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(73) Patenthaver: **Senvion GmbH, Überseering 10, 22297 Hamburg, Tyskland**

(72) Opfinder: **MITTELMEIER, Niko, Glindweg 24, 22303 Hamburg, Tyskland**
Kaus, Sebastian, Hammer Weg 32, 20537 Hamburg, Tyskland
Gollnick, Bert, Heuweg 5, 15517 Fürstenwalde/Spree, Tyskland

(74) Fuldmægtig i Danmark: **Plougmann Vingtoft A/S, Strandvejen 70, 2900 Hellerup, Danmark**

(54) Benævnelse: **FREMGANGSMÅDE OG SYSTEM TIL ANALYSERING AF EN TILSTAND AF ET VINDENERGIANLÆG**

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Method and system for analysing a status of a wind turbine

The invention relates to a method and a system for analysing an operating state of a wind turbine.

Wind turbines are generally configured in such a way that they are able to generate a specified quantity of electrical energy at a specific wind strength. If the quantity of electrical energy actually generated lies below the expected value, this can have a variety of causes. For example, it may be the case that the wind turbine does not have a free incident flow, such that actually less wind power is available for driving the rotor. It is however also possible that certain parameters of the wind turbine are not correctly configured and for this reason only a part of the wind power is converted into electrical energy. It is not easy to differentiate between these two causes. Document WO 2016/077997 A1 discloses a method and a system for monitoring the operating state of a wind turbine in which "Supervisory Control And Data Acquisition" (SCADA) data as well as wind turbine reports are collected and are used for training a full model as well as a plurality of individual models, wherein the models are subsequently supplied with real-time SCADA data. Document US 2011/0313726 A1 discloses a status-dependent servicing system for wind turbines in which performance parameters of a wind turbine and deviations of the performance parameters from expected values are ascertained and evaluated in order to determine whether a service is required for the wind turbine.

The invention is based on the problem of providing a method and system for analysing an operating state of the wind turbine, which is not easily accessible for purposes of a direct analysis. The problem is solved by the features of the independent claims. Advantageous embodiments are given in the subclaims.

In the method according to the invention, at least three different classification models are developed in a learning phase. In an operating phase, operating data are analysed using each of the classification models. On the basis of a majority criterion of the classification models, the wind turbine is assigned to a category.

In a learning phase, first learning data are determined for a first model generator, so that the first model generator calculates a first classification model. Second learning data are determined for a second model generator, so that the second model generator calculates a second classification model. Third learning data are determined for a third model generator, so that the third model generator calculates a third classification model.

The learning data are derived in each case from a plurality of learning data records, wherein each learning data record is associated with a wind turbine. Each learning data record comprises an item of category information about the wind turbine. Each learning data record contains a first parameter value and a second parameter value, which is dependent on the first parameter value. The learning data are derived from the learning data records on the basis of a classification criterion that represents the dependency between the first parameter value and the second parameter value. Moreover, the item of category information is preferably transferred into the learning data from each learning data record.

A classification model contains an algorithm which reads out the operating data from a wind turbine as input data, analyses them and delivers at least one item of category information as output data. An item of category information specifies to which category a data record or the associated wind turbine is assigned.

A model generator contains an algorithm which on the basis of learning data generates a classification model adapted to the specific application, i.e. adapted to the predetermined or predeterminable limiting conditions, such as type of wind turbine, location conditions, predetermined data records, predetermined or predeterminable classification criteria and/or predetermined or predeterminable categories.

Majority criterion means, in the case of two predetermined categories, that the wind turbine is assigned, according to the majority principle, to the category to which the majority of the different classification models has assigned the wind turbine. In the case of more than two predetermined categories, the majority principle can also include a calculation of the category which is most probable according to the present distribution of the results of the different classification models.

The classification criterion preferably includes a calculation rule by means of which from a data record an indicator can be specified which has typical features depending on the assignment of the data record to one of the categories. It is possible to derive on the basis of model calculations / simulations, from theoretical considerations and/or empirically from field measurements how the classification criterion is to be defined. By means of the definition of the classification criterion it is decided on the basis of which calculation steps the indicator is to be determined from the data record. The calculation of the indicator for a specific data record is carried out preferably by applying simple mathematical operations to the data record. Preferably, the indicator can be derived from the data record by means of a direct calculation, that is by means of a calculation which is free from estimates, forecasts and comparable uncertainties.

In the learning phase, an indicator can be determined from every learning data record on the basis of the classification criterion. The learning data based on a plurality of learning data records can include the indicator and the associated category information for each of the learning data records.

The different model generators can be supplied with identical learning data. It is also possible to use different learning data for the model generators. This includes the possibility that the learning data are determined in each case on the basis of different learning data records. This includes the possibility that the learning data are determined on the basis of different classification criteria.

In the operating phase, an indicator can be derived from an operating data record on the basis of the classification criterion. The operating data supplied to the classification model can include the indicator, or in a special embodiment can consist exclusively of the indicator. The classification criterion for each classification model is preferably identical to the classification criterion which was used in the learning phase for generating the classification model.

In the method according to the invention, learning data are supplied into each of the model generators via a plurality of wind turbines. Each of the classification models permits as a result an analysis which is based on a comparison of several wind turbines. The reliability of the statement can be increased in that the analysis is not carried out with only one classification model. The result which is assumed to be correct is the result determined from the plurality of the classification models. It is conversely the case that a result is taken to be incorrect which has been determined only from a minority of the classification models.

In the learning phase, the model generators are supplied with the information with which a classification model can be generated (learning data). The learning data specified for a model generator are based on a plurality of learning data records, wherein each data record represents information regarding one single wind turbine. Contained in the learning data record are a first parameter value and a second parameter value dependent on the first parameter value. The first parameter value can relate to an environmental condition to which the wind turbine is exposed (environmental parameter). The second parameter value can relate to an operating state of the wind turbine (operating parameter). The dependency between the parameter values can for example also consist in the second parameter value changing when the first parameter value changes. This is for example the case when the first parameter value represents the wind speed and the second parameter value represents the power output by the wind turbine. If the wind strength changes (independent parameter), the electrical power (dependent parameter) which is generated changes.

The parameter values can be individual measurement values, that is in each case a measurement value at a specific point in time. A more meaningful item of information can be obtained when the parameter values are average values of a time sequence, for example 10 minute average values. Furthermore, it can be advantageous when the first parameter value and the second parameter value include in each case a plurality of values which are captured at different points in time.

By means of the classification models, a statement is to be facilitated which is associated with one specific data record from several possible categories. In order for the classification model to be able to make this statement, with each learning data record an item of category information is made available to the model generator in the learning phase. The item of category information states to which of the possible categories a specific data record of the learning data can be assigned. Preferably, at least one learning data record is incorporated into the learning data for each of the categories between which the method according to the invention differentiates. In particular, a plurality, in particular a substantial multiplicity of data records can be incorporated into the learning data for each of the categories. A "substantial multiplicity" describes at least 5 data records, preferably at least 10 data records.

The classification models can be configured such that they differentiate between two categories. For example category pairs such as "normal" and "abnormal", "operating state optimal" and "operating state not optimal", "nacelle misalignment yes" and "nacelle misalignment no" and similar are possible. Incorporated into the learning data are preferably exemplary learning data records from each of the categories, such that the data records represent typical characteristics from the respective categories. All model generators can be supplied with the same learning data. It is also possible to use different learning data for the different model generators. Alternatively, the classification models can also be configured such that they facilitate a differentiation between several categories by means of a quantifiable result. Here, for example, categories such as "no nacelle misalignment", "weak nacelle misalignment" and "strong nacelle misalignment" are possible.

In the operating phase of the method according to the invention, the information regarding which category a specific data record is to be assigned to is initially not available. On the contrary, this information is supposed to be obtained from the data record only by using the classification models. In order for this to be possible, a classification criterion must be incorporated into the classification model, on the basis of which criterion a decision between the categories is possible.

The classification criterion can be based on a relationship determined on the basis of model calculations or theoretical considerations. On the basis of the relationship, a calculation rule can be specified for determining an indicator from a data record. The relationship and the calculating rule resulting therefrom should be selected such that typical differences between the data records become obvious, depending on which of the categories is associated with a data record.

An exemplary relationship from which a classification criterion can be derived is the varying performance of a wind turbine when there is an oblique incident flow either from the right or from the left. By means of the swirl which the wind obtains by means of the rotor, a slightly oblique incident flow from the left results in a slightly different performance curve than in the case of a slightly oblique incident flow from the right. Thus, a classification criterion can be derived from the difference between the two curves.

In a further development of the invention, this classification criterion can be suitable also for the quantitative classification of an oblique incident flow.

For example, the range of +/-25° oblique incident flow can be divided into five sectors of equal size. The difference in the performance curves between positive and negative incident flow measured at a wind turbine facilitates (in the case of a sufficiently precise evaluation) a statement as to which of the five mentioned oblique incident flow categories (no oblique incident flow, weak or strong incident flow left or right) applies for the wind turbine.

In the same way, also the difference of the current performance curve to the performance curve without oblique incident flow can constitute an exemplary classification criterion for an oblique incident flow. In the same way, advantageously, instead of a performance curve comparison, the comparison can be carried out on the level of the energy output. The energy output which is basically nothing other than the integration of the performance over time, is advantageous as a criterion particularly at locations with strong turbulences, because the integration over time has a strong averaging effect. A further advantageous classification criterion can be the application of the coefficient of performance Cp of the rotor over the wind speed or also only the determination of the maximum coefficient of performance Cp_max in comparison to the Cp_max without oblique incident flow. In the case of virtually all wind turbines, there are two anemometers on the nacelle roof which are arranged with significant spacing next to one another. The difference of the wind speed measured by these anemometers has also proved to be a significant classification criterion for recognising oblique incident flows.

By means of the model generator a method can be carried out for pattern recognition in the learning data. The pattern recognition can be used on the indicators which are derived from the learning data records on the basis of the classification criterion, wherein the items of category information contained in the learning data can be drawn upon in order to differentiate between the categories. Model generators of this sort as well as the algorithms which formed the basis thereof are basically known. Different algorithms on which the model generators can be based are known for example by the names: decision tree, random forest, naive Bayes, support vector machine and neural networks. An advantage of using indicators is an effect which is comparable to a low pass filter. Relatively high frequency learning data records are aggregated by means of the calculation of the indicators, as a result of which the data have less noise. Although the data record prepared in this manner thus contains fewer data, it contains more meaningful data which are integrated into the learning data. This also occurs in the analysis result which promises lower error rates in the classification by means of the use of problem-specific indicators. The reduced data quantity has the further advantage that the calculating time in the model generators is as a rule significantly lower than with a calculation which is carried out on the basis of complete learning data records.

The method according to the invention is preferably carried out such that the model generators are based on different algorithms. In particular, when using three model generators, three different aforementioned algorithms form the basis for the model generators. The method is preferably carried out with an uneven number of model generators/classification models. For example, the use of five model generators/classification models is possible, wherein the model generators are based on the above-mentioned five algorithms.

The classification models generated with the different algorithms have different strengths and weaknesses. Thus, in the case of each of the models, it must be expected that individual data records will not be able to be classified reliably in the operating phase. This uncertainty is evened out in the method according to the invention by using the at least three different classification models. If a majority of the classification models assigns the data record to a specific category, this category is assumed to be correct.

If a classification model is used on operating data of a wind turbine in the operating phase, the result of the evaluation can thus be a probability value that the wind turbine is to be assigned to a specific category. In order to differentiate between two categories on the basis of the probability value, a threshold value can be determined. In the case of a probability value above the threshold value, the data record can be assigned to a first category, in the case of a probability value below the threshold value, the data record can be assigned to a second category. In a further development of the invention, also a statement regarding the reliability of the classification can be derived from the probability value.

The operating data record which is evaluated in the operating phase is preferably compiled analogously to the learning data records of the learning phase, wherein the operating data record, unlike the learning phase, does not contain any category information however. Included in the operating data record are however a first parameter value and a second parameter value. In the operating phase, the working data which can process the classification models are calculated first on the basis of the classification criterion from the operating data record to be analysed. The operating data are evaluated with the three classification models, such that each classification model assigns the operating data record to one of the categories.

The final assignment to one of the categories takes place on the basis of a majority criterion. Thus, the data record which is determined by the majority of the classification models is assigned to the category. If the method is carried out with an uneven number of classification models and the choice needs to be made between two categories, the majority criterion always results in a clear result. If the method is carried out with an even number of classification models, there is need for an additional criterion for the case that different categories are determined by the same number of classification models.

The method according to the invention is suitable for a continuous optimisation of the classification models. If, for example, in the operating phase a specific data record has been assigned with a specific probability (for example 70%) to a category (for example to the category “abnormal”), thus a service technician can check whether this assignment is correct. On the basis of the category determined by the service technician, the data record concerned can be used as a learning data record, wherein the category information is specified corresponding to the category determined by the service technician. Thus, the model can be continuously further improved by the continuous further generation of learning data such that the reliability of the categorisation increases.

The reliability of the method can be further increased in that a majority of classification criteria is made available to the model generator in the learning phase. A pattern which is reflected in a majority of classification criteria regularly has a higher informative value than a pattern determined on the basis of only one classification criterion.

In a further development, the two categories, to which a data record can be assigned with the method according to the invention, can be divided into further subgroups. If there is a plurality of classification models which assign a data record to a specific subgroup within a category, thus the subgroup concerned can be output as additional information of the method. The number of the subgroups within the categories can be adapted to the expected accuracy of the method.

For the reliability of the method, it is advantageous when data records of high quality are used. This is relevant both for the learning phase and for the operating phase. Data records of lower quality can for this reason be discarded in a previous method step. For example, sensor data contained in the data record can be tested for plausibility. For example, if the measurement value determined with one sensor deviates significantly from the expected value, it can thus be concluded that the sensor is faulty and the data record concerned can be discarded. A sensor can also be faulty if the values of the sensor change very significantly in a short period of time (jump function) or the values of the sensor are much more strongly scattered than in other time periods (heteroscedasticity). Finally, also implausible values of the sensor can be an indication of an error.

Furthermore, the data can, in a proceeding method step, be subjected to an analysis as to whether a systematic change has taken place within the time period to which the data relate (change point analysis). Data records which extend beyond a systematic change are regularly not able to be meaningfully evaluated with the method according to the invention. For this reason, also such data records should be discarded.

Moreover, prior to the use of data, a consistency test can be carried out. For example, it can be checked whether the wind turbine reaches its nominal performance. By means of checking the standard deviation of the wind speed, it can be checked whether the anemometers have been installed reversed. Changes in the performance curve can be checked. For further consistency checking, minimum, maximum and median temperatures for each observed time period can be output.

In a preferred embodiment, the method is used in order to analyse whether a wind turbine is misaligned, that is, whether there is a deviation between the alignment of the nacelle and of the average wind direction. There can be two categories between which differentiation is made with the classification models, specifically the categories “nacelle misalignment yes” and “nacelle misalignment no”.

The learning data records from which the learning data are determined can include as first parameter values measurement values regarding the parameters wind speed and wind vane position. The second parameter value, dependent thereon, in the learning data record can relate to the performance which the wind turbine outputs. The parameter values are preferably time sequences which relate in each case to the same time periods. The parameter values can in particular be 10-minute average values of the parameters concerned.

In the learning phase, preferably at least four learning data records with the category information “nacelle misalignment yes” and at least four learning data records with the category information “nacelle misalignment no” are supplied to the respective model generators.

Even if the nacelle is correctly aligned in the average wind direction (nacelle misalignment no), a momentary oblique incident flow can occur as a result of continual slight changes in the wind speed. The effects of a momentary oblique incident flow on the performance curve vary, depending on whether it is an oblique incident flow from the left or an oblique incident flow from the right. There thus results a characteristic difference between the performance curves in the different directions of the oblique incident flow. This characteristic difference can be numerically evaluated, in that the performance curves are divided into several sections and the differential of the integrals of the respective performance curves is considered for each of the sections. This integral differential forms an indicator which has characteristic properties, depending on whether the wind turbine is subject to an oblique incident flow. This indicator is supplied to the model generators with the learning data. On the basis of several such indicators and taking into consideration the associated category information, the model generators can carry out a pattern recognition and from this develop in each case a classification model.

In the operating phase, an appropriate data record without category information is analysed with each of the classification models. Each of the classification models categorises the data record into one of the categories “nacelle misalignment yes” or “nacelle misalignment no”. On the basis of a majority criterion of the classification model that there then results the final assignment of the data record to one of the two categories.

In the operating phase it is to be expected that the category “nacelle misalignment no” is more frequently occupied than the category “nacelle misalignment yes”. If a data record is categorised into the category “nacelle misalignment yes” by at least half of the classification models, a service technician can be employed to check the nacelle alignment of the wind turbine concerned on site. If the service technician actually determines a misalignment of the nacelle, the category information can be confirmed. By adding the category information, a learning data record can be generated from the data record concerned. The model generators can be supplied with the learning data record in order to improve the classification models.

In the learning phase and/or in the operating phase, data records can be used which relate to the time period in which the wind turbine was operated in a part-load operating range. Phases of downtime are basically not suitable for a test. When operating the wind turbine under full load, there is the disadvantage that the wind power and the turbine performance do not correlate directly with one another.

The method can also be used advantageously for detecting irregularities in the configuration of the rotor blade angle or the speed settings (as a rule by means of a speed-torque characteristic curve) or quite generally for validating the performance curve. For all these analyses of the operating state, an evaluation of data records which concern the part-load operation is especially advantageous. During full-load operation, the method is especially suitable for analysing an operating state in regard of the present system loads.

The invention relates moreover to a system for analysing an operating state of a wind turbine. The system comprises a learning module for developing at least three different classification models. The system comprises an operating module for analysing operating data of the wind turbine using each of the classification models and for assigning the wind turbine to a category on the basis of a majority criterion of the classification models. The learning module comprises a first model generator for generating the first classification model, a second model generator for generating the second classification model and a third model generator for generating the third classification model. The model generators are configured to evaluate learning data in order to generate the classification models. The learning data are respectively derived from a plurality of learning data records, wherein each learning data record is associated with a wind turbine, wherein each learning data record comprises category information about the wind turbine, wherein each learning data record contains a first parameter value and a second parameter value which is dependent on the first parameter value, and wherein the derivation of the learning data is carried out on the basis of a classification criterion that represents the dependency between the first parameter value and the second parameter value.

The system can be further developed with further characteristics which are described in the context of the method according to the invention. The method can be further developed with further characteristics which are described in the context of the system according to the invention.

The invention will be described in exemplary manner hereinafter with reference to the attached drawings using advantageous embodiments.

Figure 1 shows a schematic representation of eight wind turbines for obtaining learning data records;

Figure 2 shows a graphical representation of a learning data record, according to the invention, of a first category;

Figure 3 shows a graphical representation of a learning data record, according to the invention, of a second category;

Figure 4 shows a block diagram of a learning phase according to the invention;

Figure 5 shows a schematic representation of wind turbines to be analysed; and

Figure 6 shows a block diagram of an operating phase according to the invention.

Figure 1 shows four wind turbines 14 which are aligned correctly to the average wind direction, which are thus free from a nacelle misalignment. Shown too are four wind turbines 15 which are subject to a nacelle misalignment. Figure 2 shows in graphic form measurement data which were taken at one of the wind turbines 14. This is the representation of a performance curve in which the wind speed V in m/s is plotted on the horizontal axis and the electrical power P generated by the wind turbine 14 is plotted on the vertical axis. Each of the points plotted on the graph represents a 10-minute average value of the performance over wind speed.

The sensor data of a wind vane arranged on the nacelle of the wind turbine 14 were also recorded at wind turbine 14. Even when the wind turbine is aligned correctly to the average wind direction, a momentary oblique incident flow can occur by reason of short-term fluctuations in the wind direction. A momentary oblique incident flow is as a result not an indicator of a nacelle misalignment. The sensor data of the wind vane correspond in each case to an item of information regarding the momentary wind direction. The data from the wind vane are also transferred into 10-minute average values and assigned to the points shown in the graph. Depending on the value of the momentary wind direction, the points are coloured in differently dark grey tones.

On the basis of the additional information regarding the momentary oblique incident flow, it is possible to determine two different performance curves, wherein one of the performance curves relates to the angle range between for example 0° and +8° between alignment of the nacelle and momentary wind direction and wherein the other performance curve relates to the angle range between -8° and 0°.

The two performance curves 16, 17 are drawn in figure 2. The performance curve 16 for the angle range 0° to +8° lies slightly above the performance curve 17 for the angle range -8° to 0°. This is explained by the fact that by means of the swirl which the wind obtains from the rotor a momentary oblique incident flow from the one direction has a different effect than a momentary oblique incident flow from the other direction.

Figure 1 also shows four wind turbines 15 in which the alignment of the nacelle deviates from the central wind direction, which are thus subject to a nacelle misalignment. Figure 3 shows a graphical representation of an exemplary data record which was captured at one of the wind turbines 15. Again, the points show 10-minute average values of the performance which are plotted against the wind speed. The colouration of the points represents the deviation between the alignment of the nacelle and the momentary wind direction shown by the wind vane. On the basis of these items of information, again two performance curves 18, 19 can be obtained, wherein the performance curve 18 corresponds to the angle range 0° to +8° between the two directions and the performance curve 19 corresponds to the angle range -8° to 0°.

The deviation between the two performance curves 18, 19 in figure 3 is less than the deviation between the two performance curves 16, 17 in figure 2. From the deviation between the performance curves can be derived an indication as to whether the wind turbine is subject to a nacelle misalignment.

For the method according to the invention, the difference between the performance curves 16, 17, 18, 19, which can be seen in figures 2 and 3, is transferred into a quantifiable classification criterion. To this end, the performance curves are divided into a plurality of sections along the horizontal axis (for example V = 5 m/s to 6 m/s; V = 6 m/s to 7 m/s etc.). In each of the sections, an integral of the two performance curves is calculated and the difference of the two integrals is determined. The difference of the integrals corresponds to the deviation between the performance curves in the section concerned. Accordingly, the integral difference forms, in the context of the invention, an indicator which has characteristics depending on the oblique incident flow. With the classification criterion, a calculation rule is prescribed with which the indicator can be calculated from a data record.

On the basis of the wind turbines 14, 15 shown in figure 1, learning data records of the type shown in figures 2 and 3 can be obtained. Learning data records are characterised by the fact that it is known whether the data record belongs in the category “nacelle misalignment yes” or the category “nacelle misalignment no”. Each learning data record is assigned to a single one of the wind turbines 14, 15.

In the learning phase of the method according to the invention, shown in figure 4, three different model generators 21, 22, 23 are supplied with learning data in order to obtain three classification models 24, 25, 26. The learning data are derived from learning data records 20, wherein each learning data records 20 contains a multiplicity of measurement values 27 of the wind speed as well as a multiplicity of sensor data 28 from the wind vane arranged on the nacelle of the wind turbine. The measurement values 27 and the sensor data 28 form first parameter values in the context of the invention.

Each learning data record 20 also comprises a multiplicity of performance measurement values 29 of the wind turbine. The performance measurement values 29, which are a function of the wind direction and the wind strength, form second parameter values in the context of the invention. Each learning data record 20 contains moreover an item of category information 36 as to whether the learning data record 20 belongs to the category “nacelle misalignment yes” or the category “nacelle misalignment no”.

The learning data records 20 as well as the associated classification criterion 37 are supplied to a computing module 38. In the computing module 38, an indicator for each of the learning data records 20 is calculated on the basis of the calculation rule defined by the classification criterion 37, thus, the above described integral difference of the performance curves 16, 17, 18, 19 is determined for each of the data records. The computing module 38 outputs learning data which contain an indicator and the associated category information 36 for each of the learning data records 20. The learning data are supplied to the model generators 21, 22, 23, wherein in this embodiment example all three model generators 21, 22, 23 are supplied with identical learning data.

In the learning data, the model generators 21, 22, 23 recognise patterns - on the basis of algorithms such as decision tree, random forest, naive Bayes, support vector machine and neural networks -, by means of which it is possible to assign the learning data records 20 to the categories. From these patterns in each case one classification model 24, 25, 26 is developed. Each of the classification models 24, 25, 26 has the capability of assigning a data record, whose category is unknown, to one of the categories.

In the operating phase of the method according to the invention, corresponding data records 32 (that is data records which are composed from corresponding measurement values) are captured at wind turbines 30, 31 (figure 5) in the case of which it is unknown whether they belong in the category “nacelle misalignment no” or the category “nacelle misalignment yes”.

The data records 32 contain according to figure 6 measurement values 27 of the wind speed and sensor data 28 of the wind vane as first parameter values, as well as performance measurement values 29 of the wind turbines 30, 31 as second parameter values. The data record 32 is supplied to the computing module 38, which on the basis of the classification criterion 37 calculates the above described integral difference of the performance curves 16, 17, 18, 19 and therewith determines an indicator for the data record 32 which is characteristic for oblique incident flow. This indicator is supplied to the classification models 24, 25, 26 and forms thereby in the context of the invention operating data for the classification models 24, 25, 26.

The classification models 24, 25, 26 analyse the indicator of the data record 32. In the case of each of the classification models 24, 25, 26, the result of the analysis is an assignment of the data record 32 either to the category 33 “nacelle misalignment yes” or to the category 34 “nacelle misalignment no”. If all classification models 24, 25, 26 render a concordant statement, the category concerned is determined as a final result of the classification.

Figure 6 shows the result of the evaluation for wind turbine 31 which is subject to a nacelle misalignment. The wind turbine 31 is classified by the classification models 25, 26 to the category 33 “nacelle misalignment yes”. In contrast, the classification model 24 does not ascertain the nacelle misalignment and classifies the wind turbine 31 into the category 34 “nacelle misalignment no”. If the classification models 24, 25, 26 output different results, thus a decision is made as to the final classification on the basis of a majority criterion. Here, the majority of the classification models has classified the wind turbine 31 to the category 33 “nacelle misalignment yes”, such that the category 33 is output as the final result 35 of the evaluation.

A service technician is then employed to check the wind turbine 31 on site. If the nacelle misalignment is confirmed, thus a checked item of category information 36 is available for the data record 32. The data record 32 can be used as a learning data record 20 which is supplied additionally to all model generators 21, 22, 23 in order to optimise the classification models 24, 25, 26.

Patentkrav

1. Fremgangsmåde til analysering af en driftstilstand af et vindenergianlæg (30, 31), hvor mindst tre forskellige klassificeringsmodeller (24, 25, 26) udvikles i en læringsfase, og arbejdsdata (32) af vindenergianlægget (30, 31) analyseres med hver af klassificeringsmodellerne (24, 25, 26) i en driftsfase, og hvor vindenergianlægget (30, 31) tildeles en kategori (33, 34) på basis af et flertalskriterium af klassificeringsmodellerne (24, 25, 26), hvor læringsfasen omfatter følgende trin:

a. bestemmelse af første læringsdata for en første modelgenerator (21), således at den første modelgenerator (21) beregner en første klassificeringsmodel (24),

b. bestemmelse af anden læringsdata for en anden modelgenerator (21), således at den anden modelgenerator (21) beregner en anden klassificeringsmodel (25),

c. bestemmelse af tredje læringsdata (20) for en tredje modelgenerator, således at den tredje modelgenerator (23) beregner en tredjeklassificeringsmodel (26),

hvor læringsdataene er afledt af en flerhed af lærings-datasæt (20), hvor hvert lærings-datasæt (20) er tildelt et vindenergianlæg (14, 15), hvor hvert lærings-datasæt (20) omfatter en kategoriinformation (36) om vindenergianlægget (14, 15), hvor hvert lærings-datasæt (20) indeholder en første parameterværdi (27, 28) og en anden parameterværdi (29), som er afhængig af den første parameterværdi (27, 28), og hvor læringsdataene er afledt af lærings-datasættene på basis af et klassificeringskriterium (37), som repræsenterer afhængigheden mellem den første parameterværdi (27, 28) og den anden parameterværdi (29).

2. Analysefremgangsmåde ifølge krav 1, **kendetegnet ved, at** den første parameterværdi (27, 28) og/eller den anden parameterværdi (29) er en gennemsnitsværdi bestemt ud fra en tidsserie.

3. Analysefremgangsmåde ifølge krav 1 eller 2, **kendetegnet ved, at** hver lærings-datasæt (20) omfatter en flerhed af første parameterværdier (27, 28) og/eller anden parameterværdier (29), fortrinsvis omfatter en større mangfoldighed af første parameterværdier (27, 28) og/eller anden parameterværdier (29).

4. Analysefremgangsmåde ifølge et af kravene 1 til 3, **kendetegnet ved, at** modelgeneratorerne (21, 22, 33) forsynes med identiske læringsdata.

5. Analysefremgangsmåde ifølge et af kravene 1 til 4, **kendetegnet ved, at** klassificeringsmodellerne (24, 25, 26) er konfigureret, således at de vælger mellem to kategorier (33, 34).

6. Analysefremgangsmåde ifølge et af kravene 1 til 5, **kendetegnet ved, at** modelgeneratorerne (24, 25, 26) udfører en fremgangsmåde til mønstergenkendelse i læringsdataene.

7. Analysefremgangsmåde ifølge krav 6, **kendetegnet ved, at** modelgeneratorerne er baseret på en eller flere af følgende algoritmer: beslutningstræ, Random Forest, Naive Bayes, support vektormaskine og neurale netværk.

8. Analysefremgangsmåde ifølge et af kravene 1 til 7, **kendetegnet ved, at** den udføres med et ulige antal klassificeringsmodeller (24, 25, 26).

9. Analysefremgangsmåde ifølge et af kravene 1 til 8, **kendetegnet ved, at** kategoriinformationen (36) bestemt med en af klassificeringsmodellerne (24, 25, 26) efterprøves manuelt, og at den bekræftede kategoriinformation (36) anvendes til at generere et yderligere lærings-datasæt (20), som forsynes til en eller flere af modelgeneratorerne (21, 22, 23).

10. Analysefremgangsmåde ifølge et af kravene 1 til 9, **kendetegnet ved, at** klassificeringsmodellerne (24, 25, 26) skelner mellem kategorierne "nacelle-fejljustering ja" og "nacelle-fejljustering nej".

11. Analysefremgangsmåde ifølge krav 10, **kendetegnet ved, at** den udføres med datasæt (32), som repræsentere delbelastningsdrift af vindenergianlægget

(30, 31).

12. System til analysering af en driftstilstand af et vindenergianlæg (30, 31), med et læringsmodul til udvikling af mindst tre forskellige klassificeringsmodeller (24, 25, 26) og med et arbejdsmodul til analysering af et datasæt (32) af vindenergianlægget (30, 31) med hver af klassificeringsmodellerne (24, 25, 26) og til tildeling af vindenergianlægget (30, 31) til en kategori (33, 34) på basis af et flertalsskriterium af klassificeringsmodellerne (24, 25, 26), hvor læringsmodulet omfatter en første modelgenerator (21) til generering af den første klassificeringsmodel (24), en anden modelgenerator (22) til generering af den anden klassificeringsmodel (25) og en tredje modelgenerator (23) til generering af den tredje klassificeringsmodel (26), hvor modelgeneratorerne (21, 22, 23) er udformet til at evaluere læringsdataene til generering af klassificeringsmodellerne (24, 25, 26), hvor læringsdataene er respektivt afledt af en flerhed af lærings-datasæt (20), hvor hvert lærings-datasæt (20) er tildelt et vindenergianlæg (14, 15), hvor hvert lærings-datasæt (20) omfatter kategoriinformation (36) om vindenergianlægget (14, 15), hvor hvert lærings-datasæt (20) indeholder en første parameterværdi (27, 28) og en anden parameterværdi (29), som er afhængig af den første parameterværdi (27, 28), og hvor læringsdataene er afledt af lærings-datasættene (20) på basis af et klassificeringskriterium (37), som repræsenterer afhængigheden mellem den første parameterværdi (27, 28) og den anden parameterværdi (29).

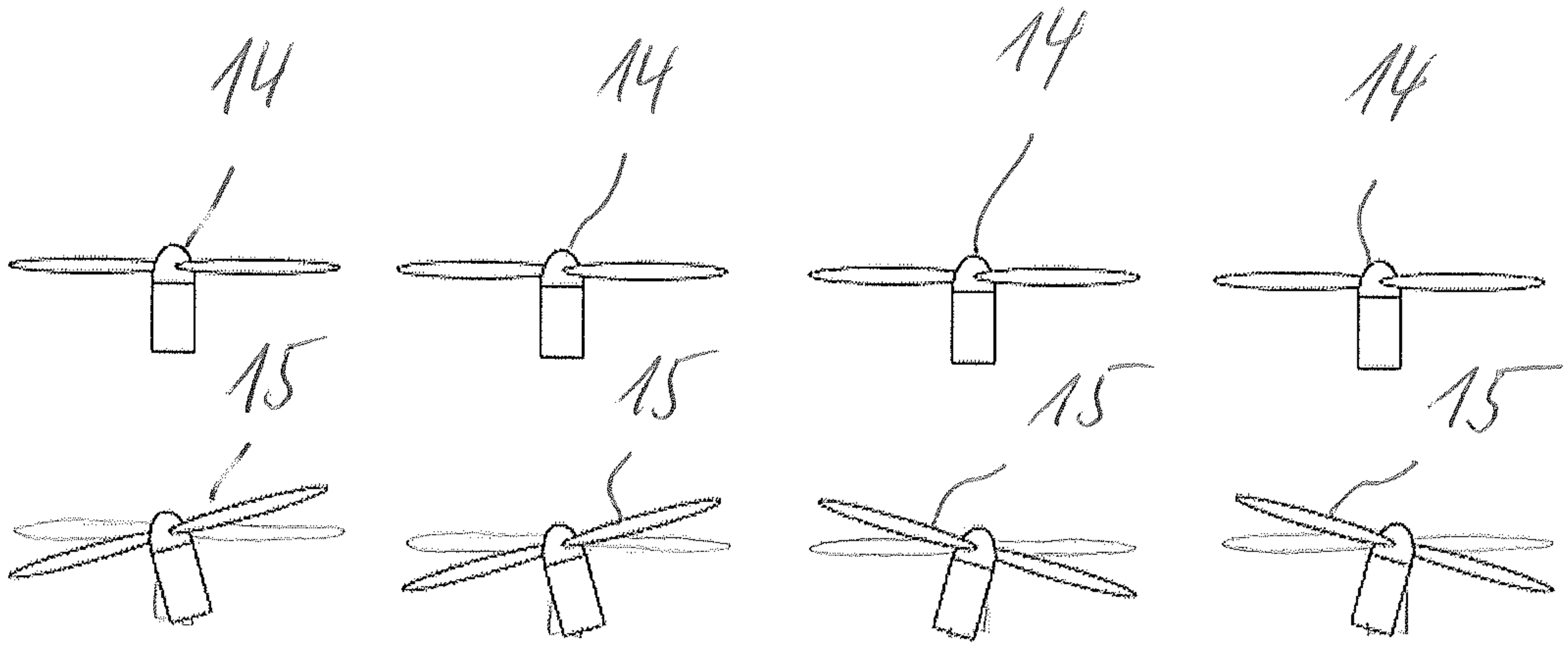

Fig. 1

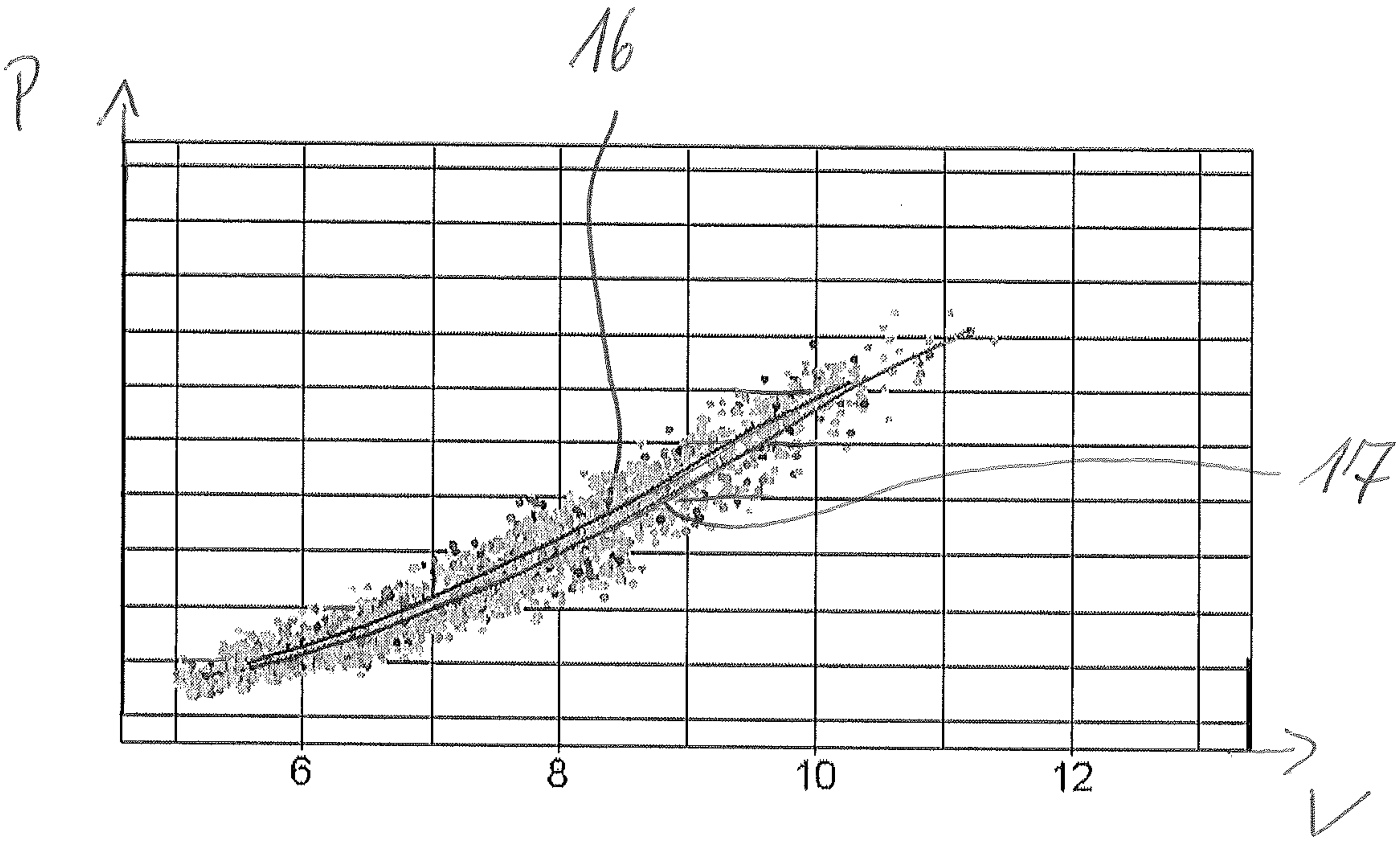

Fig. 2

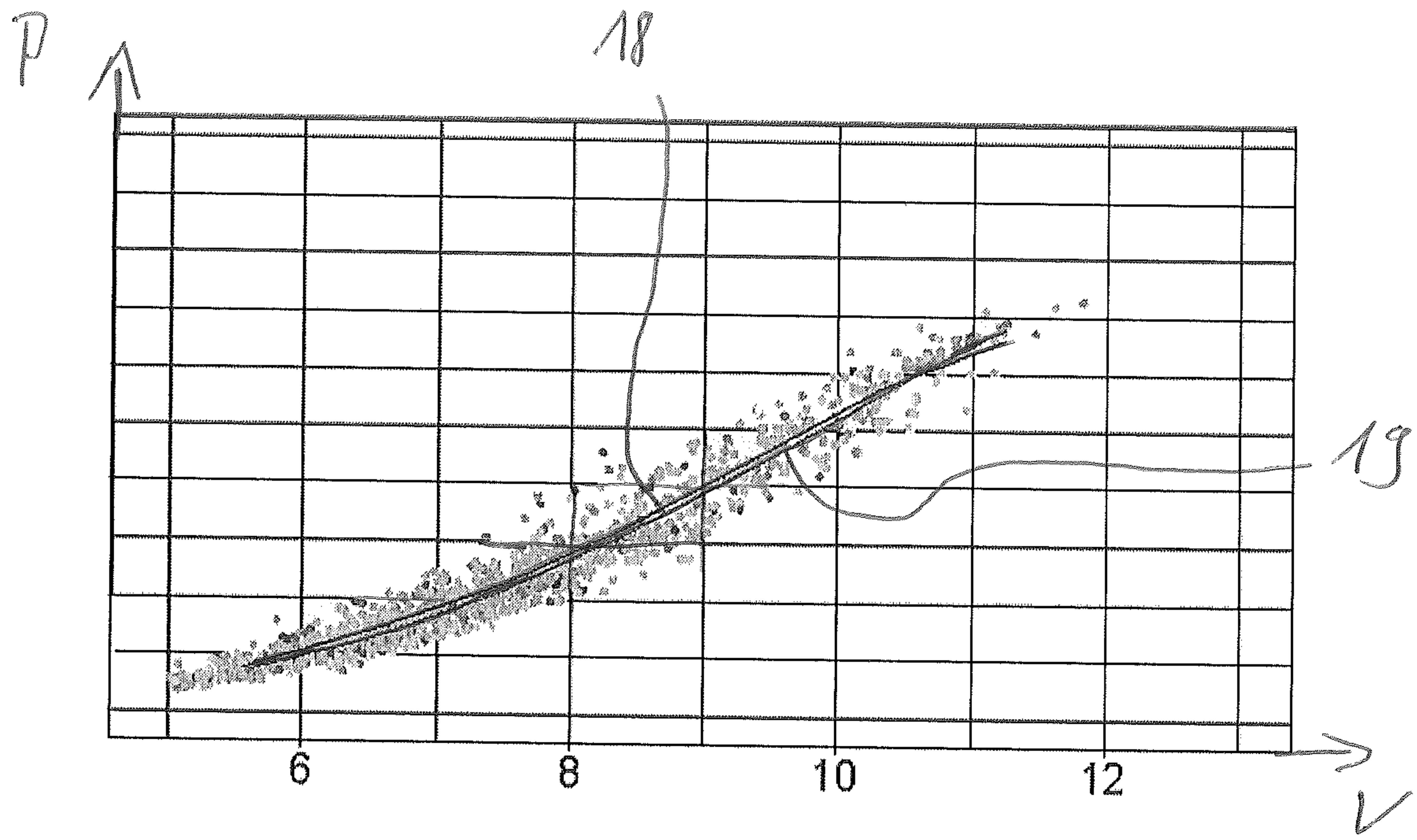

Fig. 3

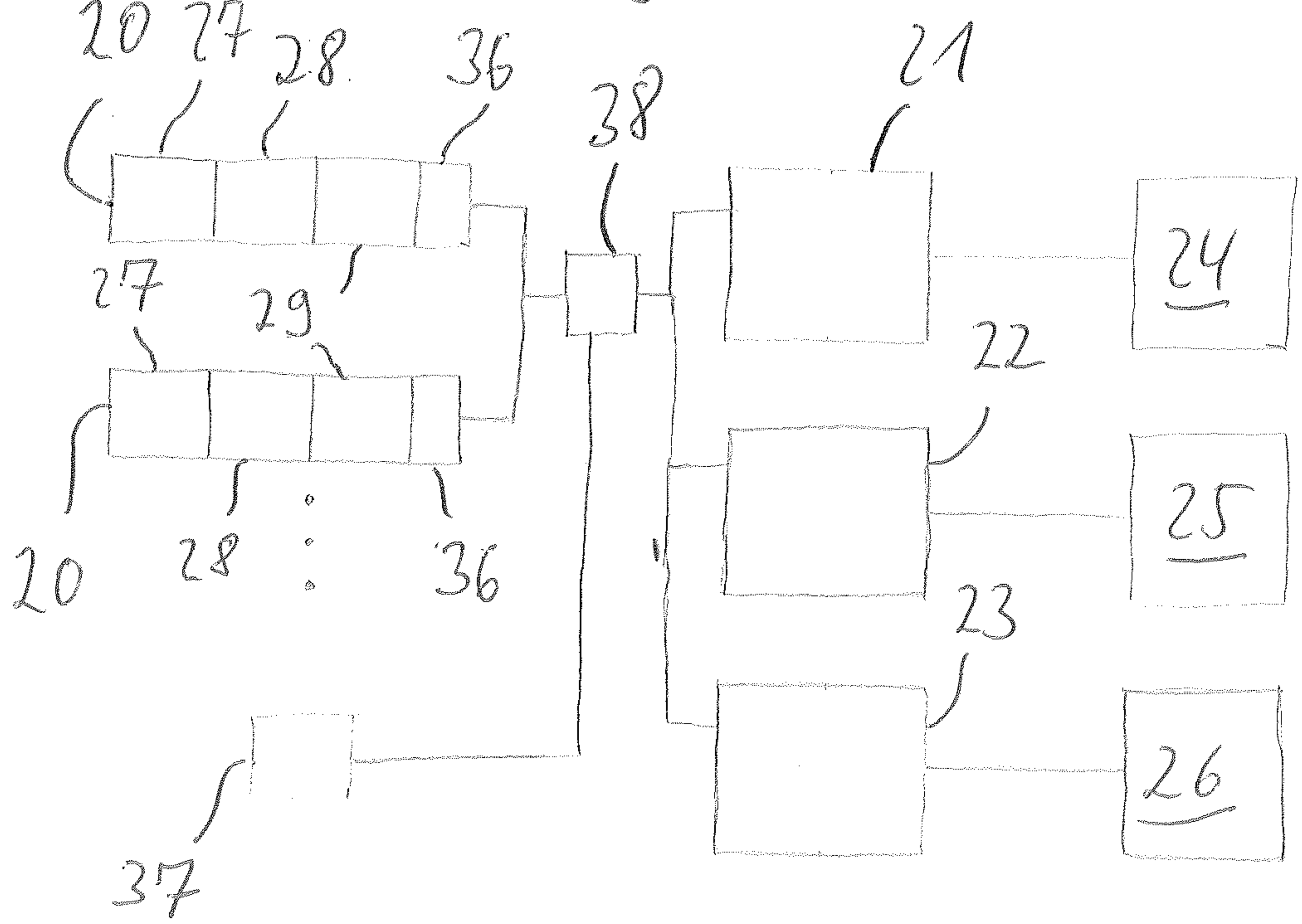

Fig. 4

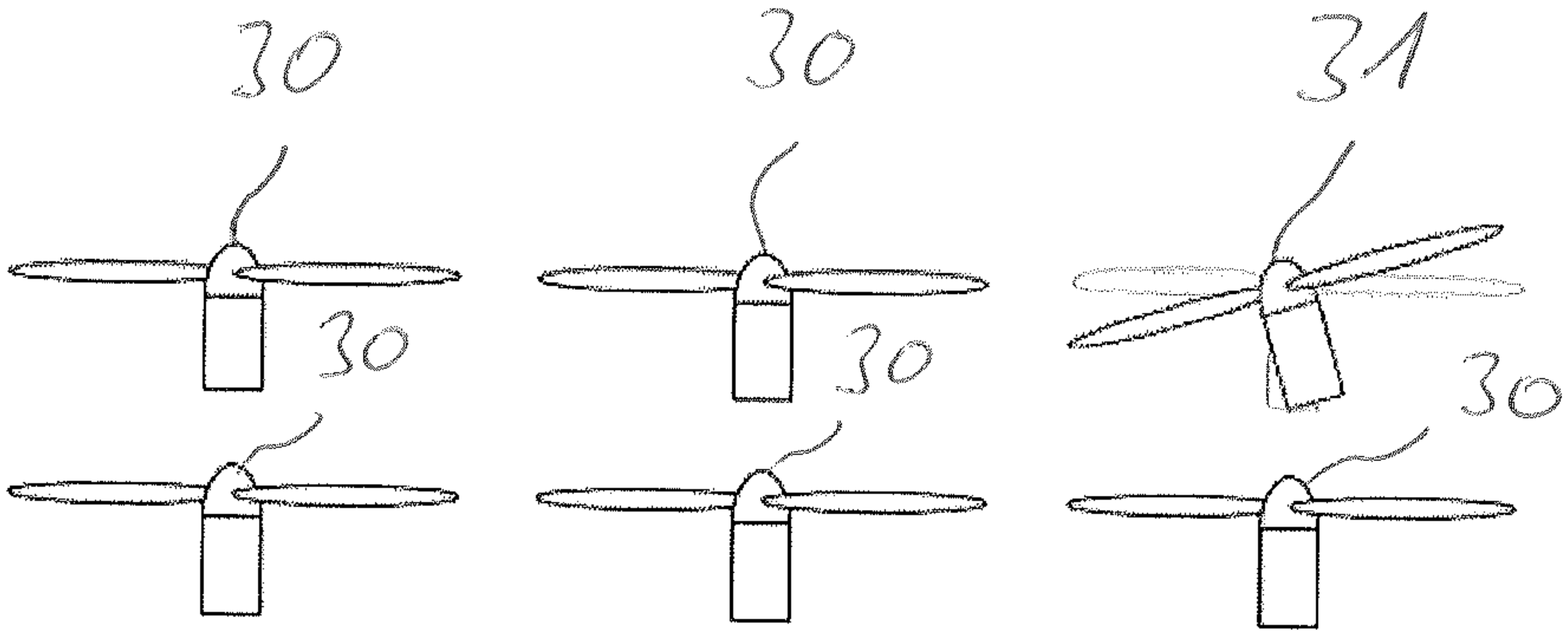

Fig. 5

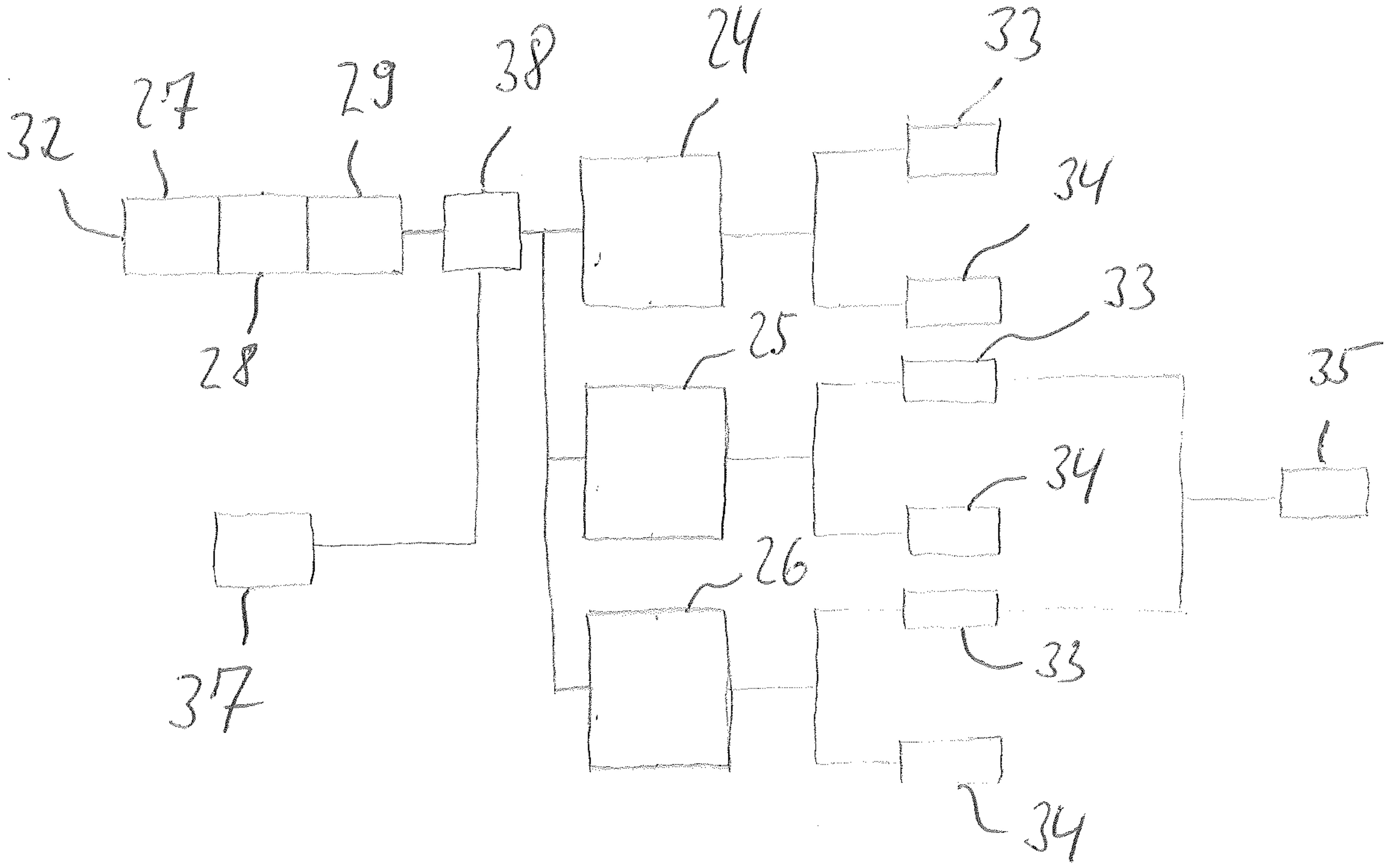

Fig. 6