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(54) **Title:** A METHOD TO COMPUTE CARGO SECURING FORCES

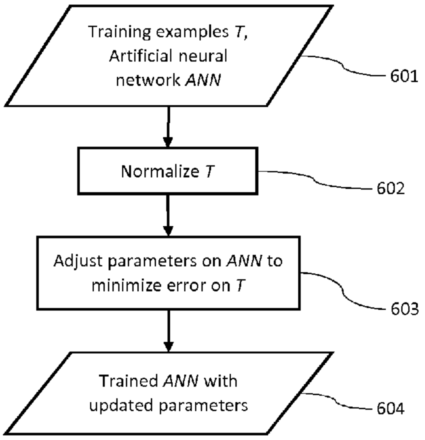


FIG. 6

(57) **Abstract:** The invention relates to method for computing cargo securing forces, the method comprising: Providing on a computer a set of training examples *T*; Fitting a model *M* using regression analysis to the set of training examples *T*; Using the model *M* to calculate the cargo securing forces and further implement correcting actions for the cargo to be secured.

A Method to Compute Cargo Securing Forces

Field of the invention

The present invention relates to securing transported cargo in general and to methods to compute forces in cargo securing equipment in particular.

Background of the invention

The purpose of cargo securing equipment such as straps, rods, locks, and dunnage is to ensure that cargo stays in place during transport. The acceleration forces acting on the cargo often expose securing equipment to high stress forces. These forces must be within the operational limits of the securing equipment.

Software tools to compute forces in securing equipment used for water, land, and air transportation (e.g., MACS3 by NAVIS, LOADSTAR by KOCKUMATION GROUP AB, VIDECK LASHING + SECURING by VIDECK, LASIPROFI by MT ONLINESHOPS GMBH, and AWBS by LOCKHEED MARTIN) usually solve mathematical equations representing mechanical models of the arrangements of cargo securing equipment.

A limitation of this method is that the time needed to compute forces in securing equipment often is long due to an increasing complexity of the equation systems that the method must solve. This negatively affects systems that depend on these calculations. As an example, software tools to support manual cargo stowage planning by a human operator may have to pause after each planning step to re-compute forces in securing equipment. This reduces their usability. More importantly, however, algorithms to automate stowage planning and optimize stowage arrangements may be unable to take forces in securing equipment into account. The reason is that such optimization algorithms usually have to search among hundreds of thousands of stowage arrangements to find candidates with high quality. This takes too long, if the algorithms must calculate forces in securing equipment for each stowage arrangement.

“Combining the dynamic relaxation method with artificial neural networks to enhance the simulation to tensegrity structures”, Domer, B., Fest, E., Lalit, V. and Smith, I.F.C Journal of Structural Engineering, Vol. 129, No. 5, 2003, pp 672-681, describes a dynamic relaxation method that is an iterative process which employs finite differences to converge to a static equilibrium position. This article considers another problem and does not inspire to applications in cargo securing systems. It proposes the use of a neural network (NN) as an intermediate error-correction step between structural analysis results using the dynamic relaxation method and the results used for the determination of control commands. The system trains the NN during service and quantify contributions to further increases in accuracy. Tensile forces in tensegrity structures are controlled by inner self-stress states. A self-stress state describes a state, where the structure is in equilibrium because of unilateral element forces. In the method described, NNs are applied in combination with dynamic relaxation to improve the accuracy of this method, not its computation time. The objective of the present invention is to apply regression analysis such as NNs to compute forces in cargo securing equipment in order to completely substitute alternative calculations with NNs to save computation time (i.e., several orders of magnitude speed-up) and not to increase the accuracy of these computations. The method actually trade some of the accuracy of the alternative calculations for faster computation time. It does not make sense to apply regression analysis such as NNs as corrective element in combination with basic computations to improve accuracy, since this would increase the computation time. The NN application does not substitute basic computations and hence does not inspire to how to reduce the computation time of such basic computations. The main challenge with tensegrity structures is that the shape of the structure changes under load. The main purpose of the dynamic relaxation method is to compute the final shape of the body and the forces in its cables and wires (equilibrium). The alternative calculations for forces in cargo securing equipment do not include an equilibrium computation. It is not a challenge to compute the final shape of a cargo securing system in order to determine whether the forces in it are acceptable. Models of cargo securing systems do not assume significant deformation. They are ordinary rigid structures that collapse under deformation. The challenge is that the maximum securing forces in a system is defined as the maximum forces in these systems under many load scenarios (like weather and vessel stability). For that reason, the subject of the article considers another problem and does not inspire to applications in cargo securing systems.

Since optimization of stowage arrangements whether manual or automated is key to maximize utilization of a transportation system, it is highly valuable to reduce the computation time of forces in securing equipment.

Object of the invention

The objective of the present invention is to reduce the computation time of forces in securing equipment.

Summary of the invention

According to the invention the objective may be achieved through a method for computing cargo securing forces that comprises

- Providing on a computer a set of training examples T
- Fitting a model M using regression analysis to the set of training examples T
- Using the model M to calculate the cargo securing forces
- Implementing correcting actions for the cargo to be secured

By applying regression analysis in order to learn these forces from training examples, the calculation time will be reduced significantly.

Since the trained regression analysis models usually are much simpler than the equation systems used in prior art to compute forces in securing equipment, they may substantially reduce the computation time of these forces.

In an embodiment, each training example in T is a pair (s,f) that maps a cargo securing state s to its associated securing force f.

In a further embodiment, the training example T is generated in accordance with the following process:

- Stack condition distribution *D* and Number of training examples *N*
- Initializing the training set *T* to an empty set
- Call loading computer to calculate lashing force *F* of state *s*
- Add training instance (*s*,*f*) to *T*
- Repeat the above until size of *T* equals *N*

In a still further embodiment, *M* is a nonlinear regression analysis model.

Hereby *M* may be an artificial neural network.

In an embodiment, such artificial neural network may be trained in accordance with the following process:

- Provide training examples *T* to Artificial Neural Network ANN
- Normalizing *T*
- Adjust parameters on ANN to minimize error on *T*
- Hereby providing a trained ANN with updated parameters.

In an embodiment, said cargo securing system is adapted for securing containers on ships that can carry containers.

In an embodiment, said cargo securing system is for securing stacks of containers on deck of cellular container vessels and, where the ANN consists of three layers of a number units of which the top layer consists of input units and the second and third layer consist of hidden units and where weight arcs fully connect the input units to the first layer of hidden units and the first layer of hidden units to the second layer of hidden units, where further, weight arcs fully connect the second layer of hidden units to a single output unit that expresses the lashing force of the stack, where a bias arc also connect into all hidden units and the output unit, where a weight and a bias arc are associated with a real number.

Hereby the hidden units and the output unit are associated with a threshold function, e.g. sigmoid, hyperbolic tangent, and rectifier functions.

Further, the input to the ANN are real numbers that after a transformation are assigned one-to-one to the input units of the ANN and hereby represent all the data for an arbitrary stack on deck that the ANN uses as input to compute the lashing force of the stack.

In an embodiment the first numbers define the containers stowed in a single stack that is maximum 11 tiers high (i.e., has 11 cells).

In an embodiment six numbers are used per cell of the stack to define: the height of a possible 20’ container in the aft part of the cell; the height of a possible 20’ container in fore part of the cell; the height of a possible 40’ or 45’ container in the cell; the weight of a possible 20’ container in the aft part of the cell, the weight of a possible 20’ container in the fore part of the cell, the weight of a 40’ or 45’ container in the cell.

In an embodiment the last eight input numbers define the position of the stack and vessel parameters that express the acceleration scenarios that the stack is exposed to, where the numbers may be: the transversal centre of gravity of the stack; the number of 45’ containers in the stack; the stability of the vessel given as metacentric height; the longitudinal centre of gravity of the stack; the sailing route of the vessel; whether the stack is outboard; whether the stack has external lashing rods on the left side, and whether the stack has external lashing rods on the left side.

The calculated cargo securing forces are as a final step used implementing correcting actions for the cargo to be secured where these correcting actions comprises one or more of the following: Rearranging the cargo items to be secured to satisfy the requirement of each securing force to be below a certain value or applying a force as determined to secure the cargo item to be secured.

Brief description of the drawings

The invention will be explained in further detail in the following description of an embodiment of the invention with reference to the drawings, in which:

Fig. 1	shows a side and top view of a cellular container vessel,
Fig. 2	shows an aft view of a container bay,
Fig. 3	shows a side view of a container bay,
Fig. 4	shows an artificial neural network,
Fig. 5	shows a flow diagram of training data generation,
Fig. 6	shows a flow diagram of artificial neural network training.

Detailed description of the invention

In this section, we describe an embodiment of the invention for computing forces in container securing equipment of cellular container vessels. In next section, we describe additional embodiments.

FIG. 1 illustrates a side 101 and top 102 view of a cellular container vessel. It has a number of bays 104. A lashing bridge 103 may separate two bays on deck. Normally, the on deck and below deck sections of a bay are separated by watertight hatch covers 105 that rest on the deck 106. On deck, a bay holds a number of container stacks. Each position in a stack is a cell. A cell can hold either one 40’ or 45’ container or two 20’ containers.

Containers are boxed formed metal structures with strong columns in the four corners that allow 10 of them or more to be stacked on top of each other. Most containers are 8’ wide and 8’6” (standard) or 9’6” (highcube) high. The dominating lengths are 20’, 40’ and 45’.

Containers may have integral refrigeration units (reefer containers) that require power from the vessel. Tank containers have tanks to carry fluids. Open top and flat rack containers are open in the top as well as the sides, respectively. These may carry oversized cargo (OOG containers). Containers of any type may hold dangerous goods (DG containers).

FIG. 2 illustrates an aft view of bay “A” shown in Fig 1, 104. Each container 201 has eight corner posts 202 of which four are visible in this view. Twist locks 203 hold the corner posts together and aligned. The lashing bridge 206 is a metal structure going across the vessel. Lashing rods 204 and 205 are strong metal bars that connect from the lashing bridge to the upper corner posts of containers. Together with the twist locks, they keep the stacks in place when the rolling of the vessel exposes them to acceleration forces. Outboard stacks are particularly exposed and may have extra lashing rods attached 205. The container stacks rest on sockets 207 that are attached to the hatch cover 208 or the deck 209.

FIG. 3 illustrates a side view of bay “A” shown in Fig. 1, 104. Notice that the aft lashing bridge 303 is two stack tiers high, while the fore lashing bridge is one tier high. This causes an asymmetric arrangement of lashing rods 306, 307, and 308. Fig. 3 shows the outboard stack of the bay that has vertical lashing rods 308 attached. It holds four 20’ containers 302 and three 40’ containers 301 that rest on the deck 305.

The maritime term for forces in securing equipment on deck of container vessels is lashing forces. Lashing forces appear in securing equipment like twist locks and lashing rods. They also appear in the on deck and container part of the securing equipment as for example racking and compression forces. All lashing forces must be within the operational limits of the equipment.

To be legal and insurable, a container vessel must be classified according to the regulations of a classification society like DNV GL and Lloyd’s Register. These regulations usually devise how to compute lashing forces and determine whether they are within limits. Typically the aft and fore parts of stacks are modelled mechanically as grids of springs and resistors and described by a large set of complex mathematical equations.

The various lashing forces can be determined from these equations and include pulling forces in lashing rods; pulling forces in twist locks; pulling, compression, and racking forces in containers; and pulling and compression forces in bottom sockets. The forces depend on the longitudinal, transversal, and vertical acceleration of the containers in the stacks, which in turn depend on rolling angle, position of the stack, vessel stability, wind exposure, and vessel speed. They also depend on the lashing arrangement and the weight, height, and type of the containers in the stacks.

A lashing force is usually expressed as a percentage of the operational limit of the securing equipment, it is associated with. Thus, a lashing force beyond 100% is breaking the limit of the equipment.

It may be necessary to compute all lashing forces for more than 20 different acceleration scenarios. This leads to substantial computation time to determine lashing forces even on modern computers.

The lashing forces associated with a single stack is usually expressed as a single number equal to the maximum of the forces in the stack. Thus, if the lashing force of a stack is more than 100%, the limit of some securing equipment in the stack for some acceleration scenario is broken.

The main idea of the invention is to use regression analysis to learn the forces in securing equipment from training examples. The embodiment of the invention for computing lashing forces in container stacks on cellular container vessels described in this section utilizes regression analysis based on artificial neural networks (ANNs). Other regression techniques, such as linear, polynomial, lasso, and logistic regression, multivariate regression, regression trees, support vector regression, and principal component analysis, are contemplated as a part of the present invention.

FIG. 4 illustrates an example of an ANN that 1) can be trained to learn lashing forces from training examples, and 2) after training can compute lashing forces faster than current methods based on solving equation systems. Other ANN designs and choices of input parameters may achieve similar results and are contemplated as a part of the present invention.

The ANN consists of three layers of 74 units of which the top layer consists of input units 401 and the second and third layer consist of hidden units 403. Weight arcs 402 fully connect the input units to the first layer of hidden units and the first layer of hidden units to the second layer of hidden units.

Moreover, weight arcs fully connect the second layer of hidden units to a single output unit 405 that expresses the lashing force of the stack. A bias arc 404 also connect into all hidden units and the output unit. A weight and a bias arc are associated with a real number. Let W and B represent the set of weights and biases in the network, respectively.

The hidden units and the output unit are associated with a threshold function. Popular threshold functions include sigmoid, hyperbolic tangent, and rectifier. The example ANN uses the rectifier threshold function (i.e., the hidden and output units are rectified linear units (ReLUs)).

The input to the ANN is 74 real numbers that after a transformation described below are assigned one-to-one to the 74 input units of the ANN. They represent all the data for an arbitrary stack on deck that the ANN uses as input to compute the lashing force of the stack.

The first 66 numbers define the containers stowed in a single stack that is maximum 11 tiers high (i.e., has 11 cells). Since it is usually not possible to stack containers higher than that, this stack can represent an arbitrary container stack.

Six numbers are used per cell of the stack to define: the height of a possible 20’ container in the aft part of the cell; the height of a possible 20’ container in fore part of the cell; the height of a possible 40’ or 45’ container in the cell; the weight of a possible 20’ container in the aft part of the cell, the weight of a possible 20’ container in the fore part of the cell, the weight of a 40’ or 45’ container in the cell. The height and weight can be given in meters and tons, respectively.

Zero can be used to denote that no container is stowed in the cell of that kind. Hence, if all six numbers associated with a cell are zero, it can denote that the cell is empty.

The last eight input numbers define the position of the stack and vessel parameters that express the acceleration scenarios that the stack is exposed to. The numbers are: the transversal centre of gravity of the stack; the number of 45’ containers in the stack; the stability of the vessel given as metacentric height; the longitudinal centre of gravity of the stack; the sailing route of the vessel; whether the stack is outboard; whether the stack has external lashing rods on the left side, and whether the stack has external lashing rods on the left side.

As for other applications of ANNs, the choice of input parameters, network design, and threshold function in the example ANN are refined continuously to improve results. For instance, an additional input parameter expressing the wind exposure of the stack gives more information about acceleration forces acting on the stack and may improve the accuracy of the lashing force computations carried out by the ANN.

Given an assignment to the 74 input units, the example ANN computes the lashing force through the following feedforward calculation:

$$u_j^k = f\left(b_j^k + \sum_{i \in L^{k-1}} w_{ij}^k u_i^{k-1}\right) \qquad \text{for all} \quad k \in \{1,2,3\}, j \in L^k,$$

where u_j^k is the real value associated with unit *j* in layer *k*, L^k is the set of units in layer *k*, b_j^k is the bias input to unit *j* of layer *k*, w_{ij}^k is the weight input to unit *j* of layer *k* from unit *i* of layer *k* -1, and *f*(*x*) is the rectifier function *max*(0,*x*).
The input units are at layer 0 and represented by u_j^0 for *j* ∈ {1,...,74}. The output unit expresses the lashing force of the stack. It is at layer 3 (i.e., L^3 = {1}) and represented by u_1^3.

Since the lashing force calculation carried out by the example ANN depends on the set of weights *W* and the set of biases *B* in the network, the lashing force output will only be sufficiently accurate for certain values of *W* and *B*.

The ANN learns these values of *W* and *B* from a set of training data. That is, from a set of examples of correct input / output values.

FIG. 5 shows a flow diagram of an example of a method to compute a set of training data. The input to the method 501 is

a) Stack condition distribution *D*: a probability distribution over stack conditions, where each stack state *s* that can be drawn from *D* is a set of input values to the ANN.
b) Number of training examples *N*: the size of the training set that we want the method to generate.

The method first initializes a training set *T* to the empty set 502. It then draws a stack state *s* according to the distribution *D* 503. The lashing force *f* of the stack state *s* can be found in different ways including: computing it from a mathematical equation system of the lashing arrangement e.g. by calling the lashing module the loading computer software; computing it using the formulas or software libraries provided by the classification societies; and measuring it from a real container vessel stowage condition that includes the stack state 504.

The resulting training example (*s*,*f*) is added to *T* 505.

The method keeps adding training examples to *T* in this way until the number training examples is equal to *N* 506. The output of the method is the final set *T* of training examples 507.

FIG. 6 shows a flow diagram of an example of a method to train the ANN using a set of training examples. The input to the method 601 is

a) Training examples *T*: a set of training examples for the ANN (e.g., computed by the method shown in FIG. 5).
b) Artificial neural network ANN: an ANN network structure (e.g., the example ANN described above).

The method first normalizes the training examples *T* 602. The normalization depends on the method applied to adjust the parameters (e.g., *W* and *B*) of the ANN. For an example (*s*,*f*) in *T*, one standard approach is to normalize an input element *x* in *s* to

$$z = \frac{x-\mu}{\sigma} ,$$

where μ is the average of the x-values in T and σ is their standard deviation. The output f can be normalized to

$$y = \frac{f}{100} .$$

The method then adjusts the parameters (e.g., W and B) in the ANN such that the total sum of error on the training examples between the lashing force computed by the ANN and the target lashing force in the training examples is minimized 603. There are multiple well-known standard approaches such as backpropagation that the method can apply to do this.

The output of the method is a trained ANN with the parameters (e.g. W and B) updated to the values with minimum error on the training examples 604.

The trained ANN can compute the lashing force of a given stack state using the feedforward calculation described above for the example ANN shown in FIG. 4.

The accuracy of the computation depends on the number of training examples N and their distribution D.

Additional embodiments

In the previous section, we described an embodiment of the present invention for computing forces in container securing equipment of cellular container vessels. In this section, we describe additional embodiments.

Regression analysis can be applied in other modes of transportation to learn forces in securing equipment to reduce their computation time. These additional embodiments of the present invention include air, land, and water transportation beyond container shipping on cellular container vessels.

These additional embodiments of the present invention may for example include the transportation vehicles, cargo types, securing equipment, and causes for securing forces mentioned below.

Transportation vehicles can for example include ro-ro vessels, general cargo vessels, barges, cars, trucks, trailers, railcars, airplanes, airships, and drones.

Cargo types can for example include containerized cargo (e.g., containers for air transportation and ISO containers on road trucks, ro-ro trailers, and rail carts) and non-containerized cargo (e.g., wood, timber, plates, coils, pipes, super bags, vehicles, machinery, break-bulk, and project cargo).

Securing equipment can for example include chains, robes, belts, tape, rods, locks, and dunnage.

The causes for forces in securing equipment can for example include weight, shape, type, and position of cargo; the type of equipment used to secure the cargo; the shape, speed, and stability of the vehicle transporting the cargo; and external factors such as turbulence, waves, wind speed, weather, and road/rail conditions.

PATENT CLAIMS

1. A method for computing cargo securing forces, the method comprising
    - Providing on a computer a set of training examples *T*
    - Fitting a model *M* using regression analysis to the set of training examples *T*
    - Using the model *M* to calculate the cargo securing forces
    - Implementing correcting actions for the cargo to be secured.

2. A method according to claim 1, where each training example in *T* is a pair (*s*,*f*) that maps a cargo securing state *s* to its associated securing force *f*.

3. A method according to claim 2, where the *T* is generated in accordance with the following process:
    - Providing stack condition distribution *D* and Number of training examples *N*
    - Initializing the training set *T* to an empty set
    - Call loading computer to calculate lashing force *F* of state *s*
    - Add training instance (*s*,*f*) to *T*
    - Repeat the above until size of T equals N

4. A method according to claim 1, 2 or 3, where *M* is a nonlinear regression analysis model.

5. A method according to claim 4, where *M* is an artificial neural network.

6. A method according to claim 5, where said artificial neural network is trained in accordance with the following process:
    - Provide training examples *T* to Artificial Neural Network ANN
    - Normalizing *T*
    - Adjust parameters on ANN to minimize error on *T*
    - Hereby providing a trained ANN with updated parameters.

7. A method according to any of the preceding claims, where said cargo securing system is for securing containers on ships that can carry containers.

8. A method according to claim 5 or 6, where said cargo securing system is for securing stacks of containers on deck of cellular container vessels and, where the ANN consists of three layers of a number units of which the top layer consists of input units and the second and third layer consist of hidden units and where weight arcs fully connect the input units to the first layer of hidden units and the first layer of hidden units to the second layer of hidden units, where further, weight arcs fully connect the second layer of hidden units to a single output unit that expresses the lashing force of the stack, where a bias arc also connect into all hidden units and the output unit, where a weight and a bias arc are associated with a real number.

9. A method according to claim 8, where the hidden units and the output unit are associated with a threshold function, e.g. sigmoid, hyperbolic tangent, and rectifier functions.

10. A method according to claim 8 or 9, where the input to the ANN are real numbers that after a transformation are assigned one-to-one to the input units of the ANN and hereby represent all the data for an arbitrary stack on deck that the ANN uses as input to compute the lashing force of the stack.

11. A method according to claim 8, 9 or 10, where the first numbers define the containers stowed in a single stack that is maximum 11 tiers high (i.e., has 11 cells).

12. A method according to claims 8-11, where six numbers are used per cell of the stack to define: the height of a possible 20’ container in the aft part of the cell; the height of a possible 20’ container in fore part of the cell; the height of a possible 40’ or 45’ container in the cell; the weight of a possible 20’ container in the aft part of the cell, the weight of a possible 20’ container in the fore part of the cell, the weight of a 40’ or 45’ container in the cell.

13. A method according to claim 8-12, where the last eight input numbers define the position of the stack and vessel parameters that express the acceleration scenarios that the stack is exposed to, where the numbers may be: the transversal centre of gravity of the stack; the number of 45’ containers in the stack; the stability of the vessel given as metacentric height; the longitudinal centre of gravity of the stack; the sailing route of the vessel; whether the stack is outboard; whether the stack has external lashing rods on the left side, and whether the stack has external lashing rods on the left side.

14. A method according to any of the preceding claims, where implementing correcting actions for the cargo to be secured comprises one or more of the following: Rearranging the cargo items to be secured to satisfy the requirement of each securing force to be below a certain value or applying a force as determined to secure the cargo item to be secured.

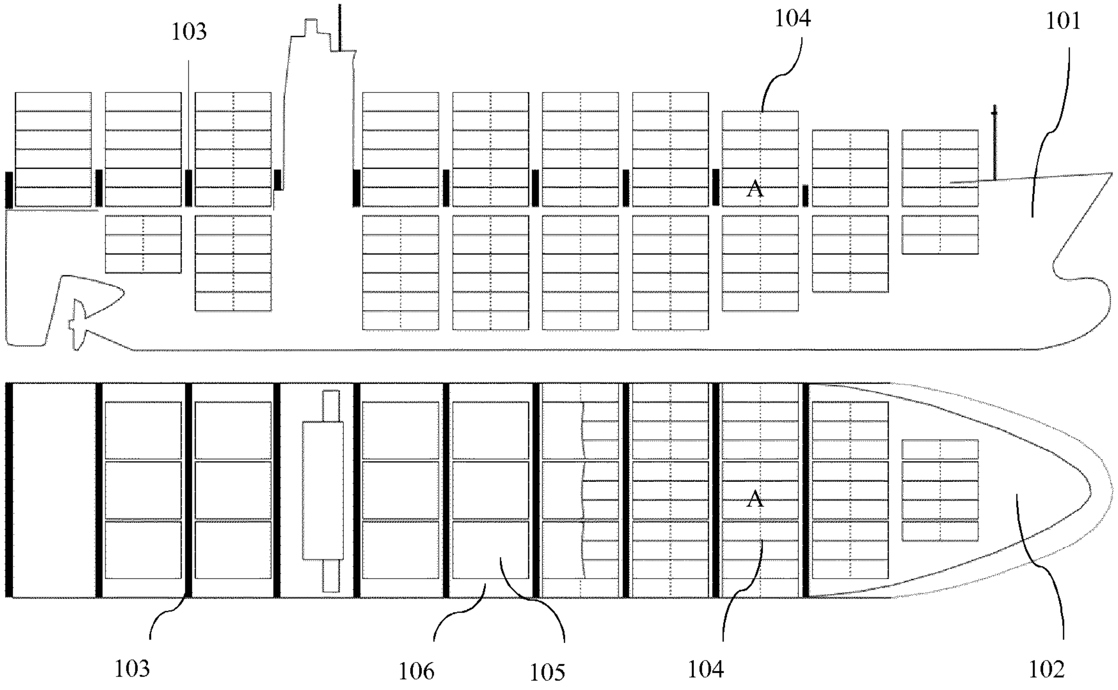
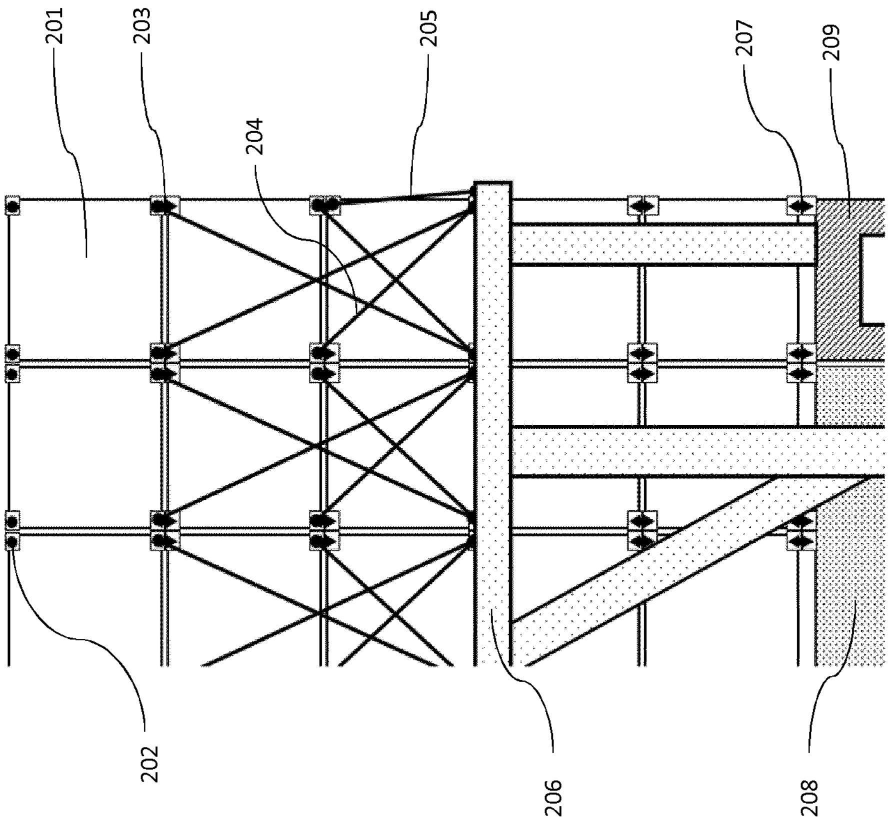


FIG. 1

FIG. 2



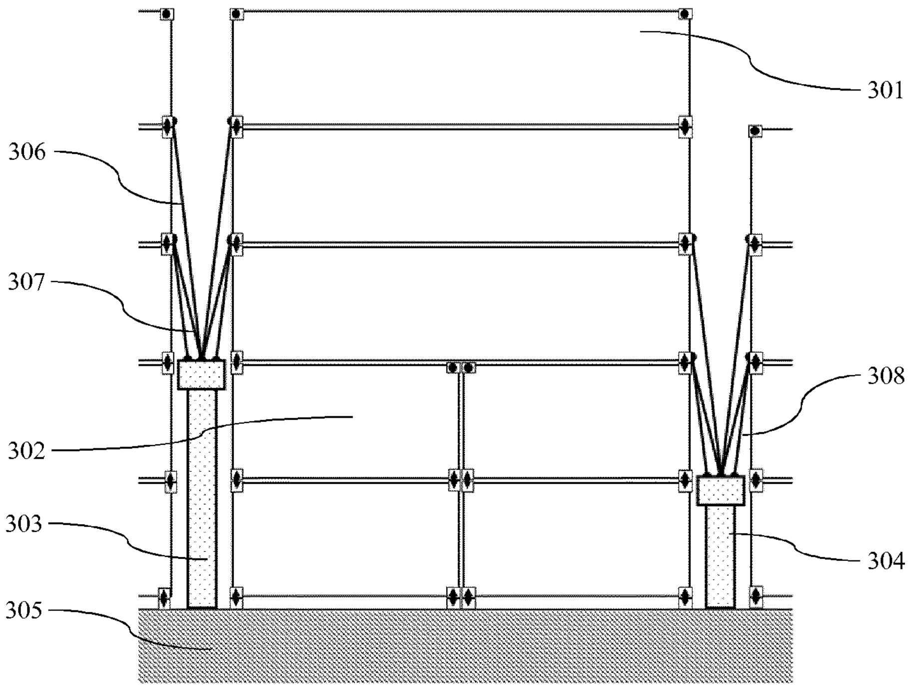


FIG. 3

FIG. 4

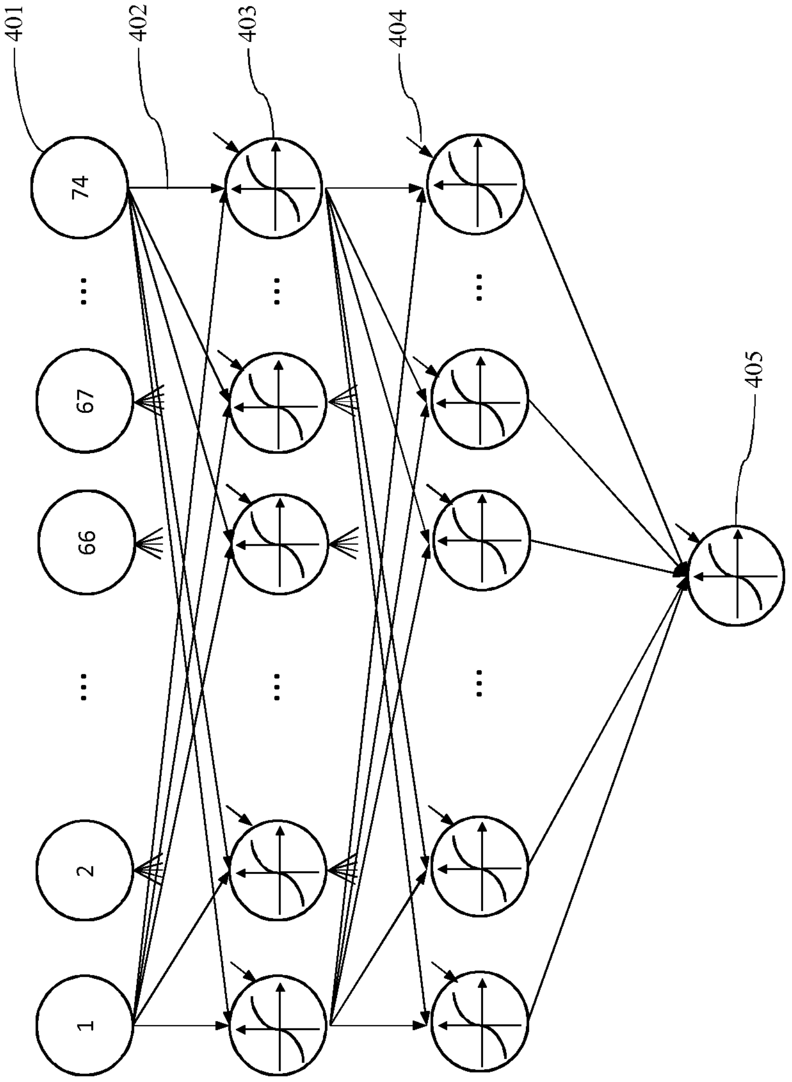
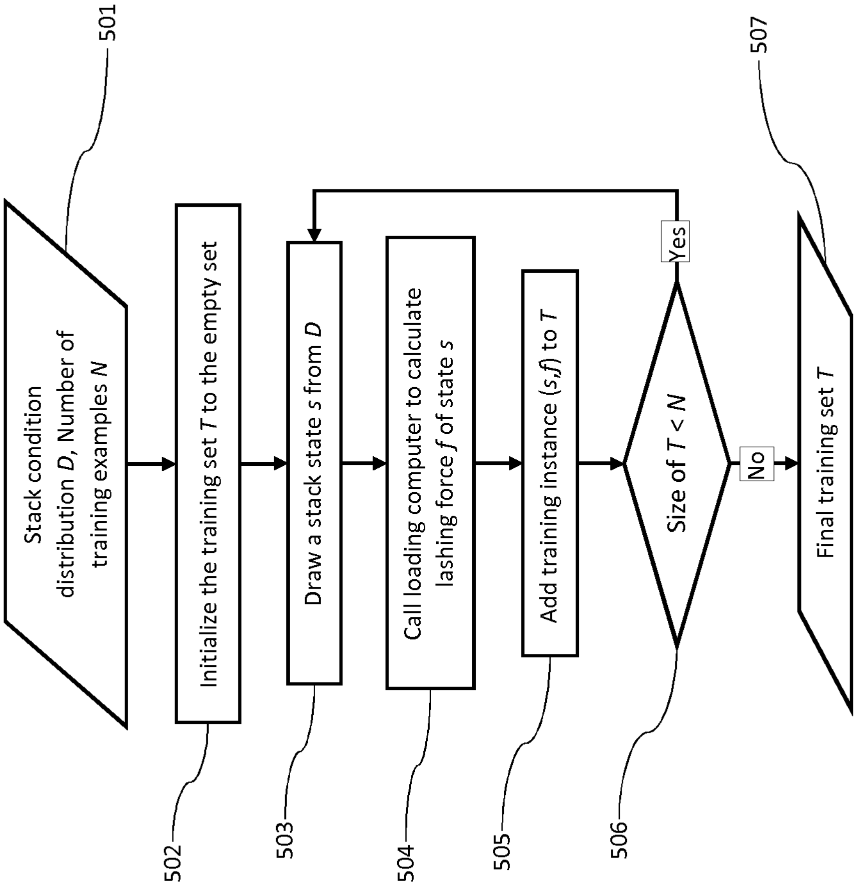


FIG. 5


501
Stack condition distribution *D*, Number of training examples *N*
502
Initialize the training set *T* to the empty set
503
Draw a stack state *s* from *D*
504
Call loading computer to calculate lashing force *f* of state *s*
505
Add training instance (*s*,*f*) to *T*
506
Size of *T* < *N*
Yes
No
507
Final training set *T*

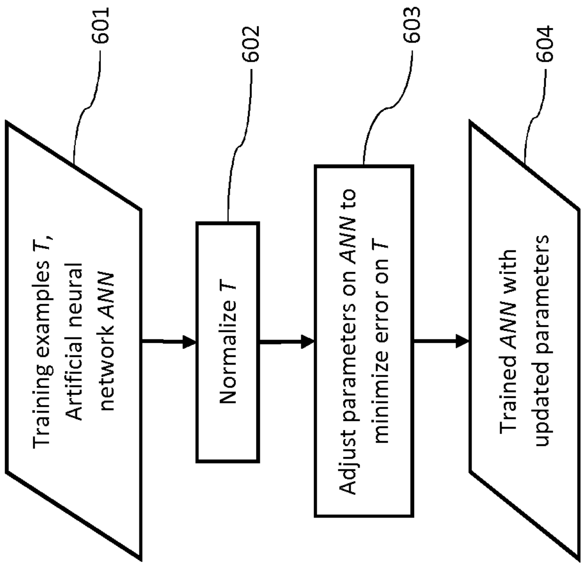

Training examples T, Artificial neural network ANN
601
Normalize T
602
Adjust parameters on ANN to minimize error on T
603
Trained ANN with updated parameters
604

FIG. 6

INTERNATIONAL SEARCH REPORT

International application No
PCT/EP2019/062210

A. CLASSIFICATION OF SUBJECT MATTER
INV. G06N3/02 G06Q10/08 G06N3/04 G06N3/08
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
G06N G06Q

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

EPO-Internal, WPI Data

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	Anonymous: "Artificial neural network - Wikipedia", , 10 May 2018 (2018-05-10), XP055608215, Retrieved from the Internet: URL:https://en.wikipedia.org/w/index.php?title=Artificial_neural_network&oldid=840504565 [retrieved on 2019-07-23] page 1 page 5 - page 9 -----	1-14
A	US 8 352 404 B2 (AP MOELLER MAERSK AS [DK]; GUILBERT NICOLAS [DK]; PAQUIN BENOIT [DK]) 8 January 2013 (2013-01-08) column 7, line 35 - column 8, line 38 ----- -/--	1-14

☒ Further documents are listed in the continuation of Box C. ☒ See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search 24 July 2019	Date of mailing of the international search report 02/08/2019
Name and mailing address of the ISA/ European Patent Office, P.B. 5818 Patentlaan 2 NL - 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016	Authorized officer Bohn, Patrice

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INTERNATIONAL SEARCH REPORT

International application No
PCT/EP2019/062210

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	GB 1 249 820 A (AMERICAN EXP ISBRANDTSEN LINES [US]) 13 October 1971 (1971-10-13) column 1, line 11 - column 2, line 91 -----	1-14
A	GUNNU G R ET AL: "An assessment of anchor handling vessel stability during anchor handling operations using the method of artificial neural networks", OCEAN ENGINEERING, vol. 140, 31 May 2017 (2017-05-31), pages 292-308, XP085114086, ISSN: 0029-8018, DOI: 10.1016/J.OCEANENG.2017.05.030 abstract page 4 - page 7 -----	1-14

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INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No

PCT/EP2019/062210

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		US 2010145501 A1	10-06-2010
		WO 2008040351 A1	10-04-2008
GB 1249820 A	13-10-1971	DE 1930133 A1	12-03-1970
		ES 368298 A1	01-05-1971
		FR 2010907 A1	20-02-1970
		GB 1249820 A	13-10-1971
		NL 6909045 A	16-12-1969
		US 3481298 A	02-12-1969