International Journal of Engineering and Environmental Sciences | *ISSN 1694-4372*
Published by ACADEMIC INK REVIEW | *https://airjournal.org/ijees*
16/18 Avenue des Longaniers, Quatre Bornes, Mauritius
airjournals@gmail.com; enquiry@airjournal.org

Triggered Tracking Adaptive Based Intelligent Algorithm

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Publication Process	Date
Accepted	November 22nd, 2021
Published	November 30th, 2021

ABSTRACT

The improperly filling of brewery industry beer bottle has become a chronic social malady that has liquidated some of the brewery industry that does not have adequate filling mechanism in their production process. This has equally made them to lose some of their big-time customers that would have elevated them to the next level if their products are standard in terms of filling. The under-filled beer bottles observed in the brewery industry is surmounted by an introduction of improving production output in brewery industrial processes using event-triggered tracking adaptive based intelligent algorithm. This is done in this manner, characterizing bottle filling process in brewery industry production, designing a SIMULINK model for the conventional characterize bottle filling process in brewery industry production, designing an adaptive rule base that will monitor the production filling process, training ANN in the designed rule to track improperly filled bottles and feed them back for proper refilling and designing a SIMULINK model for improving the design strategy for event-triggered tracking in brewed production process using adaptive based intelligent algorithm. Finally, designing a SIMULINK model for improving production output in brewery industrial processes using event-triggered tracking adaptive based intelligent algorithm. And validating and justifying the result obtained. The results obtained after implementation are conventional highest quantity of bottled beer filled is 35770 bottles of beer while that when event-triggered is introduced in the system is 39010 bottles of beer all occurred from 4 through 10 seconds, highest conventional under-filled bottles of beer is 3110 bottles while that when event-triggered is introduced in the system is 2199 bottles. With these results obtained, the percentage improvement of less quantity of under-filled bottles when event-triggered is imbibed in the system is 29%, conventional volume of the under-filled bottle of beer is 56cl while that when event-triggered is incorporated in the system is 60cl which is the ideal volume of bottled beer in brewery industry and highest conventional crates of underweight brewery bottled beer is259 crates while that when event-triggered is incorporated in the system is183. With these obtained results, it shows that including event-triggered in the system saved 76 crates of underweight brewery bottled beer that would have been wasted.

Keywords: *SIMULINK Model; Brewery Industry; Event-triggered; Adaptive; Intelligent Algorithm*

1. Introduction

Event-triggered control was developed to reduce the load of communication in networked control systems. Thus, the output or actuator signals are usually transmitted over the network when a certain condition, considered to be event-triggering, is violated whereas it is designed to ensure that a control performance can be guaranteed. Two control schemes, event-triggered and time-triggered control, abandon the periodic control paradigm. Event-triggered control is reactive and also generates sensor sampling and control actuation. This is done when the plant state deviates from the desired value of more than a certain threshold. Conversely, self-triggered control is proactive, computing the next sampling or actuation occurrence ahead of time. New methodologies and a new system theory are necessary for the analysis and design of these innovative and resource-aware control schemes. To fully understand these control schemes, it is anticipated that hybrid systems theory can play a very important role. In this research, event-triggered control is the technique used to actualize the aim which is the overall research topic.

Taking one application of inspection of bottle filling, the method is very fast, quite repetitive, and subjective. In this type of environment, machine vision systems are ideally suited for routine inspection and detection methods to inspect the filling level of the bottle and compare the performances concerning the traditional template-based edge detection techniques like Robert, Prewitt, and Sobel edge detector. We discussed the problem of filling a water bottle. Meanwhile, template-based and optimal edge detection techniques for filling level inspection using machine vision helps to get an accurate filling mechanism for the bottles. For an effective filling to take lace an algorithm will be proposed for liquid level inspection. Filling bottles using a machine with accuracy is subject to error from a wide variety of potential problems from flow rates to glass bottle variations. To ensure consistent fill levels 100% quality inspection is required. Inspection systems must also be capable of keeping up high-speed filling/bottling machinery. A schematic of bottle filling system needs to be designed. Failure to properly fill bottles to the correct volumes as stated on packaging results in loss of customer loyalty, consumer fraud allegations, and recalls. For instance, if the milk bottles are not properly filled which are prescribed for the babies then the proper nutrition in the required amount would not reach the baby's body which results in loss of customer loyalty as well as fraud allegations. Overfilling results in giving away products and profits. The inspection method chosen is fast enough to keep up with high-speed filling machines and provide accurate and repeatable results. An approach to the above problem is made by extracting the edges from the image captured by a 3.2-megapixel camera and then applying a distance-based novel technique, to decide on the above-said problem of over and underfilling bottle inspection quality assurance tasks. Backed by powerful state-of-the-art electronic technologies, machine vision provides a mechanism in which the human thinking process is simulated artificially. In machine vision-based systems many edge detection techniques proposed by many researchers are prevailing. Each technique works nicely for the particular application only.

There is not a general consensus about one or a couple of methods to be used for edge detection in the machine vision community. Significant work\ in bottle defect detection and bottle filling level inspection is done. In the area of bottle defect detection, enough literature can be found out, while in the case of bottle filling level inspection cited literature is not available due to its inherently simple task of edge detection and distance measurements. But the latest developments in the field of optimal edge detection algorithms are still untouched particularly in the application of bottle filling inspection. In (Wang et al, 2014) Proposed an algorithm for bottle finishing using Hough transform methods which would detect the defective bottle from the bulk and separate it. In (Wang et al, 2014) proposed a watershed algorithm for bottle inspection by detecting out the possible defective regions in the upper portion of the bottle called the neck of the bottle and extracting these features from the image. Further, for the purpose of classification, the optimal hyperplane concept based on the SVM method was used (Hui-MinMa et al, 2017).

2. Methodology

To characterize bottle filling process in brewery industry production
Characterizing the parameters of a bottle shape of (R_B, r_t, H_B, h_t, h_F[3,1,15,5,5]cm to be filled at 9cl/sec and 90 degrees valve dilation in a typical beer bottle dispensing system using a mathematical model.

Measurements and analysis of the characterized beer bottle shape was made and the values gotten were characterized geometrically as shown below:

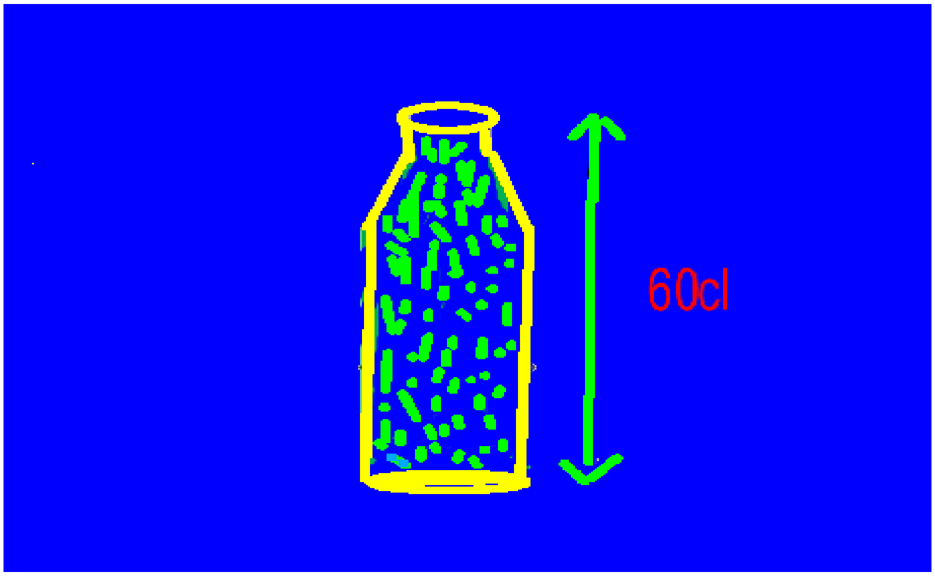

Fig 1: Bottle shape with cylindrical top, frustum neck, and cylindrical base

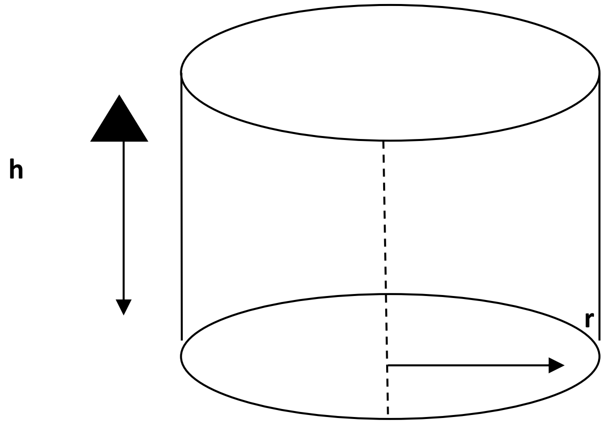

Fig 2: Top Cylindrical Shape

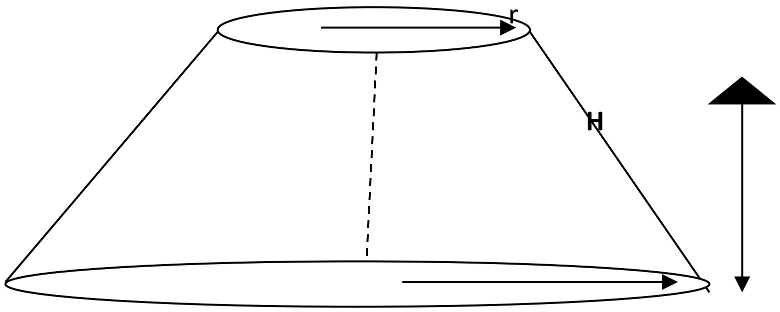

Fig 3: Middle Frustum Shape

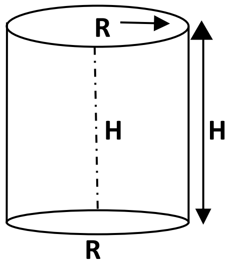

***Fig 4: Bas*e Cylindrical Shape**

Table 2.1 parameters for the Shapes

R_B	**3cm**
H_B	18.4cm
H_F	5cm
h_T	5cm
r_T	1cm

I. Radius of the topmost cylindrical shape

II. Highest of the topmost cylindrical shape

III. Radius of the top of the Frustum

IV. Radius of the base of the Frustum

V. Height of the Frustum

VI. Radius of the base cylindrical shape

VII. Height of the base cylindrical shape sum of the height of the top cylindrical shape, height of the Frustum, and that of the base cylindrical shape.

VIII. Pi (π) which is a constant for circular shapes.

Mathematically, the volume of the base cylindrical shape:

$$V_B = \pi R^2 h \qquad \text{3.1}$$

The volume of a Frustum is given by

$$V_F = \frac{\pi h}{3} (R^2 + Rr + r^2) \qquad \text{3.2}$$

The volume of the Top cylindrical shape is given as

$V_T = \pi r^2 h$

Where $V_B =$ Volume of the base cylinder

V_T = Volume of the Top cylinder

V_F = Volume of the Frustum

R_B= Radius of the base cylinder

r_t = Radius of the top cylinder

Volume as a physical quantity is a function of height and radius which varies with bottle shape. In this work, the radius and the overall height of a bottle are represented in the table below for a chosen liquid volume of …. Cl.

$V_{Full} = \pi r^2 h_T + \pi h_F (R^2 + R_B r_T + r_B^2) + \pi R^2 h_B$ ……………………………$_B$ 3.1

$V_{Full\ bottle} = 3.142 \times 1^2 \times 5 + 3.142 \times 5\ (3^2 + 3 + 1^2) + 3.142 \times 3^2 \times 18.4$

$V_{full\ bottle} = 15.71 + 5.236\ (13) + 520.32$

$= 15.71 + 68.068 + 520.32$

$V_{full\ bottle} = 597.658\ cm^3$

Approx 60cl

Ideally, liquids are not filled to the brim. Beverage companies do allow vacuums that are filled with methane gas or carbon dioxide to inhibit microorganisms from contaminating the contents. Standard liquid volumes as chosen and monitored to maintain quality and reduce waste. Standard volumes are maintained around 40 percent of the topmost cylindrical shape as it is in the shape of the bottle under study. This will also suggest the specific liquid volume that is read from the weight in the weight sensor display. Though this is monitored automatically by a neural network programme in the Programmable Logic Circuit

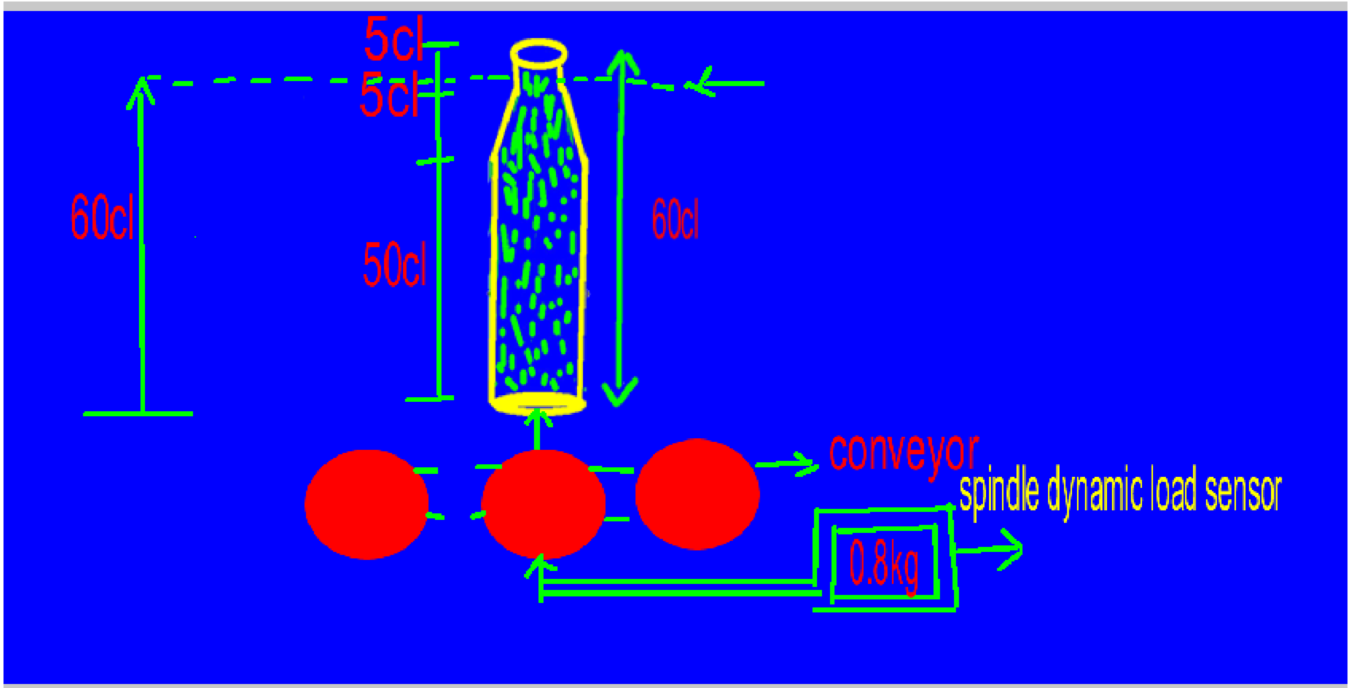

Fig 5: Weight Sensor position for a specified liquid level

Recall that our mathematical model for the bottle shape with triple geometry is given by:

$$V_{full\ bottle} = \pi r^2 h_T + \frac{\pi h_F}{3} \left(R_B^2 + R_B r_T + r_T^2 \right) + \pi R_B^2 h_B \ldots\ldots\ldots\ldots\ldots\ldots \quad 3.4$$

To achieve a liquid height of at least 40 percent of the topmost cylindrical shape, the height of the topmost cylindrical shape h_f will be taken to be 2cm.

Therefore, volume at 22cm height will be the ideal liquid level

$$V_{Liquid\ level} = 3.142 \times 1^2 \times 2 + 3.142 \times 5 \frac{(3^2 + 3 + 1^2)}{3} + 3.142 \times 3^2 \times 18.4$$

$= 6.284 + 68.08 + 520.32 = 595$

Appro= 60cl

This volume of water of density 1000kg/cm^3 is given by

$$\text{Density} = \frac{\text{Mass}}{\text{Volume}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3.5$$

Weight = Mg = Volume x density

Therefore the algorithm for a specified liquid volume and weight is given by

$$\text{Weight} = \{V_{\text{full bottle}} = \pi r^2 h_T + \frac{\pi h_F}{3}\left(R_B^2 + R_B r_T + r^2\right) + \pi R_T^2 h_B\}.\ \text{density}_B$$

$$= V_{\text{full bottle}} = \pi r^2 h_T + \frac{\pi h_F}{3}\left(R_B^2 + R_B r_T + r_B^2\right) + \pi R_T^2 h_B \times 1000\ \text{kg/cm}^3$$

Flow Rate

From the law of conservation of mass (continuity), the density and volume of fluid all change with the shape of the object within the domain of time.

In this work, the diameter of the nozzle used is 0.6cm and the speed of beer delivered through the nozzle is 7.98m/s, hence the mass flow rate was determined thus:

$$\text{Mass flow rate} = \frac{\text{Mass}}{\text{Time}} = \text{Density x Area x Velocity}$$

$$\text{Where Density} = \frac{\text{Mass}}{\text{Volume}}$$

Therefore, the flow rate in volume per unit time is given as below;

$$\frac{\text{Volume}}{\text{Time}} = \text{Area x Velocity}$$

Area of the nozzle = πr^2 where $\pi = 3.142$ and r = 0.003m

= 3.142 x 0.003 x 0.003

= 0.00002823m^2

The flow rate of the dispenser is obtained as below;

Flow rate = 7.98 x 0.00002823

= 0.0002013m^3/s

= 0.2013cl/s

= 20cl/sec

Valve Dilation / Opening

Table 2.2 Distributions of Flow Rate, Bottle Calibration, and Valve Opening

Time (s)	*Dilation Angle (°)*	*Flow Rate (cl/sec)*	*Volume (cl)*
1	90	20	20
2	67.5	15	35
3	22.5	5	40
4	22.5	5	45
5	13.5	3	48
6	9	2	60

Design Components

Load sensor – point load sensor

- Capacity: 0 – 20 kg
- Voltage rating: 24V

Photoelectric sensor

- detecting range: 10m
- position measurement: 10cm
- response time: 10ms

Solenoid valve

- Maximum dilation rate: 90cl per second

Conveyor

- 12V dc motor
- 200rpm at 12V operational voltage
- 2.5kg per cm torque
- 1/30 gear reduction ratio

Relay

- nominal voltage: DC 12V

Liquid Level Sensor

- Four (4) nodes: upper, middle, lower, and common nodes
- Voltage rating: 24V DC

Table 2.3 Data from AMA brewery industry in Enugu

VOLTAGE (V)	*SPEED REV/PM*	*NUMBER OF crates PRODUCED*	*NUMBER OF BOTTLES OF BEER PRODUCED*	*TIME OF PRODUCTION(hr)*
230	1500	3240	38880	12

8% of the bottle of beer produced in 12 hrs was underfilled to 56cl
To find the number of underfilled bottles of beer produced in the brewery industry in 12 hours
No of underfilled bottles of beer produced in brewery industry = $\frac{38880 \times 8\%}{100\%}$
No of underfilled bottles of beer produced in brewery industry =3110 bottles
No of underfilled bottles of beer crates produced in brewery industry =259.2crates
No of properly filled bottles of beer produced = (38880 -3110) bottles
No of properly filled bottles of beer produced = 35770bottles
No of properly filled bottles of beer crates produced =2980.8crates

Table 2.4 Density of Beer

DENSITY OF BEER	*VOLUME IN CL*
1g/m	60

To calculate the weight of the beer the weight sensor will deem good and bad

Recall converting c l to liters

50CL = 2liters

$$60CL = \frac{2 \times 60}{50}$$

60CL = 2.4liters

Recall

$$\text{Density} = \frac{\text{Mass}}{\text{Volume}}$$

Mass = Density x volume

Mass = 1 x 2.4

Mass = 2.4Kg

Weight = Mass x Acceleration due to gravity

W = Mg

W = 2.4 x 9.8

W = 23.52N

If the weight sensor signals the weight of the filled bottle to be within the range of 23N to 23.52N, it is properly filled. On the other hand, if the weight sensor senses the filled bottle to be below 23N. it indicates that it is improperly filled and sends it back for refilling.

To Design a Simulink Model for the Conventional, Characterized Bottle Filling Process in Brewery Industry Production

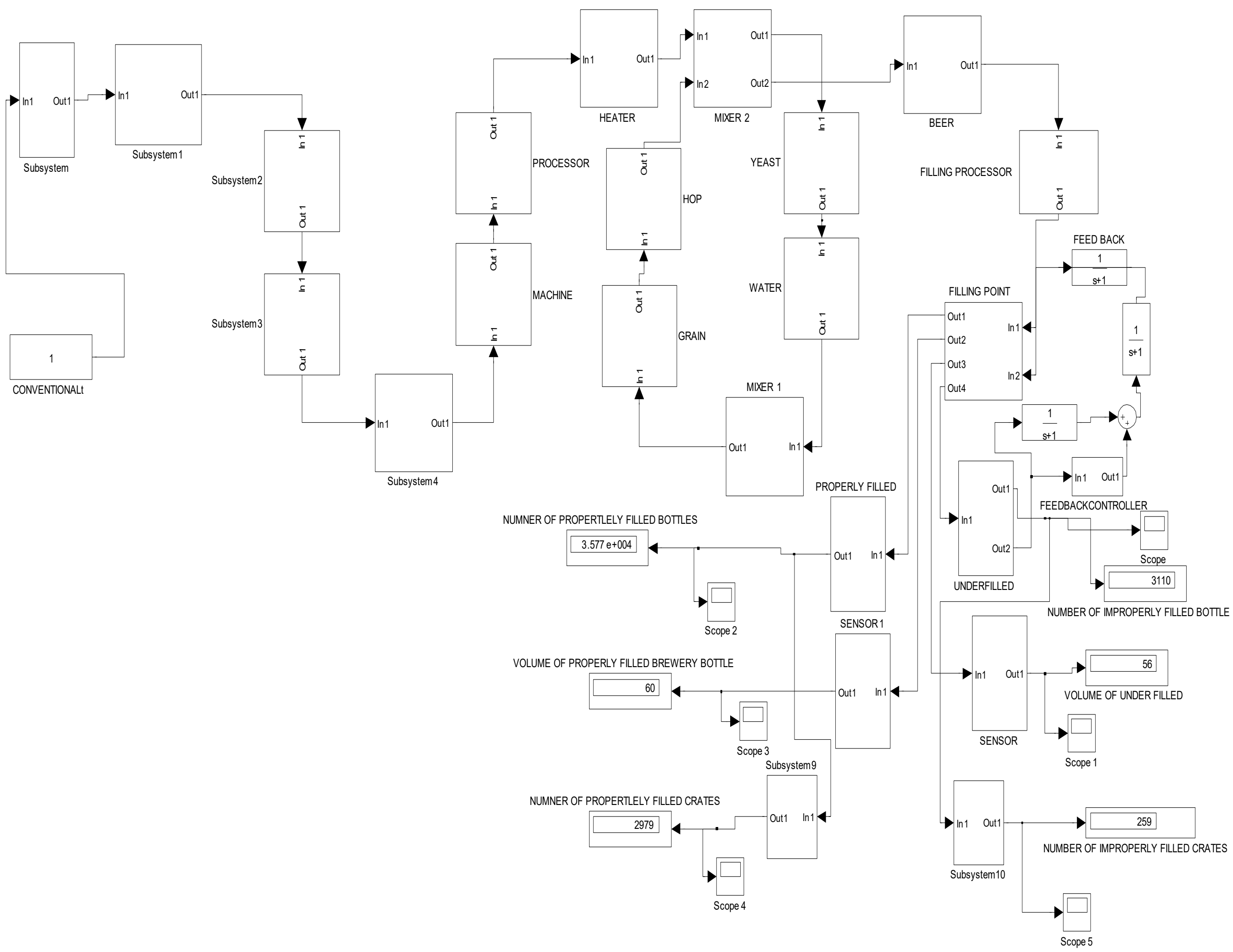

Fig 4 Designed SIMULINK model for the Conventional Characterize Bottle Filling Process in Brewery Industry production

Fig 4 shows the designed SIMULINK model for the conventional characterized bottle filling process in brewery industry production. The collected parametric and analytical data were incorporated in the designed model and simulated. The results obtained were as shown in figures 9 and 10

To design an adaptive rule base that will monitor the production filling process

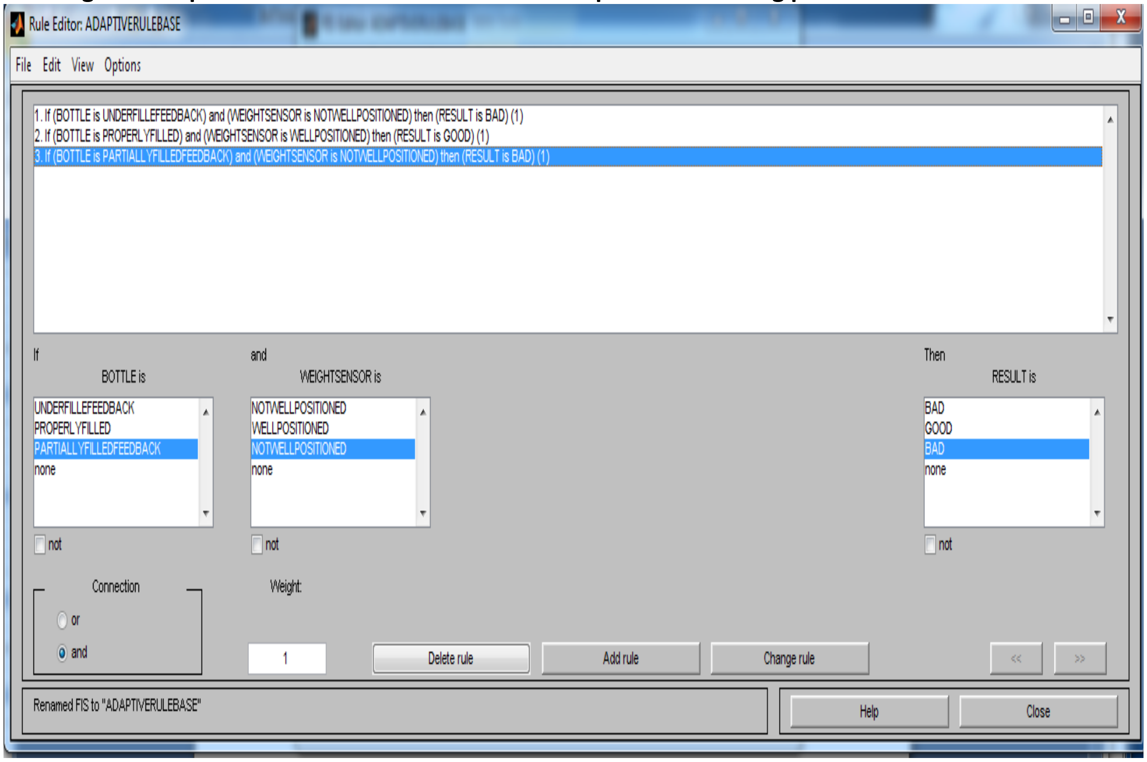

Fig 5 Designed adaptive rule base that will monitor the production filling process

Fig 5 shows an adaptive rule base that will monitor the production filling process and the comprehensive analysis is as shown in table1

Table 2.5 Adaptive Rule Base that Will Monitor the Production Filling Process

No of Rules			
1	If the bottle is underfilled feedback	And weight sensor is not well positioned	Then, the result is bad
2	If the bottle is properly filled	And weight sensor is well positioned	Then, the result is good
3	If the bottle is partially filled feed back	And weight sensor is not well positioned	Then, the result is bad

To Train Ann in the Designed Rule to Track Improperly Filled Bottles and Feed them Back for Proper Refilling

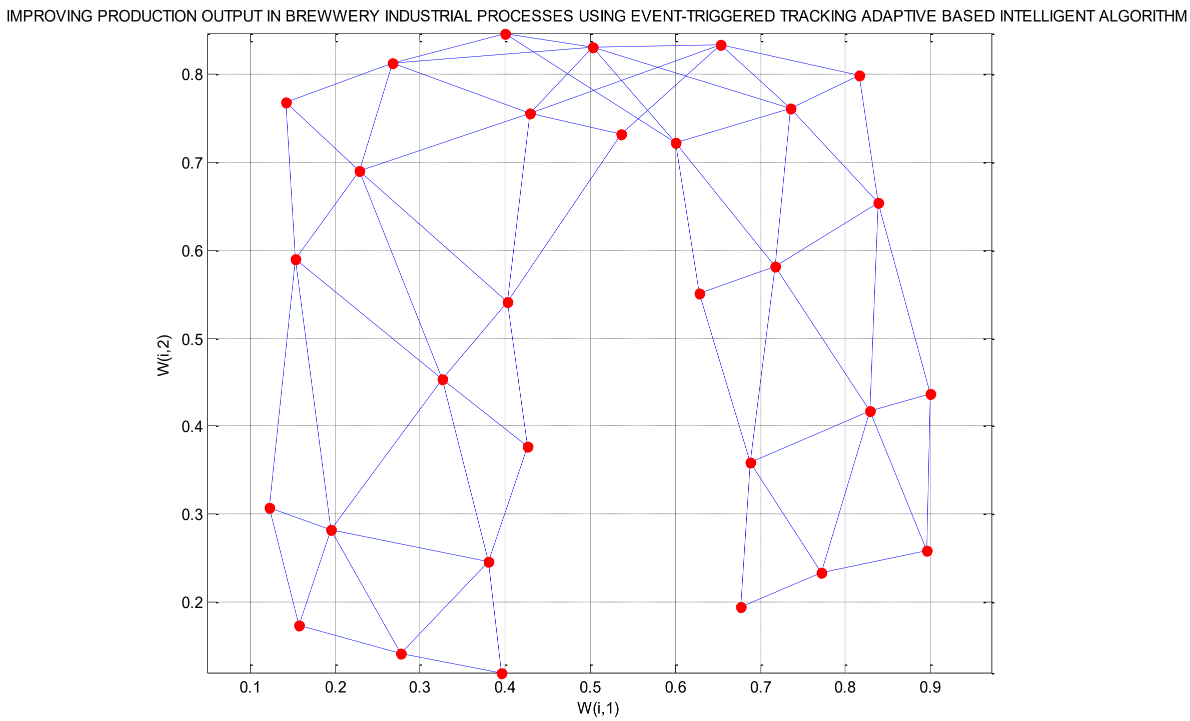

Fig 6 trained ANN in the designed rule to track improperly filled bottles and feed them back for proper refilling.

In Fig 6 the 3 rules were trained twenty times to have sixty neurons that mimic human intelligence by making sure that the volume of the beer bottle is 60cl.

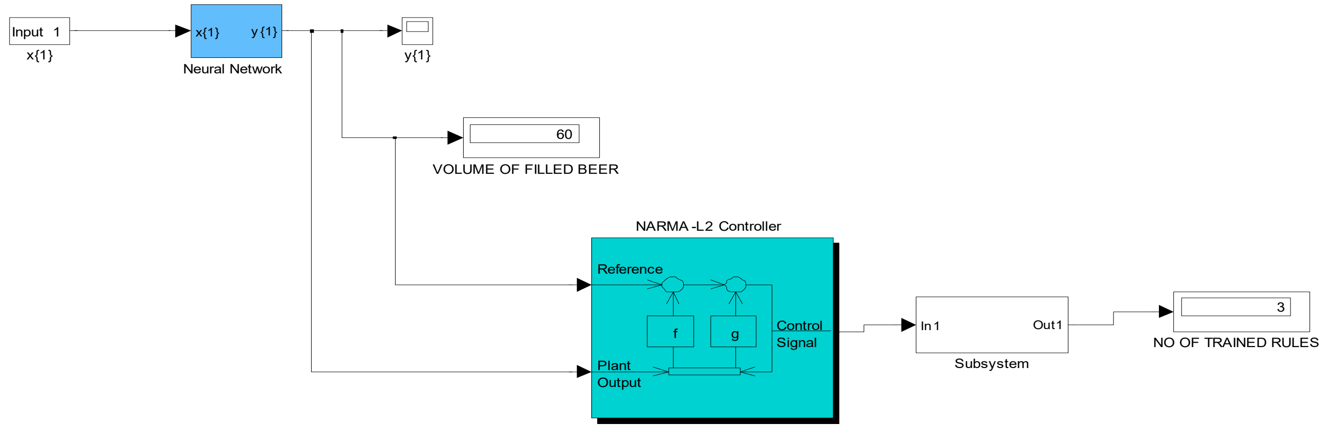

Fig 7 SIMULINK model for trained ANN in the designed rule to track improperly filled bottles and feed them back for proper refilling.

Fig 7 shows the SIMULINK model for trained ANN in the designed rule to track improperly filled bottles and feed them back for proper refilling.

To Design a Simulink Model for Improving the Design Strategy for Event-triggered Tracking in Brewed Production Process Using Adaptive Based Intelligent Algorithm

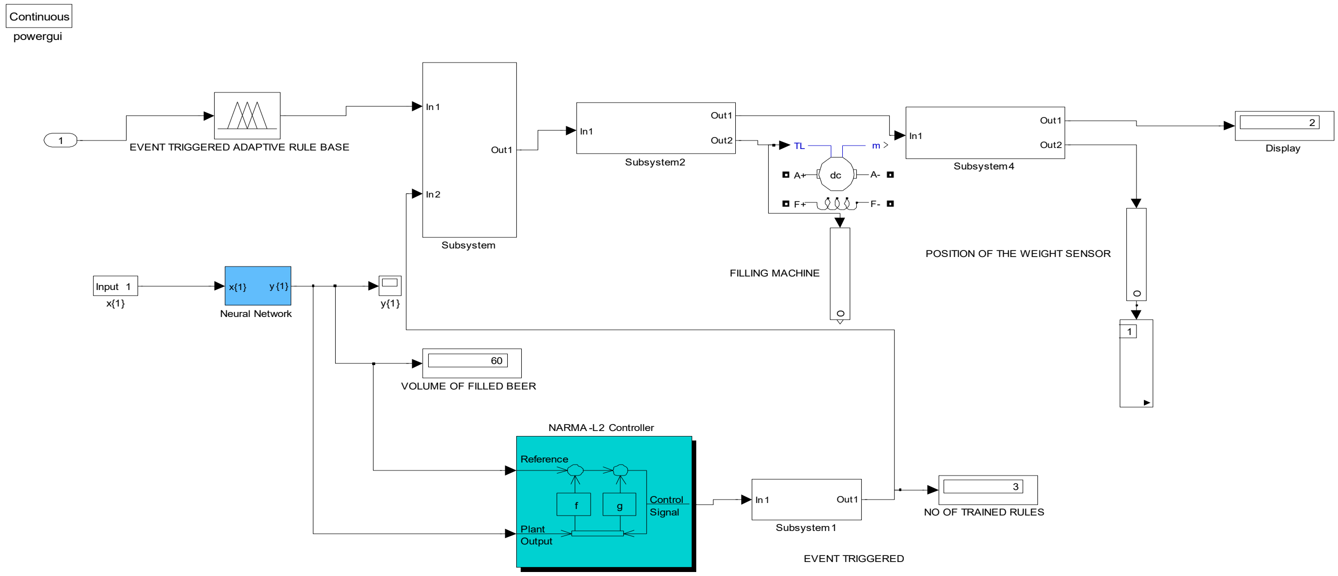

Fig 8: Designed SIMULINK model for improving the design strategy for event-triggered tracking in the brewed production process using an adaptive based intelligent algorithm.

Fig 8 shows the designed SIMULINK model for improving the design strategy for event-triggered tracking in the brewed production process using an adaptive based intelligent algorithm.

Adaptive based intelligent algorithm.

1. Identify the standard volume of the beer bottle as 60cl.

2. Identify the filling machine

3. Identify the position of the weight sensor.

4. Identify the weight sensor detector value is within range of 23N to 23.52N or out of range

5. Identify event-triggered tracker adaptive rule base.

6. Apply trained ANN in 1, 2, 3, 4 and 5

7. Is the weight sensor detector value within the range of 23N to 23.52N

8. No go to 1

9. Yes go to 13

10. Is the filled beer bottle volume at the required standard as sensed by 3?

11. No go to 1

12. Yes go to 13

13. Improved production output.

14. Stop.

15. End

3. Discussion of Result

Table 3.1 Comparing Conventional and Event-Triggered Quantity of Properly Filled Brewery Bottled Beer

Time(s)	*Conventional quantity of properly filled brewery bottled beer (bottles)*	*Event-triggered quantity of properly filled brewery bottled beer((bottles)*
0	0	0
1	23000	25000
2	31000	33000
3	33000	37000
4	35770	39010
10	35770	39010

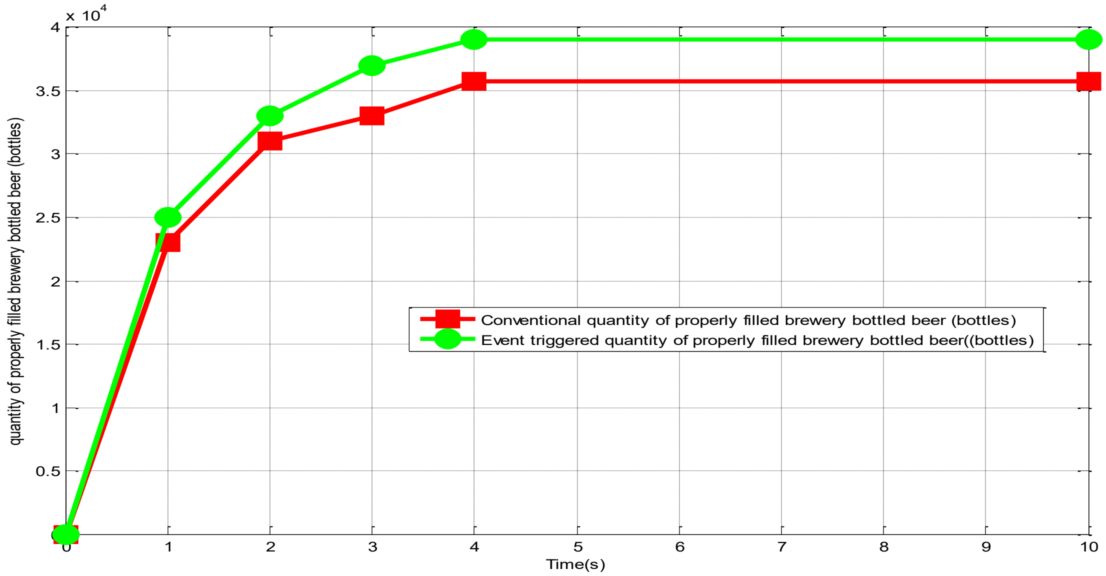

Fig 9 Comparing Conventional and Event-triggered quantity of properly filled brewery bottled beer

Fig 9 shows Comparing Conventional and Event-triggered quantity of properly filled brewery bottled beer. The conventional highest quantity of bottled beer filled is 35770 bottles of beer while that when event-triggered is introduced in the system is 39010 bottles of beer all occurred from 4 through 10 seconds.

Table 3. 2 Comparing Conventional and Event-triggered Quantity of Improperly Filled Brewery Bottled Beer

Time(s)	*Conventional quantity of improperly filled brewery bottled beer (bottles)*	*Event-triggered quantity of improperly filled brewery bottled beer((bottles)*
0	0	0
1	2000	1500
2	2700	2000
3	3000	2100
4	3110	2199
10	3110	2199

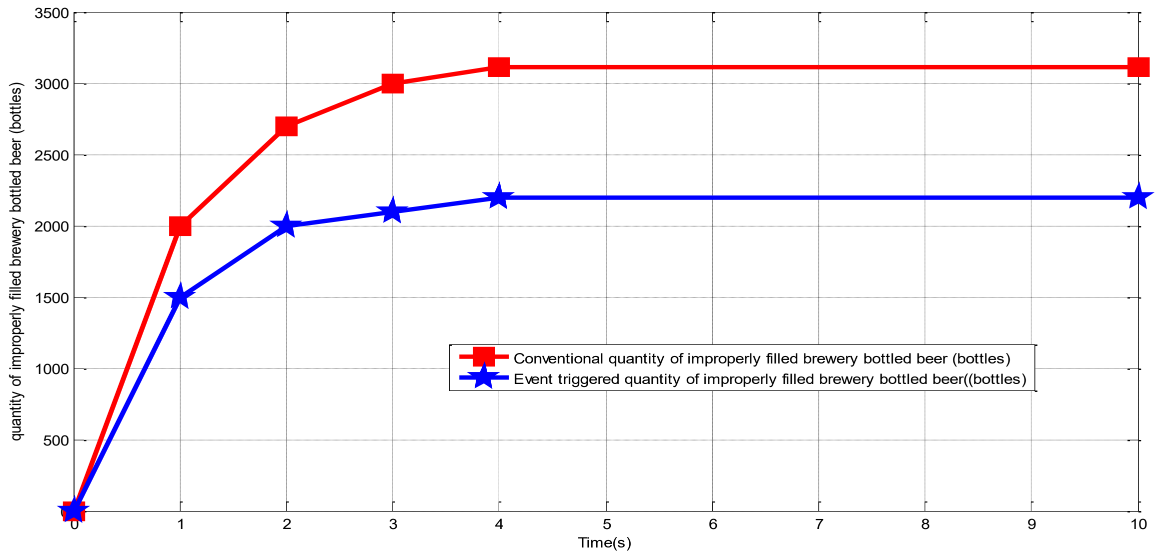

Fig 10 Comparing Conventional and Event-triggered quantity of improperly filled brewery bottled beer

Fig 10 shows Comparing Conventional and Event-triggered quantities of improperly filled brewery bottled beer. The highest conventional under-filled bottles of beer is 3110 bottles while that when event-triggered is introduced in the system is 2199 bottles. With these results obtained, the percentage improvement of less quantity of under-filled bottles when event-triggered is imbibed in the system is 29%.

4. Conclusion

The waste incurred in the brewery industry as a result of underweight or under-filled bottles of beer has drastically reduced the industry's financial growth, reputation, and loss of some of its numerous customers. This is solved by introducing improving production output in brewery industrial processes using event-triggered tracking adaptive based intelligent algorithm. This is done in this manner, characterizing bottle filling process in brewery industry production, designing a SIMULINK model for the conventional characterize bottle filling process in brewery industry production, designing an adaptive rule base that will monitor the production filling process, training ANN in the designed rule to track improperly filled bottles and feed them back for proper refilling and designing a SIMULINK model for improving the design strategy for event-triggered tracking in the brewed production process using an adaptive based intelligent algorithm. Finally, designing a SIMULINK model for improving production output in brewery industrial processes using event-triggered tracking adaptive based intelligent algorithm. and validating and justifying the result obtained. The results obtained after implementation are conventional highest quantity of bottled beer-filled is 35770 bottles of beer while that when event-triggered is introduced in the system is 39010 bottles of beer all occurred from 4 through 10 seconds, highest conventional under-filled bottles of beer is 3110 bottles while that when event-triggered is introduced in the system is 2199 bottles. With these results obtained, the percentage improvement of less quantity of under-filled bottles when event-triggered is imbibed in the system is 29%, the conventional volume of the under-filled bottle of beer is 56cl while that when event-triggered is incorporated in the system is 60cl which is the ideal volume of bottled beer in brewery industry and highest conventional crates of underweight brewery bottled beer is259 crates while that when event-triggered is incorporated in the system is183. With these obtained results, it shows that including event-triggered in the system saved 76 crates of underweight brewery bottled beer that would have been wasted.

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