A K-Nearest Clamping Force Classifier for Bolt Tightening of Wind Turbine Hubs

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ABSTRACT: *A fuzzy-logic controller supporting the manufacturing of wind turbines and the bolt tightening of their hubs has been designed. The controller embeds assembly error recognition capability and detects tightening faults like misalignment, different threads, cross threads and wrong or small nuts. According to this capability, K-nearest classifiers have been implemented to cluster the output controllers into the diverse fault scenarios. Classifiers make use of the time of execution of the tightening process, the final angular position of and applied torque of the tightening tool, the resultant clamping force and possible combinations of those parameters. Two classes and five classes configurations are considered: classifiers are initially asked to discriminate between fault and no fault scenarios (e.g. two classes); then, five classes are considered according to five different fault situations (i.e. regular tightening, bolt misalignment, dissimilar threads of bolt and nut, missing nut and small bolt). Classifiers performances are estimated in terms of re-substitution and cross-validation loss. Confusion matrixes of actual and predicted classification are also evaluated for each classifier. The low computational cost of the proposed classifiers suggests directly implementing these algorithms on micro-controller and physical computing, which may be straight integrated within the tightening tool.*

Keywords: Bolt Tightening Classifier, Bolt Tightening Error Detection, Self-Adaptive Manufacturing, Wind Turbine Manufacturing

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1. Introduction

An increasing of the current green energy market is occurring around the world, since communities have realized the benefits and positive repercussions of these emerging technologies. Especially the wind energy market is growing, due to the improving efficiency of wind turbines and the overall reduction of their costs and maintenance [1-3]. At present, the largest turbines can provide more than 5 MW of electrical power through wind blades up to 50 m long and rotors which may exceed 20,000 kg weight. As a consequence of these geometrical and mechanical characteristics, it is economically strategic to reduce their manufacturing and assembly costs while introducing automation within some of the production processes [4-8].

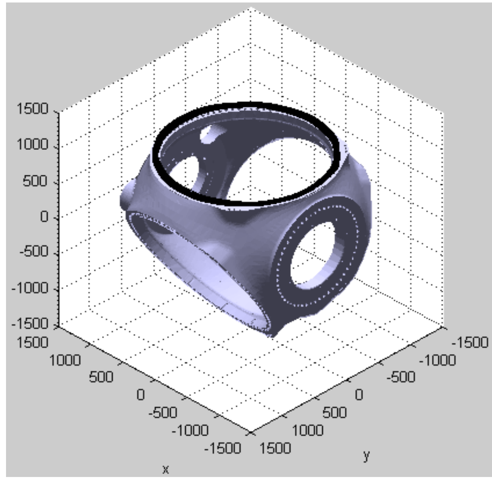

Figure 1. Assembling wind turbines of large dimension and power may require the tightening of up to 100 bolt and nuts, as it is the case of fastening the ball bearings supporting wind blades on the flange of the rotor (highlighted in black colour)

As a result of the complexity of a wind turbine plant and of the high number of components which are required to fabricate the turbine, one substantial stage of the manufacturing is the tightening of bolts and nuts around the flange of the wind turbine hub (Figure 1); the hub contains a set of ball bearings which support the wind blades: these latter ones are allowed to rotate around their longitudinal axis in order to real-time adapt their profiles vs. wind direction and speed (and therefore to maintain an optimal rotational speed of the rotor irrespective of wind speed).

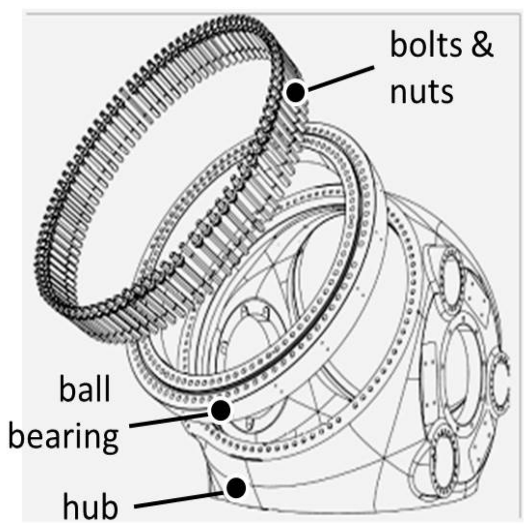

Figure 2. Assembling of the blade ball bearing which allows the pitch movement according to wind speed

A critical stage of the hub and bearings assembly is the tightening of bolts and nuts which fix these latter ones on the hub flanges (Figure 2). In the case of wide turbines, up to 100 bolts and nuts have to be fastened on the rotor to hold the wind blades; because of the vibrations and mechanical stresses occurring during the operative life of the plant, it is compulsory to attain an optimal and uniformly distribution of the clamping force alongside these flanges. It would be also very appropriate to have self-adaptive controllers of the process which are able to target the uniformity of clamping force distribution. Furthermore, the automation level of the tightening controller should be able to inherently infer any fault which may occur during a tightening process within industrial environments, as it is the case of misalignment of bolts and nuts on the tightening tool, cross threads, missing nuts or wrong nuts, etc. According to this overview, some approaches have bene proposed in recent literature, which are based on robotic manufacturing, fuzzy-logic controller and accurate modelling of screw fastening [5-11]. In particular, an accurate bolt tightening using model-free fuzzy controller has been recently introduced in 2014 [12]: this controller accurately fastens M24 bolts and nuts while promptly detecting faults of tightening. Model-free approaches are not the only methodologies which have been proposed in the literature to accomplish bolt tightening. Nevertheless, they have been unquestionably able to manage the emblematic high non-linearity of tightening and fastening, which are strongly conditioned from friction forces and physical interaction between the bolts and nuts threads, as well as, later on, from the contact of the head of the bolt and flange surfaces [13].

The literature also presents model-based approach of bolt tightening where model parameters are estimated: unfortunately a precise estimation of the correct values can be easily affected by unpredictable variations of mechanical - and environmental - properties of the materials occurring during the assembly [14-19] or by impossibility of directly measuring the tightening process performance - e.g. the resultant clamping force [20,21]. In general, besides model-free systems, model-based approaches usually require fine tailoring of their model parameters [22-27].

For these reasons, a model-free approach has been preferred and, particularly, that one who was presented in [12]; based on this work, novel k-nearest classifiers are implemented here, which infer different tightening faults of industrial practice. Fitness parameters of the classifiers are then evaluated vs. performances exhibited during the training stage (paragraphs 2 and 3).

Four further paragraphs are reported in this work: the second and third ones are presenting methods and results, respectively: in particular the second one presents the tightening process, a set of 4 fault scenarios and the nature of experiments and classifiers; the last two paragraphs outline discussion of results and finally the conclusion.

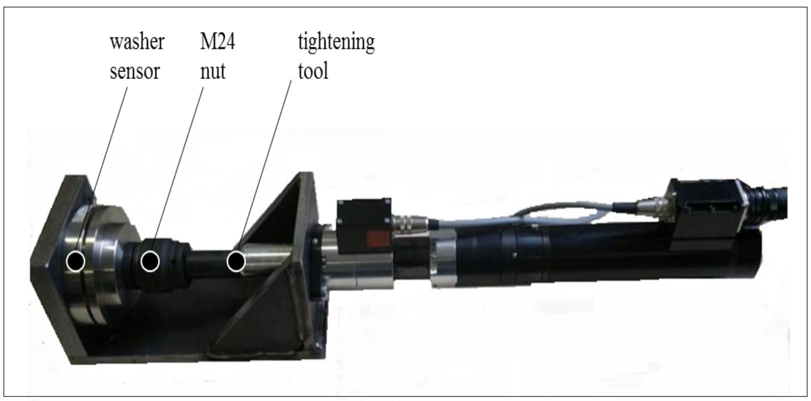

Figure 3. Laboratory set up of the experiments: the fastening tool embeds a couple of transducers for the real-time acquisitions and monitoring of the angular positions and applied torque. An external sensor on the left side and in between the flange and the tool allows measuring the pressure on the flange due to the fastening of the bolt.

2. Materials & Methods

2.1 The Tightening Process

Full tightening of bolts and nuts can be fragmented into four phases or stages as proposed by [12]: the initial alignment of the bolt and nut threads - stage 1 -, a partial and full engagement of the threads - stage 2 and 3, respectively -, and finally the proper tightening - stage 4.

In case of regular tightening with no misalignment events, first stage (stage 1) is characterized by threads of bolts and nuts getting in contact and nut rotating to specific low angular value; on stage 2, a small amount of torque is applied to achieve initial fastening between threads without cross or jamming. Full engagement (stage 3) requires torque and angular displacement simultaneously increasing (cross threads may occur at this stage, as well as wrong displacement of bolt may happen to indicate an erroneous number of inserted washers or even missing washer). On *stage* 4, which is the final tightening phase, nut reaches the flange: at this stage, tension limit of the bolt has to preserved to avoid plastic deformation of parts (i.e. permanent damage), as well as desired value of the clamping force has to targeted and applied to connecting mechanical components.

2.2 The Fuzzy-Logic based controller

A controller, which is based on Fuzzy-Logic, has been developed to perform self-adaptive tightening of M24 bolts and nuts of wind turbine manufacturing [12]; the controller integrates real-time detection of tightening faults, including misalignment of bolt and nut, inappropriate presence of different threads, missing or wrong nuts, insertion of too small bolts compared to the required ones.

In line with the 4-stage tightening process (paragraph 2, subpar. 2.1), the fuzzy controller has been implemented in 4 blocks, i.e. the control of the alignment phase, partial and full engagement of the threads and final tightening. Angle and torque - which are returned from a position and force sensors embedded in tightening tool (paragraph 2, subpar. 2.4) – are the input controllers; an external washer sensor has been used to measure the effect of the tightening, namely the effective clamping force occurring between bolt and flange during the tightening. Controller output is the tightening tool speed, which has been controlled through a Voltage-signal modulation.

Mamdani's Fuzzy inference method constitutes the logic: for each one of the four stages, a set of rules has been defined. For instance, during the first stage, a proper set of ranges of torque and angle have been experimentally determined and then membership functions are properly inferred in order to make [12]:

✓ Tool accomplishing tasks of each stage and, simultaneously

✓ System able of detecting errors: a superimposed logic is driving the tool and sending false (or true) status, which indicates absence (or occurrence) of error scenario, respectively.

Controller software and hardware are set-up within an industrial PC, which is directly coupled with tool, embedded sensors and external washer: architecture is based on Simulink Programming Language which is real-time implemented through a Beckhoff TwinCAT 3 system through a Matlab Coder (The Mathworks® Inc) [28]. A sampling frequency of 2 kHz is used to real-time execute code within the industrial PC.

2.3 Classes and Errors of Tightening

Five different scenarios or classes are considered, where the first one concerns normal or regular tightening and the other four ones entail possible faults occurring during the tightening process.

In the first condition, regular tightening (e.g. no error class) has been considered, namely M24 bolts have been regularly fastened with M24 nuts. Conversely, misalignment and jamming of bolt and nut threads, missing nut or improper coupling between bolts and nuts have been introduced in the other conditions.

The following procedure has been adopted to validate the system under the different configurations:

• Regular tightening - which will be labelled with the caption normal or regular in the following text - has been performed with M24 bolts and nuts;
• Misalignment error (misalignment) has been simulated by wrongly adjusting the alignment of the bolt with respect to the nut;
• Different threads state (diffThreads) has been fulfilled by placing a nonmetric nut, which is coupled with M24 bolt during the tightening;
• Missing nut configuration (missingNut) is arranged by removing the nut from the tightening tool before launching the process.
• Last condition of error (smallBolt) is settled by replacing the M24 nut with a wrong and smaller nut, namely an M14 nut.

According to the Fuzzy Logic implementations and membership functions, each one of these 5 conditions is expected to be detected within particular tightening phases. For instance, misalignment, jamming, and lack of nut conditions should be detected within the tightening phases 1, 2 and 3, respectively. Similarly, an insertion of improper bolts is indeed expected during the third phase of the tightening.

2.4. Equipment

In the experimental set-up a fastening tool BL 57/140 MDW, from DSM Messtechnik GmbH, performs the tightening of M24 bolts and nuts (Figure 3). The tool incorporates an analogue sensor which measures its angular position with a resolution of 1° and a force sensor for the measurement of applied torque with an error of less than 1% of the end value - e.g. 140 Nm. An external sensor – which is integrated within a metal washer – detects the pressure or clamping force which is applied at the flange: the sensor is a KMR 50 kN transducer, from MecSense Kraftmesstechnik, with a maximum error of less than 0.5% of the end value - e.g. 50 kN [12].

2.5 Experimental Set-up

The tightening tool is employed to accomplish both regular tightening processes and fastening under the error scenarios. Data of the tool angular displacement, applied torque and flange pressure or clamping force are simultaneously acquired and synchronized. Error detection status, as it is feed backed from the Fuzzy controller superimposed logic, are also acquired and synchronized.

An overall set of 50 trials has been performed, including 10 trials for each one of the 5 conditions, namely 10 trials of regular tightening and 40 trials of erroneous tightening have been performed (e.g. 10 trials for each one of the 4 types of error); a single trial of regular tightening (trial n. 2, out of 10) has been removed during the post-processing phase because of an issue during the experimental acquisition. Therefore an overall set of 49 trials (i.e. 98% of the acquired data) has been finally analyzed.

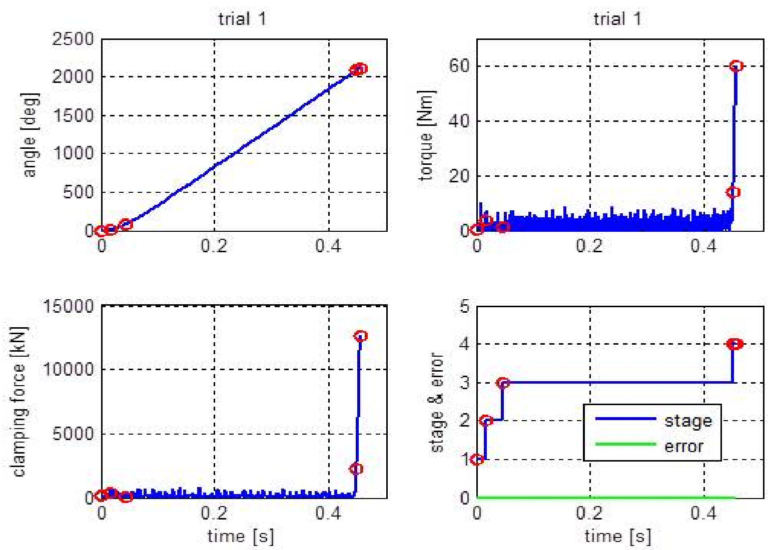

Figure 4. From top left panel to the bottom right one, angular displacement, torque, pressure, stage evolution and error detection during the normal tightening process

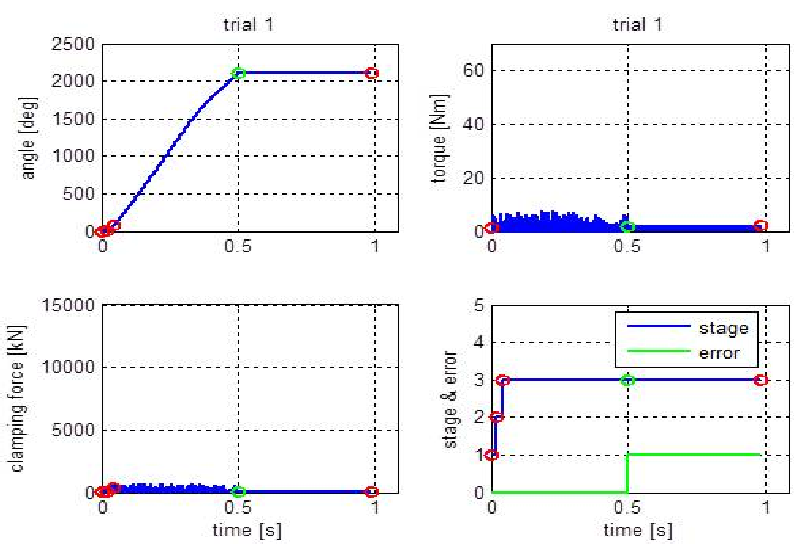

Figure 5. From top left panel to the bottom right one, angular displacement, torque, pressure, stage evolution and error detection during the missingNut tightening process

Figures 4 and 5 shows typical time patterns of angular displacement, torque and pressure during *regular* and *missingNut* tightening processes (top left, top right and bottom right panels, respectively). The figures also show the transition between the tightening phases as they are performed from the logic of the Fuzzy controller (bottom right panel). Furthermore, Figure 5 highlights the error detection capability, which is identified with a green marker within the latter panel and defines a specific stage and time of the tightening.

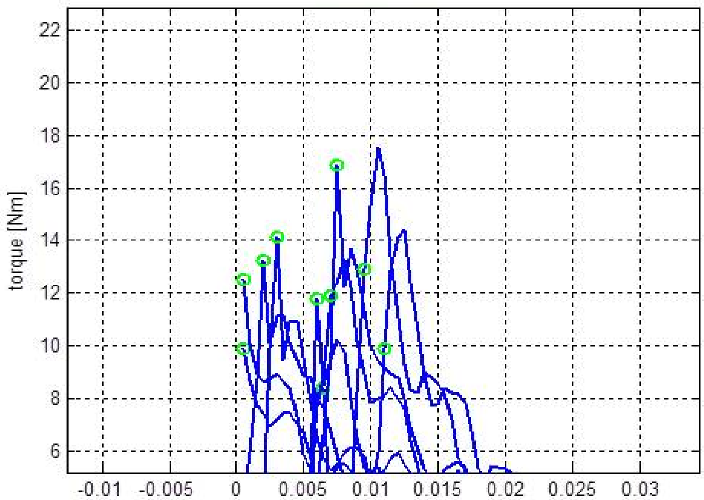

Figure 6. Detection of misalignment error as reported with a green circle during the whole set of tightening

Figures 4 and 5 represent the overall patterns of all trials. A regularity and repeatability of data is found over all the experiments: to this aim, Figure 6 displays patterns of all trials torque as during the misalignment condition; all values of the error detection time (x-axis) and of the torque on that time (y-axis) are similar (e.g. the experimental points which are highlighted with the green marker); in other words, a good repeatability of the time error detection is occurring, irrespective of the trial.

The mean and standard deviation of the execution time for the condition of normal, misalignment, diffThreads, missingNut, smallBolt, are 0.45±0.01 s, 0.56±0.10 s, 3.41± 5.01 s, 0.99 ±0.18 s and 1.08± 0.30 s respectively. Therefore, a part from the diffThreads condition, a good repeatability of the execution time is observed (Figure 7), which suggests that automatic classification process of these conditions should be achievable because of the regularity of the experimental data features.

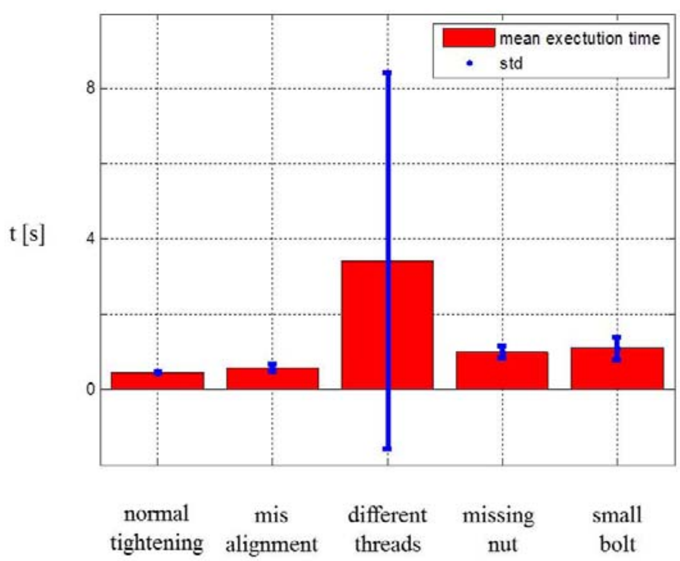

Figure 7. Average and standard deviation of the execution time of regular and erroneous tightening

2.6. The Classifier

A set of k-nearest classifiers has been designed and implemented. Each classifier aims at clustering homogenous tightening processes into the same group, according to regular tightening and the aforementioned conditions of fault. Classification relies on a set of the available signals, namely the execution time of the tightening process and the final values of the tool angle and torque, as well as of the clamping force[1].

Experimental data are processed in Matlab Programming Language environment and with Statistics Toolbox (The Mathworks® Inc). Implementation of k-nearest classifiers is performed with the same software tools [29].

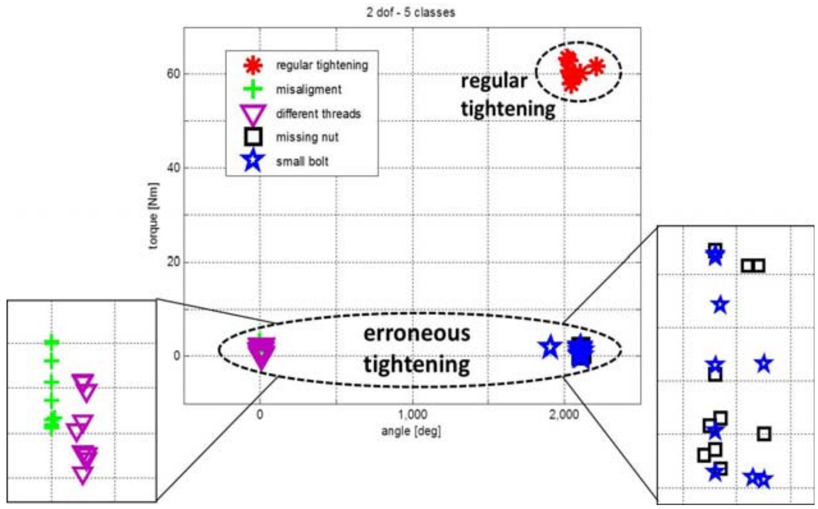

Figure 8. Classification based on 2 d.o.f. and 5 classes (details in the text): Final angular position and torque of regular and erroneous tightening, according to the different cases (regular tightening, misalignment, different threads, missing nut and small bolt)

Figure 8 presents the overall dataset, which embeds all the regular and irregular tightening cases. The graph shows the values of final angular position and torque in a 2D plot - x and y axis, respectively – assigning a specific color and symbol according to the experimental scenario and actual classification. All regular tightening points – which are represented with red stars within the figure - and all the irregular ones (which are represented with green crosses, reversed purple triangles, black squares and blue stars, referring to misalignment, diffThreads, missingNut, smallBolt, respectively) are clearly clustered into two separate and distinct regions. These regions are characterized by different ranges of the final tightening angle and torque; the two regions have been depicted with two dotted circles in the figure, a top right circle and bottom ellipse, respectively.

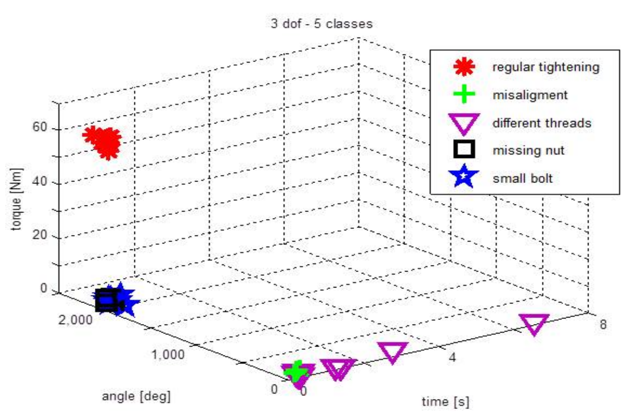

Figure 9 . Classification based on 3 d.o.f. and 5 classes (details in the text): final execution time, angular position and torque of regular tightening and erroneous tightening with misalignment, different threads, missing nut, small bolt

Moreover, the separation between the experimental points associated to the regular and irregular tightening is observable in three dimensional space (Figure 9): in this figure, the points are reported in function of the final execution time (the *x* axis in the figure), final angular displacement (*y*-axis) and torque (*z*-axis). These features of data envisage the likelihood of succeeding with a proper set of classifiers.

According to the aforementioned considerations, two- and five-nearest neighbors configurations are defined for each one of the classifier, and *two* and *five* groups of data are considered, respectively: in the second case, all five scenarios were considered separately (i.e. the regular tightening plus the four error scenarios); in the first case, ‘no error’ group, referring to the *normal* tightening processes, and ‘error group’ (i.e. the collection of all the tightening performed under the error conditions, namely the *misalignment*, *diffThreads*, *missingNut* and *smallBolt* tightening) are adopted.

For each one of the two configuration of the classifier (e.g. two- and five-nearest neighbors configurations), different sets of the degrees of freedom (d.o.f.) of the data are analyzed: classification based on the knowledge of all available data - namely the time, angle, torque and pressure - and classification based on a restricted list of this data set; specifically, six cases have been defined: in the first case (*case 1*), the time, angle, torque and pressure are used and input to the classifier, namely a four d.o.f. data set (*case 1*, four d.o.f., Table 1); alternatively, only the data of the angle and of the torque are applied (*case 2*, two d.o.f.,). In a further *case 3*, the angle, torque and pressure are used (three d.o.f.); in *case 4* only the angular measurements are used (one d.o.f.), and finally in the last two cases (*5* and *6*), the only torque and pressure are used, respectively (e.g. one d.o.f.). Table 1 summarizes all these 6 cases.

Results of each classifier are measured in terms of the ability of the algorithm to allocate the tightening process to the factual class. In particular, three performance parameters are adopted to measure such performance:

- The re-substitution loss or *rloss*, namely the fraction of misclassification from the predictions of the model;
- The cross-validation loss, *kloss*, which is the average loss of each cross-validation model when predicting on a set of data which have not been used before for the training[2];

the confusion matrix, which is the square matrix computed from the known and predicted classes, reporting the number of trials that have been properly classified in the diagonal of the matrix and those which have been misclassified in the other elements of the matrix, where the matrix rows and columns report the predicted and actual classes, respectively.

3. Results

Results are organized according to the set number of neighbors and set number of d.o.f. (paragraph 2, subpar. 2.6). All the classifiers are then modulated for the different cases and applied to the data: Table 1 reports the *confusion matrices* for each one of the case. Finally Figure 10 reports the performance values, i.e. the *kloss* and *rloss* of each classifier for each one of the cases.

4. Discussion

4.1 Two Classes Discrimination

2D plot of the experimental data shows discrimination between regular and irregular tightening (Figure 8): two classes, which have been marked with dotted lines within the figure, are easily recognized. Similarly, a 3 d.o.f. clustering of the experimental data of regular and irregular tightening processes is shown in Figure 9.

These qualitative outcomes are also supported by the classifiers performance (Table 1). In fact, in a two-classes discrimination case – i.e. the second column of the Table, namely when relying on the angular and torque patterns only -, the confusion matrix shows a 100% successful rate over all the cases: 9 trials (out of 9) are properly classified as belonging to regular tightening class and 40 ones (out of 40) are correctly assigned to the group of the irregular tightening processes. The only exception is observable within case 4 and refers to a classifier using 1 d.o.f data, namely the tool angular position; this configuration corresponds to the projection of all experimental data of Figure 8 on its x axis, where an overlapping between

[1]E.g. the final values captured from the Fuzzy controller at the end of each experimental acquisition.

[2]The partitioning of the cross-validated k-nearest classifier has been obtained by using 10-fold cross validation.

and regular irregular tightening clearly occurs; in fact, some of the trials performed in *missingNut* and *smallBolt* conditions exhibit similar values of the angle which are also comparable with those performed during the regular tightening; as a consequence, these d.o.f. do not provide sufficient information to suitably classify the data.

class	1	2	3	4	5		1	2
CASE 1 4 D.O.F. [TIME, ANGLE, TORQUE, PRESSURE]								
1-normal	9	0	0	0	0	*1-error*	9	0
2-misalignment	0	10	0	0	0	*2-no error*	0	40
3-diffThreads	0	0	10	0	0			
4-missingNut	0	0	0	9	1			
5-smallBolt	0	0	0	6	4			
CASE 2 2 D.O.F. [ANGLE, TORQUE]								
1-normal	8	0	0	1	0			
2-misalignment	0	10	0	0	0	*1-error*	9	0
3-diffThreads	0	0	10	0	0	*2-no error*	0	40
4-missingNut	0	0	0	6	4			
5-smallBolt	1	0	0	2	7			
CASE 3 3 D.O.F. [ANGLE, TORQUE, PRESSURE]								
1-normal	9	0	0	0	0			
2-misalignment	0	10	0	0	0	*1-error*	9	0
3-diffThreads	0	0	10	0	0	*2-no error*	0	40
4-missingNut	0	0	0	9	1			
5-smallBolt	0	0	0	6	4			
CASE 4 1 D.O.F. [ANGLE]								
1-normal	7	0	0	2	0			
2-misalignment	0	10	0	0	0	*1-error*	7	2
3-diffThreads	0	0	10	0	0	*2-no error*	0	40
4-missingNut	0	0	0	8	2			
5-smallBolt	1	0	0	7	2			
CASE 5 1 D.O.F. [TORQUE]								
1-normal	9	0	0	0	0			
2-misalignment	0	7	1	0	2	*1-error*	9	0
3-diffThreads	0	1	7	0	2	*2-no error*	0	40
4-missingNut	0	0	3	4	3			
5-smallBolt	0	2	3	0	5			
CASE 6 1 D.O.F. [PRESSURE]								
1-normal	9	0	0	0	0			
2-misalignment	0	10	0	0	0	*1-error*	9	0
3-diffThreads	0	0	10	0	0	*2-no error*	0	40
4-missingNut	0	0	2	6	2			
5-smallBolt	0	0	1	6	3			

Table 1. Confusion matrices with 2 and 5 groups

A similar motivation is behind the results of case 4 and five classes (Table 1): according to the confusion matrix values, two regular trials have been misclassified and interpreted as irregular tightening (i.e. missingNut processes).

A very similar effect is noticeable when the experimental data are flattened into the plane made of the angle and torque measurements (Figure 9), which corresponds to 2 d.o.f classifiers (case 2): when comparing smallBolt and missingNut scenarios, a misclassification occurs (Table 1), due to the similarity of the torque values in both the cases (Figure 9). As a consequence, four missingNut trials (out of 10) are wrongly assigned to the smallBolt class and one and two smallBolt trials (out of 10) are misclassified to the normal and missingNut classes, respectively.

Similarly, the other results can be explained by comparing the values reported within each confusion matrix (Table 1) and data graphically represented in the 2D and 3D plots (Figures 8 and 9, respectively).

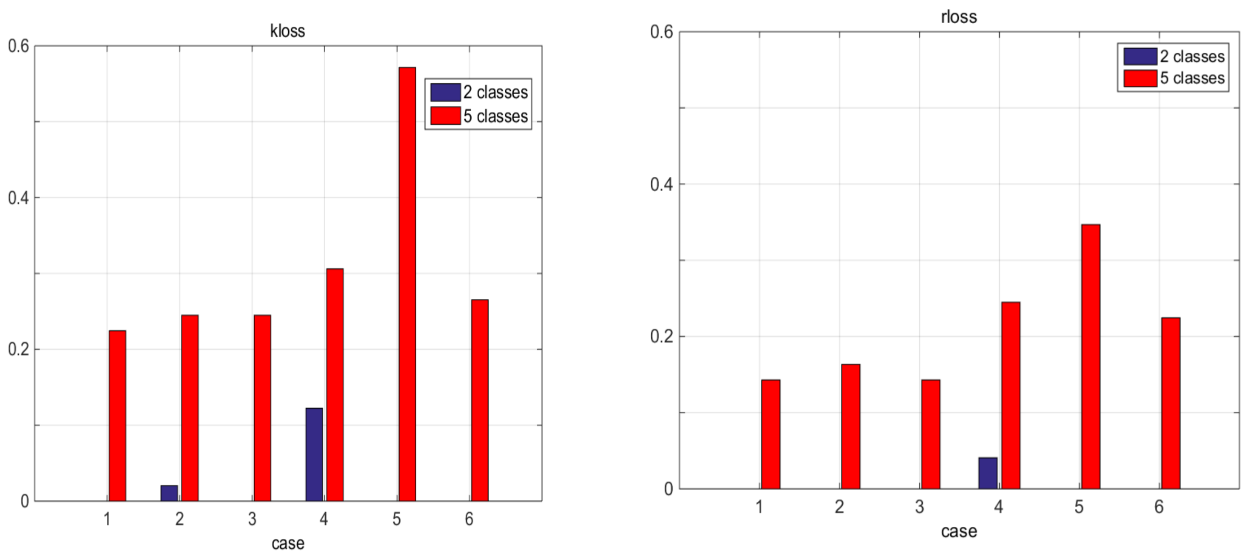

Figure 10 . On left and right panels, respectively, the kloss and rloss of 2 and 5 classes classifiers for each of the 6 cases

4.2. Five classes' discrimination

Concerning precise discrimination between 5 irregular scenarios, only two of them (e.g. the *missingNut* and *smallBolt* conditions) induce classification issues, irrespective of using low or high number of d.o.f. Misclassifications are mutually reversed, since trials belonging to the first scenario are assigned to the second one, and vice versa. This is true in all the cases, a part form the two ones where only 1 d.o.f. has been used: in the cases 5 and 6, in fact, some trials are wrongly assigned to the *diffThreads* class, due to an overlapping of the torque and clamping force values (see torque values distribution in Figure 9).

Nevertheless, if we can disregard this specific discrimination and accept to cluster these two latter cases into a singular group, then a successful classification rate of 100% is reachable, in terms of the classifier capability of discriminating between regular and irregular tightening; this performance is achievable with the only knowledge of the angle, torque and pressure values (*case 3*), as well as with the added information of the execution time (*case 1*). By tolerating a single classification error, out of 49, (e.g. an error on 2.0% of the trials), data of the angle and torque only are enough informative to perform a proper classification. Finally, if we restrict our classifier on a set-up of 1 d.o.f. only (namely the knowledge of the angular position, case 4), then only two trials (out of 49, i.e. 4.1% of the trials) are misclassified.

4.3. Overall discrimination

Figure 10 shows the bar diagrams of *kloss* and *rloss* values: *kloss*, which is an indicator of the classifier performance vs. new data, is less than 0.3 in 4 cases (out of 6) and precisely in case 1, 2, 3 and 6 (left panel, Figure 10): therefore approximately 30% of novel data may be misclassified, assuming that these latter ones have the same distribution of the training data. The error decreases at 20% or less in the graphs of the *rloss*, namely the fraction of the misclassification from the predictions of the model. Given the strong and clear separation of some classes (Figures 8 and 9), these performance may be significantly improved by acquiring a larger set of trials and experimental data.

5. Conclusion

This paper introduces a k-nearest classifier for the clustering of tightening experimental data which have been obtained under different scenarios of error. Angular displacement, applied torque, clamping force and execution time have been extracted from the raw experimental data which have been acquired with instrumented tightening tool, sensorized washer and software architecture based on Beckhoff TwinCAT 3 and Matlab Programming Language combined with an Industrial PC.

Different conditions of tightening are experimentally tested, from regular to irregular tightening: misalignment of bolts and nuts' threads, usage of incompatible threads, execution of the tightening with missing nut or wrong bolt are some of the examined scenarios (e.g. misalignment, diffThreads, missingNut and smallBolt).

According to this set-up, a set of classifiers has been proposed and performances have been characterized in terms of rloss (fraction of misclassification from the predictions of the model), kloss (average loss of each cross-validation model) and confusion matrix. Six configurations of classifiers are examined, according to different d.o.f. of the data, from applying single parameter to a maximum of five parameters together. Two types of classifiers are used, assuming 2 and 5 neighbors. Finally different classes are proposed, namely discriminating between regular and irregular tightening or between regular tightening and each one of the aforementioned error scenarios.

Results show that a k-nearest classifier based on the final values of the angle, torque and pressure can elicit a 100% correct classification, while distinguishing between regular tightening and 4 different scenarios of error. By implementing a simpler classifier based on angular and torque values only, or even on the angular values only, the performance lightly downgrades leading to an error on 2% and 4%, of the trials, respectively.

The simple structure of the proposed k-nearest classifiers and these results suggest that an implementation of the classifier is feasible on small micro-controller (PIC) with low computational power (i.e. low cost or ultra-low cost device using, for example, Atmega168 chips). Further developments may focus on directly running the classifiers within PICs which are directly coupled with the instrumented tightening tools. In an industrial scenario, the end-user may have direct and real-time feedback via simple screen or led array returning information about an occurring regular (or irregular) tightening process.

7. Funding

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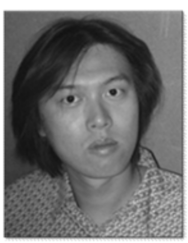

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