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Research Paper
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Cyber-Physical System-Based Adaptive Control For Liquid Filling-Capping Processes In Industrial Environments

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Abstract

The increasing demand for intelligent automation in industrial environments requires control systems capable of adapting to dynamic operating conditions. Conventional liquid filling–capping systems in industrial automation commonly depend on fixed-rule or traditional control mechanisms, which struggle to handle dynamic operating conditions such as flow variations, bottle inconsistencies, and process disturbances. These limitations reduce filling accuracy, increase spillage, and affect operational efficiency. To overcome these issues, this research proposes a Cyber-Physical System (CPS)-based adaptive control framework integrated with a Bat Optimization-tuned Dueling Double Deep Q-Network (BO-D3QN). The research gap lies in the lack of intelligent adaptive control methods capable of real-time learning and optimization in liquid filling–capping processes. Real-time sensor data including liquid level, bottle position, and flow characteristics are collected as the dataset for system state monitoring. During preprocessing, sensor noise and inconsistent readings are filtered and normalized to improve data reliability. Relevant operational features such as filling level, flow rate, and bottle alignment are extracted for decision-making. The purpose of the BO-D3QN-based adaptive control framework is to improve convergence stability, decision-making accuracy, and real-time control performance in liquid filling–capping systems under dynamic industrial conditions. The model is implemented using reinforcement learning techniques in the Python environment, where the Bat Optimization algorithm is used to tune critical hyperparameters for enhanced adaptive control efficiency. Experimental results show improved performance with 0.98 accuracy, while reducing spillage and idle time. The proposed method provides an efficient and scalable solution for smart industrial automation.

Keywords: Cyber-Physical Systems (CPS), Adaptive Control, Bat Optimization (BO), Dueling Double Deep Q-Network (D3QN), Liquid Filling &Capping System.

1. Introduction

In industrial settings, the filling and capping of liquids is done with great accuracy because it helps in handling the beverages well, packaging them properly to avoid any chances of contamination [1]. It is a fundamental process in manufacturing as it ensures precise volumes, prevents contamination, ensures proper packing, and maximizes efficiency and automation [2]. The liquid filling and capping procedure utilizes automated systems that ensure proper filling and sealing of containers while maintaining efficiency and safety in production. The process typically includes threading and end-capping, with experimental details provided in the Supporting Information [3, 4]. Bottles are categorized according to the types of caps used, and they move along conveyor belts during the filling and capping process. Each bottle is filled according to its flow density, while bottle sizes is vary, which minimizes spillage and inaccuracies [5]. Key performance attributes for the liquid filling and capping process include the bottle height, width, and liquid flow, as well as sustainability factors related to synchronized capping [6]. The capping action is performed by applying pressure from above on the middle portion of the conveyor belt using the convex portion at the front end of the closing cap arm. During manufacturing, both caps and bottles are aligned, with care taken to minimize overlap and prevent over-spillage during the filling process [7, 8].

1.1 Research Aim: This research intends to design an adaptive control system for the CPS by implementing BO-D3QN in smart liquid filling and capping operations. The goal is to enhance the accuracy of filling, minimize the spillage, and optimize the flow and cap synchronization scenarios by extracting features from sensor data and reinforcement learning.

Section 1 provides the background of the research. Section 2 focuses on reviewing existing research. Section 3 discusses the methodology of data collection, preprocessing, and feature extraction, as well as the proposed model. Section 4 includes results obtained from experimental analysis. Section 5 shows the conclusion with the performance, limitations, and future work.

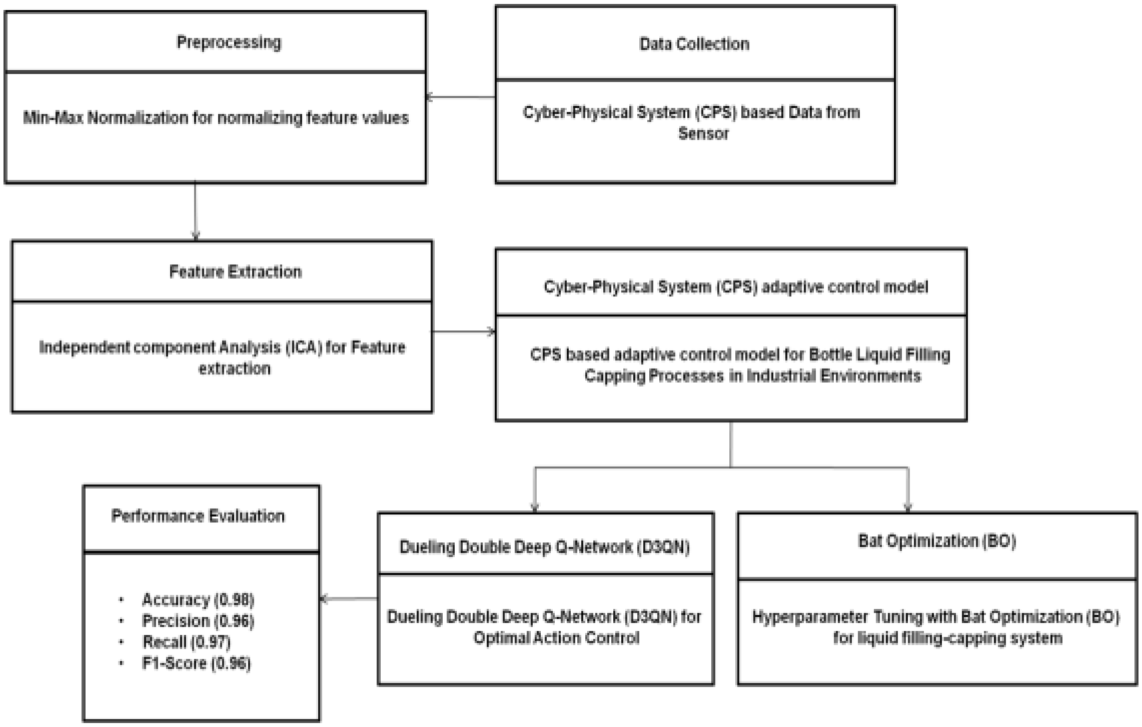
2. Related work

Improving the efficiency and interoperability of the capping machine for lower production costs was considered [9]. Implementing the Retrofit Model for the capping process projected cost savings on a timeline, result showing a high smoother transition and reduced operational disruptions, though it lacks adaptability and modularity. Examined an adaptive simulation technique in five stages designed for smart manufacturing systems [10], utilizing a Multi-Threshold technique, it enhances production rates at both upstream and downstream stations. Experimental results indicated an 18% efficiency boost and a 95.7% reduction in work-in-progress. The system functions on continuous flow constrained by the capacity of hydraulic pumps and associated components.Investigated the application of Artificial Neural Networks (ANNs) and Fuzzy Logic in developing a prediction system for estimating losses in agave liquor bottle manufacturing and packaging was examined [11]. Using the ANNs to decrease the losses, the findings indicated that packaging and capping processes significantly affected loss rates, contributing to 29% and 35% of losses during morning and afternoon shifts, respectively. One major constraint highlighted is that there is no provision for storing electricity in the electricity production process. This research [12] focused on the effects of different closures during the second fermentation of sparkling wines. Utilizing Headspace Solid-Phase Microextraction (HS-SPME), it is determined that HS-SPME improved production consistency, achieving a 66.1% area percentage. However, the process faced limitations due to thermal desorption of sampling tubes at 300°C for 8 minutes.An investigation into a bottle capping system revealed issues with sealing and leakage during transport, as investigated in this research [13]. Utilizing Image Processing for bottle flow detection, it is found that a 2% change in capacitance is small, yet the capacitance values for both uncapped (0.07%) and capped bottles (0.06%) are over 30 times smaller. To define tolerance limits to prevent the rejection of objects using 3-D imaging.As part of identifying opportunities to improve bottle packaging, the knowledge about the material and packaging was analyzed [14], by using the Polyethylene Terephthalate (PET) and Polyethene High-Density (PE-HD) for bottle caps and packaging. The findings revealed that the pack weight constitutes 58% of all samples, andthe limited ratio of filling decreases the efficiency of the package weight.The process of bottling through virtualization of Unity 3D that controls the process of filling and capping bottles was investigated [15], utilizing Totally Integrated Automation (TIA) Portal Version 16 to manage filling and capping. The average usability score achieved by 83%, indicating a limited satisfactory usability level for the virtual bottling process.Implementation of a Sequential Convolutional Neural Network (S-CNN) model for detecting and classifying bottle-fill levels for correct filling and capping processes was investigated [16] through incorporating the S-CNN model for evaluating the effectiveness of the correct filling process. The result shows the accuracy of filled levels is 97%, but the model performs poorly because of its sensitivity to different bottle types and industry interruptions.

3. Methodology

An intelligent adaptive controller is developed using the CPS method for bottle liquid filling and capping processes. Initially, preprocessing of sensor data is performed using the Min-Max Normalization technique to improve data consistency and reliability. Following that, the ICA technique is implemented for signal decomposition and the extraction of meaningful process signals. Figure 1 depicts the entire working mechanism of the CPS-based adaptive control system. In the final stage, the adaptive control algorithm based on the BO-D3QN method is used to decide the actions for the bottle filling and capping processes that result in enhanced system performance and efficiency.

Figure 1: Methodology Overflow of the CPS-Based Adaptive Control for Liquid Filling-Capping Processes



3.1 Data Collection

The research employs data generated through the simulation of the liquid filling and capping process in a CPS setting, in a bid to allow for adaptive control through BO-D3QN. This dataset contains 7,621 instances with 43 attributes, covering bottles, the filling process, conveyor belt details, cap properties, CPS sensor data, adaptive control decisions, rewards, and performance metrics. The dataset is publicly available at Kaggle (https://www.kaggle.com/datasets/programmer3/cps-based-liquid-filling-and-capping-dataset/data),consists of 43 columns with 30 numeric features, 5 integer features, 6 string features, and 2 additional features. It is designated for 80% training and 20% testing to support intelligent CPS-based liquid filling and capping control in the industry.

3.2Normalizing feature values using Min-Max Normalization

The Min-Max normalization method is implemented in the proposed CPS-based liquid filling and capping control system model to standardize the various sensory and process signals to the [0,1] interval, ensuring that the learning performance of the varying bottle, liquid volume, and flow rate is maximized. Normalization is vital in this instance because of the presence of varied inputs measured in different units and ranges, expressed as Equation (1).

$$Y_{new} = \frac{(Y - Y_{min})}{Y_{max} - Y_{min}} \qquad (1)$$

Where Y represents the initial bottle feature value, and Y_{new} is defined as the new bottle feature values that are achieved from capping processes with operating, and liquid flow properties of bottles used in manufacturing. Y_{min}andY_{max} are the minimum and maximum of liquid deviations of bottle positions and flow rates with filling times.

3.3Feature extraction using Independent Component Analysis (ICA)

Feature Extraction using ICA in the Bottle Filling & Capping System enables the independent extraction of features from the dynamic process embedded in the sensor data, which leads to better representation of process dynamics such as bottle level variations, bottle placement errors, flow instability, and synchronizations in the capping stage, as expressed in Equation (2).

$$z(t) = Bo(t) \tag{2}$$

Where, $z(t)$ refers to the sensor vector data acquired using the capping process, including liquid level signal data, conveyor position feedback data, flow rate data, variations in bottle geometry (i.e., height, width, and inside diameter), and capping sensor signal data, and $o(t)$ refers to the underlying independent time tsource signal vectors associated with industrial processes including actual flow and bottle alignment, and B refers to the mixing matrix in industrial processes in Equation (3).

$$\hat{u}(t) = Iz(t) \tag{3}$$

Where $\hat{u}(t)$ denotes the independent features used for the adaptive decision-making process during the controlling bottle liquid Filling-Capping tasks, and $Iz(t)$ denotes the separation matrix used for bottle reconstructing the independent signals.

3.4Bat Optimization-tuned Dueling Double Deep Q-Network (BO-D3QN) Driven Cyber-Physical System (CPS)-based adaptive control framework for Smart Bottle Filling and Capping

Dynamic states of the proposed CPS framework for liquid filling and capping are determined using real-time sensing parameters such as liquid level, flow rate, and bottle position. The BO algorithm aims to find the best values for the hyperparameters of the reinforcement learning algorithm for increased stability of the learning process and efficiency of control actions. The D3QN is to find out the actions that provide optimal control in terms of controlling the filling process time, the flow of liquid, and capping. The resulting CPS system will learn and adapt to different industrial environments.

3.4.1 Dueling Double Deep Q-Network (D3QN) for Optimal Action Control: An adaptive control which employs CPS techniques in an industrial liquid filling-capping system, the D3QN technique is used for taking optimal action based on the state dynamics. The technique involves differentiating between state value and action advantage to prediction of Q-value while avoiding the local maxima. Through Reinforcement Learning, timing and rate of filling and capping without risking spillage, as presented by Equation (4).

$$B\pi(s,a) = R\pi(s,a) - V\pi(s) \tag{4}$$

Where s denotes the total state of the Filling-Capping process of the liquid, which encompasses the level of liquid in the bottle, properties like ID, and pressure.$R\pi(s,a)$denotes the total performance for taking an bottle action a in state s, representing the performance accuracy and avoiding any overflowing and bottle capping issues. $V\pi(s)$represents the baseline performance of the system when only the current production state is considered, independent of action choice, reflecting the current combination of bottle liquid level, and flow condition for operation. $B\pi(s,a)$represents the relative improvement by selecting the bottle action, outputs of a combined Network Q-value expressed in Equation (5).

$$R(s,a\,;\theta,\alpha,\beta) = V(s;\theta,\beta) + B(s,a;\theta,\alpha) \tag{5}$$

Where, $R(s,a\,;\theta,\alpha,\beta)$ represents the estimated Q-value of the proposed BO-D3QN model.$s$denotes the current state of the liquid filling and capping system obtained from sensor signals. $a$indicates the adaptive control action selected for the filling and capping process. θrepresents the shared neural network parameters used for extracting common features from real-time sensor data. αdenotes the advantage stream parameters used for estimating the contribution of a specific action. βrepresents the value stream parameters used for evaluating the significance of the current system state. $V(s;\theta,\beta)$ indicates the state value function that measures the stability and importance of the current operational state irrespective of the selected action. $B(s,a;\theta,\alpha)$represents the advantage function that evaluates the effectiveness of a selected action in improving filling accuracy, reducing spillage, and enhancing bottle synchronization.

$$R(s,a\,;\theta,\alpha,\beta) = V(s;\theta,\beta) + (B(s,a;\theta,\alpha) - \mathrm{avg}A(s,a'\,;\theta,\alpha)) \tag{6}$$

In Equation (6), a refers to all possible actions that the machine can bottle liquid state level with respect to the possible combination of flow rates, valve settings, and cap controls. $\mathrm{avg}A(s,a';\theta,\alpha)$is the average advantage of the possible actions, avoiding the advantage of high score, and Loss function expressed in Equation (7).

$$y^{D3QN} = E_{(s,a,r,s')}[r + \gamma \cdot QT(s', \mathrm{argmax}QM(s',a';\theta,\alpha,\beta);\theta',\alpha,\beta)] \tag{7}$$

Where $E_{(s,a,r,s')}$, the value of s' is the subsequent state of the system after taking the action a, with the value of the system's state referring to the change in the liquid levelr, the new position and the resulting dynamics of the flow. The parameter γ is a discount factor that captures the bottle process performance. The function QM is the primary y^{D3QN} neural network that evaluates the current bottleparameters θ, α, β, while the function QT is the target function with parameters θ', α, β. The $\mathrm{argmax} QM(s', a'; \theta, \alpha, \beta)$ computes the optimal next bottle action of the subsequent liquid state s', as expressed in Equation (8).

$$L(\theta, \alpha, \beta) = E_{(s,a,r,s')}[y^{D3QN} - QM(s', a'; \theta, \alpha, \beta)^2] \quad (8)$$

The parameters $L(\theta, \alpha, \beta)$ are the weights of the common, advantage stream, and value stream networks, respectively. $QM(s', a'; \theta, \alpha, \beta)^2$is the predicted Q-value for the main network corresponding to the bottle state and action. The loss function evaluates the squared difference between the predicted and target Q-values. The aim is to make better control decisions for more accurate liquid, steady capping, and minimizing spills despite changing bottle shapes and liquid.

3.4.2 Hyperparameter Tuning with Bat Optimization (BO): The CPS-based adaptive control framework integrated with the BO algorithm is utilized to optimize the hyperparameters of the D3QN model in the liquid filling–capping system. The BO technique is a method based on how bats find prey by using echo-location, in which bats change their location, velocity, frequency, and emission rate of pulses to find a solution. In the proposed system, the BO algorithm is employed to determine the optimal hyperparameter settings of the D3QN model, thereby improving convergence stability, learning efficiency, and adaptive control performance, as expressed in Equation (9).

$$\gamma_i = \gamma_{min} + (\gamma_{max} - \gamma_{min})\beta \quad (9)$$

Where, γ_i represents the hyperparameter scaling factor for the i^{th} bat (candidate solution) in the BO algorithm for the liquid Filling-Capping system, $(\gamma_{max} - \gamma_{min})$ define the lower and upper bounds of the hyperparameter search space controlling learning bottle behavior of discount sensitivity, and β is a uniformly distributed random value in [0,1] that introduces stochastic bottle exploration to adapt control under varying bottle, liquid level, and flow disturbancesas expressed in Equation (10).

$$b_i^{t+1} = b_i^t + (c_i^t - c_*)\gamma_i \quad (10)$$

b_i^{t+1}indicates the speed or search bottle momentum of bat i during iteration t, b_i^t indicates the change in the hyperparameter set for a particular manufacturing industrial process to feedback from the CPS. c_i^tdenotes the position of bat i related to a certain set of D3QN hyperparameters that bottle control spillage rate, timing, and liquid control.$\gamma_i$denotes the adaptive frequency factor of bat i, which controls the search step size and exploration capability during the optimization process.$c*$denotes the global bottle optimal solution, which is the best combination of hyperparameters to minimize spillage and improve the filling accuracy, and adaptive factor of bat as expressed in Equation (11).

$$c_i^{t+1} = c_i^t + b_i^{t+1} \quad (11)$$

c_i^{t+1}represents the updated position of the i th solution (or agent) at iteration$t + 1$, corresponding to the optimized D3QN hyperparameter set. c_i^tdenotes the current position of the i th solution at iteration t. b_i^{t+1} indicates the feedback-based adjustment factor applied at iteration $t + 1$, derived from CPS sensor information such as liquid level, bottle positioning, and liquid flow measurements. irefers to the index of the solution, agent, or hyperparameter candidate in the optimization process. trepresents the current iteration number, while $t + 1$ denotes the subsequent iteration.

$$c_{new} = c_{old} + \in A^{(t)} \quad (12)$$

In Equation (12)c_{new}represents the updated or newly generated bottle position, c_{old} is the previous bottle parameter set for the D3QN controller, and $\in$ is the random bottle exploration term representing the strength of randomness in bottle cap searching the parameter space. While $A^{(t)}$ is the amplitude of the bat algorithm at time t, which incorporates feedback on bottle filling and capping systems, such as spillage and synchronization lag as expressed in Equation (13).

$$c_{new} = c_{old} + \sigma \in_t A^{(t)} \quad (13)$$

$\sigma$is a scaling factor that controls the convergence bottle speed and stability of hyperparameter tuning in the CPS environment.

3.4.3 Hyperparameter of Proposed BO-D3QN Model: Hyperparameters involved in the BO-D3QN model for liquid Filling-Capping using CPS are selected in such a way that provide stability and flexibility towards varying industrial demands. The hyperparameters include learning rate (α= 0.0001–0.001), discount factor (γ= 0.95–

0.99), and exploration factors (ε= 1.0), (εmin = 0.01), and (εdecay = 0). Experience replay memory (50,000–100,000), batch size (32/64), and 500–2000 episodes support efficient training. Bat Optimization tunes key RL parameters using population sizes of 20–50 and 30–100 iterations, improving filling accuracy, reducing spillage, and enhancing capping synchronization in bottle filling systems.

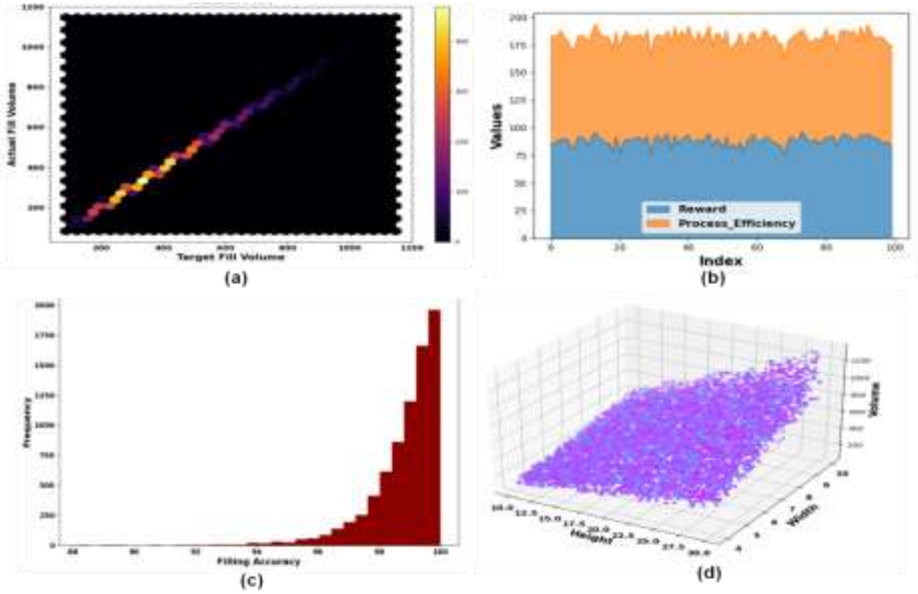
4. Results and Discussion

An adaptive control algorithm using CPS and BO-D3QN greatly enhances the effectiveness of liquid filling and capping processes in industries. The suggested model effectively depicts the system behavior and implements optimal control decisions, such as adjusting the filling duration, filling velocity, and capping synchronization. The efficacy of the proposed model is proven through experimental analysis using measures such as accuracy, precision, recall, and F1-score. The CPS adaptive liquid filling-capping system based on BO-D3QN is designed utilizing Intel i9/AMD Ryzen 9 CPUs, NVIDIA RTX 4080/4090 GPUs, Python, TensorFlow/PyTorch, and CUDA 12.x.

4.1 Exploratory Data Analysis

The graph depicted in Figure 2(a) shows the connection between the target and the actual filling volumes in various bottle situations, which indicates that the BO-D3QN-based CPS filling system is highly accurate and stable. There is a perfect correlation between both parameters, which indicates that the adaptive control model is very effective. Figure 2(b) shows the changes in system reward and process efficiency, illustrating how the model can be used for optimizing operations with the help of intelligent control measures. As shown in Figure 2(c), the distribution of filling accuracy is presented by most of the values that are highly concentrated at the maximum range. In Figure 2(d), the dimensions used for depicting the bottle parameters that affect the filling and capping optimization process have been shown.

Figure 2: Data visualization Analysis of (a) Analysis of target and actual filling volume, (b) Evaluation of process efficiency, (c) Values distribution of accuracy and (d) Visualization of height, width and volume for CPS adaptive control system for the liquid filling-capping process



(a) (b)

(c) (d)

4.2 Evaluation Metrics

The performance of the suggested CPS adaptive control system based on the BO-D3QN algorithm for the liquid Filling-Capping process is analyzed based on important classification parameters. Accuracy reflects the overall accuracy of the control decisions made to regulate the duration of filling, the rate of filling, and synchronization of capping. The precision parameter measures the accuracy of predicted optimal actions under different bottling situations. Recall determines how well the model can detect all the optimal states of control.

4.3 Performance Evaluation

Table 1 and Figure 3 present the evaluation result of performance involving the comparison of the BO-D3QN-based CPS adaptive control with an existing Sequential CNN-based methodis controlling the industrial liquid Filling-Capping process. The Sequential CNN [16] method achieves low accuracy, precision, recall, and F1-score in controlling the dynamic behavior of filling and capping processes. The proposed BO-D3QN method provides better results by providing higher accuracy (0.98), precision (0.96), recall (0.97), F1-score (0.96), and reduced spillage with enhanced decision-making for bottle fillingand capping control.

Table 1: Comparison Analysis of Existing and Proposed Methods

Method	Accuracy	Precision	Recall	F1-Score
Sequential CNN [16]	0.97	0.95	0.95	0.95
BO-D3QN [Proposed]	0.98	0.96	0.97	0.96

Figure 3: Performance Evaluation of Existing and Proposed Methods for Liquid Filling-Capping Process

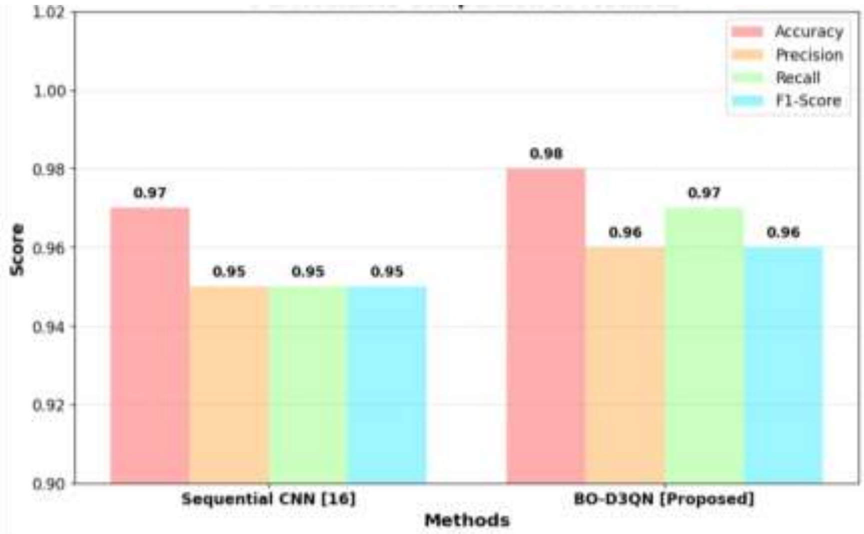


Table 2 presents the ablation study of the proposed BO-D3QN framework by removing key components individually. The complete model achieved the highest performance with 0.98 accuracy and 0.96 F1-score, demonstrating the effectiveness of integrating Bayesian Optimization, D3QN, and Self-Attention Memory. Performance degradation observed after removing each component confirms their significant contribution to accurate and reliable decision-making in the proposed intelligent CPS-based filling system.

Table 2: Ablation Study of the Proposed BO-D3QN Model

Model Variant	Component A (BO Optimization)	Component B (D3QN)	Component C (Self-Attention Memory)	Accuracy	Precision	Recall	F1-Score
Full BO-D3QN (Proposed)	✓	✓	✓	**0.98**	**0.96**	**0.97**	**0.96**
w/o BO Optimization	✕	✓	✓	0.95	0.93	0.94	0.93
w/o D3QN	✓	✕	✓	0.92	0.90	0.91	0.90

w/o Self-Attention Memory	✓	✓	✗	0.94	0.92	0.93	0.92

4.4 Discussion

Design an Adaptive Control Framework for the Liquid Filling–Capping Process based on the CPS using BO-D3QN for increased accuracy, less spillage, and improved decision-making ability. Despite the high accuracy rate of 0.97 in the Sequential CNN Model [16], the model can be hindered by the sensitivity to light variations, different shapes of bottles, and many interruptions in the industrial process. The BO-D3QN model overcomes all the above shortcomings by integrating data from sensors used in CPS together with reinforcement learning algorithms and the BO method to achieve intelligent and stable control.

5. Conclusion

An adaptive control system using BO-D3QN for an industrial Filling and Capping systems is presented within the framework of CPS. Significant information on liquid level, bottle location, flow properties, and capping properties is continuously being acquired. The data pre-processing steps performed include Min-Max Normalization, after which feature selection is performed using ICA. BO-D3QN is capable of developing an optimal policy and is successful, resulting in accuracy, precision, recall, and F1 score of 0.98, 0.96, 0.97, and 0.96 respectively. However, there are some issues associated with this research which include simulation data used in the experiment and extreme sensitivity to disturbance. To improve on this, it would be advisable for future researches to implement this system into instantaneous industrial practice.

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