Machine learning in intelligent manufacturing system for optimization of production costs and overall effectiveness of equipment in fabrication models

Carla Acosta P, Héctor C. Terán, Oscar Arteaga and María B. Terán
Universidad de las Fuerzas Armadas ESPE, Sangolquí, Ecuador

E-mail: obarteaga@espe.edu.ec

Abstract: The study proposes optimize the production costs with the implementation of an intelligent autonomous system applied to adaptive control and supervision to in computer-integrated manufacturing. For the validation, a horizontal band saw was used with 3 axes of displacement implementing 2 cameras with stereoscopic vision and finding an estimation of depth in the cut. With the dimensional deviations (x,y,z) of the cut, the shape and dimension of the cuts in the pipe, are defined to be manipulated and classified in correct and in-correct cuts by means of a separator coupling. For this purpose, algorithms were developed on two computer platforms: LabVIEW, which obtains the images, controls the automatic separator and the material feeder; Matlab, which processes dimensional deviations by recognizing patterns with the "Principal component analysis" (PCA) technique, in turn compares with an ideal pattern and optimizes the cutting parameters: Cut speed, cutting index ,through a derivative Integral Proportional PID algorithm with the interaction of machine learning (ML) based on SVM theory. Autonomously corrects errors without human supervision, obtains the lengths and depths with the optimum cut-offs and result of adaptive supervision, increases production, product quality and reduces operating costs for each cutting cycle by complying with Overall Equipment Effectiveness parameters (OEE) and integrating into intelligent manufacturing systems.

Keywords: Production costs, Optimization, Intelligent manufacturing, Machine learning, Overall effectiveness of equipment.

1. Introduction

The industrial manufacturing of the future is determined by the dynamic characterization of products with a flexible manufacturing system, is to say manufacturing production faces changes in some factors such as advances in manufacturing, materials, intelligent and automated machines, thus leading to effective equipment (OEE) in a new era of production [1]. A branch of Artificial Intelligence (AI) encompasses Learn machine (LM) and prop to the Support-Vector Machines that builds a solution model in terms of subset with the training information [2].

The use of support vector machines (SVM) in artificial neural networks (ANN) avoids that local minimums converge instead of global minimums obtaining a general image of the system and less time in adapting, that is to say, the number of support vectors is exactly the number of training samples [3,4].

Intelligent manufacturing is a fragment of an optimization, in which manufacturing and research methods that integrate innovations in manufacturing, management and market forms, that allow optimizing production processes, discovering greater flexibility, effectiveness and creating an economic value proposition in the industry relevant to the needs of its market [5].
2. Cutting system scheme

The cutting system is in a closed loop, designed to automatically keep cutting parameters controlled and consists of three stages: the manufacturing stage with the metal saw, automation using quality control (QC) with machine vision (MV) and optimization of artificial intelligence integrated with learning machine (LM), so the machine operates autonomously without human supervision. Each of these stages are communicated to modify movements and cutting parameters and optimize production costs (see figure 1).

![Diagram of the Cutting System]

**Manufacturing: Cutting Parameters**

Proper machining depends on the cutting parameters and influences the morphology and roughness of the surface [6]. Thus, in band saw cutting it is necessary to determine the working revolution \( n \) in [rpm] with the factors: cutting speed \( V_c \) in [m/min], pipe diameter \( D \) in [mm], type of cooling, and material to be machined. To be modified these parameters are optimized with the correction factors \( f_c \) found with the implementation in machine vision (MV) with machine learning (ML), determined by:

\[
n = \frac{V_c \cdot 1000}{\pi \cdot D} \cdot f_c \tag{1}
\]

The morphology of the cut depends largely on the cutting index \( IC \) in [cm²/min], with the factors: Cutting time \( T_c \) in [min], Pipe area \( A \) in [cm²], determined by:

\[
IC = \frac{A}{T_c} \cdot f_c \tag{2}
\]

| Cutting parameters | Data | Cutting parameters | Data |
|--------------------|------|--------------------|------|
| Material           | Steel AISI 1030 | Cutting speed \( V_c \) | 67 [m/min] |
| Cutting time       | 0.13 [min] | Cutting index \( IC \) | 58 [cm²/min] |
| Coolant            | Mixed oil (mineral oil + 5% - 30% grease and oil) | Dimension | \( D = 40 \text{ mm}, \) thickness 3mm |

**Automation: Machine vision (MV) using Quality Control (QC)**

For the recognition and analysis of its components in machine vision (MV) the technique of "Principal component analysis" (PCA) was applied, for its simplicity and capacity to reduce its dimensions, minimizing the
quadratic error of reconstruction by combining the latent variables in linear form as main components. This method, based on the covariance matrix, was applied due to the homogeneity of the dimensions in the longitudinal and tangential deviations due to similar values when cutting the pipe.

The objective is transforming an X dataset of n·m dimensions into another Y dataset of smaller n·l dimensions with minimal information loss. A matrix of n samples with each variable m, i.e. the longitudinal and tangential deviation in the pipe cut, was obtained, where the conditions l ≤ min{n,m} were established and that the components of l must be lower than the dimensions of X [7].

In the main matrix, the vectors scores were entered with samples related to each other with orthogonal properties. The loadings pa vectors accumulate their deviation or error in the matrix E

\[ X = \sum_{a=1}^{l} t_a p_a^T + E \]  

(3)

It is reached with the projections of X in p_a, where \( \tau_a \) contains the information of the samples, i.e. the amount of accumulated variance.

\[ \sum_{a=1}^{m} \tau_a = 1 \]  

(4)

In the PCA, it is broken down into the covariance matrix's own vectors, where \( \tau_a \) are values that are part of the defined vectors by p_a

\[ t_a = x \cdot p_a \]  

(5)

These data are found in the directions of axes in the space of variables, is considered the distribution of Gaussian form with optimization and elimination of error to the minimum with the use of techniques of learn machine (LM). A HAWK 1000x Camera was used with NI Vision Acquisition Software that supervises and acquires the data (SCADA) through a Data logging and Supervisory Control Module (DSC). An NI CVS-1459RT performs image acquisition, captures successive images of the position of the tube to be cut on the table 1, these data are interpreted by a computer, where machine vision algorithms are performed with LabVIEW software (see figure 2).

**Figure 2.** Supervisory environment, classification of the cutting system.

**Optimization: Learn machine (LM)**

For the adaptability of the cutting parameters of interest, a derivative Integral Proportional PID algorithm was implemented due to its effectiveness, where the constants with conventional mathematical methods are necessary; but a safe response of the system is not obtained, for this the machine learning (ML) was applied, based on the theory of the SVM with the structural risk minimization (SRM) [8]. SVMs have been shown to perform better than machines with neural networks and are powerful tools for solving classification problems [9].
Specifically \( w \in \mathbb{Z} \) and \( b \in \mathbb{R} \). It is established that it is linearly separable if it exists \((w,b)\) such that the inequalities are validated for the data of the set \( S \), an optimal hyperplane can be found where the projections in its margins of two different classes are maximized.

\[
(w \cdot z_i + b) \geq 1, \quad y_i = 1 \quad (6)
\]
\[
(w \cdot z_i + b) \geq -1, \quad y_i = -1 \quad i = 1,1,...,l \quad (7)
\]

For the study you get the product point of entry into the space of characteristics \( Z \), this is Using Kernel polynomial \( d \)

\[
K(x_i, x_j) = (1 + x_i x_j)^d \quad (8)
\]

The function is defined by including the decision function (see figure 3).

\[
f(x_i) = \text{sign}(w \cdot z_i + b) = \text{sign}\left(\sum_{i=1}^{l} \alpha_i y_i K(x_i, x_j) + b\right) \quad (9)
\]

**Economy with Optimization of cut in the pipe**

In order to obtain the minimum production cost, four components were applied:

**Cost of the time in handling the piece** \( (C_{cp}) \). For this purpose, the time spent loading and unloading the pipe to be cut \( (T_h) \) was measured in [min] and the cost rate \( (C_o) \) in [$/min] for the machine vision stage with learn machine \( (MV-LM) \) is defined by.

\[
C_{cp} = C_o \cdot T_h \quad (10)
\]

**Cost of machining time** \( (C_m) \).
The machining time was evaluated in a complete cycle of the final product \( (T_m) \) in [min] and the cost rate \( (C_o) \), determined by.

\[
C_m = C_o \cdot T_m \quad (11)
\]

**Cost of time in tool changeover** \( (C_{tct}) \).
It was defined by the cost rate \( (C_o) \), the changeover time of the cutting saw \( (T_i) \) in [min] and the number of finished machined parts \( (n_p) \).

\[
C_{tct} = C_o \cdot \left( T_i / n_p \right) \quad (12)
\]
Tool cost per unit ($C_{tu}$).
The cost of the tool ($C_t$) was delimited in [$\$]$ and the number of finished machined parts in units of product ($n_p$).

$$C_{tu} = \left( \frac{C_t}{n_p} \right)$$ (13)

Thus, deriving with respect to $v$ and with an equation equal to 0 in equation (13) we obtain the cutting speed that produces the minimum cost per piece.

$$v_{min} = c \left( \frac{n}{1-n} \cdot \frac{c_p}{c_o + c_t} \right)^n$$ (14)

3. Experiments and Results

For the autonomous control of the parameters for the optimal cuts of the material, a hybrid system of quality control by machine vision incorporated machine learning (MV-ML) was implemented to analyze its performance and determine the influence on the economy of the final product. The atypical input values measured by (MV) were related to grant the deviations of the system through the data set $M$ samples and $n$ attributes, generating anomalous points displacing the samples out of the limit of the training data set, being these real values as op-posed to fictitious when using (ML) only.

Performance of the machine vision (MV) cutting system.

In order to evaluate the cutting system performance only implemented (MV), samples are taken grouped in initial data, corresponding to "Correct finished product". The 5% of the samples were artificially modified to transform them into "Incorrect finished product", varying at random for each sample two parameters and their values replaced as maximum or minimum values. The performance of the cutting system was analyzed with Area under Curve (AUC) parameters, with an analogy between true positives and false positives, is the standard deviations (SD) of the AUC achieved in interactions and training time.

The MLP was achieved with the Matlab function typewriter (train) depending on the number of neurons in the hidden layer, which must be less than the number of inputs. Different configurations were experimented in relation to normalization, initially with a normalization of 0 to 1 [10], then with z score and finally the effects with-out normalization. If the reconstruction error is greater than that obtained with 99% of the training set, it is considered incorrect. More optimal results can be seen in table 2.

The configuration of the system observed in the table 2, describes with the labels: "best" those that are considered better, in this case, with an interaction of 7 the function "obetive" corresponds to each interaction, "BestSoFar" is the best value of the objective function that has found in that moment with the iterations carried out, in this case the value 0, "Box Constraint" is a parameter that controls the maximum penalization imposed in the observations that exceed the margins and helps to prevent the excessive adjustment; that is to say a regularization of 1.55 , the AUC with 77.86% of parameters under the curve and a standard deviation of 0.6 % in a time of 1.09 min. Then, the software applies the appropriate Kernel standard to calculate the Gram matrix

| Norm. No. | Neur. | Iter | Eval Result | Obj. | Best SoFar | Box Con. | AUC (%) | STD (%) | Time (min) |
|----------|-------|------|-------------|------|------------|----------|---------|---------|------------|
| No. Norm | 1     | 1    | Accept      | 0.06 | 0.12       | 0.975    | 73.25   | 0.48    | 0.99       |
| 3        | 5     | 7    | Accept      | 0.04 | 0.25       | 1.26     | 76.45   | 0.55    | 1.13       |
| 0 to 1   | 10    | 0    | Accept      | 0.01 | 0.01       | -0.823   | 76.25   | 0.59    | 1.23       |
| 1        | 12    | 0    | Accept      | 0.00 | 0.00       | -0.006   | 75.45   | 0.63    | 1.25       |
| Z core   | 14    | 0    | Accept      | 0.02 | 0.23       | 76.36    | 0.54    | 1.31     |
| 3        | 17    | 17   | Accept      | 0.0   | 0.0        | -5.632   | 76.58   | 0.56    | 1.46       |
| 5        | 19    | 0    | Accept      | 0.0   | 0.0        | -6.562   | 74.23   | 0.50    | 1.47       |

Figure 4 (a) compares the behavior of the ideal system with that estimated solely with the control of machine vision, approximately from 5 to 10 the interaction is stable and optimal, but the entire cycle of operation is destabilized and outside the permissible ranges. Figure 4 (b) shows the classification of the "correct final product" and the "incorrect final product", are in proportion of 60% and 40% respectively, with a minimum
The standard deviation in the cutting of the pipe from 5.5 x 10^-1 mm and 6.4 x 10^-1 and a correction factor, its machining with high cutting speed is without precaution in the useful life of the tool, dimensional tolerances in the cut and result in increased production cost per unit.

![Figure 4](image)

**Figure 4.** (a) Min. Objective vs. Number of function evaluations (b) Machines classification with machine vision (MV)

**Performance of the machine vision and machine learning cutting system (MV-LM)**

The incorporation of automatic learning with support vector machines (SVM) allows to know the regression and classification of the data obtained by images and processed with machine vision (MV) to be modified with the mapping of the data set in the high dimensional space by means of a nucleus function, a hyperplane is implemented that maximizes the distance between the data and the origin [11]. The one-class SVM classifier was achieved using the Matlab `fitcsvm` function. The kernel function was established as Gaussian, the percentage of the strange fraction of the training data was modified from 0 to 2 [12]. The most optimal results are presented in table 3.

| Norm. No. | Neur. | Iter | Eval Result | Obje. | Best | SoFar | Box Cons. | AUC (%) | STD (%) | Time (min) |
|-----------|-------|------|-------------|-------|------|-------|-----------|---------|---------|------------|
| 0 to 1    | 1     | 4    | Best        | 0.3   | 0    | 0     | 125.87    | 98.4    | 0.41    | 1.2        |
| 2         | 5     | 11   | Accept      | 0     | 0    | 0     | 124.75    | 97.68   | 0.47    | 1.59       |
| Z core    | 0     | 15   | Accept      | 0     | 0    | 0     | 998.32    | 97.68   | 0.47    | 1.59       |

The behavior of the optimized system implemented vision and machine intelligence, the observed objectives are superimposed with the estimated objectives, from interaction 1 onwards, during the whole cutting cycle with better results in the permissible ranges (see figure 5 a). The standard deviation is minimized from 4.5 x 10^-1 to 5 x 10^-1; the correction factor of 3.5 to 5.1 widens the cutting speed range and the parametric work area, optimizing the tool edges with better tolerances and reducing production costs (see figure 5 b).
Minimization of costs

The maximum cutting speed and the actual minimum cutting speed of the system are determined according to Taylor's equation [13]. Conventional cutting machines tend to maintain the maximum cutting speed and cutting rate without optimizing production and production costs in real time. For material machining the cutting speed is modified with the Correction Factor, provided by machine learning (LM), autonomously per cycle in an ideal "high effectiveness range" range.

In figure 6, the critical points of the system in relation to costs are obtained. The critical cost limit when cutting with the saw is shown by the intersection between the cost of machining time (C_m) and the cost of tool change time (C_ctc): a cutting speed of 57 m/min is determined with a correction factor of 0.850 producing a value of the cut in each cycle of 0.5 $ and placing the useful life of the tool at the limit.

At the same time, the minimum cutting speed of 20.9 m/min with a correction factor of 0.311 shows that the production is deficient and critical with the inter-section between the Cost of time in the handling of the piece (C_cp) and cost of machining time (C_m) with a correction factor of 0.311 producing slowness in the execution of the operation. The equilibrium point found by learn machine in the cutting system with the cost of machining time (C_m) and the cost of tool change time (C_ctc), is obtained the ideal total cost per part in the cycle (C_t) with a cutting speed of 39.9 m/min with a correction factor of 0.595 at the minimum cost of production of 0.39 $ for each cutting cycle.

Analogy of system performance

A universal indicator to measure the productivity of industrial equipment is the Overall Equipment Effectiveness (OEE), in this case with the Availability: depending on the working cycle of the equipment,
Performance: depending on the pressure of the finished parts correctly implemented learn machine and Quality: depending on the accuracy achieved with the quality control of machine vision.

\[ OEE = \text{Recall} \cdot \text{Precision} \cdot \text{Accuracy} \]  \hspace{1cm} (15)

The analogy of the system is executed with the evaluation of the prediction models quantitatively, where TN is the true negative rate, TP is the true positive rate, FN is the false negative rate and FP is the false positive rate [14], the following factors were used:

\[ \text{Accuracy: } (TP + TN)/(TP + TN + FP + FN) \]  \hspace{1cm} (16)

\[ \text{Precision: } TP/(TP + FP) \]  \hspace{1cm} (17)

\[ \text{Recall: } TP/(TP + FN) \]  \hspace{1cm} (18)

The results with the two types of classifiers (MV) and (MV-LM) are shown in table 4.

| Classifier | Testing Accuracy (%) | Precision | Recall | OEE (%) |
|------------|----------------------|-----------|--------|---------|
| Machine vision (MV) | 73.327 | 0.606 | 0.998 | 44.34 |
| Machine vision with machine learning (MV-LM) | 99.950 | 1.00 | 1.00 | 99.950 |

The cutting system with the stages of manufacturing, quality control and artificial intelligence (AI) using learn machine (LM), can be incorporated into the manufacturing integrated by computer (CIM) and the Industrial Internet of Things (IIoT), covering requirements to reduce errors, speed, flexibility, integration and production costs.

The accuracy of the system only with (MV) for quality control is 73.32 % compared to the proposed (MV-ML) is 99.50 % higher than those established by the norms and standards (MAP) manufacturing automation protocol and complies with the model OSI (open system interconnection).

An Overall Equipment Effectiveness (OEE) of 99.5% was achieved with precision finished parts of 99.95%, an availability of 1.00 by feedback with-stante data and a quality with accuracy of 1.00, this system meets the recommendations for the world's elite manufacturing companies by the World Economic Forum (WEF).

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