



Improving Industrial Quality Control by Machine Learning Techniqu

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Article Info

Article history:

Received 6 August 2024

Received in revised form

68September 2024

Accepted 20 September 2024

Keywords:

Machine Learning Techniques

Flexibility

Industrial Control

Sustainability

Production Systems

Energy Consumed

Cost

Abstract

In light of the development of computing systems and machine learning techniques, the development of industrial control processes in production processes has become easier, more accurate, and more flexible. Machine learning techniques, after being integrated with industrial control processes, have become one of the most important tools that achieve sustainability in the field of industry. Thus, economic sustainability is achieved. Through it, production systems can be improved, costs reduced, energy consumption reduced, quality increased, and future malfunctions predicted. Thus, reducing the cost of repair and maintenance. The study aims to clarify the importance of machine learning techniques in industrial control processes, and that integrating machine learning techniques with industrial control techniques contributes to achieving sustainability in the field of industry. The study also aims to identify the obstacles and challenges facing the field of machine learning techniques in the industrial control process and how to solve them. Through a combination of description, analysis, comparison and simulation methodologies, the results indicated that 10% to 20% of the total cost was saved, 1% to 10% of the energy consumed was saved, and the response was improved by a rate ranging between 10% and 20%. The results also indicated to improve system flexibility using machine learning techniques, increase product quality, and reduce operation time. The use of machine learning techniques to improve the proposed model led to an improvement in reducing the cost by 10%, improving energy consumption by 1%, and improving the response by 1%.

Introduction

Machine learning techniques in industrial control processes are among the most important tools that can contribute to the sustainability of the industrial sector. Machine learning plays an important role in industrial control processes, as it can improve performance, reduce energy consumption, reduce costs, improve quality, and also add more Flexibility and efficiency in production systems or processes (Mokhtari et al., 2021). Through machine learning techniques, malfunctions can be predicted by using algorithms to analyse operating data and predict potential malfunctions before they occur, which paves the way for carrying out preventive maintenance operations and avoiding malfunctions that may hinder the workflow, thus reducing the cost of repair. And improving productivity. Also, through machine learning techniques, optimal control of production processes is possible, by improving time control parameters, based on operating conditions, as well as all variables that may lead to improving the efficiency of the process and in terms of quality, reducing time, reducing energy consumption, and reducing the consumption of raw materials. Not only that, but through computer vision, which means realizing vision through computer programs that is very similar

to human vision, but instead of using biological organs such as the eye, specific algorithms and programs are used that simulate human perception of some specific processes, and through computer vision. Product inspections can be carried out automatically by using what are known as robots and controlling them. Hussein All robots perform some complex tasks and are used for collecting, sorting, processing and organizing the work mechanism (MR et al., 2021).

One of the most important challenges facing machine learning techniques and industrial control processes is the need for data and algorithms that match that data. There is also a need for the diversity of this data. The greater the diversity and the greater the volume of data, the more effective, more flexible, and more accurate the machine learning techniques are. In addition, the use of machine learning techniques and machine learning algorithms is relatively complex, and difficult for any ordinary person to understand (Umer et al., 2022). It requires experience and knowledge of programming processes, artificial intelligence, digital computing, and technical information about automatic control in industrial processes. Also, the cost of using machine learning and industrial control is relatively high; Therefore, these challenges must be overcome by using fairly flexible and easy algorithms that can be easily dealt with, trying to reduce costs while implementing machine learning processes, and also through the diversity of data, as we mentioned, and the amount of data that must be large, in order to make machine learning techniques effective. It is flexible and gives accurate results, which contributes to achieving the difficult equation of high quality with the lowest cost and lowest energy consumption (Sokolov et al., 2019).

The study aims to clarify the importance of the role of machine learning techniques in industrial control processes, as well as clarifying the importance of control in industrial processes and how and the importance of combining machine learning techniques and industrial control processes, in developing the industrial sector. The study aims to clarify the most important obstacles and challenges facing machine learning techniques in control processes. industry and how to overcome these challenges. It is through a methodology that relies on a combination of more descriptive methodologies, analytical and comparative methodologies, and quantitative and practical methodologies in studying machine learning techniques in industrial control processes. Through the description methodology, the basic concepts and theories that can be relied upon in industrial control processes and machine learning technology can be defined. Through the analysis methodology, the data can be analysed and evaluated, and that analysis can be used to build a specific model that contributes to the success of industrial control processes. Through a methodology of comparison between the best technologies, especially machine learning technologies that are suitable for industrial control applications, especially since each application has its own inputs, outputs, and internal processes that may be appropriate with some technologies and may not be appropriate with some other technologies.

The importance of studying machine learning techniques in industrial control processes is due to the fact that its important role is expected to expand and develop in the future, especially with the continued development of machine learning techniques. The importance of the study is also due to it clarifying the importance of these technologies and the importance of industrial control processes in achieving sustainability in the field of industry, especially as the global markets are witnessing ongoing crises.

Basic concepts and theoretical analyses

Through this section, we will present and analyse the most important basic concepts and the most important analytical theories used in the study, because through this presentation a clear vision and conscious understanding of the study procedures can be formed for any reader who is not specialized in these topics.

Dynamics and Control (PDC)

Process Dynamics and Control (PDC) Production Process Dynamics is one of the engineering dynamics that is based on analysing and modelling data to control dynamic processes during the production steps. Mathematical modelling, aims to transform data into mathematical relationships or equations through which relationships can be found. It ensures smooth dynamic control of production processes, whether these are biological, chemical, engineering, or any production-related processes. In this report, we will study the dynamics of control in control processes (Ghorbel et al., 2020). The goal of the dynamic control process is to ensure that operations run efficiently, effectively, and safely by designing systems that ensure safe control and ideal control of these operations, by controlling some of the properties of the operations, whether they are physical properties, mechanical properties, or other properties. It is necessary to ensure that the required values are within the permissible limits and that the restrictions and requirements are met. Which we aim to achieve (Patraşcu et al., 2017).

Control theory

Control theory, especially in food and beverage operations, is a general theory that is applied in all fields. The main elements of control theory include, as shown in Figure 2:

System inputs: Inputs include natural resources that will enter the system, such as food, energy, water, and some industrial elements, such as materials such as preservatives and modified materials (Glad & Ljung, 2018).

System operations: include the operations and activities that will take place during the control and processing process.

System outputs: include the final product, whether it is food or beverages packaged and ready for distribution (Zabczyk, 2020).

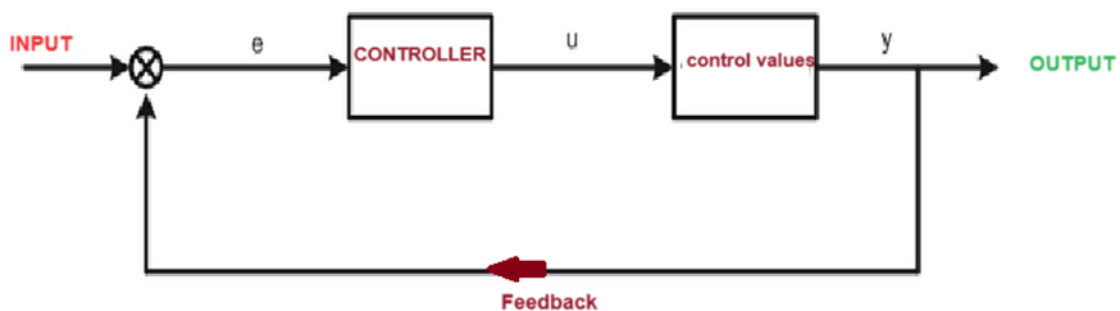


Figure 1. shows the block diagram of Control theory

Control operations, as shown in Figure No. 1, are subject to Equation No. 1:

$$u = K_c e + b \dots\dots\dots \text{Eq (1)}$$

where:

u is the controller output

K_c is the proportional gain

e is the error or the controller input

b is the bias value

Machine learning techniques

Machine learning techniques are a branch of artificial intelligence, where, through the use of computers and programming, it is possible to formulate models through which the

performance of certain tasks can be improved, at certain times, by analysing data, identifying patterns, and making decisions that were previously predicted as a result of the use of machine learning algorithms (Bhavitha et al., 2017).

They are divided into several types, see figure number one, which are as follows:

Supervised machine learning techniques. In this type, the data is pre-classified and the inputs are pre-determined, as well as the outputs (Somvanshi et al., 2016).

Non-green supervised machine learning techniques, which are the opposite of the first type, where the data is not classified and there are no specific signs. Rather, the goal is to explore hidden patterns within the data and take advantage of these patterns to discover any problems or any strange patterns that can be discovered, analysed, and eliminated from unwanted ones (Sarker, 2021). The most important of these algorithms are: 1) Classification algorithms; 2) Linear regression algorithms; 4) Described tree algorithms; 5) Random forest algorithms

Reinforcement learning: In this type of machine learning techniques, a model is created that simulates reality and learns through certain experiences based on error, trial and error, and this model adjusts its behavior over time. Examples of these algorithms include temporary deep learning and non-temporary deep learning (Akalin & Loutfi, 2021).

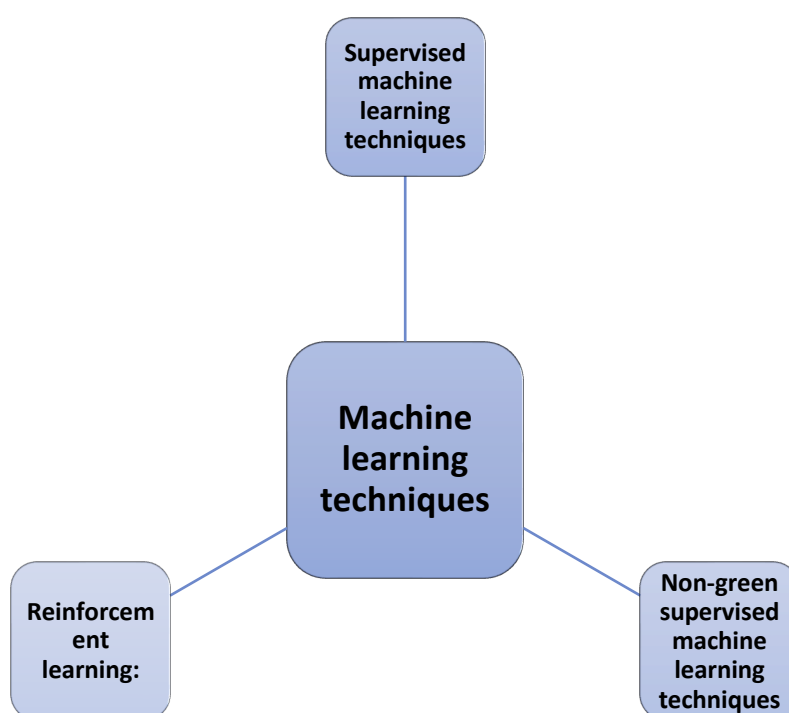


Figure 2. shows the types of Machine learning techniques

Neural network technology

Neural network technology is one of the machine learning techniques. Neural networks are used to imitate the processes carried out by the human brain in processing data and making decisions (Belkacem et al., 2023). This technique is based on an interconnected structure of nodes called layers, where these nodes are organized into multiple layers including the input layer, hidden layers, and the output layer. Neural networks consist of layers: input layers, which deal with raw data and raw features; Hidden layers, where data is subject to processing through mathematical operations; and output layers responsible for forecasting and analysis. Nodes within these layers include weights, which indicate the strength of the connection between nodes, and biases that promote model learning. Training involves feed-forward

operations, where data moves from the input layers to the output layers, and passes through the intermediate layers to calculate the final output (Raschka et al., 2022). Then, error coefficients are calculated by comparing the predicted output with the actual data (Wu & Feng, 2018). One prevalent type is recurrent neural networks (RNNs), which are particularly useful for processing sequential data in diverse industries (Abiodun et al., 2018).

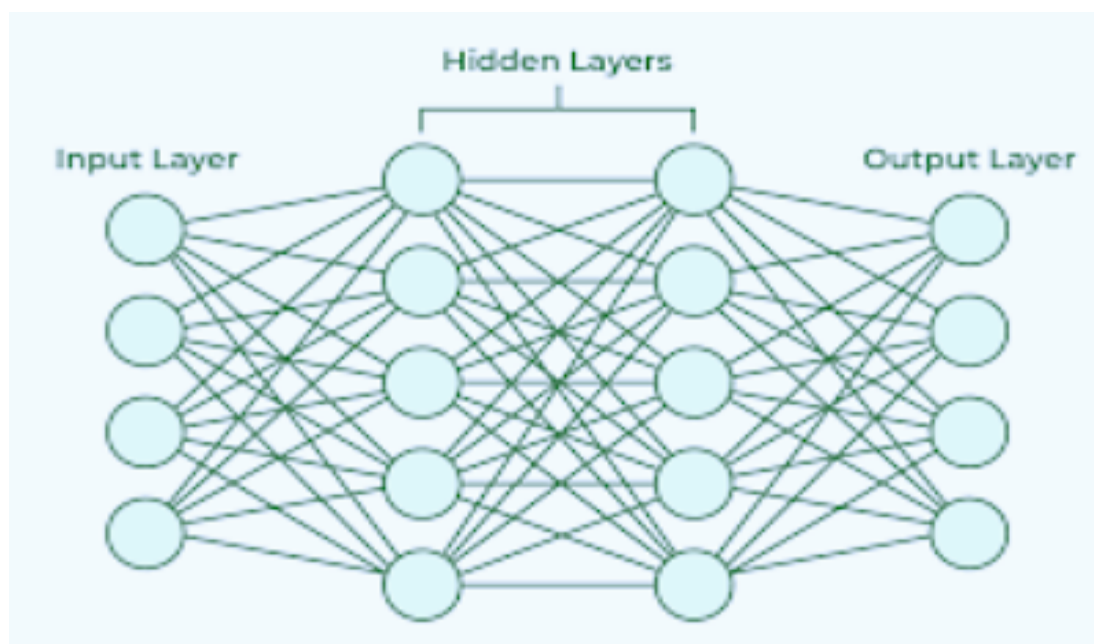


Figure 3. shows the Interconnection of neural networks

Industrial control processes

The industrial control process is a set of tools, tools, programs, and devices through which industrial processes can be controlled automatically. Its goal is to ensure that the processes proceed in an efficient and efficient manner. The most important of these processes are: 1) Monitoring operations: These are operations that take place at all stages of the control process, where variables are monitored, such as temperatures, pressures, flow rates, energy consumption states, and machine conditions, and restrictions are applied and requirements are met; 2) Analysis processes: These are processes through which the collected data is analysed to identify any deviations, or any strange patterns present in the system to get rid of them; 3) Control processes: In which measures are taken to control the progress of the production process, within the standards and restrictions set in advance, the aim of which is to ensure that the production process proceeds flexibly and without any problems.

Components of industrial control systems:

Any basic industrial control system consists of several devices, which are as follows, and as Figure (4) shows: 1) Sensors: These are devices used to collect data. They may be traditional devices, or they may be modern, dynamic devices. Traditional devices such as cameras, an infrared system, and a laser system, or modern Danish non-traditional devices such as three-dimensional analysis devices, motion sensors, and touch sensors; 2) Control units: These are the units through which data is processed, analysed, and appropriate decisions are made. Actuators: Actuators are devices or components used to send signals to control devices in the field of the production process; 3) Communication networks: These are the networks that are used to connect components to each other; 4) Control software: It is software on which control units are programmed according to operating restrictions and rules.

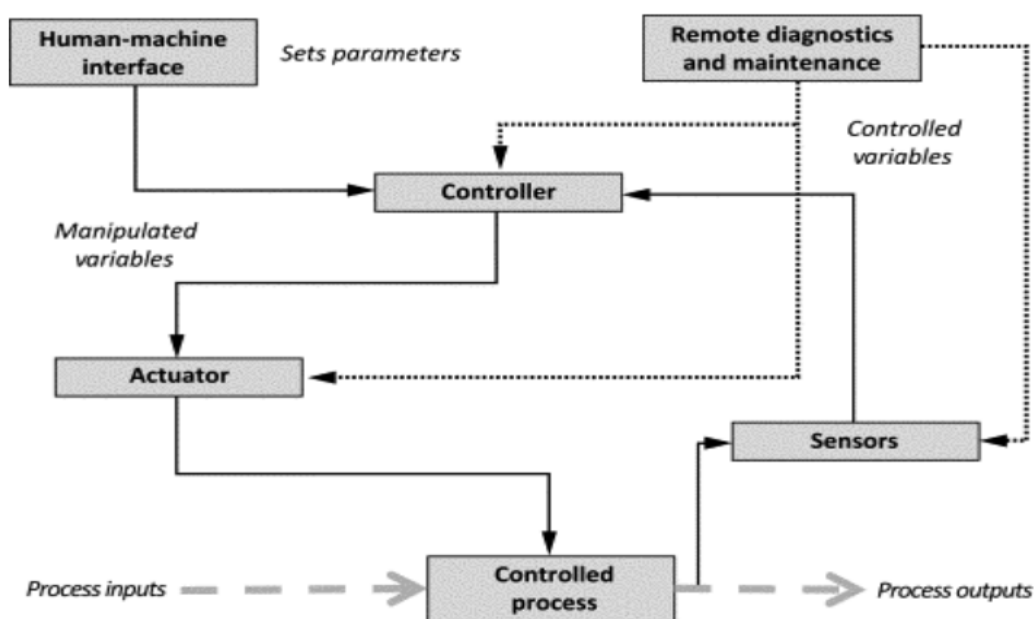


Figure 4: shows Components of industrial control systems

Types of industrial control systems

Industrial control systems can be classified into a group of systems as follows: 1) Continuous control systems: These are systems in which operations are continuous and manufacturing is continuous and often include refining operations and chemical materials manufacturing operations (Alexander et al., 2020); 2) Intermittent control systems: These are systems that operate intermittently in some processes, such as assembly and manufacturing processes, which are phased processes during the production process; 3) Logical control systems: It is a process used in logical operations such as operation, shutdown, and emergency situations; 4) Distributed control systems: These are processes used to control distributed processes and link them to one main control system. These processes are controlled regardless of the area of the production process (Shin & Xu, 2017).

Basic operations in food and beverage using the PDC system

We mentioned that the control process includes three important procedures: inputs, which have been defined as raw materials, whether they are natural materials or manufactured materials used in food industries, outputs, which are the final product in a final form ready for distribution. As for the most important stage, which is the stage of activities and processes that The control process takes place as follows AS shown in fig (5):

Physical separation operations: which include operations such as filtration, refining, and sifting (Ntawubizi et al., 2020). Examples of filtration and refining include sugar industries and salt industries, while sifting includes grains and other products that have different sizes, as well as centrifugal operations such as cheese separation, oil manufacturing, and others. Also, one of the most important processes is adsorption, which includes removing impurities. Using a substance allows you to reach these impurities, such as bleaching star recordings and others.

Mechanical processes are processes that depend on mixing and miniaturization, i.e. reducing the product size and composition, such as beverages, dough, and materials industries that include emulsification processes. Industries that require production, such as the industries of fatty materials for making biscuits and some other industries. As well as shaping processes that depend on converting materials from one form to another, such as converting chocolate

into solid chocolate or converting dairy into dried powder, and all of these processes are in addition to pasteurization processes and fermentation processes.

Chemical preservation processes: These are processes aimed at preserving the product and treating it chemically, including the fermentation process and the manufacture of alcohol and vinegar.

Preservation processes are all processes that include controlling temperature, taste, shelf life, and the final testing of the product in order to ensure the suitability of its products and their safety for human consumption (Datta et al., 2018).

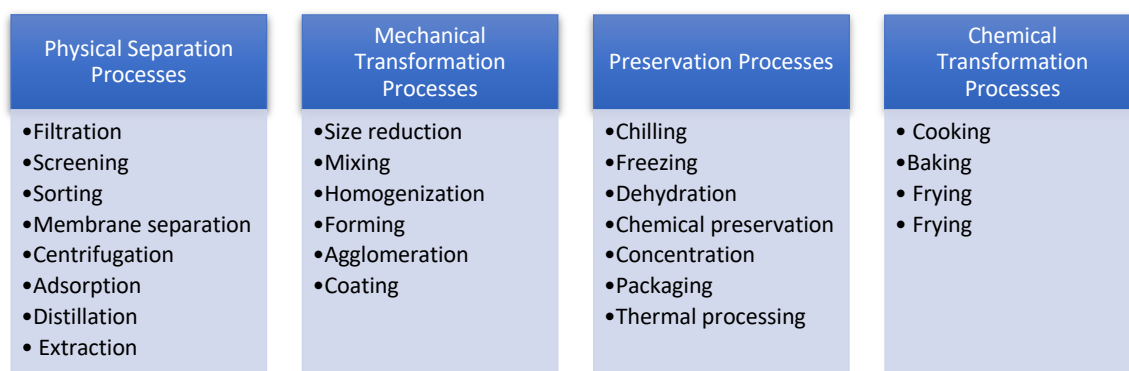


Figure 5. shows the block diagram of Basic operations in food and beverage using the PDC system

Methods

In this part, the materials and tools used in the study will be presented, as well as the methodology used and procedures used in the study. As previously mentioned, the methodology is a mixture of descriptive methodologies, analysis, quantitative methodologies, and comparison methodologies through which it is determined how to use machine learning technology in the industrial control process, comparing these technologies, and choosing the best one according to each application. Machine learning applications will be used in automated food and beverage control processes (Knapp, 2024).

The applied framework of the study

The study was carried out on a set of procedures, as shown in Figure(6), which are as follows :
 Defining the problem: Defining the problem in a more correct sense, determining the type of application. Is it food? Is it natural drinks? Type of food. Nature. Type of beverages? Collect all data and collect all data related to this problem. System modelling: Modelling the system mathematically and creating a simulation system, whether through some programs such as MATLAB, Simulink, or some specialized programs, where the data is converted into relationships and rates that can be simulated and the relationships linked to each other (Jordan & Mitchell, 2015). Controller design and testing: Designing the system where the inputs, outputs, and activities are determined and the type of control present or required in the process is determined. Implementation and monitoring: Implementing the controller in the empty system, monitoring performance, determining the techniques used, and then identifying problems; Evaluation and development: Evaluate the system and develop it according to constraints, outputs, inputs, and activities

Some basic variables must be taken into account, such as temperature control, flow control, quality control, productivity control, and cost control. All of these variables must be taken

into account in order for the system's performance to be successful. Also, an important item must be achieved: flexibility, as the system must be flexible enough (Nise, 2020).

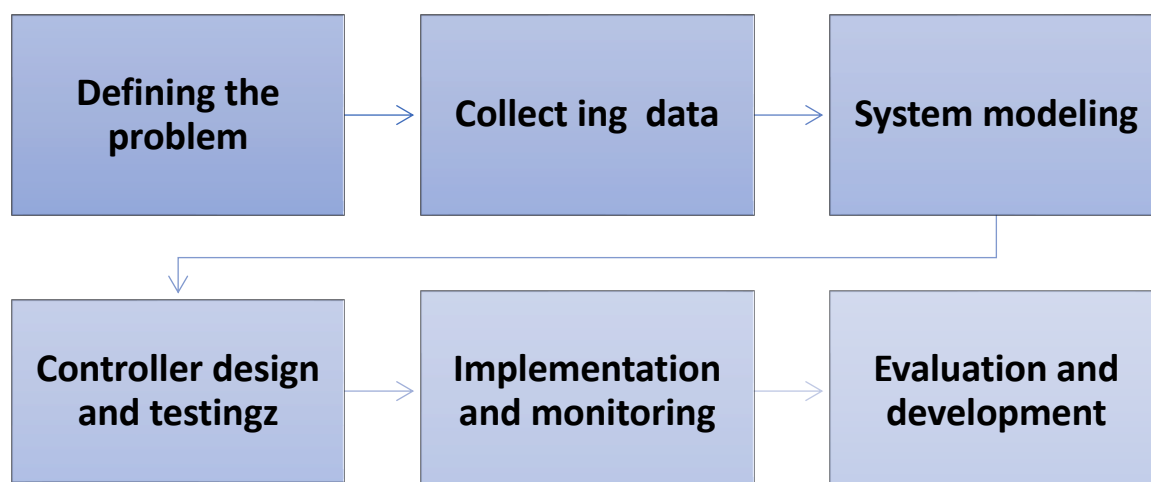


Figure6. show Applied framework for operations in food and beverage

Materials and tools

To conduct the study, a set of tools and data were used, which are commonly used in such studies: 1) Databases that contain visual and written data and previous studies; 2) Data processing tools: These are data processing and cleansing tools; 3) Machine learning techniques for building models and techniques for improving those models; 4) Simulation of the proposed model (MATLAB) Computers

Mathematical Modelling

Machine learning techniques can be used to achieve two of the most important goals of industrial control :The first is to predict malfunctions during operation by analysing operating data for machines, which allows for preventive maintenance and avoiding sudden malfunctions; Second: Optimal control by improving time control parameters based on changing operating conditions, which leads to improving the process efficiency, accuracy, and response speed.

First, create a mathematical model that uses artificial neural networks (ANN) to predict the occurrence of faults. We can use a neural network that estimates For a data set of N samples: $D = \{(x_i, y_i), i=1, 2, \dots, N\}$

- System definition:

$$x(t+1) = f(x(t), u(t))$$

Where:

$x(t)$ is the state vector at time t ,

$u(t)$ is the control vector.

the probability function:

$$f(x) = P(y=1|x),$$

$$P(y=1|x) = \sigma(o) \quad P(y=1 \mid x) = \sigma(o)$$

where:

x_i : is the input data vector for the machine i at time t (including operating time, operating conditions, etc.).

y_i : is a binary variable that indicates whether a malfunction occurred ($y_i=1$) or did not occur ($y_i=0$) which represents the probability of a fault occurring based on the input data.

$\sigma(o)$ is a Sigmoid function that transforms the output into the range $[0, 1]$.

Mathematical equations of a neural network:

Input layer to the first hidden layer:

$$h_1 = \sigma(W_1 x + b_1)$$

where:

W_1 is the weight matrix between the input layer and the first hidden layer.

b_1 is the bias vector of the first hidden layer.

σ is the activation function (Sigmoid).

First hidden layer to second hidden layer:

$$h_2 = \sigma(W_2 h_1 + b_2)$$

where:

W_2 is the weight matrix between the first hidden layer and the second hidden layer.

b_2 is the bias vector of the second hidden layer.

The second hidden layer to the output layer:

$$o = (W_3 h_2 + b_3)$$

where:

W_3 is the weight matrix between the second hidden layer and the output layer.

b_3 is the bias vector of the output layer.

Loss function:

$$l = \frac{1}{m} \sum_{i=1}^m (y^i - \hat{y}^i)^2$$

$$L = (1/M) * \sum [(y_i - \hat{y}_i)^2]$$

Where:

M : is the number of samples.

y_i : is the true value of the rating (0 or 1).

\hat{y}_i : is the expected value from the model (the probability that the sample belongs to class 1)

Inputs and outputs of a machine learning model

The Inputs and the outputs of a machine learning model for predicting faults and optimal control of industrial processes can be determined as the following:

Inputs

The inputs here are data related to operation, such as operating time, operating conditions of temperature, pressure, flow of raw materials, data related to preventive measures, and any data related to control processes and operations that take place on beverages and foods, such as physical separation processes, cooking processes, fermentation processes, Pasteurization, refining operations, size reduction operations, product segmentation, refrigeration operations. In addition to chemical preservation operations, product preservation operations, and packaging operations.

Outputs

The outputs here are the probability of a malfunction occurring, and they are values ranging between zero and one as probability values, where zero means no malfunction, 1 means that there is a malfunction, and values from zero to one mean the probability of a malfunction occurring at a certain percentage as well. Among the most important outputs are the flow of raw materials, quality. The product, cost, energy consumption, pressure, temperature, optimal time and product safety, and the extent of the system's response. By creating a code in MATLAB and performing a simulation by entering the inputs, obtaining the outputs, and evaluating them, the code was created in several steps as shown in fig (7):

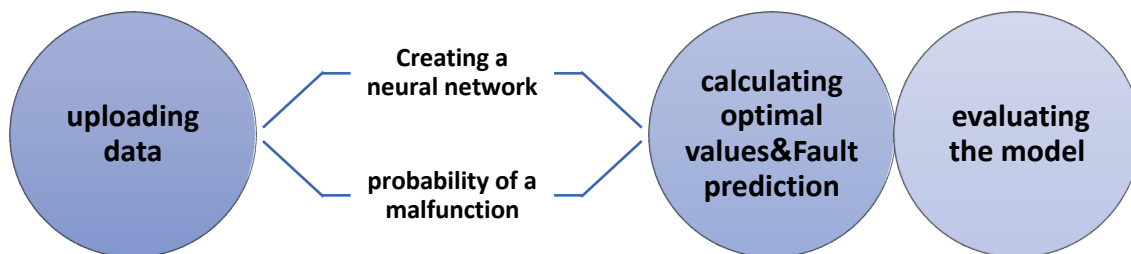


Figure 7. shows the code steps

```
% Loading recorded operating data  
trainingData = load('trainingData.mat');  
  
% Extract inputs and outputs  
time = trainingData.time;  
operatingConditions = trainingData.operatingConditions;  
preventiveActions = trainingData.preventiveActions;  
controlParameters = trainingData.controlParameters;  
faultProbability = trainingData.faultProbability;
```

Figure 8. The process of entering and uploading data

```
% Create an artificial neural network

net = feedforwardnet([size(operatingConditions,2), 10, 1]);

% Set activation functions

net.transferFcn = {'tansig', 'purelin'};

% Set learning algorithm

net.trainFcn = 'trainlm';
```

Figure 9. Creating an artificial neural network, setting activation functions & learning algorithm

```
% Prediction of the probability of a malfunction

predictedFaultProbability = net(inputData);

% Using a mathematical model of the industrial control process to calculate
ideal values

% based on the probability of a malfunction

optimalCost = calculateOptimalCost(predictedFaultProbability);

energyConsumption =

operatingTime = calculateOperatingTime(predictedFaultProbability);

controlSystemResponse =
```

Figure 10. calculating optimal values

```
% Performance evaluation

performance = perform(net, testOutputs, predictions);

disp(['Performance on test data: ', num2str(performance)]);

% Show results

figure;

plotregression(testOutputs, predictions);

title('Regression between test outputs and predictions');
```

Figure 11. Evaluating the model & showing the results

Results and Discussion

In this part, we will present the results that were extracted from the study and discuss them according to the results that were presented.

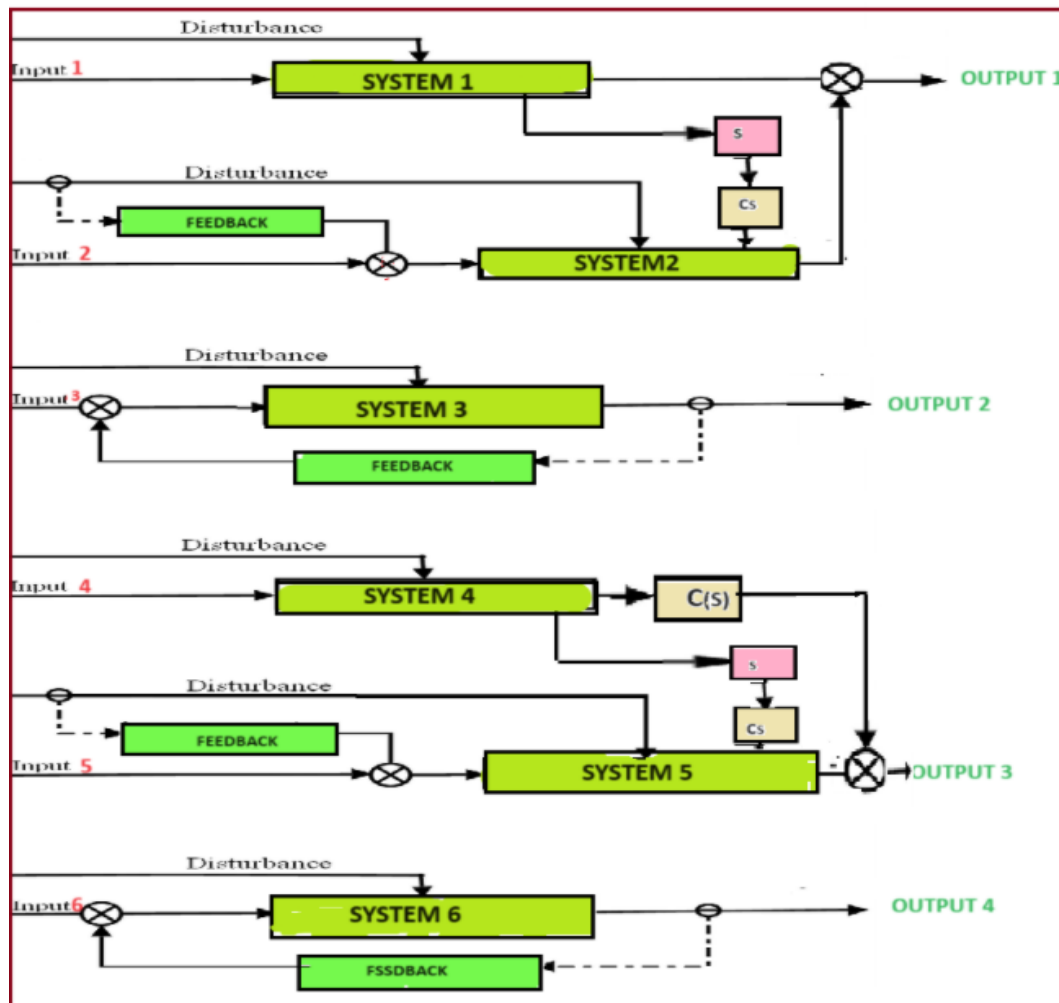


Figure 12. shows Industrial control system

Figure No. (8) shows an industrial control system using machine learning techniques, which is the LBI system. The figure shows the components of the system, which are various actuators and feedback processes, and a set of production processes (system), which are controlled through control elements, with some valves through which the process is also controlled, in addition to a network of Wires, monitoring, monitoring and measuring devices, and actuators.

```

Outputs
disp('Predicted Outputs for the given inputs:');
disp(['Fault Probability: 0.023,num2str(newOutput(1))]);
disp(['Optimal Cost: 1100, num2str(newOutput(2))]);
disp(['Energy Consumption: 520, num2str(newOutput(3))]);
disp(['Runtime: 9.8 num2str(newOutput(4))]);
disp(['Control System Response: 0.92 num2str(newOutput(5))]).
    
```

Figure 13. shows the output of the simulation of the model

Figure No. (9) shows the simulation outputs that were carried out using a model that works with machine learning techniques through the use of neural network technology and its integration with industrial control techniques, where six inputs were entered: operating conditions, temperature, pressure, flow quantity, list of possible faults, types Operating processes. And extracting a set of outputs such as cost, energy consumption, system response, as well as possible malfunctions, in addition to some secondary outputs, which are the flexibility and quality of the products. As the figure shows, the outputs were the cost of 1100 dollars, and the percentage or probability of malfunctions was 23 out of 1000, which is an excellent percentage and it was the response rate of the system was 92%, while the average power consumption was 520 kilowatts.

```
newOutput = net(newInput);
disp('Predicted Outputs for the given inputs:');
disp(['Fault Probability:0.022,num2str(newOutput(1))]);
disp(['Optimal Cost: 1100 , num2str(newOutput(2))]);
disp(['Energy Consumption:518 , num2str(newOutput(3))]);
disp(['Runtime: 9.10 num2str(newOutput(4))]);
disp(['Control System Response:0.95 num2str(newOutput(5))]).
```

Figure 14. shows the output of the simulation of the model after improvement

Figure No. 10 shows the same outputs as the previous one, but after algorithms were used to improve the model and apply the model, the results were a 1% improvement in the rate of electricity consumption, a 1% improvement in the response rate of the system, which reached 93%, and a 10% improvement in cost reduction, which reached Less than \$1000. The accuracy of the code used in the simulation was tested to reach 94% accuracy, and after improvement, it reached 96% accuracy.

Table 1. shows the output of the simulation of the model related to time

Falut Probability	Time	Cost	Response	Energy
0.011	60	122.22	0.94	57.77
0.015	120	244.44	0.94	115.54
0.019	180	366.66	0.93	173.31
0.023	240	488.88	0.93	231.08
0.023	300	611.1	0.92	288.85
0.023	360	733.32	0.92	346.62
0.023	420	855.54	0.92	404.39
0.023	480	977.76	0.92	462.16
0.023	540	1100	0.92	520

Table 1 shows the simulation outputs that were carried out using a model that works with machine learning techniques through the use of neural network technology and its integration with industrial control techniques, where six inputs were entered: operating conditions, temperature, pressure, flow quantity, list of possible faults, types Operations and extracting a set of outputs such as cost, energy consumption, system response, and potential malfunctions, in addition to some secondary outputs, which are the flexibility and quality of the products.

Table 2. shows the output of the simulation of the model related to time after improvement

Falut Probability	Time	Cost	Response	Energy
0.01089	60	109.998	0.9494	57.1923
0.01485	120	219.996	0.9494	114.3846

0.01881	180	329.994	0.9393	171.5769
0.02277	240	439.992	0.9393	228.7692
0.02277	300	549.99	0.9292	285.9615
0.02277	360	659.988	0.9292	343.1538
0.02277	420	769.986	0.9292	400.3461
0.02277	480	879.984	0.9292	457.5384
0.02277	540	990	0.9292	514.8

Table 3. shows comparison between the output of the simulation of the model related to time before & after improvement

	Befor Imoroving				After Improving			
Falut Probability	Cost	Energy	Response	Falut Probability	Cost	Energy	Response	
0.011	122.22	57.77	0.9494	0.01089	109.998	57.1923	0.9494	
0.015	244.44	115.54	0.9494	0.01485	219.996	114.3846	0.9494	
0.019	366.66	173.31	0.9393	0.01881	329.994	171.5769	0.9393	
0.023	488.88	231.08	0.9393	0.0221	439.992	228.7692	0.9393	
0.023	611.1	288.85	0.9292	0.0221	549.99	285.9615	0.9292	
0.023	733.32	346.62	0.9292	0.0221	659.988	343.1538	0.9292	
0.023	855.54	404.39	0.9292	0.0221	769.986	400.3461	0.9292	
0.023	977.76	462.16	0.9292	0.022	879.984	457.5384	0.9292	
0.023	1100	520	0.9292	0.022	990	514.8	0.9292	

Table 2 shows a comparison between the simulation outputs that were made using a model that works with machine learning techniques through the use of neural network technology and integrating it with industrial control techniques, as well as a comparison between the same inputs and in the same conditions, after performing optimization processes. This was done for the total time of the operation process, which amounted to 550 minutes. The advantage was a 1% improvement in the rate of electricity consumption, a 1% improvement in the response rate of the system, which reached 93%, and a 10% improvement in reducing the cost, as it reached less than 1000 dollars. The accuracy of the code used in the simulation was tested to reach 94% accuracy, and after improvement, it reached 96% accuracy.

Table 4. Results of statistical analysis of variance, degree of significance, and correlation coefficient of results

ANOVA								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	1	173400	173400	28.49296	0.001078			
Residual	7	42600	6085.714					
Total	8	216000						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	16053.33	2951.349	5.439321	0.000967	9074.502	23032.16	9074.502	23032.16
X Variable 1	-17000	3184.785	-5.33788	0.001078	-24530.8	-9469.18	-24530.8	-9469.18

As for Table 4 it is the Anova statistical test table. The importance of the data is clear from the table, as the p-value was less than 5%, which was about 0.00096. The more the value was 5%, the more important the data was. Likewise, the table shows that The variance has a large value, which means that the data is statistically significant, as variables, inputs and outputs were compared and multiple linear regression was studied for the relationship between

variables and with time. However, time was considered to be the dependent variable while the rest of the inputs and items are independent variables.

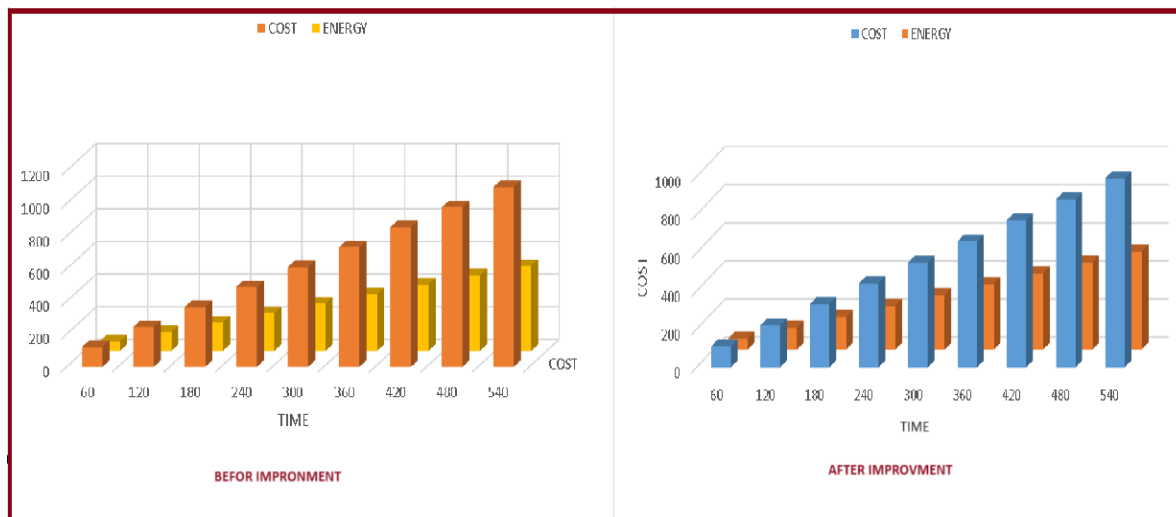


Figure 15. shows comparison between the output of the simulation of the model (cost and energy)

Figure 15 shows a comparison between the energy consumption rate and the cost before and after performing the improvement operations. It is clear from the figure that the cost has decreased by 10% and the energy consumption rate has reduced by 1%. The failure rate has also changed from 0.023 and decreased to 0.022 as well. System response improves from 92% to 93%.

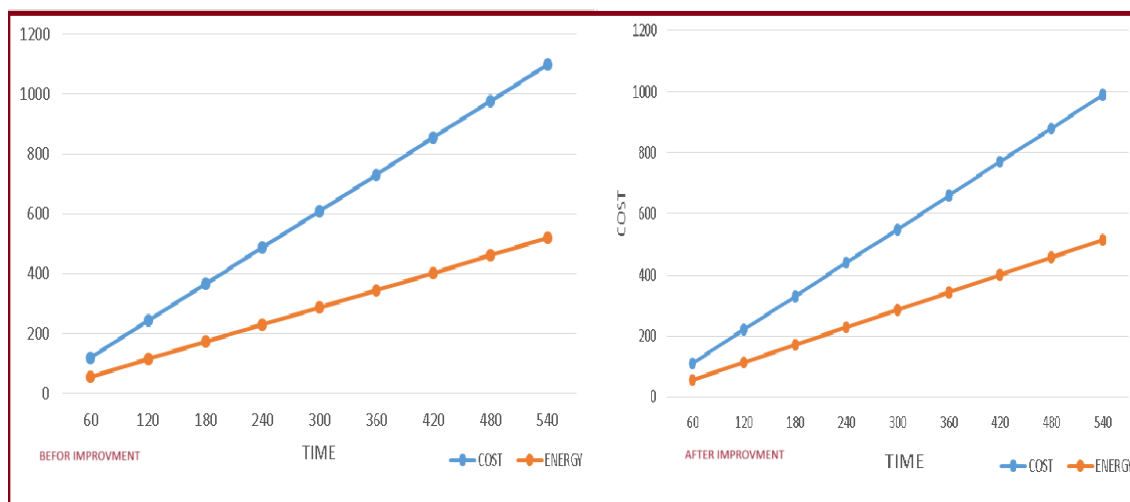


Figure 16. shows comparison between the output of the simulation of the model (cost and energy)

Figure 16 also shows a comparison between the rate of energy consumption and the cost before and after the improvement operations, but with the figure occluded. The linear relationship was drawn between both the cost and the energy consumption rate on the failure rate also changed from 0.023 and decreased to 0.022 as well. System response improved from 92% to 93%.

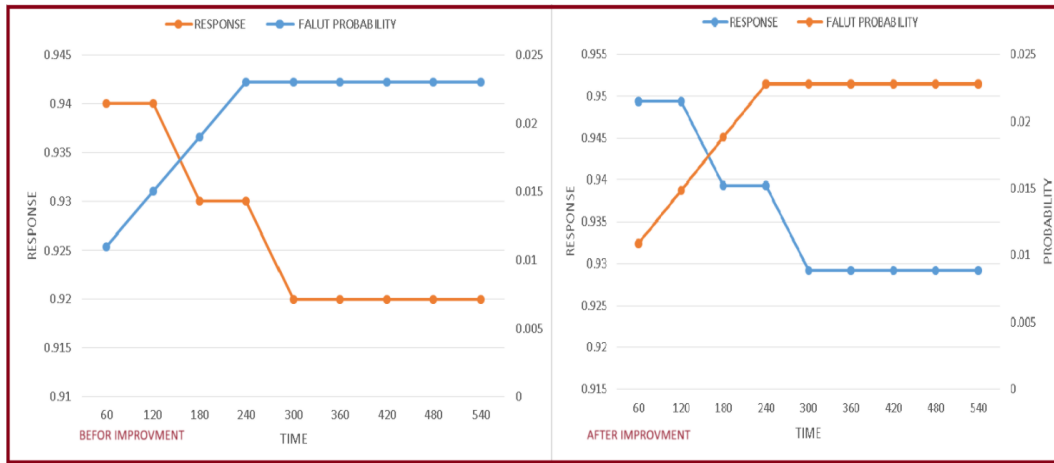


Figure 17. shows comparison between the output of the simulation of the model (response & probability)

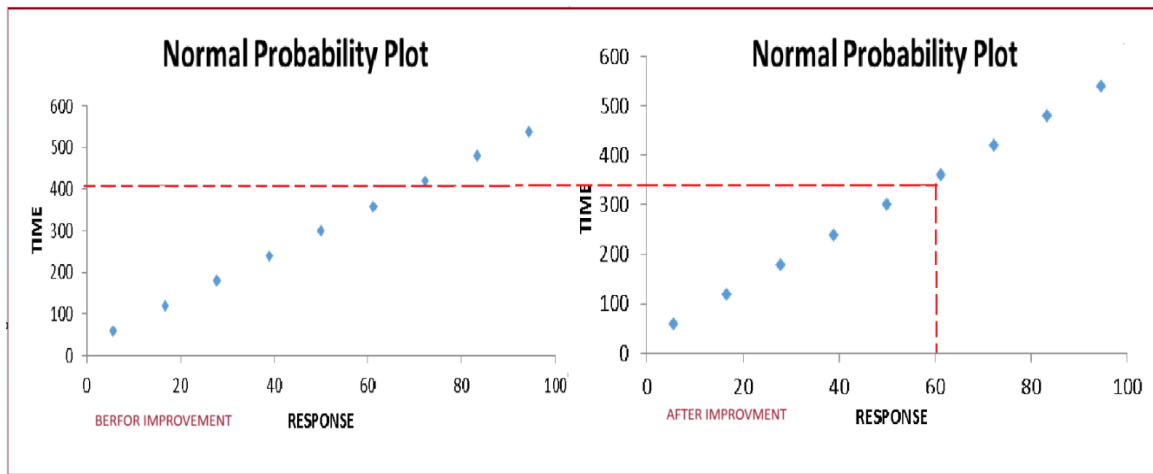


Figure 18. shows comparison between the output of normal probability of the model response & probability)

Figure 18 shows a comparison between the density function for the distribution of the response in relation to time and before and after the optimization processes. As is clear from the figure, over the time periods, which are represented on the y-minute axis and the response on the x-axis. The response was greater after the improvement operations than before the improvement operations at a constant rate in the beginning, which eventually reached approximately 1%. I noticed that at the 400th minute, the response rate before the improvement was about 79%, while after the improvement process it reached 80%.

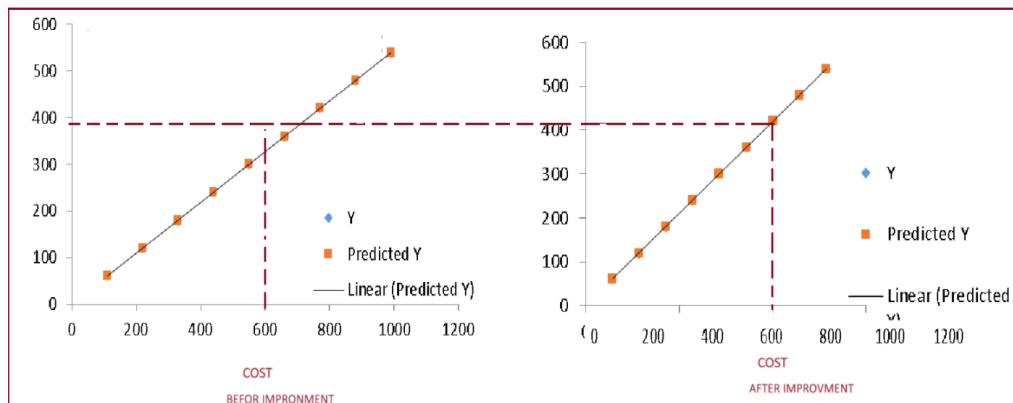


Figure 19. shows comparison between the output of the predicted of the model (cost and energy)

Figure 19 shows a comparison between the density function for the distribution of the cost in relation to time and before and after the optimization processes (Kumar et al., 2021). As is clear from the figure, over the time periods, which are represented on the y-minute axis and the cost on the x-axis. Cost was smaller after the improvement operations than before the improvement operations at a constant rate in the beginning, which eventually reached approximately 10%. The difference between the expected values and the values obtained is smaller after the optimization processes than the difference between the expected values and the values obtained after the optimization process.

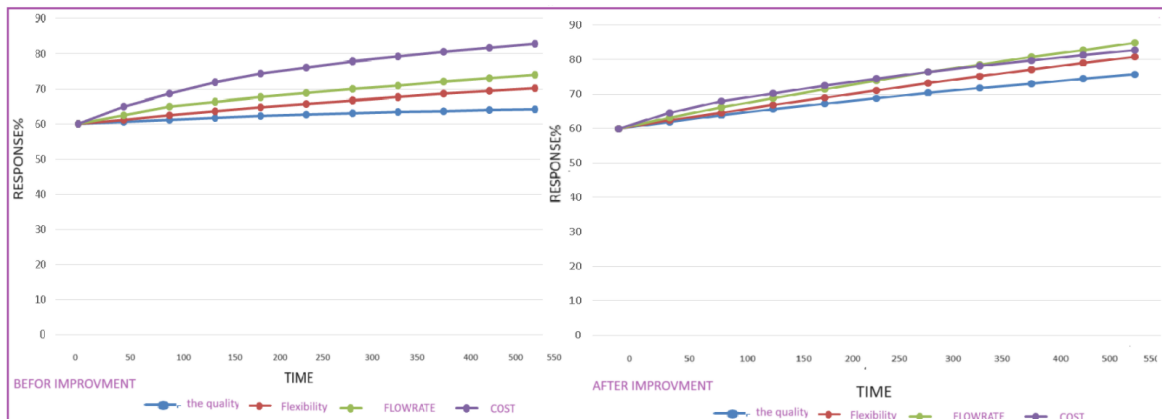


Figure 20. shows comparison between the output of the model (cost and energy, Flexibility and quality)before & after improvement

Figure 20 shows the comparison between cost, flexibility, and product quality, Response before and after improvements. We notice from the drawing that the cost was reduced by 10%, better after the improvement than it was before the improvement process (Raschka et al., 2022), while the product quality increased and flexibility increased after the improvement process by 1%. The red lines represent flexibility, the blue lines represent quality, the green lines represent responsiveness, and the purple lines represent cost. Let us take, for example, the time of 200 minutes represented on the x-axis, we find that the response after the optimization process reached 65%, while before the optimization process. The percentage was 64%, but cost decreased by 10% at one point, while flexibility increased by 1% and quality increased by 1%.

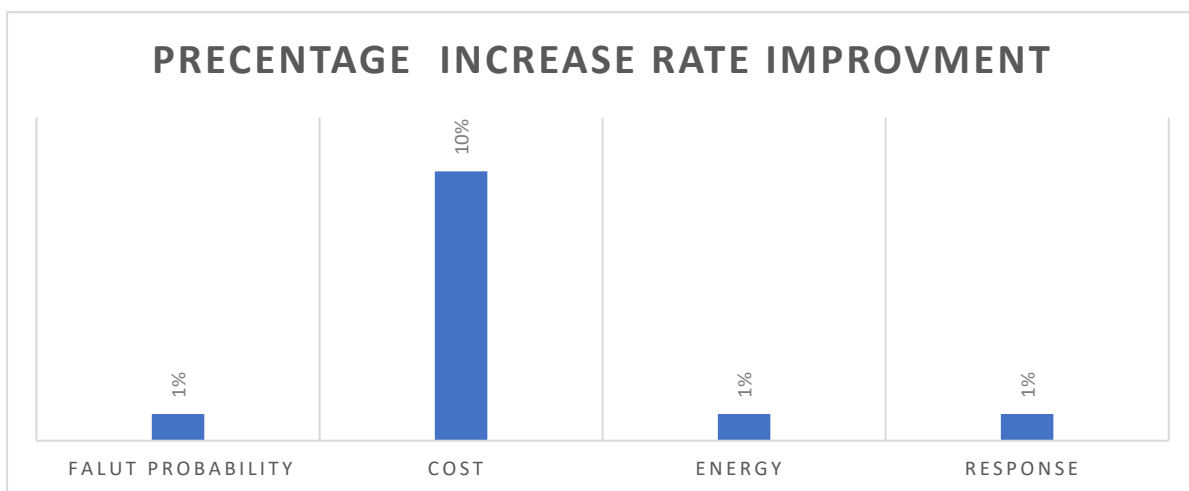


Figure 21. Percentages of improvement in cost reduction, energy consumption, response, and expected probability of malfunctions

Figure 21 shows the increase in the rates of improvement in the four outputs, where the percentage of improvement in cost reduction reached 10%, the improvement in the energy consumption rate by 1%, the improvement in the response rate by 1%, as well as an improvement in the value of the expected probability of failure by one percentage in Minya, and this gives significance. It is clear how important model improvement processes are.

Conclusion

One of the most important conclusions drawn from the study is that machine learning techniques are very important tools in industrial control processes. Through the use of machine learning technology and industrial control techniques, it is possible to achieve sustainability in the field of industry, and thus achieve economic sustainability, which is linked to achieving social sustainability and then environmental sustainability, as controlling industrial processes saves energy consumption and reduces gas emissions and thus achieves environmental sustainability.

Machine learning techniques are techniques from digital computing, and one of the branches of artificial intelligence. They are very important techniques in many applications through which models can be formulated and these models can be trained to learn using many algorithms, and thus through them it is possible to derive patterns and discover new patterns that can be analysed graphically. It is also possible to create new insights and strategies to enhance the potential of machine learning technology.

It is possible to optimally control and predict expected faults using machine learning techniques, but it must be taken into account that the machine learning technique is suitable for the application in which it is used. As there are techniques that are suitable for some applications, and not suitable for some other applications, therefore, careful consideration must be given to choosing the appropriate technology for developing the appropriate one.

Although there are many challenges and obstacles facing machine learning technologies, the continuous development of digital computing and artificial intelligence makes overcoming these challenges and obstacles not far away, and even encourages the continued development of these technologies.

One of the key conclusions and anticipated outcomes of employing the PDC system in controlling processes within the food and beverage industries is its significant effectiveness and critical role in ensuring the health and safety of products for human consumption. Additionally, these systems promote sustainability in the sector by reducing costs, conserving energy, and producing high-quality, safe products. Another important conclusion is the existence of numerous and diverse control techniques that rely on the system's inputs, outputs, activities, and quality of control. Therefore, when selecting an appropriate control system for an application, it is crucial to consider the nature of the outputs, inputs, and required activities to develop a highly efficient and effective control system. The chosen system should also be easy and flexible to implement, as these characteristics are vital for the system's success in meeting all necessary requirements and constraints.

Recommendations

One of the most important proposals presented by the study is the interest in developing machine learning techniques and discovering new algorithms that help develop these techniques. Also, integrating some technologies with each other to benefit from the advantages of each technology, as the process of combining technologies has many positive aspects. Also, make more efforts and research related to developing machine learning techniques and industrial control techniques.

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