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Research Article

Fuzzy Based Tool Wear Monitoring of the CNC Milling Machine

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Abstract: In machining systems, cutting tool wear causes errors in precision manufacturing processes. It causes a waste of raw material processed in faulty production and a waste of time spent in vain. Continuous monitoring of tool wear and generating an automatic warning in case the wear value falls outside the tolerance value will resolve these issues. Vibration values and the powers drawn by the motors provide important clues in the non-contact monitoring of cutting tool wear during production. In this study, thanks to the use of low-cost sensors and the applied fuzzy decision mechanism , the cutting tool status could be detected online with an accuracy of 90.17 percent. The RMS value of the power drawn by the spindle motor, average value of fiber optic sensor output voltage, and the average values of selected fiber optic sensor output wavelet transformations are the inputs of the designed system. The output of the system is the cutting tool wear value estimated by the fuzzy decision mechanism.

CNC Freze Tezgahının Bulanık Tabanlı Takım Aşınma Takibi

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Anahtar Kelimeler
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Wavelet dönüşümü

Öz: Talaşlı imalat sistemlerinde kesici takım aşınması, hassas imalat süreçlerinde hatalara neden olur. Hatalı üretim de işlenen hammadde israfına ve boşuna harcanan zaman kaybına neden olur. Takım aşınmasının sürekli izlenmesi ve aşınma değerinin tolerans değerinin dışına çıkması durumunda otomatik uyarı verilmesi bu sorunları çözecektir. Titreşim değerleri ve motorların çektiği güçler, üretim sırasında kesici takım aşınmasının temassız izlenmesinde önemli ipuçları sağlar. Bu çalışmada düşük maliyetli sensörlerin kullanımı ve uygulanan bulanık karar mekanizması sayesinde kesici takım durumu yüzde 90,17 doğrulukla çevrimiçi olarak tespit edilebilmiştir. İş mili motorunun çektiği gücün RMS değeri, fiber optik sensör çıkış voltajının ortalama değeri ve seçilen fiber optik sensör çıkış dalgacık dönüşümlerinin ortalama değerleri tasarlanan sistemin girdileridir. Sistemin çıktısı, bulanık karar mekanizması tarafından tahmin edilen kesici takım aşınma değeridir.

1. Introduction

Tool wear must be taken into account to produce the product processed in CNC milling machines with minimum error. If tool wear is detected by the skill of the working operator, it is almost impossible not to make a mistake. For this reason, various algorithms have been proposed before and various sensors have been used to accurately detect cutting tool wear. However, it cannot be said that a reliable and correct approach has been revealed yet. (Jiang et al., 1987) has shown experimentally that cutting tool wear can be revealed quickly and accurately by carrying the frequency band-energy method of vibration signals to the time domain. (Rangwala & Dornfield, 1990) tried to obtain the cutting tool wear value with the artificial neural network algorithm by using the acoustic emission and force sensor information during the turning process. The cost of the force measurement sensor used in this method is quite high. In addition, the neural network learning algorithm needs 20000 cycles or more. In the meantime, there is also the possibility of giving wrong results if the local zero point is caught. (Lee et al., 1997) tried to determine the cutting tool wear by measuring the stator current value in the end milling process. In his experimental studies, it showed that the square of the stator current is related to the motor torque. (Jun & Suh, 1999) tried to determine the vibration sensor data, which he attached to the spindle guard during the milling process, for two different statistical methods, type I false alarm and type II cutting tool breakage not being detected errors. It demonstrated the validity of the results of the statistical methods used in experimental studies for the detection of cutting tool breakage. (Dimla & Lister, 2000) using the Kistler dynamometer and vibration sensor, tried to detect cutting tool wear according to two different types of cutting tools used in the turning process. (Li et al., 2000) investigated the cutting force and feed force according to the current value he measured using a hall-effect sensor in the turning process. They tried to find the tool wear value from the force values determined by the fuzzy neural network algorithm. (Axinte & Gindy, 2003) has shown that acoustic emission, vibration, cutting force, hydraulic pressure signals are sensitive to wear in the hydraulic broaching machine. In addition, it is explained whether these sensors are suitable for use. As can be seen, the use of multiple sensors is also applied in this study. (Ertekin et al., 2003) investigated the correlation of cutting tool wear with acoustic emission, spindle vibration, and cutting force value for three different workpieces in vertical milling. It tried to determine the cutting tool change time according to the results he obtained. (Susanto & Chen, 2003) Kistler dynamometer data was applied to a fuzzy rule-based decision mechanism and claimed to be able to predict tool wear with 90% accuracy. Since the dynamometer is an expensive device, it will be very costly to apply this study to the industry. (Tatar & Gren, 2008) tried to correlate the laser vibration device data with the amount of cutting tool wear. This solution, which is recommended for high-speed milling processes, brings with it the disadvantages that will prevent vibration detection like precise positioning of the laser vibration device, cleaning of the laser head, cooling liquid and metal burrs separated from the workpiece. (Zang & Chen, 2008) measured the vibration values in the x, y, z-axis using the accelerometer in the integrated circuit structure with the help of a microcontroller. These values were visualized using a visual basic program and ready-made graphic program and cutting tool wear was tried to be estimated. Although this research is claimed to be inexpensive, it cannot be said that the electronic sensor circuit will not be affected by high temperature and coolant during processing. In addition, the stability of the signals that the sensor structure mounted on the milling workpiece clamping table will produce during movement cannot be guaranteed. (Gücüyener & Emel, 2009) was able to measure the spindle vibration values in the CNC milling device with a their designed fiber optic sensor. In that design, laser light had been injected into the plastic fiber by the laser diode light. In the designed structure, laser light reaches the receiver circuit by passing through the fiber curled structure. On the receiver side, there are high-pass filters, preamplifier, instrument amplifier, and low-pass filter, respectively. The amount of decrease in laser light passing through the fiber during any vibration was associated with the spindle vibration value. (Besmir & Kim, 2017) applied the dynamometer force gauge, accelerometer, microphone, current sensor values to the rule-based fuzzy inference mechanism. It investigated the correlation between the sensors. And also it has been explained that the filtering processes should be done sensitively. It is reported that this study will shed light on future research. (Gücüyener, 2018) examined accelerometer transducer data with a PCI data acquisition card. With the software designed, he visualized the values of vibration values in the time domain and frequency domain. It has been presented that the data can be evaluated with few errors thanks to the accelerometer signals in the piezo crystal structure and a 16-bit analog-to-digital converter. (Gücüyener, 2021) investigated machine vibrations with a piezo-crystal sensor and newly designed software. Time domain, frequency domain, and wavelet transform difference values of vibration values are visualized. In the FFT and Wavelet transform investigations, the frequency band ranges that can show vibration with the least error were determined. By applying the determined band gap values to the fuzzy extraction mechanism, the status of the machine was created in the form of ‘Good, Normal, Bad’ on the visual screen.

Detection of the wear of the cutting tool during the milling process is an inevitable condition for creating a defect-free product. In many previous studies, this process has been tried to be done by using more than one sensor. The important thing here is that the sensors used do not complicate the process, are not affected by the cooling liquid and metal particles that come out during processing. For this reason, in this study, a newly designed fiber optic sensor that can detect cutting tool wear without contact and a hall-effect sensor that will show the power value of the spindle are used. In addition, it is emphasized that fuzzy-based algorithm inference produces accurate results in many studies. Thanks to the non-contact sensors used in the study and the fuzzy membership functions, which have been reproduced in sufficient quantities, an online monitoring system has been created that will detect the cutting tool status accurately and is inexpensive. In the following sections, the structure of the sensors used, the experimental studies, and the results will be explained.

2. Material and Methods

The structure of fuzzy-based tool wear monitoring is shown in Figure 1. PH-3A model power cell is used to obtain the power consumption signal of a spindle motor. The power cell has 3 balanced Hall Effect devices, each with a flux concentrator. Each of the 3 phases passes through a flux concentrator. The Hall Effect sensor senses a magnetic field that is proportional to the current flowing in the conductor. This conductor is taken from CNC milling machine spindle motor driver output. Each sensor unit is excited with a signal that comes from the voltage sample for that phase. The Hall device multiplies the voltage and current signals. This is a vector multiplication that also calculates the lag or lead of the current. The resulting output is then proportional to power (Volts x Amps x Power Factor). The signal for each of the 3 phases is summed and the analog output (0-10 Volts) signal is proportional to the 3 phase power. This sensor is installed electronic control unit of the CNC milling machine.

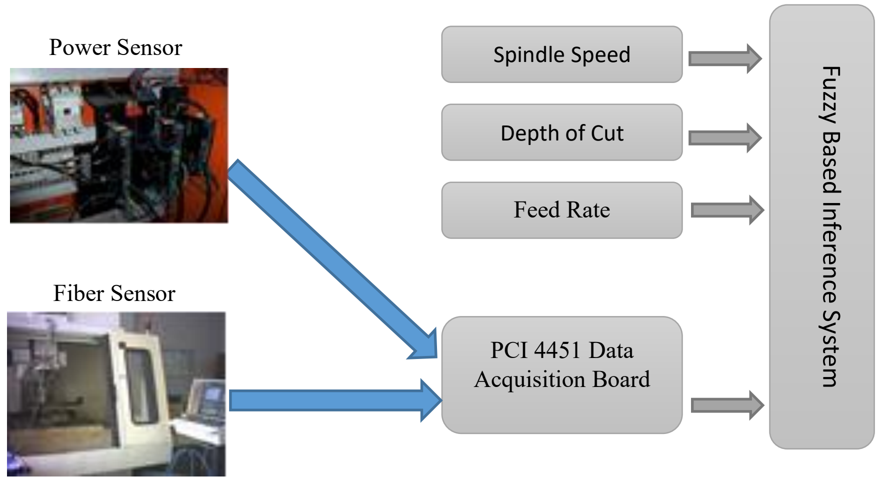


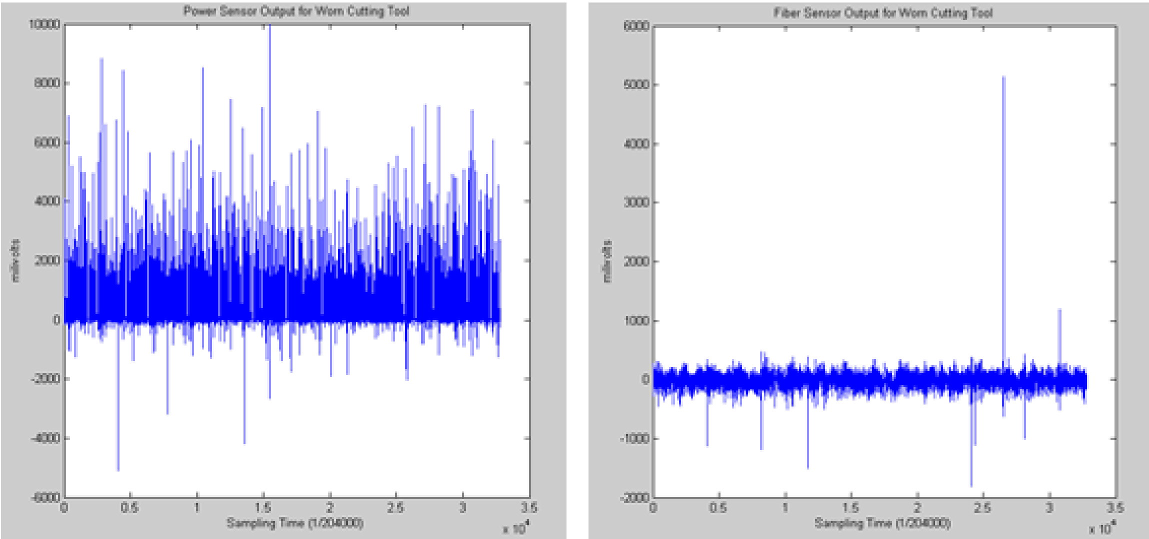
Figure 1. Structure of fuzzy-based tool wear monitoring system.

Fiber optic bending sensor (Gücüyener & Emel, 2009) is mounted on the cylindrical surface of the spindle. This sensor produces -15 to +15 volts analog output according to the vibration magnitude of the moving surface. Raw signal of both sensors has connected to PCI 4451 National Instrument data acquisition board via electrical connection unit.

Cutting information used in any machining operation can be generated differently. The sensors used will produce different signals for different cutting conditions. Therefore, the software should be informed of the preferred cutting conditions. The designed rule-based fuzzy inference software is needed spindle speed, cutting depth, and feed rate information before any machining operation. The system is produced results thanks to the read sensor signals and process input information.

2.1. Evaluation of the sensor signals

Tool ware monitoring system is tested on Taksan TMC 650V face milling machine. The sampling frequency of the data acquisition board is 204000 sample/s. Sensor signals in the time domain are very complex and they are shown in Figure 2. It is extremely hard to find any result from those signals. As mentioned before, it is an obligation to use signal processing technics on the data coming from sensors.



(a) (b)

Figure. 2. (a) Power sensor signal. (b) Fiber sensor signal.

In the designed tool ware monitoring system RMS value of power sensor signal is used according to Equation 1. In this equation U is sensor signal voltage value, m is sampling number, j is jth RMS value.

$$RMS_j = \frac{\sum_i^m |U|_{ij}^2}{m} \tag{1}$$

Discrete wavelet transform is applied for the fiber sensor signal. 'Equation 2.' shows the applied formula for this transform.

$$\emptyset_{k,m}(n) = \frac{1}{2^k}\left[\sum_{i=0}^{2^{k-1}-1} \delta\left(n - i - 2^k(m-1)\right) - \sum_{j=2^{k-1}}^{2^k-1} \delta\left(n - i - 2^k(m-1)\right)\right]$$
$$d(k,m) = \sum_{n=0}^{N-1} X(n)\emptyset_{k.m}(n) \tag{2}$$

In Equation 2. $\emptyset$ is discrete-time mother wavelet transform, d is the difference transform value in mother wavelet transform function and $X(n)$.is fiber sensor signal in discrete time. Equation 1. and Equation 2. produce the crisp values of the fuzzy decision mechanism. The designed software transforms these values into fuzzy variables and applies them to the fuzzy rule base. Table 1. shows the difference between sharp and worn cutting tool RMS values of power sensor signals. According to the selected cutting conditions, the values in Table 1 show that there is a difference between the sharp cutting tool and the worn cutting tool. Since the cutting process has many different factors, it cannot be said that these values are sufficient to produce results even if they are different.

Table 1. Power sensor RMS values

Depth of cut	Spindle speed (rpm)	Feed rate (mm/min)	Sharp tool RMS output (mV)	Worn tool RMS output (mV)
1 (mm)	800	100	385.98	680.37
	800	300	628.08	833.32
	1000	100	455.26	688.63
	1000	300	715.6	892.93
	1200	100	394.19	634.74
	1200	300	643.66	777.46

Table 2. Fiber sensor average values

Depth of cut	Spindle speed (rpm)	Feed rate (mm/min)	Sharp tool Fiber Sensor average (mV)	Sharp tool Wavelet Scales average (mV)	Worn tool Fiber Sensor average (mV)	Worn tool Wavelet Scales average (mV)
1 (mm)	800	100	40.64	5.87	47.54	14.11
	800	300	45.23	10.4	49.56	13.22
	1000	100	45.66	8.21	50.85	16.09
	1000	300	49.38	11.26	51.81	14.23
	1200	100	38.99	5.92	50.91	12.54
	1200	300	50.96	10.6	60.52	15.02

The other inputs of the monitoring system are the average of the absolute magnitude of spindle vibration, and the average of the absolute magnitude of sensitive wavelet analysis scales. Table 2 shows these average values for the sharp and worn cutting tool as in the same cutting conditions. These sensor values produced under different cutting conditions are at the millivolt level. It should be taken into account that these values may change with side factors such as electromagnetic noise and heat during the application. Therefore, if one of the sensor values is wrong, the other sensor data will have an effect to eliminate this error. Fuzzy algorithm application does not work with exact values. One of the strengths that enable the designed system to produce accurate results is that it uses multiple sensors and uses a fuzzy logic algorithm. (Zhou & Xue, 2018) examined many articles monitoring the wear of the cutting tool in the milling process between 2005 and 2017 years. According to their investigation, they declared following advantages of fuzzy logic based solutions.

i) Fuzzy-based algorithms use a small amount of learning data
ii) It can easily adapt to expert data
iii) It can be applied to the new situation with small changes even if the working conditions change.

Abu-Mahfouz et al. (2016) investigated the vibration values using an accelerometer sensor in milling process. They used the fuzzy clustering to predict the surface roughness of the aluminum workpiece. The fuzzy algorithm gives good results especially for solutions with many unknowns. The unexpected signals of the sensors caused by the environmental noise are not reflected the output value with sudden changes. In addition, it can be said that the fuzzy algorithm tolerates the discontinuity on the result due to the effect of digital devices their discrete time operation.

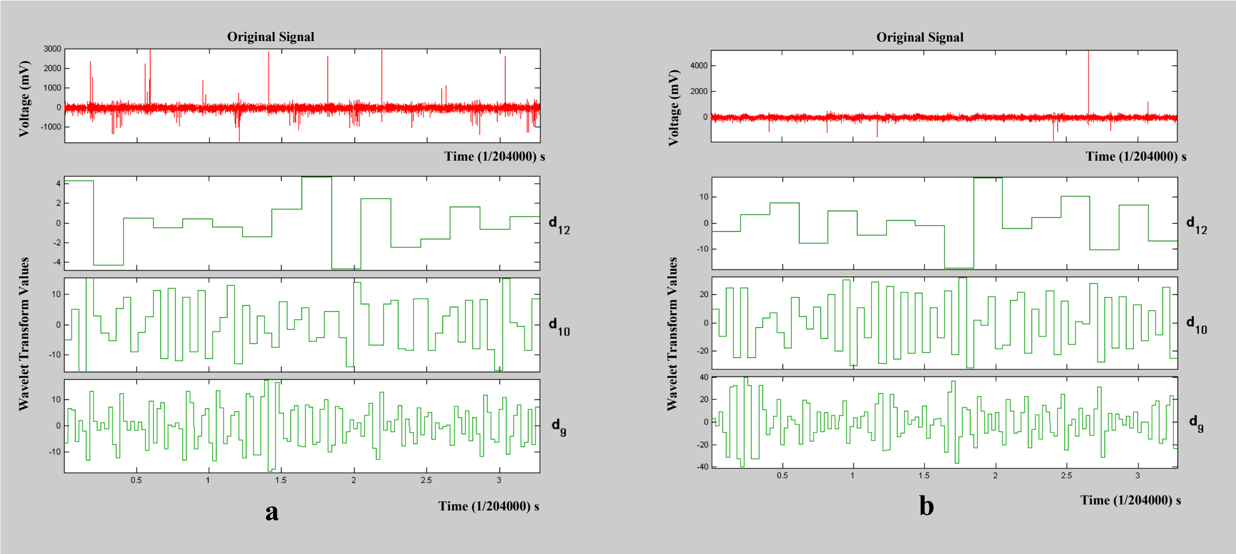


Figure 3. (a) Fiber sensor signal of sharp tool. (b) Fiber sensor signal of worn tool.

Measured vibration in the milling process is generated from rotating components of the machine and ambient noise. In the case of cutting tool teeth breakage or wear, unbalanced rotate becomes (Zang & Chen, 2008). This situation causes increased vibration. The frequency of vibrations is at frequencies other than the natural frequency of the machine. Monitoring a wide frequency range will create processing intensity and sometimes the vibration values originating from the cutting tool may be overlooked. The wavelet transform was used to data compression, data filtering, and time variation of frequency bands. (Zhou & Xue, 2018) stated in his review article that the wavelet transform is used in many studies for cutting tool state estimation. (Merainani et al., 2016) tried to find rolling bearing errors from vibration signals with a transform called Empirical Wavelet Transform, which can be tuned to frequencies that are sensitive as a result of FFT. Wavelet transform is capable of giving the time change of frequency bands. For this reason, Wavelet transforms difference values, which can show the cutting tool vibrations, will be able to distinguish the frequencies where wear occurs without the processing intensity. In the experimental studies carried out in this study, the frequency bands that are sensitive according to different cutting conditions were determined by wavelet transform. The frequency bands in the wavelet transform were used as the input of the fuzzy decision mechanism.

2.2. Fuzzy decision mechanism

The fuzzy decision mechanism has three inputs which are power sensor RMS value, fiber sensor absolute magnitude average value, and average values of the wavelet transform selected scales. At first, acquired data is being converted to the fuzzy variable with fuzzification software component. Fuzzification defines the membership function of crisp data in the universe of discourse. According to Table 1. and Table 2. every cutting condition works with a different universe. Seven different linguistic variables are defined for every signal input and output. Figure 4. shows defined linguistic variable for cutting tool ware. The total number of linguistic variables which are used in the software is 28. In the software design, fuzzy linguistic variables were shown with the short named matrixes. According to this process xlc="Super Sharp", xlk=" Very Sharp ", xlz = "Little Sharp ", xlo= "Medium ", xls = "Little Worn ", xla="Very Worn ", xli ="Ultra Worn" has been named.

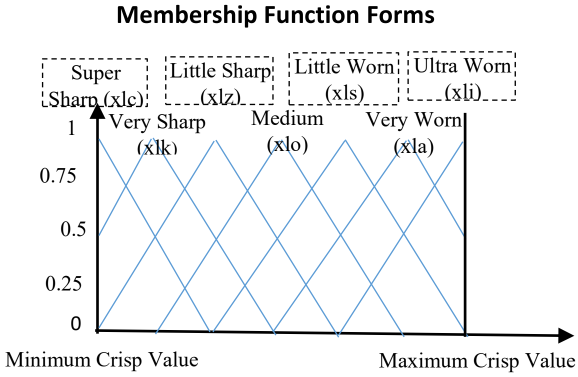


Figure 4. Linguistic variables for cutting tool ware.

At every cutting condition, experimental measurements were repeated 10 times either the sharp cutting tool or worn cutting tool. The result of the measurements is used to specify values of the universe of discourse for every cutting condition in Table 1 and Table 2. Fuzzyfied values are applied to the rule base. The rule base is established with 343 different rules. One of the examples of rule base is shown in Equation 3. By applying these input values to the fuzzy rule base, the predictive value of the cutting tool wear condition is produced.

$$Rule\ 1{:}\ if\ Rmsgir\ is\ glc\ \cap Wavgir\ is\ wlc\ \cap Avegir\ is\ fbc\ then\ Res\ is\ xlc \quad (3)$$

Where Rmsgir is the power sensor fuzzified input, Wavgir is the fuzzified value of wavelet result, Avegir is the fuzzified value of fiber sensor absolute average, glc, wlc, fbc, xlc are linguistic variables in their universe of discourse. Inputs are applied to all fuzzy rules and are obtained fuzzy results. The obtained fuzzy result is converted to the crisp value of tool wear in mm. with following Equation 4.

$$v_0 = \frac{\sum_j \mu(v_j).v_j}{\sum_j \mu(v_j)} \quad (4)$$

Where v_0 is the crisp value of fuzzy inference system, $\mu(v_j)$ is the membership values of result, and v_j is the universe of discourse.

3. Results

The purposed monitoring system must be reliable, have low cost, and do not disturb the machining process. In this study, the purposed fiber-optic sensor and power sensor can be applied simply and cost-effectively in the manufacturing environment. The developed monitoring system is written with C++ programming language and gives tool wear value continuously. The starting phase program asks spindle speed, depth of cut, and feed rate for the applied machining process. After this procedure RMS value of the power sensor, an average of fiber sensor output voltage, and an average of wavelet scales of the fiber sensor signals are calculated. These values are applied to fuzzification, rule base, and defuzzification components in the program serially. Some measured wear values and estimated wear values are shown Figure 5. It has been determined that it has an accuracy of 90.17253 percent according to the estimated values and the actual measurement values.

It may not always be possible to obtain error-free data from sensors. Also, zero error in conversion to digital values is never possible. For this reason, a hundred percent result has not yet been obtained in dozens of studies. (Trejo-Hernandez & Osornio-Rios, 2018) made the measurement of servo motor current and vibration values and flank wear with the Field-programmable gate array programming (FPGA) they have done and declared that they estimated correctly with an error of less than 10 percent. (Karandikar et al., 2015) tried to predict cutting tool wear by applying naïve Bayes classifier method to dynamometer data. They have obtained approximately 85 percent accurate prediction values on their experimental studies. (Lin et al., 2017) suggested that cost effective tool wear monitoring with spindle motor current value data. They showed that they were able to detect normal cutting tool below a certain threshold of 96 percent and broken cutting tool at 100 percent. (Zang et al., 2016) estimated the amount of tool wear and remaining useful life using various wireless sensors. They explained that they obtained correct prediction values with fuzzy neural network. Although the preferred method uses many sensors, there are differences between the actual wear and predicted wear especially in the large wear values. In this study, using the self designed fiber optic sensor and combining this data with spindle motor power sensor data stand-out as a good method for non-contact detection in milling process cutting tool monitoring.

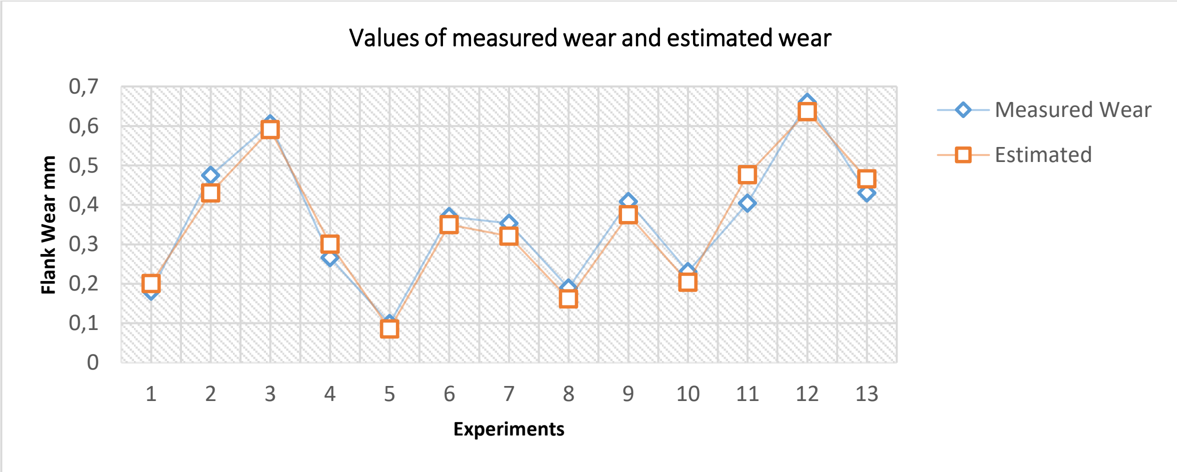


Figure 5. Measured values and estimated values.

4. Discussion and Conclusion

The proposed the milling machine cutting tool wear monitoring system reads the spindle vibration and spindle motor power to predict cutting tool wear. The electronic circuit of the designed fiber optic sensor is in a structure that will eliminate the electromagnetic noise caused by environmental conditions. At the same time, it is cheaper than fiber grating sensors and does not depend on foreign countries. The original software produces the result value by applying both sensor information to the fuzzy logic inference algorithm. The designed software uses wavelet transform to monitor the appropriate frequency bands of the fiber sensor signal. By means of software, the online detected sensor signal is transformed into a wavelet packages, and then it is brought to the fuzzy variable value. The power sensor is purchased ready-made. By making the connections suitable, the power drawn by the spindle motor is made to be read as analog data.Taking the average value of the power sensor analog signal makes it act like a low-pass filter. In this way, it is ensured that sudden noise values that will produce false values to the system are eliminated. Fuzzy logic produces very good results in systems where there are a lot of influences on the inference. As a result, a cutting tool monitoring system that is cost effectieve and least affected by environmental conditions has been designed.

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