Neural-network-based prediction of mooring forces in floating production storage and offloading systems

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Marcelo Godoy Simoes
Colorado School of Mines

H. M. Morishita
University of São Paulo

Neural-Network-Based Prediction of Mooring Forces in Floating Production Storage and Offloading Systems

Marcelo Godoy Simões, *Senior Member, IEEE*, Jhonny Leonidas Merma Tiquilloca, *Member, IEEE*, and Hélio Mitio Morishita

***Abstract*—This paper describes the development of a neural-network-based prediction of mooring forces of a deep-sea oil exploitation production process. The evolvement of a neural network simulator for analysis of the dynamic behavior of a system consisting of a turret-floating production storage and offloading (FPSO) system and a shuttle ship in tandem configuration is described. The turret-FPSO is a vessel with a cylindrical anchoring system fixed to the sea bed my mooring lines and a shuttle ship is connected during the oil transference. This system has quite complex dynamics owing to interactions of the forces and moments due to current, wind, and waves. In general, the mathematical model that represents the dynamics of these connected floating units involves a set of nonlinear equations requiring several parameters difficult to be obtained. In order to deal with such complexities, a neural network has been devised to simulate an FPSO tandem system. This approach opens new horizons for maintenance of mooring lines, preventing collisions of the ships.**

***Index Terms*—Neural networks, offshore simulation, oil exploitation.**

I. Introduction

SEVERAL countries have been investing in finding oil fields in offshore deep and ultradeep sea waters. A very attractive solution for the exploitation of such basins is the floating production storage and offloading (FPSO) system. This is a conventional tanker adapted to operate temporarily as a platform to receive and store oil collected from the reservoir. The vessel requires a station-keeping device to withstand environmental forces. A suitable solution is an anchoring system in which the vessel is free to rotate about a huge cylindrical structure (turret) installed at the longitudinal center line of the ship. Mooring lines connect the turret to anchors on the seabed. The cargo of the FPSO system is transferred periodically to a shuttle vessel, which takes the oil to onshore installations. During such offloading operation, both ships are connected to each other through a hawser, in tandem configuration, as depicted in Fig. 1.

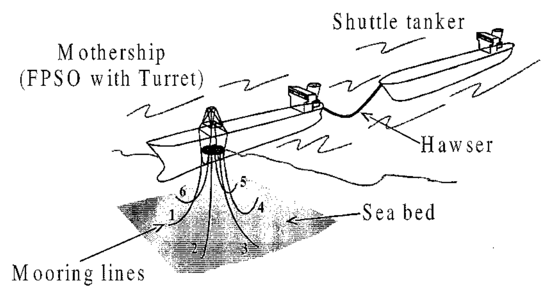

Fig. 1. Floating production storage and offloading system.

The study of the dynamics of this system under action of current, wind, and waves is of primary concern, because the environment imposes motions on ships, stressing the mooring lines and the hawser.

The main purpose of this paper is the prevention of collision by monitoring the forces in order to take proper countermeasures. However, analysis of the dynamic behavior of the turret-FPSO system with shuttle vessel in tandem configuration is quite intricate since it depends on the relative magnitude and direction of the wind, current, and waves as well as the displacement of the ships. Moreover, the complexity of the mathematical model precludes an easy understanding of the problem.

Modeling external forces and moments involves nonlinear equations and their parameters usually require test beds to determine scaled parameters. In addition, a computer program that simulates the dynamics of an FPSO tandem system is usually time consuming, since it demands a huge amount of numerical calculation in order to try to represent the actual system dynamic behavior. Therefore, a neural network was selected to get a reasonable model of the system, performing a faster simulation than the conventional use of test beds and scaled models. This paper opens new horizons for maintenance of FPSO systems. Those oil exploitation systems are well instrumented and historical data from ship state variables, heading, position, speed and yaw rate and mooring cable forces are usually available, facilitating the training of neural networks in the field.

II. Modeling FPSO Systems

The development of the present neural network simulator for an FPSO tandem system is based on the mathematical knowledge of the system. Three orthogonal coordinate reference systems are used to describe the system dynamics [1] as shown in Fig. 2. Three-dimensional reference frames are defined for the

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M. G. Simões is with the Engineering Division, Colorado School of Mines, Golden, CO 80401-1887 USA (e-mail: m.g.simoes@ieee.org).

J. L. M. Tiquilloca and H. M. Morishita are with the University of São Paulo/EPUSP, 05508-900 São Paulo, Brazil.

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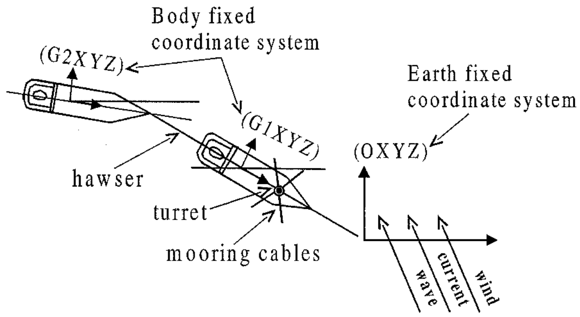

Fig. 2. FPSO tandem system coordinate system geometry.

problem; the first one, $OXYZ$, is earth fixed (also called by inertial frame); the other two, $G1XYZ$ and $G2XYZ$ (also called by local frames), are body fixed in the center of gravity of the FPSO system and shuttle vessel. The axes of each body-fixed coordinate system coincide with the principal axes of inertia of the vessel.

The ship has motions with six degrees of freedom. Ship motions in the horizontal plane (surge, sway, and yaw) have dynamics resulting from the combination of high-frequency and low-frequency terms. The former is due to the action of the first-order wave; motions in the heave, yaw, and row directions have only high-frequency terms. The latter results from the forces and moment due to current, wind, and second-order waves forces. The vertical component along the GZ axis can be decoupled for low-frequency analysis due to the extremely slow time constants, thus, all analyses can proceed on a two-dimensional basis by time window analysis of sliced XY planes, adding the first-order terms for pitch, heave, and roll. Under such considerations, the motions of each vessel including added mass forces are given by [2], [3]

$$(m-m_{11})\dot{u} = (m-m_{22})vr - (mx_g - m_{26})\dot{r}^2 - (m_{11}-m_{12})v_c r + X \quad (1)$$

$$(m-m_{22})\dot{v} = (m_{11}-m)ur - (mx_g - m_{26})\dot{r} - (m_{11}-m_{12})u_c r + Y \quad (2)$$

$$(I_z - m_{66})\dot{r} = -(mx_g - m_{26})(\dot{v} + ru) + N \quad (3)$$

where m is the mass of the vessel; $m_{i,j}$, $i, j = 1, 2, 6$ are the added mass in surge, sway, and yaw, respectively; u and v are the surge and sway velocities of the vessel; u_c and v_c are current speeds related to GX and GY directions; r is the yaw rate; I_z is the moment of inertia about the GZ axis; X, Y and N represent the total external forces and moments in surge, sway, and yaw directions due to current, wind, second-order wave term, wave drift damping, cross flow, hawser, and mooring lines; x_g is the coordinate of the vessel's center of gravity along the GX axis; and the dot means time derivative of the variable. The position and heading of each vessel related to the earth-fixed reference frame are obtained from the following equations:

$$\dot{x}_0 = u\cos(\psi) - v\sin(\psi) \quad (4)$$

$$\dot{y}_0 = u\sin(\psi) + v\cos(\psi) \quad (5)$$

$$\dot{\psi} = r \quad (6)$$

where $\dot{x}_0$ and $\dot{y}_0$ are the components of the vessel's speed in the OX and OY axes, and ψ is the vessel heading. The components u_c and v_c of the current are calculated as

$$u_c = V_c\cos(\psi_c - \psi) \quad (7)$$

$$v_c = V_c\sin(\psi_c - \psi) \quad (8)$$

where V_c and ψ_c are the velocity and direction of the current.

To complete the model, high-frequency terms need to be added to the position determined by (4)–(6) related to the effects of heave, pitch, and roll as well. The high-frequency terms can be obtained from convolution of the response amplitude operator (RAO) of the vessel and wave spectrum [1], but it is not considered in this neural network approach.

Several difficulties arise in parameterizing the above differential equations due the need of a test-bed scale model, frequency representation of statistical variables, and variation of parameters [4], [5]. The usual approach in dealing with the mooring line force is by considering an isolated line defined by a catenary equation [6]. Some commercial software like Visual-OrcaFlex use finite-element analysis (FEA) for designing flexible risers and mooring systems. However, an integrated approach of an FPSO tandem system under an FEA methodology of an FPSO tandem system has not yet been reported, because it demands huge computational time. These issues motivated the development of the proposed work in this paper. A neural network was selected for modeling, aiming to decrease the development time and integration to actual measurements. In this simulation-based research, a scaled simulator model called DYNASIM [7] was used to provide ship state variables and to verify the performance of the modeling strategy for a future integration with real measurements.

III. Neural-Network-Based FPSO System Modeling

Applications of neural networks for several engineering problems have flourished in the past few years, due to their capabilities of learning nonlinear input/output mapping [8], [9]. Although there are hundreds of neural network paradigms, the multilayer-perceptron (MLP) trained by backpropagation algorithm reigns in more than 90% of neural network solutions [9]. An FPSO system is very complex, the nonlinear dynamic equations are hard to compute and, therefore, a neural network approach was demonstrated to be a good solution for this kind of problem as already shown in previous complex industrial problems [9]–[12].

It is of paramount importance to emphasize how the physical modeling helped to formulate the neural network topology, instead of just looking at the problem under a black-box focus. It is indeed possible to correctly build up small network units, corresponding to the differential and algebraic equations of the forces and accelerations involved; temporal responses are embedded by time delays, formulating a structured neural network mirroring the physical understanding.

The neural network simulator is designed under the assumption that, as measurements of ship states like heading, position, speed, and yaw rate are undertaken by various navigation devices like gyrocompass, rate-gyro, and global-positioning

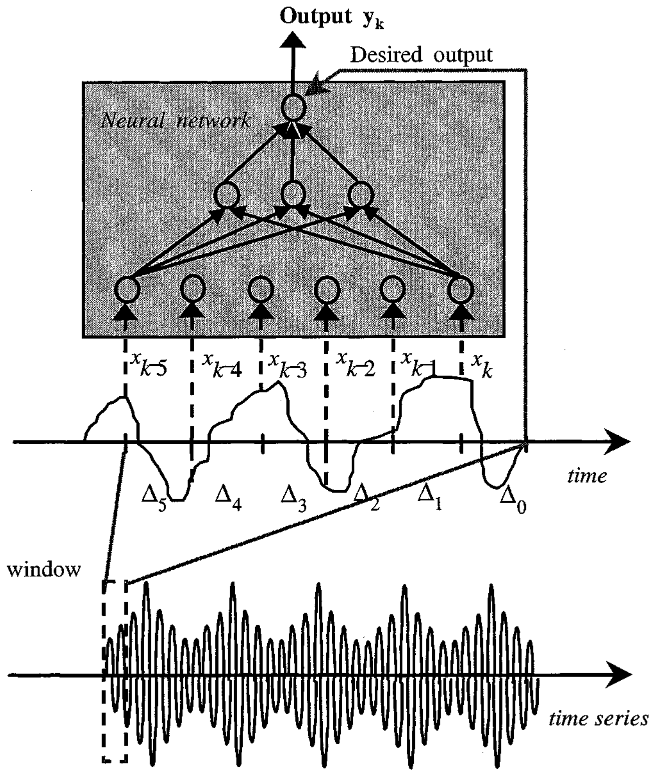

Fig. 3. Time-series-based input-lagged neural network estimator.

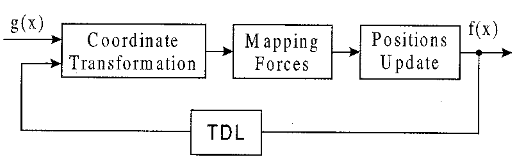

Fig. 4. Step-by-step time series neural network estimation.

system, mooring cables forces can also be measured in the field for performance evaluation. This paper investigates two neural network solutions which were integrated into an FPSO tandem system modeling: 1) time-series approach and 2) a structured neural network defined based on the knowledge of the topology of a set of differential equations.

A. Calculation of Vessels Positions With a Time-Series Neural Network

Fig. 3 portrays a typical time-series neural network where the input data are shifted like a transversal filter [13]; every sampling time, a new sample is introduced in the input layer so as to predict the new output. Fig. 4 shows the approach used to predict position of the vessels, i.e., kinematic data were fed to the time-series neural network to generate the vessel positions, which were then used to map the forces. In order to get a time series of linear and angular positions and forces in the anchoring lines, data for training were obtained running DYNASIM [7], a scaled simulator developed in the Naval Architecture and Ocean Engineering Department, University of São Paulo, São Paulo, Brazil. The variables were scaled and fed to the neural network in per-unit for training and then denormalized for testing. The

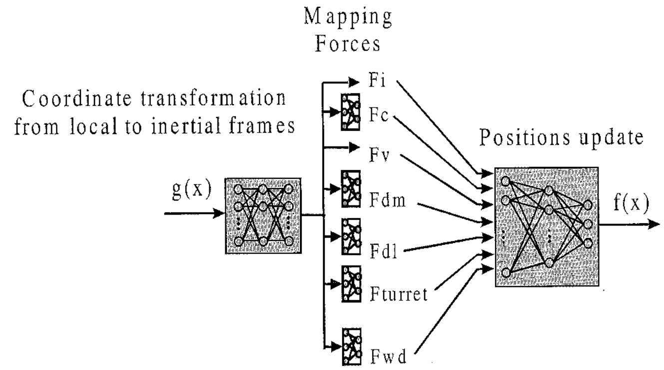

Fig. 5. Building block for structured neural network.

time-series neural network calculates through the following data input and output requirements:

$$\textbf{Input:}\quad g(x) = [f(x + \Delta t),\, C] \tag{9}$$

where C is environmental conditions, i.e., wind, waves, and current are lumped in the external forces X, Y, and N of equations (1)–(3) and $f(x + \Delta t)$ are time-delayed vessel displacements

$$\textbf{Output:}\quad f(x) = (x_1, x_2, \ldots, x_6) \tag{10}$$

where $f(x)$ are vessel displacements.

The time-series neural network was developed to replace the parameterized scaled simulator model, enabling an inner model reference capable of being trained in the field by real data. Such model reference integrates the vessel displacements in a step-by-step simulation fashion, as indicated in Fig. 4. In addition, a time-series network is capable of providing the dynamics to the system, i.e., delayed kinematics perform the required dynamics and the forces computations only use algebraic calculations. Therefore, such reference model permitted the development of small network units, corresponding to the structure of the physical modeling, i.e., the design of the structured neural network discussed next.

B. Computation of Forces With a Structured Neural Network

A structured neural network is defined by considering the overall dynamical modeling, i.e., the knowledge of the system physics guides the connection of several blocks that map forces to the environment input variables. For example, the trigonometric relation of body-fixed frames (local) to earth-fixed (inertial) frames were embedded in a neural network unit that performed such conversion, indicated in Fig. 5, developing the data for calculation of the forces that interact with the ships.

A hybrid modeling [13] is used because the linear forces ($\mathbf{F_i}$ inertial and $\mathbf{F_v}$ wind force), are computed from algebraic multiplications, and the nonlinear forces ($\mathbf{F_o}$ wave, $\mathbf{F_{dl}}$ slow sway force, $\mathbf{F_{dm}}$ average sway force, $\boldsymbol{F_{turret}}$ turret force $\mathbf{F_{wd}}$ damping force) are derived from neural network blocks. Fig. 5 shows the forces computations for one vessel. It is incorporated in Fig. 6, which displays a complete system identification neural network configuration, combining the interaction of the two ships (FPSO system and shuttle) [14].

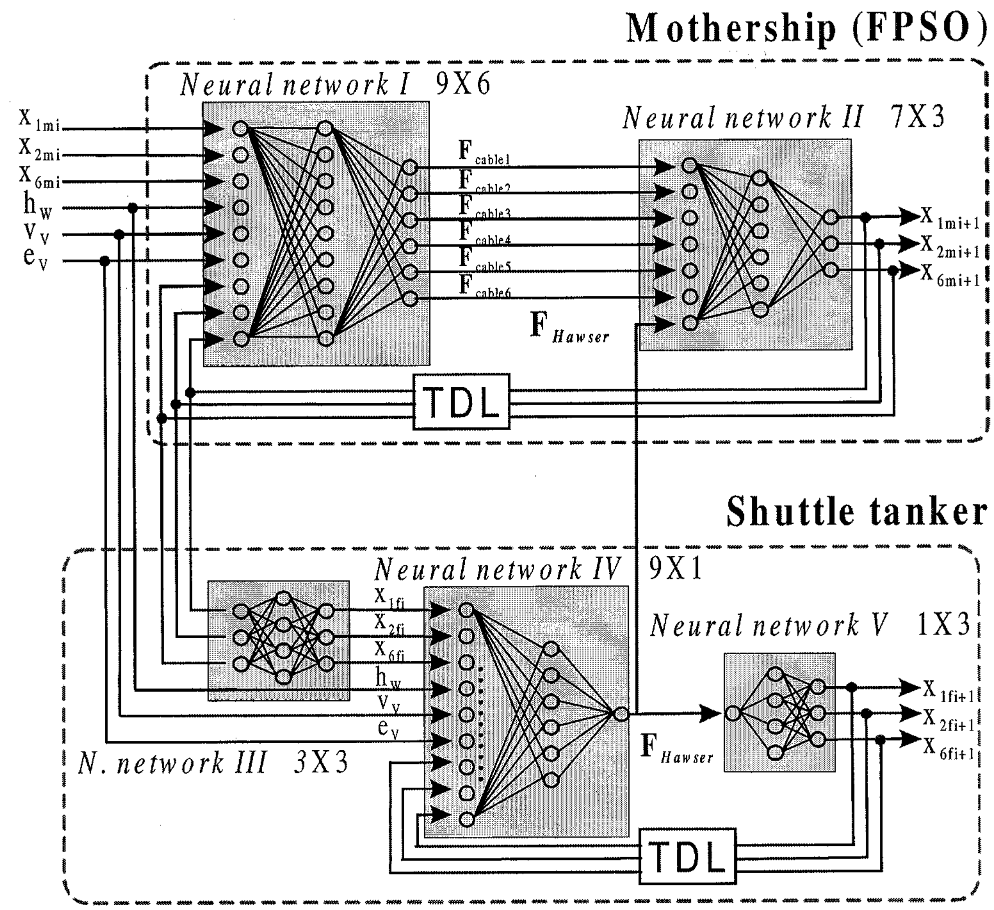

Fig. 6. Full-fledged neural network FPSO system–shuttle model.

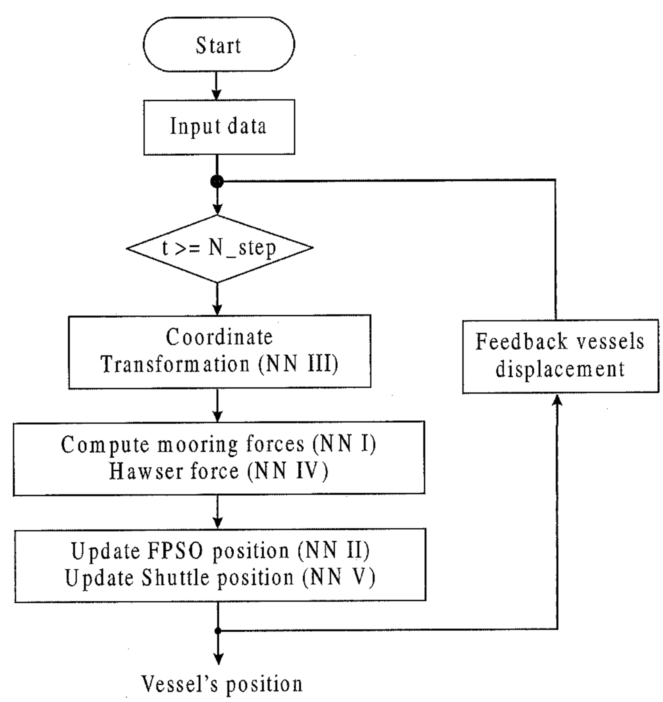

Fig. 7. Simulation flowchart.

TABLE I
FPSO SYSTEM AND SHUTTLE DIMENSIONS

FPSO	
Lenght	L=320 m
Draught	C=7 m
Beam	B=54 m
Depth	P=27 m
Turret with 6 mooring lines	
Shuttle	
Lenght	L=250 m
Draught	C=11.8 m
Beam	B=39.4 m
Depth	P=22.5 m

Fig. 6 is considered a full-fledged simulator because it has all the physical variables interconnected through several structured neural network blocks. FPSO system modeling is consolidated with *neural network I* (NN I) and *neural network II* (NN II). NN I computes forces on the six mooring cables connected to the turret. NN II produces the FPSO system displacement by receiving the six mooring cable forces plus the hawser cable computed from NN IV. The FPSO system acquires the input data $g(x)$, environment conditions and initial movements of the ship by the *neural network I*, delivering at the output the forces on the mooring cable (turret). The estimated forces, coming

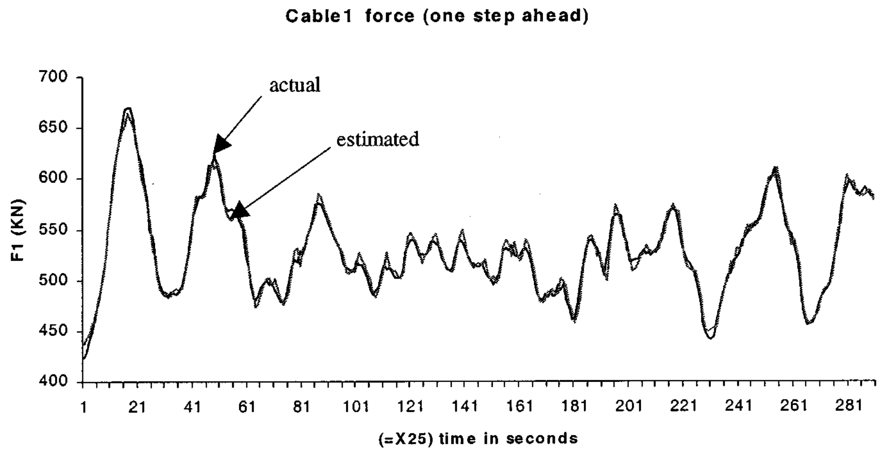

Fig. 8. Mooring cable estimation by time series neural network (one step ahead).

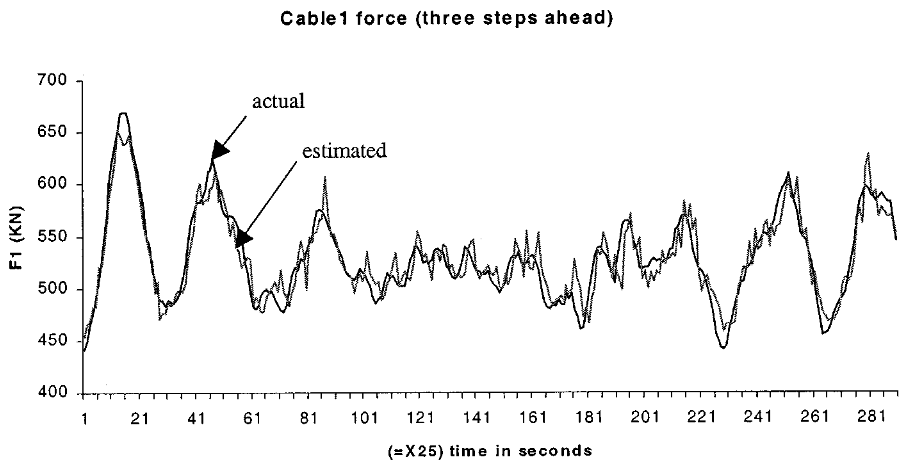

Fig. 9. Mooring cable estimation by time series neural network (three steps ahead).

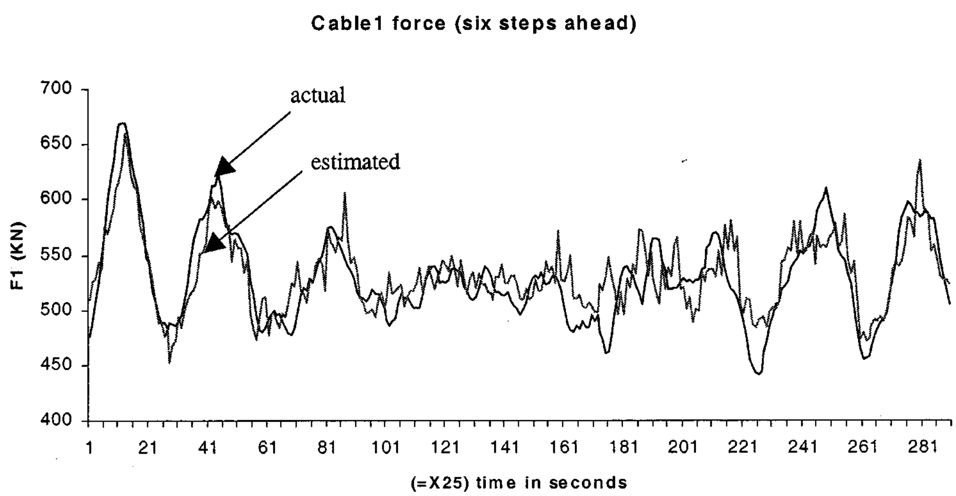

Fig. 10. Mooring cable estimation by time series neural network (six steps ahead).

from neural network I update the new ship position, which just considered the cables forces on the hawser with *neural network II*. Thereafter, the new movement is delayed and fed back to the *neural network I*. There is an interdependence from the movement of the FPSO coordinates system to the shuttle tanker (body-fixed frames $G1XYZ$ and $G2XYZ$) considered by NN III. The *neural network IV* computes the force on the hawser and eventually the neural network V calculates the displacements of the shuttle tanker.

The training algorithm for each of these neural networks was a standard backpropagation. Each neural network of Fig. 6 was trained separately by data conveniently batched from

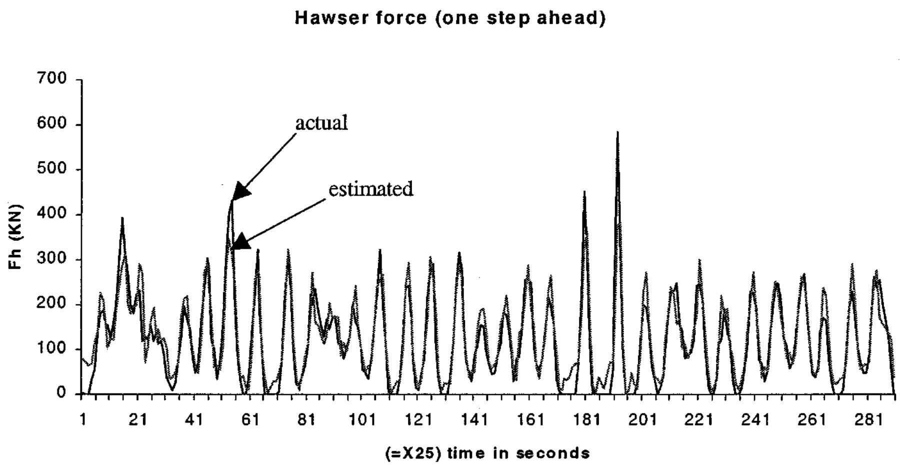

Fig. 11. Hawser forces estimation (one step ahead).

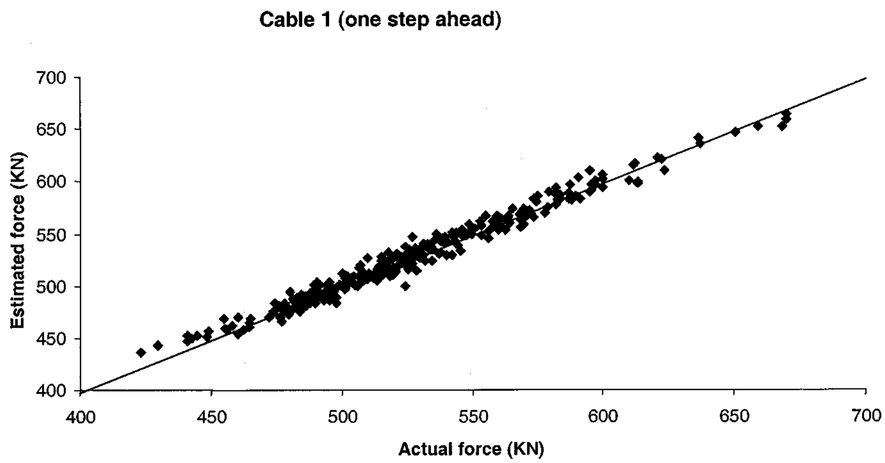

Fig. 12. Scattering diagram showing the mooring cable dispersion estimation.

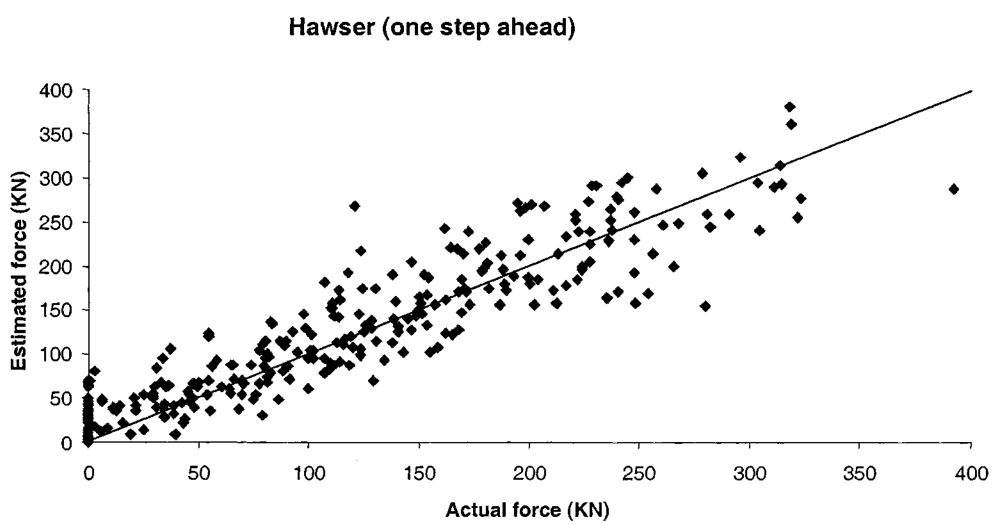

Fig. 13. Scattering diagram showing the hawser dispersion estimation.

DYNASIM. One important reason to have a structured neural network, formed on the basis of physical modeling, is the grouping of meaningful data for training inner networks. The simulator was implemented in C++ due to the flexibility of the target operating system implementation and to the function overloading possibilities, i.e., allowing functions that perform similar tasks operating with different data types of objects; in addition, C++ provides encapsulation, inheritance, and dynamic run-time binding, allowing reusable code. Fig. 7 depicts the system simulation flowchart where the calculation runs up

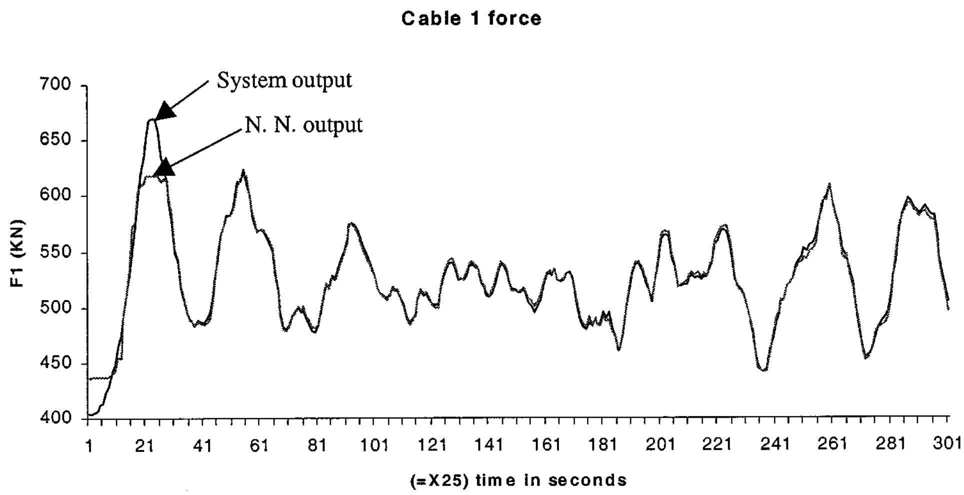

Fig. 14. Force estimation for mooring cable #1.

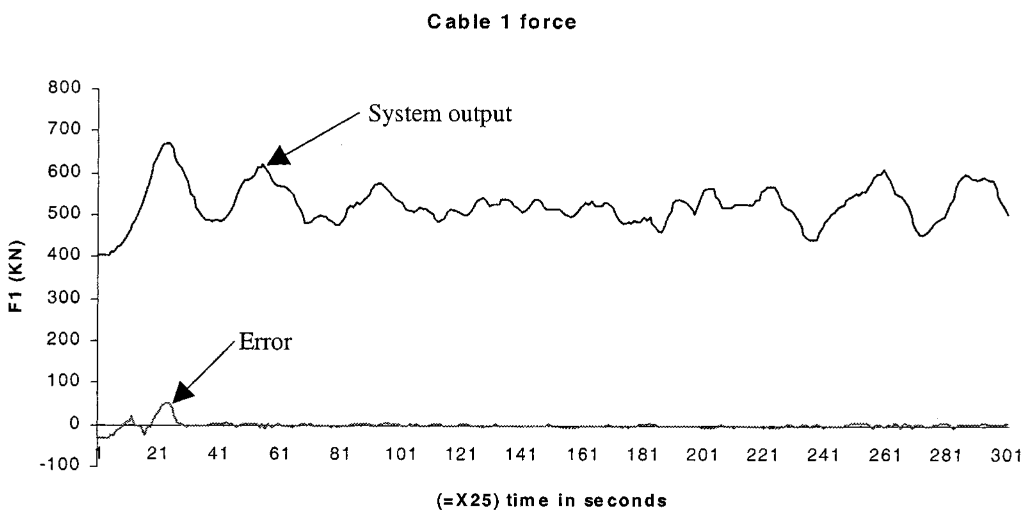

Fig. 15. Estimation convergence for mooring cable #1.

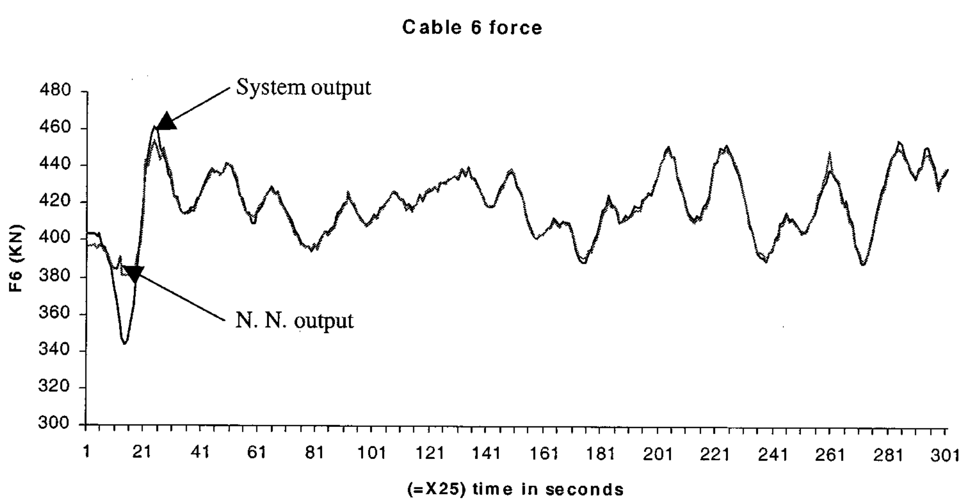

Fig. 16. Force estimation for mooring cable #6.

to the maximum prescribed simulation time. The coordinate transformation block refers to NN III, the external forces are received from the input data, and then the mooring and hawser forces are computed by NN I and IV, the position update block

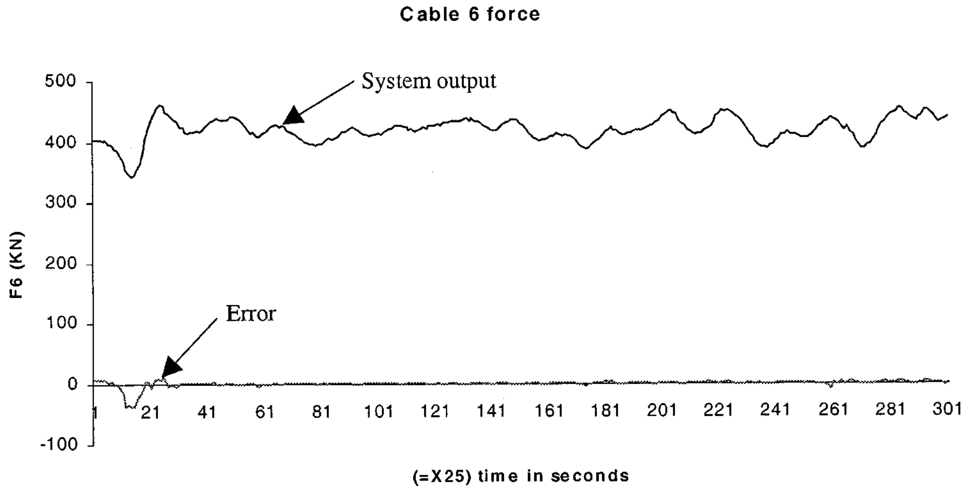

Fig. 17. Estimation convergence for mooring cable #6.

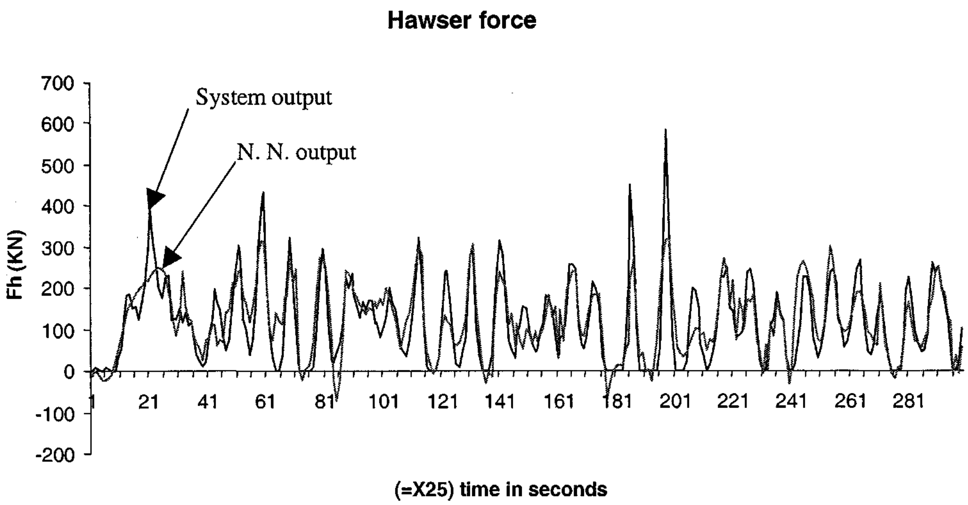

Fig. 18. Hawser force estimation.

calculates the delayed displacements of the FPSO system and shuttle by NN II and NN V, which are fed back to the input of NN I, NN III, and NN IV.

IV. Modeling Results

Several parameters can denote the performance of a neural network model, and the most important is the figure of merit of number of tested (recalled) correct patterns. Training the neural network system to an excessively low error tolerance can result in overall poor performance by the network; in effect, the network begins memorizing the training set and might lose its ability to generalize. Convergence may be measured by the overall error over the ensemble of training vectors to be less than some specified minimum value. By sequentially training and testing with an independent data test set, the error can be compared to the learning phase total error and a generalization loss. The generalization loss can then be used heuristically to determine whether there are too many hidden units and the hidden layer size should be decreased, or the training set does not adequately represent the decision class and should be augmented.

A trial-and-error procedure has been used to optimize the performance and the following results compare mooring and hawser forces for two ships in the physical configuration indicated in Table I. An input time-lagged neural network as previously indicated in Fig. 3 was used to predict the forces in a mooring cable and hawser. Two data sets supplied by the scaled laboratory model were used for training. The sets contained 300 samples of 25 s each, of the forces in cable 1 and in the hawser. The neural network weights were frozen at the end of training epoch (281 $\times$ 25 s) and tested with several other data not presented, in order to approach the performance. Figs. 8–11 show the results for this time-series modeling approach with excellent estimation accuracy.

The scattering results of Figs. 12 and 13 were produced by plotting how the neural network estimation output would match the desired patterns, allowing measurement of network performance learning and testing. Both figures show a high correlation for cable #1 and hawser forces estimation.

In order to validate the generalization capabilities, the data were split into two sets, one used for training and the other for testing. The recalled output data are shown in the next figures, where the mooring cable forces on lines #1 and #6 are estimated; the hawser force is also shown. Fig. 14 shows the real data (from

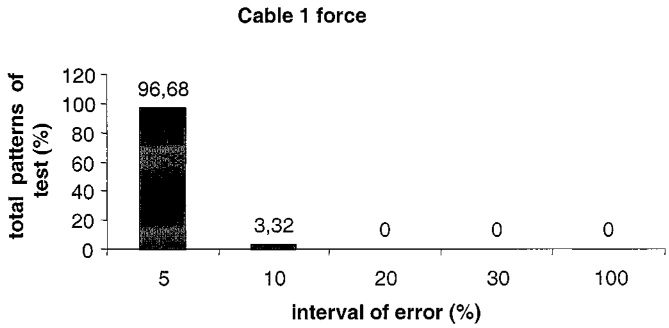

Fig. 19. Precision of cable #1 force identification.

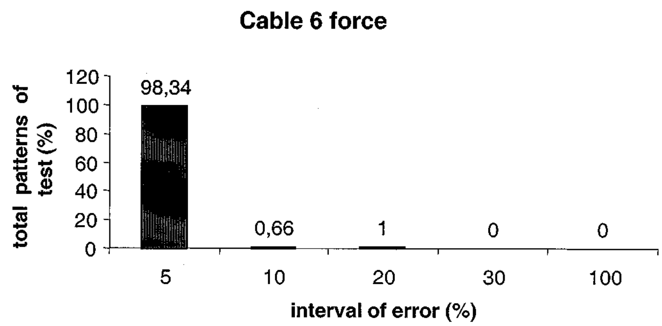

Fig. 20. Precision of cable #6 force identification.

DYNASIM) and estimated force on cable #1 where it can be seen that the network has learned the mapping within 5% accuracy; the error is shown in Fig. 15. The force estimation and error for mooring cable #6 are depicted in Figs. 16 and 17, which also show a good accuracy. All the forces estimated on mooring lines #2, #3, #4, and #5 have the same kind of behavior with good estimation performance.

The FPSO system and the shuttle have a strong interaction. Even for small shuttle displacements, great forces are produced on the hawser; the environmental effects also influence such coupling. Fig. 18 shows the estimation of hawser force. Although the high-frequency content has not been captured by the neural network (as expected by the low-frequency formulation previously discussed), the average value is properly estimated. Figs. 19 and 20 show graphically the precision reached by the neural network on the identification of the forces in cables #1 and #6. Cable #1 has a margin of precision within 3.32% and Cable #2 has 1.66% of accuracy.

V. Conclusion

This paper has explored a methodology of using a time-series-based neural network and a structured neural network for modeling and analysis of the dynamic behavior of the movements of an FPSO system in tandem configuration with a shuttle tanker. The FPSO system is fixed to the bottom of the sea by very long steel cables, which are stressed due to currents, waves, and wind. The main purposes were to develop a neural network simulation of floating production systems based on an amenable architecture for implementation in parallel computing. The neural network approach showed a capacity of nonlinear mapping and dynamic features extraction of a quite complex and highly nonlinear system: mooring cables stresses and the hawser cable connection. The estimation was tested with a scaled simulator model called DYNASIM which provided ship state variables. The overall implementation was considered to have a good performance. The system is expected to be integrated with online monitoring variables such as heading, position, speed and yaw rate, and cable forces by various sensor apparatus, contributing to improvement of maintenance of mooring lines and prevention of collisions.

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Marcelo Godoy Simões (S'89–M'95–SM'98) received the B.E. and M.S. degrees from the University of São Paulo, São Paulo, Brazil, the Ph.D. degree from the University of Tennessee, Knoxville, and the D.Sc. degree (Livre-Docência) from the University of São Paulo, in 1985, 1990, 1995, and 1998, respectively.

He was a faculty member at the University of São Paulo from 1989 to 2000. He authored the first book on fuzzy modeling and control published in Portuguese. He is currently an Associate Professor at the Colorado School of Mines (CSM), Golden, CO, where he is working to establish several research and educational activities. His interests are in the research and development of intelligent applications, fuzzy logic and neural networks applications to industrial systems, power electronics, drives, machines control, and distributed generation systems.

Dr. Simões is currently the IEEE Power Electronics Society Educational Chairman.

Jhonny Leonidas Merma Tiquilloca (M'98) was born in Puno, Perú, in 1971. He received the B.S. degree in electronic engineering in 1995 from the National University of San Agustin, Arequipa, Perú, and the M.S. degree in mechanical engineering in 1999 from the Polytechnic School, University of São Paulo, São Paulo, Brazil, where is currently working toward the Ph.D. degree.

His fields of interest are modeling and simulation, neural networks, fuzzy logic, and fault diagnosis in power systems.

Mr. Merma is a member of the IEEE Industry Applications and IEEE Computer Societies.

Hélio Mitio Morishita received the B.S., M.S., and Ph.D. degrees in naval architecture and marine engineering from the University of São Paulo, São Paulo, Brazil, in 1975, 1979, and 1985, respectively.

Since 1974, he has been teaching in the Department of Naval Architecture and Ocean Engineering, University of São Paulo. His research interests include adaptive control theory, dynamics of ocean vehicles in single and tandem configurations, and dynamic positioning systems of floating vessels.