Using Physics-Informed Machine Learning and NVIDIA Modulus for Virtual Metering in Electrical Submersible Pump (ESP) Oil Wells

Nataliia Susulovska, Tymofii Nikolaienko, Harpreet Sethi, Hatem Nasr

nsusu@softserveinc.com tniko@softserveinc.com hasethi@nvidia.com hnasr@softserveinc.com

Developing soft-sensing methods, which constitute a foundation of digital-twin models of upstream oil production systems, is crucial for the oil and gas industry. Much attention has been devoted to virtual flow metering (VFM) of ESP-lifted oil wells, where accurate flow rate measurements are challenging to obtain due to the high cost of the required equipment and technical limitations caused by reservoir and well dynamics. We showcase the ESP VFM problem within physics-informed ML paradigm, which incorporates both the phenomenological model of the physical system and empirical data from ancillary sensors. Our PINN-based hybrid VFM application developed within NVIDIA Modulus framework leverages the power of GPU computations to train a highly parameterized model.

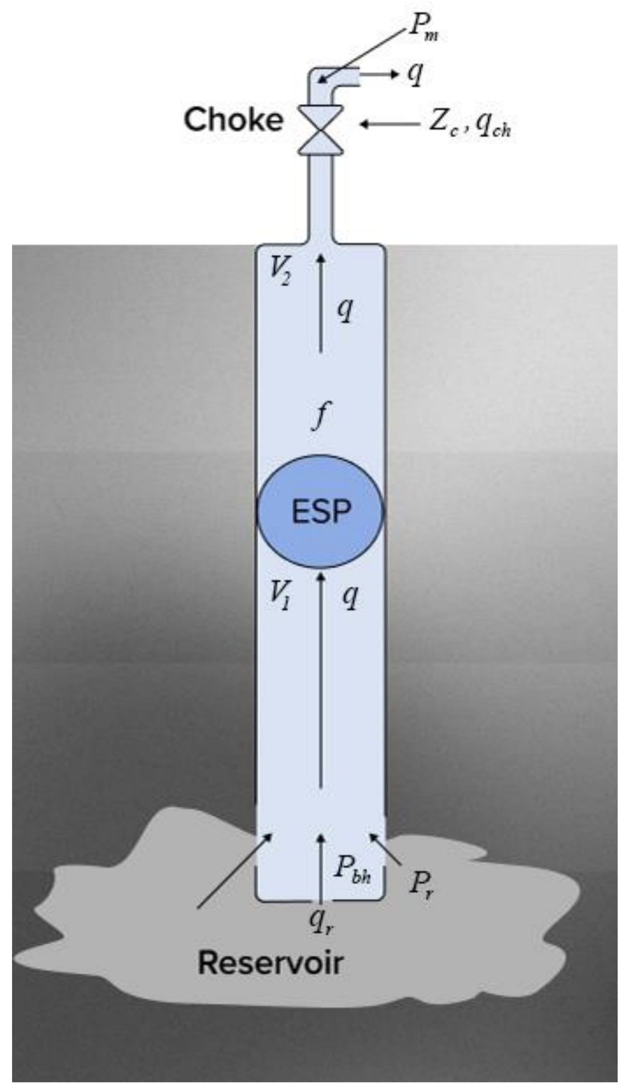
MOTIVATION

- ESP is a prevailing technology in the artificial-lift oil extraction.
- Physical multiphase flow meters are expensive, unreliable and prone to abrupt failures.
- Accurate flow rate estimates are required to perform ESP fault diagnosis and oil production optimization.
- PINNs promise unique computational advantage for parameterized problems.

PROBLEM FORMULATION

Dynamic two-volume model of an ESP oil well

The oil extraction process is governed by a system of first order ODEs [1,2], where ***bottomhole pressure*** P_{bh}, ***wellhead pressure*** P_{wh} and an ***average volumetric flow*** through the well q are unknown functions of time. Since the oil production can be controlled by externally adjusting ***pump frequency*** f and **production choke valve opening** Z_c, these equations are parameterized. The ***manifold pressure*** P_m is treated as a disturbance in the model.



Objective

Given historical sequences of sensor data for pressures P_{bh}, P_{wh} , control parameters f, Z_c and measured disturbance P_m , estimate the average flow q on the time domain bounded by the first and the last pressure measurements. Note that no prior empirical knowledge is available for the flow.

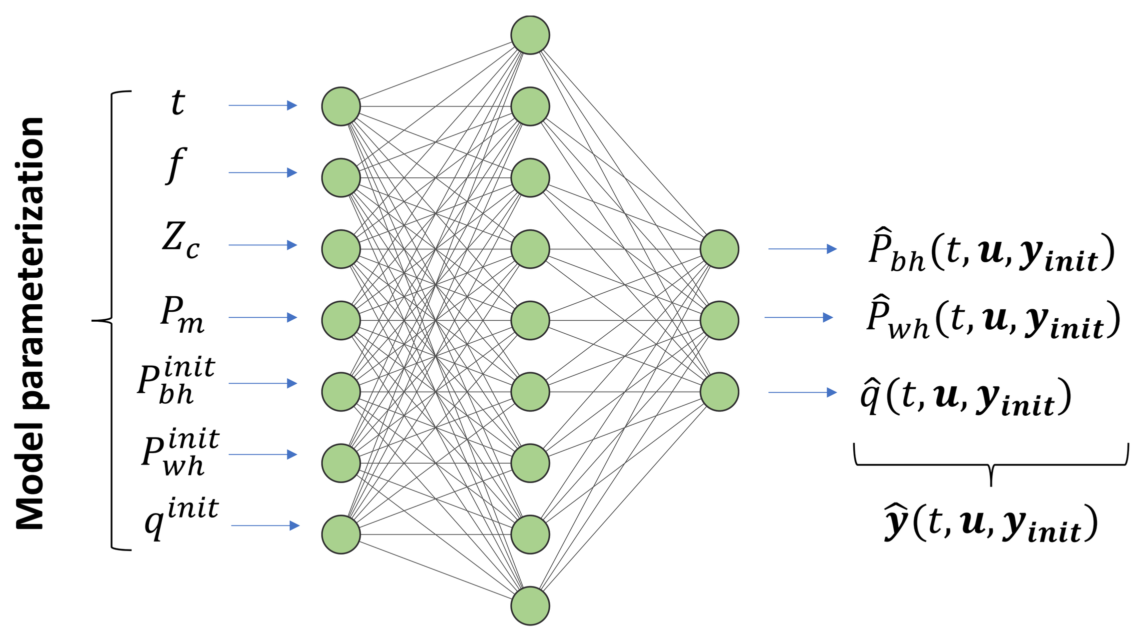
TRAINING

ODEs: $\dfrac{d\boldsymbol{y}(t)}{dt} = F(\boldsymbol{y}(t), u), \quad t \in [0, \Delta t],$

$\boldsymbol{y}(t) = [P_{bh}(t), P_{wh}(t), q(t)], \quad \boldsymbol{u} = [f, Z_C, P_m],$

Boundary conditions: $\boldsymbol{y_{init}} = [P_{bh}^{init}, P_{wh}^{init}, q^{init}] = \boldsymbol{y}(0)$

Fully-connected PINN



Loss: $L = \int_0^{\Delta t} \left(\frac{d\hat{\boldsymbol{y}}(t, \boldsymbol{u}, \boldsymbol{y_{init}})}{dt} - F(\hat{\boldsymbol{y}}, \boldsymbol{u}) \right)^2 dt + (\hat{\boldsymbol{y}}(0, u, \boldsymbol{y_{init}}) - \boldsymbol{y_{init}})^2$

INFERENCE

Sensor data

$\{P_k^{obs} = P^{obs}(k\Delta t)\}$ $\quad \boldsymbol{P_k^{obs}} = [P_{bh,k}^{obs}, P_{wh,k}^{obs}]$

$\{u_k^{obs} = u^{obs}(k\Delta t)\}$ $\quad k = 0, \dots, N$

Flow rate estimation:
Classical minimization procedure

$$q_k^{pred} = \min_{q^{init}} \left(\hat{\boldsymbol{P}}\left((k+1)\Delta t, u_k^{obs}, \boldsymbol{P_k^{obs}}, q^{init}\right) - \boldsymbol{P_{k+1}^{obs}} \right)^2$$

$\hat{\boldsymbol{P}} = [\hat{P}_{bh}, \hat{P}_{wh}]$

IMPLEMENTATION

Stage 1. Training

- PINN, which makes a central element of our application, was trained using NVIDIA GRID A100-2-10C 40GB GPU.
- Apart from the time variable, PINN takes control variables of the physical model and boundary conditions sampled from predefined ranges as an input.
- The training is performed by minimizing loss function, where both residues of ODEs and boundary conditions are accounted for.
- As an output we obtain a family of approximate solutions parameterized by the controls and the boundary conditions, including the initial flow parameter.

Stage 2. Inference

- Empirical data for the controls on the given time interval as well as pressures on both of its ends is incorporated into the model.
- The inference is performed over the entire predefined range of the initial flow parameter.
- We add a classical subroutine to estimate the optimal flow rate at the initial point on the time interval by minimizing the corresponding deviation between the predicted and the observed values of pressures at the final point.

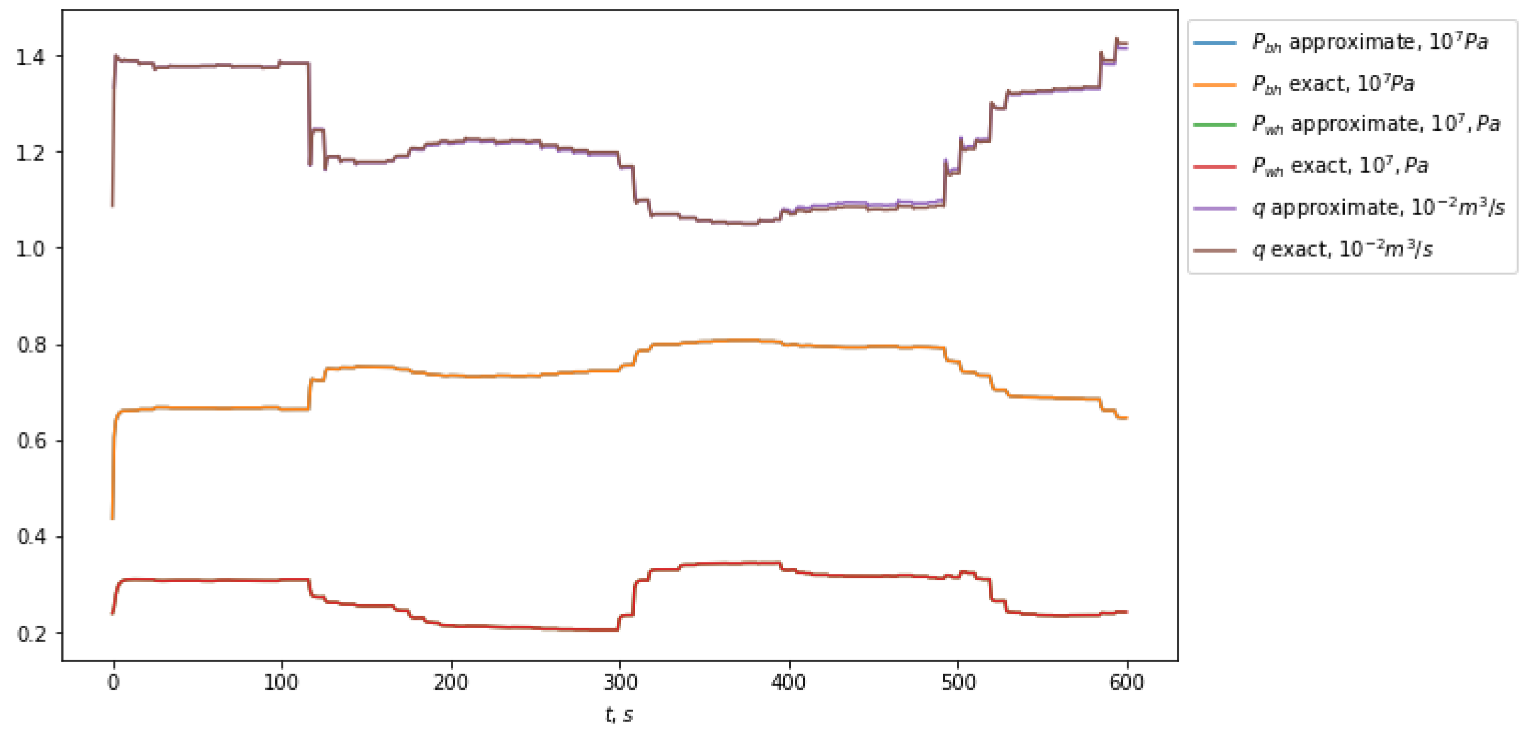
Results

Performing this procedure iteratively allows us to estimate the flow rate over the whole period covered by the historical sequences of auxiliary pressure sensor measurements.

ADVANTAGES

- Our solution operates over a wide parameter range and can be used for different wells without any need for retraining.
- Training relies solely on the knowledge of underlying physics. An end-user interacts with a fully pretrained model by feeding in specific empirical data.
- The proposed VFM application can serve as an element of more comprehensive digital-twin models of ESP-enhanced oil production facilities.

VIRTUALLY METERED FLOW RATE



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2. T. S. Franklin, L. S. Souza, R. M. Fontes et al., *Digit. Chem. Eng. 5*, 100056 (2022).