(19) DANMARK

(10) **DK/EP 3953580 T3**

Patent- og Varemærkestyrelsen

(12) Oversættelse af europæisk patentskrift

(51) Int.Cl.: ***F 03 D 17/00 (2016.01)*** ***F 03 D 7/02 (2006.01)*** ***G 05 B 23/02 (2006.01)***

(45) Oversættelsen bekendtgjort den: **2023-11-20**

(80) Dato for Den Europæiske Patentmyndigheds bekendtgørelse om meddelelse af patentet: **2023-10-25**

(86) Europæisk ansøgning nr.: **20732774.3**

(86) Europæisk indleveringsdag: **2020-06-02**

(87) Den europæiske ansøgnings publiceringsdag: **2022-02-16**

(86) International ansøgning nr.: **EP2020065196**

(87) Internationalt publikationsnr.: **WO2020245108**

(30) Prioritet: **2019-06-06 EP 19178834**

(84) Designerede stater: **AL AT BE BG CH CY CZ DE DK EE ES FI FR GB GR HR HU IE IS IT LI LT LU LV MC MK MT NL NO PL PT RO RS SE SI SK SM TR**

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(54) Benævnelse: **FREMGANGSMÅDE TIL COMPUTERIMPLEMENTERET MONITORERING AF EN KOMPONENT I EN VINDMØLLE**

(56) Fremdragne publikationer:

US-A1- 2018 119 677

HASEGAWA TAKANORI ET AL: "Tandem Connectionist Anomaly Detection: Use of Faulty Vibration Signals in Feature Representation Learning", 2018 IEEE INTERNATIONAL CONFERENCE ON PROGNOSTICS AND HEALTH MANAGEMENT (ICPHM), IEEE, 11 June 2018 (2018-06-11), pages 1-7, XP033395788, DOI: 10.1109/ICPHM.2018.8448450

ZHENG HUAILIANG ET AL: "Cross-Domain Fault Diagnosis Using Knowledge Transfer Strategy: A Review", IEEE ACCESS, vol. 7, 23 September 2019 (2019-09-23), pages 129260-129290, XP011746957, DOI: 10.1109/ACCESS.2019.2939876

ZHANG ET AL: "An Overview of Deep Learning in Prognostics and Health ManagementLiangwei", 2019 ANNUAL RELIABILITY AND MAINTAINABILITY SYMPOSIUM (RAMS), IEEE, 28 January 2019 (2019-01-28), pages 1-7, XP033580280, DOI: 10.1109/RAMS.2019.8768978

LEI JINHAO ET AL: "Fault diagnosis of wind turbine based on Long Short-term memory networks", RENEWABLE ENERGY, PERGAMON PRESS, OXFORD, GB, vol. 133, 9 October 2018 (2018-10-09), pages 422-432, XP085591803, ISSN: 0960-1481, DOI: 10.1016/J.RENENE.2018.10.031

DESCRIPTION

[0001] The invention refers to a method and an apparatus for computer-implemented monitoring of a component of a wind turbine. Furthermore, the invention refers to a corresponding computer program product and a corresponding computer program.

[0002] The invention refers to the field of fault detection with respect to components within a wind turbine based on vibration analysis. It known from the prior art to use machine learning models, like neural networks, in order to detect faults in wind turbines. Such machine learning models receive vibration signals of a monitored component in the wind turbine as an input and provide an output indicating the presence or absence of a specific fault occurring in the component.

[0003] Machine learning models for detecting a specific fault need to be trained by appropriate training data including fault data, i.e. vibration signals present at the occurrence of the specific fault within the wind turbine. However, such fault data are rare or need to be generated based on expensive test stands where faults (e.g. damages) are introduced to the components to be monitored. Moreover, machine learning models trained for one turbine type only have a good performance when used for monitoring this turbine type and not other turbine types.

[0004] Document HASEGAWA TAKANORI ET AL: "Tandem Connectionist Anomaly Detection: Use of Faulty Vibration Signals in Feature Representation Learning", 2018 IEEE INTERNATIONAL CONFERENCE ON PROGNOSTICS AND HEALTH MANAGEMENT (ICPHM), IEEE, 11 June 2018, pages 1-7, describes a method for anomaly detection of a predetermined wind turbine based on vibration signals. In this method, features are extracted by a deep neuronal network based on the vibration signals of the predetermined wind turbine between a normal state and a faulty state. The neuronal network has been trained based on other types of wind turbines than the predetermined wind turbine. Subsequently, an anomaly detection using Gaussian mixture models is performed based on the extracted features for the predetermined wind turbine.

[0005] It is an object of the invention to enable a monitoring of a component of a wind turbine by using a machine learning model having been trained for one or more wind turbines of another type than the monitored wind turbine.

[0006] 3. The invention is defined by independent claims 1, 8, 10 and 11. Preferred embodiments of the invention are defined in the dependent claims. The method of the invention enables a computer-implemented monitoring of a component of a wind turbine. The wind turbine having the monitored component is designated as the first wind turbine and the monitored component is designated as the first component. The method has access to an already trained machine learning model which has been trained for one or more second components of the same type of one or more second wind turbines, the one or more second wind turbines being wind turbines of another type than the first wind turbine. I.e., the training data are operation data from the one or more second components. In a preferred embodiment, the one or more second components of the one or more second wind turbines each have a function equivalent to the function of the first component of the first wind turbine. However, the function of the second components and the function of the first component may also be different. This difference is reflected by the mapping of step ii) described below. E.g., the first component may refer to a planet wheel whereas the type of the second components is a high speed pinion.

[0007] The trained machine learning model is configured to provide an output referring to a predetermined fault occurring at a second component of a second wind turbine by processing vibration signals in a predetermined domain which are measured in the vicinity of the second component during the operation of the second wind turbine. This second component can be any second component out of the one or more second components. In step ii) described below, reference is made to this second component. The trained machine learning model may be any known data driven model having been trained by machine learning using training data comprising vibration signals. Depending on the circumstances, the machine learning may be a supervised learning or unsupervised learning. In supervised learning, it is known for the vibration signals of a training data set whether the predetermined fault is present. This is not the case for unsupervised learning.

[0008] In a step i) of the method according to the invention, vibration signals in the predetermined domain (being or having been) measured in the vicinity of the first component during the operation of the first wind turbine are provided. The process of measuring those vibration signals may be part of step i). Nevertheless, it is also possible that the vibration signals have been measured and stored beforehand so that step i) merely comprises the step of reading the vibration signals having been previously measured and stored. The vibration signals provided in step i) are based on outputs of one or more vibration sensors. However, the vibration signals need not refer directly to the sensor outputs but to signals derived from these outputs. Particularly, the vibration signals may be derived from the sensor outputs by a transformation, e.g. a Fourier transformation.

[0009] In a step ii) of the method according to the invention, the vibration signals are mapped to corresponding vibration signals valid for the second component based on one or more given kinematic parameters of the first component and one or more given kinematic parameters of the second component.

[0010] In a step iii) of the method according to the invention, the machine learning model is applied to the vibration signals valid for the second component which are determined in step ii). Due to the mapping in step ii), this will lead to an output referring to the predetermined fault occurring at the first component. This output may be stored in a storage and/or may be provided on a user interface, e.g. a display, in order to inform the user about the occurrence of a fault.

[0011] The invention is based on the finding that vibration signals of different components can be mapped to each other by considering the kinematics of both components. Hence, the machine learning model applied to the mapped vibration signals will provide the correct output with respect to the vibration signals of the monitored turbine. The inventors found out that good results can be achieved provided that a mapping of the vibration signals can be found, irrespective of the type of mapping. However, particularly good results can be achieved in case that a linear mapping is used between the vibration signals of the first component and the vibration signals of the second component.

[0012] In a particularly preferred embodiment, the vibration signals provided in step i) are determined in the frequency domain, i.e. the vibration signals include a frequency spectrum of the vibrations. Nevertheless, the vibration signals may also be provided in the well-known cepstrum-domain or any other domain.

[0013] In another preferred embodiment of the invention, the one or more given kinematic parameters of the first component are described by the same function type as the one or more given kinematic parameters of the second component but with different function parameters.

[0014] In another variant of the invention, the one or more given kinematic parameters of the first component are one or more specific values within the predetermined domain contained within the vibration signals measured in the vicinity of the first component in case that the predetermined fault occurs. Analogously, the one or more given kinematic parameters of the second component are one or more specific values within the predetermined domain contained within the vibration signals measured in the vicinity of the second component in case that the predetermined fault occurs. E.g., the one or more specific values may refer to specific frequencies in the frequency domain or to corresponding values in the cepstrum-domain. It is known beforehand that a particular fault is associated with such specific values.

[0015] In another preferred embodiment, the component being monitored is a part of the drivetrain of the monitored wind turbine. E.g., the component may refer to a bearing supporting the rotor or to a gearbox or to a generator providing the electric power produced by the wind turbine.

[0016] In another preferred embodiment, the predetermined fault refers to a damage of a gearwheel or a damage of a bearing race or a damage of balls or rollers in a ball or roller bearing. These elements may e.g. be included in one of the above components of a drivetrain in a wind turbine.

[0017] In another preferred variant of the invention, the machine learning model is based on one or more neural networks or on Principal Component Analysis. However, any other machine learning model may be used as well.

[0018] Besides the above method, the invention refers to an apparatus for monitoring of a component of a wind turbine, where the apparatus comprises a means for performing the above described step i), a means for performing the above described step ii) and a means for performing the above described step iii). The means for performing step i) may comprise a measuring means for acquiring the vibration signals. I.e., the means may comprise one or more vibration sensors. Nevertheless, the means may only be implemented as a means for reading the vibration signals from a storage in case that the vibration signals have been stored beforehand. This type of means is used within the computer program product and the computer program as defined below.

[0019] The apparatus of the invention is preferably configured to perform one or more preferred embodiments of the method according to the invention.

[0020] The invention also refers to a computer program product with program code which is stored on a non-transitory machine-readable carrier, for carrying out the method of the invention or one or more preferred embodiments of this method when the program code is executed on a computer.

[0021] Furthermore, the invention refers to a computer program with program code for carrying out the method according to the invention or one or more preferred embodiments of this method when the program code is executed on a computer.

[0022] In the following, an embodiment of the invention will be described with respect to the accompanying drawings, wherein

Fig. 1
: shows an example of a wind turbine being monitored by an embodiment of the invention;

Fig. 2
: shows a wind turbine based on which the machine learning model used for monitoring the turbine of Fig. 1 has been trained;

Fig. 3
: is a flowchart showing the steps of a method according to an embodiment the invention; and

Fig. 4
: is a diagram illustrating the components used for performing the method shown in Fig. 3.

[0023] The method as described in the following is used for monitoring a component in a wind turbine. An example of such a wind turbine is shown in Fig. 1. The wind turbine is designated with reference numeral 1 and comprises a tower 2 on top of which a nacelle 3 is arranged. The nacelle is connected to a rotor having a hub 4 at which three rotating blades 5 are attached. A drivetrain for the wind turbine is accommodated within the nacelle 3. In the embodiment of Fig. 1, this drivetrain comprises a main bearing 6 for supporting the hub of the rotor as well as a gearbox 7 and a generator 8 for converting the mechanical power generated by the rotation of the rotor into electric power. Within the nacelle 3, there are provided three vibration sensors 9, 10 and 11. The vibration sensor 9 is located adjacent to the bearing 6, the vibration sensor 10 is located adjacent to the gearbox 7 and the vibration sensor 11 is located adjacent to the generator 8. The invention is not restricted to the use of just three vibration sensors. I.e., in other embodiments, a higher or lower number of vibration sensors may be used.

[0024] In the embodiment described herein, one of the components 6 to 8 of the drivetrain is monitored by processing the vibration signals detected by the sensor adjacent to the component. However, the method described in the following may be used for each of the components 6 to 8 so that all components within the nacelle are monitored. In another embodiment, the signals of several vibration sensors detecting vibrations of a respective components may be used for monitoring the respective component. Without loss of generality, the invention is described in the following for monitoring the gearbox 7 based on the vibration signals of sensor 10.

[0025] As a prerequisite of the method described herein, there already exists a pre-trained machine learning model. This machine learning model has been trained by training data from another turbine than the turbine 1. This turbine is shown in Fig. 2 and designated with reference numeral 1'. The turbine has the same components as the turbine in Fig. 1. Nevertheless, the turbine 1' is a turbine of another type than turbine 1 which is indicated by using apostrophes for the elements of the turbine in Fig. 2. The turbine 1' may be a turbine having the same construction as the turbine 1 but being from another manufacturer. In a modified embodiment, the machine learning model has been trained based on training data from several turbines 1' of the same type.

[0026] For the turbine 1', the above-mentioned machine learning model has been trained based on vibration signals of the sensor 10' where it was known whether the vibration signals refer to an operation of the wind turbine 1' where a specific fault and particularly a specific damage was present within the gearbox 7'. The training was based on a high number of training data sets including a considerable amount of vibrations signals referring to an operation accompanied by the specific fault within the gearbox 7'. Depending on the circumstances, the machine learning model can be trained for different fault types. E.g., a fault type may refer to a damage of a gearwheel or a damage of an inner race or outer race of a bearing or a damage of the balls or rollers of a bearing. The machine learning model was trained for one of such particular fault types.

[0027] In a preferred embodiment, the machine learning model refers to a neural network. However, other machine learning models, e.g. Principal Component Analysis, may be used. The machine learning model may be trained by any suitable learning method. In the embodiment described herein, the learning method is based on supervised learning where the training data include the information whether a fault is present in the gearbox for the respective training data sets. Nevertheless, the machine learning model may also be used in combination with a training based on unsupervised learning.

[0028] In order to use the trained machine learning method with respect to the turbine 1', vibration signals of the vibration sensor 10' are input into the model during the operation of the wind turbine 1' resulting in an output indicative of the specific fault. Depending on the circumstances, the output may be such that it indicates if the fault is present or not. However, the output may also be a probability with respect to the presence of the specific fault.

[0029] The idea of the invention is to enable a monitoring of the turbine 1 based on the trained machine learning model although the training of the model was performed for another wind turbine 1'. This is achieved by an appropriate mapping taking into account kinematic parameters with respect to both turbines 1 and 1'. This will be described in the following with respect to Fig. 3 and Fig. 4.

[0030] Fig. 3 shows a flowchart illustrating an embodiment of the invention for monitoring the gearbox 7 of the turbine 1. In step S1, vibration signals VS originating from the sensor 10 are recorded. The vibration signals need not refer to the direct sensor outputs but may be pre-processed signals. In the embodiment described herein, the vibration signals are the sensor data after having applied a Fourier transform, i.e. the vibration signals are signals within the frequency domain.

[0031] In a step S2, the vibration signals VS valid for the sensor 10 of the turbine 1 are converted by a mapping into vibration signals VS' which are vibration signals which would have been occurred in the turbine 1' in case that the operation states of both gearboxes 7 and 7' were the same. I.e., in case that the vibration signals VS refer to a fault within the gearbox 7, this fault would also be present in the gearbox 7' if vibration signals VS' were detected. In order to perform the mapping, the knowledge of kinematic parameters KP1 with respect to wind turbine 1 and of kinematic parameters KP2 with respect to turbine 1' is used. The kinematic parameters KP1 refer to the component 7 and the specific fault being monitored. Analogously, the kinematic parameters KP2 refer to the component 7' and the specific fault being monitored.

[0032] In the following, an example for a mapping from VS to VS' is described. As the kinematic parameters for both turbines 1 and 1', so-called damage frequencies occurring at the specific fault are used. Those damage frequencies are known beforehand and can be expressed by the following formula:

$$f = n \cdot f_c + z \cdot f_m \qquad (1)$$

[0033] The frequencies f_c and f_m are completely described by the kinematics of the respective components 7 and 7' and the rotation speed of the shaft. In the above formula, f_c represents the gearmesh frequency in case that a damage of a gearwheel is the specific fault. Analogously, f_c may refer to the frequency of an inner race or an outer race in case of a specific fault referring to cracks in these races or it may refer to a ball or roller spin frequency in case of a specific fault referring to the balls or rollers within a ball/roller bearing. The frequency f_c is known but is different for the components 7 and 7'. Furthermore, f_m in the above formula represents a known sideband frequency present when the specific fault occurs. Analogously to the frequency f_c, the frequency f_m is known but is different for the components 7 and 7'. Moreover, n, z are integers.

[0034] In the following, the frequencies occurring in the gearbox 7 of wind turbine 1 are designated by the index A, whereas the frequencies occurring in the gearbox 7' of wind turbine 1' are designated as B. In other words, index A refers to the component 7 and index B refers to the component 7'.

[0035] In the embodiment described herein, a linear mapping T(·) is used for converting the vibration signals VS into the vibrations signals VS'. I.e., the mapping is described by the function T(x) = ax + b. However, other mappings than linear mappings also provide good results in case that a corresponding mapping can be found.

[0036] Using the above formula (1), the kinematic parameters for the gearboxes 7 and 7' are as follows:

$$f^A = n \cdot f^A{}_c + z \cdot f^A{}_m$$

$$f^B = n \cdot f^B{}_c + z \cdot f^B{}_m$$

[0037] Based on the above equations, parameters a and b shall be determined such that $f^B = T(f^A)$. Thus, the following applies:

$$f^B = T(f^A) \quad \Leftrightarrow \; n \cdot f^B{}_c + z \cdot f^B{}_m = a \cdot (n \cdot f^A{}_c + z \cdot f^A{}_m) + b$$

$$\Leftrightarrow \; 0 = n \cdot (a \cdot f^A{}_c - f^B{}_c) + z \cdot (a \cdot f^A{}_m - f^B{}_m) + b$$

[0038] In order to determine a and b, the following two equations (i) and (ii) are solved:

$$\text{(i)} \quad 0 = n \cdot (a\ f^A{}_c - f^B{}_c) + b$$

$$\text{(ii)} \quad 0 = z \cdot (a\ f^A{}_m - f^B{}_m)$$

[0039] Solving equation (ii) will provide the parameter a as follows:

$$\text{(ii)} \quad a = f^B{}_m / f^A{}_m \text{ for } z \neq 0$$

[0040] Solving equation (i) will provide the parameter b as follows:

$$\text{(i)} \quad b = n \cdot (f^B{}_c - a \cdot f^A{}_c) = n \cdot (f^B{}_c - f^A{}_c \cdot f^B{}_m / f^A{}_m) = n \cdot (f^B{}_c \cdot f^A{}_m - f^A{}_c \cdot f^B{}_m) / f^A{}_m$$

[0041] The above mapping is dependent on n. The mapping was derived within the frequency domain. Nevertheless, the mapping may also be derived in the same way for the well-known cepstrum-domain.

[0042] Based on the mapping T, the vibration signals VS are converted in step S2 into the vibration signals VS' as shown in Fig. 3. In a next step S3, the vibration signals VS' are fed as input data to the trained machine learning model which is designated as ML in Fig. 3. As mentioned above, the machine learning model provides an output indicative of the specific fault where this fault is designated as FT in Fig. 3. Hence, when applying the machine learning model ML to the vibration signals VS', the output OU referring to the fault FT is generated. Due to the mapping, this output will indicate whether there is a fault within the gearbox 7 of the wind turbine 1 although the machine learning model has been trained for a different gearbox 7' in another wind turbine 1'.

[0043] The invention as described in the foregoing is based on the knowledge that vibration signals of rotating machines are characterized by variations in amplitudes and frequencies that can be explained by the kinematics of the machine components. These characteristics change when anomalies occur. Thus, a fault or damage type has a vibrational pattern that can be described by the component kinematics. Therefore, for each fault type, the vibration signals from one component can be mapped to another component using the kinematics of both components.

[0044] Fig. 4 shows an apparatus for performing the method described with respect to Fig. 3. The apparatus comprises a means M1 providing the vibration signals VS. In the embodiment described herein, means M1 comprises the vibration sensor 10 detecting the vibrations. Nevertheless, in a modified embodiment, the vibration sensor is not part of the apparatus. In this case, the vibration signals have been acquired and stored beforehand and means M1 just accesses the storage for retrieving the vibration signals. To do so, means M1 is part of a computer program implemented on a computer. This computer program also comprises means M2 and M3 which are described in the following.

[0045] Means M2 performs the mapping as shown in step S2 of Fig. 3. The vibration signals VS' resulting from this mapping are processed by means M3 which performs step S3 of Fig. 3. I.e., the machine learning model ML is implemented in means M3 and, by applying this model to the vibration signals VS', the output OU indicative of the specific fault is generated. This output may be stored in a storage and/or may be provided on a user interface, e.g. a display, in order to inform the user about the occurrence of a fault.

[0046] The embodiment described above has several advantages. Particularly, a pre-trained machine learning model can be used for monitoring a wind turbine other than the wind turbine for which the machine learning model has been trained. This can be achieved by an appropriate mapping based on known kinematic parameters with respect to the monitored wind turbine and the wind turbine used for training the machine learning model. Due to the use of a pre-trained machine learning method, there is no need for developing fault detection algorithms for new wind turbines. Moreover, the method of the invention artificially generates new training data and allows for further development and design of new machine learning algorithms.

REFERENCES CITED IN THE DESCRIPTION

Cited references

This list of references cited by the applicant is for the reader's convenience only. It does not form part of the European patent document. Even though great care has been taken in compiling the references, errors or omissions cannot be excluded and the EPO disclaims all liability in this regard.

Non-patent literature cited in the description

- Tandem Connectionist Anomaly Detection: Use of Faulty Vibration Signals in Feature Representation Learning**HASEGAWA TAKANORI et al.**2018 IEEE INTERNATIONAL CONFERENCE ON PROGNOSTICS AND HEALTH MANAGEMENT (ICPHM)IEEE201806111-7 [0004]

PATENTKRAV

1. Fremgangsmåde til computerimplementeret monitorering af en komponent i en vindmølle, hvor vindmøllen er en første vindmølle (1), og komponenten er en første komponent (6, 7, 8), og hvor fremgangsmåden har adgang til en trænet maskinlæringsmodel (ML), der er blevet trænet for én eller flere sekundære komponenter (6’, 7’, 8’) i den samme type af én eller flere sekundære vindmøller (1’), idet den ene eller flere sekundære vindmøller (1’) er vindmøller af en anden type end den første vindmølle (1), hvor den trænede maskinlæringsmodel (ML) er konfigureret til at tilvejebringe et output (OU), der vedrører en forudbestemt fejl (FT), som optræder i en anden komponent (6’, 7’, 8’) i en anden vindmølle (1’), ved processering af vibrationssignaler (VS’) i et forudbestemt domæne, der måles i nærheden af den anden komponent (6’, 7’, 8’) under driften af den anden vindmølle (1’), hvilken fremgangsmåde omfatter følgende trin:

i) tilvejebringelse af vibrationssignaler (VS) i det forudbestemte domæne, målt i nærheden af den første komponent (6, 7, 8) under driften af den første vindmølle (1);

kendetegnet ved, at fremgangsmåden omfatter følgende trin:

ii) afbildning af vibrationssignalerne (VS) på tilsvarende vibrationssignaler (VS’), der gælder for den anden komponent (6’, 7’, 8’), på basis af én eller flere givne kinematiske parametre (KP1) for den første komponent (6, 7, 8) og én eller flere givne kinematiske parametre (KP2) for den anden komponent (6’, 7’, 8’);

iii) anvendelse af maskinlæringsmodellen (ML) på vibrationssignalerne (VS’), der gælder for den anden komponent (6’, 7’, 8’), hvilket resulterer i et output (OU), der vedrører den forudbestemte fejl (FT), som optræder i den første komponent (6,7,8).

2. Fremgangsmåde ifølge krav 1, hvor det forudbestemte domæne er frekvensdomænet eller cepstrum-domænet.

3. Fremgangsmåde ifølge krav 1 eller 2, hvor den ene eller flere givne kinematiske parametre (KP1) for den første komponent (6, 7, 8) beskrives med den samme funktionstype som den ene eller flere givne kinematiske parametre

(KP2) for den anden komponent (6', 7', 8'), men med forskellige funktionsparametre.

4. Fremgangsmåde ifølge et af de foregående krav, hvor den ene eller flere givne kinematiske parametre (KP1) for den første komponent (6, 7, 8) er én eller flere specifikke værdier inden for det forudbestemte domæne, indeholdt i vibrationssignalerne (VS), målt i nærheden af den første komponent (6, 7, 8), i tilfælde af at den forudbestemte fejl (FT) optræder, og hvor den ene eller flere givne kinematiske parametre (KP2) for den anden komponent (6', 7', 8') er én eller flere specifikke værdier inden for det forudbestemte domæne, indeholdt i vibrationssignalerne (VS'), målt i nærheden af den anden komponent (6', 7', 8'), i tilfælde af at den forudbestemte fejl (FT) optræder.

5. Fremgangsmåde ifølge et af de foregående krav, hvor den komponent, der monitoreres, er en del af eller drivenheden i vindmøllen (1).

6. Fremgangsmåde ifølge et af de foregående krav, hvor den forudbestemte fejl (FT) vedrører en skade på et tandhjul eller en skade på en lejering eller en skade på kugler eller ruller i et kugle- eller rulleleje.

7. Fremgangsmåde ifølge et af de foregående krav, hvor maskinlæringsmodellen (ML) er baseret på ét eller flere neurale netværk eller en hovedkomponentanalyse.

8. Apparat til monitorering af en komponent i en vindmølle, hvor vindmøllen er en første vindmølle (1), og komponenten er en første komponent (6, 7, 8), og hvor fremgangsmåden har adgang til en trænet maskinlæringsmodel (ML), der er blevet trænet for én eller flere sekundære komponenter (6', 7', 8') i den samme type af én eller flere sekundære vindmøller (1'), idet den ene eller flere sekundære vindmøller (1') er vindmøller af en anden type end den første vindmølle (1), hvor den trænede maskinlæringsmodel (ML) er konfigureret til at tilvejebringe et output (OU), der vedrører en forudbestemt fejl (FT), som optræder i en anden komponent (6', 7', 8') i en anden vindmølle (1'), ved processering af vibrationssignaler (VS'), i et forudbestemt domæne, som måles i nærheden af den anden komponent (6', 7', 8') under driften af den anden vindmølle (1'), hvor apparatet omfatter:

- et middel (M1) til tilvejebringelse af vibrationssignaler (VS) i det forudbestemte domæne, målt i nærheden af den første komponent (6, 7, 8) under driften af den første vindmølle (1);

kendetegnet ved, at apparatet omfatter:

- et middel (M2) til afbildning af vibrationssignalerne (VS) på tilsvarende vibrationssignaler (VS'), der gælder for den anden komponent (6', 7', 8'), på basis af én eller flere givne kinematiske parametre (KP1) for den første komponent (6, 7, 8) og én eller flere givne kinematiske parametre (KP2) for den anden komponent (6', 7', 8');

- et middel (M3) til anvendelse af maskinlæringsmodellen (ML) på vibrationssignalerne (VS'), der gælder for den anden komponent (6', 7', 8'), hvilket resulterer i et output (OU), der vedrører den forudbestemte fejl (FT), som optræder i den første komponent (6, 7, 8).

9. Apparat i henhold til krav 8, hvor apparatet er konfigureret til at udføre en fremgangsmåde ifølge et af kravene 2 til 7.

10. Computerprogramprodukt med programkode, som er lagret på en ikke-flygtig maskinlæsbar bærer, til udførelse af en fremgangsmåde ifølge et af kravene 1 til 7, når programkoden afvikles på en computer.

11. Computerprogram med programkode til udførelse af en fremgangsmåde ifølge et af kravene 1 til 7, når programkoden afvikles på en computer.

DRAWINGS

FIG 1

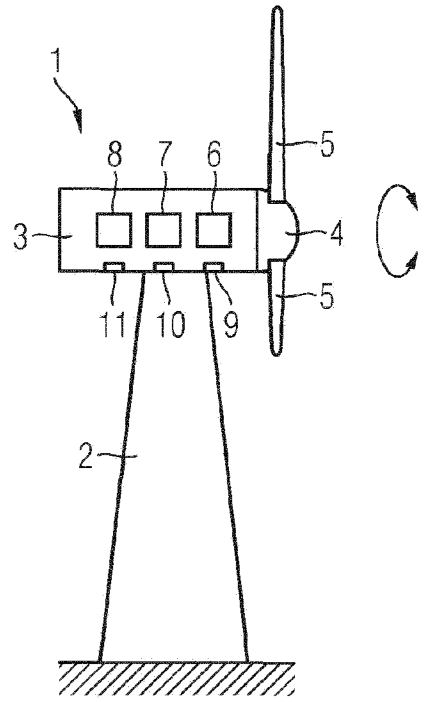

FIG 2

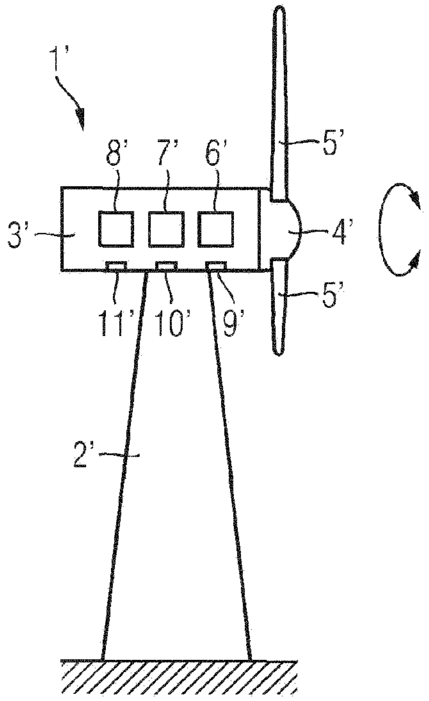

FIG 3

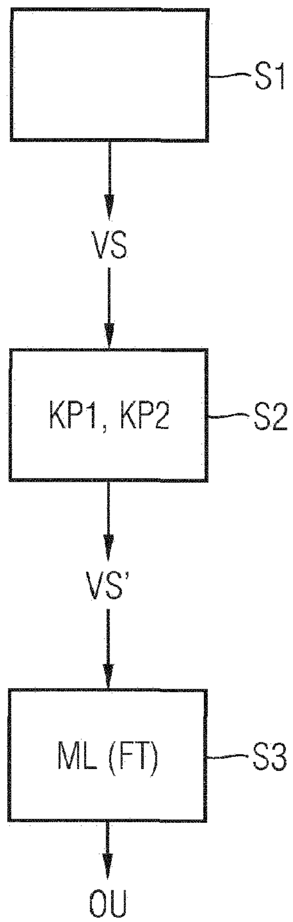

FIG 4