Neural Networks as Routine for Error Updating of Numerical Models

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Abstract: This paper describes a somewhat alternative approach to combining observations and numerical model results in order to produce a more accurate forecast routine. The approach utilizes artificial neural networks to analyze and forecast the errors created by numerical models. The resulting hybrid model provides very good forecast skills that can be extended over a forecasting horizon of considerable length. The method has been developed for the purpose of operational forecasting of current speeds in the Danish Øresund Strait. The forecast system was used as a planning tool during the construction of the 16 km-long fixed link across the Øresund Strait, linking the countries of Denmark and Sweden.

INTRODUCTION

The desire to predict the future and understand the past governs the search for laws that explain the behavior of observed phenomena. If the underlying deterministic equations are known, in principle they can be solved to forecast the outcome based on knowledge of the initial conditions and evolution of forcing terms. In hydraulic modeling, for example, governing laws are the Navier-Stokes equations, whereas the forcing term is the evolution of the status of atmosphere (atmospheric pressures and resulting wind fields). Initial conditions describe the sea status (current speeds and directions, water levels) in the entire computational domain at the beginning of computation. Once the initial and forcing terms are precisely specified, it should be possible to precisely calculate the evolution of the status of the sea from its specified initial conditions and as a consequence of applied forcing.

However, even under these almost ideal circumstances, the model results are not precise. Every model is indeed only a model of reality; it employs a number of simplifying assumptions, e.g., depth averaging of velocities in vertically integrated 2D models, which inevitably produces inaccuracies. In a numerical modeling one discretizes a domain, and therefore is not able to resolve numerous subgrid phenomena. Also, the errors in the model parameterization (mainly because most model parameters cannot be directly measured) greatly contribute to errors of numerical models. Finally, it is impossible to precisely define initial conditions and forcing terms in the entire computational domain. All these imprecisions and uncertainties can accumulate to produce fairly poor model results despite our perfect knowledge of governing laws.

HOW CAN WE MAKE MORE ACCURATE MODELS?

It is an accepted fact that numerical models are far from being perfect. In the present problem, the used numerical model is a hydraulic numerical model forced by dynamic open-boundary conditions and the output of a regional atmospheric model. The degree of simplifications that are introduced in this model (model physics, numerical solution, grid discretization, model parameters, etc.) together with the error associated with the forcing (open boundary conditions and atmospheric forcing) are the main sources of errors in the model solution.

Various schemes may be utilized to make models more accurate. When observations of the modeled phenomena are available and some knowledge of the aforementioned errors exists, data assimilation methods can be used in order to improve the model solution. Data assimilation is a methodology that can optimize the extraction of reliable information from observations and combine it with, or assimilate it in, numerical models.

A number of different data assimilation procedures can be adopted. These are designed to either improve description of initial conditions at the time of forecast or provide correction of model predictions during a forecast period. The data assimilation procedures may be classified according to the variables modified during the updating process. In [World Meteorological Organization (WMO) (1992)] and Refsgård (1997) four different methodologies have been defined (Fig. 1). The four methodologies can be defined as follows:

1. Updating of input parameters—This is the classical method justified by the fact that input uncertainties may be the dominant error source in operational forecasting.
2. Updating of state variables—Adjustment of the state variables can be done in different ways. The theoretically most comprehensive methodology is based on Kalman filtering (Gelb 1974). Kalman filtering is the optimal updating procedure for linear systems, but can also, with some modifications, provide an approximate solution for nonlinear hydrodynamic systems.
3. Updating of model parameters—Continuous adaptation of model parameters is a matter of continuous debate. The prevailing view seems to be that for hydrodynamic models of nontrivial complexity recalibration of the model parameters at every time step has no real advantages, as the operation of any hydrodynamic system cannot significantly change over the short interval of time.
4. Updating of output variables (error prediction)—The deviations between the simulation mode forecast and the observed variables such as current speed, are model errors. The possibility of forecasting these errors and superimposing them onto the simulation mode forecasts, usually gives a more accurate performance. This method is most often referred to as error prediction and is the method employed in the present study.

If forecasting interest is limited to only a few variables at some specific locations with a high degree of accuracy and for a considerably long forecast lead-time, a data assimilation

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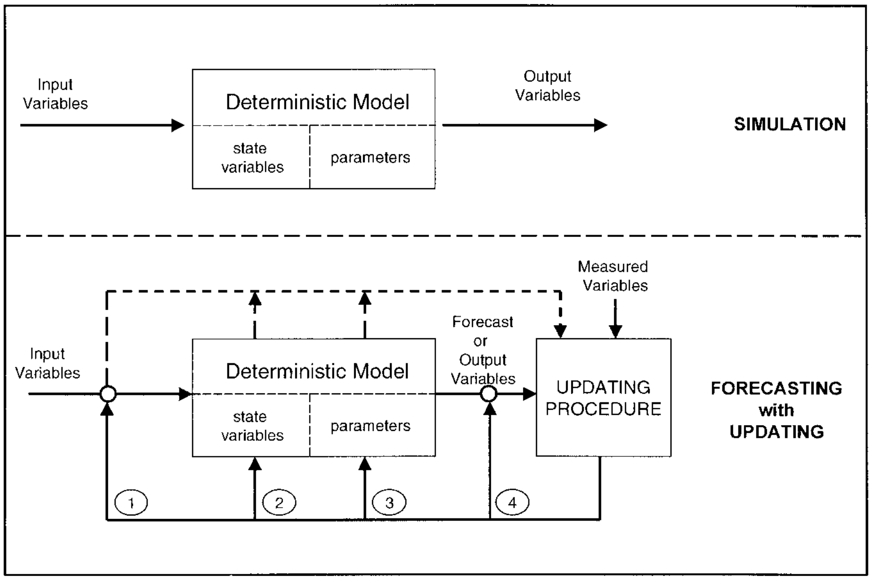

FIG. 1. Schematic Diagram of Simulation and Forecasting with Emphasis on Four Different Updating Methodologies (Adapted from Refsgård 1997)

scheme based on updating of output variables (error prediction) may be the most suitable approach. In model error prediction other techniques such as artificial neural networks (ANNs) (Babovic 1996; Van den Boogaard and Kruisbrinck 1996; Minns 1998) or an approach based on chaos theory (Babovic and Keijzer 1999) have demonstrated very good forecast skills. By using these techniques, one can combine the forecast of the numerical model (model output) at the point of interest with the latest observed data in order to obtain an improved forecast. Another advantage of such an approach is that it allows the combination of different variables (e.g., atmospheric data such as wind speed) to improve the accuracy. This cannot be done in conventional data assimilation methods where the data has to be introduced in the model state in order to be assimilated.

This paper describes an error correction data assimilation scheme based on ANNs. The approach was developed to meet exceptionally high accuracy demands in order to enable precise planning of towing and immersion operations of 175 m long, 55,000 ton heavy tunnel elements that form a part of a fixed link between Sweden and Denmark across the Øresund Strait. The paper also describes a forecasting computer system developed around the concept, which provides forecasts in a real-time mode.

ARTIFICIAL NEURAL NETWORKS

Neuron

Simulations of interconnected networks of simple threshold-based processing units called neurons have been an object of scientific investigation ever since the earliest days of the computer (McCulloch and Pitts 1943; Hebb 1949). These neurons are in fact a special form of general automaton (Hoppcroft and Ullman 1979) that in fact form a conceptual basis for any computer programming language. The McCulloch-Pitts neuron is depicted in Fig. 2.

An individual neuron has a finite number of scalar inputs $\{x_i,\ i = 1, 2, \ldots, n\}$ and one scalar output $\{y\}$. Associated with each input is a scalar weighting value $\{w_i,\ i = 1, 2, \ldots, n\}$. The input signals are multiplied by these weighting values and added at the summation junction, i.e., $u = \sum_{i=1}^{r} w_i x_i$. The combined signal is then passed through an activation function $\gamma(u)$ producing the output signal. The activation function $\gamma(u)$ can take a variety of forms, one of the most common being a sigmoid function

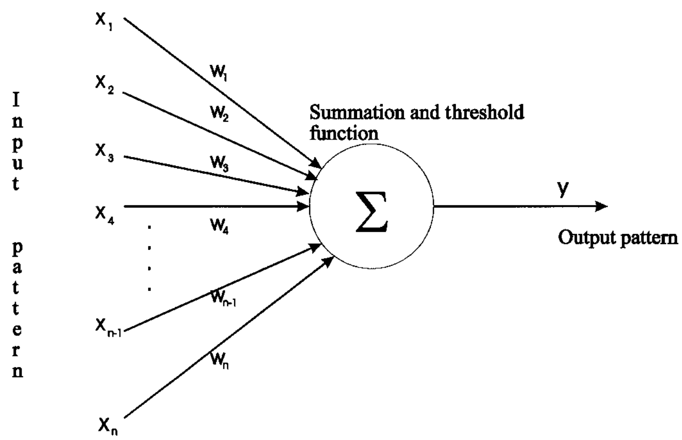

FIG. 2. Schematization of McCulloch-Pitts Neuron

$$\gamma(u) = \frac{1 + e^{u+\theta}}{1 + e^{-u-\theta}} \tag{1}$$

where $u = \Sigma\, x_i w_i$ being the weighted sum of all input signals x_i that the neuron receives; and θ = threshold value associated with the neuron. Many other forms of activation function $\gamma(u)$ are possible and they range from linear form ($\gamma(u) = au + b$) to other nonlinear-bounded forms, such as $\gamma(u) = \tanh(u)$.

The activation function $\gamma(u)$ of the form (1) serves as a nonlinear element in a neuron and also acts as a limiter that bounds the incoming signal. This activation function has a linear range about the origin, and is bounded between -1 and $+1$. If an output of a neuron is bounded between $-\alpha$ and $+\alpha$ a neuron can still approximate this function as long as it takes $\bar{\gamma}(u) = \alpha\gamma(u)$ as its activation function. Therefore, the activation function can be taken to be between -1 and $+1$ provided that an additional factor is inserted after the neuron. In practice this implies that all the data that a neural network operates upon has to be normalized (usually between -1 and $+1$). A denormalization process can be performed at the output signal without any loss of generality.

Multilayer Neural Networks

A neural network is simply a set of interconnected individual computational elements called neurons. In the case of the multilayer neural networks, the neurons are arranged in a series of layers. A layer is usually a group of neurons, each of which is connected to all neurons in the adjacent layer.

Neurons in the input layer are connected only to those in the hidden layer. In the single-layer network, the neurons in the hidden layer are connected to those of both the input and the output layer, while those of the output layer have no connections other than to those of the hidden layer. There are no connections between the neurons within any of the three layers.

In practical applications, the design of the multilayer neural network architecture requires specification of many factors, such as the number of neurons in the different layers, the number of hidden layers, and the type of neuron transfer function $\gamma(u)$ to be used. Multilayered neural networks are rather standard today, and therefore, their description here is kept very short. For thorough treatment the interested reader is referred to Haykin (1994).

Training

In order to induce the model that approximates the data, one must present the ANN with a selected set of representative patterns and let it learn from them. In practice, an ANN's configuration values (weights on the connections between processing units) have to be adjusted until the error function measuring the difference between the ANN-produced output values and desired output values are minimized. This phase is referred to as a training phase of an ANN. It is clear that a neural network is essentially an overparameterized set of equations with a potentially very large number of free parameters $w_i\{i = 1, 2, \ldots, n\}$ and $\theta = w_{n+1}$. During the training phase the set of optimal weights w_i are sought on the basis of response to training data. The training process establishes a set of free parameters w_i that produce the most accurate input-output mapping.

The training data usually consist of inputs as well as desired responses to these stimuli. During training, the output calculated by the network y_i is compared with the actual (desired) output d_j and the difference between the two is calculated. These differences are then added over the entire training set containing Tr samples to form the error function, i.e., $E = \sum_{j=1}^{Tr} |d_j - y_j|$. The value of the neural network output y_j is a function of the free parameters w_i. The aim of training is to find a set of weights that will produce the minimum of the error function $E = f(w_i)$. There are several methods for finding the minimum of the error function $E = f(w_i)$. The interested reader is again referred to Haykin (1994) for a review.

Issues in Connectionist Learning

It has been shown that an artificial neural network, given a sufficiently long training time and a sufficiently rich topology (i.e., sufficiently large number of hidden layers with sufficiently large number of neurons in each of them), can act as a universal function approximator (Hornik et al. 1989). Thus, given a sufficiently long training time, a sufficiently complex network architecture, and a sufficiently representative training data set, an artificial neural network can approximate any function to an arbitrary degree of accuracy. This is an extraordinary property, as it opens avenues for application of this technology directed toward improvement of our existing modeling skill.

Once trained, the ANN model should be able to correctly recall the output vector values when presented with the input vector again. This is easily accomplished as ANNs have a large number of free parameters. However, the principal goal in model induction is the formulation of models capable of generalization. Clearly, ANNs should not be trained to only memorize training data, but to approximate a system that produced the data. Thus, the trained ANN should be able to reproduce patterns that were not included in the training set. This highlights the need to control balance between the complexity of the model (i.e., number of free parameters) in order to achieve the best generalization. Considerable insight into this phenomenon can be obtained by introducing the concept of the bias-variance trade-off, in which the generalization error is decomposed into the sum of the bias squared plus the variance. A model that is too simple or too inflexible will have a large bias, while one that has too much flexibility in relation to the particular data set will have large variance. Bias and variance are complementary quantities, and the best generalization is obtained when we have the best compromise between the conflicting requirements of small bias and small variance. For excellent treatment of the topic, the reader is referred to German et al. (1992) and Friedman (1997). In the present study a considerable effort has been devoted to the selection of neural networks of the most appropriate complexity. The optimal configurations for each of the forecast lead-times was determined using cross-validation and analysis based on bias-variance decomposition of error. The details of optimal configurations are described in the Forecast Skill section.

Dynamic Networks

Many applications of neural networks involve data $x = x(\tau)$ which varies as a function of time τ. The goal is to predict the value of x at some time in the future. Techniques based on feedforward networks, of the kind described in the previous sections, can be applied directly to such problems. Let us for simplicity consider a single-channeled time-dependent variable $x(\tau)$. One common approach is to sample $x(\tau)$ at regular time intervals to generate a series of discrete values $x_{\tau-1}$, x_τ, $x_{\tau+1}$, and so on. A set of d such values $x_{\tau-d+1}, x_{\tau-d+2}, \ldots, x_\tau$ can be used as inputs to a feedforward network, and the value $x_{\tau+1}$ as the target output of the network as indicated in Fig. 3. By stepping along the time axis, a training data set can be created consisting of many instances of input values with corresponding target values. One of the main problems of applying ANNs in a time domain is determining a length of the memory buffer d. Too large memory may lead to overfitting, whereas too small to an underrepresentation of the process and poor accuracy.

A dynamic neural network can be best understood as a static neural network with an extended memory mechanism that is able to store past values of the input signal. The simplest way of providing memory is creating a tap delay-line operator which functions as a local memory kernel. The tap delay-line operator simply stores past values in a memory kernel, thus providing a history of input signal. As the basic ANN archi-

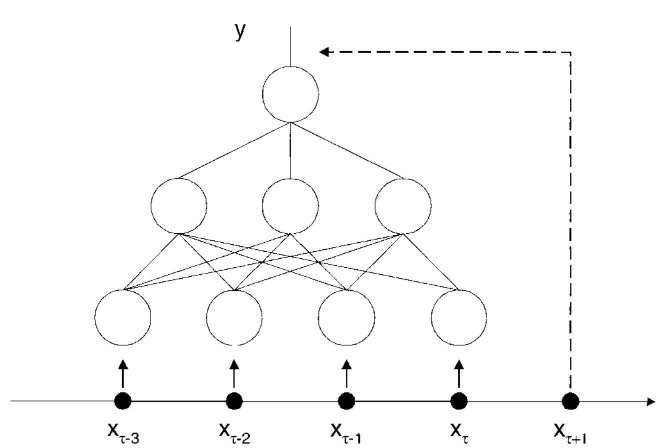

FIG. 3. Sampling of Time Series at Discrete Steps Used to Generate Set of Training Data for Feedforward Network

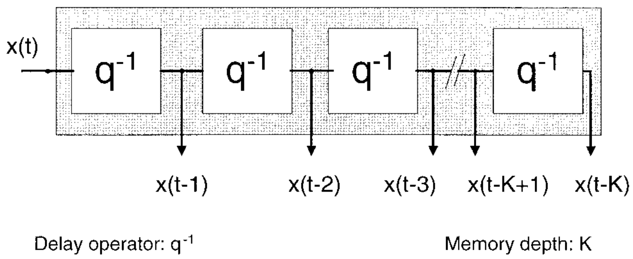

FIG. 4. Tap-Delay Line Operator

TABLE 1. TDNN Network versus Static Equivalent

Network Dimension: Node (1)	Network Dimension: Order (2)	Variable parameters (3)	Static equivalent (4)
$2 \times 2 \times 2 \times 1$	2:2:2	30	150
$5 \times 5 \times 5 \times 5$	10:10:10	605	36,355
$3 \times 3 \times 3$	9:9	180	990
$3 \times 3 \times 3 \times 3$	9:9:9	270	9,990
3^n	9^{n-1}	$(n - 1)90$	10^{n-10}

Note: Numbers of nodes in networks are calculated as (number of inputs × hidden neurons × outputs). Order denotes number of TDNN synapses in each layer (adapted from Wan 1993).

tecture for the present forecasting application—a special dynamic network—a so-called time-delayed neural network (TDNN) (Lang and Hinton 1988) structure has been selected. Essentially, TDNN has the same architecture as a multilayer neural network additionally equipped with short-term memory structures as depicted in Fig. 4. The main reason for choosing TDNN here lies in the dramatic reduction in complexity over its static counterparts. Wan (1993) shows (Table 1) that the size of static neural networks grows geometrically with the number of layers and tap delays and that TDNN is a compact representation of a larger static network.

TDNNs with the memory confined to the input only can be thought of as an input preprocessor. The information is represented across time instead of simply across the static input patterns. Memory can be applied to any layer in the network, producing very sophisticated neural topologies which can be useful for time series prediction and system identification, and temporal pattern recognition.

Given a signal in time the network must process that signal to determine where in time the relevant information lies. A brute force approach would be to use a long time window. However, this method does not work in practice because it creates very large networks that are difficult to train (particularly if the data is noisy) and rather susceptible to overfit. In TDNN, establishment of an optimal memory depth K is an integral part of the training process, thus providing a very good alternative to the brute force approach.

Termination of Training

One practical issue always appears while training neural networks. What is the criterion that is to be used as a termination of a training process? Quite obviously, one trains a neural network with one prime objective in mind—to create a truthful model of the underlying process. As indicated earlier, the goal is not to blindly minimize the error created on the training set, but rather to maximize an ANN's generalization capabilities, i.e., to develop an ANN that is general enough and capable of truthfully reproducing the entire data set. If the ANN is overtrained it will produce an overly detailed representation that tends to individualize more and correspondingly learn even the noise included in the training signal. The network loses its ability to generalize on the input domain.

One method for deciding when to terminate the training process is cross-validation. Weights are corrected only on the basis of an ANN performance on the training data, and simultaneously tested on a so-called cross-validation data set. The training process should be terminated at the moment when the error on the validation set starts increasing. When the error on the validation set starts increasing, it is said that the network is being overtrained, i.e., the network starts fitting even the noise inherent to the dynamics of the system contained in the training set. (The underlying assumption here is that the data contained within both training and validation data sets, truthfully represent underlying physical processes. More clearly, it is assumed that the minimum of error on the validation set would correspond to the universally maximal generalization properties, i.e., that validation on some other data set would result in exactly the same generalization ANN's characteristics.)

The correct performance of the resulting model is evaluated with a set of testing patterns. Testing the network with new (unseen) patterns is the best way to make sure the induced model performs as well as it should. This phase is referred to as validation of a model. The data used during the testing phase should also be representative for the problem under consideration.

One final point should be emphasized here. An ANN is a data-driven technique and the quality of its performance primarily depends on the quality of the data employed for its training, cross-validation, and testing. Data should comprise of all characteristic phenomena as well as provide the most relevant input-output pairs of observations. The choices of the most representative data to be employed are obviously domain-specific and require a wealth of knowledge and insight. While neural networks are powerful modeling techniques, they are almost useless without physical understanding of the processes that are being approximated. The responsibility for careful selection of the most relevant data is on the shoulders of a modeler. ANNs are universal function approximators, and can truly approximate physical systems only when this system is correctly represented by observations. It is the modeler's task to employ his professional judgment and understanding when choosing the representative data sets.

THE STAGE—ØRESUND STRAIT FIXED LINK

The construction of the fixed link across the Øresund Strait—following the 1991 agreement between the Swedish and Danish governments—is now completed. Aimed at improving transport connections between the two countries and thereby strengthening cultural and economic cooperation, the link is expected to stimulate the development of a joint labor and housing market at each side of the Øresund Strait.

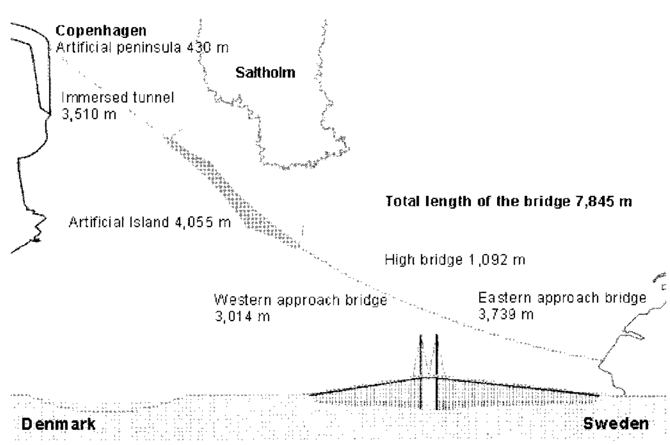

FIG. 5. Schematized Map of Øresund Strait Fixed Link

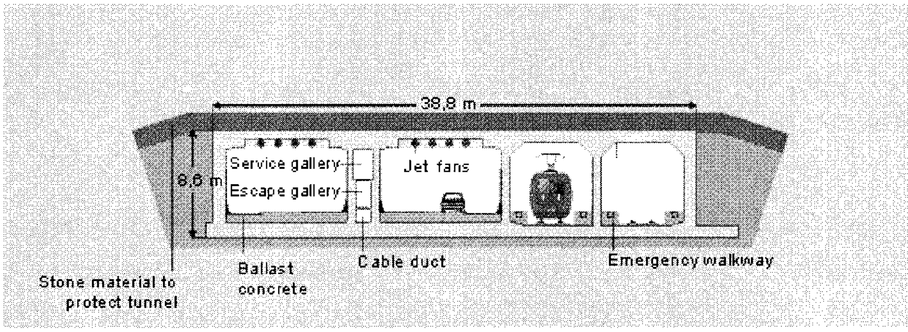

FIG. 6. Cross Section of Tunnel Element

The fixed link consists of a combined twin-track railway and a four-lane motorway. The total link length extends just under 16 km between Kastrup on the Danish coast and Lernacken on the Swedish coast. The link's key elements are (Fig. 5):

- An artificial peninsula extending 430 m from the Danish coast at Kastrup
- An immersed tunnel 3,510 m long under the Drogden navigation channel
- An artificial island 4,055 m long, south of Saltholm
- A western-approach bridge 3,014 m long between the island and the high bridge
- A cable-stayed high bridge 1,092 m long across the Flinten navigation channel
- An eastern approach bridge 2,739 m long from the high bridge to the Swedish coast at Lernacken
- A terminal area with toll station and link control center on the Swedish coast at Lernacken

Tunnel

The immersed part of the tunnel consists of 20 concrete elements, each approximately 175 m long, resulting in a total immersed tunnel length of 3,510 m. Each element is made from eight sections, joined together by temporary prestressing. The outer cross-sectional dimensions are 8.6×38.8 m, enclosing two railway tubes, two motorway tubes, and a central escape and installation gallery (Fig. 6).

The elements are placed in a predredged trench, and founded on a gravel bed. Backfilling along the sides and on the roof is designed to offer a permanent cover and protection of the tunnel in all situations. The final tunnel is, in general, below seabed level, and at the Drogden navigation channel the top of the cover is 10 m below water level. All 20 tunnel elements are fabricated in a purpose-built casting yard at the Nordhavn area of Copenhagen harbor (Fig. 7).

The transportation distance from the casting yard to the tunnel site is approximately 15 km and the route followed is based upon 1.0 m keel clearance for the element. The towing configuration is with two leading tugs and two assisting tugs, i.e., one at each corner of the element. The towing route is predominantly along the north-south direction. Once the element approaches the trench, it has to be rotated to an almost exact east-west direction of the trench and precisely lowered to its final location. During this final stage of placement, tunnel elements are exposed along its longer axes to predominantly north-south currents and consequently receive the largest forces. At the same time, elements must be lowered with extreme accuracy as the allowed misalignment is only 2.5 cm. Consequently, the immersion and alignment of an element can be successfully carried out only under fairly quiet flow conditions, well within the operational limit. Once the element is lowered to its definitive location, it is covered with stone ma-

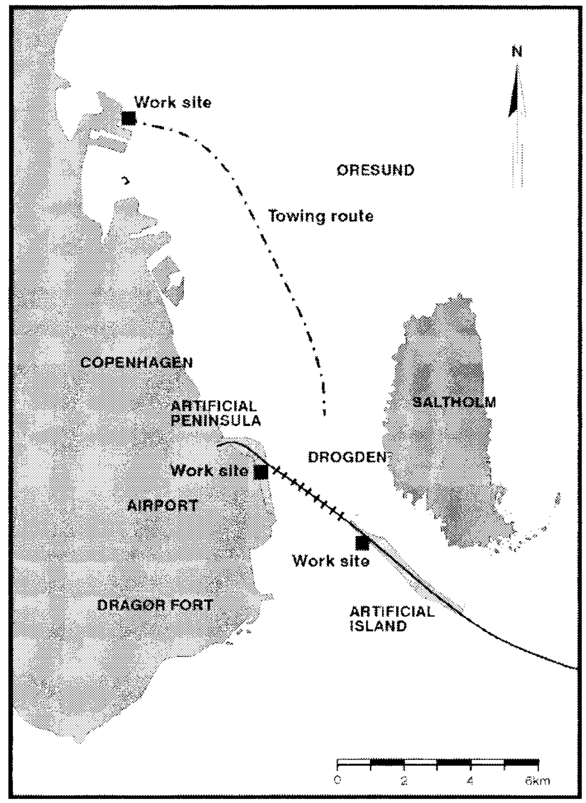

FIG. 7. Towing Route between Casting Yard Located to North of Copenhagen and Tunnel Site

terial (backfilling). The total duration of a towing and immersion operation is on the order of 24–36 h.

As each tunnel element weighs 55,000 tons, and since the entire towing operation can last up to 36 h, it is obviously very important to plan and execute towing operations under favorable flow conditions. At the same time the predominant flow conditions in the Øresund Strait are rather violent. In order to demonstrate the degree of ferocity, results of a statistical analysis of long-term observations of current speeds (DHI/LIC 1997) are summarized in the sequel. This analysis is actually an analysis of duration of current-related weather windows for the current measurements at the Nordre Røse station situated in the Øresund Strait. In this case a weather window is defined as a continuous period of time in which the current speed is constantly below a critical current speed.

It can be seen from Table 2 that 49% of the time in July is covered by weather windows in which the current speed is constantly below 0.75 m/s for longer than 48 consecutive hours. At the same time, 83% of the time in July is covered by weather windows with durations longer than 0 h, meaning simply that 83% of the time the current speed is below 0.75 m/s.

Table 3 provides a summary of results of statistical analyses for instantaneous current speeds, whereas Table 4 provides results for 36 h-long weather windows. It is obvious from Table 4 that for example in the month of February, there were only 14.5% occasions where current speeds were below 0.75 m/s over a 36 h-long window. Even in the quietest month of April, one can expect with only 54.0% probability that currents would remain under a 0.75 m/s threshold.

An independent analysis carried out for the contractor, Øresund Tunnel Contractors, estimated two critical current speeds: (1) An operational limit of 0.75 m/s; and (2) a survival limit of 1.2 m/s. Operational limit signifies an upper speed limit for normal working conditions. With currents below an operational limit, the contractor should be able to conduct towing operations, lower each of the tunnel elements, as well as align them with required accuracy. Survival limit denotes the upper limit of current speeds and related forces acting on the tunnel element that the contractor should be able to sustain. However, immersion and precise alignment are not possible with current speeds above an operational limit.

The contractor's requirement for safe execution of towing and immersion, rather severe flow conditions in the Øresund Strait, and very tight deadlines for tunnel completion call for an accurate and reliable current forecast procedure. Especially with very strict deadlines, the contractor is forced to perform the tow and immersion throughout the year, thus critically relying on 36 h-long windows with acceptable current speeds.

TABLE 2. Percentage of Time Covered by Weather Windows of Various Durations for Current Speed of 0.75 m/s

Month (1)	Duration 0 h (2)	6 h (3)	12 h (4)	18 h (5)	24 h (6)	36 h (7)	48 h (8)
January	61	55	46	39	28	17	13
February	51	45	33	26	19	15	10
March	52	48	38	32	27	22	10
April	79	76	68	65	61	54	50
May	77	74	67	62	59	48	44
June	78	75	67	63	55	45	31
July	83	80	68	66	60	52	49
August	75	71	62	59	51	40	38
September	72	69	59	56	52	45	41
October	63	58	51	44	38	26	17
November	59	53	45	36	26	17	9
December	61	55	47	37	30	20	16

TABLE 3. Percentage of Time Covered by Weather Windows Longer Than 0 h

Month (1)	0.25 m/s (2)	0.50 m/s (3)	0.75 m/s (4)	1.00 m/s (5)	1.25 m/s (6)	1.50 m/s (7)
January	16.1	37.9	60.6	81.1	93.9	98.0
February	12.0	28.9	51.0	72.8	88.8	97.1
March	11.6	28.3	51.9	77.9	92.5	97.6
April	24.4	53.4	78.6	94.9	99.4	99.9
May	22.1	48.5	76.8	93.0	98.8	99.9
June	19.9	49.5	78.0	91.7	96.5	98.8
July	22.0	54.1	82.5	97.3	99.9	100.0
August	20.4	47.9	74.8	92.2	97.6	99.5
September	14.0	42.7	72.3	88.0	94.8	97.5
October	18.4	39.5	63.3	82.5	94.7	98.3
November	13.7	33.2	59.1	81.1	93.2	97.8
December	16.6	36.3	60.8	82.1	92.3	97.3

TABLE 4. Percentage of Time Covered by Weather Windows Longer Than 36 h

Month (1)	0.25 m/s (2)	0.50 m/s (3)	0.75 m/s (4)	1.00 m/s (5)	1.25 m/s (6)	1.50 m/s (7)
January	0.0	1.2	17.2	47.9	86.6	95.1
February	0.0	4.6	14.5	41.2	71.1	92.5
March	0.0	0.0	22.2	47.6	81.4	97.4
April	0.0	16.7	54.0	86.1	99.4	99.9
May	0.0	9.7	47.9	83.3	96.4	99.6
June	0.0	12.4	44.5	85.3	95.5	98.5
July	0.0	12.6	51.7	93.9	99.9	100.0
August	0.0	11.4	40.0	84.8	96.8	99.0
September	0.0	3.6	45.4	72.5	88.9	94.6
October	0.0	5.5	26.0	55.7	86.6	98.3
November	0.0	3.4	17.4	53.0	84.6	96.8
December	0.0	1.3	20.3	52.8	80.8	96.0

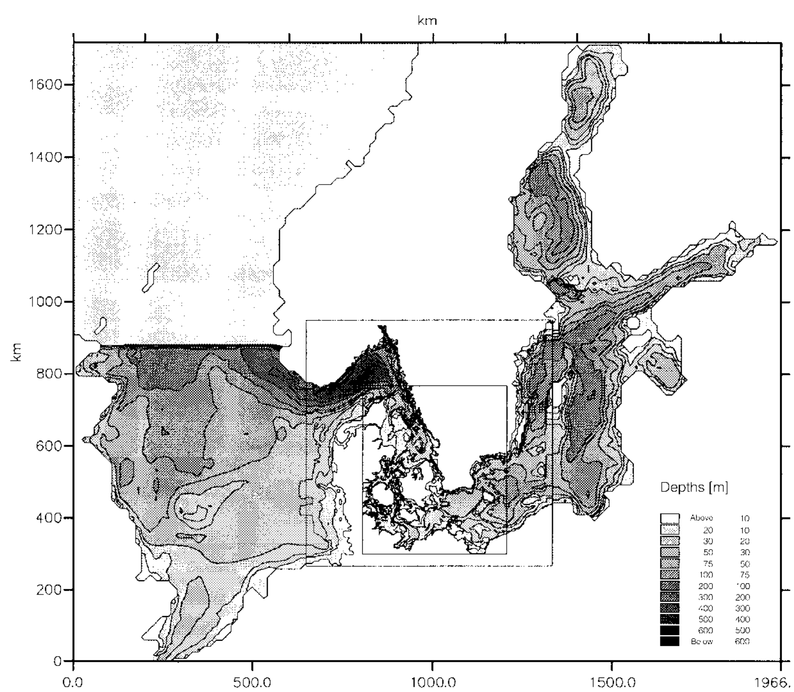

FIG. 8. Computational Grid Setup for Deterministic Model: Coarse Grid Covers Area of Baltic and North Seas with Grid Size of 9 Nautical Miles; Intermediate Grid Covering Kattegat and Skagerak Is of Resolution of 3 Nautical Miles; Finest Grid Covering Inner Danish Waters Is of 1 Nautical Mile Resolution (All Grids Are Dynamically Two-Way Coupled)

FORECAST PROCEDURES

The planning of the transportation and installation of tunnel elements requires a wealth of knowledge about the current conditions in the Øresund Strait. In order to assist in a planning of such a critical operation the Danish Hydraulic Institute developed a real-time forecast system producing predictions of speed and direction of currents at the location called Nordre Røse (situated near tunnel site; Fig. 10) as well as water levels at Nordre Røse and Dragør.

The hydrography of the Øresund Strait is primarily determined by the weather conditions over Scandinavia and only to a lesser degree by the tide, which is relatively weak in this area. A deterministic 2D modeling system (MIKE 21) has been established for the area to describe the hydrography of the North Sea and the Baltic Sea systems and the complicated flow exchange through the Danish waters (Fig. 8). The model runs operationally at the Danish Meteorological Institute. The objective is to model the sea status as a consequence of the meteorological forcing so that, for example, events such as strong changes in the current intensities due to the passage of a depression can be successfully predicted. However, the resolution of the existing hydrodynamic model is rather coarse to simulate the currents and water levels in the narrow Øresund Strait in great detail. At the same time, such a purely deterministic modeling setup does not utilize any of the observations that are collected in an on-line fashion from some 38 stations operating in the area.

The deterministic hydrodynamic model, MIKE 21, is run every 12 h in operational mode. The model sea state is updated using analyzed meteorological fields of wind and pressure (hindcast) to obtain the best possible initial field of currents and water levels for the successive forecast. The expected accuracy of such a relatively simple model covering a large area is limited in relation to the requested accuracy. Inaccuracies are particularly pronounced in the meteorological fields produced by the meteorological model HIRLAM (higher resolution limited-area model), poor spatial resolution of the hydro-

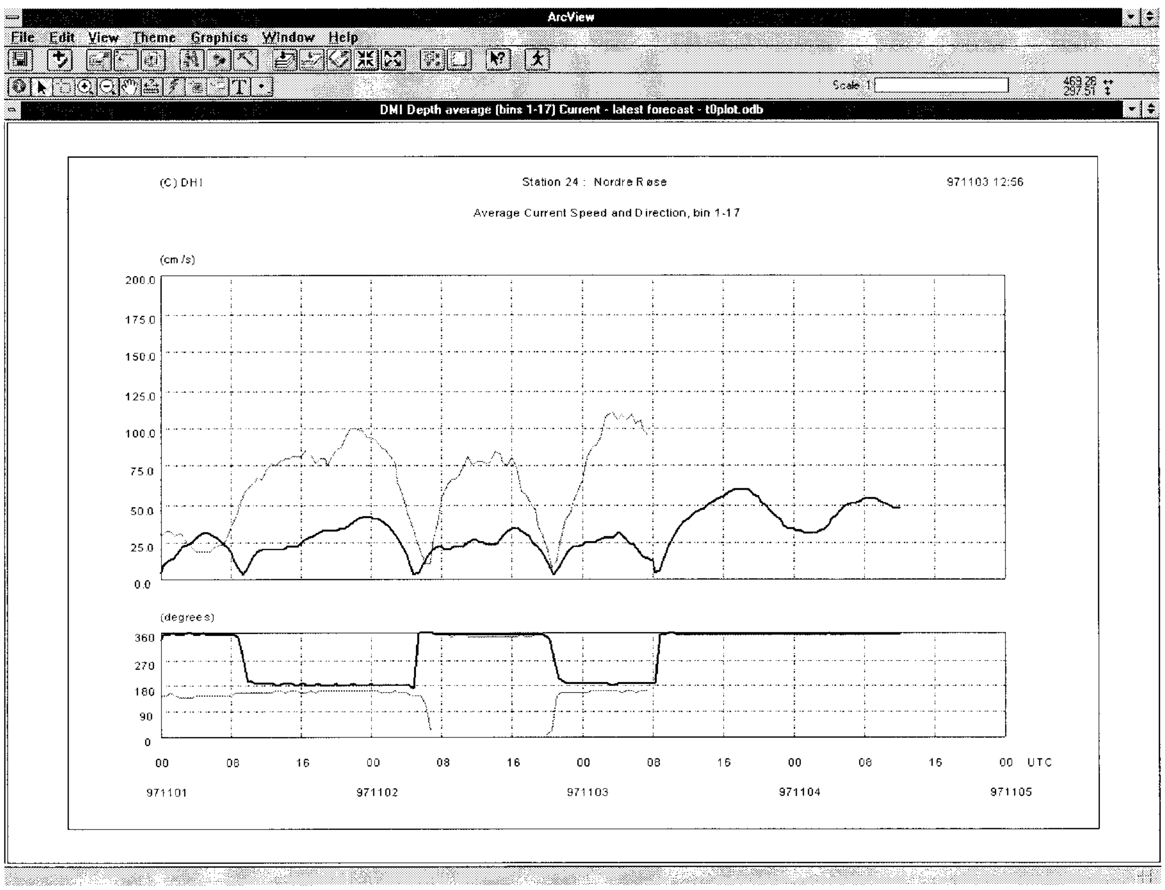

FIG. 9. Typical Results from Deterministic Model: Thin Line Indicates Measured Current Speed, Thick Line Is Deterministic Model's Output; There Is Obvious Amplification Error and Degree of Phase Error

TABLE 5. Correlation Coefficients for Observed Quantities

Data subset (1)	Average speed (2)	Surface speed (3)	Viken water level (4)	Hornbæk water level (5)	Skanör water level (6)	Rødvig water level (7)	Kastrup, N wind (8)	Kastrup, E wind (9)	Hornbæk-Rødvig (10)
Average speed	1.00	—	—	—	—	—	—	—	—
Surface speed	1.00	1.00	—	—	—	—	—	—	—
Viken water level	−0.50	−0.50	1.00	—	—	—	—	—	—
Hornbæk water level	−0.63	−0.63	0.90	1.00	—	—	—	—	—
Skanör water level	0.52	0.52	0.17	−0.06	1.00	—	—	—	—
Rødvig water level	0.53	0.52	0.08	−0.12	0.98	1.00	—	—	—
Kastrup, N wind	−0.27	−0.28	0.25	0.33	0.10	0.14	1.00	—	—
Kastrup, E wind	0.57	0.56	−0.59	−0.65	0.31	0.41	−0.04	1.00	—
Hornbæk-Rødvig	−0.78	−0.77	0.56	0.76	−0.67	−0.74	0.13	−0.71	1.00

dynamic model, as well as the long integration time without any assimilation of observations. All these indicate a need for further treatment of the raw mode outputs in order to produce better forecast skills.

It is obvious from Fig. 9 that although the deterministic model captures some of the features of the current flow, it does not resolve it to a sufficient degree of accuracy (especially when one tows a 55,000 ton element). Therefore an alternative and much more accurate approach to the forecast had to be developed.

The deterministic model provides a global description of the system. It takes into account global status of the sea and it applies meteorological forcing over the entire North Sea and Baltic Sea areas. However, due to inherent complexity of the system, relatively coarse numerical grids, imperfections of meteorological forecasts, intrinsic limitations of numerical models, etc., numerical models typically produce results of inadequate accuracy. In order to improve the deterministic model's accuracy, local observations have to be assimilated. This novel forecast method combines deterministic models with observations and uses ANNs to merge the two sources of information and produce more accurate forecasts. Now, in addition to the MIKE 21 output, a number of local observations for generation of forecasts were used. Such a hybrid approach combines global and local information and updates the deterministic model results on the basis of collected observations. ANNs are used to approximate a fraction of results not resolved by the deterministic model.

TABLE 6. Data Utilization

Data (1)	Period (h) (2)
Training	Jul. 1, 1995 at 13:00 GMT–Mar. 12, 1996 at 11:00 GMT (6,000)
Cross-validation	Mar. 12, 1996 at 12:00 GMT–Sep. 3, 1996 at 01:00 GMT (4,190)
Testing	Mar. 7, 1997 at 00:00 GMT–Jun. 5, 1997 at 20:00 GMT (2,180)

Note: GMT = Greenwich mean time.

TABLE 7. Main Statistical Properties for Used Data (Depth-Averaged Currents at Nordre Røse)

Property (m/s) (1)	Data (2)	Speed (3)	N-S component (4)	E-W component (5)
Mean value	Training	0.084	0.098	0.023
Mean value	Cross-validation	0.075	0.087	0.018
Mean value	Testing	0.171	0.175	−0.019
Standard deviation	Training	0.550	0.509	0.203
Standard deviation	Cross-validation	0.466	0.432	0.168
Standard deviation	Testing	0.557	0.519	0.201

Description of Data

As previously mentioned there are 38 measuring stations in the Øresund Strait where data are collected in an on-line fashion. Not all of these observations are, however, related to the forecast of the current speed and their direction, and the choice had to be made to use the most relevant ones.

After the initial screening and on the basis of many years of experience in modeling Danish waters, the following data subset was selected:

- ADCP measurements of velocity at Nordre Røse at 17 levels
- Water level in Viken
- Water level in Hornbæk
- Water level in Rødvig
- Water level in Skanör
- E-W component of wind in Kastrup
- N-S component of wind in Kastrup

All these data were carefully screened for outliers and quality assured before being subjected to further analysis. Correlations among these quantities are summarized in Table 5. The correlation analysis indicates that the ''strength'' in which the data are mutually related. In addition to the raw data, an additionally derived quantity—water level difference between stations in Hornbæk and Rødvig—is introduced. It is rather obvious that even such a simple operation adds to the quality of correlation.

After additional analysis, the observations from Viken and Hornbæk as well as from Skanör and Rødvig were mutually strongly correlated, thus eliminating the need for observations from Viken and Skanör. Finally, the following subset of observations was chosen:

- Current speed and direction at Nordre Røse (depth-averaged and at the surface)
- Water level in Hornbæk
- Water level in Rødvig
- East-West component of wind in Kastrup
- North-South component of wind in Kastrup

In addition to these observations, the following MIKE 21 outputs were extracted:

TABLE 8. Depth-Averaged Velocity Components—Accuracy Assessment on Validation Data Set

Performance (1)	Average E-W+1 (2)	N-S+1 (3)	E-W+3 (4)	N-S+3 (5)	E-W+6 (6)	N-S+6 (7)	E-W+12 (8)	N-S+12 (9)	E-W+18 (10)	N-S+18 (11)
R	0.989	0.988	0.973	0.953	0.923	0.929	0.828	0.833	0.796	0.787
R^2	0.979	0.994	0.947	0.976	0.849	0.860	0.686	0.693	0.633	0.619

Note: Forecast based on measurements alone.

TABLE 9. Top Layer Current Components—Accuracy Assessment on Validation Data Set

Performance (1)	Top E-W+1 (2)	N-S+1 (3)	E-W+3 (4)	N-S+3 (5)	E-W+6 (6)	N-S+6 (7)	E-W+12 (8)	N-S+12 (9)	E-W+18 (10)	N-S+18 (11)
R	0.983	0.993	0.965	0.975	0.906	0.913	0.833	0.843	0.799	0.822
R^2	0.965	0.985	0.932	0.951	0.821	0.834	0.693	0.710	0.638	0.676

Note: Forecast based on measurements alone.

- Depth-averaged current speed and direction at Nordre Røse
- Water levels in Hornbæk
- Water level in Rodvig

All these data were available in the period from Jul. 1, 1995 to Jun. 05, 1997 at a temporal resolution of 1 h. These data were then split into training, cross-validation, and testing data in a fashion outlined in Table 6. Some elementary statistics for the used data sets are presented in Table 7. A number of time-delayed neural networks were created and trained using the data set defined in Table 6. All measured and deterministic model result values were used as inputs, whereas measured current speeds shifted in time as a desired output. Thus, for every forecast lead time (+1 h, +3 h, +6 h, etc.), a different ANN was developed using as inputs both observed and calculated values and as desired outputs future observed current speeds and their direction.

Forecast Strategies

One strategy for current forecasts may be to generate procedures based on observations alone. This is a viable approach for short-term forecasting. Tables 8 and 9 provide correlation coefficients r and Pearson's R^2 for forecasts based on measurements alone. These results should be compared to results presented in Tables 12 and 14. In general, accuracy is almost equivalent for shorter times of forecast horizon. However, once the horizon extends over a single tidal cycle (12 h), the forecast strategy based on the knowledge of initial conditions alone is not possible. Observations (representing initial conditions) are simply washed away after a tidal period and precise further evolution of the physical system cannot be determined solely on that basis. One has to employ additional physical insights to be able to extend the forecast horizon further into the future. This constitutes the main justification for using neural networks in a data assimilation mode. Investigation of forecast skill for a hybrid (ANN plus deterministic model) forecast strategy is presented in the Forecast Skill section.

Once the forecast horizon exceeded 12 h the measured quantities clearly became obsolete. Consequently, for lead times longer than 12 h, TDNNs used only deterministic model results as inputs. Basically, in this case neural networks were employed to detect and correct errors in the deterministic model. This is a pure correction of the deterministic model, as no observations are assimilated.

TABLE 10. Sensitivity of East-West and North-South Components of Average Current Velocity for Lead Time of 3 h to Its Inputs

Sensitivity (1)	Average E-W+3 (2)	Average N-S+3 (3)
Hornbæk water level	0.1610	0.4237
Rødvig water level	0.0497	0.1259
Hornbæk water level M21	0.0294	0.0722
Rødvig water level M21	0.0328	0.1001
E-W M21	0.3436	1.5991
N-S M21	0.0896	0.3344
Average E-W	0.3745	0.2389
Average N-S	0.0407	0.3870

TABLE 11. Depth-Averaged Speed Intensity—Deterministic Model

Performance (1)	+1 (2)	+3 (3)	+6 (4)	+12 (5)	+18 (6)
Mean squared error	0.092	0.092	0.093	0.095	0.097
Normalized mean squared error	0.752	0.753	0.755	0.757	0.760
Mean absolute error	0.247	0.249	0.251	0.255	0.257
Minimum absolute error	0.000	0.001	0.001	0.001	0.001
Maximum absolute error	1.092	1.092	1.093	1.094	1.095
R	0.676	0.675	0.673	0.671	0.670
R^2	0.457	0.456	0.455	0.453	0.451

Note: Accuracy assessment on validation data set.

Sensor Coverage and Data Availability Indicator

For the purposes of towing it was required to develop a modeling system capable of operating in real time. That is, as soon as a new set of observations becomes available the forecast system should take them into account and update the forecast. Such a strategy results in a most up-to-date and most accurate quality of forecast. However, it also calls for some sort of on-line quality assurance routine. For example, once the sensor is faulty, it produces an erroneous value. One strategy may be to, as soon as a single sensor drops out, replace a particular routine's output with another routine's output, e.g., to employ a less accurate, but available pure correction routine.

In the Øresund Strait, the estimated sensor coverage is 91%. This means that, on the average, each sensor can be out of normal operation 9% of the time. Since a number of sensors were used in generation of the forecasts, it may turn out that switching from a more to a less accurate routine may occur frequently and sometimes not necessarily. A single missing observation may not be significant enough to justify switching to a less accurate routine. Particularly, as the data are time-varying and the ANN performance is not equally sensitive to all of them, an alternative way of establishing how much data is available needs to be introduced. In order to tackle the problem a data availability indicator (DAI) was developed.

For example, Table 10 represents a sensitivity of outputs of an induced TDNN to its inputs. In this case, TDNN produces

TABLE 12. Depth-Averaged Velocity—Accuracy Assessment on Validation Data Set

Performance (1)	Average E-W+1 (2)	N-S+1 (3)	E-W+3 (4)	N-S+3 (5)	E-W+6 (6)	N-S+6 (7)	E-W+12 (8)	N-S+12 (9)	E-W+18 (10)	N-S+18 (11)	E-W (12)	N-S (13)
Mean squared error	0.0007	0.0034	0.0019	0.0116	0.0048	0.0311	0.0081	0.0523	0.0080	0.0539	0.0076	0.0526
Normalized mean squared error	0.0177	0.0125	0.0480	0.0434	0.1190	0.1160	0.2001	0.1955	0.1988	0.2016	0.1877	0.1955
Mean absolute error	0.0201	0.0439	0.0333	0.0839	0.0525	0.1355	0.0671	0.1682	0.0660	0.1727	0.0654	0.1718
Minimum absolute error	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001
Maximum absolute error	0.1814	0.3821	0.2469	0.5211	0.3739	1.1135	0.3834	0.8943	0.4724	1.2124	0.3700	0.9125
R	0.9912	0.9940	0.9772	0.9802	0.9436	0.9466	0.9073	0.9112	0.9016	0.9016	0.9048	0.9026
R^2	0.9825	0.9880	0.9548	0.9607	0.8905	0.8961	0.8231	0.8302	0.8129	0.8128	0.8187	0.8147
Taps	3	3	3	3	6	6	10	10	11	11	8	8

two outputs (east-west and north-south components of an average current velocity), for the lead time of 3 h. Sensitivity to a particular input may be interpreted as an indicator of an extent to which erroneous information in the input would be felt in the output.

Since this particular forecast routine uses a tap-delay line with a memory of 3, it is necessary to calculate a DAI for the observed data as

$$\begin{aligned}\text{DAI} &= \text{DAI(E-W)} + \text{DAI(N-S)}\\ &= (3 \times 0.1610 + 3 \times 0.0497 + 3 \times 0.3745 + 3 \times 0.0407)\\ &+ (3 \times 0.4237 + 3 \times 0.1259 + 3 \times 0.2389 + 3 \times 0.3870)\\ &= 4.9695\end{aligned}$$

Thus, if all the data were available, the maximum DAI for this particular routine would be 4.9695. However, if a particular sensor drops out for a single hour, say the water level observation in Hornbæk, the new quality indicator of the available data would be

$$\begin{aligned}\text{DAI} &= (2 \times 0.1610 + 3 \times 0.0497 + 3 \times 0.3745 + 3 \times 0.0407)\\ &+ (2 \times 0.4237 + 3 \times 0.1259 + 3 \times 0.2389 + 3 \times 0.3870)\\ &= 4.3848\end{aligned}$$

which represents 88% of the full quality indicator. In the present implementation and on the basis of experience with the operational system, once the quality indicator would drop below 90%, a switching to an alternative model was employed.

FORECAST SKILL

Before presenting detailed analysis of the forecast skill after the error correction has been applied, an analysis of raw numerical model results is presented. This is in order to estimate a degree of improvement that error correction routine introduces. Table 11 summarizes some of the essential statistics regarding the performance of the numerical model without any data assimilation. As the numerical model is based on vertically averaged velocities, Table 11 provides only the intercomparison with depth-averaged measured velocities. It is worth

TABLE 13. Depth-Averaged Velocity—Sensitivity Analysis

Sensitivity (1)	Average E-W+1 (2)	N-S+1 (3)	E-W+3 (4)	N-S+3 (5)	E-W+6 (6)	N-S+6 (7)	E-W+12 (8)	N-S+12 (9)	E-W+18 (10)	N-S+18 (11)	E-W (12)	N-S (13)
Hornbæk water level	0.1091	0.2711	0.1610	0.4237	0.2163	0.5126	0.1061	0.3147	0.0894	0.5235	—	—
Rødvig water level	0.0099	0.0355	0.0497	0.1259	0.0805	0.2341	0.1016	0.4122	0.0656	0.1939	—	—
Hornbæk water level M21+1	0.0206	0.0471	0.0294	0.0722	0.1489	0.2234	0.1119	0.2742	0.1061	0.2154	0.1063	0.2871
Rødvig water level M21+1	0.0243	0.0200	0.0328	0.1001	0.0682	0.1512	0.1092	0.3268	0.0709	0.1311	0.0215	0.1119
E-W M21+1	0.2899	0.5064	0.3436	1.5991	0.5762	2.0145	0.5687	0.9342	1.0284	1.3989	0.4761	3.5823
N-S M21+1	0.0441	0.0987	0.0896	0.3344	0.2689	0.8269	0.3839	1.0443	0.4040	0.9113	0.4701	1.3957
Average E-W	0.4829	0.1008	0.3745	0.2389	0.4005	0.6864	0.3127	0.2812	0.1991	0.1134	—	—
Average N-S	0.0277	0.5546	0.0407	0.3870	0.0888	0.1465	0.0586	0.1182	0.0505	0.0690	—	—

TABLE 14. Top Layer Current—Accuracy Assessment on Validation Data Set

Performance (1)	Top E-W+1 (2)	N-S+1 (3)	E-W+3 (4)	N-S+3 (5)	E-W+6 (6)	N-S+6 (7)	E-W+12 (8)	N-S+12 (9)	E-W+18 (10)	N-S+18 (11)
Mean squared error	0.0016	0.0060	0.0039	0.0203	0.0090	0.0532	0.0135	0.0916	0.0114	0.0897
Normalized mean squared error	0.0311	0.0165	0.0743	0.0565	0.1710	0.1479	0.2557	0.2549	0.2153	0.2483
Mean absolute error	0.0304	0.0560	0.0481	0.1099	0.0723	0.1775	0.0888	0.2261	0.0804	0.2235
Minimum absolute error	0.0000	0.0002	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0000	0.0001
Maximum absolute error	0.2981	0.6889	0.2998	0.7739	0.4753	1.0144	0.6133	1.4590	0.4375	1.3289
R	0.9850	0.9919	0.9674	0.9759	0.9303	0.9383	0.8864	0.8913	0.8958	0.8885
R^2	0.9702	0.9838	0.9359	0.9524	0.8654	0.8805	0.7856	0.7944	0.8025	0.7894
Taps	2	2	4	4	8	8	13	13	9	9

TABLE 15. Top Speed—Sensitivity Analysis

Sensitivity (1)	bin15 E-W+1 (2)	bin15 N-S+1 (3)	bin15 E-W+3 (4)	bin15 N-S+3 (5)	Ul15 E-W+6 (6)	Ul15 N-S+6 (7)	Ul15 E-W+12 (8)	Ul15 N-S+12 (9)	bin15 E-W (10)	bin15 N-S (11)
Hornbæk water level	0.1017	0.2808	0.1697	0.5321	0.2707	0.7765	0.1443	0.4092	—	—
Rødvig water level	0.0183	0.0475	0.0202	0.0538	0.0424	0.1042	0.2125	0.4746	—	—
Hornbæk water level M21+1	0.0414	0.0799	0.0615	0.2112	0.2803	0.7525	0.3491	1.0611	0.0891	0.3723
Rødvig water level M21+1	0.0232	0.0627	0.0794	0.1171	0.1656	0.6095	0.1972	0.5608	0.0309	0.2617
E-W M21+1	0.2056	0.4481	1.3785	2.9666	1.1599	2.8121	1.4558	6.6128	1.6221	5.3177
N-S M21+1	0.0271	0.1143	0.2749	0.6385	0.3228	1.0590	0.6422	2.0554	0.4823	1.6732
bin15 E-W	0.5020	0.0506	0.4065	0.2602	0.2355	0.3020	0.2735	0.5295	—	—
bin15 N-S	0.0258	0.5412	0.0287	0.4562	0.0381	0.3389	0.0668	0.1105	—	—

noting from this table that although the overall accuracy is rather poor, it does not deteriorate with advancing forecast lead time.

A complete and detailed analysis of the forecast skill after error correction routines have been applied is summarized in Tables 12–15. These tables provide a number of statistical measures of accuracy for a number of lead times. This analysis is performed independently on north-south and east-west components of currents. As the dominant flow direction is in the N-S direction (Fig. 10 and Table 7), the associated errors in the N-S direction are larger than errors in the E-W direction. Graphical representation of the forecast skill for the lead time of 3 h and 6 h is illustrated in Figs. 11 and 12, respectively.

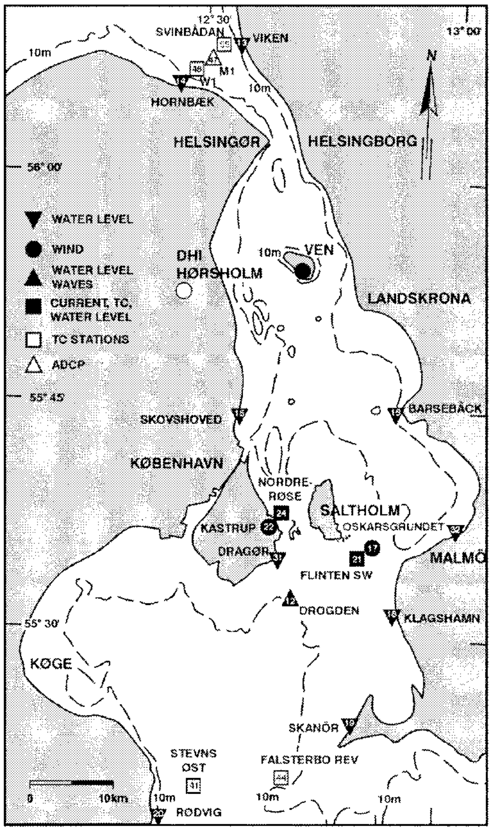

FIG. 10. Overview Map with Measuring Stations

The internal structures of all the neural networks used in this exercise of current forecasting were examined in great detail. Here we refer to a number of hidden layers, the number of neurons in each of the layers, and in particular a length of memory buffer TDNNs used. The purpose of this examination was to identify architectural features that guarantee the best bias-variance trade-off and consequently the best generalization properties. In general, all neural networks used here were based on two hidden layers. The first hidden layer was equipped with a 3 time-step memory buffer, and the second hidden layer with a 1 time-step memory. The number of optimal memory taps at the input layer are provided in Tables 12 and 14 for all lead times.

An intercomparison of the three possible approaches: (1) Purely deterministic (with associated accuracy given in Table 11); (2) the approach based on data alone (Tables 8 and 9); and (3) the error correction approach (Tables 12 and 14) clearly indicates the best forecast strategy. While a deterministic forecast does not result in a very accurate skill, this performance does not deteriorate with longer lead times. Forecast strategy based on data lone provides very good skill for short lead times, but it cannot be extended for nontrivial forecast lead times, i.e., longer than a single tidal cycle. The error correction approach hybridizes the two forecast strategies and effectively provides the combination of the best of the two worlds—a good forecast skill that can also be extended far in the future.

Since these observations are collected continuously, a forecast model that could be invoked continuously was developed. In practice, this means that every time a new observation arrived, a forecast model could be triggered in order to provide a prediction that is even more accurate. This is very useful, particularly during the towing operations when the forecast can be updated on an hourly basis. In the case of depth-averaged velocities for forecast horizons larger than 18 h and 12 h for the case of surface velocities, the neural network error-correction scheme was based only on inputs from MIKE 21. The significance of observations within a forecast scheme simply deteriorates over time and after a certain empirically determined forecast horizon it is not useful to utilize observed values as inputs. The role of a neural network then becomes one of correcting systematic errors of a deterministic model.

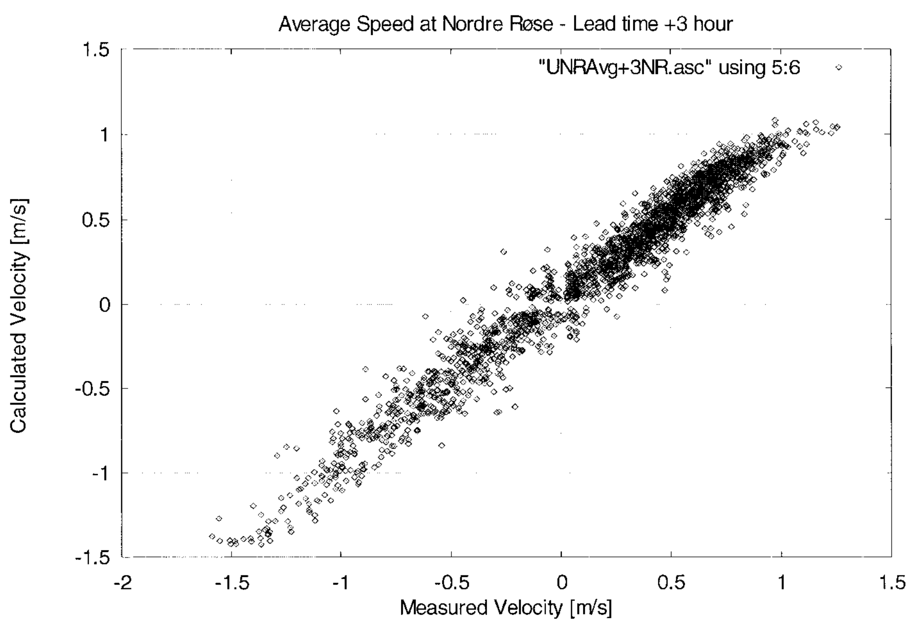

FIG. 11. Scatter Plot for Average Speed for Lead Time of 3 h—Test Period

In the end, the resulting hybrid model was based on a number of ANN routines that combine deterministic forecasts with observations or that correct a deterministic model's systematic errors. The final model performs extremely well, as depicted in Fig. 13. As the system operates in real time, the forecast was updated every hour during towing, generating more accurate predictions. However, as Fig. 13 shows, even the first forecast was of remarkably good quality.

OPERATIONAL IMPLEMENTATION

An operational forecast system was established on a computer running Windows NT. The system comprised a database with measurements and forecasted meteorological wind and currents and a number of programs developed to collect data and produce the forecasts. The database was automatically updated twice per hour with the latest measurements and twice

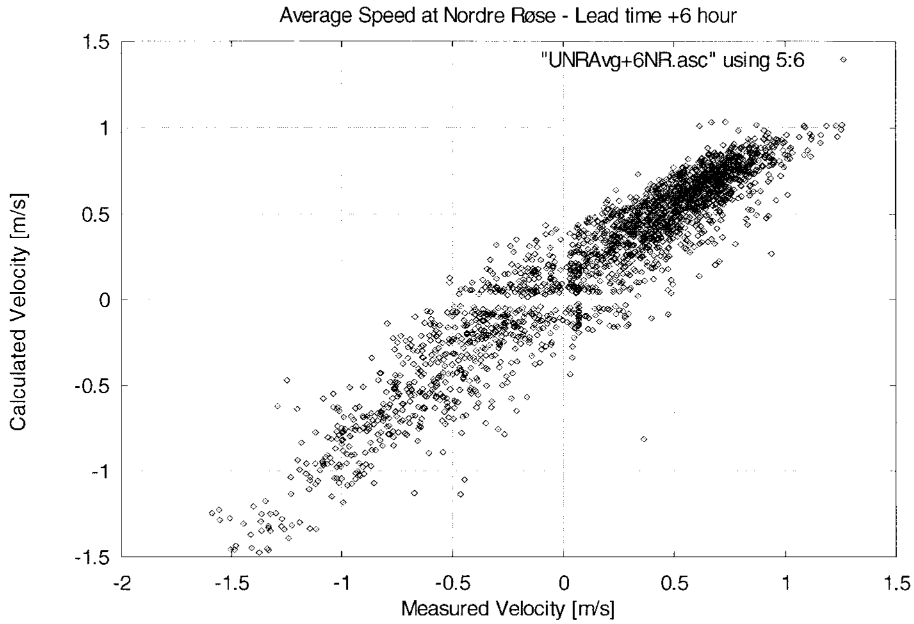

FIG. 12. Scatter Plot for Average Speed for Lead Time of 6 h—Test Period

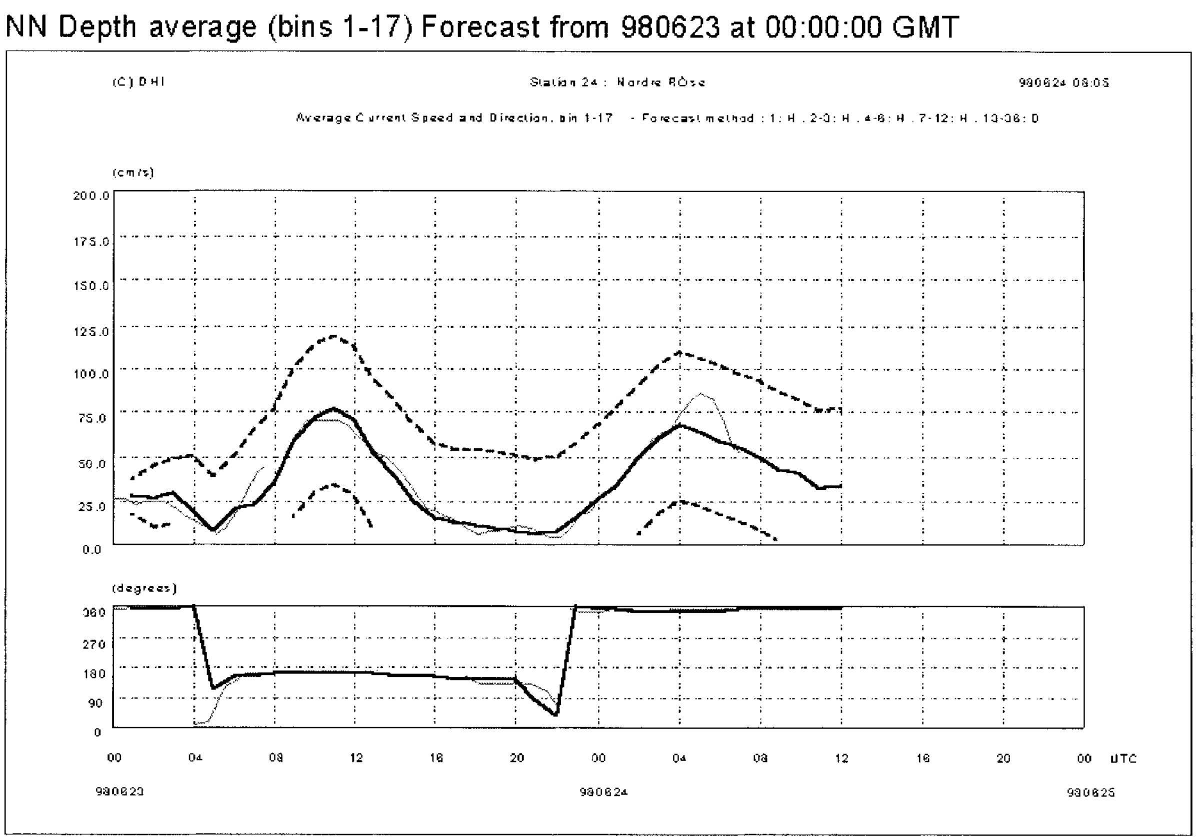

FIG. 13. First, 36-h-Long Forecast, Issued during Tow of Element 11: Thick Line Indicates Forecast Whereas Dotted Lines Show 90% Confidence Intervals; Observe Missing Values and Outliers in Measured Data (Thin Line) (GMT = Greenwich Mean Time)

a day with new forecasts of wind and currents having arrived from the Danish Meteorological Institute. Every hour a scheduled sequence of programs was run to forecast the currents at Nordre Røse. Every run took approximately 5 min to execute. The steps in this sequence comprised the following: (1) Data collection (extraction of measurements from all the data sources in the database needed for the forecast and extraction of meteorological wind-forecast data and currents from the deterministic modeling system, MIKE 21); (2) input data treatment (removal of spikes from measurements); (3) calculation of the data availability indicator; and (4) ANN execution and output creation (calculation of uncertainty interval, and graphical and tabular outputs). In addition to this, the operational system also provides information on which data sources necessary for ideal forecasts were missing, e.g., a sensor dropout or transmission problems in the reception of the deterministic forecasts.

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

Means for data collection and distribution have never been as advanced as they are today. While advances in data storage and retrieval continue at a breakneck pace, the same cannot be asserted about advances in information and knowledge extraction from data. Without such developments, however, we risk missing most of what data have to offer. However, as this paper demonstrated, forecasting on the basis of the data alone is not the complete story, at least not in scientific and engineering domains. Although a datacentric approach is at the focal point in many research areas, the current paper advocates a slightly different approach. Clearly, there is an enormous amount of knowledge and understanding of physical processes that should not merely be discarded. Forecast skill based on deterministic models should not be ignored. We strongly believe that the most appropriate way forward is to combine the best of the two approaches—theory-driven, understanding-rich with data-driven modeling processes.

The present paper presented an approach where a theory-driven deterministic model was coupled with a data-driven technique to produce a hybrid model with very good forecast skills. The resulting hybrid model performs much better than each of its constituents taken exclusively. The benefits of coupling were expressed not only in terms of accuracy, but also in terms of extension of the forecast horizon.

At the time of the preparation of this paper, all 20 elements of the Øresund Strait link's tunnel were successfully placed on their final positions. The first tunnel element was towed on Aug. 11, 1997, and the final and 20th element was successfully immersed on Jan. 6, 1999—20 towing operations in 17 months! The tunnel completion, despite rather severe flow conditions throughout this period, was carried out even ahead of schedule. It is alleged that the accurate forecasting routine presented in this paper was one of the key factors in this achievement. The Øresund Strait Link was opened to the public on Jul. 1, 2000.

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