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Predictive Model Control and Intelligent Agent application in Optimizing the Precision Control of an Electro-Pneumatic Actuator-Based Robotic Bottle Capper

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Abstract. The inferior corking performance observed in bottled drinks from breweries is attributed to poor precision. To address this issue, an enhanced precision control system for an electro-pneumatic actuator-based bottle capper is introduced, utilizing model predictive control and intelligent agent technologies. This involves characterizing the electro-pneumatic actuator system, developing a conventional model for the robotic bottle capper, and designing a rule base to improve precision in the capping mechanism, thereby boosting production capacity per unit time. To achieve this, AI is trained to design a rule-based model ensuring optimal efficacy of the capping mechanism, thus enhancing the brewery industry's production capacity and revenue generation. A SIMULINK model is developed to demonstrate the improved precision control of the electro-pneumatic actuator robotic bottle capper using model predictive control and intelligent agent. Results show a significant increase in corking precision from 94.4% with conventional methods to 99.9% when intelligent agents are incorporated into the system. This translates to a 5.5% improvement in corking precision, with production capacity increasing from 27,000 crates using conventional methods to 28,570 with model predictive control. Moreover, with the integration of intelligence, the production capacity further rises to 342,500 bottles.

Keywords: Improving, Electro Pneumatic, Actuator, Bottle Capper, Intelligent Agent.

1. Introduction

Packaging of brewery bottled beverages, especially beer drinks are typically associated with the act of drawing the product mixture from the mixed solution container, filling it into the bottles by an automated filling control system or machine). These bottled drinks are then been capped, labeled and packed into crates or cartons ready for distribution respectively [1]. Lack of fervency as well as low production capacity of capped bottle of beer in the brewery industry is as a result of poor or low precision associated with an electro pneumatic actuator based robotic capper. This can be resolved by deploying more robust precision controller with some Predictive model controller incorporated with an artificial intelligent. Model predictive control is used to optimize the precision control of the electropneumatic actuator-based robotic bottle capper [1], [2].

Soft pneumatic robotics have attracted more attention due to their deformation capabilities, and high-precision and low-cost backpropagation (BP) neural network-based model method is employed to control the pneumatic actuator [3]. Intelligent control algorithms based on MPC are developed to regulate the targeted pressure in variable-rate capping robots as well as the motion control of the lowering plunger head and conveyor belt [4], [5]. MPC-based motion control framework in the designed based-rule for spherical robots, which includes an optimal velocity controller and an optimal

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orientation controller [4]. The controllers in the framework utilize extend states observers (ESO), multilayer perceptron (MLP), and changing weights to achieve accurate bottle tracking of target commands, minimize fluctuations in attitude and motor currents, and optimize control performance [6].

Thus, a servo pneumatic actuator based lunar robots can be applicable to any form of industrial processes be it: static or dynamic systems, measurement and material evaluations, self-driven vehicles, assembly robots, biomedical engineering, physiotherapy or orthotics systems, and a lot more [7]. Other aspect of intelligent agent is motion planning autonomous mobile robot using recurrent fuzzy neural network (RFNN) trained by extended Kalman filter but was only suitable for simple systems. The RFNN used in the research cannot fit in where complex systems are required [8].

However, a review of other scholar article presented by Zhao et al. achieved feedback linearization controller which achieved high accurate output voltage control in a boost-type DC/DC converter [9]. The controller included integral action to improve performance and reduce steady-state error. The proposed method outperformed an existing two-loop controller in terms of both dynamical and steady-state behavior [10]. Retnaraj et al. applied feedback linearization to an electric hovercraft system for path tracking and achieved satisfactory results [11]. They modeled the nonlinear system and used simple linear controllers for path tracking [12]. The robustness of feedback linearization was analyzed by considering parametric and structural uncertainties as well as unmodeled dynamics [12].

Thus, Model Predictive Control (MPC) is chosen for its optimized precision control stability and applications in the process line, bridging the constraint gap, and satisfying inherent limitations. The proposed MPC algorithms and control frameworks have been experimentally validated and shown to outperform traditional control systems such as PID and sliding mode controller (SMC) in terms of rapidity, accuracy, stability, and energy consumption [13], [14]. Therefore, the motivation for this research is to introduce a novel approach utilizing Model Predictive Control (MPC) and neural network (NN) known for its optimized precision control stability. By leveraging MPC, the aim is to bridge the gap in precision control within the brewery industry's production line while addressing inherent limitations and ensuring stability in the control system.

2. Method

2.1 Characterization of Electro Pneumatic Actuator (ETA) System for Capper Robot

The optimization precision of the Electro Pneumatic Actuator (ETA) relied on several key assumptions. Firstly, considerations were made regarding the height and dimensions of the capper process system to achieve a desirable production rate per hour. This involved ensuring that the system could efficiently accommodate the necessary equipment and facilitate smooth operations within the specified timeframe. Secondly, the diameter of the appropriate cap was carefully taken into account. This ensured compatibility with the capping machinery and minimized the risk of errors or inefficiencies during the capping process. Additionally, proper evaluations were conducted regarding the area of the electro pneumatic actuator to ensure it could cover the precise circumference of the bottle. This was crucial for achieving consistent and accurate capping results across different bottle sizes and shapes. By integrating these considerations into the optimization process, the ETA could effectively meet production targets while maintaining quality standards in capping operations.

Speed RPM	Number of Crates Produced	Time of Production (hr)

Table 1. shows the Intl Breweries PLC (IBP) Lagos beer production capacity data

1350	27000	12

In the case of bottle and cap production, there are two main factors that affect the production process:

a. Capping Time (T), T is the time taken to close one bottle with the cap.
b. Conveyor Speed (S), S is the speed of the conveyor motor that carries the bottles from the production site to the capping site.

Our goal is to maximize the total number of bottles wrapped (P). However, we have to keep in mind two constraints that have been given:

c. Production Capacity Limit: The total time taken to wrap the bottles and the conveyor speed must not exceed 1000, in any relevant unit (seconds for time, rpm for conveyor speed).
d. Maximum Production Limit: The total time and conveyor speed should not exceed the maximum number of bottles that can be produced, which is 324,000 bottles.

Given these constraints, we have the following objective equation describing the total number of bottles wrapped (P):

$$\boldsymbol{P = 133.3T + 4.2S} \quad (1)$$

Then, we have two constraints that must be met:

a. Production Capacity Constraint: $133.3T + 4.2S \leq 1000$
b. Maximum Production Constraint: $43200T + 1350S \leq 324000$

In this context, P is the total number of bottles wrapped, T is the time taken to wrap the bottles, and S is the speed of the conveyor motor. Hence, our objective is to find the values of T and S that satisfy both constraints while maximizing the total number of bottles wrapped.

```
%IMPROVING PRECISION OF ELECTROPNEUMATIC ACTUATOR BASED ROBOTIC BOTTLE CAPPER USING MODEL PREDICTIVE CONTROL
% Maximize P = 133.3T + 4.2S
% Subject to
% 133.3T + 4.2S ≤ 1000
%  43200T + 1350S ≤ 324000
%Where
%P is the total number of bottles corked
%T is the time taken to cork the bottles.
%S is the speed of the conveyor motor to convey the bottles to the corking point.

      f=[-133;4.2];
      A=[133.3 4.25;43200 1350];
      b=[1000;324000];
      Aeq=[0 0];
      beq=[0];
      LB=[0 0];
      UB=[inf inf];
      [X,FVAL,EXITFLAG]=linprog(f,A,b,Aeq,beq,LB,UB)
```

```
%IMPROVING PRECISION OF ELECTROPNEUMATIC ACTUATOR BASED ROBOTIC BOTTLE CAPPER USING MODEL PREDICTIVE CONTROL
% Maximize P = 133.3T + 4.2S
% Subject to
% 133.3T + 4.2S ≤ 1000
%  43200T + 1350S ≤ 324000
%Where
%P is the total number of bottles corked
%T is the time taken to cork the bottles.
%S is the speed of the conveyor motor to convey the bottles to the corking point.
      f=[-133;4.2];
      A=[133.3 4.25;43200 1350];
      b=[1000;324000];
      Aeq=[0 0];
      beq=[0];
      LB=[0 0];
      UB=[inf inf];
      [X,FVAL,EXITFLAG]=linprog(f,A,b,Aeq,beq,LB,UB)
Optimization terminated.
X =
    7.5000
    0.0000
FVAL =
 -997.5000
EXITFLAG =
     1
```

Figure 1. Optimization Calculation

Based on the optimization results obtained, within 7.5 seconds, 998 beer bottles were successfully closed. Therefore, to find the optimal time needed to cork one bottle of beer, we can use the formula:

$$\textbf{Optimum time per bottle} = \frac{\textbf{Total time}}{\textbf{Number of bottles}} \qquad (2)$$

Replaces the given values:

$$\textbf{Optimum time per bottle} = \frac{\mathbf{7.5\ s}}{\mathbf{998\ bottles}} = \mathbf{0.007515\ s}$$

So, the optimization results show that the optimal time required to close one bottle of beer is about 0.007515 seconds.

Table 2. shows the IBP Lagos production cap dimensions

Cap Dimensions	Appropriate Lid Height	Appropriate Cap Height	Suitable Lid Diameter	Suitable Cap Diameter
Height of a cap	8.5mm	9mm	26mm	29mm

In the evaluation of bottle closing precision, several aspects are the main focus. The circumference of the closure is an initial consideration. A precise bottle closure has a circumference of about 81.69 mm, while an imprecise one has a circumference of about 91.1 mm. The percentage precision of the closure circumference is calculated to be about 9.9%. Furthermore, the closure area is also an important consideration. The precise bottle closure has an area of about 660.6 mm^2, while the imprecise one has an area of about 531 mm^2. The precision percentage of the closure area is calculated to be about 19.6%. Finally, closure time is another important aspect. The conventional closing time is about 0.1333 seconds, while the optimised closing time is about 0.007515 seconds. This results in a closing time precision percentage of about 94.4%. Thus, this precision evaluation gives an idea of how well the bottle closing process is performed, with an emphasis on precision in circumference, area, and closing time.

Table 3. showing the results of precision in time of corking the cap of the bottle

% Accuracy when closing the Bottle Cap	Number of Crates Produced	Number of Bottles Produced	Time of Production (hr)
94.4%	28000	336000 bottles	12

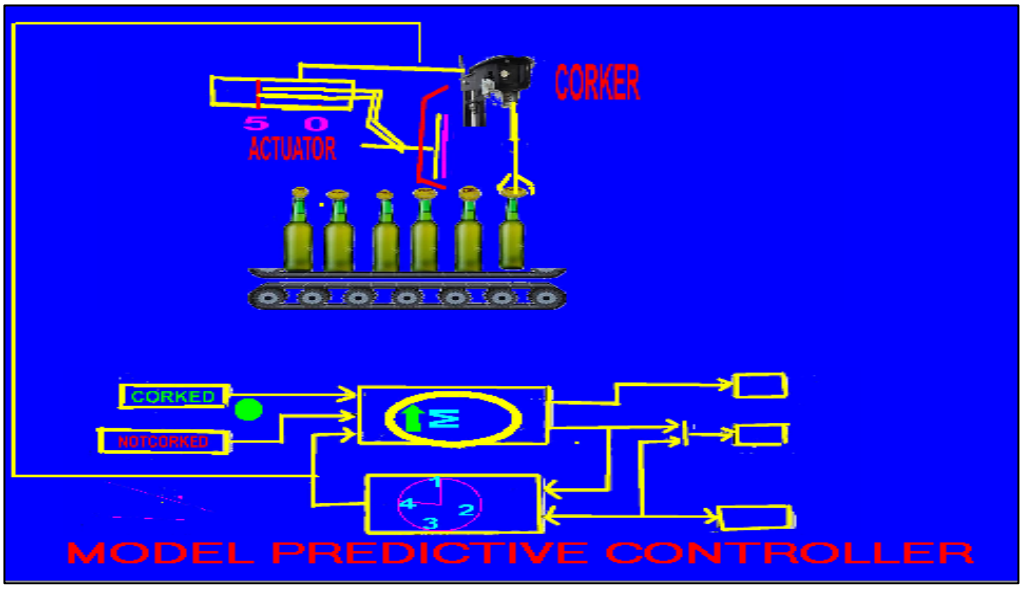

Figure 2. Model Predictive Controller

Figure 2. Above shows the improved MPC developed ground rules to optimize the electro pneumatic actuator-based bottle corking mechanism when the bottle is corked respectively and shows the MPC sensor indicating that the bottle has been corked well before the conventional model SIMULINKS below.

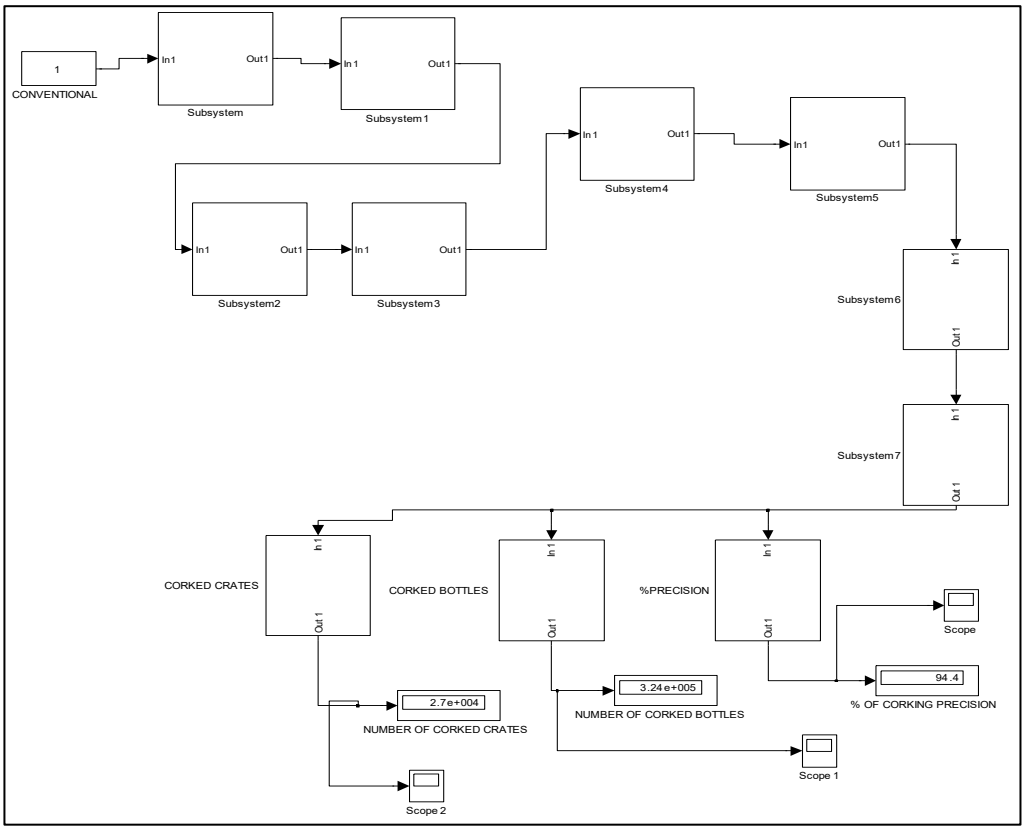

Figure 3 Conventional Improving Precision Control of Electro Pneumatic Actuator Based Bottle Capper

The results obtained in figure 3 are as shown in figure 4. To design a rule base that increases precision in the bottle closing mechanism of electro pneumatic actuators thereby increasing production capacity.

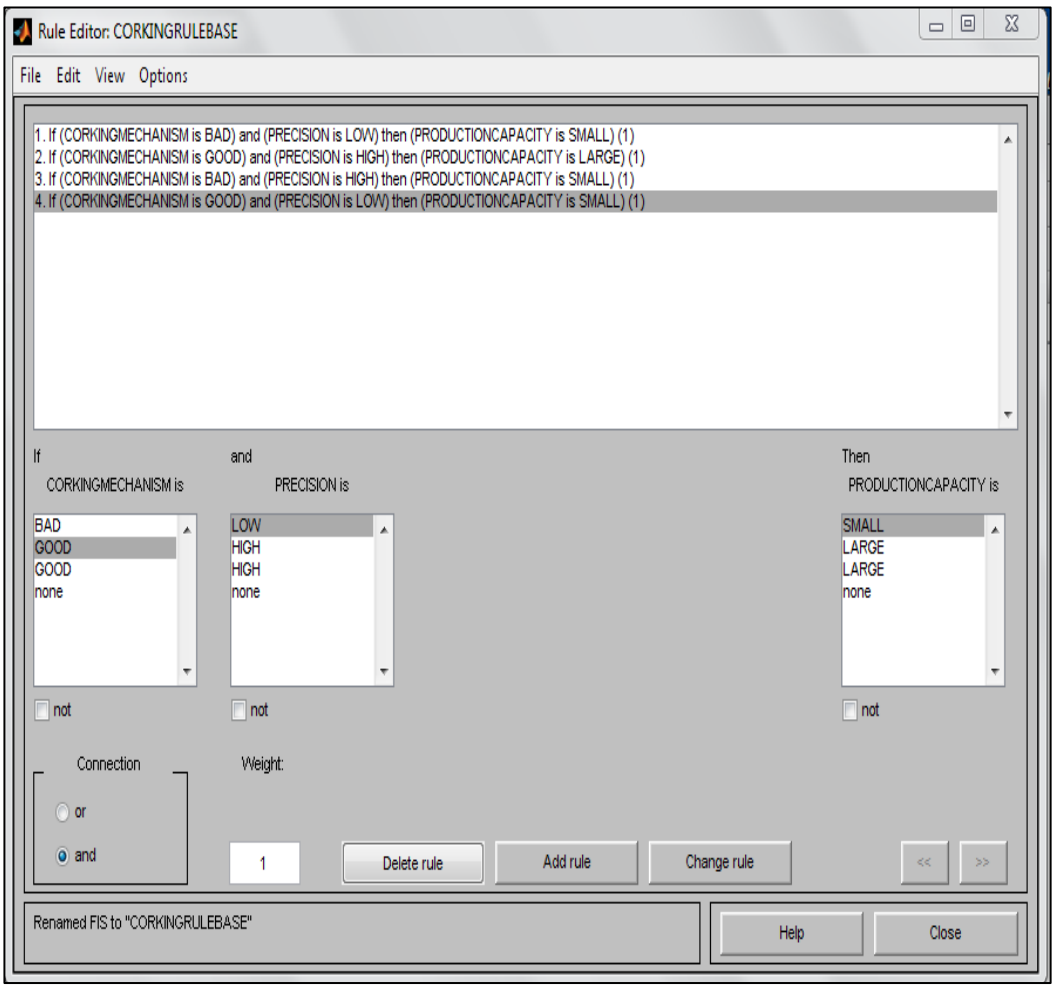

Figure 4 Designed Rule Base That Increases Precision in Capping Mechanism of Electro Pneumatic

Based on figure 4, there are a series of rules designed to improve the precision in the closing mechanism of the electropneumatic actuator bottle closure, with the goal of increasing the overall production capacity. Each rule describes a different condition of the closure mechanism, the level of precision, and its impact on production capacity. Comprehensive details of the rules are as shown in table 4.

Table 4 Base Rule for Improving Precision in Capping Mechanism of Electro Pneumatic Actuator Bottle Capper Thereby Increases Production Capacity

No.	Closing Mechanism	Precision	Production Capacity
1	Bad	Low	Small
2	Good	High	Large
3	Bad	High	Small
4	Good	Low	Small

To improve efficiency in bottle closure precision and thereby increase production capacity in the brewing industry, the first step required is to train an Artificial Neural Network (ANN) according to the designed ground rules. This will help in optimising the improved bottle closure precision, thereby increasing the overall production capacity in the brewing industry.

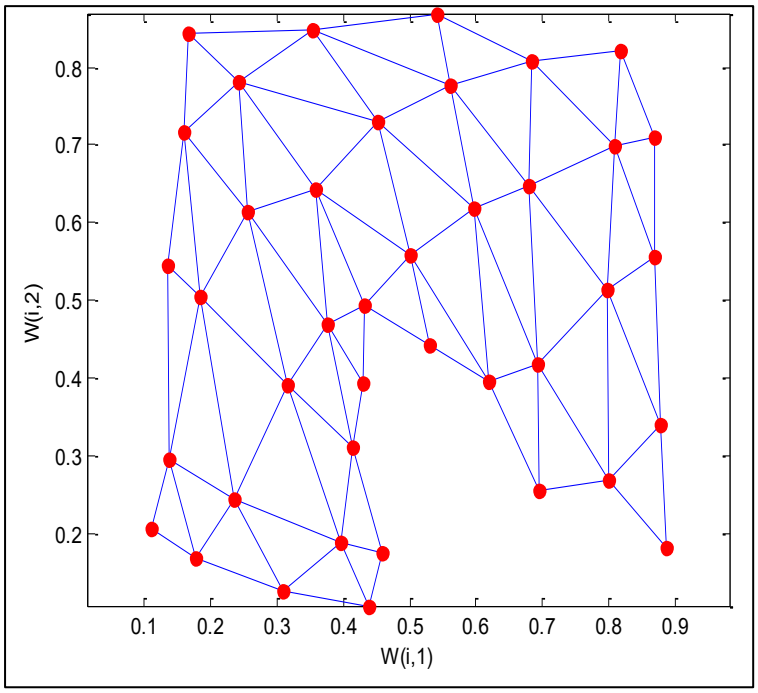

Figure 5. Trained ANN in The Designed Rule Base

Figure 5. Trained ANN in the designed rule base to enhance the efficacy of increasing capping precision thereby enhancing production capacity of brewery industry. Based on Figure 5, Artificial Neural Network that has been trained using the basic rules that have been designed. The aim is to increase precision in the bottle capping process, with the hope that this will result in an increase in overall production capacity in the brewing industry.

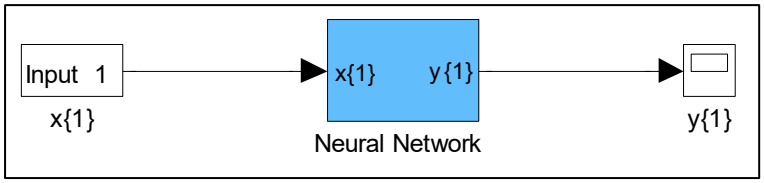

Figure 6. ANN in Basic Rules Designed

Based on Figure 6, an artificial neural network (ANN) model trained in basic rules designed to increase effectiveness in improving closing precision, thereby increasing production capacity in the brewing industry. Artificial Neural Network model that has been trained using the designed ground rules. The aim is to improve the precision in the bottle closing process, which will hopefully result in an increase in the overall production capacity in the brewing industry. To develop a SIMULINK model for improved precision control of electropneumatic actuator-based bottle closures using intelligent agents, can be done by combining modelling of the bottle closure system with intelligent control methods in a SIMULINK environment. This could involve the use of appropriate SIMULINK blocks to represent the bottle closure system and the implementation of intelligent control algorithms to improve the precision of the process presented in Figure 7.

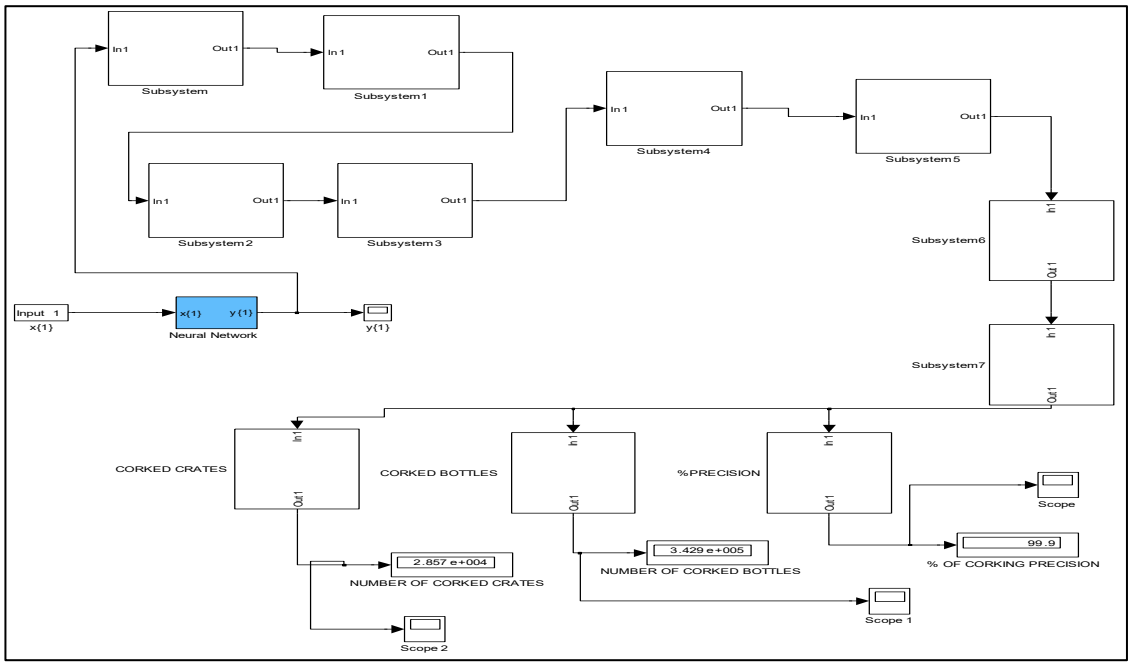

Figure 7 Developed SIMULINK Model for The Improved Precision Control of Electro Pneumatic Actuator Based Bottle Capper Using Intelligent Agent

Figure 7 shows the SIMULINK model that has been developed to control the bottle closing precision using electropneumatic actuators and intelligent control approach. The model is designed to improve the precision in the bottle closing process. The results obtained are shown in figures 8 and 9 respectively.

3. Result and Discussion

The results of the comparative analysis of conventional and intelligent closing precision in the context of improving the precision control of electropneumatic actuator-based bottle closures are presented in Table 5.

Table 5 Comparing Conventional and Intelligent Corking Precision of Improving Precision Control of Electro Pneumatic Actuator Based Bottle Capper

Time (s)	Conventional Corking Precision (%)	Intelligent Corking Precision (%)
0	0	0
1	59	60
2	80	85
3	90	91
4	94.4	99.9
10	94.4	99.9

Table 5 compares conventional closing precision with intelligent closing precision in the electropneumatic actuator-based bottle closing precision control. The observed results show a significant difference between these two approaches. The conventional closing precision starts from 0% initially and increases with time, reaching 94.4% at the 4th second and remaining stable until the 10th second. Meanwhile, the smart closing precision also starts from 0% initially, but increases faster than the conventional process. This precision reached 99.9% at the 4th second and remained stable until the 10th second. These results highlight the superiority of the intelligent control method in achieving higher precision in less time. Thus, the use of an intelligent control approach is able to significantly improve shutdown precision, which in turn will improve production quality in the brewing industry.

The implementation of intelligent controls allows the system to respond and adapt more quickly to changing conditions and variability in the bottle capping process. This can include more accurate adjustments to air pressure, closing speed and bottle position, all of which contribute to increased overall precision [15]. Thus, the use of intelligent control approaches significantly increases closing precision, which in turn will improve

production quality in the brewing industry. In addition, the increased closing precision achieved by using intelligent controls can also reduce waste of raw materials and improve overall operational efficiency. This will result in a more consistent and reliable end product, reducing the need for manual adjustments and quality inspections, and reducing the risk of product waste or defects. Thus, investment in intelligent control technology can provide significant long-term benefits to the brewing industry.

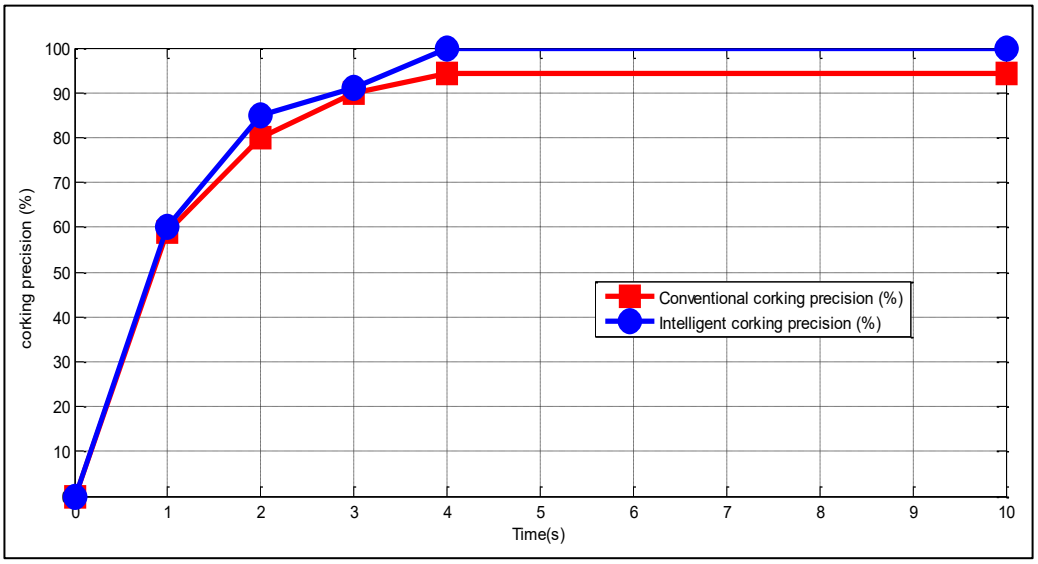

Figure 8 Comparison of Electro-Pneumatic Actuator Based Bottle Closing Techniques

Figure 8 shows that the conventional closing precision is 94.4%, whereas when intelligence is implemented in the system, the closing precision increases to 99.9%. Therefore, there is an increase in closing precision of 5.5% when intelligence is integrated in the system. This shows that the use of intelligence in the system has successfully improved the closing precision significantly, providing more accurate results in the bottle closing process. The development process includes integrating artificial intelligence into the system, which requires careful design and implementation of precise control algorithms. The use of intelligence in the system allows for the optimization of parameters such as air pressure, closing speed and bottle position with greater precision, thereby improving the overall quality of closures. In addition, this approach also involves the establishment of a strong feedback loop, which allows the system to continuously monitor and adapt its operations according to changing conditions [16]. This provides faster response to variations in environmental or operational conditions, which in turn increases bottle closing precision.

The end result of this development was a significant achievement in improving efficiency and quality in the brewing industry. The use of intelligence in the system has succeeded in substantially increasing closing precision, creating a more reliable and consistent solution for the bottle closing process, and in turn contributing to increased productivity and product quality in the industry [16]. Next, compare conventional and smart cork crates to improve the precision control of bottle caps based on electro-pneumatic actuators which can be seen in Table 6.

Table 6 Comparison of Conventional and Intelligent Corking Methods for Enhancing Precision Control in Electro-Pneumatic Actuator-Based Bottle Cappers

Time (s)	Conventional corked crates (crates)	Intelligent corked crates (crates)
0	0	0
1	17000	18000
2	24000	25000
3	26000	27000
4	27000	28570
10	27000	28570

Table 6 compares the effectiveness of the conventional closure method with the intelligent closure method in improving precision control in electropneumatic actuator-based bottle closures. The observed results show a significant difference between these two approaches. The number of bottle baskets successfully closed by the conventional method increases with time, reaching 27000 baskets at the 4th second and remaining stable until the 10th second. On the other hand, the smart closure method successfully closed a larger number at each time interval, reaching 28570 baskets at the 4th second. This shows that the use of the intelligent closure method is able to increase efficiency in the number of bottles closed in the same time period. Thus, the integration of intelligence in the bottle closure system can result in a significant increase in overall production capacity in the brewing industry.

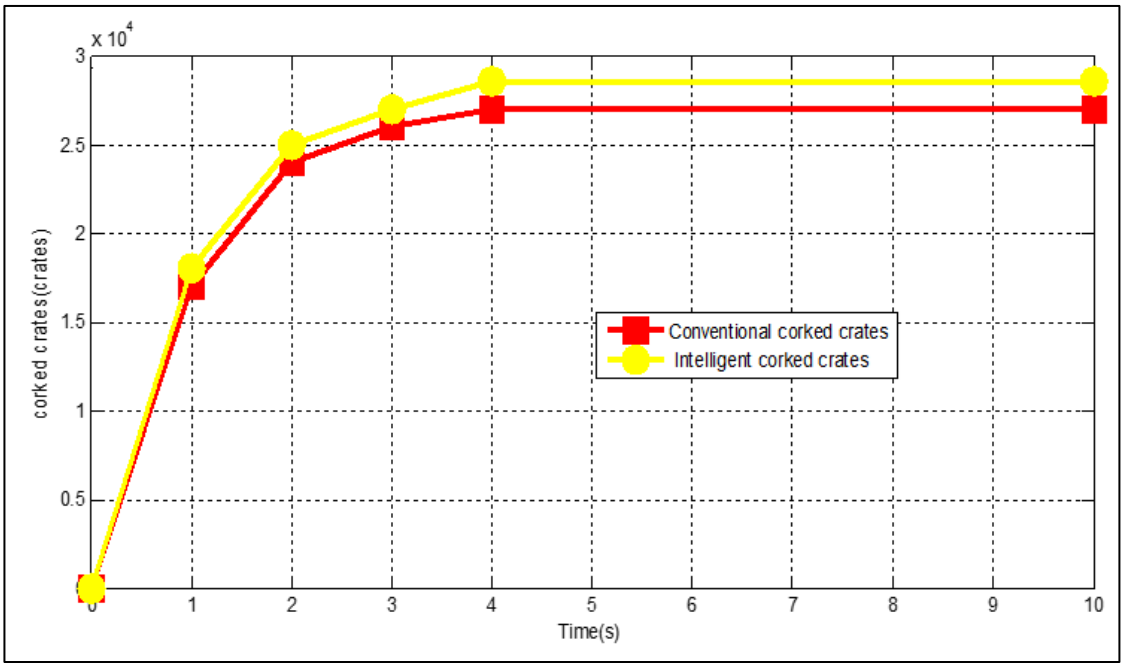

Figure 9 Comparison of Conventional and Intelligent Corking Techniques for Enhancing Precision Control in Electro-Pneumatic Actuator-Based Bottle Capper

Based on Figure 9, the number of conventionally closed beer bottle baskets in the brewing industry is 27000 baskets. However, when intelligence is implemented in the system, this number increases to 28570 baskets. This shows that by using a more intelligent approach in the bottle closing process, the brewing industry can increase production by closing more bottle baskets in the same period of time. The increase in the number of closed beer bottle baskets from 27,000 to 28,570 when implementing intelligence in the process shows the positive impact of using a smarter approach. Under the conventional system, production is limited to 27,000 bushels. However, with the intelligence applied, production increased to 28,570 bushels, representing an increase of approximately 5.8%.

This improvement reflects greater efficiency in the beer bottle capping process, perhaps through optimizing resource use or reducing the time required to complete the task. The implementation of intelligence can enable systems to process data faster, make better decisions, or even learn from experience to improve future performance. In addition to increasing production volumes, the use of intelligence in the beer bottle closing process can also bring other benefits, such as improving product quality or reliability, reducing waste, or even saving production costs in the long term [17]. This shows that investing in technology and intelligence is not just about increasing productivity but also improving various aspects of operations and bottom line.

4. Conclusion

The poor corking mechanism of breweries bottled drinks is as a result of low precision. This is overcome by introducing an improved precision control of electro pneumatic actuator-based bottle capper using intelligent agent. It is done in this form characterizing an electro pneumatic actuator system, developing a conventional model of electro pneumatic actuator based robotic bottle Capper, designing a rule base that increases precision in capping mechanism of electro pneumatic actuator bottle capper thereby increasing the production capacity per time. To this effect, we have to train AI in the design a modeling base rule to ensure that the efficacy of capping mechanism is optimized, thereby enhancing production capacity of brewery industry and revenue drive. The study tends to archive it result by developing a SIMULINK model for the improved precision control of the electro pneumatic actuator robotic based bottle Capper using intelligent agent. The results obtained were compared with the conventional precision output at 94.4% to when intelligent agent was incorporated in the system, and we obtain a corking precision of 99.9%. Finally, the percentage improvement in corking precision while justifying the conventional methods to intelligent agent was 5.5%, with the production capacity of 27000 crates for conventional, 28 570 using MPC. On the other hand, when intelligence is imbibed in the system it increased to 342500 bottles.

5. Author's Declaration

Author contributions and responsibilities - The authors made major contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation and discussion of results. The authors read and approved the final manuscript.

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Availability of data and materials - All data is available from the author.

Competing interests - The authors declare no competing interests.

Did you use generative AI to write this manuscript? - I do not use AI assistance in my manuscript.

Declaration of generative AI and AI-assisted technologies in the writing process - During the preparation of this work the author did not use AI to write, edit, or other things related to the manuscript.

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