EWO seminar series – CAPD CENTER CMU/ChemE

Digital Technologies in Offshore and Subsea Oil & Gas Production

Argimiro R. Secchi

Chemical Engineering Program PEQ – COPPE

Universidade Federal do Rio de Janeiro

Technological Center, Rio de Janeiro – RJ

LADES
Solutions for Process Control and Optimization
COPPE | UFRJ

online
16th February, 2021

PSE–UFRJ
Process Systems Engineering – UFRJ

Outline

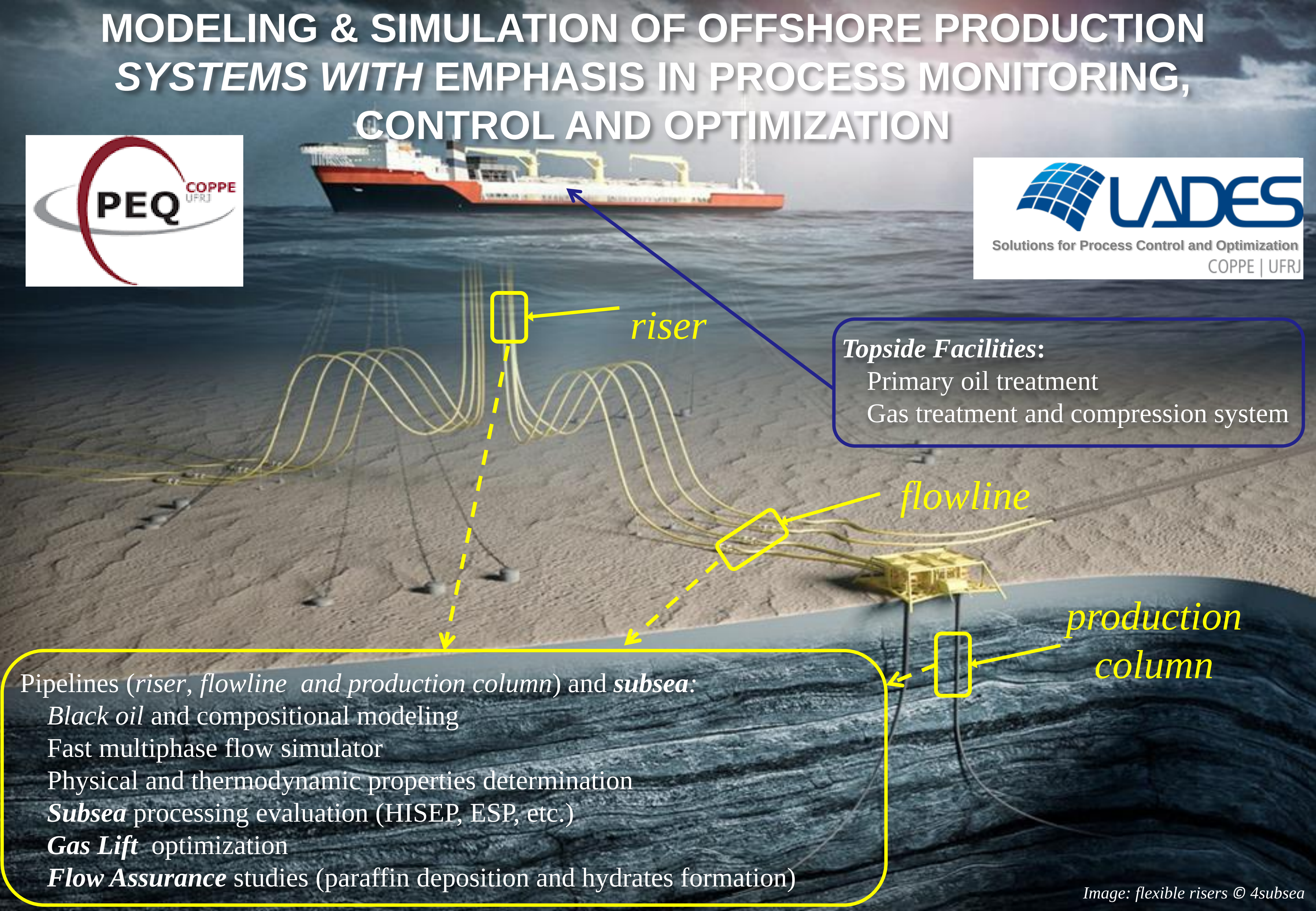
- Introduction
- Fundamentals
- Objective of this Presentation
- Portfolio of Case Studies
- Final Remarks

Introduction

MODELING & SIMULATION OF OFFSHORE PRODUCTION *SYSTEMS WITH* EMPHASIS IN PROCESS MONITORING, CONTROL AND OPTIMIZATION

PEQ COPPE UFRJ

LADES
Solutions for Process Control and Optimization
COPPE | UFRJ



***Topside Facilities*:**

Primary oil treatment

Gas treatment and compression system

Pipelines (*riser*, *flowline and production column*) and ***subsea***:

Black oil and compositional modeling

Fast multiphase flow simulator

Physical and thermodynamic properties determination

Subsea processing evaluation (HISEP, ESP, etc.)

Gas Lift optimization

Flow Assurance studies (paraffin deposition and hydrates formation)

Image: flexible risers © 4subsea

Introduction: Offshore Processing

Formulation of control and optimization problems aiming to:

- Ensure Process Stability and Safety
- Flow Assurance (prevent: hydrate, paraffin, asphaltene, fouling)
- Ensure Quality Specification (oil, water & gas)
- Maximize Production (oil & gas)
- Maximize remaining useful lifetime
- Minimize Losses (flare & TOG)
- Minimize Energy Consumption (heat & power)
- Minimize Operational Costs (maintenance & shutdowns)
- Minimize Process variability

Introduction: Subsea Processing

- Accelerates the production during field lifespan.
- Makes the production in remote and marginal fields feasible.
- Improves recovery and production rates from the reservoir by reducing backpressure on wells.
- Provides advantages in flow assurance risk management.[1]

[1]Kondapi *et al*. (2017)

Introduction: Subsea Processing

Subsea processing installations
Difficult access
High intervention costs
High complexity

External disturbances	Unknown
Parametric uncertainties	Insufficient data
Structural uncertainties	Simplification in the model
Measurement errors	Noise and/or sensor lack

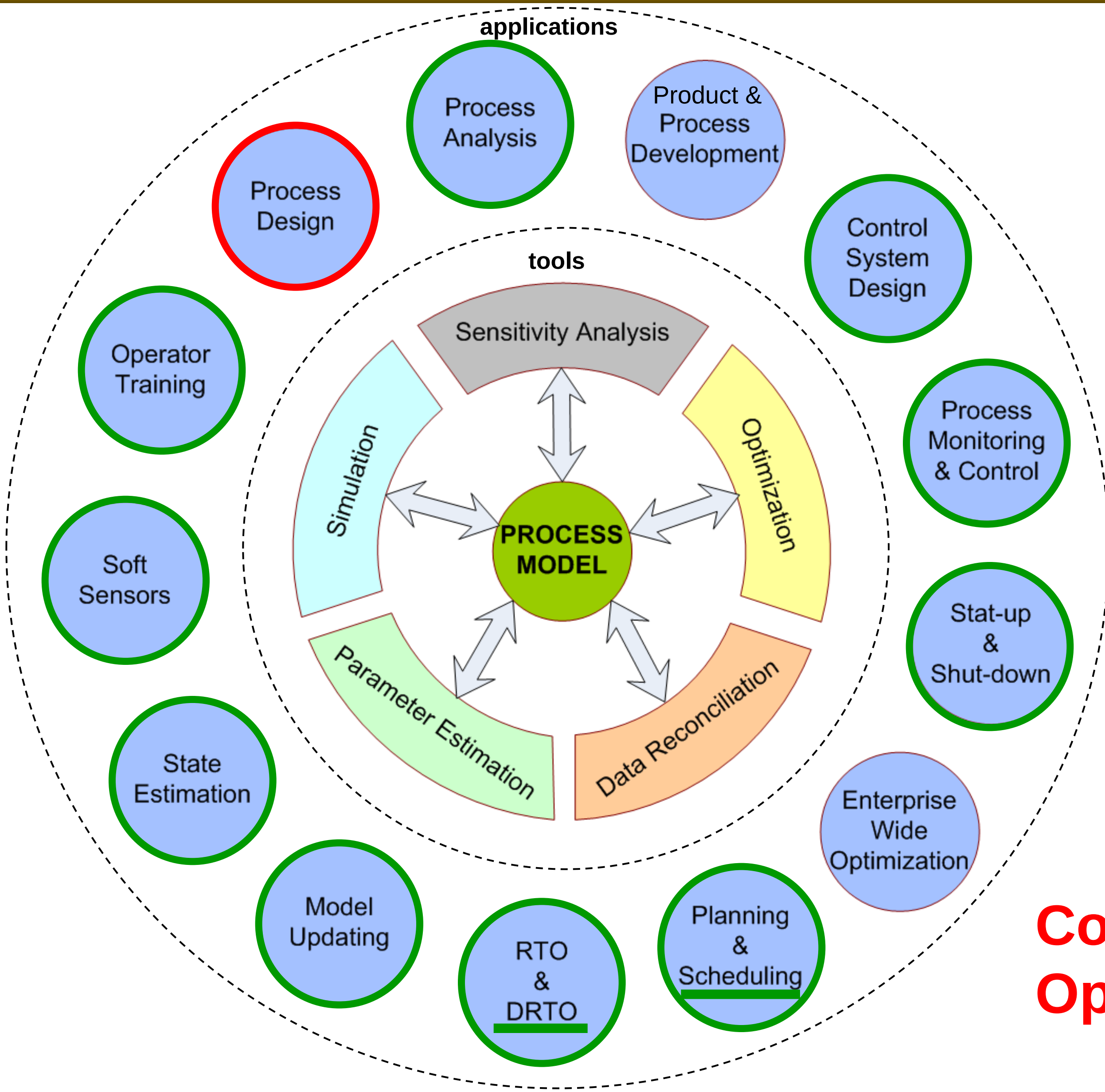
Operation under uncertainty[2]

[2]Krishnamoorthy et al. (2016)

Introduction: CAPE Tools

PSE

CAPE



Inherently Dynamic

Controlability & Operability

Introduction: Digital Technologies

Cloud Computing *AI* *Deep Learning*

Digital Twin *Machine Learning*

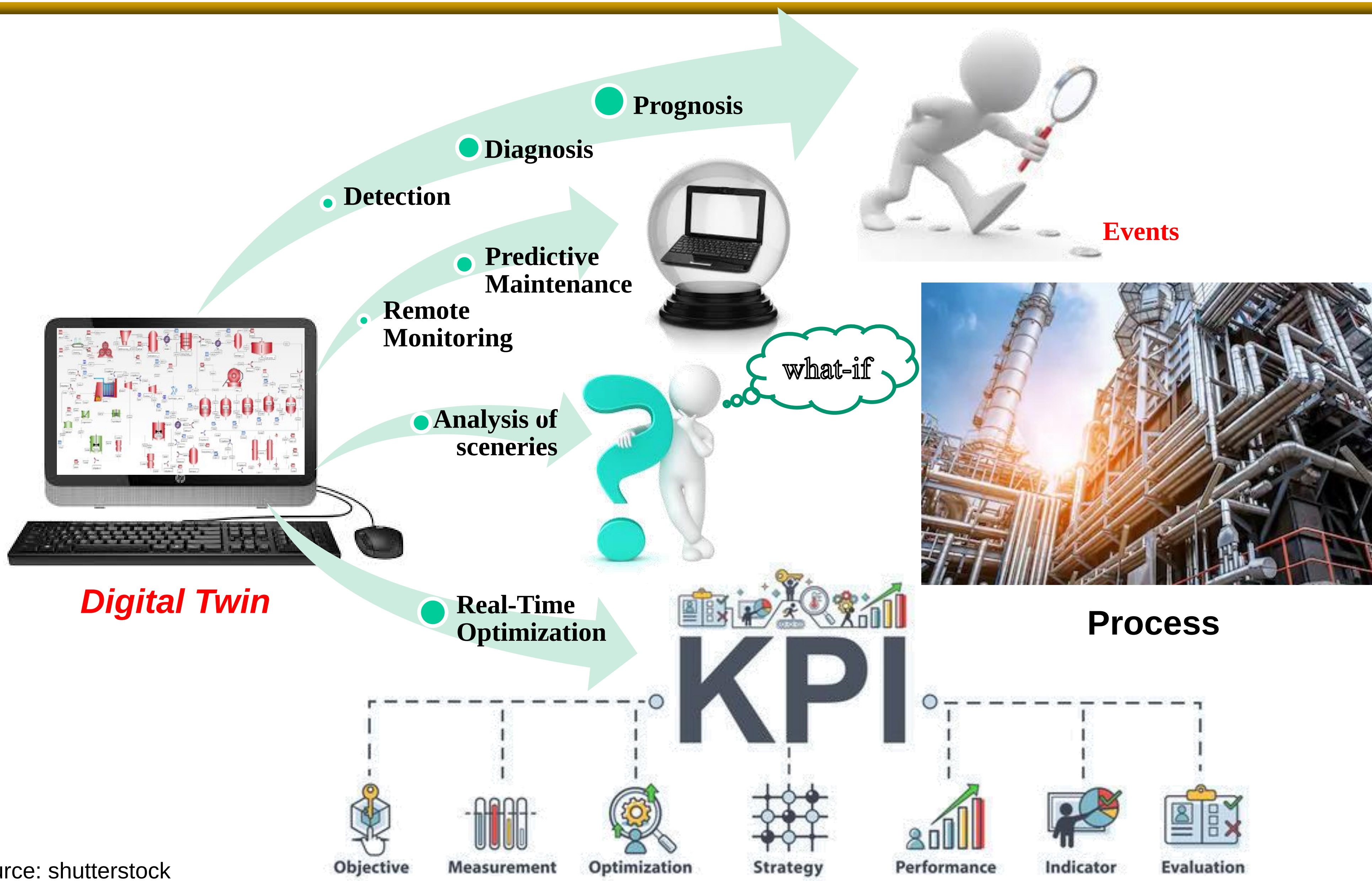
Transfer Learning **PSE** *Reasoning*

Big Data *Quantum Computing* *IoT*

Reinforcement Learning *Soft Sensors*

Industry 4.0

Introduction: Digital Technologies



Source: shutterstock

Introduction: Digital Technologies

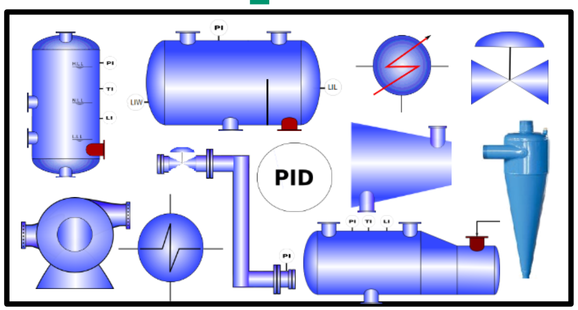
Digital Twin

Process

Source: neilpatel

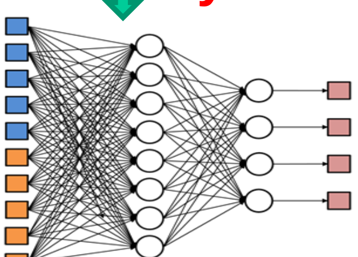
Introduction: Digital Technologies

Digital Twin

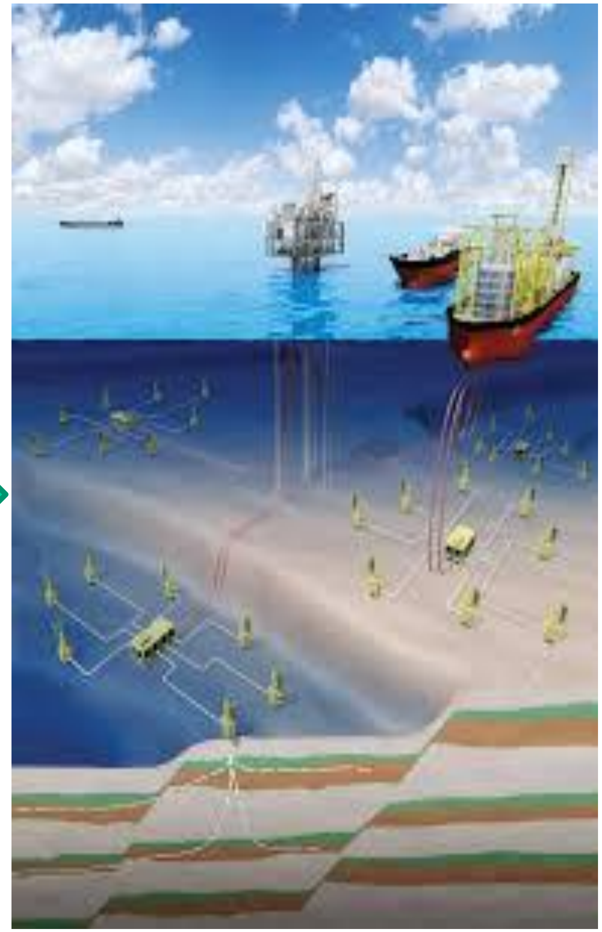


First-principles model

Hybrid model



Data-based model



Remote Monitoring

Process Control

Process Optimization

Downtime prediction

Fundamentals

5D Modeling Approach

$$M_{DT} = f(PE,VM,Ss,DD,CN)^3$$

- *Physical Entities* (**PE**): physical laws + uncertainty;
- *Virtual Models* (**VM**): first principles, data based, stochastic, and rules from experts;
- *Services* (**Ss**): monitoring, optimization, diagnosis, prognostics and health management, advanced control, soft sensor, health-aware control;
- *Digital Twin Data* (**DD**): multi-temporal scale, multi-dimension, multi-source and heterogeneous data;
- *Connections* (**CN**): CN_PV, CN_PD, CN_PS, CN_VD, CN_VS, CN_SD.

[3]Qi et al. (2019)

Fundamentals: 5D Models

Health-Aware Control

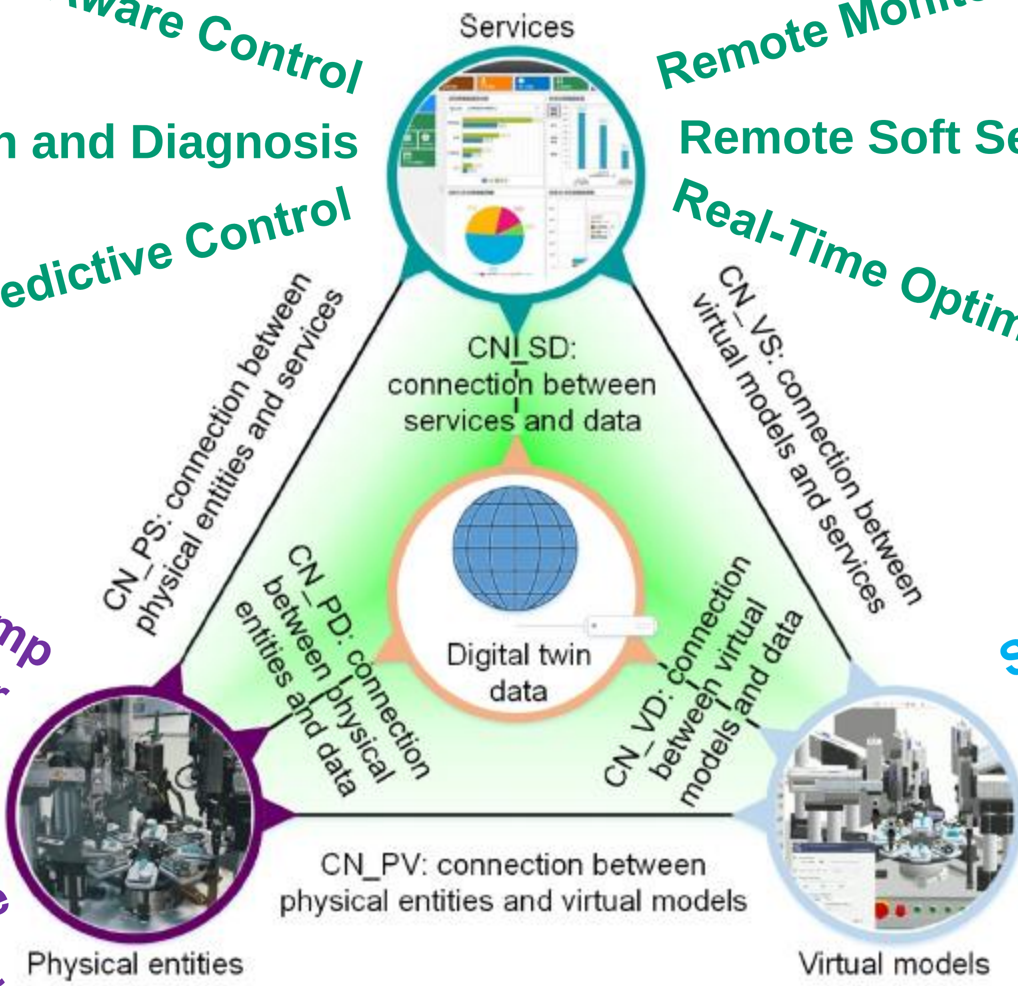
Fault Detection and Diagnosis

Model Predictive Control

Remote Monitoring

Remote Soft Sensor

Real-Time Optimization



Electric Submersible Pump

Subsea CO_2 Separator

Water Injection Pump

Dry Gas Seal

Gas Compression Unit

Production Choke Valve

Gas Lift

Support Vector Machine

Surrogate Kriging

First Principles

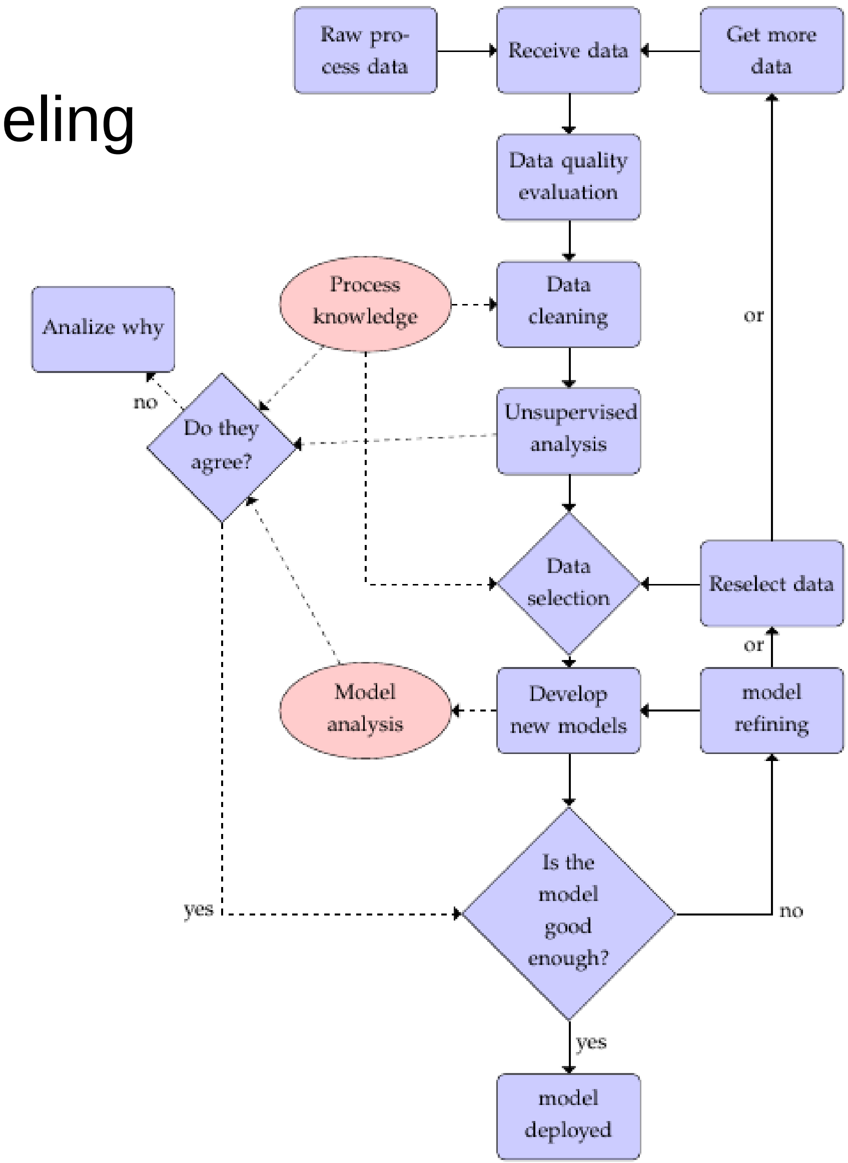
Neural Network

Decision Trees

[3]Qi et al. (2019)

Fundamentals: Data driven

Data-based Modeling



[4]Soares (2020)

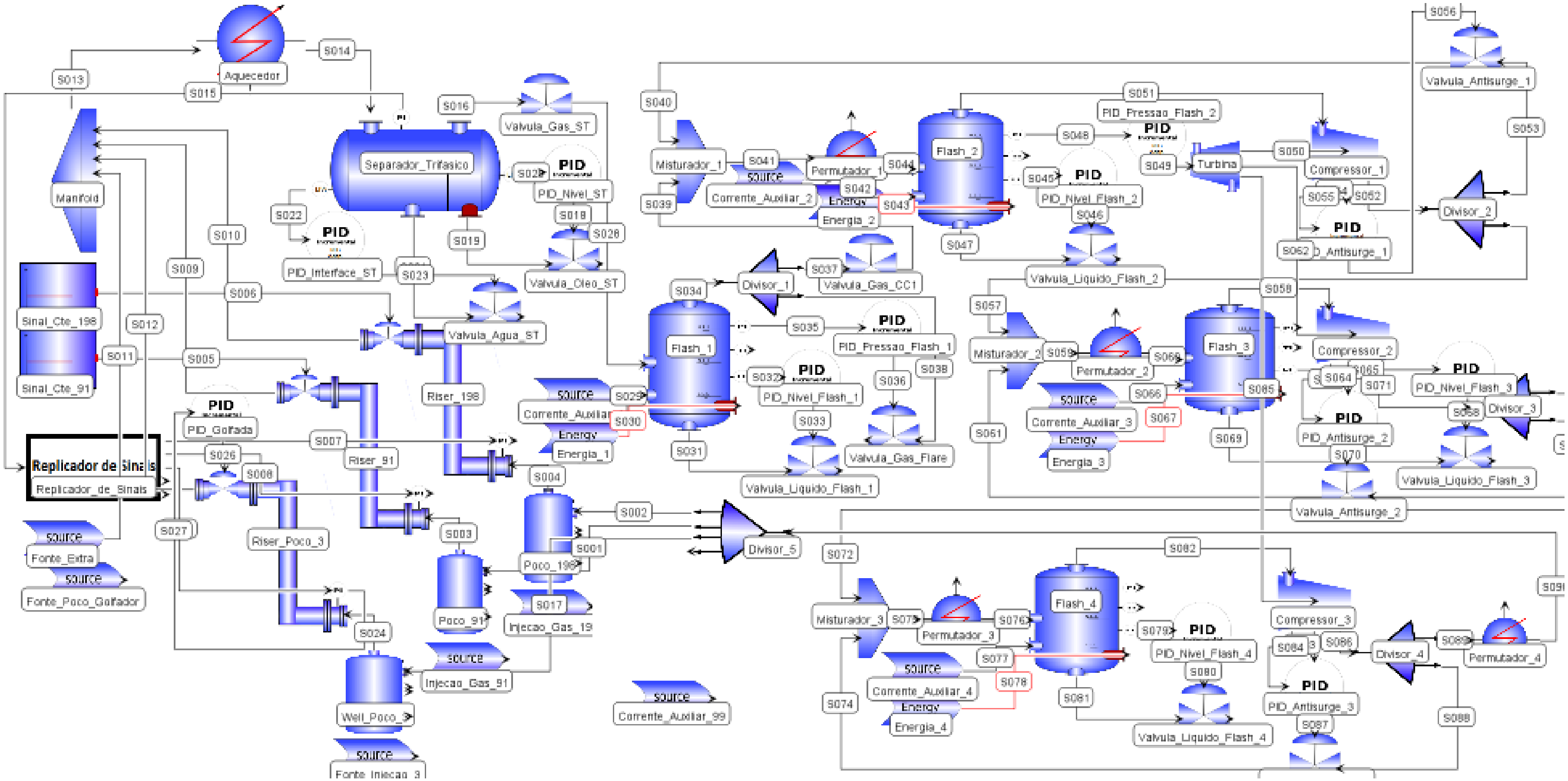
Fundamentals: First Principles

PE: conventional and pre-salt platforms, including production well and riser, topside separation equipment (3-phase and electrostatic separators, molecular sieves, gas-separation membrane, hydro-cyclones), gas compression cycle and auxiliary equipment (flash vessels, heat exchangers, PID controllers, etc.), subsea processing (3-phase LLV or LLL separators, pumps, heat exchangers, valves).

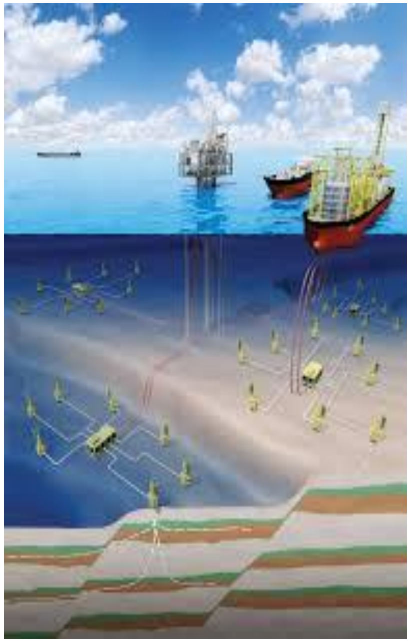
VM: equipment library implemented in EMSO (Environment for Modeling, Simulation and Optimization), an equation-oriented simulator and optimizer, with an object-oriented modeling language.

Fundamentals: First Principles

PE and VM: Offshore Platforms & Subsea Operations



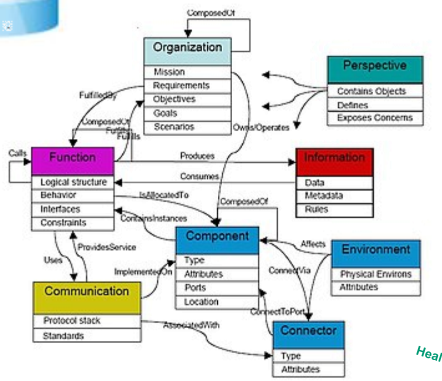
Digital Technology Infrastructure



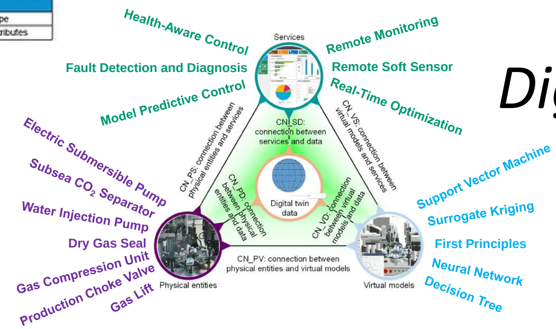
Industry

Sensors and remote connections

Data treatment and storage



Data modeling and sytems interoperability



Digital Technologies

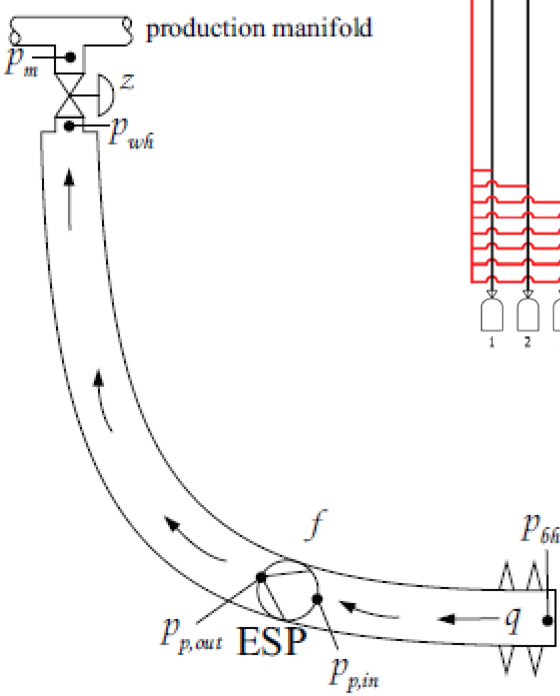
Required infrastructure

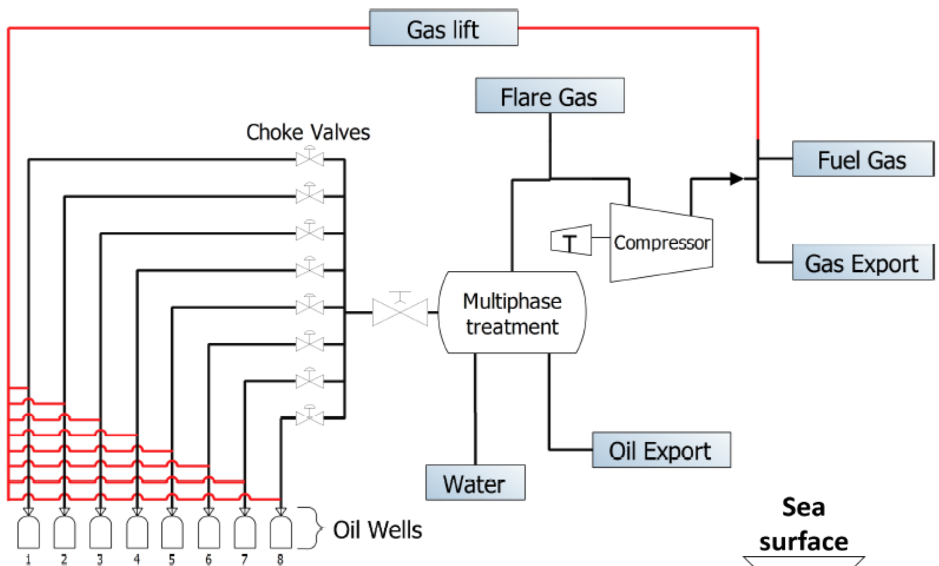
Human-Machine Interface

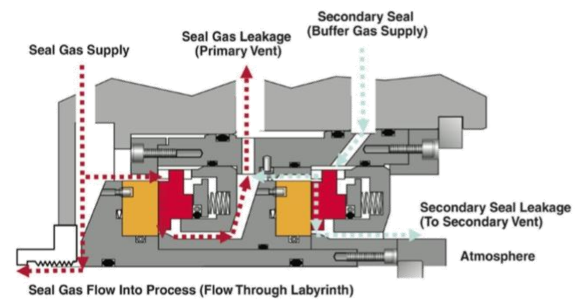
Objective of this Presentation

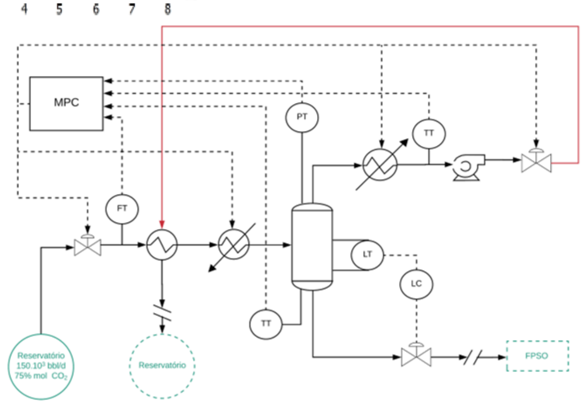
Objective of the Presentation

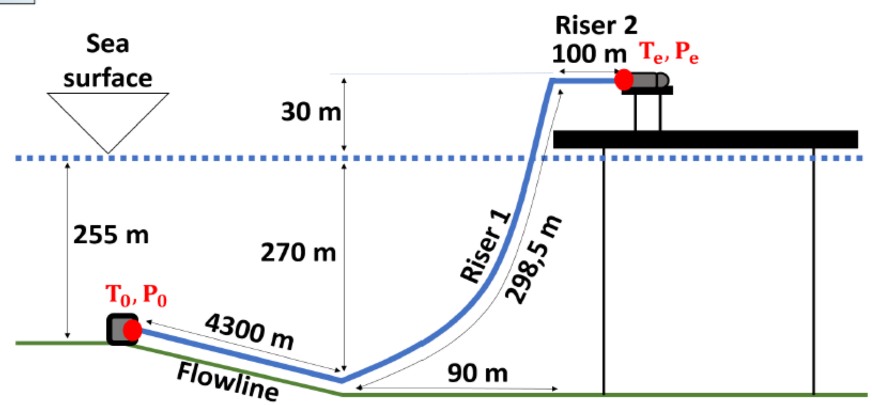
Brief overview of Digital Technologies developments carried out at LADES/PEQ/COPPE-UFRJ for offshore and subsea O&G applications.







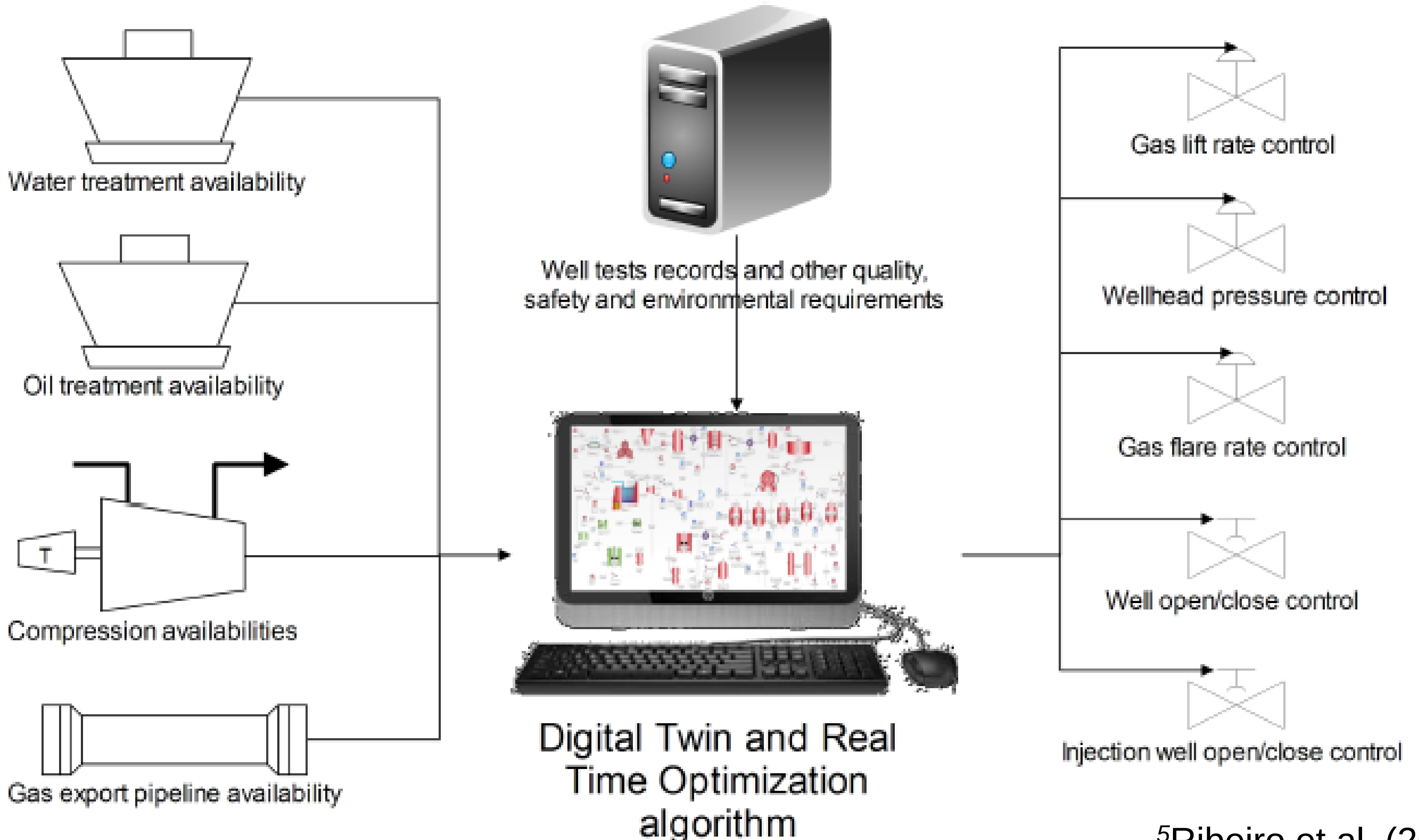




Portfolio of Case Studies

Ss: Short-Term Production Optimization

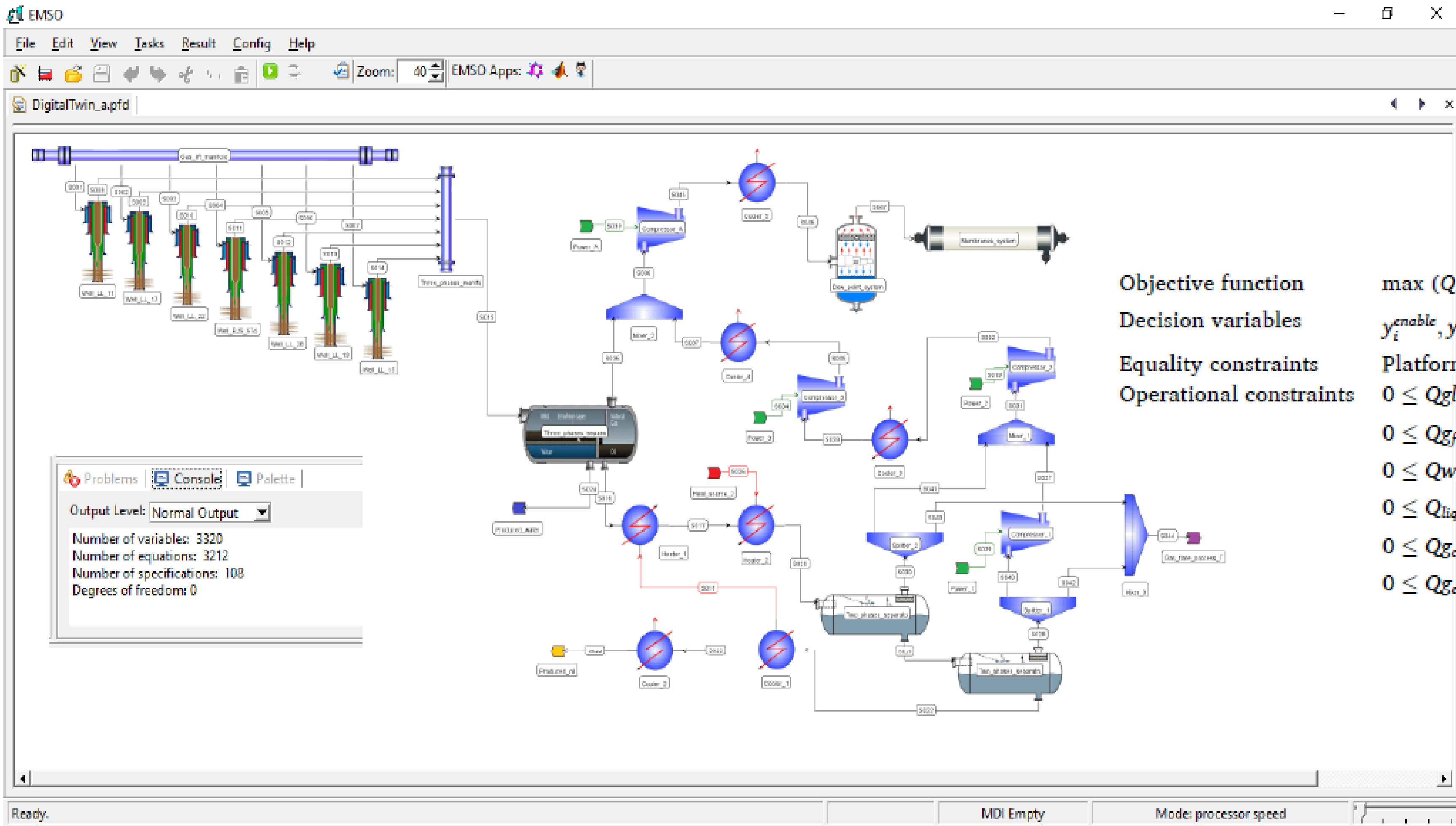
PE: Wells and topside **VM**: First Principles, **Ss**: MILP-MINLP



[5]Ribeiro et al. (2019)

[6]Carpio et al. (2020)

Ss: Short-Term Production Optimization



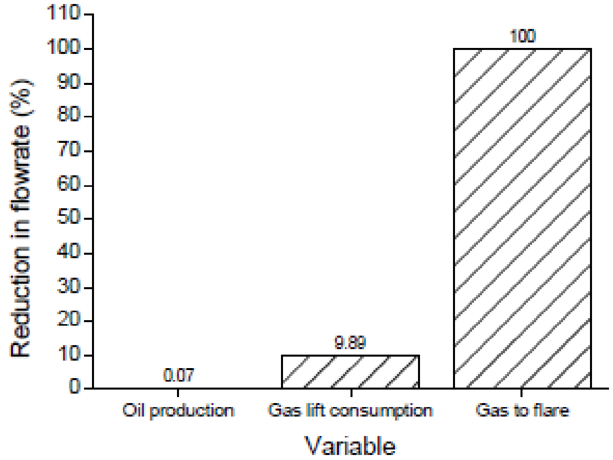
Objective function	$\max\,(Qo_{total})$ $\quad \min\,(Qgl_{total} + Qg_{flare})$
Decision variables	$y_i^{enable}, y_{ij}^{whp}, Qgl_i, Qg_{flare}$
Equality constraints	Platform model
Operational constraints	$0 \le Qgl_i \le Qgl_i^{max}$
	$0 \le Qg_{flare} \le Qg_{flare}^{max}$
	$0 \le Qw_{total} \le Qw_{total}^{max}$
	$0 \le Q_{liquid} \le Q_{liquid}^{max}$
	$0 \le Qg_{comp} \le Qg_{comp}^{max}$
	$0 \le Qg_{export} \le Qg_{export}^{max}$

Kriging surrogate model

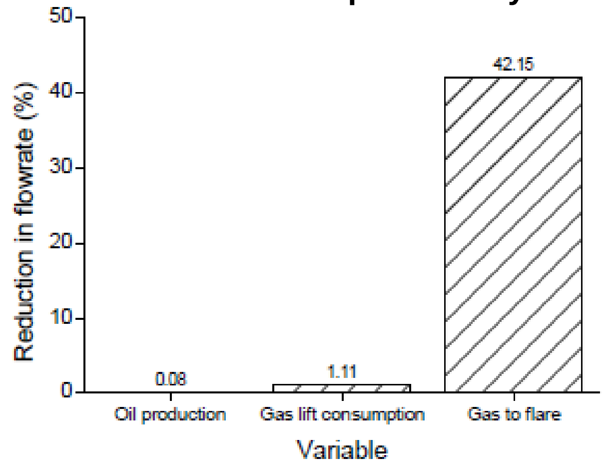
[6]Carpio et al. (2020)

Ss: Short-Term Production Optimization

Limitation on compression system

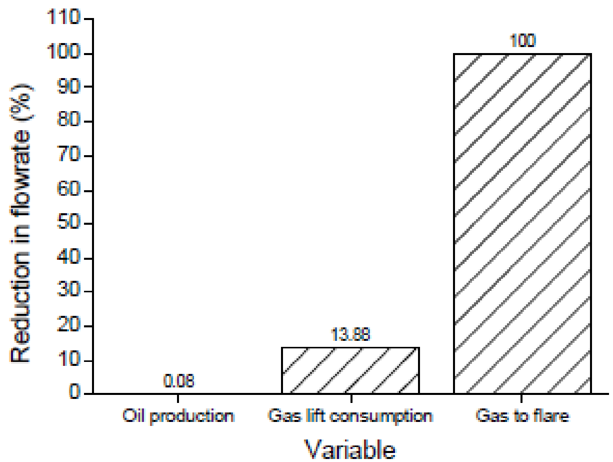


(a)



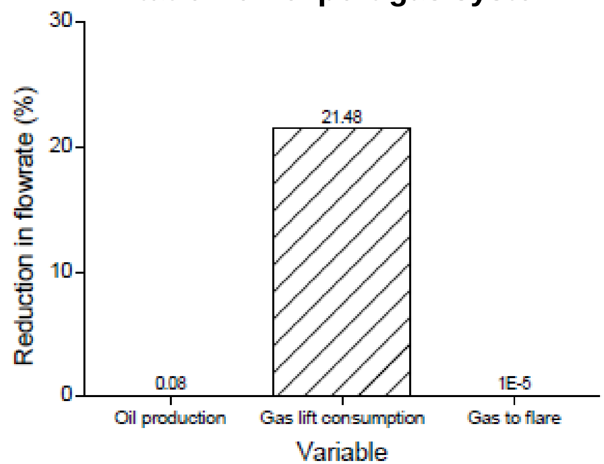
(b)

Limitation on water treatment system

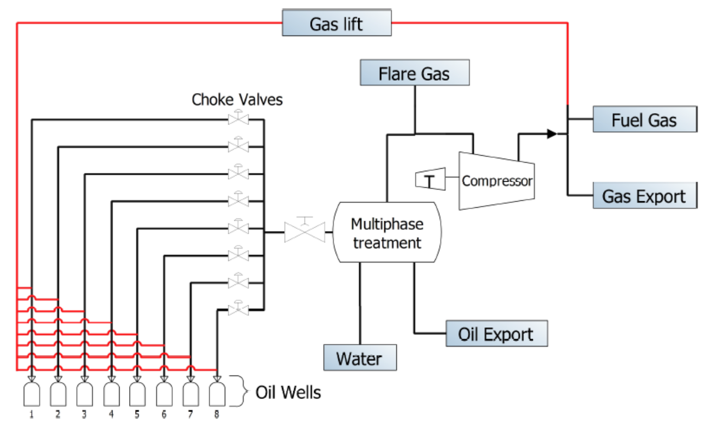


(c)

Limitation on export gas system



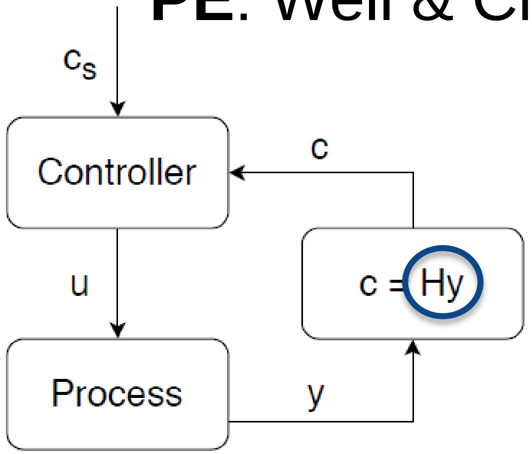
(d)



[6]Carpio et al. (2020)

Ss: Data-based Self Optimizing Control

PE: Well & Choke, **VM**: Data-based Linear Network, **Ss**: SOC[7]



$$J \approx J^* + [J_u^* \;\; J_d^*]\begin{bmatrix}\Delta u\\ \Delta d\end{bmatrix} + \frac{1}{2}[\Delta u^T \;\; \Delta d^T]\begin{bmatrix}J_{uu}^* & J_{ud}^*\\ J_{du}^* & J_{dd}^*\end{bmatrix}\begin{bmatrix}\Delta u\\ \Delta d\end{bmatrix} \qquad \Delta \boldsymbol{y} = \widetilde{\boldsymbol{G}}_{\boldsymbol{y}}\begin{bmatrix}\Delta \boldsymbol{u}\\ \Delta \boldsymbol{d}\end{bmatrix}$$

$$J \approx J^* + \underbrace{[J_u^* \;\; J_d^*][\tilde{G}^y]^{\dagger}}_{J_u^*}\Delta y + \frac{1}{2}\Delta y^T \underbrace{[\tilde{G}^y]^{\dagger^T}\begin{bmatrix}J_{uu}^* & J_{ud}^*\\ J_{du}^* & J_{dd}^*\end{bmatrix}[\tilde{G}^y]^{\dagger}}_{J_{yy}^*}\Delta y$$

$$H = f(y) = G^{y^T} J_{yy}$$

$$\boldsymbol{J} \approx \boldsymbol{J}^* + \boldsymbol{J}_{\boldsymbol{y}}^* \Delta \boldsymbol{y} + \frac{\boldsymbol{1}}{\boldsymbol{2}}\Delta \mathbf{y}^{\mathbf{T}} \mathbf{J}_{\mathbf{yy}}^* \Delta \boldsymbol{y}$$

Quadratic model

$$J = \beta_0 + \beta_1 y_1 + \beta_2 y_2 + \cdots + \beta_{n+1} y_1^2 + \beta_{n+2} y_1 y_2 + \beta_{n+n+1} y_n^2$$

$$J = \beta_0 + [\beta_i]_{1xn}\Delta y + \frac{1}{2}\Delta y^T [\beta_j]_{nxn}\Delta y$$

[7]Jäschke & Skogestad (2013)

[8]Dias et al. (2019)

Ss: Data-based Self Optimizing Control

Linear network: $J = B_2 + \boldsymbol{LW}(\boldsymbol{B_1} + \boldsymbol{IW} \cdot \boldsymbol{y})$

$$J = B_2 + \sum_{j=1}^{NN}\left(lw_j \cdot \left(\sum_{p=1}^{Ny} iw_{j,p}y_p + b_{1_j}\right)\right)$$

$$\beta_0 = B_2 + \sum_{i=1}^{NN}(lw_i b_{1_i}) \qquad \beta_t = \sum_{j=1}^{NN} lw_j iw_{j,t}$$

1) Collect and scale data;

2) Find G^y, G_d^y;

3) Find *H* and compute the loss;

4) Choose the *H* with the lower loss.

But database are:

- Huge;
- Significant amounts of useless data;
- Measurement noise;
- Outliers;
- Frozen values;
- Missing values…

It is important to select the **best subset** of variables

⇩

EVALUATING THE LOSS!

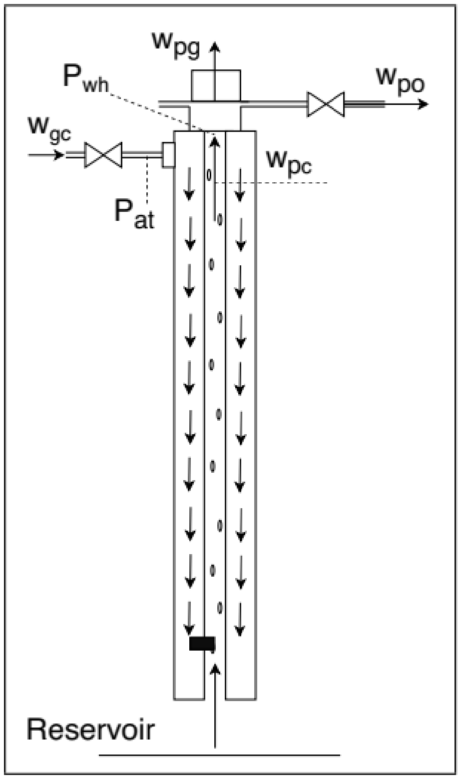
$$L_{av} = \frac{1}{2}\left\| J_{uu}^{\frac{1}{2}}(HG^y)^{-1}H[FW_d \quad W_n]\right\|_{Fr}$$

[8]Dias et al. (2019)

$$F = G_d^y - G^y J_{uu}^{-1} J_{ud} \qquad J_{uu} \approx G_y^T J_{yy} G_y \qquad J_{ud} \approx G_d^{y,T} J_{yy} G_y$$

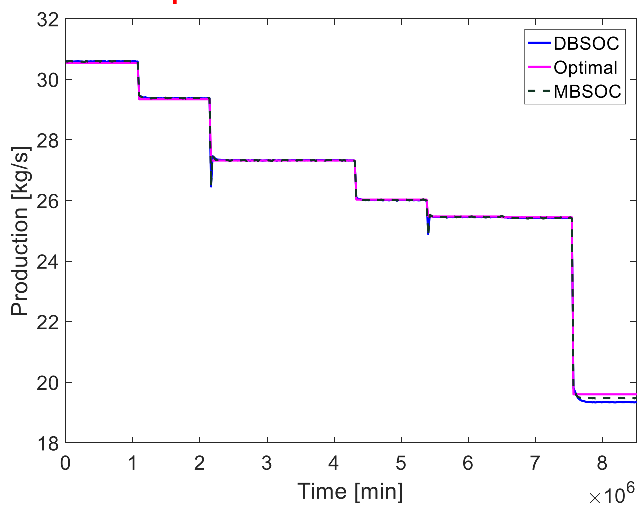
Ss: Data-based Self Optimizing Control

$$J = w_{po} - 0.1w_{gc}$$

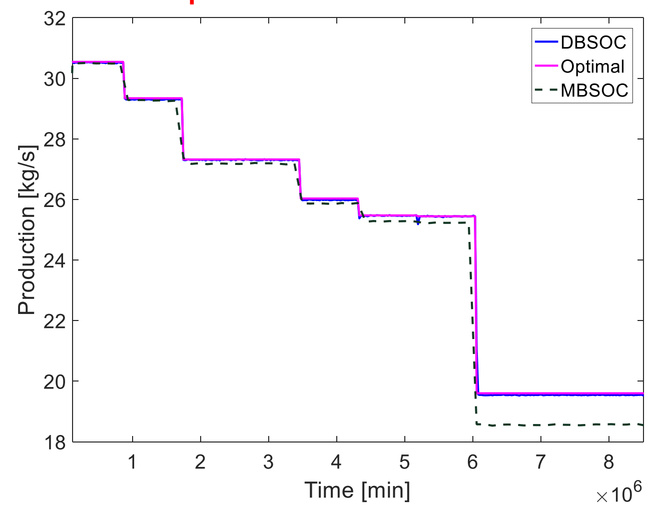


Comparison between Exact Local method (model based) and data-based method:

No plant-model mismatch



With plant-model mismatch



DB for SOC can be better than MB and does not require a deep knowledge about the process neither a derivative step, but require large set of historical data.

G^y & G_d^y from data:

$$G^y = [1.00 \quad 1.11 \quad 1.01 \quad 1.88 \quad 2.34]$$

$$G_d^y = [0.00 \quad 32.9 \quad 30.71 \quad -39.12 \quad 75.94]$$

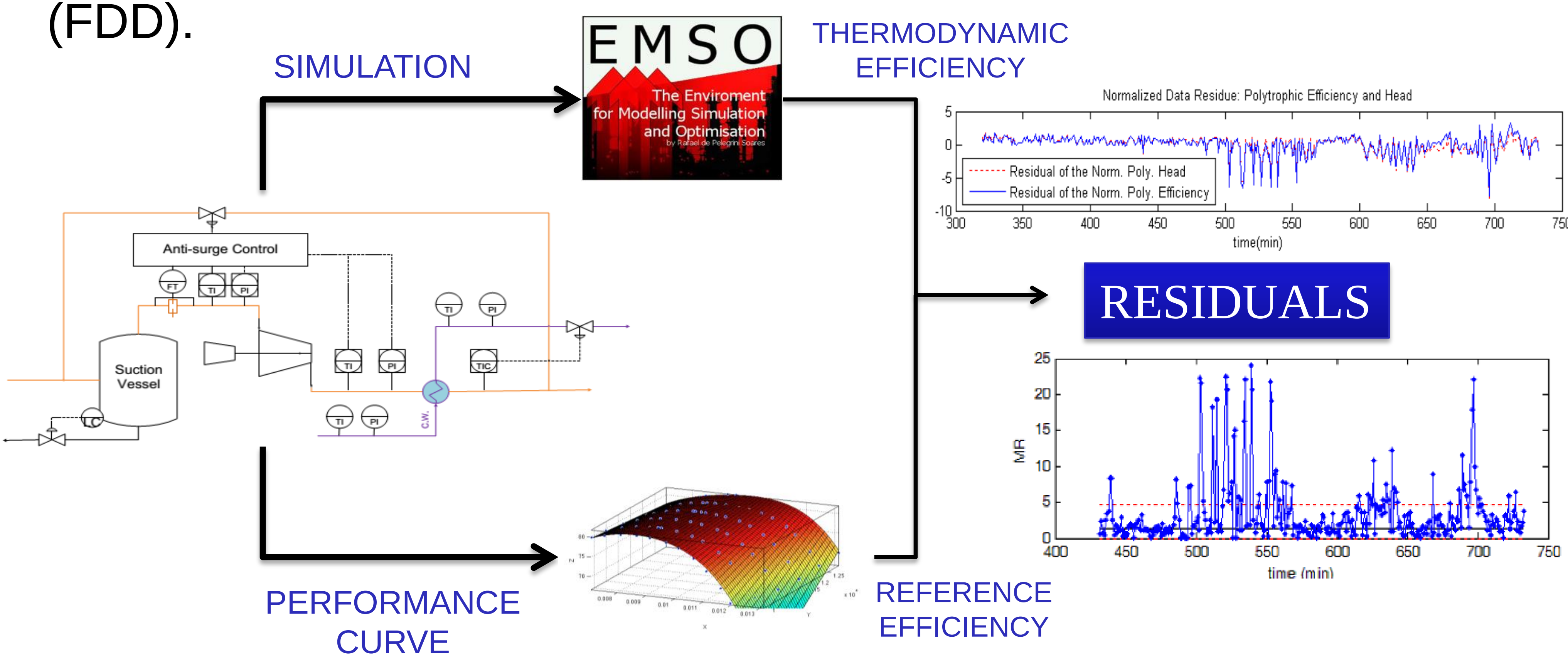
Gas lift well

[8]Dias et al. (2019)

Ss: Remote Monitoring & FDD

PE: Gas compression system, **VM:** Hybrid model (first principles + performance curve + univariate quality control charts)

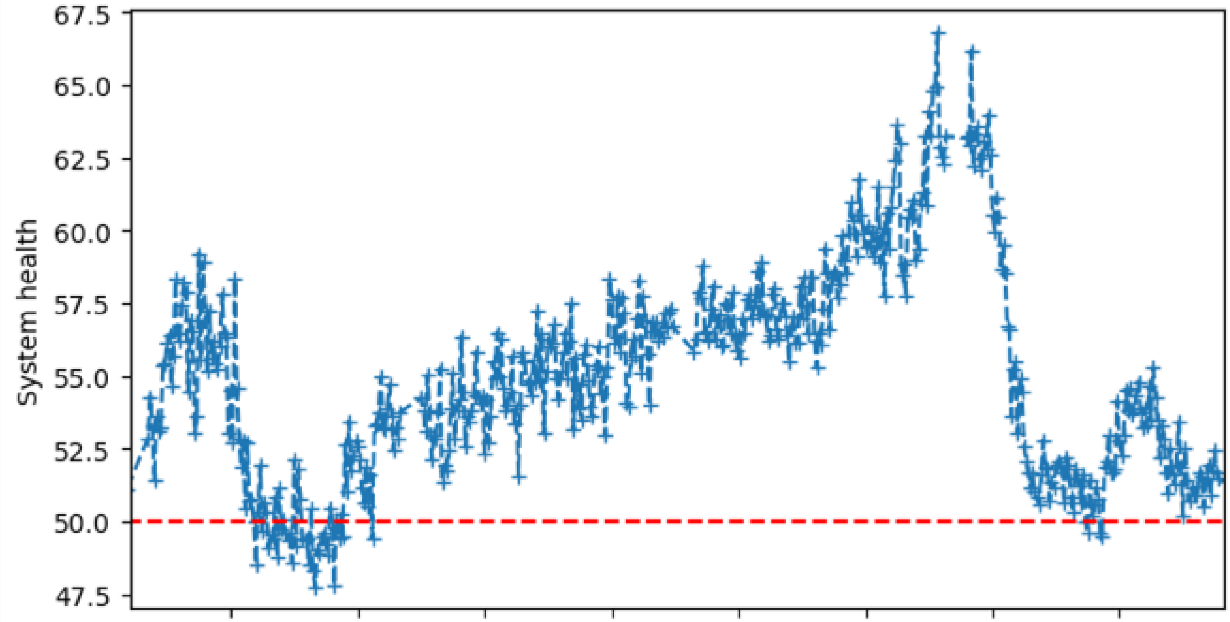
Ss: Monitoring of performance and Fault Detection and Diagnosis (FDD).

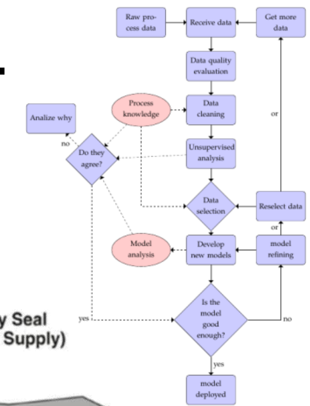


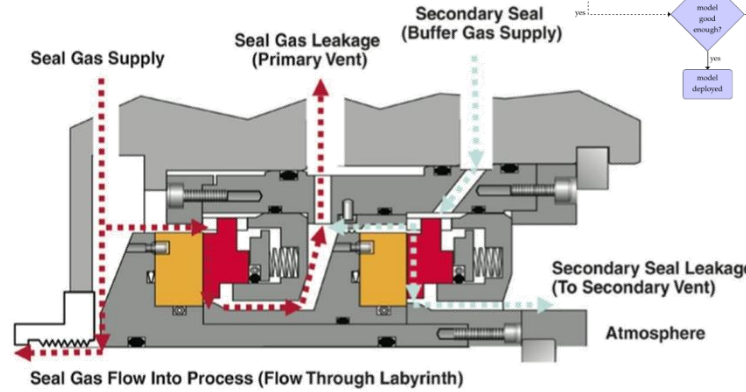
[9]Miyoshi et al. (2012)

Ss: Remote Monitoring & FDD

PE: Dry Gas Seal, **VM:** Data-based SVM, **Ss:** FDD.





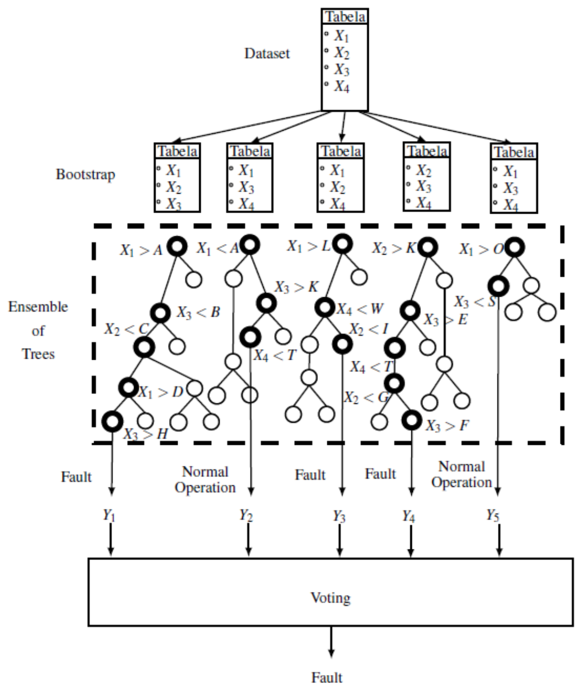


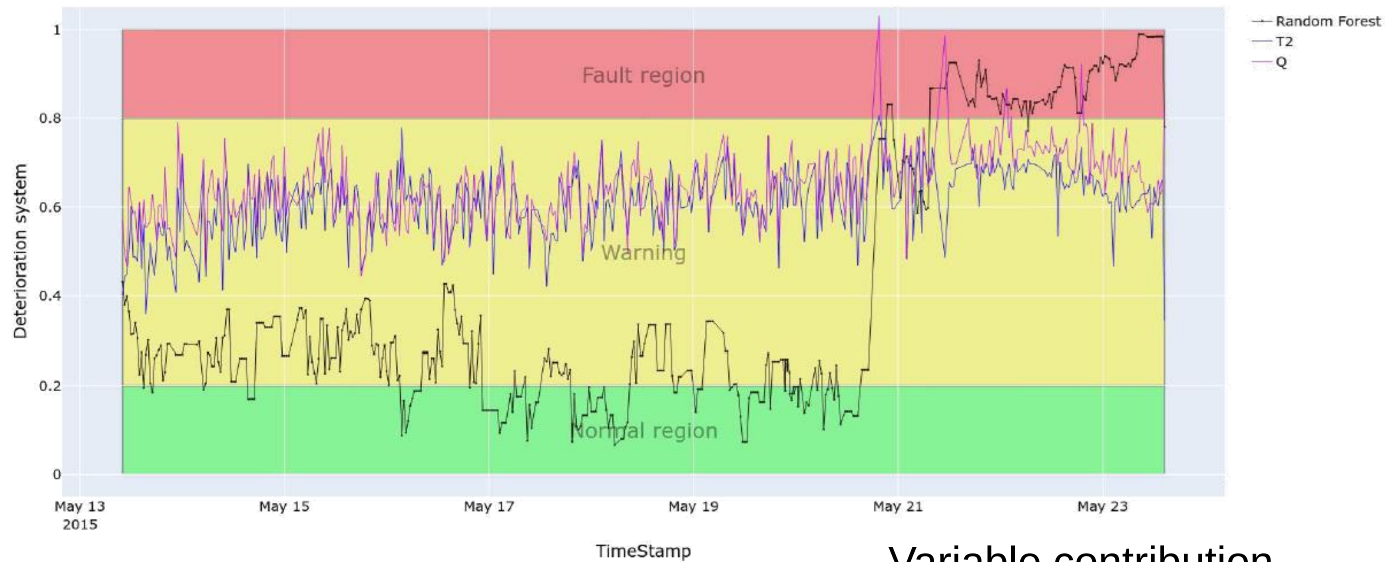
- Fault detection model that also indicates the level of "health" in the system: how close it is from fault or normal operation
- This model helps preventing faulty operation of a dry gas seal system

[4]Soares (2020)

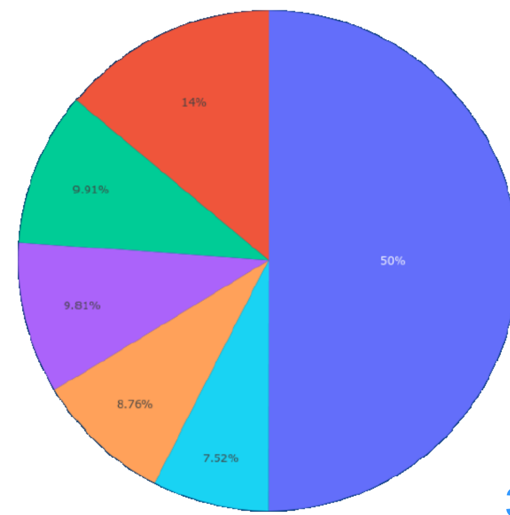
Ss: Remote Monitoring & FDD

PE: Water Injection Pumps, **VM:** DB Random Forest + PCA, **Ss:** FDD.





Variable contribution

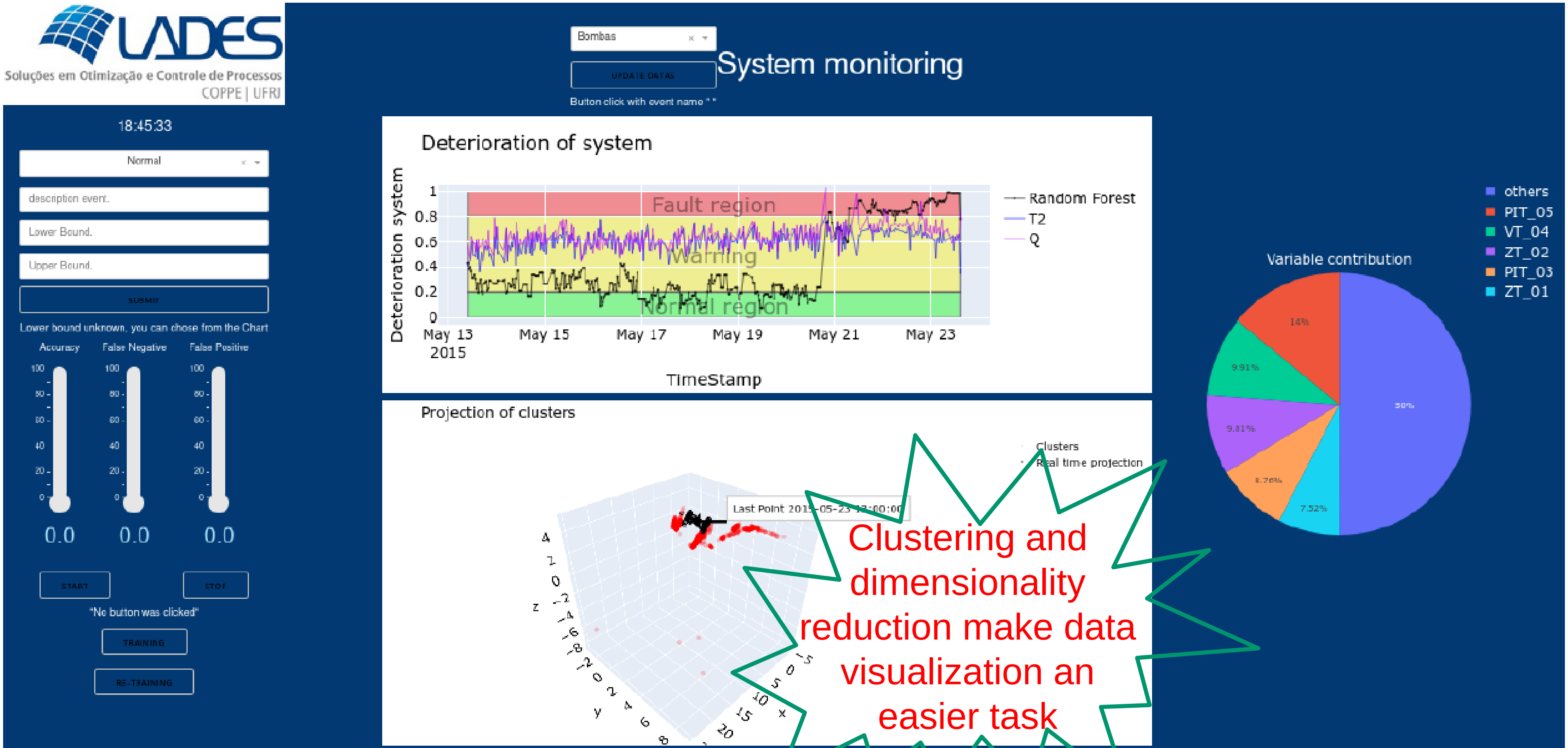


- Fault and pre-fault detection by abnormal vibration
- Use of data clustering[11] and dimensionality reduction method[12] for data visualization in a 3D scatter plot

[10]Souza et al. (2020), [11]Xavier & Xavier (2011), [12]Xavier (2016)

Ss: Remote Monitoring & FDD

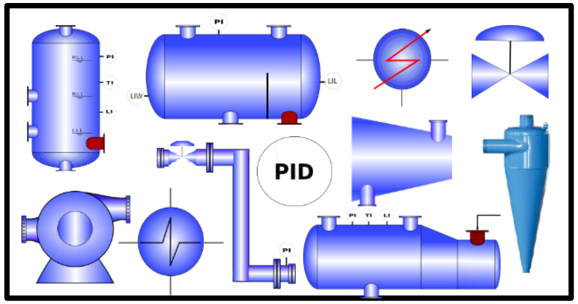
Web application for remote monitoring and FDD



Clustering and dimensionality reduction make data visualization an easier task

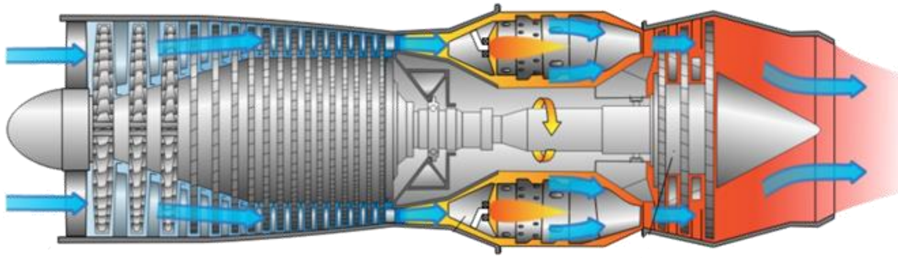
[10]Souza et al. (2020)

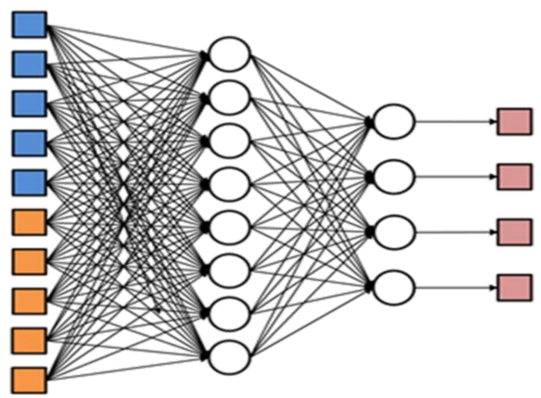
Ss: Remote Monitoring & FDD



Minimize Gibbs energy

Gas Turbines

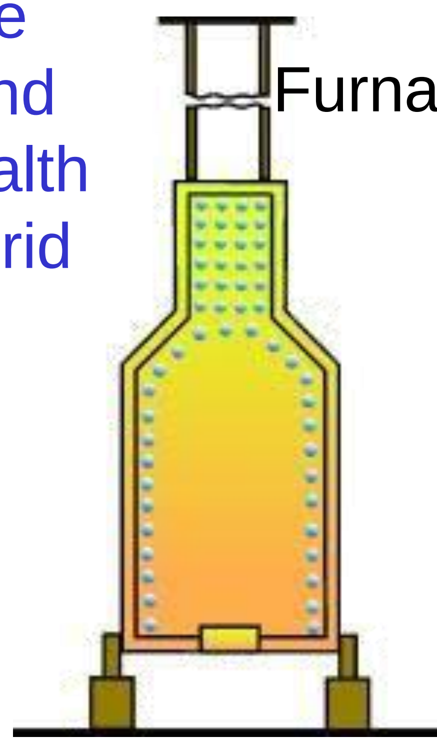




Residual modeling

Performance monitoring and equipment health based on hybrid models

Furnaces

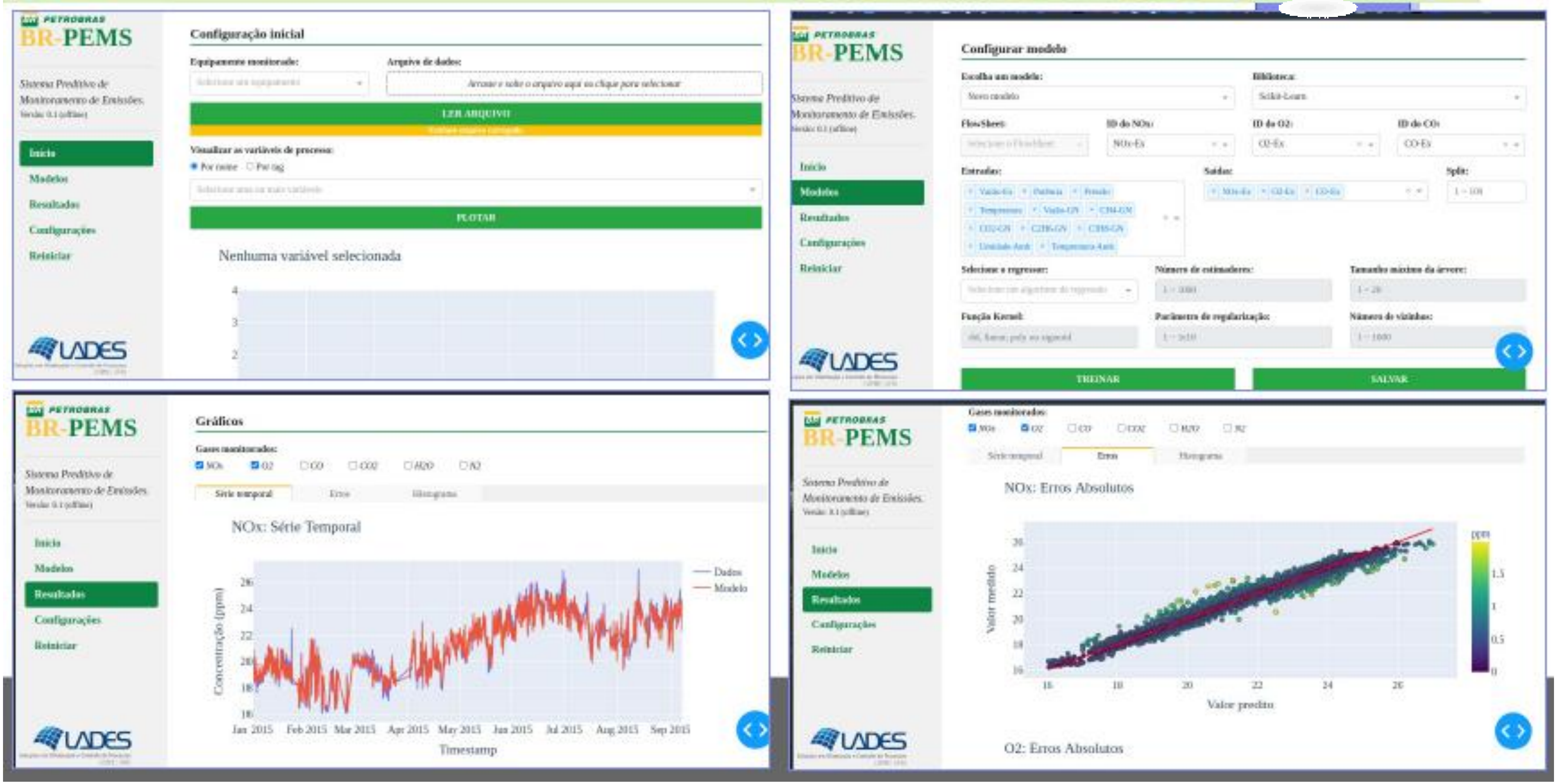


Continuous Emission Monitoring System (CEMS)

Predictive Emission Monitoring System (PEMS)

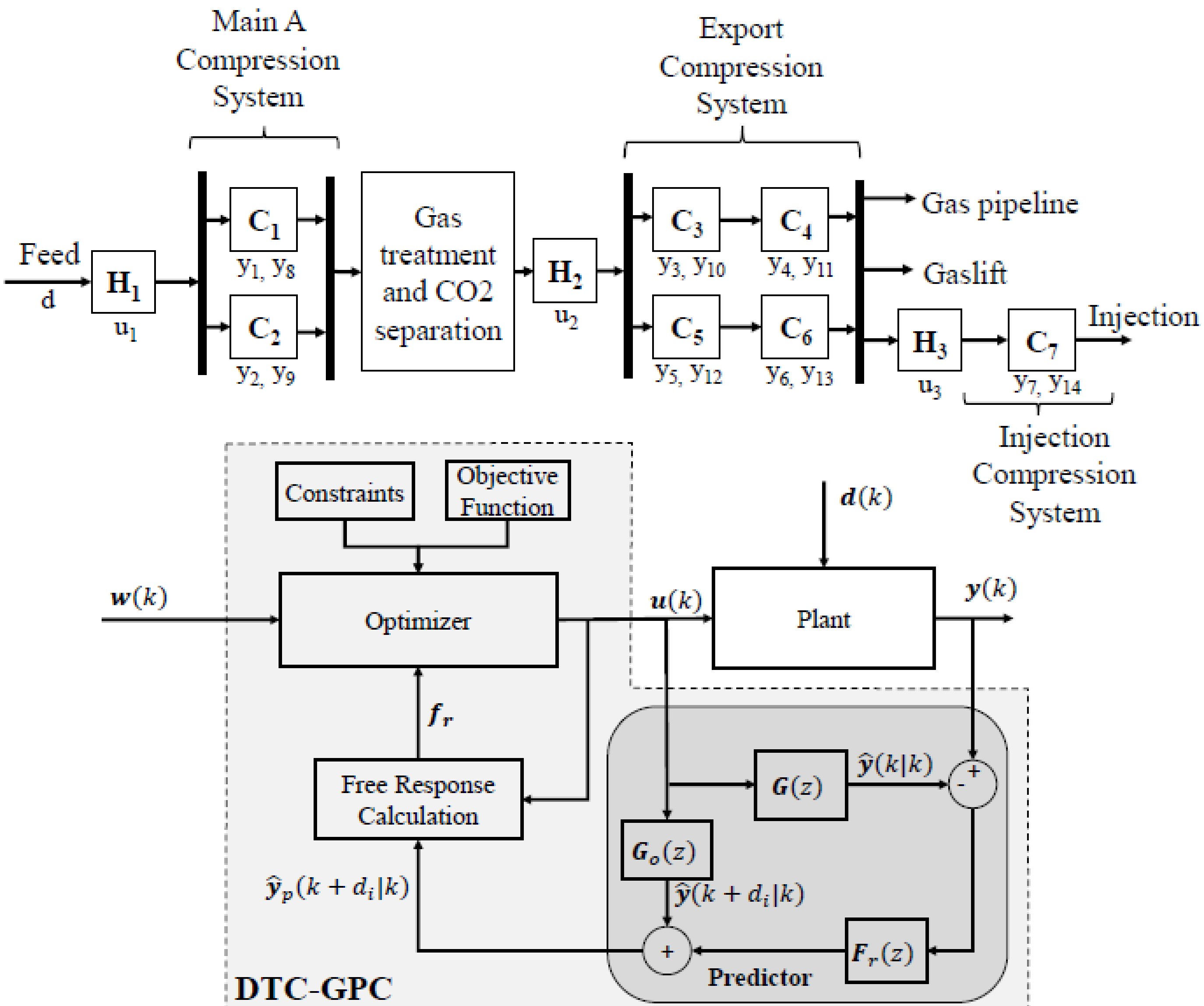
Ss: Remote Monitoring & FDD

PE: Gas turbines, **VM:** Hybrid model, **Ss:** PEMS.



Ss: DTC–MPC in Compression System

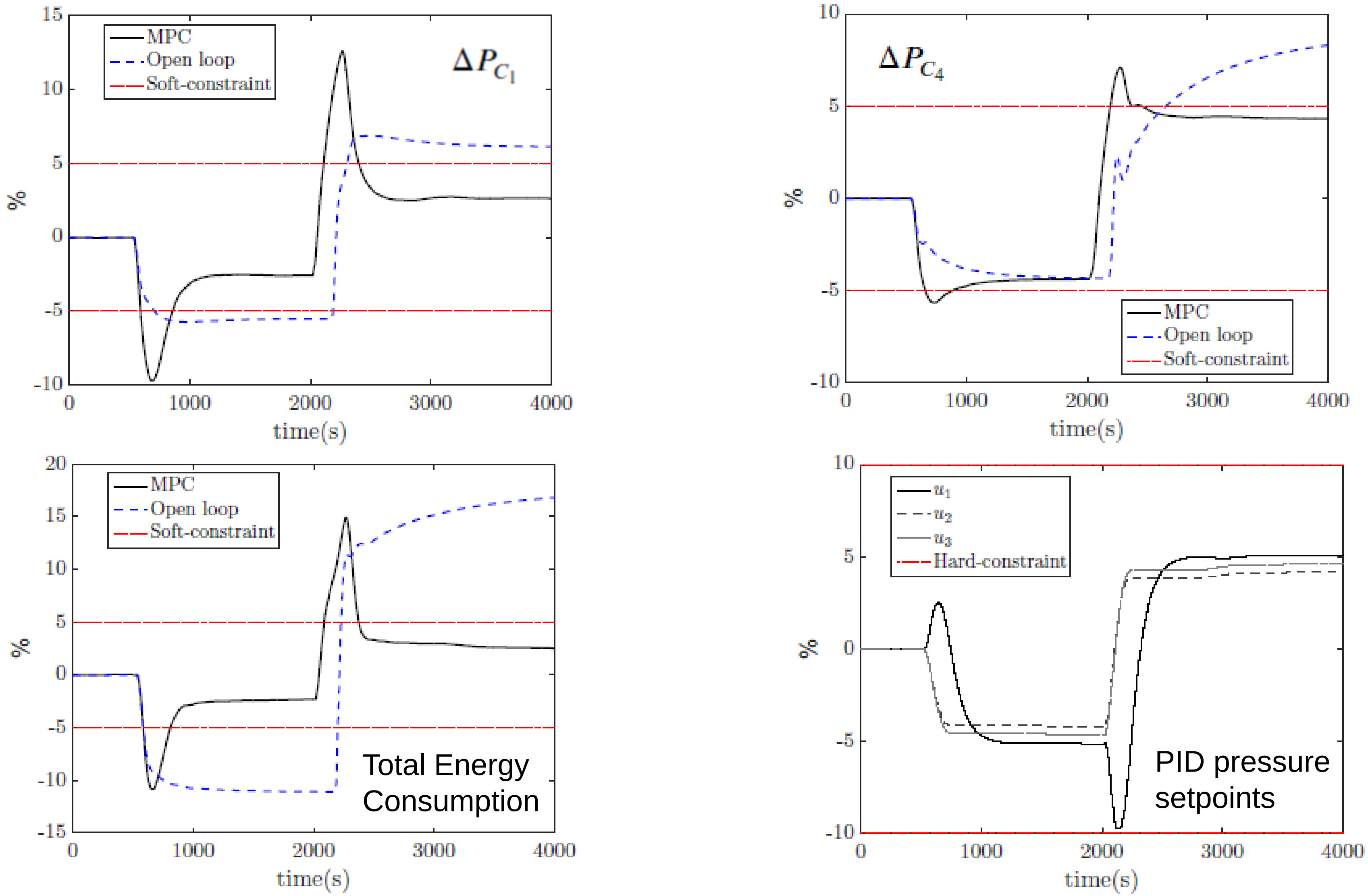
PE: Gas compression system, **VM:** Data based, **Ss:** DTC-MPC.



MPC with dead-time compensator strategy to provide setpoints for the regulatory control layer of a gas compression system, which aim to avoid excessive energy consumption, decrease variability of the plant, and guaranty a stable and safe operation against load disturbances.

[13]Giraldo et al. (2020)

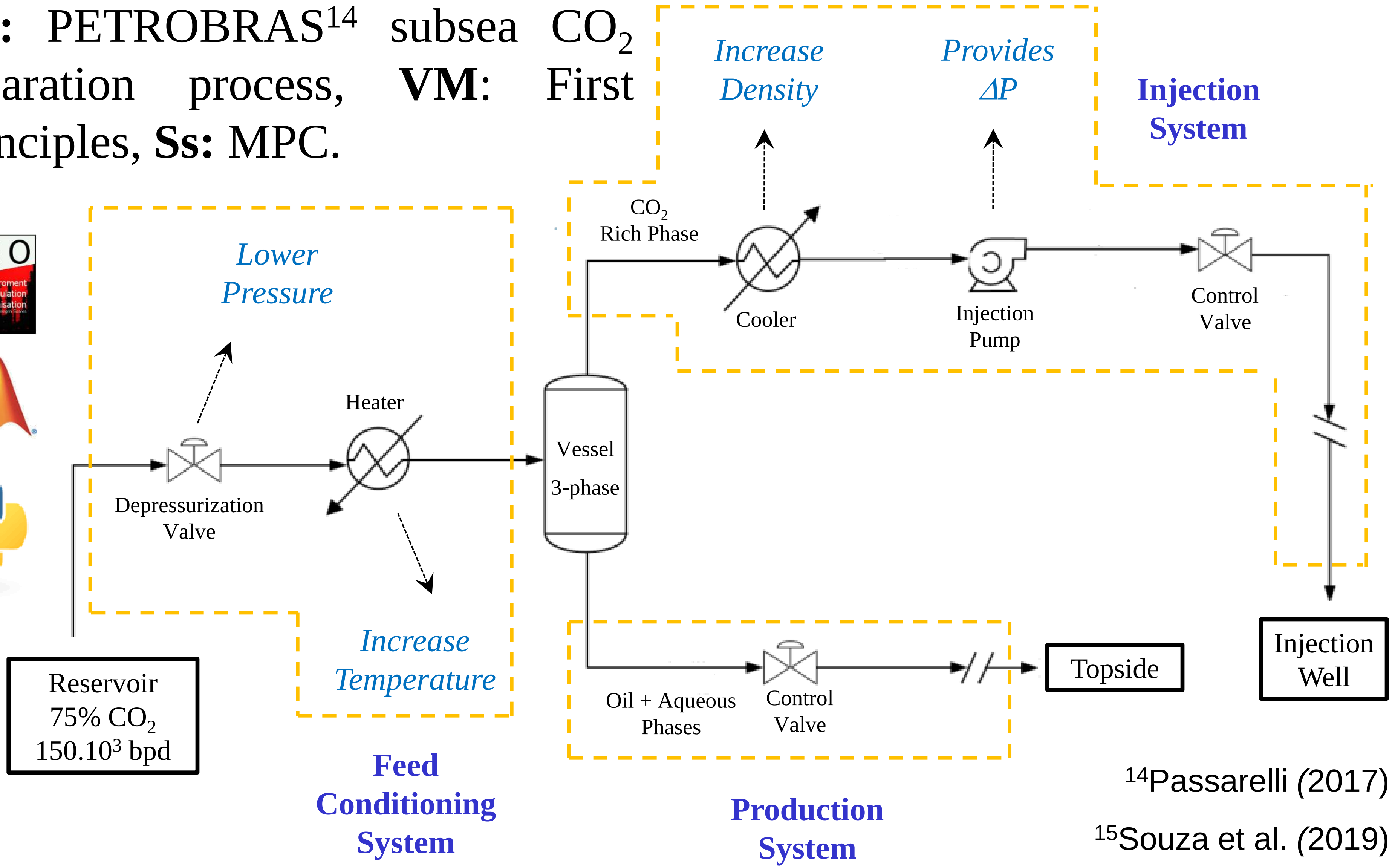
Ss: DTC–MPC in Compression System



[13]Giraldo et al. (2020)

Ss: MPC in CO_2 Subsea Separation

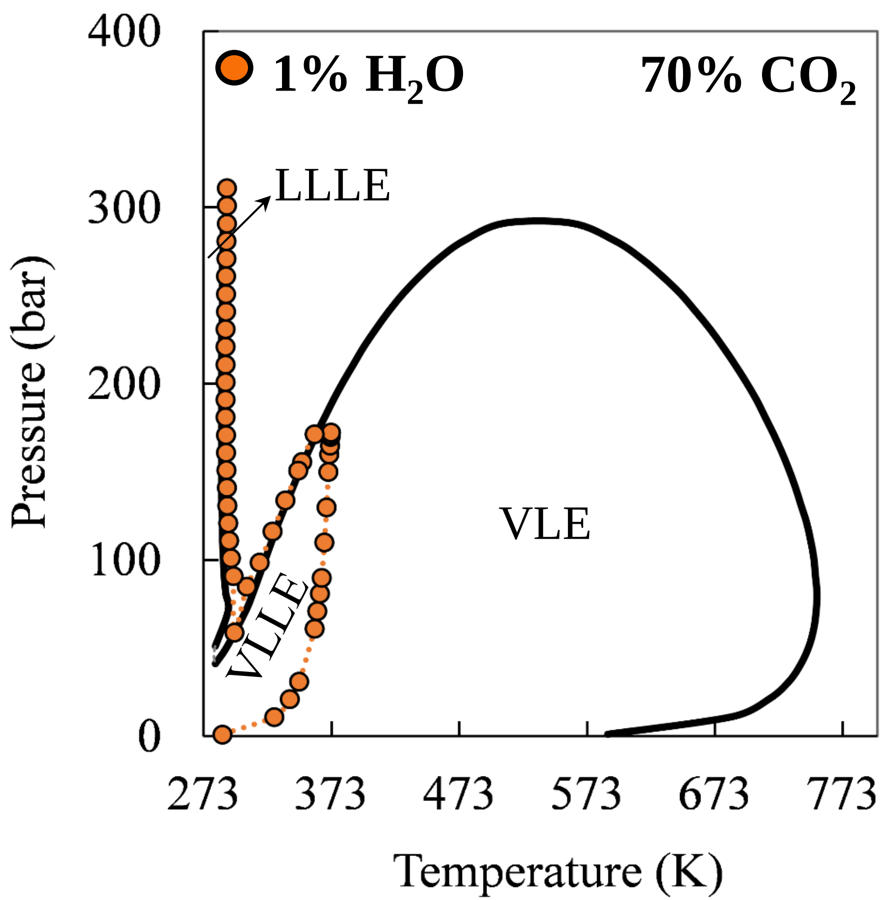
PE: PETROBRAS[14] subsea CO_2 separation process, **VM:** First Principles, **Ss:** MPC.

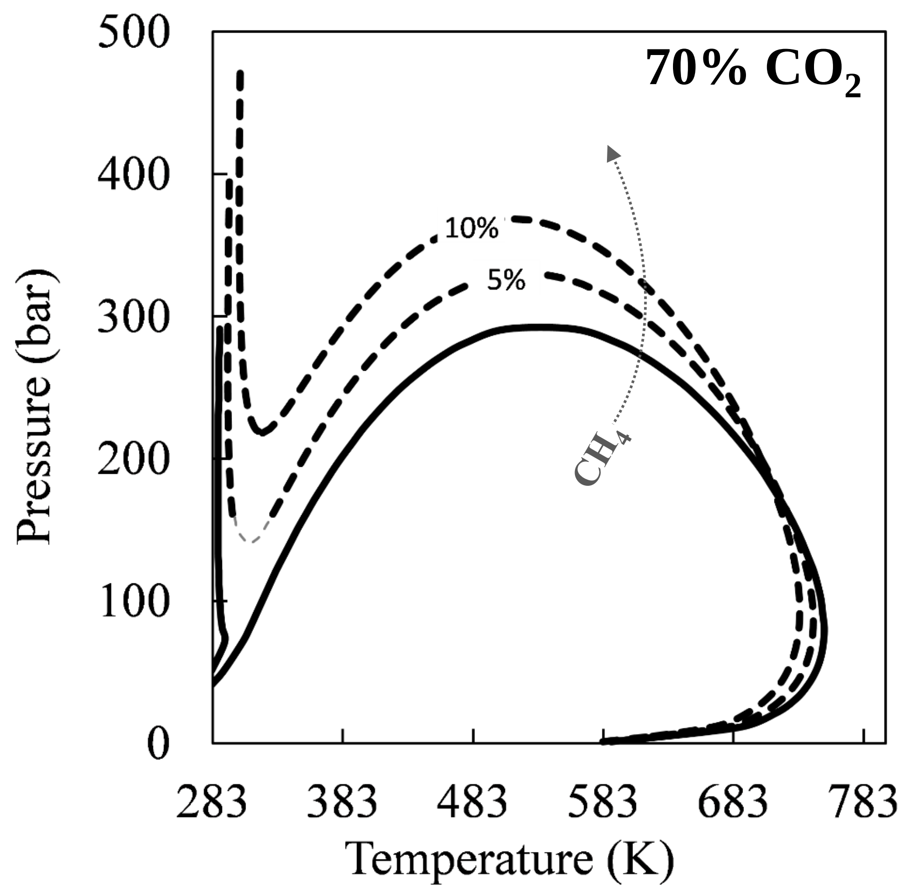


[14]Passarelli (2017)

[15]Souza et al. (2019)

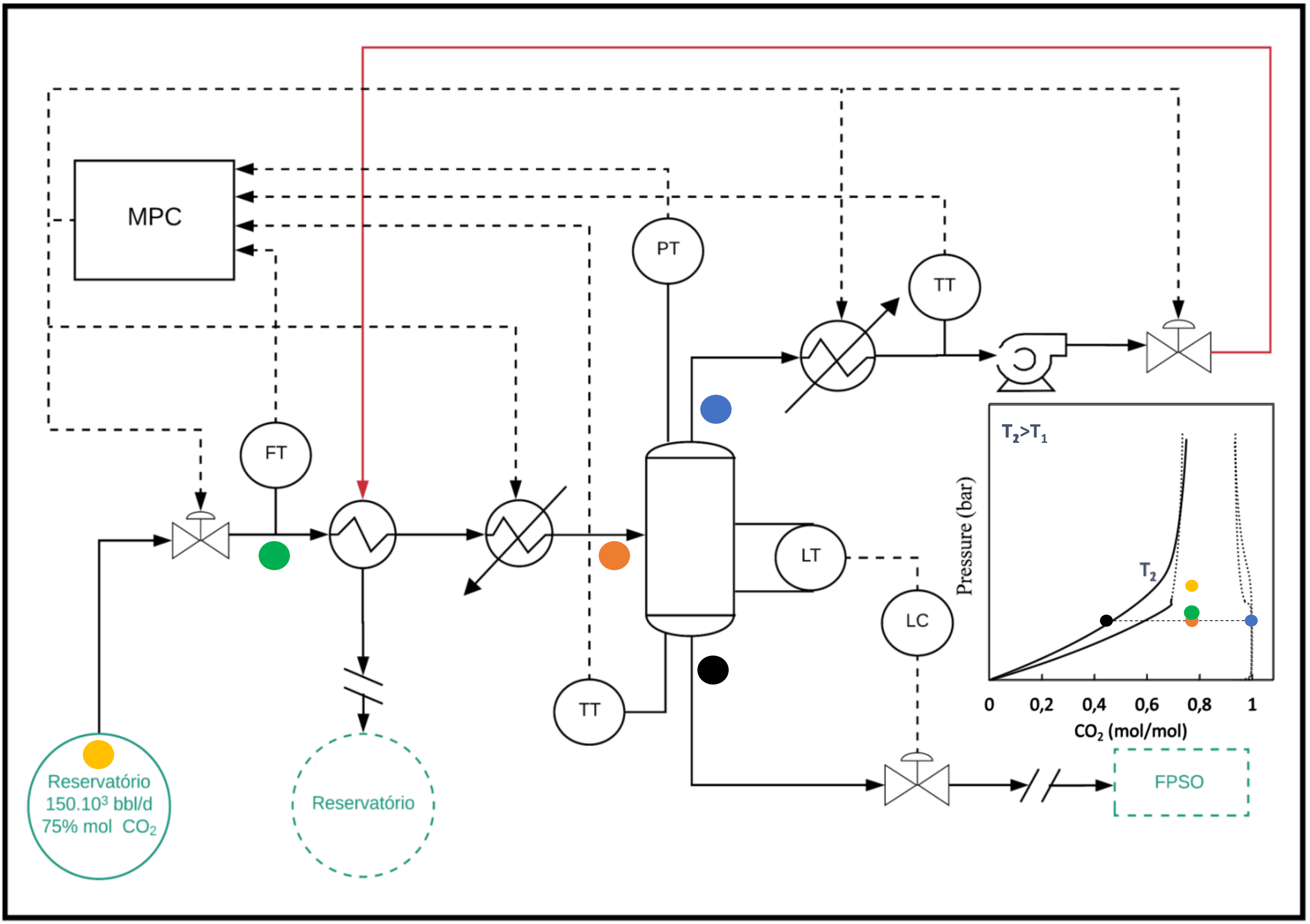
Ss: MPC in CO_2 Subsea Separation

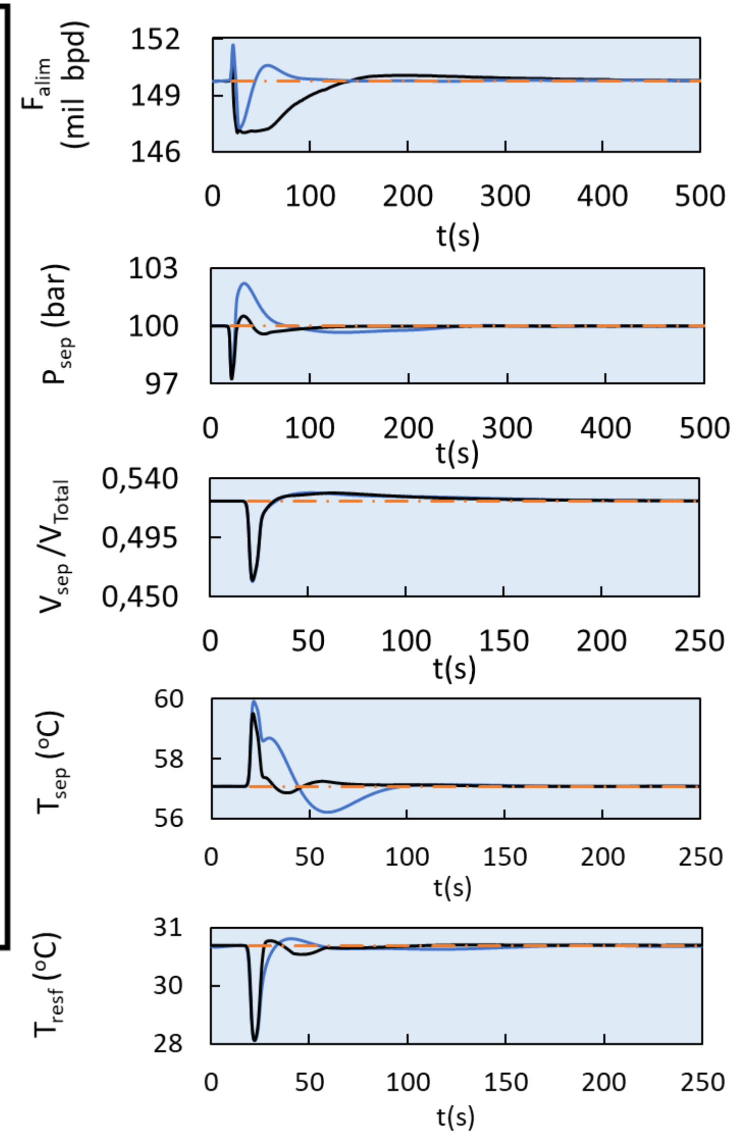




[15]Souza et al. *(*2019)

Ss: MPC in CO_2 Subsea Separation





[15]Souza et al. (2019)

PID (—), MPC (—)

PE: liquid CO_2 pump, **VM:** Stochastic, **Ss:** HAC

<u>PROGNOSTIC MODULE:</u> a pump wear stochastic model was proposed including dependence with pump operating power. Particle filters were employed to estimate states and predict **Remaining Useful Lifetime** (RUL).

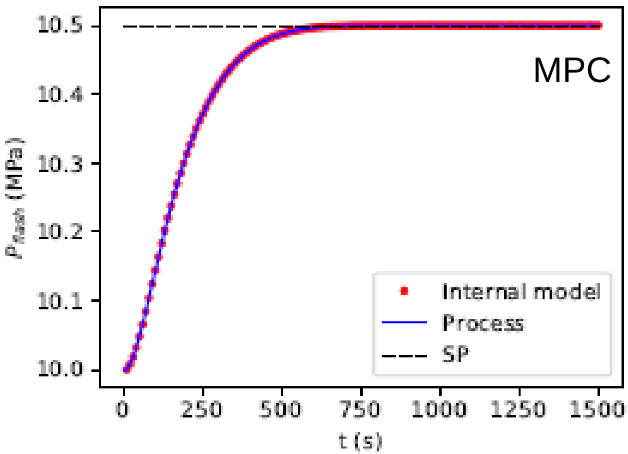
<u>HEALTH-AWARE CONTROL (HAC):</u>

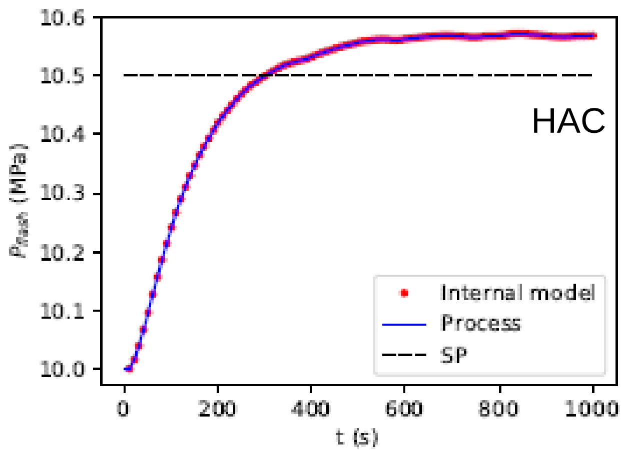
$$J_{HAC} = \overset{\text{Pump Health}}{\boxed{-w_{HAC}\overline{RUL}}} + \overset{\text{Multivariable Control}}{\boxed{\sum_{i=1}^{N_y}\sum_{j=1}^{N_p} {q_i}^2 (y_{i,k+j} - y_{i,k+j}^{sp})^2 + \sum_{i=1}^{N_u}\sum_{j=0}^{N_c-1} {s_i}^2 (\Delta u_{i,k+j})^2}}$$

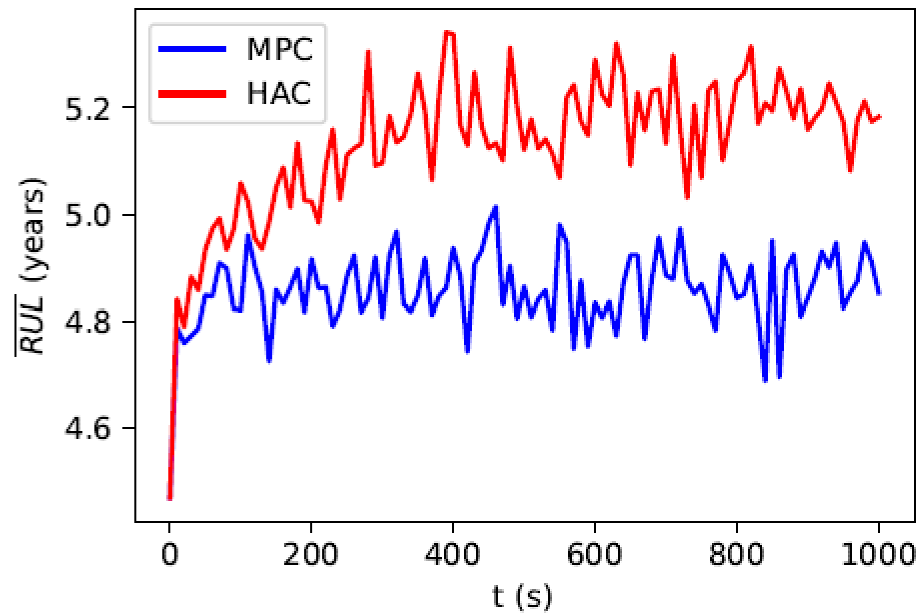
[16]Bernardino et al. (2019)

Ss: Health-Aware Control & Prognosis

As health and control objectives compete against each other, the obtained solution is a compromise between these objectives.







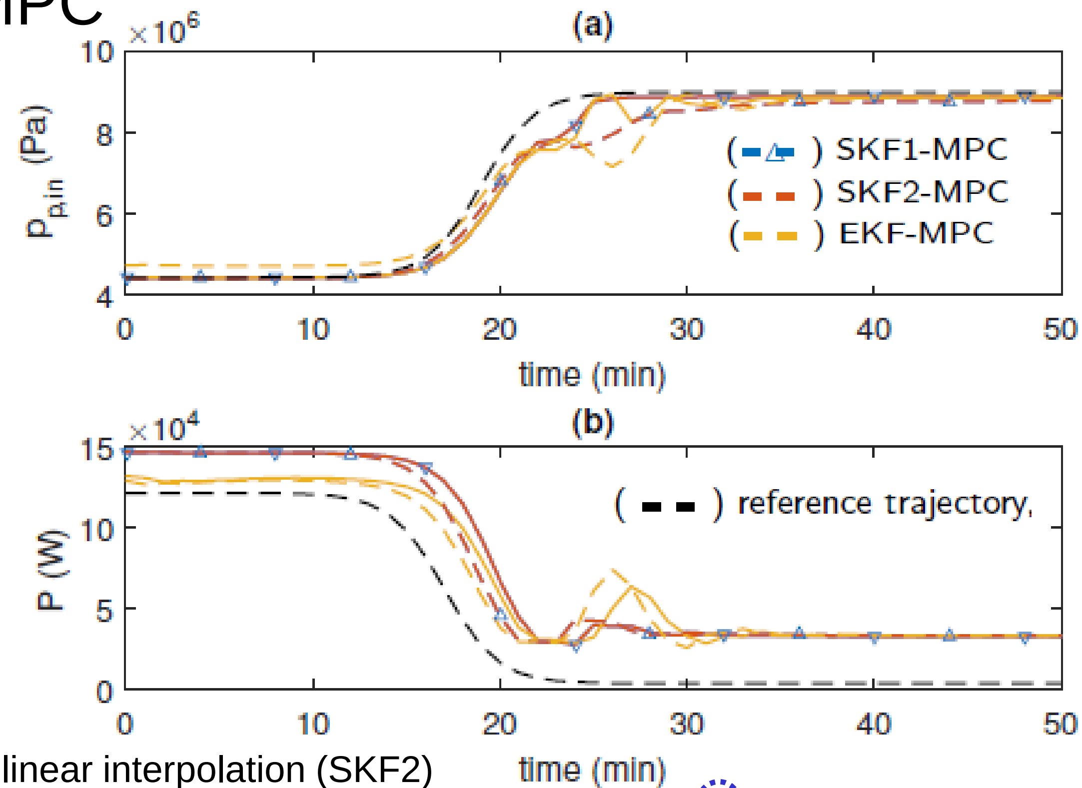
Flash pressure set-point change

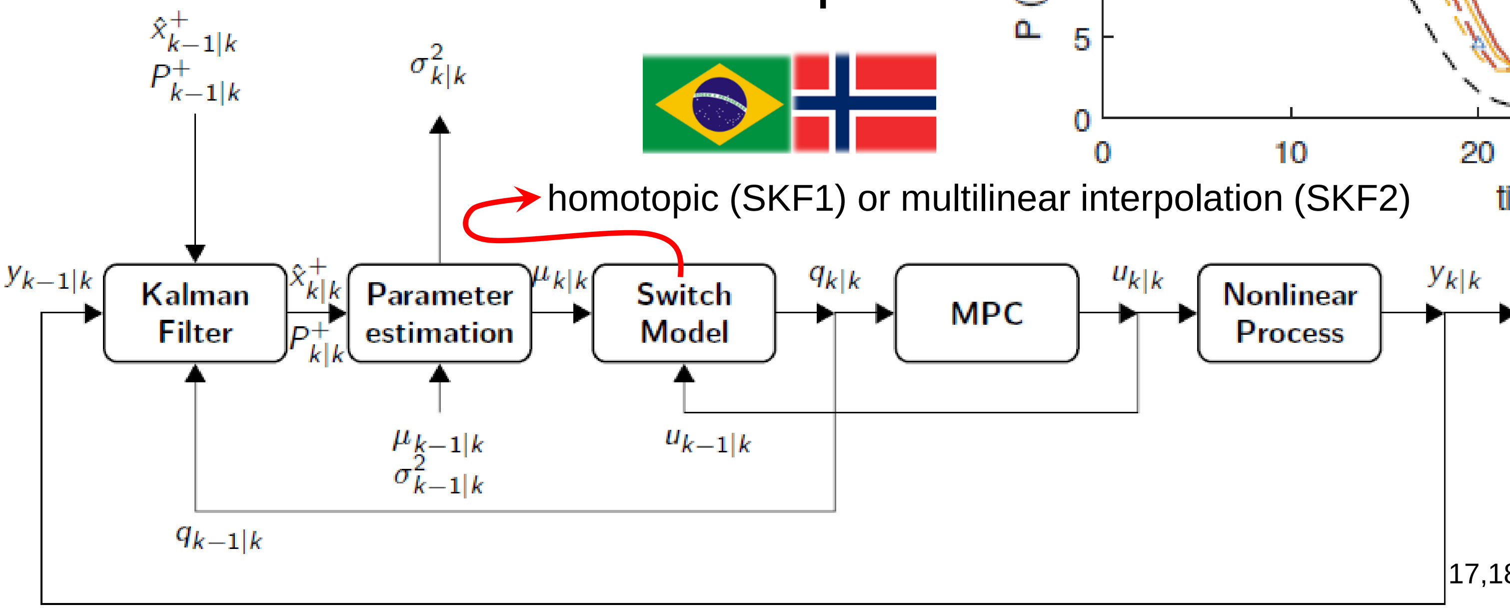
[16]Bernardino et al. (2019)

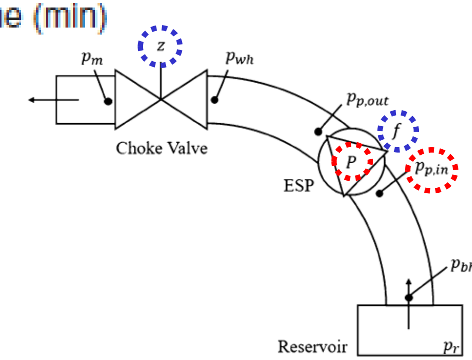
Ss: Adaptive MPC control of ESP

PE: ESP, **VM:** Data based, **Ss:** AMPC

The adaptive MPC control was capable of dealing with process nonlinearities and lack of measurements enhancing the control performance within a wide range of operation of an Electrical Submersible Pump.





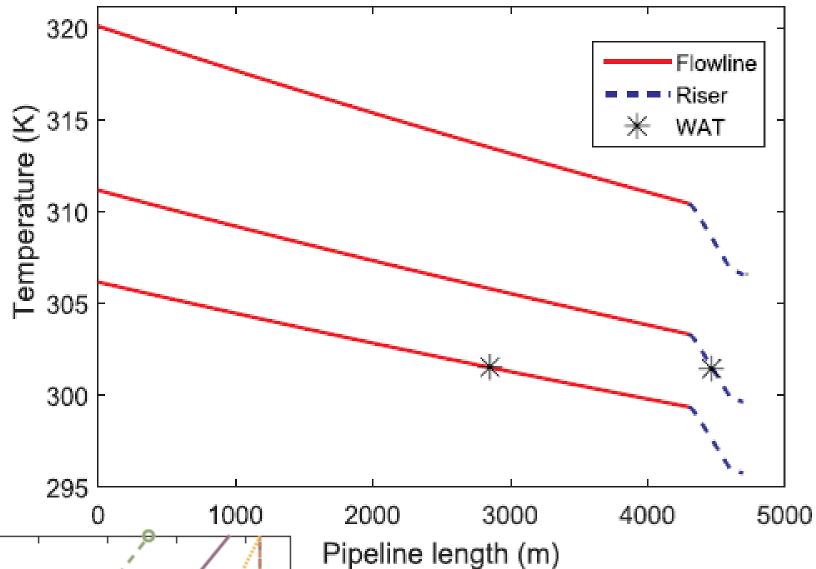


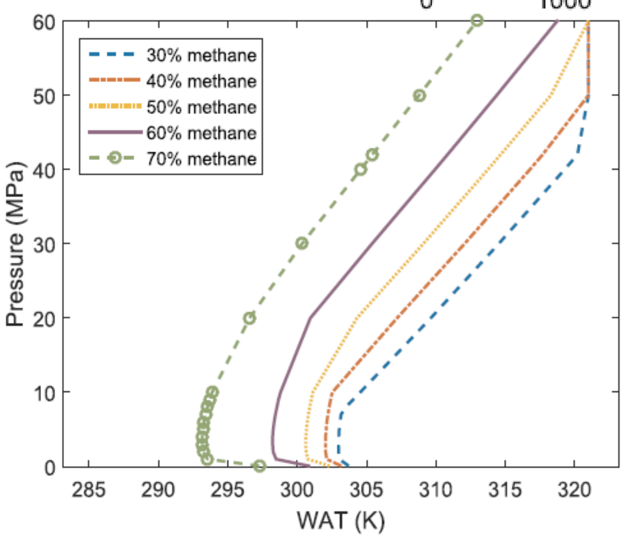
Delou et al. (2019,2020)[17,18]

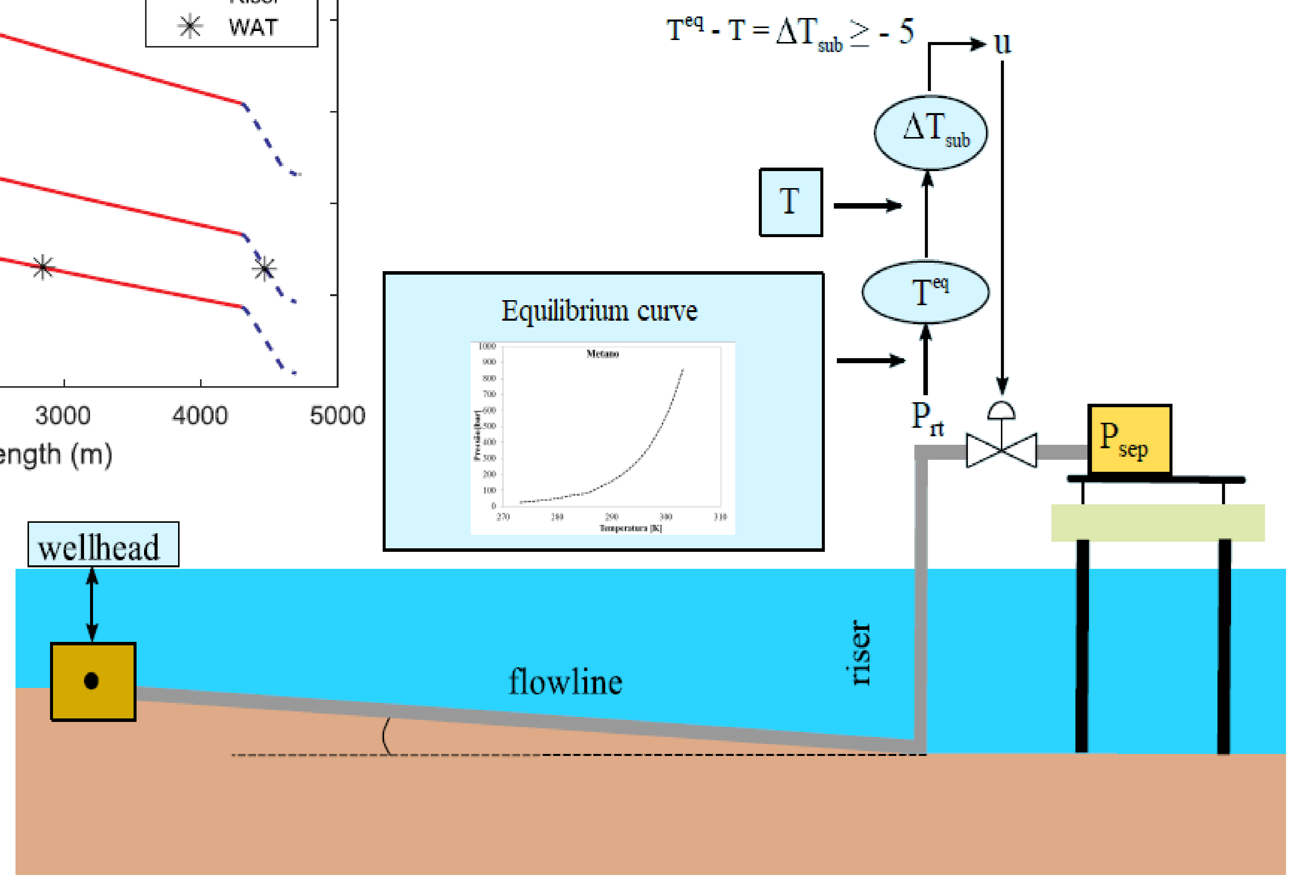
Ss: Flow Assurance Control

PE: Flowline + riser, **VM:** First Principles, **Ss:** Flow assurance control.

Drift-Flux model to predict the location of wax (WAT) or hydrate (HAT) appearance temperature.



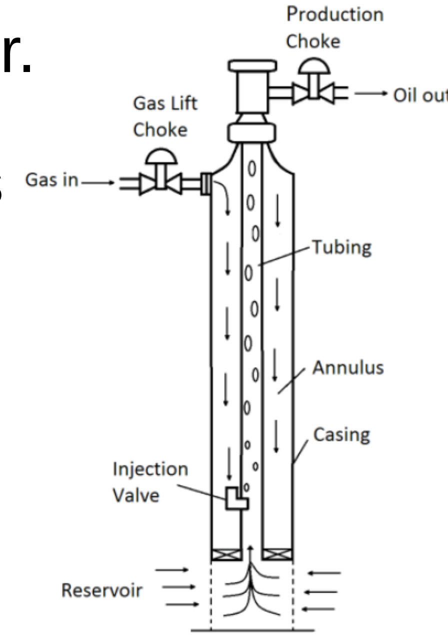




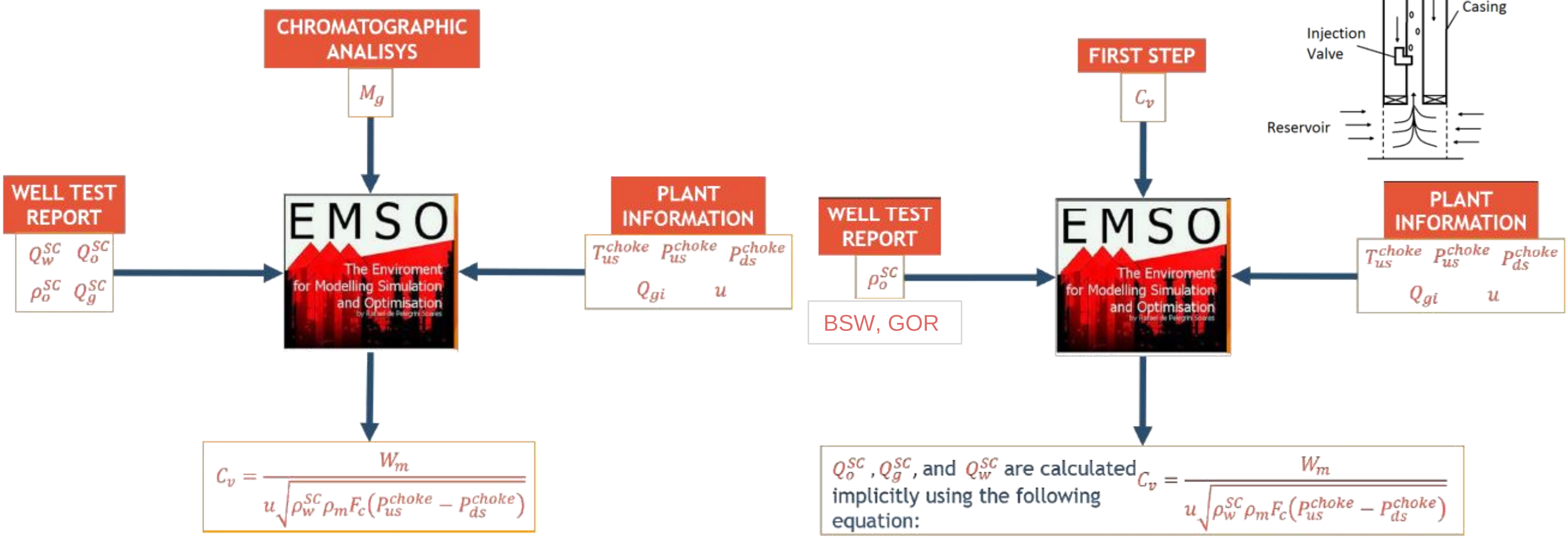
[19]Góes et al. (2019)

Ss: Virtual Flow Metering

PE: Choke Valve, **VM:** First Principles, **Ss:** Soft Sensor.



Predict the oil, water and gas flow rates of each well as function of measured variables available in plant data collected in real time.

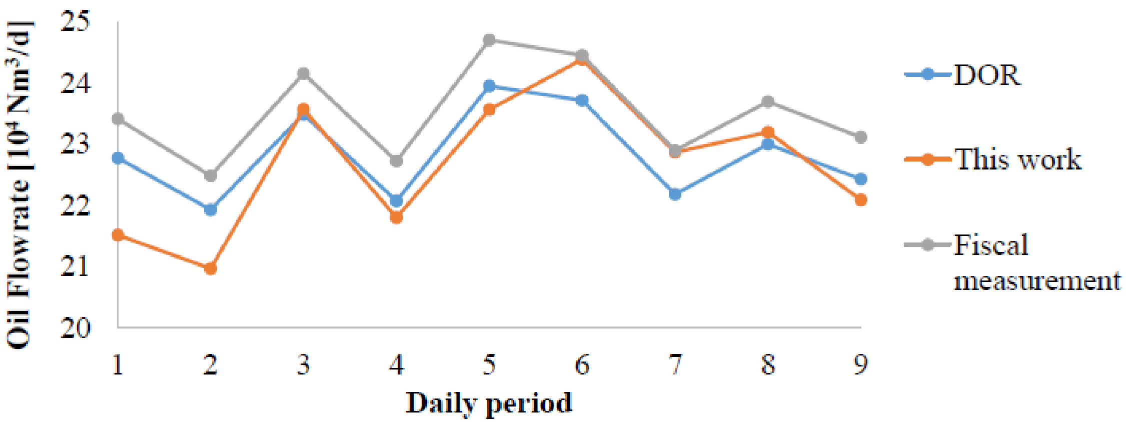


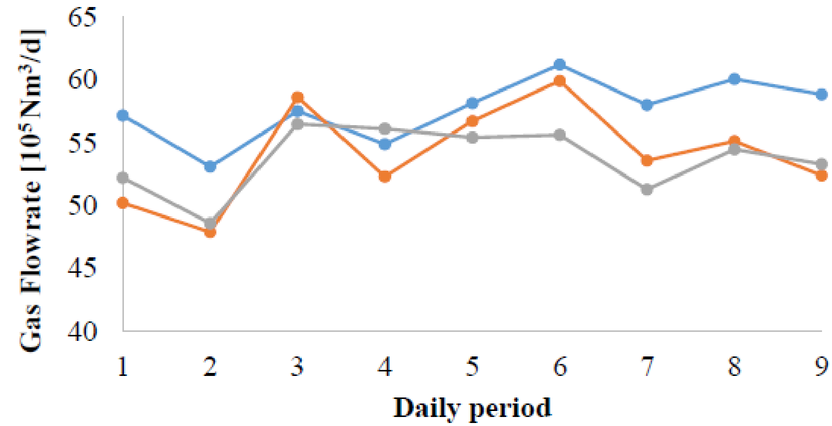
[20]Góes et al. (2020)

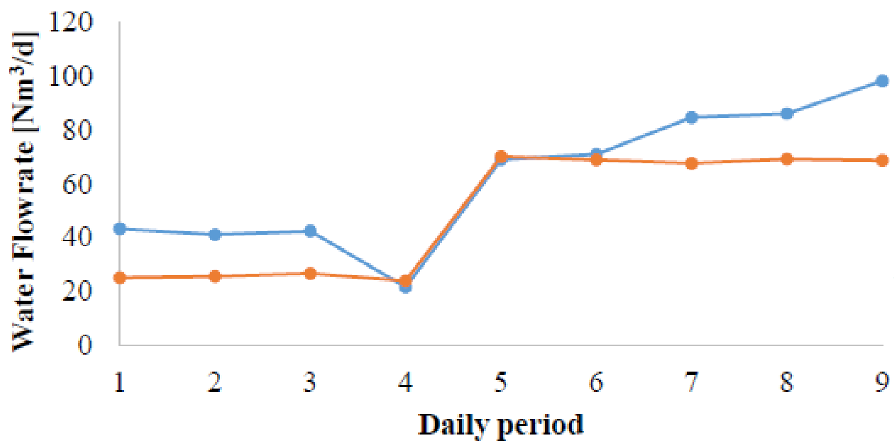
Ss: Virtual Flow Metering

PE: Choke Valve, **VM:** First Principles, **Ss:** Soft Sensor.

The proposed method presented good agreement with fiscal measurement and Daily Operation Report (DOR), with relative errors below 3.5%.







Opens new alternatives for production optimization

[20]Góes et al. (2020)

Final Remarks

Final Remarks

- Implementation of first-principles models for topside and subsea environments are relevant in many stages of DT developments;
- The hybridization of first-principles model with data-based model enhances its predictive-adaptive capability;
- Data treatment and analysis are important and time consuming. Feedback from operators is beneficial in machine learning projects;
- Identification of the real starting moment of the fault (pre-fault) before system power off occurs is highly relevant and challenging;
- The Digital Technologies need an integrated and standardized cyber-physical infrastructure for effective application (e.g.: OPC-UA and https://www.opengroup.org/).

Team

Professors:
Adilson E. Xavier
Argimiro R. Secchi
Bruno D. O. Capron
José Carlos Pinto
Maurício B. de Souza Jr.
Paulo L. C. Lage
Príamo A. Melo Jr.
Vinicius Xavier

Pos-Docs:
José Manuel G. T. Perez
Leonardo S. Souza
Rodrigo G. D. Teixeira
Roymel R. Carpio

Engineers:
Carlos R. Paiva
Silvio Cisneiros

PhD students:
Ana Carolina S. R. Dias
Ataíde S. Andrade
Daniel M. Silva
Felipo D. Rojas Soares
Gabriela Dias B. Magalhães
Marcelo Silva
Maria Rosa R. T. Goes
Pedro A. Delou
Rafael M. Soares
Rafael O. dos Santos
Reinaldo C. Spelano
Rodrigo Curvelo Santos
Ruan de Rezende Faria
Sergio A. C. Giraldo
Thamires A. L. Guedes

MSc students:
Felipe C. Silva
Joaquin Lujan
Nathália T. G. Machado
Pedro Ricardo C. Gonçalves
Rafael C. Vasconcelos
Tamires S. A. Silva
Thiago C. Dávila

Undergrad. students:
Daniel P. Taira
Isabella Q. Souza
Letícia Leal
Lucas Marques
Matheus de Freitas
Rodrigo Moyses
Vinícius C. C. Plácido

Secretariat:
Rosemary Cezar

References

1 – Kondapi et al..(2017), Offshore Technology Conference, Houston, Texas, USA, doi:10.4043/27661-MS.

2 – Krishnamoorthy et al. (2016), Processes, 4 (4). doi:10.3390/pr4040052.

3 – Qi et al. (2019), Computer Integrated Manufacturing Systems, 25 (1), 1-18, doi:10.13196/j.cims.2019.01.001.

4 – Soares (2020), Improving Monitoring and Process Control with Machine Learning, COPPE/UFRJ.

5 – Ribeiro et al. (2019), IFAC PapersOnLine 52 (1), 502-507, doi:10.1016/j.ifacol.2019.06.112.

6 – Carpio et al. (2020), J. of Petroleum Science and Engineering, 108141, doi:10.1016/j.petrol.2020.108141.

7 – Jäschke & Skogestad (2013), IFAC Proc. Vol., 46 (32), 451-456, doi:10.3182/20131218-3-IN-2045.00108.

8 – Dias et al. (2019), Databased Self-Optimizing Control, Proceedings of the 22nd NPC Workshop.

9 – Miyoshi et al. (2012), IFAC Proc. Vol., 45 (8), 245-250, doi:10.3182/20120531-2-NO-4020.00019.

10 – Souza et al. (2020), Expert Systems with Applications, submitted.

11 – Xavier & Xavier (2011), Pattern Recognition, 44, 70-77, doi:10.1016/j.patcog.2010.07.004.

12 – Xavier (2016), Dimensionality Reduction, Ph.D. thesis, COPPE/UFRJ.

13 – Giraldo et al. (2020), Journal of Process Control, submitted.

14 – Passarelli (2017), lens.org/181-301-137-556-927.

15 – Souza et al. (2019), IFAC PapersOnLine 52 (1), 790-795, doi:10.1016/j.ifacol.2019.06.158.

16 – Bernardino et al. (2019), Processes, 8 (2), 148–171, doi:10.3390/pr8020148.

17 – Delou et al. (2019), IFAC PapersOnLine 52 (1), 784-789, doi:10.1016/j.ifacol.2019.06.157.

18 – Delou et al. (2020), Brazilian Journal of Chemical Engineering, 37, doi:10.1007/s43153-020-00079-x.

19 – Góes et al. (2019), J. of Petroleum Science and Engineering, 177, 274-283, doi:10.1016/j.petrol.2019.02.057.

20 – Góes et al. (2020), J. of Petroleum Science and Engineering, submitted.

PEQ COPPE UFRJ

... thank you for your attention!

LADES

LADES
Solutions for Process Control and Optimization
COPPE | UFRJ

Process Systems Engineering Research Group

- Prof. Argimiro Resende Secchi, D.Sc.
- Phone: +55-21-3938-8307
- E-mail: arge@peq.coppe.ufrj.br

Prof. Maurício B. de Souza Jr., D.Sc.

- Phone: + 55-21-3938-7315
- E-mail: mbsj@eq.ufrj.br

- http://lades.peq.coppe.ufrj.br/

PSE–UFRJ
Process Systems Engineering – UFRJ

LASAP
Simulações Avançadas de Processos
PEQ | COPPE | UFRJ

LMSCP
PEQ/COPPE/UFRJ

PROJETO ALSOC

http://www.enq.ufrgs.br/alsoc