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A Metamodel for the Management of Large Databases: Toward Industry 4.0 in Metal Forming

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Abstract

Metal forming machines can be servo-controlled and their numerical control can easily record and monitor several on-line process signals and loading curves, as a function of time, with a given sampling frequency. If these signals are collected and stored inside a designed database, any single forming process can generate a large amount of information that can be preciously used for process improvement and optimization. The database can be generated and stored locally at the machine, but it becomes more useful if it is transferred to a centralized big database. In both cases, if sampling frequencies are selected in order to follow the actual process dynamics, the amount of data stored can very easily and rapidly reach unpractical and unfeasible dimensions, in the order of magnitude of terabytes. A smart, designed and comprehensive strategy is therefore required for large data collecting and processing. Such a comprehensive strategy is difficult to be generalized for any forming process, but it must be specifically designed for each type of operation. In this paper, a framework for the management of large databases in the rotary draw tube bending process is proposed. A metamodeling technique for data compression is described and tested with actual process data, obtained during several rotary-draw bending of round stainless-steel tubes. Tube bending tests have been performed with CN controlled benders, where 12 axes can be actuated and 16 simultaneous output signals or loading curves have been recorded. The proposed method is able, for some of the selected signals, to reduce the amount of required data with a 75:1 ratio, with no significant loss of technological information.

Keywords: Metal forming; Big Data Management; DCT; Industry 4.0; Data Compression

1. Introduction

The thrust toward renovation of manufacturing technologies, coming from the so-called “Industry 4.0” revolution, sets the challenge for new ways to deal with manufacturing process data. The very large amount of data that can be potentially gathered during metal forming processes requires new methods to manage them. In fact, many modern metal forming machines are servo-controlled, e.g.: mechanical servo-presses and hydraulic presses for sheet metal forming, rotary tube benders, etc. Their numerical control can easily record and monitor several on-line process signals and loading curves, as a function of time, with a given sampling frequency. If these signals are collected and stored inside a designed database, any single forming process can generate a terrific amount of information that can be useful, if properly managed and analyzed, for multiple purposes, including forming process improvement and optimization. The database can be generated and stored locally at the machine, but it becomes more useful if it is transferred to

Nomenclature

α	(°)	bend angle
OD	(mm)	outer diameter of tube
R_m	(mm)	mean radius of bend
t_0	(mm)	initial thickness of tube

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a centralized big database. In both cases, if sampling frequencies are selected in order to follow the actual process dynamics, the amount of data stored can very easily and rapidly reach unpractical and unfeasible dimensions, in the order of magnitude of terabytes.

A smart, designed and comprehensive strategy is therefore required for 1) sorting and selecting the most relevant signals to be included in the database, 2) selecting the correct sampling frequency for each signal, 3) cleaning and filtering the signals, 4) computing some relevant metrics, 5) compressing/uncompressing the signals before/after storage or transfer, 6) using the signals, e.g. for process improvement or optimization. Such a comprehensive strategy is difficult to be generalized for any forming process, but it must be specifically designed for each type of operation.

In this paper, a framework for the management of large databases in the rotary draw tube bending process is proposed, briefly discussing the steps from 1) to 4) and then focusing on step 5). A metamodeling technique is then described for data compression, that uses the Discrete Cosine Transform [1].

The technique is tested with actual process data, obtained during several rotary-draw bending operations of round stainless-steel tubes. Tube bending tests have been performed with CN controlled benders, where 12 axes can be actuated and 16 simultaneous output signals or loading curves have been recorded. Some examples of these signals are the torque vs. time of the main bending die, the axial force vs. time of the mandrel, the radial displacement vs. time of the clamping die.

1.1. Description of rotary draw bending process and machines

The specific process taken into consideration is the rotary draw bending process. It performs bend on tubes with the use of 5 main tools, represented in fig.1.

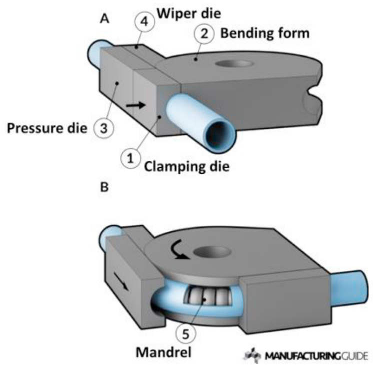

Fig. 1. Typical tooling setup of the rotary draw bending process.

As the bending form (or die) rotates, the bend is produced thanks to the action of clamping die, while the pressure die holds the tube and allows the formation of the curve. The wiper die prevents the formation of defects on the intrados of the bend, while the mandrel, placed inside the tube, prevents the collapse or ovalization of section.

Generally, CNC machines working in the field of metal forming are provided with several controlled axis. In the presented case, the rotary draw bending machine is equipped with 12 controlled axes, whose nomenclature is given in Fig. 2. Out of each axis, 3 different signals may be acquired vs. time with a given frequency: speed, position or torque. This produce a total of 36 potentially available signals. It is possible to say that position and speed may be obtainable one from another and therefore on of them is redundant. Nevertheless, a total of 24 signals are required to completely characterize the state of the machine.

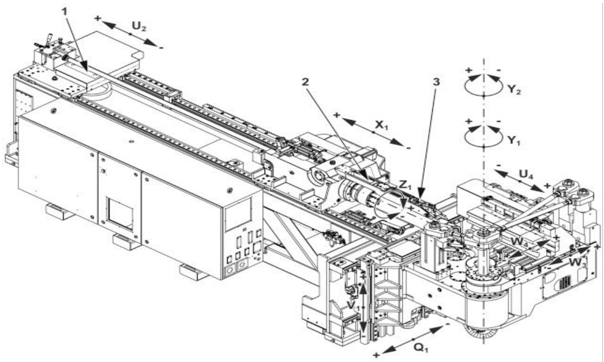

Fig. 2. Machine configuration and nomenclature of controlled axes.

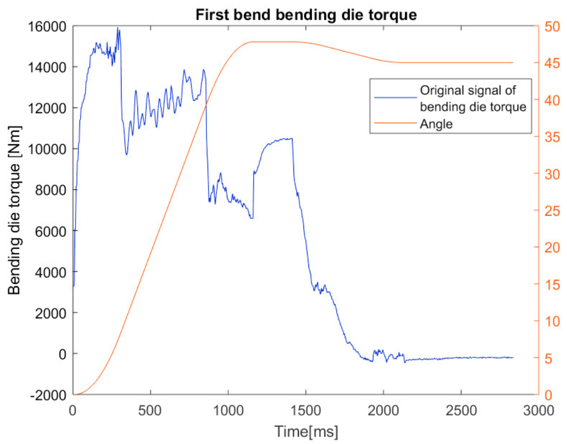

Fig. 3. Bending die (Y1 axis) torque signal of one single bend.

As an example, in Fig. 3 a plot is given of the bending die (Y1 axis) torque vs time for a single bend at α=45°. The machine is able to perform a part with four bends in about 20 seconds. The available acquisition software acquires the signals, in this case, with a sampling frequency of about 250 Hz (a value is recorded each 4 ms). This is the typical sampling frequency which is able to capture the dynamics of the process.

The total number of sampled points during one single bend is around 750. This however generates a large amount of data during production processes. A very large volume of information per minute is gathered. The amount of storage necessary for one signal relative to one single bend, using a common data analysis software, may be quantified in roughly 50 kB. This means that at a hypothetic production speed a total amount of circa 14 Mb/min is generated, resulting in a huge volume of data along the lifetime of the machine, but also along one single day of production or one single shift.

1.2. State of the art

The scientific literature on data processing, industry 4.0 and other IT related innovations in the sheet metal forming industry is rather limited. In [3], the authors propose a framework to support IoT (Internet of Things) for sheet metal forming, especially to be used in combinations with bending servo-presses. However, the authors do not face the issue of "big data" handling.

Nowadays, storage of large amount of data coming from metal forming or other similar processes, is mainly performed by saving only synthetic statistical parameters of the signals, such as mean and maximum values, or the integral as the representation of the energy that the machine consumes to perform the operation [4].

This method however misses a complete description of the trend of signals that may indicate state of the machine, product quality or eventual process variations.

A different approach, explained in [5], consists in using data exploration methods to reduce number of variables, according to data mining instruments. In fact, using algorithms able to detect patterns and relations in large dataset, a reduction can be performed in terms of decrease the variables to be considered to those having a greater influence on the outcome of the process. It is shown as the results indicate the same most important predictors as a sensitivity analysis would have done, with a much lower need of large datasets and time and resource consuming calculations.

The present work is, however, slightly different, since it aims at finding a suitable model to reduce storage space needed for each signal, and not to choose some signal above others according to which are the most influent in the process.

1.3. Experimental setup and preliminary signal processing

The signals taken into consideration to test the compression algorithm come from a machine able to perform bends on large tubes, with OD of 88.9 mm and initial thickness t_0 of 1.6 mm. The computer connected to the machine is able to acquire only 8 signals at a time, but for the purposes of the present work the compression algorithm has been tested onto two signals only. In particular on bending die torque (Y1 axis) and on axial mandrel force (U2 axis).

These two signals have been selected as representative to test the method, because they have a very different profile.

In figures 3 and 4 the two original signals of bending die torque and of mandrel force are represented, corresponding to one single bend of 45° of a produced part.

Some operations have been performed onto the represented signals. First of all, the signals have been acquired with a so-called "empty machine". In other words, the machine performed the bend with no tube, so that the force and torque contribution due to the plastic deformation of the tube can be isolated.

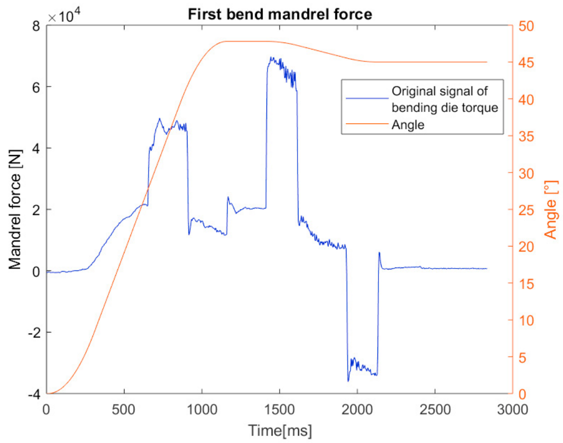

Fig.4. Mandrel force signal of one single bend.

This allows to have a representation of machine inertia (the "empty" line displayed in fig. 5). The empty curve can be subtracted from the original signal of bending die torque, in order to elide the inertial peaks, the machine frictional dissipations, and to obtain a pure process signal, "cleaned" from the machine influence.

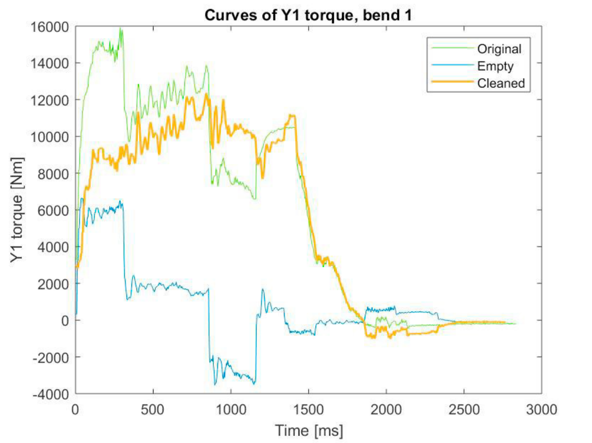

Fig.5. Subtraction of empty machine curve from the original signal.

For some signals this "cleaning" operation is useful, in other cases it is not relevant, when the machine load is relatively too high or too low. In some other cases, the "cleaning" operation cannot be possible, typically when the speed of the empty operation accelerates and therefore it is not possible to superpose perfectly the original and empty signals vs. time. As far as the mandrel force is concerned, due to time delays in the empty machine curve with respect to original signal, the cleaning operation could be done.

However, both signals have been filtered with a specific filter, called Savitzky-Golay filter [6], which performs a polynomial interpolation over a moving window of a given framelength. This has been done in order to have a smoother representation of curves. In particular, both signals have been filtered with a third order polynomial. The length of the filtering moving window must be selected in order not to neglect or underestimate the peaks of the profiles. In the given example, for the bending die torque Y1 a framelength of 804 ms was used; for the mandrel force U2 a shorter framelength of 124 ms has been used. In fact, the two curves have very different profiles and for the mandrel force a wider frame would have neglected important peaks.

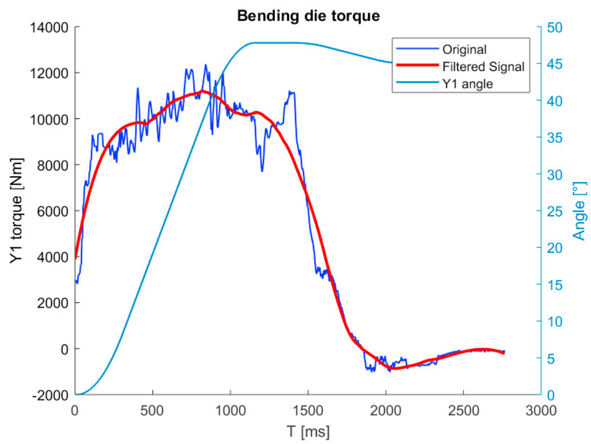

Fig.6. Filtering of bending die torque (3rd order polynomial interpolation over a framelength of 804 ms).

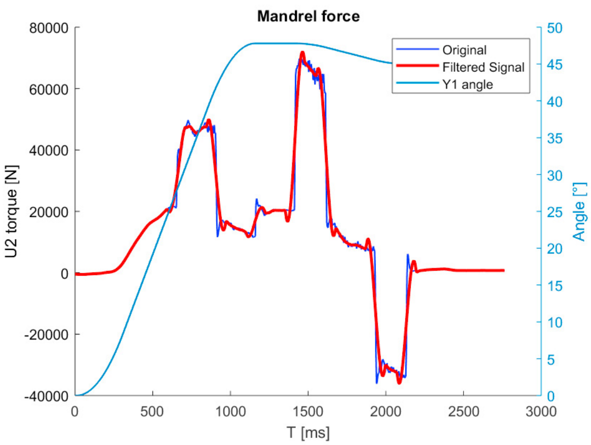

Fig.7. Filtering of mandrel force (3rd order polynomial interpolation over a framelength of 804 ms).

The outcomes are reported in fig. 6 and 7. The filtered signal of the mandrel force is very close to the original signal, and the application of the Savitzky-Golay filter does not significantly change the information contained in the curve. On the contrary, the original Y1 profile is highly nervous, with strong variations within short times. This nervous profile reduces the repeatability of the curve. In order to improve its predictability and repeatability, it seems useful to apply the mentioned Savitzky-Golay filter.

2. Compression algorithm

The proposed approach to data reduction involves the transformations of signals through a general data compression technique. The selected method is the Discrete Cosine Transform.

The DCT is a form of lossy compression, meaning that some loss of information is accepted in order to save storage space. It is frequently applied in digital media compression standards ([1]), and it was firstly brought up by Ahmed et al. in 1974; the authors proposed it as a method for image compression. It was later also modified to be applied to modern audio compression format ([7]) and represents the basis for the simplest and most efficient data compression method. In the sheet metal forming literature, the DCT has been frequently used as a method for geometrical representation of complex formed parts and their errors. As an example, DCT was used by Huang and Ceglarek [8] to model part form errors, decomposing the error field into a series of independent error modes.

The Discrete Cosine Transform (DCT) represents a method for decomposition of signals into a sum of cosine functions, each with different frequency. It is very similar to a Discrete Fourier Transform, but instead of using both sine and cosine with imaginary numbers, it only uses real numbers and cosine functions. This way of decomposing a signal is more effective than a normal Discrete Fourier Transform since it can be demonstrated that fewer cosines terms are needed to better represent a typical signal with respect to sine functions.

For completeness, the expression of the implemented DCT-II transform is reported below, where x_n are the sample points and X_k are the transformed ones.

$$X_k = \sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{n}\left(n+\frac{1}{2}\right)k\right] \quad (1)$$

This instrument allows to synthesize the signals with a limited number of cosine functions, whose coefficients may be used to reconstruct the curve without storing all the sampled points.

However, the number of the coefficients to be stored in the database is to be defined, in order to have a good representation of the signal and no loss in terms of technological features of the curves. This could involve a threshold on energy: for example, a good compression should preserve the right information on work performed by the tool to carry out the process. Thus, a possible way is to set the limit of coefficients on the minimum number needed to preserve a percentage of energy of the original signal, say 95%. However, if the number of coefficients required to preserve 95% of the curve energy is too large, the purpose of data compression might not be satisfied. As a consequence, a limit on the maximum number of coefficients that can be used by the methods must be set. In this case, the limit has ben set at 7. When more than 7 coefficients are required by the DCT, in the proposed algorithm, the additional coefficients are discarded.

It was also observed that the Discrete Cosine Transform works better with signals purified from their long run trend. In other words, it works well with signals which are centered around a constant mean. To this purpose, before performing the DCT, a third order polynomial fit has been operated on the signal and the output of this operation is subtracted from the original one. This adds 4 necessary coefficients to be saved in order to reconstruct the curves, for a maximum of 11 required coefficients.

3. Application of the method on the signals

The compression algorithm has been applied on the signals, after the preliminary transformations described in Section 1.3, therefore to the filtered and cleaned profiles. The preliminary transformation of the signals and the DCT transformations can be done locally at the forming machine. The original signal can be completely discarded afterwards, with a considerable saving of memory allocation.

3.1. Bending die torque

The outcome of the compression algorithm applied on bending die torque Y1 is reported in fig. 8, where the fitting polynomial and the signal rebuilt after the Inverse Discrete Cosine Transform have been plotted.

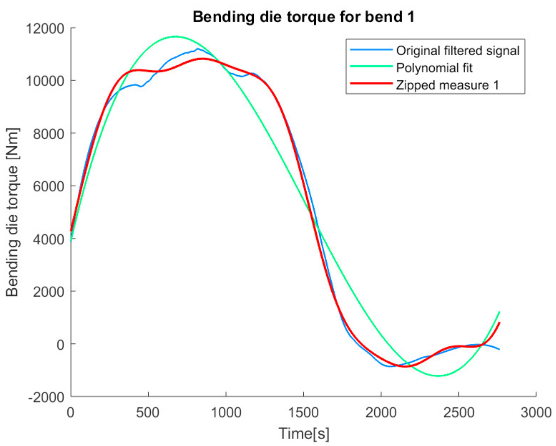

Fig.8. Compression algorithm outcome of bending die torque: the original signal is shown along with the 3rd order polynomial curve and the (zipped) signal produced after DCT compression.

As clearly shown by Fig. 8, it is possible to extract valuable information from the compressed signal, which is not dissimilar from the original filtered one. First of all, due to the DCT transformation method, at least 95% of the original signal energy is still represented by the compressed one. Indeed, the DCT signal also contains the additional information provided by the polynomial fit and, therefore, the energy of the red curve is for sure conserved at more than 95%. Then, it can be observed that the general profile of the signal, as the bending process evolves, is preserved vs. time. This means that if some process variation occurs and is visible on the original signals, , the same modification should be observed on compressed signals, too.

3.2. Mandrel force

As far as the mandrel force profile is concerned, it is intuitive that probably the selected type of algorithm works better with signals with a more regular long run trend. In fact, the sum of cosine functions may not follow so strictly curves with sharp edges and rapid variations.

In fig. 9 the resulting compressed signal of mandrel force is displayed. It can be observed that the general trend of the signal is preserved, but the real values and peaks and some behavior of the curve is slightly distorted. A further observation on this second signal considered is that the number of cosine functions needed to respect the threshold on energy is higher than the limit imposed on 7 at maximum. This is the main reason why the “zipped” profile does not loyally represent the original one. In particular, 15 coefficients should be required to obtain a 95% energy conservation.

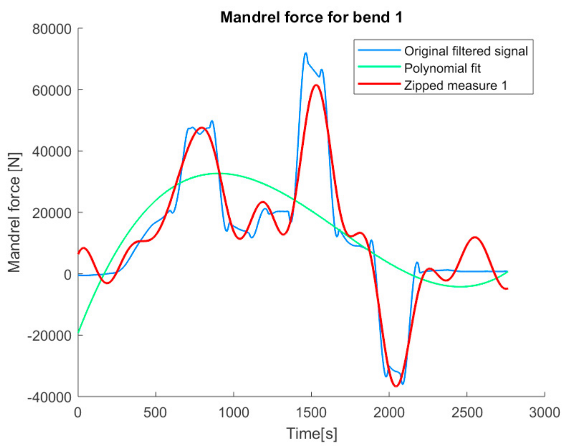

Fig.9. Compression algorithm outcome of mandrel force.

If a higher fidelity of the compressed curve is required, clearly, the used must accept a lower compression ratio, i.e. a larger number of coefficients. In case where the constraint on the maximum number of coefficients can be removed, it is interesting to observe how the proposed method performs with the rotary draw bending profiles. This study is performed in the following Section 4.

4. Sensitivity analysis

It is now possible to investigate how the algorithm behaves if the limits are removed or slightly changed. In particular it is recalled that two limits were set:

- Threshold on energy to be preserved;
- Limit on maximum number of coefficients to be saved.

It would be interesting to know what happens to the compressed signal if these limits are changed.

In fig. 10 is reported how the compressed signal of bending die torque would change if the limit on energy is increased from 95% to 98%. The representation of the trend is closer to the original one, without a significant increase on storage needed, since only 7 coefficients are needed.

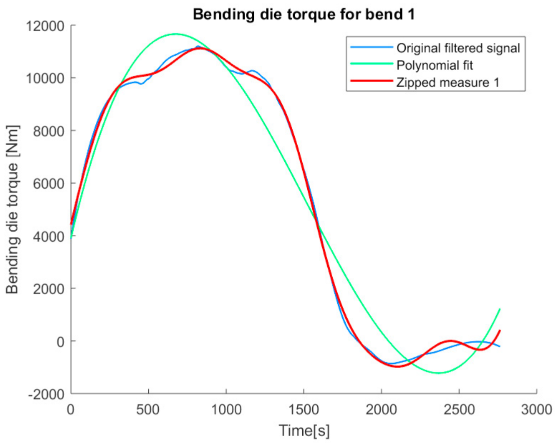

Fig.10. Compression algorithm outcome of bending die torque with energy threshold increased at 98%.

While for mandrel force, changing the requirement only on energy would not cause any variation in the reconstructed signal, because already in the previous case the compressed signal would have required a number of coefficients larger than 7.

In figures 11 and 12 the outcome for mandrel force signal is displayed, after changing both limits. In table 1 the actual number of coefficients needed to rebuild the two signals is reported, according to different thresholds on energy.

In figure 11, the compressed curve reconstructs the signal without a limit on maximum number of coefficients and by keeping the threshold on energy at 95%. In Figure 12, still no limit on the coefficients is applied and the energy threshold is increased to 98%.

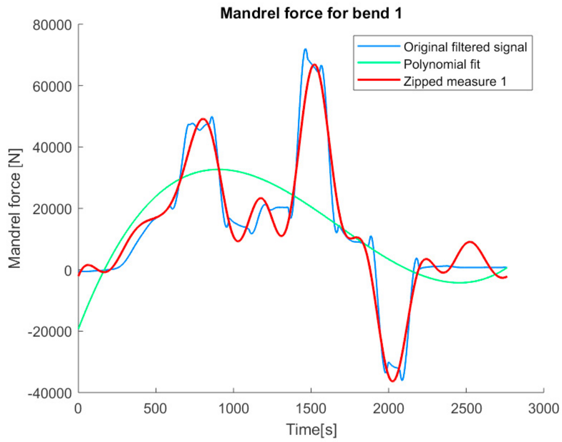

Fig.11. Compression algorithm outcome of mandrel force with threshold on 95% of energy but no limits on the number of coefficients.

The result of the sensitivity analysis on the signal of mandrel force is that probably the 95% threshold on energy is enough for a good representation, when the limit on the coefficients is removed. As reported in table 1, it does not even require a very large amount of storage space (only 10 coefficients, instead of 7). On the contrary, raising the threshold on energy may not only require more space but could also be detrimental for a clear and correct representation of the original signal.

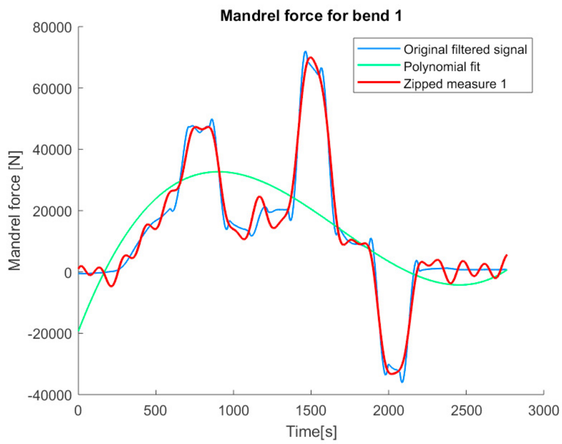

Fig.12. Compression algorithm outcome of mandrel force with threshold on 98% of energy but no limit on coefficients.

Table 1. Number of coefficients needed by the Inverse Cosine Transform to rebuild the signal with different percentages of energy from original signals preserved

Energy of the original signal preserved	95%	98%
Bending die torque	5	7
Mandrel force	10	15

5. Conclusions

The proposed algorithm represents an effective and efficient way to face the problem of data storage of large amount of data coming from servo presses or CNC controlled machines. The proposed compression method preserves more information, if compared to a technique that only saves some synthetic statistical parameters of each curve.

The proposed method is able to retrieve a close representation of original signals, reducing from roughly 750 sampling points to about 10 or slightly more needed coefficients. This 70:1 compression ratio could decrease the storage occupied by the amount of data produced at production rate, without losing so much information about the process.

The results show that if the machine signals are cleaned, filtered, fit by a 3rd order polynomial and finally DCT transformed, their useful technological information can be preserved. The energy of the original curves can be preserved at a value larger than 95%.

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