An implementable zone-based NMPC with Echo State Networks applied to an ESP-lifted oil well for maximum oil production

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Abstract

This study proposes an implementable approach involving nonlinear model predictive control (NMPC) with economic objectives for optimizing the production of an electrical submersible pump (ESP)-operated artificial lift system in the oil industry. The controller considers a zone control scheme to systematically accommodate the time-varying operational constraints commonly encountered in ESP systems (downthrust and upthrust). The constraints are effectively managed by incorporating these features into the control approach, thus yielding a nonlinear programming solution feasible for real-time implementation. Aiming to improve the computational challenges of the proposed NMPC law, an Echo State Network (ESN)-based data-driven model is integrated into the closed-loop feedback system for predicting controlled variables of the oil production system equipped with ESP installations. The ESN-based NMPC approach is implemented using open-source software, namely Python/CasAdi. The results obtained from the simulated scenarios indicate economic gains when the controller drives the ESP plant in the region of maximum flow rate, meeting the operational limits of the process. Furthermore, the controller's low computational time suggests the feasibility of embedding the algorithm in industrial hardware (PLC), making it more attractive for field operations.

**Keywords**: Nonlinear model predictive control, Echo state network, Electrical submersible pump, Artificial lift method, Oil production

* 1. Introduction

Advanced control of oil wells operated by electrical submersible pumps (ESP) has recently received significant attention. This interest is due to maximizing production, minimizing operating costs, and increasing equipment safety. In this context, the use of model predictive control (MPC) along with its extensions has emerged as a potential technique for the optimal operation of oil production processes equipped with ESP installations (Pavlov et al., 2014; Fontes et al. 2020; Santana et al., 2022).

In many systems operated by ESP, especially in offshore environments, building phenomenological models for MPC presents a considerable challenge. In this regard, data-driven modeling efforts have emerged as a promising alternative. Recent scientific research has focused on developing data-oriented, model-based MPC for ESP systems. Jordanou et al., (2022) introduce two distinct NMPC formulations based on Echo State Networks (ESN) for ESP control in simulated environments showing promising results. Similarly, Grønningsæter (2023) used an ESN-based model to compensate for process disturbances and to improve NMPC performance in an ESP system. However, it is essential to highlight some limitations of these controllers. The operational constraints of the pump, often referred to as the operating envelope, were not directly incorporated into the formulation of the control law, implying that the control system did not explicitly address specific pump limitations, such as downthrust and upthrust. Another critical point is that the controllers did not focus on maximizing production goals in ESP systems, considering that extracting significant volumes of oil from wells is a feature of ESP systems, which is an advantage compared to other methods.

To overcome the mentioned limitations, Matos et al., (2022) propose the implementation of a controller based on a data-oriented linear fuzzy model. This approach considers the pump's operational constraints (downthrust and upthrust) in formulating the control law. Furthermore, economic objectives are incorporated into the controller. The results were evaluated through a simulation scheme, specifically in scenarios with disturbances. However, it is essential to note that the controller utilizes a linear model set with parameter variations. This aspect presents challenges in implementing the control law in the real world, which is subject to changes based on the conditions of the oil field, as well as in the reservoir and fluid properties, which are dynamic. Additionally, the model does not provide predictions of other variables important to the system. For example, the average flow rate in the production column is used to represent the operating envelope of the pump indirectly.

Therefore, this paper attempts to fill the following gaps: *i*) the implementation of a zone nonlinear model predictive control that explicitly considers pump constraints (downthrust and upthrust) and seeks economic objectives, and *ii*) the integration of ESN-based NMPC, which considers process variables in the model, as well as the average production rate flow in the ESP system. This includes analyzing the controller's computational time for possible implementation in industrial hardware.

The remainder of this paper is structured as follows: Section 2 details the ESP dynamic model and explains the theoretical foundations of the control law and ESN. Section 3 presents the simulated results, and Section 4 concludes the paper, providing overarching insights and potential avenues for future work.

* 1. The proposed zone NMPC with echo state networks scheme for economic performance in ESP system
     1. Model of ESP-lifted oil well

The mathematical model that describes the behavior of an oil field with ESP installations is presented by Costa et al., (2021). The equations are written as follows:

where  is the annulus level; , and represent the reservoir flow rate, the flow rate in the production column, and the flow rate in the choke, respectively. means the wellhead pressure, while stands out to the bottom hole pressure. is the pressure increment provided by the pump that is defined by *H* (head), given by the manufacturer. Finally, and represent the variation in hydrostatic pressure, and the pressure drop through friction. More details about the model parameters (, , , , , ), and the constitutive equations that make up the model defined in (1)-(3) can be found in Costa et al., (2021).

* + 1. The proposed zone NMPC+ESN with economic performance

The NMPC law, integrated with an ESN, explicitly accommodates the ESP operational envelope constraints (upthrust and downthrust) via a zone control scheme that seeks to solve the following optimization problem:

subject to:

where is the vector of the controlled output prediction, i.e., and , and is the vector of the proposed ESN outputs that have been trained, namely , at time step based on the plant information at time step . is used as an output disturbance-type integral action in the optimization problem, and is the vector of the control actions , making up the entire control sequence computed by optimizer ; and are the adjustment parameters for the controlled variables and the control efforts; and define the prediction and control horizons that make up the remaining controller tuning parameters; represents the vector of economic targets on the manipulated variables, whereas is its associated weighting matrix.

**Assumption 1**: The controlled variables will have their = as a decision variable vector in the resulting control optimization problem, being able to assume any value within the output range in Eq. 7. In particular, *H* is defined as a controlled variable by zone tracking rather than setpoint, whose downthrust and upthrust envelope-type time-varying operational limits are calculated ( ) from rotational frequency *f*. This control zone scheme yields a softening NMPC law, providing a solution with a lower computational load and thus meeting the real-time implementation requirements. Furthermore, the nonlinear program (NLP) is solved through the package IPOPT (Interior Point Optimizer) in the open-source software Python/CasADi to find the optimal solution at every time step.

**Assumption 2**: The controller employs an ESN-based predictive model, initially introduced by Jaeger (2001). This model is defined in discrete state equation as follows:

In this formulation, the state associated with the hidden layer (reservoir) is represented by , represents the network's internal states, whereas and are the ESP input and output; acts as the leak rate parameter; the weights , , and are associated with the inputs, bias, and outputs, respectively. The activation function in this context is denoted by (hyperbolic tangent). Additional details can be referred to Jordanou et al., (2022) for a more in-depth discussion. It is important to emphasize that the output vector is made up by , in which data corresponding to is obtained from a nonlinear state estimator coupled with the phenomenological model.

A visual representation of the integrated zone NMPC and ESN approach within the ESP system is illustrated in a block diagram, as shown in Fig. 1.

* 1. Results and discussion

This section presents the simulated results of NMPC+ESN applied to an oil well equipped with ESP. For this study, we created scenarios that simulate realistic conditions in ESP. These scenarios cover: *i*) well startup in manual mode; *ii*) controller activation and disturbance compensation; and *iii*) economic benefits, such as maximum flow rate, while maintaining compliance with operational constraints (upthrust or downthrust). To meet these objectives, control actions were designed with a bounded variation, i.e., , along with the control signal constraints are and . Additional NMPC parameters ensuring feasibility include: a sampling time of econds; diagonal matrices for output and control penalties , and . Note that weights just choke valve opening (maximum production goal). Finally, the ESN was trained and validated using datasets generated by the open-loop model, as described in Eqs. . Due to the complexities involved in measuring the flow rate in the production column , an Extended Kalman Filter (EKF) was used to capture the dynamics of this variable. The hyper-parameters obtained in the network test were: reservoir size = 20; = 0.10; and bias\_scale = 5.

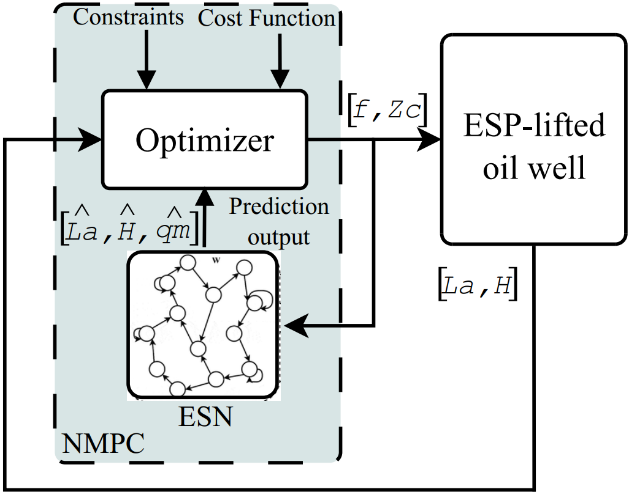


Figure 1: Implementation diagram of the zone NMPC scheme using an ESN model to control an ESP-lifted oil well.

Fig. 2 shows the simulated results of the closed-loop system. The ESP is started up with a frequency of 20 and a choke valve position of 0 %. The operator increases the frequency to 40 and adjusts the choke valve to 20 %. After 2.0 h, the pressure (head) and the flow rate in the well are within the operational envelope (see Fig. 2 (f)). Then, the operator activates the controller ("Control ON") to regulate the annulus level (), which affects the intake pressure of the pump. The controller starts at and . The controlled variables are outside the ideal zone. The controller identifies the prediction error and redirects ( to an optimal point, indicated by . After 2.5 h, a disturbance was introduced into the plant to simulate a change in the reservoir pressure. The controller effectively compensated for this disturbance by adjusting to within the predefined operating zone. This adjustment was made within the limits of upthrust and downthrust, involving modifications in the manipulated variables (MV), as shown in Fig. 2 (a-b | d-e). Such actions are aligned with **Assumption 1** since ESP operates safely within time-varying limits that guarantee the viability of the control law (optimal solution).

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Figure 2: Simulated results of the closed-loop ESP system.

Due to the need to increase production after reaching a steady state in 5.0 h, the operator activated the economic target. The target for the manipulated variable () was defined in 39 %. Subsequently, the controller adjusted the choke valve to drive the plant to its maximum production flow rate in 6.0 h. This was achieved while respecting the operational constraints of the pump and the limitations of the final control elements (see Fig. 2 (e)).

Fig. 2 (f) illustrates the operational envelope of the ESP throughout the simulation. The ESN-based model was trained offline using the average flow rate data from the production column, acquired through the proposed EKF. The results, represented in Fig. 2 (c), demonstrate dynamics very similar to those of the actual model used for simulation. Combined with PV (*H*), it made it possible to trace the operational trajectory of the plant. Notably, ESP maintained operational limits (upthrust or downthrust) in varied scenarios. In Fig. 2 (g), the average computational time of NMPC+ESN is shown. When the controller is active, the solution time at each time step is approximately 0.01 s. During perturbation scenarios, this time can extend up to 0.07 s without compromising the required sampling time of the controller. In this sense, this result proves to be promising for implementing industrial hardware (PLC), commonly used in oil wells equipped with ESP.

* 1. Conclusions

This paper presents an implementable ESN-oriented NMPC method that employs a zone scheme to manage an ESP-lifted oil well. The proposed controller is designed to meet control objectives while seeking economic benefits. The controller effectively maintained the plant within defined operational limits and economic production targets upon activation. Furthermore, the computational requirements for this approach are feasible for implementation on industrial hardware such as PLCs. As a future work, we will implement the proposed algorithm on a fully instrumented pilot plant installed at the Artificial Lift Laboratory (LEA) of the Federal University of Bahia (UFBA), representing dynamics close to the reality of an oil well equipped with ESP.

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