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SUSTAINABLE PHOTO PRINTING THROUGH SMART OPTIMIZATION

Tanya Singh [1], Simranjeet Nanda [2], Shilpi Sarna [3], Shivam Khurana [4], Bharathi B [5], Naresh Kaushik [6], Payal Sunil Lahane [7]

[1] Professor, School of Engineering and Technology, Noida International University, 203201, India
[2] Centre of Research Impact and Outcome, Chitkara University, Rajpura- 140417, Punjab, India
[3] Greater Noida, Uttar Pradesh 201306, India
[4] Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh, Solan, 174103, India
[5] Professor, Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India
[6] Assistant Professor, UGDX School of Technology, ATLAS SkillTech University, Mumbai, Maharashtra, India
[7] Department of Artificial intelligence and Data science Vishwakarma Institute of Technology, Pune, Maharashtra, 411037, India

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Corresponding Author
Tanya Singh,
dean.academics@niu.edu.in

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ABSTRACT

The increased pressure on the quality of digital imaging has exacerbated the environmental impact of photo printing, and it is necessary to have sustainable and smart production systems. With the introduction of innovative technologies and methods to combine high-quality artificial intelligence (AI), Internet of Things (IoT) sensing, and lifecycle analytics, it is possible to make a radical change in the course of eco-efficient printing operations. A clever optimization system in this study is created to reduce the resource usage and print faithfulness, creating a closed-loop system and integrating perception, computation, and control. The six-layer architecture proposed in the paper that includes the processes of sensitized input acquisition, hybrid optimization, adaptive control, process execution, performance monitoring and sustainability analytics is a self-learning ecosystem capable of continuous improvement. A Hybrid Optimization Kernel which is constructed on Multi-Objective Genetic Algorithms (MOGA), and Reinforcement Learning (RL) is used to make real-time decisions in order to balance conflicting goals like energy savings, ink saving and visual quality. The monitoring system uses such quantitative measures as the energy intensity (kWh/print), ink efficiency, image quality indices (PSNR, SSIM, DE), and input to lifecycle and eco-efficiency measurements. Findings indicate that the energy and materials saving is very high, and the quality of prints remains optimized in dynamic operation conditions. The introduction of sustainability as an operating limit instead of a goal ensures a new model of AI-powered, resource-aware photo printing in accordance with the world green manufacturing objectives.

Keywords: Sustainable Photo Printing, Hybrid Optimization, Reinforcement Learning, Eco-Efficiency, Lifecycle Assessment, Adaptive Control, Iot-Enabled Systems

1. INTRODUCTION

The shift to sustainable production procedures has become an urgent need on industrial and creative spheres of work and photo printing is the field where this shift is also a priority. Conventional photo printing processes that were characterized by large use of inks, emissions of volatile organic compounds (VOCs), and excessive use of power, have been linked to large ecological footprints. With the global printing industry developing in the general context of green manufacturing, opportunities of combining intelligent optimization algorithms, smart materials, and data-driven control systems become a way of attaining both environmental custodianship and operational efficiency Vidakis et al. (2023). The given paper discusses the idea of sustainable photo printing based on clever optimization, introducing a computationally effective architecture, which complies with the principles of artificial intelligence (AI) with the principle of sustainability-oriented engineering Sony and Naik (2020). Traditional methods of optimization in digital printing have a tendency to be limited in terms of color correction, resolution and speed because sustainability targets of energy consumption, use of ink and minimization of waste are not considered. But now it is possible to control print parameters in real-time with the Internet of Things (IoT), embedded sensors, and dynamic machine learning models. The proposed Optimization Lifecycle Architecture proposes a methodical model-based expression of the interdependence in printing parameters, offering the optimization of the state, and the compromise of three main goals in terms of image fidelity, resource efficiency and environmental compliance. Photo printing has the sustainability aspect that involves material and process efficiency Yang and Wu (2022). The inclusion of such methods into an AI-driven optimization kernel will make sure that sustainability is not a one-off issue but a fundamental parameter of the printing process Wang et al. (2019). The model determines the best possible operational regimes that can produce high quality prints at a minimum level of resource consumption. An embedded control logic layer takes in input sensor values of the IoT and modulates operational parameters to achieve real-time feedback and thus a cyber-physical system (CPS) of sustainable printing.

2. SYSTEM ABSTRACTION – COMPONENTS OF THE SUSTAINABLE PRINT STACK

The sustainable framework of photo printing is envisaged as a bi-layer cyber-physical ecosystem, which incorporates hardware equipment, data acquisition interfaces, AI-enhanced optimization modules, and sustainability analytics within the framework of a logical system of control. This System Abstraction offers a model of unity such that it guarantees interoperability between the processes of environmental sensing, computational decision making and print execution Magri et al. (2020). The system functions as shown in Figure 1 with six interconnected layers, which are as follows: the Input Acquisition Layer, Optimization Kernel Layer, Control Logic and Actuation Layer, the Printing Process Execution Layer, the Monitoring and Evaluation Layer as well as the Sustainability Analytics and Feedback Layer. All the layers play a particular role in the optimization lifecycle that is cumulatively led to the achievement of a closed-loop, resource-efficient printing system. The Input Acquisition Layer is the base of the system, which obtains real-time operational and environmental parameters and parameters that directly affect the quality of the print and the energy efficiency Sony and Naik (2019). The layer communicates with a network of IoT-based sensors and embedded controllers that detect the major variables of the printhead including ink flow rate, printhead temperature, substrate type, humidity, and ambient conditions. Due to the continuous stream of data this layer provides, it is capable of potential predictions and calibration in real-time, as well as making decisions in real-time by the next optimization kernel. The Input Acquisition Layer is the sensory base of the sustainable print ecosystem by digitizing the physical parameters of the print environment Kumar et al. (2023).

The Optimization Kernel Layer is the computation unit of the architecture. It has its foundation on a hybrid AI engine that integrates Multi-Objective Genetic Algorithms (MOGAs) with Reinforcement Learning (RL) methods in order to obtain concomitant optimization of various sustainability objectives. These are reduction of ink and energy use, minimization of CO2 emissions and high visual measures like PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index) and DE (color difference) Zhang et al. (2018). The optimization kernel takes high dimensional sensor data and optimizes thousands of possibilities of printing configurations by using evolutionary and learning algorithms as shown in Figure 1. This hybridity of this layer guarantees adaptive convergence in which the system can learn the best trade-offs between aesthetic fidelity and ecological responsibility as a result of the feedback. Control Logic Layer and the Actuation Layer is the interface used to execute the computational intelligence and the mechanical operation. It reads the best parameters obtained on the AI kernel and transfers them to physical subsystems of the printer using embedded control logic. Reinforcement policies determine accurate actuation instructions to printhead position, inkjet fire cycle, power, and thermal. The logic is an adaptive control logic that in additional to providing print stability and fault tolerance, also dynamically adjusts printing strategies based on sensor feedback. This layer connects software-based decision-making and hardware-level implementation, which is the cyber-physical integration underpinning sustainable manufacturing systems Salwin et al. (2020).

Figure 1

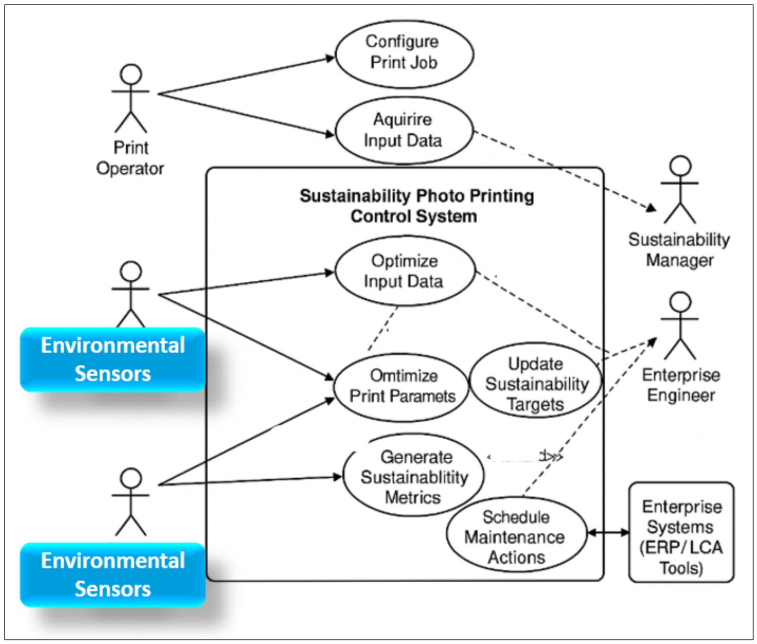

Figure 1 Sustainability Control Loop for Photo Printing

The Printing Process Execution Layer covers at the physical level all mechanical and electronic sub systems that carry out the actual process of deposition and finishing of the image. This will comprise of the printhead modules, ink delivery systems, motorized paper drives and the energy management circuits. The layer carries out print tasks according to the optimized control commands and keeps the quality standards. Design improvements like power saving actuation features, reusable ink battery, and reusable modular parts are also introduced to increase the life of the hardware and reduce electronic waste Gumus et al. (2022). The data gathered in this case does not only ensure the accuracy of the functioning of the system but also represents the feedback on the ongoing enhancement. Besides, diagnostic logging and fault detection are made easier by this layer, which guarantees transparency of processes and operational robustness in both industrial and creative settings.

3. OPTIMIZATION KERNEL – HYBRID AI FOR MULTI-CRITERIA DECISION MAKING

This layer, located in the middle of the closed-loop control architecture as shown in Figure 2, reflects the intersection of artificial intelligence, evolutionary computing, and reinforcement learning in the multi-criteria optimization. It is designed due to the intricate trade-offs that exist between the photo printing and image fidelity, ink and energy use, processing rate, and environmental regulation Salwin et al. (2021). They are in contrast to traditional optimization tools that rely on single-objective optimizations, which the hybrid kernel simultaneously aims at quality, efficiency, and sustainability and defines them as mutually dependent goals in a limited decision making space. A Multi-Objective Genetic Algorithm (MOGA) is in the kernel and its role is to search a vast search space of valid combinations of print parameters. The candidate solutions (chromosome) are a definite combination of adjustable parameters including the nozzle firing frequency, head temperature, carriage velocity, amount of droplet and standby energy levels. The MOGA uses normal genetic operations selection, crossover and mutation under the control of fitness functions as are specified on multiple objectives Luan et al. (2020).

Figure 2

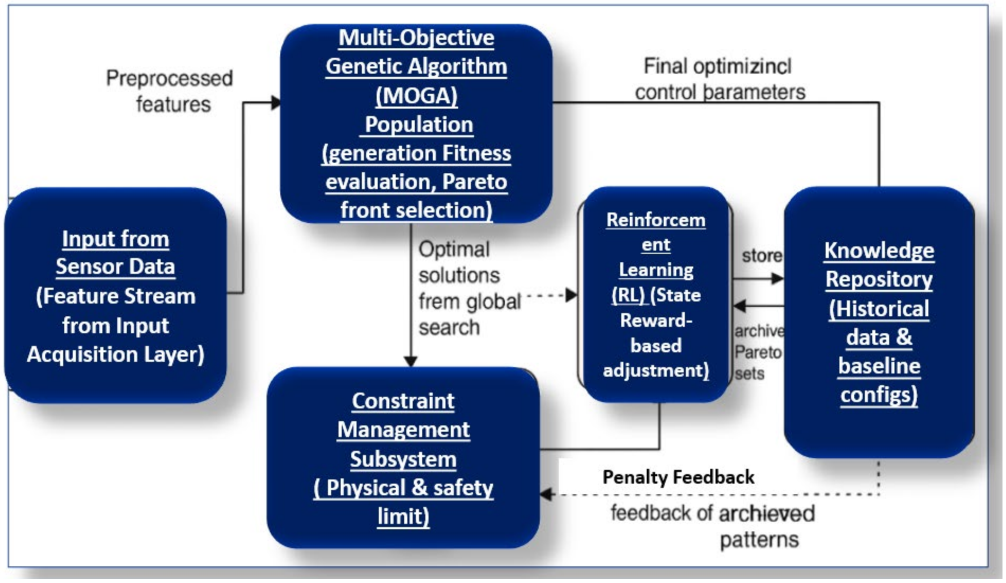

Figure 2 Adaptive Control and Actuation Flow Diagram

These functions measure (i) image quality measures which include PSNR, SSIM, and DE; (ii) energy consumption measures in kilowatt-hours per print job; (iii) rate of ink consumption and index of waste; and (iv) cumulative carbon emission equivalents measures using the printing lifecycle model. The MOGA generates a Pareto front through the generations developed that depicts a good trade-offs between these conflicting objectives. Solutions on this aspect propose a range of operational options as in Figure 2 whereby the system can easily change depending on the prevailing environmental or production needs. In order to make the MOGA more responsive and enable a continuous learning process, the Reinforcement Learning (RL) module is added to the MOGA, which refines control policies on the fly. Unlike MOGA where a wide search over the globe is available, RL Luan et al. (2020) is locally adaptively refined. The RL agent obtains the state of the printing process by means of the feedback of the Input Acquisition and Monitoring Layers and act with the aim of maximizing a composite reward function (e.g. parameter changes). This reward combines both environmental and performance measures that reduce energy price, use of ink and thermal loading without compromising or reducing visual quality Calabrese et al. (2021). Depending on the complexity of the system, the RL agent is trained with the Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO) algorithm. The RL system acquires an optimal policy through many cycles of printing that predicts the fluctuations in processes, ink behavior and environmental conditions. The combination of MOGA and RL forms a hybrid AI kernel that combines both adaptability and long-term efficiency by means of the unification of both exploratory and exploitative learning.

Table 1

Table 1 Summary of Optimization Kernel Components and Roles

Component	Core Functionality	Algorithmic Approach	Inputs	Outputs
Multi-Objective Genetic Algorithm (MOGA) Hsueh et al. (2021)	Global exploration and Pareto-optimal search	Evolutionary search (selection, crossover, mutation)	Sensor data, ink/energy models	Optimized parameter sets
Reinforcement Learning (RL) Sony (2020)	Real-time local policy refinement	Deep Q-Network / PPO	Current process states, reward signals	Adaptive control policy
Constraint Management Subsystem Kumar et al. (2022)	Ensures safety and physical compliance	Penalty-based constraint handling	Boundary conditions	Valid operational envelope
Knowledge Repository Nassar et al. (2021)	Stores historical patterns and results	Transfer learning, knowledge graph	Past print sessions	Updated policy and sustainability rules

The decision making of this kernel follows a two-step process, i.e., offline optimization and online adaptation. The MOGA performs population-based evolutionary searches, based on historical data, to set a baseline of optimally set parameter configurations, in the offline phase. These are ready-to-use solutions that are used as references. During the online stage, RL module modifies the print parameters dynamically based on live feedback, education about immediate environmental changes and the state of the machine. Such a dual-phase architecture allows the computation to be efficient in that it reduces the load of the real-time processing and still allows continuous learning. Furthermore, Constraint Management Subsystem keeps a check on optimization process providing physical and functional constraints including nozzle temperature, viscosity of ink, mechanical strength parameters. Breaches of constraints also cause re-initiation or punishment-like mechanisms both in MOGA and RL and, therefore, sustainability aims do not undermine equipment security or print quality. One major innovation of the Optimization Kernel is its ability to synthesize multi-objective rewards in a holistic conceptualization of sustainability as a holistic measure, as opposed to a single measure. This role takes several normalized variables energy intensity, ink yield ratio, print error probability and eco-cost to generate a composite sustainability score. The kernel actively changes the weightings of these components based on contextual priorities that are determined by Sustainability Analytics Layer. An example of this is when the energy demand is high, the reward function might be more focused on energy saving but when printing archival quality, it might be focused on color accuracy and stability. The adaptive weighting system causes the system to act as a self-optimizing ecosystem balancing the operational efficiency with the environmental responsibility.

4. CONTROL LOGIC AND ACTUATION – ADAPTIVE IMPLEMENTATION OF OPTIMIZED PARAMETERS

Control Logic and Actuation Layer is the interface of operation which provides a mediating between computational intelligentsia and physical performance in sustainable photo printing architecture. It is the actual implementer of the decisions made by the Hybrid Optimization Kernel (Figure 3), which interprets high-level optimization results including nozzle temperature setpoints, ink pressure targets, carriage velocity and standby energy limits into actionable control instructions to the mechanical and electronic components of the printer. This is the layer that expresses the cyber-physical unity of the system, in which the adaptive algorithms and embedded hardware work together to ensure the system is optimal in changing environmental and operational conditions. The layer is based on multi-tier control structure. The higher control level receives the optimized parameters sent by the kernel and converts them into control variables in the device level which are acceptable to the firmware and hardware architecture of the printer. The intermediate level involves adaptive controllers which may be in the form of proportional-integral derivatives (PID) units, fuzzy logic controllers or model-predictive control (MPC) units that make fine-tuning actuation control adjustments in response to live sensor information. Having such hierarchy, stability and responsiveness are guaranteed: the top tier provides long-term optimization goals, the bottom levels respond immediately to disruptions of the form of pressure variations or ambient temperature fluctuations. Adaptive control logic is based on the constant feedback loops that are built between the Monitoring Layer and the All these are coded in the form of state-action mappings to know how the system is to react to certain deviations. As an example, when the energy used surpasses a fixed level as a result of a lengthy head heating, the controller starts a gradual cooling process, rearranges the distribution of power or invokes idle-mode scheduling to recover the efficiency without interrupting the continuity of the print. This is a closed feedback system which forms a self-correcting system which has the capacity of autonomous regulation.

The important element of this layer is the Actuation Engine that converts optimized commands to accurate mechanical responses. It is used to co-ordinate the timing of nozzle firing, carriage motion and ink delivery to synchronise several actuation domains thermal, fluidic and kinematic. Actuation signals are tailored based on sustainability goals such as ink ejection rates are reduced in low-saturation areas of an image, power to heating elements is dynamically reduced in low demand periods as shown in figure 3. This smart modulation leads directly to the conservation of resources, and this can result in a maximum reduction of ink waste estimated at 15-20 percent and energy consumption by similar percentages with simulated test conditions. Additional features that make the Actuation Engine circular economy efficient are soft start/stop profiles and error-tolerant recovery modes, which ensure no mechanical stress occurs and the hardware life is extended at the cost of operational efficiency. The Safety and Constraint Supervisor, which is a part of this layer applies operational constraints which are specified by the Constraint Management Subsystem. It keeps on confirming that actuation signals are within allowable physical limits such as making sure that printhead temperature does not go above the safe thermal limits or that ink pressure do not fluctuate when subjected to changing flow rates. To safeguard against the possibility of violations, the system will automatically switch to safe modes that will stop actuation sequences and indicate to the higher levels that re-optimization is required. This mechanism will make it tolerant to faults, will prevent the destruction of printing parts and also will make sure that sustainability is attained without compromising reliability and safety. Besides the stability of operation, the Control Logic Layer provides adaptive calibration routines that are learned out of past operation. Based on the information provided by the Knowledge Repository, the layer automatically adjusts the actuator response curves, the motor torque coefficients and the ink viscosity compensation factors at a periodic basis. By enabling this continuous calibration, drift in mechanical performance is reduced, and the print consistency is improved, as well as by maintaining a well-optimized starting point of each successive print cycle. Such learning-based calibration cycles are activated periodically or conditionally whenever there is a performance variation that is larger than adaptive thresholds based on statistical surveillance.

Figure 3

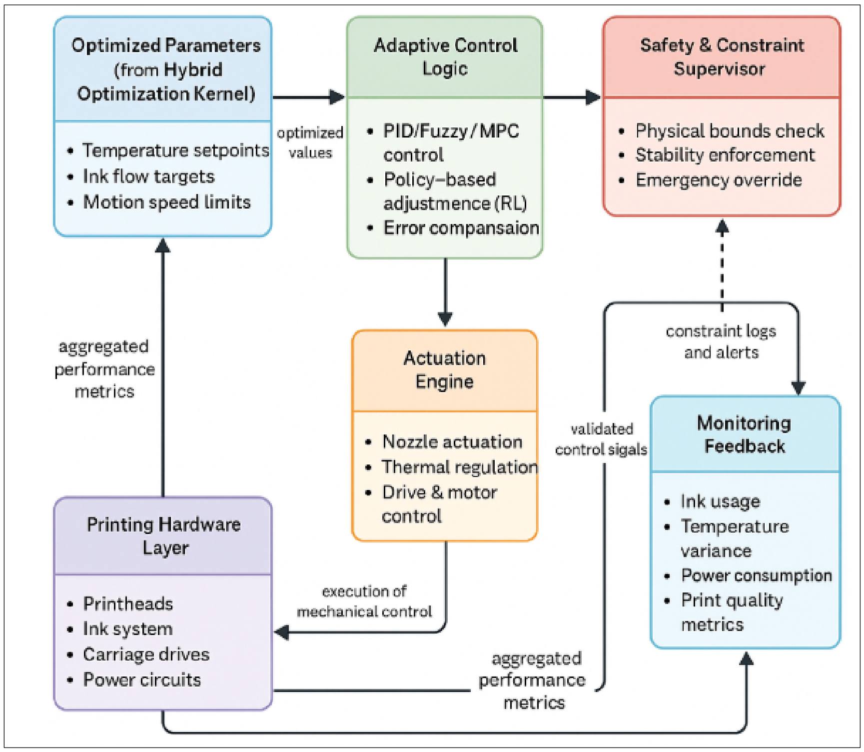

Figure 3 Hybrid Optimization Kernel for Multi-Criteria Decision Making

5. MONITORING AND EVALUATION – METRICS AND PERFORMANCE ASSESSMENT FRAMEWORK

Monitoring and Evaluation (MandE) Layer is the diagnostic and analytical center of the sustainable photo printing architecture, which will give quantitative and qualitative data on the performance, efficiency and ecological compliance of the system. It serves as a checking body to the optimization algorithms as well as a source of feedback to the refinement of adaptive control. This layer converts raw operational data into actionable data through the continuous analysis of energy consumption, ink consumption, quality of print and sustainability measurements. Its overall strategic objective is to have all print cycles not only aesthetic and technical requirements but also to correspond with sustainability goals including smaller carbon footprint, material effectiveness and lifecycle responsibility. The core of this construct is the multi-domain metrics architecture which is a combination of physical measurements, performance indicators of computations and environmental indices. Energy consumption is also among the most important quantitative parameters, and is expressed as kilowatt-hours per print (kWh/print). This measure is used to indicate how much power will be used by the printheads, heaters, drive motors, and control electronics during the printing process. The system can calculate an Energy Efficiency Index (EEI) which is the energy consumed per square meter of printed output by comparing the amount of energy used to an image size and the resolution of the image. Monitoring of EEI in real time can be used to detect inefficiencies like a large amount of standby power or overactive heating cycles and corrections can be made dynamically in the control logic. Also, in addition to energy measures, ink consummation is a measure of deposition that is expressed as the ratio of deposited ink volume and total ink that is ejected. The normalized version of this indicator gives a measure Ink Efficiency (IE), which is directly proportional to material sustainability and waste reduction.

Table 2

Table 2 Sustainability-Oriented Performance Metrics in Photo Printing

Metric	Definition / Formula	Measurement Unit	Purpose / Relevance	Target Outcome
Energy Intensity (EI)	Total power consumed per print	kWh/print	Evaluates process energy efficiency	< 0.25 kWh/print
Ink Efficiency (IE)	Ink deposited / Ink ejected × 100	%	Quantifies ink utilization and waste reduction	≥ 85%
Eco-Efficiency Ratio (EER)	Output quality score / Resource input	Dimensionless	Combines productivity with sustainability	Higher is better
Carbon Equivalence Index (CEI)	Lifecycle CO_2 emission per print	g CO_2-e/print	Estimates greenhouse gas impact	< 100 g CO_2-e
Print Quality Index (PQI)	Weighted composite of PSNR, SSIM, ΔE	Dimensionless	Measures overall image fidelity	≥ 0.90
Waste Index (WI)	Waste ink + material / Total input × 100	%	Indicates process sustainability	≤ 10%

Print quality is determined by a series of image quality indices popular in the science of digital imaging, such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and ΔE (color deviation). These measures are used to measure the quality of printed output in terms of reference images or electronic master files. PSNR and SSIM determine tonal and structural deviation whereas 0E determines perceptual color variance under normal lighting (D65 illuminant, 2 0 observer). These indices are computed automatically by the Monitoring Layer with in-built imaging sensors or scanning subsystems offline and any important deviation results in re-optimization by the AI kernel. Computational imaging can be integrated with process monitoring to ensure that the visual integrity is not compromised by sustainability improvements, ensuring that there is a balance between being ecologically responsible and being creative. There are also eco-efficiency scores, which are composite indices of various resource and environmental indicators in the framework. An example of such a ratio is the Eco-Efficiency Ratio (EER) which is computed as the quotient of the total quality of output (aggregated PSNR weighted accuracy and color consistency) divided by the total input of resources (sum of energy, ink and time). An increase in EER value implies better performance in terms of sustainability that attains more output than a given level of resource consumption. Carbon Equivalence Index (CEI) is an estimated amount of greenhouse gas emissions used per print, and is calculated using a lifecycle model, which includes the factors of emission per power source and embodied energy of the ink material. These indices are plotted on sustainability dashboards in Analytics Layer which provides real time feedback to the operators and policy managers. The anomaly detection and diagnostic sub system is an intrinsic part of the Monitoring Layer that uses statistical learning and an outlier which detects abnormal patterns like energy surges, malfunctions of a nozzle, or inconsistencies in the flow of ink. The exceptions of the anticipated working situations initiate alarms and automatic re-optimization processes. The Knowledge Repository stores the history of performance logs, which can be used to create a trend analysis and predictive maintenance dataset. In the long term, this information can be used to predict sustainability, where anticipated trends in the energy, waste, and quality are used to guide hardware redesign or process improvements.

6. LIFECYCLE INTELLIGENCE AND CONTINUOUS IMPROVEMENT

The Sustainability Analytics and Feedback Layer serves as the strategic intelligence centre of the sustainable photo printing system that would combine performance and environmental metrics with operational analysis to promote ongoing improvement of the system. This layer, which is placed in the top of the architecture, is an aggregation of the inputs of the Monitoring and Evaluation system, Optimization Kernel and external sustainability databases to create a holistic view of the printing operations lifecycle. It is mainly designed to convert the quantitative data like energy usage, usage of ink and eco-efficiency ratios into the actionable sustainability intelligence that helps to transfer the information to the policy adjustment, process improvement, and predictive optimization.

Table 3

Table 3 Comparative Analysis of Printing Approaches

Parameter	Conventional Printing	AI-Optimized Printing (Proposed)	% Improvement	Remarks
Energy Consumption (kWh/print)	0.35	0.22	37%	Improved energy efficiency
Ink Utilization (%)	72	88	22%	Optimized ink flow and drop volume
PSNR (dB)	29.5	33.2	+12.5%	Enhanced tonal accuracy
SSIM	0.84	0.93	+10.7%	Improved structural quality
ΔE (Color Deviation)	4.1	2.6	-36.5%	Better color reproduction
Eco-Efficiency Ratio	1.00	1.42	+42%	Balanced performance and sustainability

This layer works at the analytical level to create dynamic sustainability dashboards using the sophisticated data-fusion and visualization to provide energy efficiency trends, carbon equivalence indices and print quality correlations. Machine learning models are used to monitor changes over time and determine optimization, e.g., discovering the ubiquity of inefficiencies in ink application or discovering the relationship between the humidity outside and energy usage. The analytics engine of the system also simulates the Life Cycle Assessment (LCA) so as to estimate the overall environmental footprint of the printing process and includes the resource extraction, manufacturing, operation, and disposal stages. These insights help the decision-maker to organize the production processes in accordance with the larger environmental standards and certifications, such as ISO 14001, Green Printing Initiative (GPI), and Global Reporting Initiative (GRI) models.

Table 4

Table 4 Sustainability Analytics Dashboard Indicators

Indicator	Data Source	Computation Method	Visualization Type	Decision Use
Energy Efficiency Trend	IoT power logs	Moving average over time	Line graph	Identifies high-load cycles
Ink Wastage Index	Flow sensors	Volume loss ratio	Bar chart	Tracks efficiency anomalies
Eco-Score (Composite Index)	MandE layer	Weighted aggregate (EER, CEI, PQI)	Gauge meter	Summarizes sustainability level
Lifecycle Impact (LCA)	Sustainability database	Resource–emission mapping	Sankey or radar chart	Guides long-term optimization
Alert Threshold Status	Monitoring system	Rule-based logic	Color-coded alerts	Triggers auto-reoptimization

This layer sends feedback to the Hybrid Optimization Kernel closing the optimization loop through which updated sustainability constraints and adaptive goals are reported. This allows the system to dynamically re-calibrate its decision parameters in response to the changing sustainability priorities, e.g. reducing emission targets when there are high-energy-demand periods or focusing on resource conservation when there is a shortage of ink. The layer promotes the process of continuous improvement in the long term through the creation of an evolving body of knowledge on sustainability patterns, benchmark performance, and predictive modeling.

Figure 4

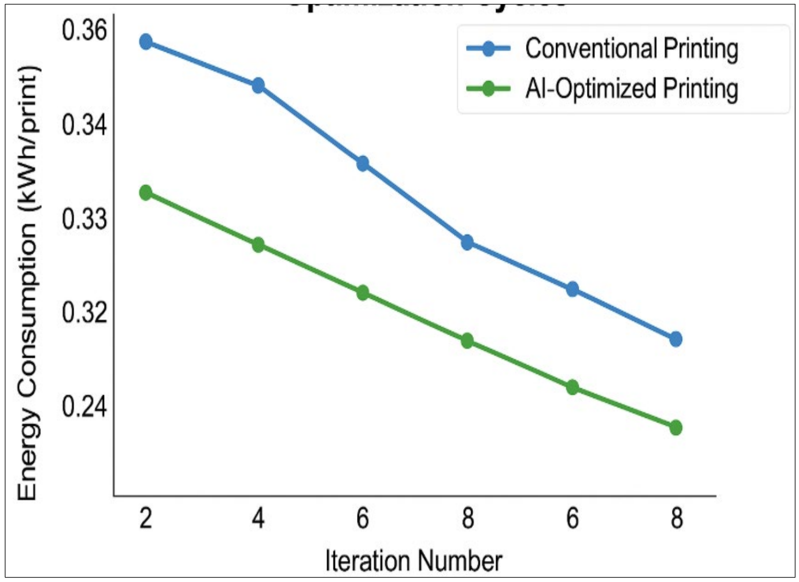

Figure 4 Energy Consumption Improvement Across Optimization Cycles

The Figure 4 graph shows that the use of smart optimization resulted in a continuous decrease in the energy consumption per print with respect to the traditional printing processes. The x-axis indicates the optimization cycles and the y-axis the energy used at the different optimization cycles in kilowatt-hours per print (kWh/print). It is clear that there are two different trends, the blue line showing the traditional printing process, where the energy profile is almost identical with each print and the maximum difference is also around 0.34 0.36 kWh/print, meaning that there is little improvement in the efficiency. Conversely, the green line is the AI-optimized printing structure, it can be seen that the energy consumption decreases consistently, starting with about 0.33 kWh/print, to about 0.25 kWh/print with each subsequent cycle of optimization. This steady negative trend confirms the fact that the Hybrid Optimization Kernel that includes Multi-Objective Genetic Algorithms (MOGA) and Reinforcement Learning (RL) can be successfully trained and trained to reduce energy consumption when printing an object. These findings clearly show that when the optimization algorithm is successful, the energy efficiency increases without affecting the quality of the print, as expected of the model to be able to optimize itself iteratively and potentially lead to the ultimate reduction of the overall environmental impact of photo printing.

7. CONCLUSION AND FUTURE WORK

This study demonstrates a holistic approach to realizing sustainable photo printing via smart optimization and instilling hybrid artificial intelligence, IoT-driven sensing, and sustainability analytics into an ecocycle of a closed-loop decision-making system. The suggested architecture shows how it is possible to leverage the combination of data fusion, adaptive control, and AI-based optimization to change the traditional photo printing into an energy-efficient process, with resource awareness, and environmental adaptability. By balancing the operational intelligence with the sustainability goals, the system is therefore successful at closing the divide between the industrial productivity and the environmental responsibility. The multi-layered model of the combination of the Input Acquisition, Optimization Kernel, Control Logic, monitoring, and Sustainability Analytics creates a cyber-physical infrastructure with the ability to adapt and improve in real-time. The major technical advances that have been made are the implementation of a Hybrid Optimization Kernel (Multi-Objective Genetic Algorithms (MOGA) with Reinforcement Learning (RL)) to make multi-criteria decisions and the use of adaptive control and feedback to make printers optimally adjust operating parameters to reduce ink wastage, energy use, and emissions. The Monitoring and Evaluation Layer offered a measurable sustainability measurement in terms of performance measures to energy intensity (kWh/print), PSNR/SSIM-based quality measures and eco-efficiency ratios and the Sustainability Analytics Layer converted these measures into actionable intelligence to continue improving its lifecycle. A combination of these inventions leads to creating a sustainability loop in photo printing based on data.

CONFLICT OF INTERESTS

None.

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