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Metamodelo baseado em redes neurais de estado de eco para o problema de resfriamento de petróleo estagnado em linhas de produção do tipo *pipe-in-pipe*

Echo state network-based metamodel for the problem of stagnant petroleum cooling in pipe-in-pipe flowlines

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As baixas temperaturas encontradas em águas submarinas combinadas com o transporte de hidrocarbonetos em linhas de produção provocam o problema de deposição de sólidos no interior das mesmas, principalmente de parafinas e hidratos, que consistem em um considerável problema para a indústria do petróleo. Para superar este problema, a simulação computacional demonstra-se um aliado. Entretanto, estas simulações podem ser computacionalmente custosas tornando seu uso inapropriado. Nestes casos, metamodelos, que são modelos mais baratos do ponto de vista computacional, podem ser uma alternativa. O presente artigo propõe o uso de uma Rede de Estado de Eco como modelo substituto para o problema de resfriamento de fluido de produção estagnado em um sistema *pipe-in-pipe* submarino munido de aquecimento elétrico ativo. O metamodelo implementado mostra-se ser até vinte e quatro vezes mais rápido quando comparado ao Método dos Volumes Finitos, embora este tenha demonstrado correlações consistentes para todos os *lags* quando uma análise de auto correlação foi performada.
Palavras-chave: metamodelagem, simulação computacional, garantia de escoamento.

The low temperatures found in subsea water combined with the transport of hydrocarbons in flowlines that are immersed in this environment brings the problem of solid deposition inside the flowlines, mainly of paraffin and hydrates, which consists of considerable problems to the petroleum industry. To overcome this issue, computational simulation might be an ally. However, such simulations sometimes can be computationally demanded, making their use unpractical. In these cases, metamodels, which are computationally cheaper models, can be an alternative. The present paper proposes using an Echo State Network as a surrogate model for the problem of stagnant production fluid cooling in a subsea pipe-in-pipe system with active electric heating. The implemented metamodel shows to be twenty-four times faster than the Finite Volume Method, although it showed consistent correlations for all lags when a residual autocorrelation analysis was performed.
Keywords: metamodeling, computational simulation, flow assurance.

1. INTRODUCTION

Petrobras conceived the term flow assurance in 1990 decade [1], which refers to ensuring successful and economical flow of hydrocarbon stream from the reservoir to the sales or storage points [2]. The more critical aspect of this definition is the conduction of these hydrocarbons from the reservoirs to the collection facilities [1].

Among the issues that need to be considered about the flow of hydrocarbons is the solid deposition, including paraffins and hydrates. The low temperatures encountered in depths between 1500 m and 3000 m are between 274.15 K and 277.15 K make even worse the process of these deposits in the context of offshore exploration [3].

When considering production pipes, the difference in temperature between the production fluid and the pipe wall gives origin to a radial temperature gradient and a concentration gradient in the same direction once wax solubility is temperature dependent. This solubility gradient allows mass transport from the center of the pipes to the wall [4]. Once the paraffin reaches the regions near the wall, it finds temperatures lower than the wax appearance temperature, which starts the process of wax deposition. Another problem that might be found is the problem of aging which is the phenom in which the paraffin deposit hardens with time. Such phenom is due to the internal temperature gradient, which promotes a concentration gradient that leads to internal diffusion of paraffin molecules through the trapped solvent in between the incipient gel layer [5].

Gas clathrate is a solid solution in which water molecules are linked to each other by hydrogen bonding, forming cavities called host lattices that enclose several varieties of guest molecules. There is no chemical bonding between the water molecules and the guest molecules. The clathrate hydrate crystals may exist in temperatures below or above the water freezing point and may form deposits [6]. Solid deposits may lead to significant financial losses because these can form blockages to the hydrocarbon flow [3]. So, these are considered a massive problem in petroleum exploration.

To mitigate the problem of hydrates and paraffin deposition, pipe-in-pipe comes as a solution [7]. It consists of two concentrical pipes in which the annular space is filled with insulating material. The inner pipe transports the production fluid while the external provides mechanical protection [8]. Also, to mitigate the already cited deposition problems, active electrical heating associated with pipe-in-pipe may be used. In active electric heating, the heat is generated by applying an electrical current through some conductive element. It may be classified as direct electric heating, when the current flows through the inner pipe, or indirect electric heating, when the current flows through conductive material, like wires [9] in such a way that, in both cases, the generated heat is transferred to the production fluid.

Also, in the mitigation of the cited deposition problems, the computational simulation might be a great ally because, through it, it is possible to estimate variables associated with the heat transfer process that cannot be measured to implement strategies associated with the predictive control model given the mitigation of paraffin and hydrates deposition through monitoring. However, these are just possibilities and are not part of this paper's scope. Notwithstanding, some computational simulations may have a high computational burden taking a long time to be evaluated. So, to overcome these issues, metamodels, also called surrogate models, may be used [10].

2. METAMODELING

The use of computational simulations is a widespread issue in engineering practice. In chemical engineering, for example, it may include modeling of chemical production processes or complex thermodynamics. Nonetheless, because of the complexity of the studied phenomena, these simulations may be of high computational cost in such a way that simulations take many hours to be accomplished, making their use unpractical. Therefore, metamodels may be applied to reduce computational costs [10].

A metamodel is a mathematical model that map or regresses, the input-output relationships of a more complex, computationally demanding model [10]. That is, metamodels are less costly mathematical models that approximate some costly objective function and use it instead, or even together, with the computationally demanding model.

In general way, to construct a metamodel, first needed to determine a design of experiments, proceed with the numerical simulations at the points given by the design of experiments, and so, use the obtained data to construct the metamodel. Once it is done, the metamodel needs to be assessed. If necessary, one might go back to the design of experiments step [11].

There are several techniques to construct a metamodel such a way in [12] are listed twenty-eight different metamodeling techniques, the most common polynomial regression, moving least squares, radial basis function, kriging regression, support vector regression, and artificial neural network [13].

Achieving an accurate surrogate model demands adequate input and output data. Given the cost of experimental work, training points are often generated through precise numerical simulations that consider several parameters for an observation, which can require considerable computation time [14, 15]. Concerning the computational costs, recently, surrogate models was used to optimize the design of aerodynamic shapes, significantly reducing the computational effort required for each design evaluation [16]. An application to the use of Gaussian process surrogate models for uncertainty analysis in environmental models and demonstration of the use of surrogate models for real-time control in robotics, enabling faster and more efficient control actions [17, 18]. Qui et al. (2022) [19] compared a surrogate model with a commercial simulator for pipeline gas transport, producing result with high accuracy, below 6%, and CPU cost 1250 times faster than LedaFlow software. This approach could be beneficial when large amount of simulations runs is required, like inverse problems, where stochastic and recursive algorithms, like Monte Carlo method, are used to estimation of states and parameters.

Using finite element analysis, Mentani et al. (2023) [20] developed metamodels to predict the tensile capacity and secant stiffness of steel piles driven in the sand. The metamodels were based on robust finite element models and evaluated with full-scale test data. The results showed that these metamodels provided highly accurate results in several soil-stake configurations, avoiding the complexity and computational cost of finite element models. Furthermore, the authors suggest using the model applied in statistical analysis to deal with variability and uncertainties in foundation problems, especially in offshore environments. Sebastjan et al. (2023) [21] studied the application of metamodels in the adjustment of optimization algorithm parameters associated with the nonlinear buckling phenomenon of the automotive shock absorber. To solve the direct problem, the authors used a commercial finite element simulation application. In addition, they employed a surrogate model that reproduces the behavior of real simulation of nonlinear finite elements. This surrogate model was used to significantly reduce the simulation time, allowing the study of numerous combinations of algorithm parameters and the performance of adjustments. The results of this study indicate that the use of metamodels can improve the performance of optimization algorithms.

In studies carried out by Li et al. (2022) [22], a neural network was used as a substitute model to simulate reactive transport modeling (RTM) based on processes that integrate thermodynamic and kinetically controlled fluid-rock interactions, considering the flow of fluid through porous media in the underground and surface environment. The results reveal that the duly trained surrogate model proved particularly advantageous when several executions are required, such as in sensitivity analysis or model calibration, allowing a significant reduction in computational time compared to that needed for the RTM. Im et al. (2021) [23] proposed a practical framework for the surrogate modeling of a large-scale elasto-plastic finite element (FE) model, using long short-term memory neural networks combined with adequate orthogonal decomposition. The results show that the proposed substitute models proved computationally efficient and accurate in predicting elastic-plastic responses.

3. ARTIFICIAL NEURAL NETWORKS

An Artificial neural network is an information-processing paradigm inspired by the way biological nervous systems such as the brain process information, that is, a way of processing information based on biological nervous systems. The artificial neural networks are formed by several processing elements called, by analogy, neurons that are linked by weighted connections [24].

Each of the neurons has a linear combinator that sums the input values multiplied by its weights. The value obtained by the linear combination is summed to a value called bias. The obtained value passes through an activation function consisting of the neuron's output [25]. Mathematically:

$$u_k = \sum_{i=1}^{n} w_{kj} x_j \quad (1)$$

$$v_k = u_k + b_K \quad (2)$$

$$y_k = \varphi(v_k) \quad (3)$$

In Eq. 1 to 3, u_k denotes the output of the linear combinator, w_{kj} the weight of the j-th input associated to the k-th neuron, x_j the value of the j-th input, v_k the activation potential, $b_k$the bias associated to the k-th neuron, y_k the output of the k-th neuron and φ the activation function [25].

There are several kinds of neural networks that differs from each other because of its topology such as back propagation, radial basis function and cerebella model articulation controller [26]. However, in this work, the focus is on Echo State Networks.

4. ECHO STATE NETWORKS

Echo State Networks are well suited tool to solving temporal series, regression or forecasts [27]. ESNs were used, for example, in the classification of insulators based on the ultrasound signal [28], in the monitoring and detection of failures in industrial processes [29], and as a metamodel of the dynamic instability of the casing heading as a predictive control strategy for a gas lift well [30]. The ESN is a recurrent neural network with three layers: the input layer, the reservoir layer, and the output layer. The reservoir layer includes hundreds or thousands of sparsely and recursively connected neurons [31].

The synaptic weights between the input layer and the reservoir, so as the weights of the reservoir are initialized randomly and remain fixed during training, that is, they remain the same along the training phase such a way that are trained only the weights between the reservoir and the output layer which are obtained by a linear regression [32]. The activation of internal units and the output units are updated according to [33]:

$$\boldsymbol{x}(n+1) = f\left(\boldsymbol{W}\boldsymbol{x}(n) + \boldsymbol{W^{in}}\boldsymbol{u}(n+1)\right) \quad (4)$$

$$\boldsymbol{y}(n+1) = f^{out}\big(\boldsymbol{u}(n+1), \boldsymbol{x}(n+1)\big) \quad (5)$$

In above equations f is an element-wise application of the activation function; $\big(\boldsymbol{u}(n+1), \boldsymbol{x}(n+1)\big)$ is a vector concatenated from $\boldsymbol{u}(n+1)$ and $\boldsymbol{x}(n+1)$; f^{out} is the activation function in output; $\boldsymbol{W}$ is the internal connection weights matrix; $\boldsymbol{W^{in}}$ is the matrix of weight connections from the input unit into the network and $\boldsymbol{W^{out}}$ is the output weights matrix [33]

In the activation of internal units equation, an optional feedback may be used in which case the equation becomes [34]:

$$\boldsymbol{x}(n+1) = f\left(\boldsymbol{W}\boldsymbol{x}(n) + \boldsymbol{W^{in}}\boldsymbol{u}(n+1) + \boldsymbol{W^{back}}\boldsymbol{y}(n)\right) \quad (6)$$

Where $\boldsymbol{W^{back}}$ is the feedback weights matrix and $\boldsymbol{y}(n)$ is the output activation vector. Optional noise is also an option [34]. A complete review of designs and application of Echo State Networks could be found in [35].

5. PHYSICAL PROBLEM FORMULATION

Consider a condition in which production fluid is stagnant inside a pipe-in-pipe with direct electric heating flowline. Because of the temperature difference between the production fluid and the environment, heat is conducted through the pipeline in such a way the temperature of the production fluid tends to the environment temperature. Considering the symmetry of the system, the heat is conducted through the different layers of the pipe-in-pipe according to the unidimensional transient heat conduction in cylindrical coordinates as can be found in Orlande et al. (2012) [36]. With the proper considerations the model becomes:

$$\rho_i(T)C_{p_i}(T)\frac{\partial T_i(r,t)}{\partial t} = \frac{1}{r}\frac{\partial}{\partial r}\left(rk_i(T)\frac{\partial T_i(r,t)}{\partial t}\right) + g_i \text{ for } r_i \leq r \leq r_{i+1}, t > 0 \quad (7)$$

The following boundary conditions must be observed:

$$-k_0(T)\frac{\partial T_0(r,t)}{\partial r} = 0 \; for \; r = r_0 = 0, t > 0 \quad (8)$$

$$-k_i(T)\frac{\partial T_i(r,t)}{\partial r} = -k_{i+1}(T)\frac{\partial T_{i+1}(r,t)}{\partial r} \text{ at the interfaces } r = r_{i+1}, i = 0, \ldots, 2,\; t > 0 \quad (9)$$

$$-k_3(T)\frac{\partial T_3(r,t)}{\partial r} + hT_3(r,t) = hT_s \text{ at } r = r\_4, t > 0 \quad (10)$$

In above equations, ρ is the specific mass $[kg/m]$, C_p is the specific heat at constant pressure $[J/(kgK)]$, T is the temperature $[K]$, t is the time $[s]$, r is the radial dimension $[m]$, k is the thermal conductivity $[W/(mK)]$, T_s is the sea temperature $[K]$ and the index i goes from 0 to 3.

Considering the proposed model, this paper aims to obtain a metamodel based on Echo State Network for the transient evolution of the temperature of a specific control volume of the considered system. In this case, the chosen control volume is the one that represents the boundary of the inner pipe because it is assumed that if it is above some critical temperature in which solid deposition occurs, which in this work it will be considered of 293,15 K, all the previous control volumes will be above this temperature.

6. METHODOLOGY

In order to solve the problem, the differential equation that governs the problem was solved using the finite volume method. Considering the system's symmetry, the conduction becomes one-dimensional so that only the radial temperature gradient is analyzed. This radius was divided into fifty control volumes: thirty for the fluid domain, five for the inner pipe ten for the insulating domain, and five for the outer pipe. The fluid domain has a radius of 0.1 m, the inner pipe has an external radius of 0.125 m, the insulating layer has an external radius of 0.175 m, and the outside pipe has an external radius of 0.2 m. An implicit scheme was used to solve the equation with a Δt of 120.96 s adding 12009600 s of analysis. The thermal properties of the production fluid were considered to vary with the temperature. The thermal properties of the other domains [37] are listed in Table 1.

Table 1: Pipe-in-pipe thermal properties.

Component	Material	Specific Mass (kg/m^3)	Specific Heat $[J/(kgK)]$	Thermal Conductivity $[W/(mK)]$
Inner pipe	Carbon steel	7700	502.1	52.34
Insulating layer	Polypropylene	750	2000	0.17
Outer pipe	Carbon steel	7700	502.1	52.34

Once the Finite Volume Method program had been implemented, it was used to generate the data set to train the Echo State Network. The inputs of the training data set and of the Echo State Network were the initial temperature T_{in}, sea water temperature T_s, and the electrical heating power G. The sea water and the electrical heating power were varied accordingly to a Random Gaussian Signal with up to fifty signal repetitions within the bounds exposed in the Table 2, while the initial temperature was kept constant. This way, 10000 timesteps were evaluated, 8000 for the Echo State Network training and 2000 for testing, resulting in a given temperature profile.

Table 2: Random Gaussian Signal bounds.

Input Variable	Lower bound	Upper bound
Sea water temperature $[K]$	272.25	275.15
Electrical heating power $[W/m^3]$	0	30

7. RESULTS AND DISCUSSION

In the training phase, the Echo State Network has achieved a unitary R^2, while for the testing phase, it has achieved an R^2 of 0.98. The results are presented in the Figure 1.

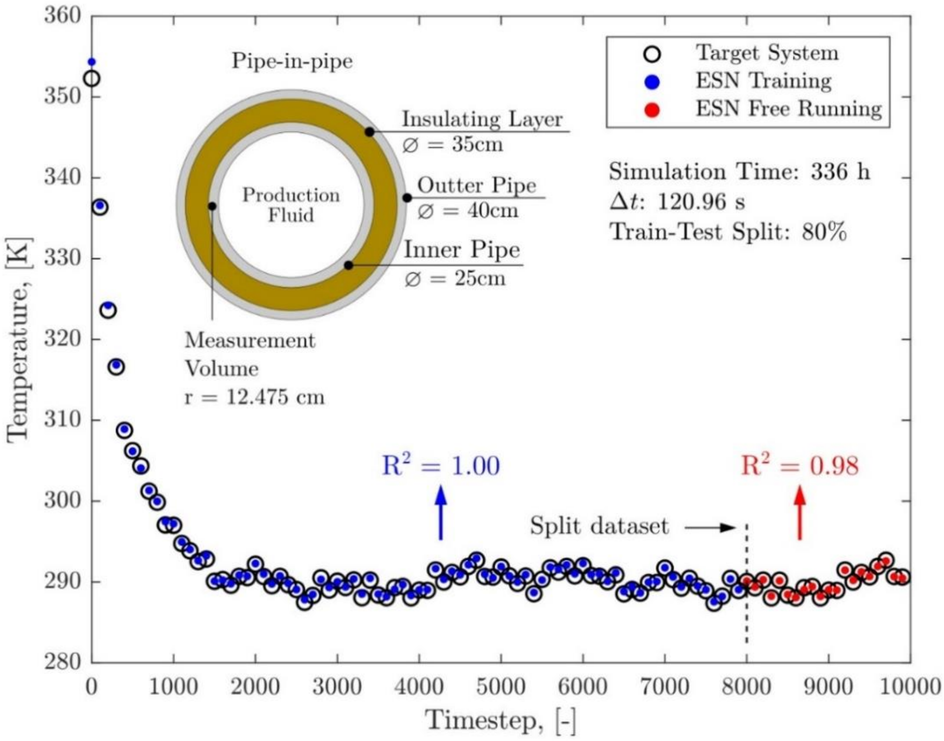

Figure 1: Training and testing Echo State Network.

When the Echo State Network is requested to predict some output for a given input between the training limits, it may do it successfully with an interval of $\pm 2.2\ K$, which is the error expected from a type J thermocouple. For example, in the Figure 2, the Echo State Network is requested to predict the temperature profile in such a condition that the initial temperature equals 343.15 K, the sea temperature equals 274.15 K, and the power of electrical heating equals 20 W/m^3. The Echo State Network shows twenty-four times faster than the Finite Volume Method. In this case, the elapsed time to compute the Finite Volume Method was 4.66 s against 0.19 s to compute Echo State Network prediction, which shows the effectiveness of the employment of the Echo State Network as a surrogate model in this problem.

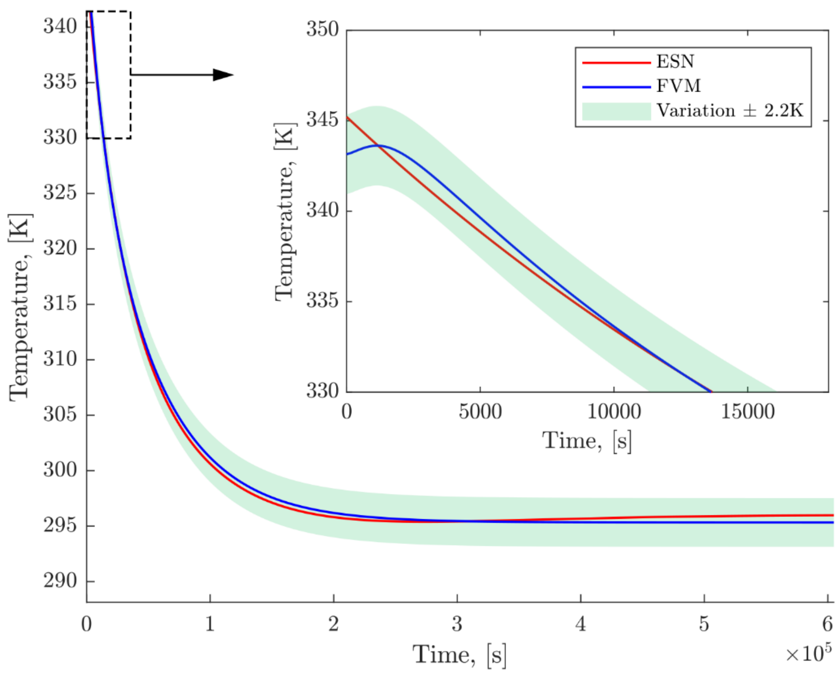

Figure 2: Echo State Network prediction compared to Finite Volume Method.

$$Error[\%] = max\left|\frac{T_{ESN} - T_{FVM}}{T_{FVM}}\right| .100 \qquad (11)$$

In order to illustrate that the results of our surrogate model and finite volume model are close, we calculate the maximum absolute percentage error (Eq. 11) for temperature, acquiring a maximum error value of 2.99 %. So, it proves that our model has good accuracy.

A basic assumption about residuals of a model is that the experimental data points are independent observations. If the residual exhibit autocorrelation for any lag, except for zero lag which is always one, then the observations are not independent or the mathematical model did not correctly describe the experimental data [38]. The residuals obtained during the training and testing phases showed strong autocorrelations with all the analyzed lags, as seen in the Figure 3, whose correction is left as suggestion for future works.

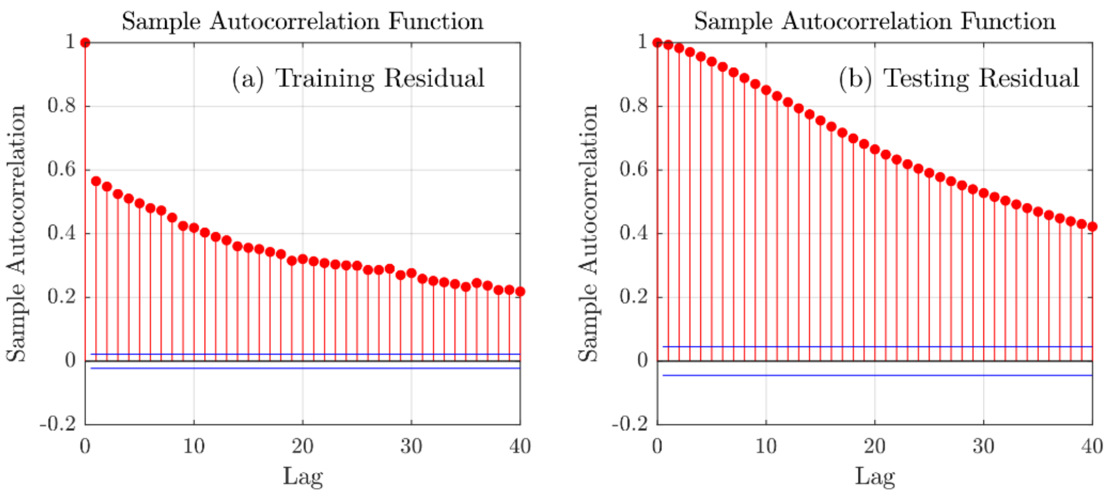

Figure 3: Training and Testing Residuals Autocorrelation.

8. CONCLUSION

This paper proposes the use of an Echo State Network as a metamodel to cool stagnant production fluid inside a pipe-in-pipe system with an electrical active heating problem. The Echo State Network was twenty-four times faster than the Finite Volume Method used to solve the governing differential equation, although it showed strong autocorrelations for all analyzed lags, whose correction is left as a suggestion to future works.

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