical variables, the proposed approach is based on multi-criteria optimization.

The central element of the proposed engineering solution is the calculation of an integral Sustainable Development Compliance Index (I_{sd}). This index enables a quantitative assessment of deviations between the current operating mode of the facility and an ideal state defined by the enterprise's strategic objectives. The mathematical model of the index is expressed as follows:

$$I_{sd}(t) = \sum_{i=1}^{n} w_i(t) \frac{KPI_i^{fact}(t) - KPI_i^{target}(t)}{KPI_i^{max}(t) - KPI_i^{min}(t)}, \quad (1)$$

where:

1) $KPI_i^{fact}(t)$ – denotes the actual value of the i-th indicator obtained from instrumentation and control systems in real time;
2) $KPI_i^{target}(t)$ represents the target (reference) value of the indicator in accordance with the sustainable development strategy;
3) $KPI_i^{max}(t)$, $KPI_i^{min}(t)$ correspond to the maximum and minimum allowable values of the indicator, respectively;
4) $w_i(t)$ are dynamic weighting coefficients that determine the priority of a particular KPI at a given time instant.

The dynamic nature of the model is ensured by the adaptive adjustment of the weighting coefficient vectors $w_i(t)$. For example, when sensors detect a sharp increase in pollutant concentration at the influent (a change in Category 1 indicators), the algorithm automatically increases the weighting coefficients of environmental KPIs (Category 2). This results in an immediate recalculation of setpoints for actuating mechanisms, whereby the priority of effluent water quality exceeds that of energy efficiency indicators (Category 3).

Thus, the proposed model transforms the concept of sustainable development from a declarative framework into a level of direct algorithmic control of technological equipment. This enables the automation system not only to maintain process stability but also to function as a tool for dynamic balancing between economic feasibility and environmental responsibility of an industrial enterprise.

3.2 Development of a KPI-Based Control Architecture

For the practical implementation of a sustainable development strategy, a two-level control architecture is proposed. At the lower level, conventional PID controllers are employed to stabilize process variables, while the upper level is represented by a KPI-oriented supervisory controller that acts as a coordinator of objectives.

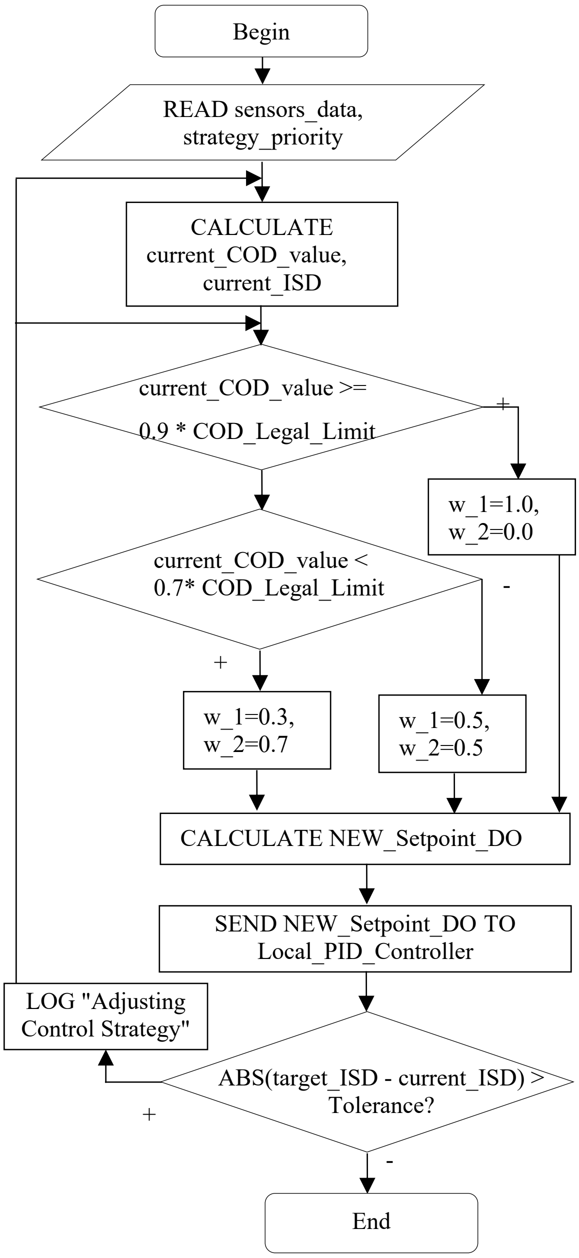

Figure 1: Algorithm of dynamic KPI control.

The key novelty of the approach lies in transforming strategic KPIs into dynamic reference signals for local control loops. This mechanism is illustrated using the example of the biological treatment process in an aeration tank (Figure 1). The proposed dynamic control algorithm is based on a continuous Data-to-Action processing loop implemented at the supervisory level of the automated process control system. The operational logic of the Dynamic KPI Control module consists of the sequential execution of four stages.

First, environmental performance indicators are evaluated using a mathematical soft-sensor model, which enables real-time estimation of COD without the delays inherent to laboratory-based analyses. Second, the algorithm performs adaptive adjustment of the weighting coefficients w_1 and w_2, which define the priority balance between environmental safety and energy conservation depending on the proximity of current process variables to regulatory discharge limits. At the third stage, the integral I_{sd} is calculated and used as the criterion for the optimization model. The final step involves the generation of a dynamic setpoint for the local PID controller of the aeration system, thereby ensuring the immediate translation of the enterprise's strategic objectives into physical operating variables of the equipment.

This approach enables the closure of the control loop based on KPIs, providing system flexibility under conditions of unstable influent loading.

The proposed hierarchical automation architecture (Figure 2) implements vertical integration of sustainable development strategic objectives into control loops through three interconnected levels. At the Field Level, primary data acquisition and physical execution of control commands are performed using the sensor infrastructure and actuating mechanisms, such as variable frequency drives.

The Control Level serves as an intelligent intermediate layer, where indirect estimations of environmental variables are generated using soft sensors and transmitted to the upper level, while PID control is implemented based on the received setpoints.

The highest level, the Management/Cloud Level, provides supervisory control, where the Dynamic KPI Control module dynamically recalculates controller setpoints based on monitoring of the sustainable development strategy, balancing environmental safety and energy efficiency objectives.

This closed-loop structure ensures continuous adaptation of the technological process to enterprise-level global KPIs, transforming the automation system into an active instrument for implementing environmental strategy.

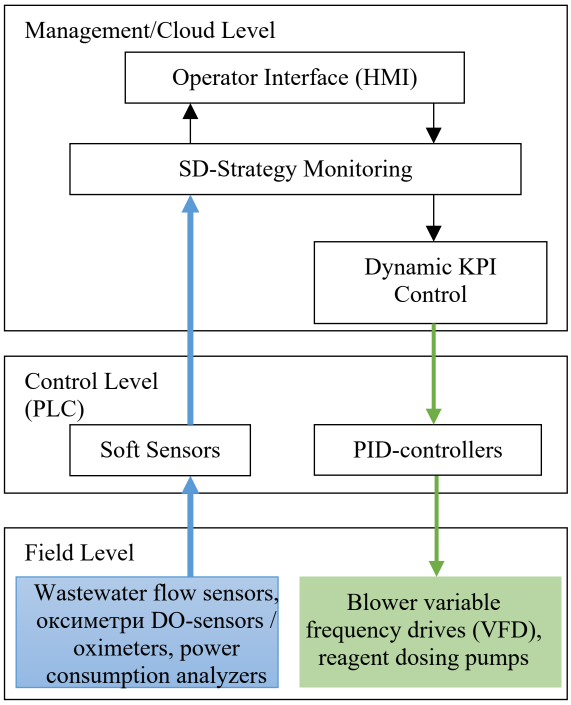

Figure 2: Hierarchical KPI-based control architecture for water.

3.3 Consideration of Digital Maturity of APCS

The effectiveness of the dynamic KPI model is directly constrained by the level of digital maturity of the technological facility. For automation engineers, this primarily refers to the availability, accuracy, and sampling resolution of data acquired from field devices.

Not all sustainable development indicators can be obtained directly from physical sensors in real time. Depending on the instrumentation level of the facility, KPIs can be classified into three levels of availability:

1) Direct KPIs (Direct Measurements) are based on data obtained from standard instrumentation such as flow meters, ammeters, and level sensors. They are used to calculate overall water or energy consumption and represent the most reliable data, forming the foundation of digital maturity (Levels 1–2);
2) Derived KPIs (Derived Metrics) are obtained through mathematical operations applied to direct measurements. An example is specific

energy consumption (kWh/m³). Such calculations require time synchronization of data from power analyzers and flow meters within a single PLC program cycle;

3) Soft sensor–based KPIs (Soft Sensors) rely on mathematical models (regression-based or neural network–based) that predict pollution indicators using indirect variables such as turbidity, electrical conductivity, pH, and aerator power consumption. These KPIs are used for complex environmental indicators (COD, BOD, nitrogen), where the installation of online analyzers is either economically infeasible or technically impractical. At facilities with a high level of digital maturity (Levels 4–5), these models are directly integrated into the SCADA system for dynamic setpoint generation.

To assess the feasibility of implementing the dynamic model at a specific facility, the use of an availability matrix (Table 2) is proposed. This matrix enables automation engineers to quickly identify bottlenecks in the instrumentation and control architecture and to plan the required deployment of virtual sensors.

As shown in Table 2, the environmental KPIs that are most critical for Sustainable Development (COD/BOD) exhibit the highest implementation complexity due to the high cost or technical difficulty of direct measurements. This supports the conclusion that, for enterprises with a medium level of digital maturity, the optimal approach is the deployment of soft sensors. Such solutions enable the acquisition of the data required for the dynamic model by leveraging existing low-complexity instrumentation (flow meters and power sensors), thereby significantly reducing the capital expenditures associated with upgrading automated process control systems.

Measurement accuracy within automation systems is of critical importance for "green" control strategies. In conventional APCS, a sensor error of up to 5% may be acceptable for maintaining tank levels; however, within a sustainable development framework, such an error can lead to incorrect activation of optimization algorithms. In this case, the system may excessively reduce power consumption under the assumption that environmental standards are being met, while in reality polluted wastewater is being discharged. Furthermore, insufficient reliability of energy-related KPIs prevents an objective assessment of the economic return on implemented energy efficiency measures.

To ensure the reliability of sustainable development KPIs, the APCS architecture must include dedicated data validation modules. The dynamic model algorithm should verify input data for value freezing, out-of-range conditions, and anomalous spikes before using them for setpoint recalculation.

Thus, the implementation of dynamic KPIs requires a balance between the available instrumentation infrastructure and the complexity of control algorithms. Facilities with low digital maturity should focus on simple energy-related KPIs, whereas the transition to comprehensive environmentally driven control is feasible only with the deployment of intelligent data analysis tools and soft sensors.

4 RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed control architecture, simulation modeling of the biological wastewater treatment process was performed based on a typical dairy processing plant. According to the initial data of the study, such facilities are characterized by high influent flow variability (with a coefficient of variation of up to 1.5) and significant concentrations of organic pollutants (COD in the range of 1500–4500 mg/dm³).

Table 2: Availability matrix of sustainable development KPIs in APCS.

Indicator (KPI)	Source / Instrument	Complexity	Engineering Notes
Flow rate	EM / Ultrasonic meter	Low	Baseline variable for most systems
Energy consump-tion	Smart Meter + PLC	Low	Requires integration of digital communication protocols
DO level	Optical / EC sensor	Medium	Needs regular cleaning & calibration
pH value	pH-electrode	Medium	Requires temperature compensation
COD / BOD (online)	Spectro-photometer	High	High cost; complex sample prep
COD (predicted)	Soft sensor (Model)	High	Model based on indirect variables
Nitrogen removal	Ion-selective electrode	High	Interference sensitive; high maintenance

The rationale for the comparative analysis is based on testing the hypothesis that transitioning from static setpoints to dynamic KPI-based control enables the implementation of a sustainable development strategy without major restructuring of the technological scheme. Two simulation scenarios were selected for analysis:

1) Scenario 1 (Baseline). A conventional automated process control system configured to maintain a constant dissolved oxygen concentration (DO = 2.5 mg/L) to ensure reliable oxidation under peak loading conditions;
2) Scenario 2 (Adaptive). Implementation of the dynamic model in which the DO setpoint is adjusted by a supervisory controller based on the calculated Sustainable Development Compliance Index (I_{sd}) and predicted COD values obtained via a soft sensor.

The simulation was conducted over a 24-hour time horizon, covering equipment cleaning cycles and peak production discharges. The results of the comparative analysis of technical and environmental performance indicators are presented in Table 3.

Analysis of the obtained data indicates that Scenario 2 provides a significant reduction in energy consumption (by 28.1%) by eliminating the effect of "excessive aeration" during periods of low load. Although the average COD concentration in the second scenario increased, it consistently remained below the established environmental limit (MPC = 100 mg/dm³), confirming the validity of the selected sustainable development strategy.

Table 3: Comparison of control strategy performance indicators.

Performance Metric	Scenario		Deviation
	1	2	
Average daily energy consumption, kWh	420	302	-28,1%
Specific energy intensity, kWh/m³	0,92	0,66	-28,3%
Average effluent COD concentration, mg/dm³	68	84	+23,5%
Maximum effluent COD value, mg/dm³	92	98	+6,5%
Reagent consumption for pH neutralization, L	45	34	-24,4%

The results demonstrate that the use of KPIs as dynamic setpoints enables the automation system to operate in a "smart compromise" mode between environmental safety and energy efficiency. The dynamic model allows equipment power to be adapted to the actual oxidation demand, which is particularly critical for food industry enterprises characterized by uneven operating schedules. Despite the overall reduction in aeration intensity, the system responds predictively to shock loads, maintaining wastewater variables within regulatory environmental limits.

Thus, practical recommendations for automation engineers can be formulated as follows:

1) Implementation of soft sensors. For facilities where real-time direct measurement of COD/BOD is economically infeasible, the use of regression-based models relying on power consumption and water flow data is recommended;
2) Priority configuration. When programming PLCs, environmental KPIs should be implemented as hard constraints that override energy-saving algorithms. Specifically, when COD approaches 90% of the maximum permissible concentration (MPC), energy optimization functions should be disabled in favor of intensified treatment;
3) Phased digitalization. The implementation of dynamic KPIs should begin with process units characterized by the highest energy consumption (aeration tanks, secondary pumping stations), followed by gradual expansion of the architecture to the entire facility.

5 CONCLUSIONS

This study demonstrates that the implementation of a sustainable development strategy at industrial facilities is feasible only if KPIs are transformed from static reporting indicators into dynamic state variables of automation systems. The proposed mathematical model, based on the calculation of an integral sustainability index, enables real-time balancing between environmental standards and energy efficiency through adaptive recalculation of local controller setpoints, without requiring fundamental changes to the existing technological structure.

The object-oriented approach, combined with the use of soft sensors for predicting complex variables such as COD, ensures a high level of control reliability even under limited digital maturity of instrumentation and control systems. Simulation results obtained for a dairy wastewater treatment case study confirm the possibility of reducing specific energy consumption by 28% while fully complying with environmental limits. This demonstrates the practical applicability of the proposed approach for retrofitting existing facilities.

Future research will focus on the integration of digital twin technologies, adaptive learning mechanisms for soft sensors, and large-scale validation across different industrial sectors. Overall, the developed architecture can be regarded as a universal and scalable tool for modernizing contemporary automated process control systems within the framework of the global "green" transition.

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