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ARTIFICIAL INTELLIGENCE CO-OPERATION WITH CONVENTIONAL METHODOLOGIES FOR CONTROLLING OVER WEAR

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ABSTRACT

Over wear is one of the problems facing industry especially in the third world countries where storing conditions of inserts and workpieces are not ideal. The climates are completely different during day time and at night. The long storing time causes hardening of pieces specially those stored in open areas.

This paper proves that (Artificial intelligence) AI techniques were the key of designing a solution of the over wear problem. (Neural Network) NN proved ability to make more representing model of the turning process than the conventional methods of developing mathematical models. Data used for constructing this model were measured using an experiment of longitudinal turning performed on a CNC machine using force dynamometer of type TELC2010 with a cermet insert fixed to it, work pieces were of steel 52 [1].

Also, combination of expert system technique with conventional (Proportional Integral) PI controller using bumpless technique is the key of achieving acceptable behavior of the system under control.

KEY WORDS

Artificial Intelligence; Over wear.

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INTRODUCTION

The selection of optimal cutting variables, like the depth of cut, feeding and speed, are very important issues for every machining process. In workshop practice, cutting variables are selected from machining databases or specialized handbooks, but the range given in these sources are actually starting values, and are not the optimal values [1].

Zuperl and Reibenschuh [2] studied the milling process and tried to control the feeding rate in order to decrease the cutting tool wear. They thought that the increase of the feeding rate more than the initial values is the suitable online solution and they used neural networks to do that. Kim and Jeon [3] used fuzzy control to manage the cutting force (to control wear) by controlling feeding rate. They sensed the current of the feeding motor as indication of the cutting force.

This system can face two main problems in real world:
1- Fuzzy control systems are not fast enough to accomplish mission in the real world with such high speeds of all types of machining machines.
2- Due to the use of indirect parameters of electrical measurements as an indication of wear and lack of learning capabilities in the fuzzy control systems, any damping in whole system will not be considered. So the system will not be robust and the defects caused by mechanical subsystems will not be identified.

This paper shows that the co-operation between artificial intelligent techniques and conventional techniques is essential for modern trend of dealing with problems especially when the problem is a complicated one like over wear of inserts in turning process.

METHODOLOGY

In the experiments performed for taking measurements; steel bars were used with their standard inserts shown in “Kroloy” catalogues [4]. Forces exerted on the insert were chosen as indication of occurrence of the mechanical wear. Only two components of these forces are concerned with indicating insert wear, the first and most important one is cutting force (F_c) the other one is the feeding force (F_f).

Two experiments were performed on st52 workpieces shown in Fig. 1 with its normal state which indicated hardness 0HRC = 49 HRA (Rockwell scale for materials with low hardness) one of these measurements became the reference for controller. The selection was according to stability of the forces measurement and roughness of the machined surface.

The same experiments were performed on hardened bars of the same material their hardness was raised to 25 HRC in average. Experiments were performed with different values of feeding and cutting speed distributed along the standard range keeping the depth of cut at 0.2 mm [4].

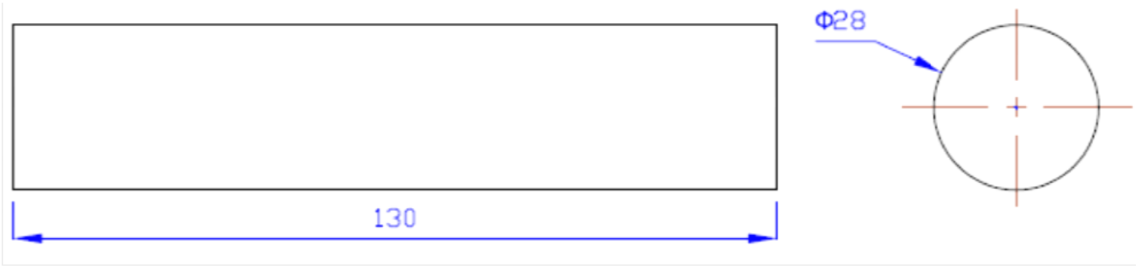

Fig. 1. Workpiece.

Measurements of forces obtained from turning the hardened workpieces were used to model the behavior of the machining process as whole as a black box with cutting speed and feeding as inputs and forces components (F_c and F_f) as outputs.

Many mathematical models and Neural Networks (NNs) NNs were developed to understand the accurate behavior of the process in both transient and steady state stages, respectively. Little architecture of NNs was tried then back-propagation architecture proved it is the most convenient for modeling this process. So it was used with different data sets in order to decrease noised sets without losing the defected behavior [4].

Mathematical models were able to simulate the behavior of the process for one measurement per model but they were not able to simulate the process under other conditions. So NNs are more effective for modeling the process because of its generalizability.

Then many control methodologies were tried until getting the best one, which was found to be a hybrid one mixing between PI controller and expert system. Bumpless control was the key to achieve smooth switching between the two control techniques [4].

After achieving the model a controller was designed to keep the values of forces resulting from machining of hardened materials as close as possible to the reference forces values (F_c and F_f) measured.

MODELING

Mathematical Model

In this section, it was tried to get a mathematical formula for the plant using Matlab tool called "ident" for any MIMO (multi input multi output) plant, Matlab represents its mathematical model with a model combined of separate SISO (single input single output) models, each one contains a formula representing a model between one input and one output. The final model must contain models for all inputs with all outputs. Forces sample modeled here was taken at feeding rate of 0.25 mm/sec and cutting speed of 2800 rpm this one was chosen because it is one of the most stable measurements as shown in Figs1 and 2.

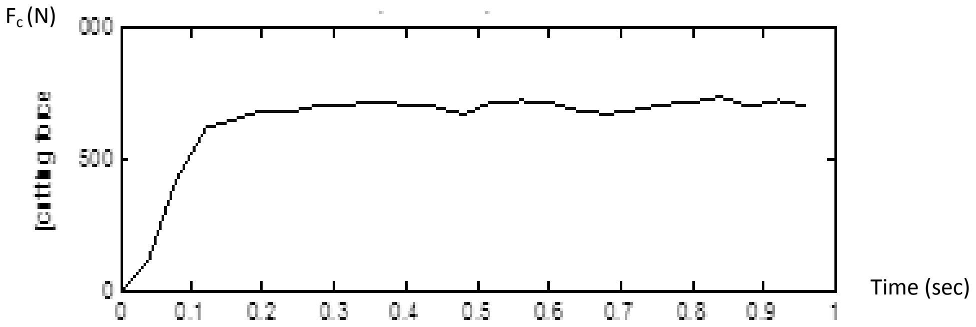

Fig. 1. Cutting force F_c measurement (output 1) [4].

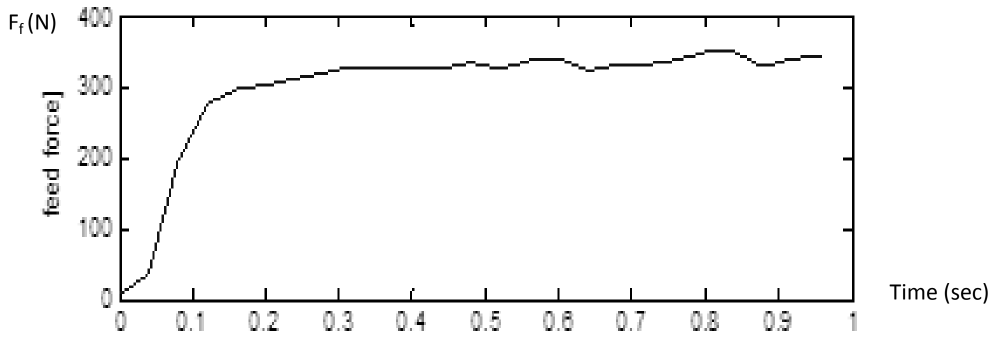

Fig. 2. Feeding force F_f measurement (output 2) [4].

Data

a) First set (short one)

This data set is a short one containing only 10 samples representing the transient stage and the beginning of the steady stage. This set is used for developing a model getting focused view of this period.

b) Second set (long one)

After getting the focused view, a general view was required to get deeper knowledge about the modeled plant. So, another set of data containing the full length of the measurement was used to make other models of it.

Best mathematical models

a) 2 inputs (feeding rate and rotational spindle speed) 2 outputs (cutting force F_c and feeding force F_f)

MIMO models were obtained for the above sample with the 2 sets for the short set the best model showed a consistency of (83.7%) between the measured and simulated the cutting force as shown in Fig. 3 and (84.88%) for the feeding force as shown in Fig. 4.

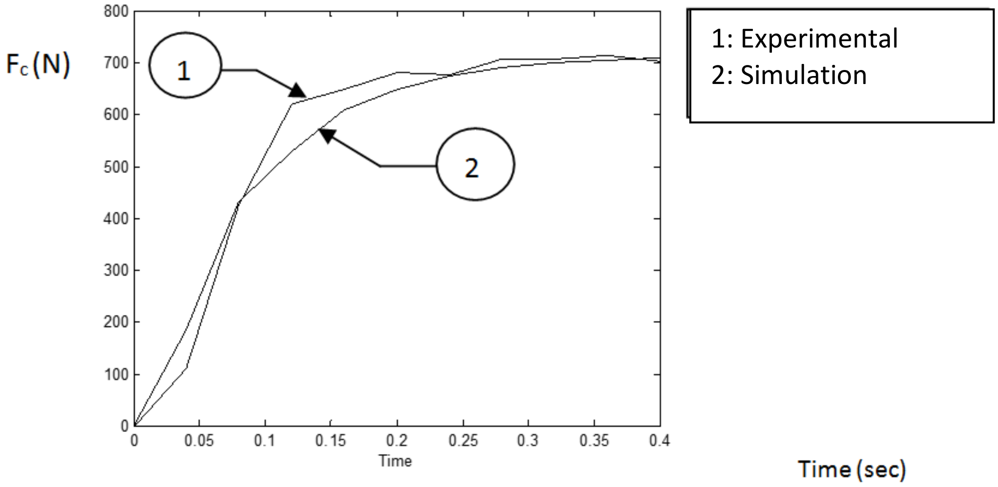

Fig.3. Comparison between the time histories of the measurement and output of the model for F_c.

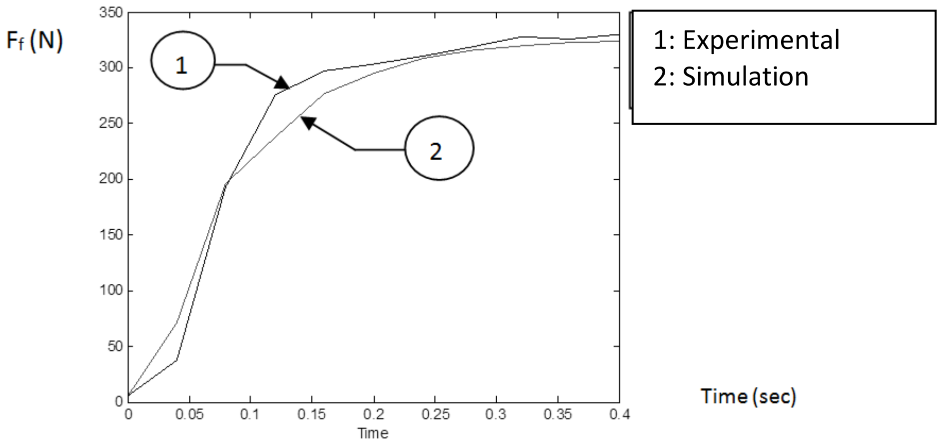

Fig. 4. Comparison between the time history of the measurement and output of the model for F_f

Transfer function from input feed to output cutting force: (1)

$$\frac{7.068\mathrm{e}^{-006}s^2 + 0.0004603s + 0.006718}{s^2 + 36.03s + 294.5}$$

Feed input to output feed force: (2)

$$\frac{2.871\mathrm{e}^{-006}s^2 + 0.0002034s + 0.003069}{s^2 + 36.03s + 294.5}$$

Transfer function from input cutting speed to output cutting force:

$$\frac{0.07916s^2 + 5.155s + 75.25}{s^2 + 36.03s + 294.5} \quad (3)$$

From input cutting speed to output feed force:

$$\frac{0.03216s^2 + 2.278s + 34.38}{s^2 + 36.03s + 294.5} \quad (4)$$

For the long set, the best models showed regression of (91.4611%, 91.46% and 91.423%) for the cutting force as shown in Fig. 5 and (93.4%, 93.4%, and 92.01%) for the feeding force as shown in Fig. 6.

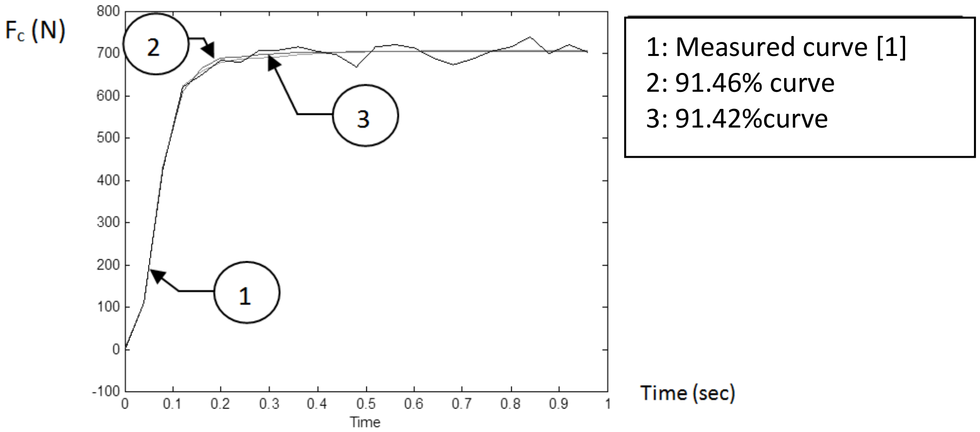

Fig. 5. Comparison between the time histories of the measurement and output of the model for F_c.

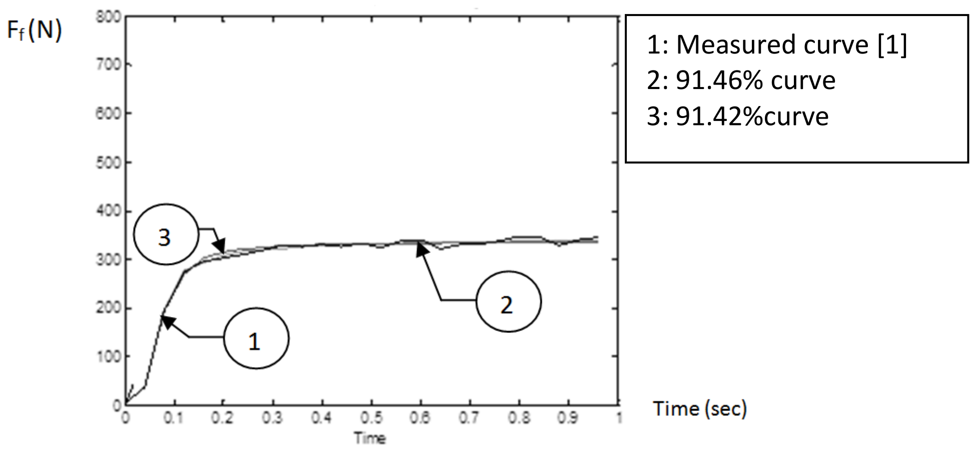

Fig. 6. Comparison between the time histories of the measurement and output of the model for F_f.

a) First model:

Transfer function from input feed rate to:

cutting force: (5)

$$\frac{1.221e^{-005}+0.001417s^4+0.1395s^3+7.953s^2+206.5s+1255}{s^5+96.18s^4+9840s^3+4.881e^{005}s^2+1.031e^{007}s+5.584e^{007}}$$

Feed force:

$$\frac{5.519e^{-006}s^5+0.0006377s^4+0.06259s^3+3.562s^2+92.93s+596.6}{s^5+96.18s^4+9840s^3+4.881e^{005}s^2+1.031e^{007}s+5.584e^{007}} \quad (6)$$

Transfer function from input cutting speed to:

cutting force: (7)

$$\frac{0.1368s^5+15.87s^4+1562s^3+8.907e^{004}s^2+2.313e^{006}s+1.406e^{007}}{s^5+96.18s^4+9840s^3+4.881e^{005}s^2+1.031e^{007}s+5.584e^{007}}$$

Feed force:

$$\frac{0.06181s^5+7.143s^4+701s^3+3.989e^{004}s^2+1.041e^{006}s+6.682e^{006}}{s^5+96.18s^4+9840s^3+4.881e^{005}s^2+1.031e^{007}s+5.584e^{007}} \quad (8)$$

b) Second model:

Transfer function from input feed rate to:

cutting firce:

$$\frac{1.604e^{-005}s^7+0.002093s^6+0.2472s^5+16.86s^4+829.9s^3+2.659e^{004}s^2+4.674e^{005}s+2.251e^{006}}{s^7+114.2s^6+1.435e^{004}s^5+9e^{005}s^4+4.445e^{007}s^3+1.354e^{009}s^2+2.266e^{010}s+9.971e^{010}}$$

(9)

Feed force:

$$\frac{6.485e^{-006}s^7+0.0008889s^6+0.1065s^5+7.456s^4+370.3s^3+1.184e^{004}s^2+2.071e^{005}s+1.073e^{006}}{s^7+114.2s^6+1.435e^{004}s^5+9e^{005}s^4+4.445e^{007}s^3+1.354e^{009}s^2+2.266e^{010}s+9.971e^{010}}$$

(10)

Transfer function from input cutting speed to:

cutting force:

$$\frac{0.1796s^7+23.44s^6+2769s^5+1.888e^{005}s^4+9.294e^{006}s^3+2.979e^{008}s^2 5.235e^{009}s+2.521e^{010}}{s^7+114.2s^6+1.435e^{004}s^5+9e^{005}s^4+4.445e^{007}s^3+1.354e^{009}s^2+2.266e^{010}s+9.971e^{010}}$$

(11)

Transfer function from input cutting speed to:

feed force:

$$\frac{0.072263s^7+9.956s^6+1193s^5+8.351e^{004}s^4+4.147e^{006}s^3+1.326e^{008}s^2+2.32e^{009}s+1.202e^{010}}{s^7+114.2s^6+1.435e^{004}s^5+9e^{005}s^4+4.445e^{007}s^3+1.354e^{009}s^2+2.266e^{010}s+9.971e^{010}} \tag{12}$$

As it can be seen from regression values of each set it is relatively too low regression especially for the short set which represents the transient stage. This application requires very fast correction actions to prevent damage of tools or workpieces during controlling the process. It must be mentioned here that the selected measurement for modeling was one of the most stable measurements taken for hardened workpieces. It means that these models cannot be accepted as representative models in order to be controlled.

Till now regression values are not sufficient especially for the long data set. Which means this way of modeling is not sufficient for this process and if we take in consideration that the modeled set here belong for only one measurement which its results are completely different from others because each one of them was different from others it will be a must to use another way of modeling. So NN (neural networks) were used to model the process [4].

NN Model

Using NN with different architectures proved that the FFBP (Feeding forward back propagation) is the best architecture for modeling this process [4, 5]. The data used for modeling the process was all measurements with different feeding rate and speed across the nominal range. Some measurements taken at specific cutting speed values were excluded for other models. In order to avoid discarding of each measurement samples, it was important to enter the samples' time sequence as input.

The best model was FFBP with 2 hidden layers, the first one contained 25 neurons and the second one contained 30 neurons. The regression value of training was 0.897, for validation was 0.983 and for testing was 0.890. The MSE (mean square error) was 9566. A lot of tests were performed on this network to know if it is well representative of the process or not.

One of these tests was using 100 samples of one measurement. Figure 9 shows the difference between the measured F_c and the corresponding F_c values resulting from the network.

As shown in Fig. 9, the difference reaches values of +130 and -90 N which is absolutely not acceptable especially the reference steady state value where its reference measurement peak value is 650 N; it means the error is 21.8%. After a lot of fallen trials, it was noticed that the measurements of the first 3 cutting speed values with all feeding rates are obviously unstable. In addition the worker was refusing during experiment to perform the machining process with these values.

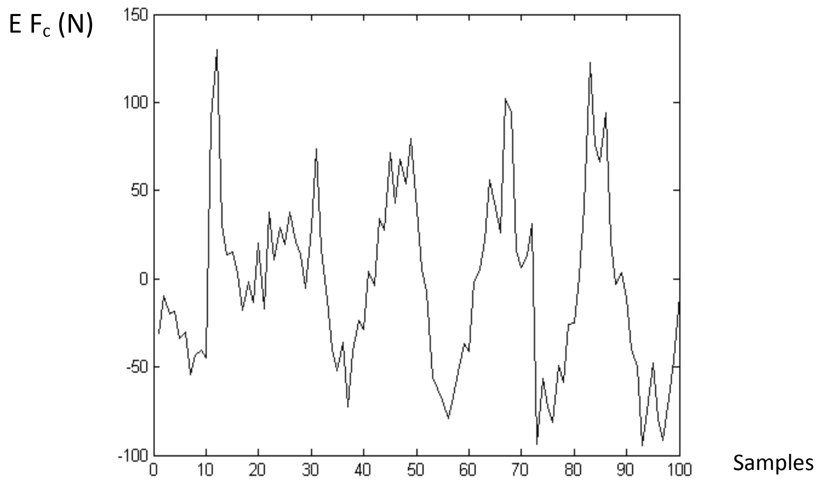

Fig. 9. Difference between measured and simulated 100 samples of the Net 25_30 for F_c.

These measurements were thought to be the cause of the defect of the resulting models. So the worst measurements taken at 2 of these cutting speed values were excluded from modeling data.

The best network resulting from this data set was a FFBP with 2 hidden layers, the first one contained 25 neurons and the second contained 20 neurons the resulting regression value for training was 0.98222, for validation regression was 0.98309 and for testing regression was 0.97267. The MSE was 935.1985. The big development in the values of regression and MSE was very encouraging so other models were developed using data set in which the measurements taken at the third cutting speed value.

The best network resulting using this data set was a FFBP with 2 hidden layers, the first one contained 17 neurons and the second contained 20 neurons the resulting regression value for training was 0.99159, for validation regression was 0.9867 and for testing regression was 0.98609. The MSE was 352. It is obvious that both of the networks have no over fitting.

It was noticed here that the exclude of the measurements taken at the third cutting speed value caused huge reduction in the MSE value and increasing regression values. This was not sufficient testing of the network so both of the two networks were tested simultaneously by entering different values of inputs and seeing which one will be closer to the measured or expected outputs and fulfills the condition of dependency more.

The developed network using the last data set and contained 17 and 20 neurons was found to be the best one. So it continued as the best model in control stage.

CONTROL

There were different control methodologies discussed as will be illustrated to make the forces close enough to the reference forces without making sudden or huge modification in inputs. Because the two forces F_c and F_f are just components of one force. Controlling the most important of them Fc, using the most affecting variable cutting speeds becomes the selected way.

PI Controller

Many PIDs were tested. For the first P controller tested, it resulted in a negative value at the beginning and at the steady state stage it resulted in a big steady state error. So PI controller was used to solve the problem of the steady state error.

Many PI controllers were tested the best one gains are listed in table.1. Figures 10 and 11 show the controller and the network results compared to the reference respectively.

Table.1. Best PI controller gains:

K_p	**0.00345374785930276**
K_I	**0.172687392965138**

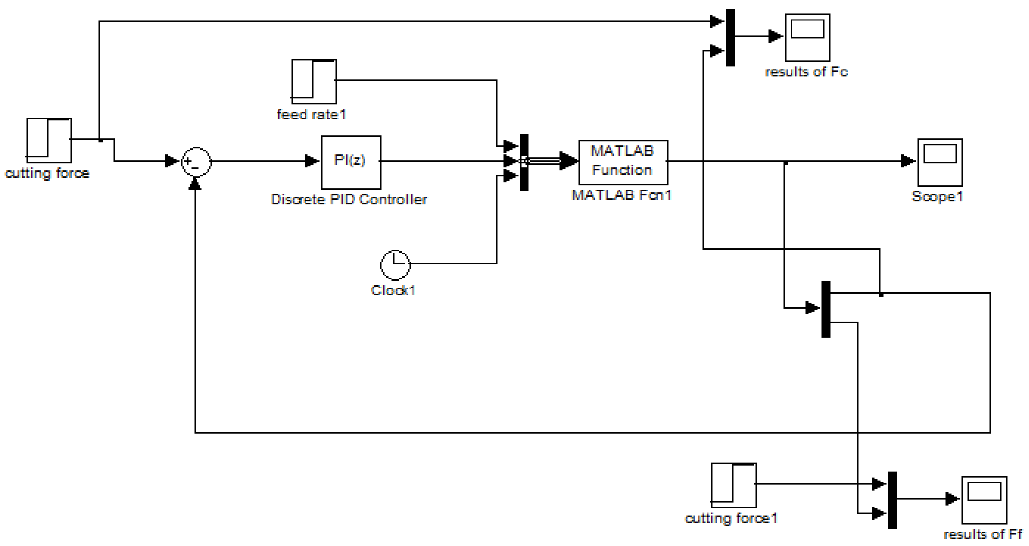

Fig.10. PI controller with Fc feedback signal and Cutting speed as controlled input.

As it is obvious in Fig. 11, the start of the transient stage has a huge negative value which cannot be accepted as a behavior of the system under control although the problem of the steady state error was solved. Before trying to solve the problem of the huge negative start the disturbance rejection tested using random disturbance and the system shows good behavior as there was no difference from the behavior shown in Fig. 11.

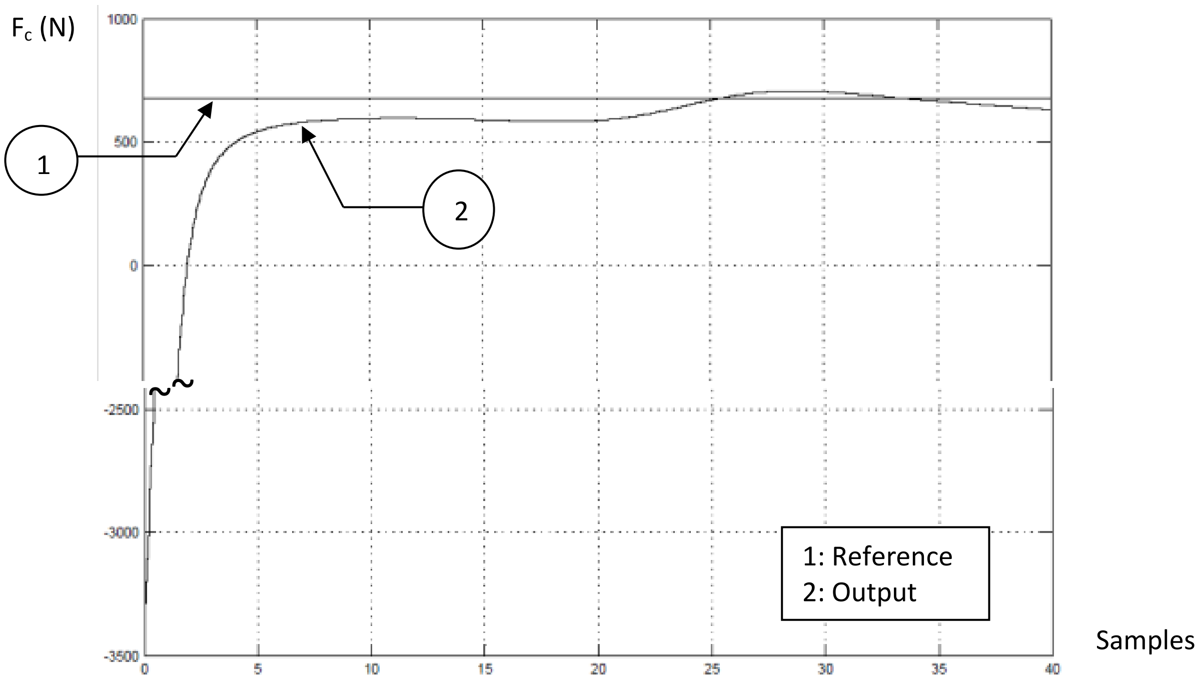

Fig.11. Results of PI controller trial with Fc feedback signal compared to average steady state value.

Expert system is suggested as a solution of the negative start of the system under control.

Hybrid Controller

A hybrid controller by which the expert system controls the model in open loop at the transient stage, then the PI controller continued the control of the model in closed loop.

After applying this hybrid controller, the problem of switching between the two controllers arose because the system showed a sudden negative response at the switching point as shown in Figure.12. Postponing the switching point was suggested as a solution of this problem, because it was thought to be caused as the system did not settle yet. But it wasn't effective solution.

Then using saturation of the PI controller was thought to be a solution which can prevent the control action at the switching point from dropping under the lower limit of working range of the model. But also this solution was not effective because the control action after switching staked to the low limit of the saturation limits and caused very high overshoot which was about 25% of the average steady state value.

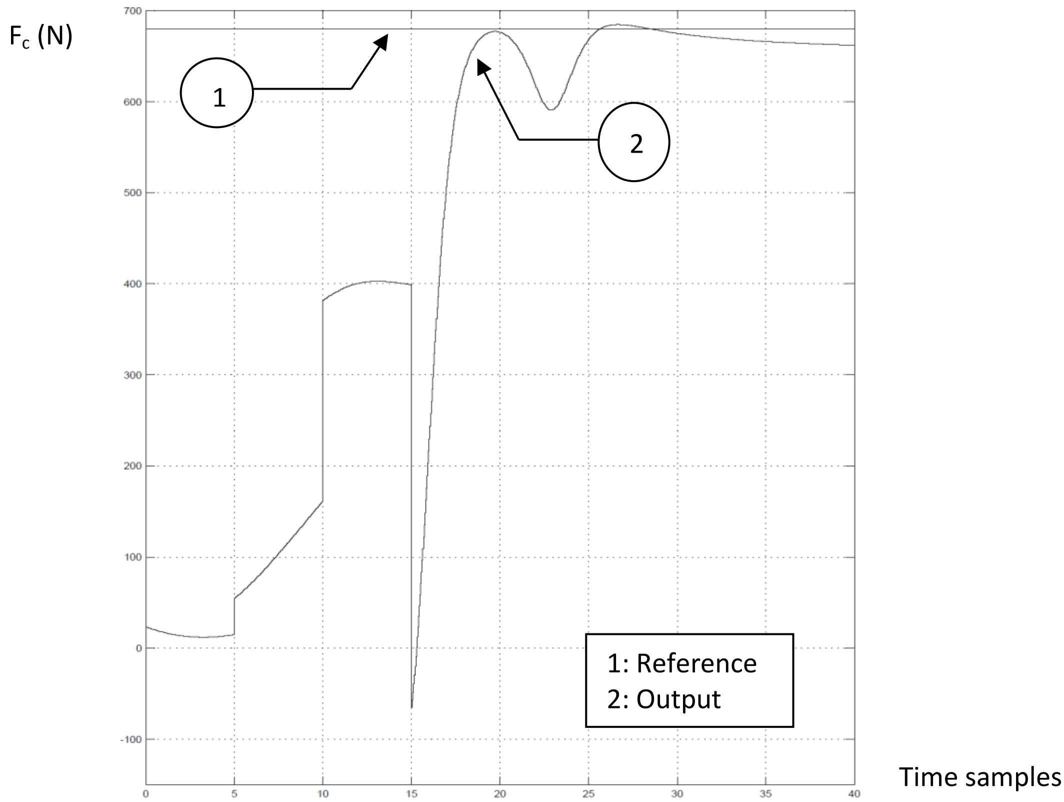

Fig. 12. System response under control of the hybrid controller.

Till now the average steady state value was used as reference it was thought that the huge difference between the model outputs and the reference at the transient stage is the cause of the huge sharp negative output at transition point so the full reference measurement curve was used as reference instead. But this was not so effective. There was sharp transition output value also at the end of output figure the output got high error and didn't settle well at the reference so it could not be considered as solution.

The reason for this was thought to be the controller experience accumulated during the action of the expert system couldn't help it to take good action during its work. So Bumpless control was thought about as a solution for this problem Figure 13 shows how it was applied.

It was successful solution and resulted in a good output behavior Figure 14 shows the output after using bumpless control.

As it can be noticed in Fig. 14, the transition became smooth, overshoot does not exceed the maximum value of measured reference also steady state error became small enough. This performance was satisfying.

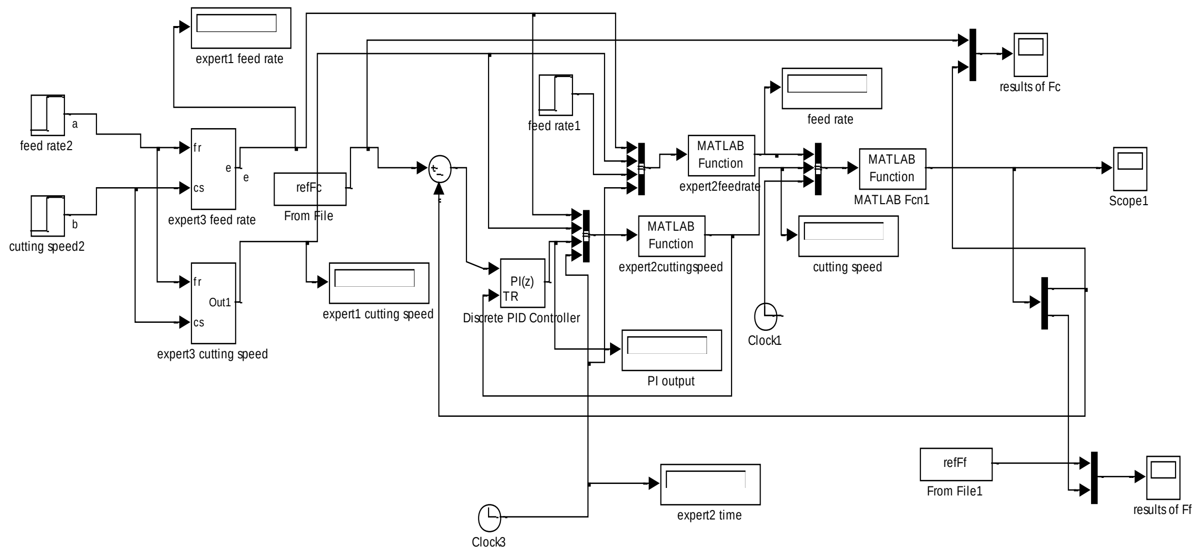

Fig. 13. Bumpless PI controller with expert system.

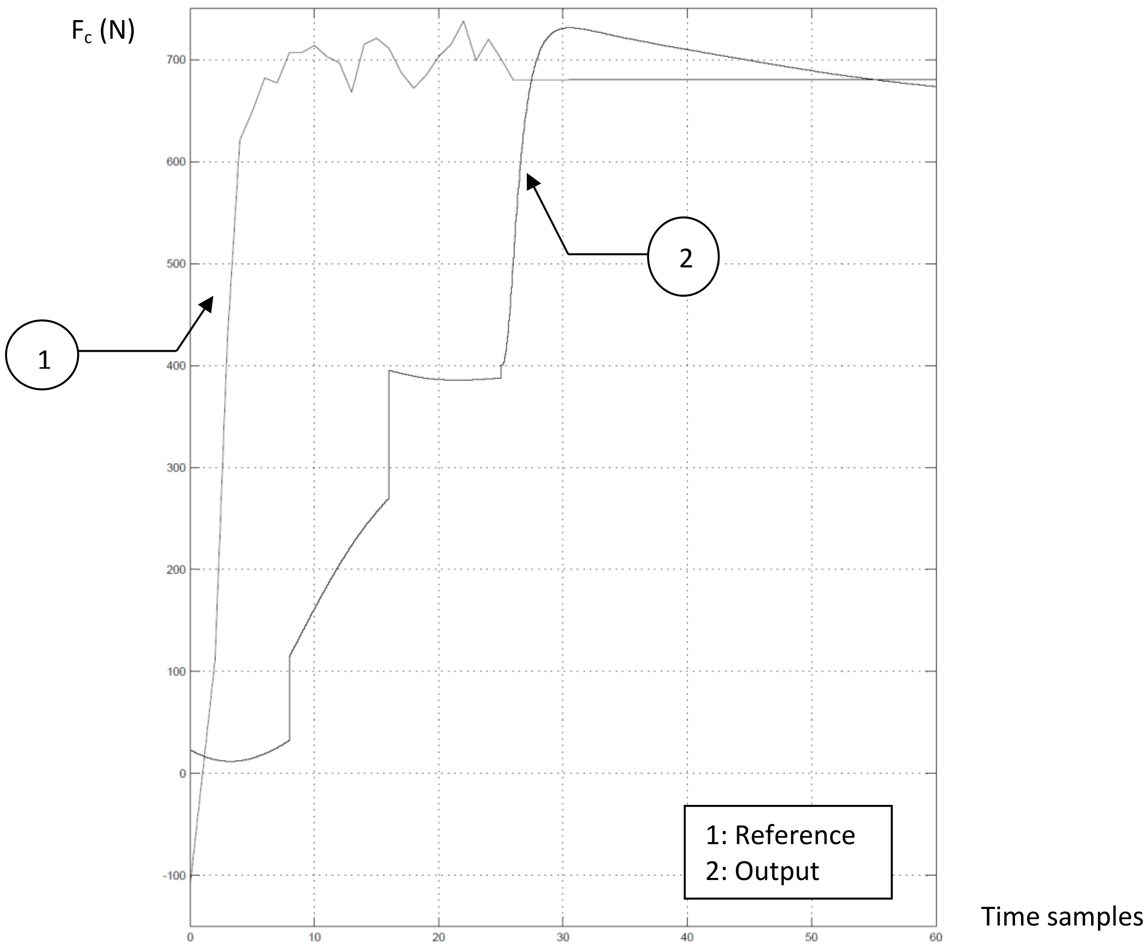

Fig. 14. Results after using bumpless technique.

CONCLUSION

1. Artificial intelligence is essential for dealing with complicated problems. For modeling of complicated behaviors like over wear in this case because it was more efficient than the mathematical model also it could model the process under all conditions in contrast of the mathematical model which only could model one measurement at a time.

2. For control the conventional PI controller was efficient to get rid of the steady state error but not efficient for solving the whole problem. It was a must to combine it with the expert system to get appropriate controller, and without bumpless technique it was not to be accomplished.

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