

# An evolutionary sensor approach for self-organizing production chains

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**Abstract.** Industry 4.0 is the actual great step in industrial progress. Convergence of industrial equipment with the power of advanced computing and analysis, low-cost sensing, and new connecting technologies are presumed to bring unexpected advancements in automation, flexibility, and efficiency. In this context, sensors ensure information regarding three essential areas: the number of processed elements, the quality of production and the condition of tools and equipment. To obtain this valuable information, the data resulted from a sensor has to be firstly processed and afterward used by the different stakeholders. If machines are linked together, this information can be employed to organize the production chain with few or without human intervention. We describe here the implementation of a sensor in a milling machine that is part of a simple production chain, capable of providing information regarding the number of manufactured pieces. It is used by the other machines in the production chain, in order to define the type and number of pieces to be manufactured by them and/or to set optimal parameters for their working regime. Secondly, the information achieved by monitoring the machine and manufactured piece dynamic behavior is used to evaluate the product quality. This information is used to warn about the need of maintenance, being transmitted to the specialized department. It is also transmitted to the central unit, in order to reorganize the production by involving other machines or by reconsidering the manufacturing regime of the existing machines. A special attention is drawn on analyzing and classifying the signals acquired via optical sensor from simulated processes.

## 1. Introduction

Nowadays, we face a trend in industrial development which is known as Industry 4.0. The idea is making equipment to self-organize and to collaborate with other machines and with people [1-5]. The actual state of implementing the principles in the industry of some developed countries in is found in [6]. According to these principles, the structure and organization for a factory is described in [7]. Here, the role of sensors and actuators collaborating via a central system and implemented algorithms is crucial and constitute a specific pillar of Industry 4.0. Thus, classical machines are equipped with sensors, which permit both machine state assessment and manufacturing process parameter extraction. In this way failure occurrence in machine parts and in manufactured pieces is observed. This makes classical machines to become intelligent and collaborative and reduces the need for major investments. Several attempts to integrate sensors in machines and to use the acquired data to gain complex information are described in [8-12], a significant amount of interesting results being presented.



In concordance to the actual legislation, machines should operate with low level of noise and vibration [13], [14]. Any deviation from the regular parameters indicates an anomalous behavior, indicating, beside machine or tool wear, a problem in the quality of machined pieces. The aim of manufacturing process monitoring is the observation of significant parameter changes. Usually, these parameters are acceleration, pressure or temperature, and are measured on the machine or on the manufactured piece. Manufacturing process monitoring consist of condition monitoring, used on machineries containing rotating or oscillating elements, and non-destructive testing techniques that is employed for stationary elements [15].

This paper aims presenting an example how optical sensors can be attached to a universal milling machine in order to supply data used to assess the manufactured pieces quality, to optimize the operation regime of machines linked in the production chain and to perform maintenance in due time.

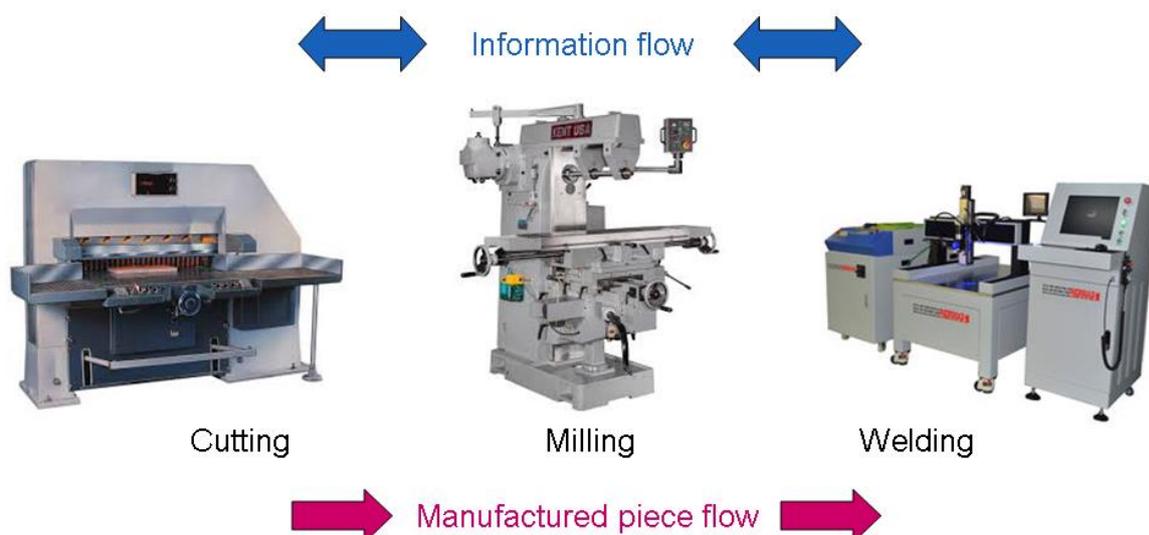
## 2. The self-organizing concept for a simple production chain

The self-organizing process in an industrial structure is the process where the order arises from local interactions between elements of the disordered system. The process is spontaneous and need not to be controlled by any external entity, i.e. human intervention in the case analyzed in this paper. The self-organizing process is activated by random fluctuations and the resulting organization is completely decentralized, being distributed over all elements of the industrial structure. As such, the structure is able to self-repair substantial perturbation.

In this study, the perturbation consists of machine wear, tool wear or improper operational regime, simulated by different kind of actuation of the manufactured piece. The implemented optical sensor observes the perturbation and transmits the parameter changes to the central unit which takes action based on implemented algorithms.

### 2.1. The production chain

In this paper, by reason of simplicity, a production chain consisting of three machines is employed. The manufacturing process of a gas turbine palette, which has in the initial state the shape of a prismatic bar, is simulated. The operations are as following: (i) cutting to obtain the desired length, made on a cutting machine, (ii) milling the lateral surface in order to get the final shape, made on a universal milling machine, and (iii) welding the achieved elements on a rotor, made by a welding machine.



**Figure 1.** Production chain involving three operations, with indication of the piece respectively information flow

The chain is presented in Figure 1; one can observe in this figure the unidirectional flow for the manufactured piece, in the above-described succession of operation. On the other hand, the information flow follows two directions, to the cutting and welding machine which are placed before respectively after the milling machine in the production chain. Obviously, the information is transmitted to the staffs that are: the plant engineer, the accounting and sales representative, the quality assurance responsible and the maintenance team leader. The aim of transmitting data to staff members is for information purposes only, the human action being asked just for interventions that machines cannot handle. However, decision is taken by the central unit based on a priori developed algorithms.

### 3. Optical sensor implementation

The supervising process is exemplified on a universal milling machine which got attached an optical displacement sensor. This sensor acquires distances with high-precision, even for dynamic regimes. The responses to different operating scenarios are transmitted to the central unit, in this way a simple experimental stand being obtained. Since the aim of the paper is to demonstrate how sensors can be used to create self-organizing production chains, the study presented herein is limited to analyzing and classifying the signals transmitted by the sensor.

#### 3.1. Sensor implementation

The optical sensor involved in the experiment is of type LG10A65PU; it can operate in analog and discrete mode as well. Figure 2 shows the experimental stand, where the machined piece is represented by a steel beam with dimensions 200x40x3 mm. The sensor produces a logic switching at the presence of an object, and analog voltage in relation with the distance till the pointed location signalized by red spot light is registered. Any distance variation determines a proportional voltage variation. The output voltage is analog-to-digital converted by the NI USB-6259 M series Multifunction DAQ (presented in Figure 3) and transmitted to the personal computer. Here, the signal is visualized and registered via the embedded Measurement & Automation application developed by National Instruments. Figure 3 also present the double power source, used to supply the optical with 0-3 A control and 0-30 V DC stabilized direct current voltage.



**Figure 2.** Experimental stand, consisting of a universal milling machine, machined piece and the optical sensor



**Figure 3.** Setup for the sensor calibration made before employing it in the operation monitoring process

The optical sensor (Laser Displacement Sensor) is a high-precision sensor that has a measurement range from 75 to 125 mm and the focal point at 180 mm. The analog resolution at 100 mm is as following: Fast: < 150  $\mu\text{m}$ ; Medium: < 50  $\mu\text{m}$ ; Slow: < 10  $\mu\text{m}$ . It has one discrete PNP output (max. 100 mA) and output saturation DC voltage < 1.2 V at 10 mA respectively < 1.6 V at 100 mA.

Data acquisition module NI USB-6259 M series has 32 analog inputs (32 single ended or 16 differential), 4 analog outputs and 48 (32 clocked) digital I/O. The frequency range is 1.25 mega samples per second by 16 bits resolution, the data acquisition module being optimized for superior accuracy at fast sampling rates.

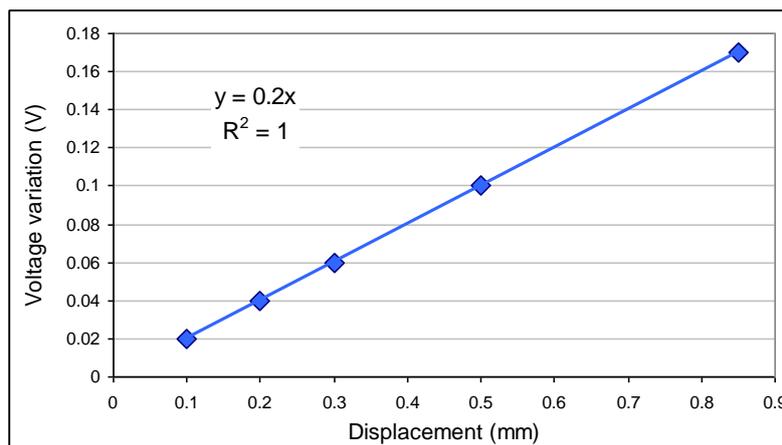
### 3.2. Sensor calibration

In order to acquire precise data, calibration is requested before the milling operation is monitored. As shown in Figure 3, the steel beam representing the machined piece is fixed on one end in a screw vice and has the other end free. The optical sensor is also fixed in a vise, the distance between sensor and piece being 100 mm. Both vices are rigid fixed on the table of the universal milling machine.

To check the precision of the optical sensor measurements, concerning the piece free end displacement, a standard dial gauge with 10  $\mu\text{m}$  resolution is used. The dial gauge is placed on the beam free end, opposite to the Laser spot. The beam's free end displacement is accomplished by imposing, to the milling machine table, a displacement relative to the milling head. Calibration was made for the five displacement values indicated in Table 1, scaled to the relative voltage values.

**Table 1.** Example of calibration test values

Test No.	Displacement (mm)	Voltage (V DC)
1	0.1	0.02
2	0.2	0.04
3	0.3	0.06
4	0.5	0.1
5	0.85	0.17

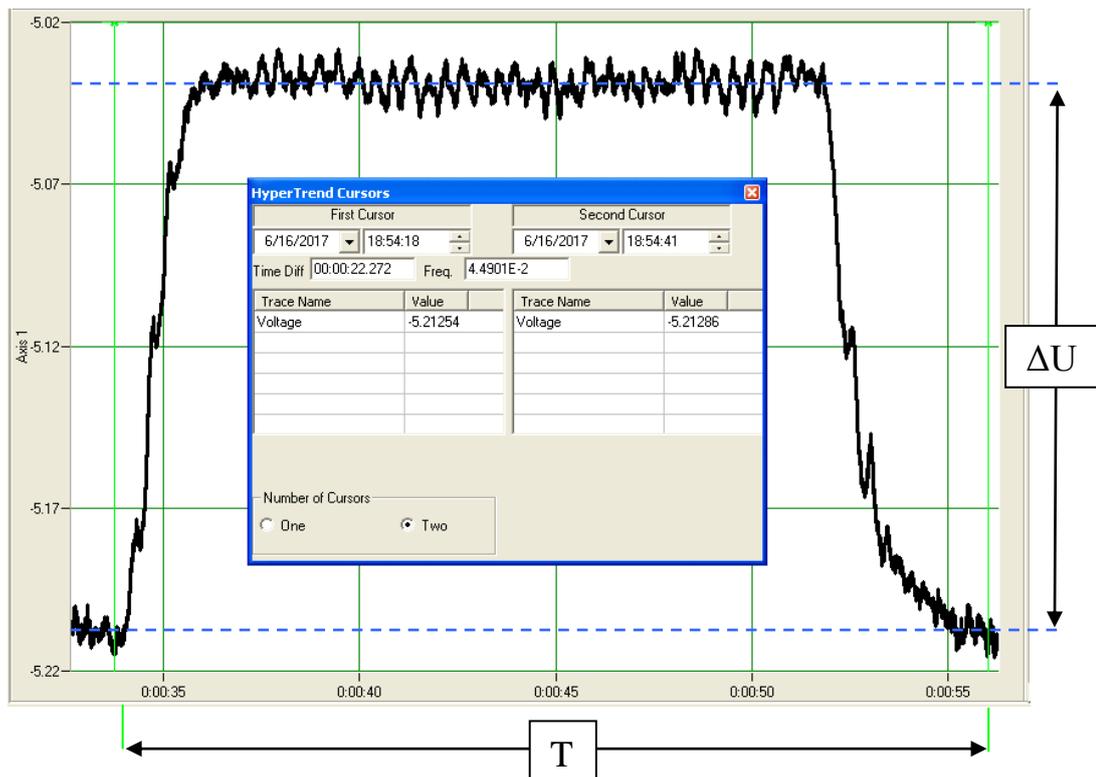


**Figure 4.** Displacement-voltage relationship

A sufficient DC voltage variation, i.e. 0.02 V, could be determined, even at a low displacement as 0.1 mm. The calibration results confirm the analog linearity indicated by the manufacturer (see Figure 4, namely  $\pm 0.2$  mm from 75 to 125 mm;  $\pm 0.02$  mm from 95 to 100 mm).

### 3.3. Sensor output

The Measurement & Automation permits a facile connection of the LG10A65PU sensor through the NI USB-6259 Multifunction DAQ. The data acquired for a 0.85 mm displacement is shown in Figure 5. From this figure clearly results, on the horizontal axis, the time interval  $T$  for which the displacement of 0.85 mm is applied. The value can be also read from in the *HyperTrend Cursors* window, resulting  $T = 22.272$  seconds.



**Figure 5.** Data acquisition interface

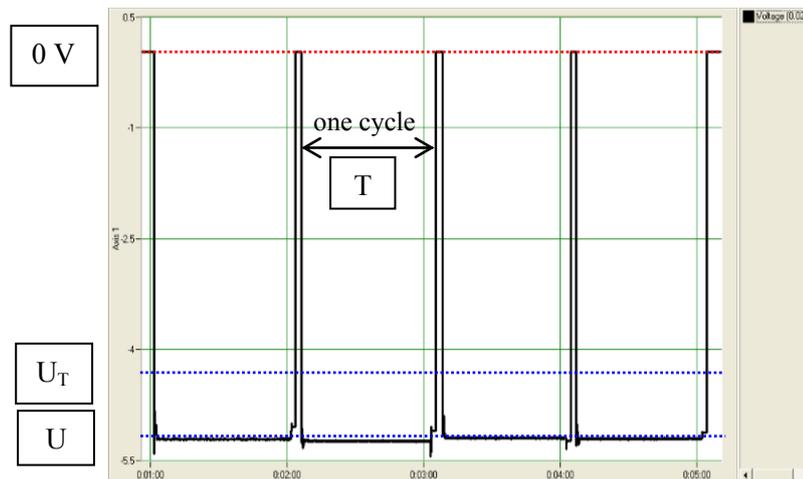
Another parameter possible to be identified is the output voltage  $\Delta U$ , proportional with the displacement of the free end due to the action of the milling head. This data can be also read from the *HyperTrend Cursors* window, if the horizontal cursors are adequately placed. The software can also compute the frequency that corresponds to the cycle framed between the vertical cursors, making possible an easy and fast quantification and adjustment of the operation cycles.

## 4. Results and discussions

Universal milling machines are not equipped, in the normal case, with any digital device for transmitting data to a central unit that can process it. By employing an optical sensor, the operation of the machine can be monitored and the gained information may be and used to plan production and maintenance. The decision can be taken by humans or by the central unit itself, in this latter case it being an algorithm-based management.

If long-term monitoring of the operation process is performed, the central unit recognizes the number of manufactured pieces. Figure 6 presents the acquired data in graphical form. Here, the optical sensor indicates 0 voltage output if the processed piece is not present in the vice. If the piece is loaded, the system indicates a voltage  $U$  proportional with the distance to the piece, that is  $U = -5.22$  V in this example. Thus, the optical sensor's measurement output clearly indicates the process cycle time  $T$  used to manufacture one piece on the milling machine.

Another information resulted from Figure 6 is the time required for discharging and reloading the milling machine, i.e. the elapsed between two process cycles. If this time is in a predefined range, the process runs normally. Otherwise it indicates either a lack of raw material, or the need of maintenance. If this information is available in real time, a rapid reaction is possible to normalize the situation. In all cases, the stationary time over an analyzed time period can be found out.

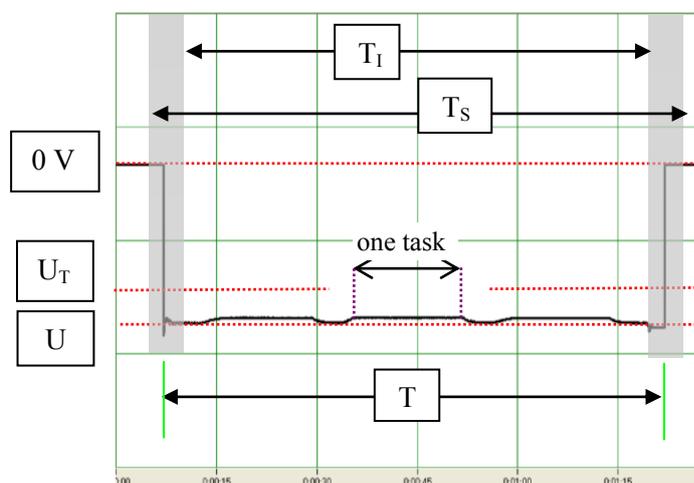


**Figure 6.** Long-term monitoring of the manufacturing process

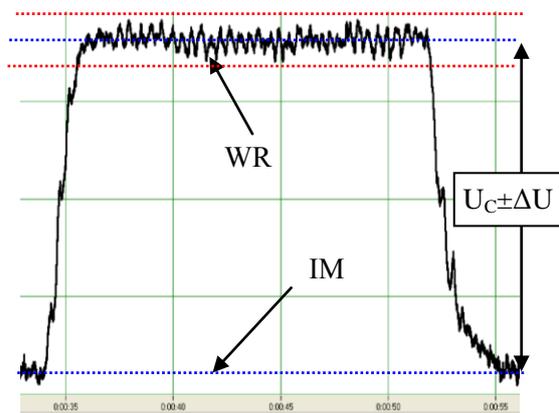
From Figure 6 one can recognize that four pieces were processed, indicated by the four signal deviations from zero. The central unit automatically counts these pieces, by the algorithm:

*if*  $U > U_T$   
*and*  $T_I < T < T_S$   
*than* milled piece = milled piece + 1

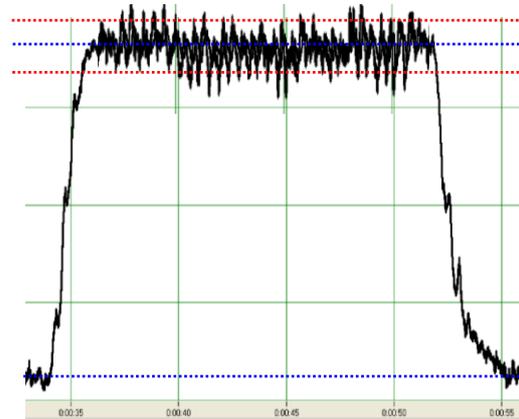
The lower time limit  $T_I$  and upper time limit  $T_S$  are best visualized in Figure 7. This detailed view of a signal that comprises one process cycle shows that during the manufacturing process the signal amplitude varies in concordance with the loads applied to the bar and the resulted deformations. One can observe that three tasks are fulfilled during one process cycle. This variation of voltage is small, but the zoom on one task is better represented in Figure 8.



**Figure 7.** Zoom on one process cycle



**Figure 8.** View on the signal portion corresponding to one task



**Figure 9.** Signal portion representing a task with conditions indicating machine/tool wear

In Figure 8 the signal indicates the idle mode (IM) and the working regime (WR) of the milling machine. Obviously, during operation, due to the pressure exercised by the milling cutter, the bar is pushed closer to the sensor, this being indicated by a voltage decrease. One can observe the voltage alteration  $U_C$  due to the shift from the idle mode to the working regime.

The amplitudes  $\pm\Delta U$  around the rest position WR, marked with red dotted lines in Figures 8 and 9, show if the machine respectively the tool is in good condition [16], [17]. Evidently, the higher amplitudes are associated with failure or machine/tool wear [18], [19].

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if  $|\pm\Delta U| < \Delta U$  threshold
  than milled piece = milled piece + 1
else reject no. = reject no. + 1
and !machine/tool alert!
and !supply raw material +1!

```

Thus, the information is transmitted to the cutting machine, in order to ensure the proper number of bars. Also, the quality assurance and maintenance departments are informed about the problem. If a longer term is requested to fix the problem, the information is transmitted to the cutting and welding machines in order to optimize the working regimes.

The above presented algorithm can be used, separately or simultaneously, for the idle mode as well. Numerous other scenarios can be imagined and algorithms implemented. The idea is to finally achieve a totally independent and self-organizing production chain.

## 5. Conclusions

This study shows how universal machines that are originally not foreseen with specialized monitoring systems can be equipped with sensors, in order to acquire and transmit digital data to a central unit. Algorithms implemented in the central unit convert this data in valuable information for the other machine composing the production chain and adjacent departments, e.g. maintenance and quality assurance. In this way, a self-organizing manufacturing process which quickly adjusts the malfunctions occurred due to perturbations is achieved, making the process as efficient as possible.

Simulations involving a simple production chain have shown that the developed concept, including a monitoring system and algorithms, provide adequate and trustful information, making it proper in industrial applications.

### Acknowledgement

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