Machine Learning-based industrial process control with explainable decision support

About me

Research interests

Education

2017 - now

PhD's Degree in Mining and Engineering Geology

AGH University of Science and Technology
Faculty of Drilling, Oil and Gas

Thesis topic: Application of autoadaptative decision trees to hydrocarbon wells control

2017 - 2018

Masters's Degree in Computer Science (Intelligent systems), GPA: 4.89/5

AGH University of Science and Technology
Faculty of Electrical Engineering, Automatics, Computer Science and Biomedical Engineering

Thesis topic: Application of artificial intelligence methods to industrial process control. A case study of underground gas storage

2016 - 2017

Masters's Degree in Mining and Geology (Production of fluid minerals resources), GPA: 4.91/5

AGH University of Science and Technology
Faculty of Drilling, Oil and Gas

Thesis topic: Computer model of intelligent control of oil reservoir

2012 - 2016

Bachelor's Degree in Oil and Gas Engineering, GPA: 4.92/5

AGH University of Science and Technology
Faculty of Drilling, Oil and Gas

Thesis topic: Project of computer application for production forecasting from oil reservoirs using material balance

Experience

2020 - now

Data Scientist

Hitachi Energy (prev. Hitachi ABB Power Grids)
Poland Hitachi Energy Research

2019 - 2020

Data Scientist

ABB Corporate Research Center
PLCRC

2018 - now

Research Assistant

AGH University of Science and Technology
Faculty of Drilling, Oil and Gas

2017 - now

Reservoir engineering R&D projects

AGH University of Science and Technology
Research team member

Application of machine learning methods to hydrocarbon production from underground reservoir

Motivation

Genesis

- ❑Control of hydrocarbon production based **solely on engineering experience**
- ❑Effective reservoir operation but not optimal

Aim

- ❑Improving the **techno-economic efficiency** of hydrocarbon production

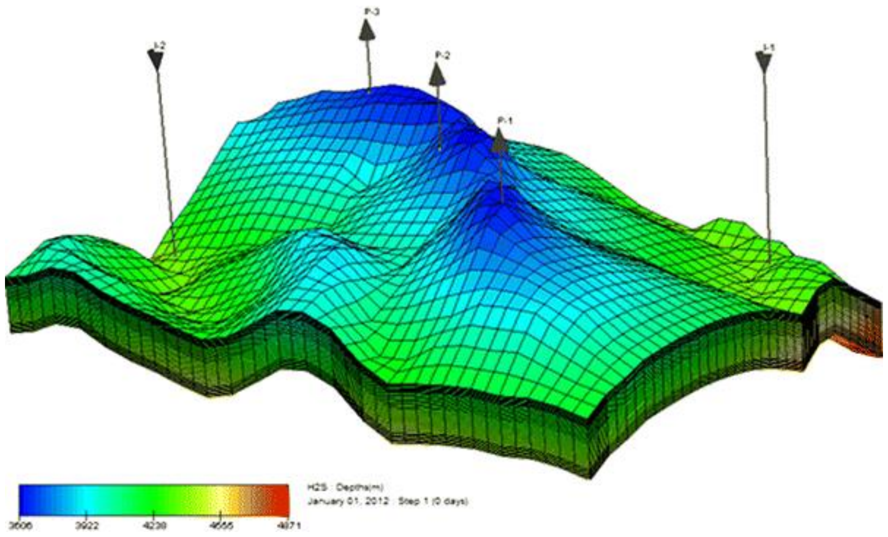
Realization

- ❑**Combination of optimal control theory**, artificial intelligence methods and industrial experience
- ❑**Intelligent wells control**

Optimal control vs. reservoir simulation

Reservoir Simulation

- iterative scenario analysis
- non optimal solution



Optimal Control

- automatic determination of the best scenario
- optimal solution

New solution:
combination of optimal control and reservoir simulation

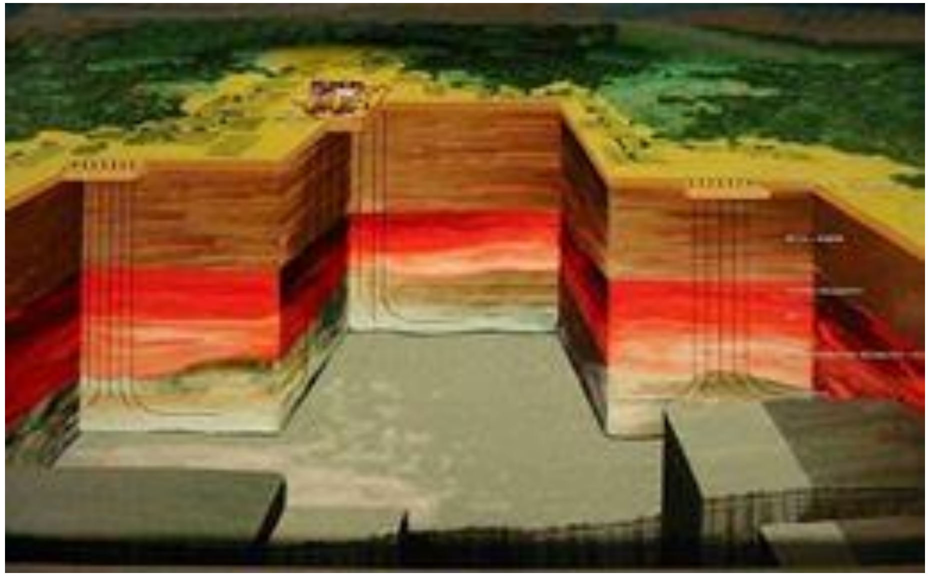
Optimal control of hydrocarbon reservoir

The purpose of the optimal control of hydrocarbon reservoir is to determine the **control policy** that maximizes or minimizes a specific criterion, subject to the **constraints** imposed by the **physical nature** of the problem in the form of differential equations describing the dynamics of the system.

$$\frac{dx}{dt} = f\left(x, \nabla x, \nabla^2 x, u\right)$$

The optimization objective may include:

- ❑ minimizing water production
- ❑ maximizing the calorific value of the extracted gas
- ❑ maximizing the economic value of the project

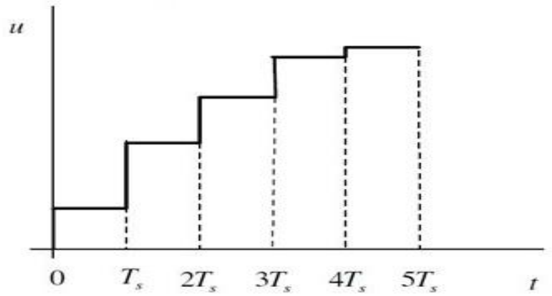


$$J\left(u(t)\right) = \Phi\left[x(t_k), t_k\right] + \int_{t_0}^{t_k} \Psi\left[x(t), u(t), t\right] dt$$

$$J(\hat{\boldsymbol{u}}) = \max_{\boldsymbol{u}} J(\boldsymbol{u})$$

Reservoir optimal control difficulties

Reservoir optimal control problem can be **decomposed into subproblems** where control of individual well is determined in each time step.



$$\hat{u}_{PMG} = \begin{pmatrix} \hat{u}_{11} & \hat{u}_{12} & \dots & \hat{u}_{1T} \\ \hat{u}_{21} & \hat{u}_{22} & \dots & \hat{u}_{2T} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{u}_{W1} & \hat{u}_{W2} & \dots & \hat{u}_{WT} \end{pmatrix}$$

Modeling of reservoir dynamics with the use of reservoir simulators causes that its control optimization is a **black-box problem** with a high evaluation time.

As a result, the applicability of traditional optimal control methods is limited. An alternative solution is to use **artificial intelligence methods**, which have a great potential in solving complex engineering problems.

AI in Oil & Gas industry

- ❑ creating proxy reservoir models - ANN, SVM
- ❑ interpretation of geophysical logs – ANN
- ❑ determination of the reservoir characteristics and properties of reservoir fluids - ANN, SVM
- ❑ optimization of the drilling process - FS + ANN
- ❑ determination of production processes control - **ANN + GA**

Novel approach:

Application of parameterized automatically adaptive decision trees that have not been used so far to the wells control

Parameterized automatically adaptive decision trees

Assumptions

- use of **expert knowledge**, good practices, engineering experience - making the whole process fully interpretable

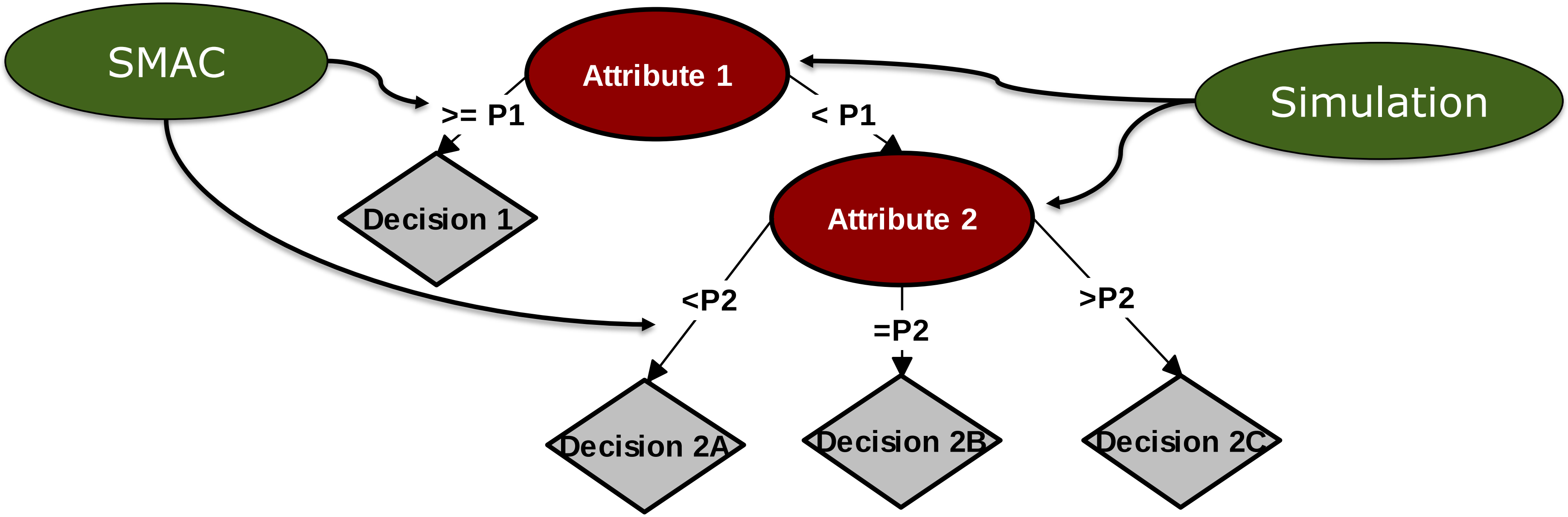
- use of a **simulation model** - a better understanding of the physical basis of the defined control

- automatic adjustment of the general algorithm to a specific problem

- increased efficiency of calculations - applicability to complex simulation models of real processes

Proposed autoadaptive solution

Process control can be defined on the basis of a **decision tree** what allows its unambiguous physical interpretation, while tree **parameterization** consisting in replacing the limit values assigned to tree branches by parameters allows **optimization** of decision conditions.



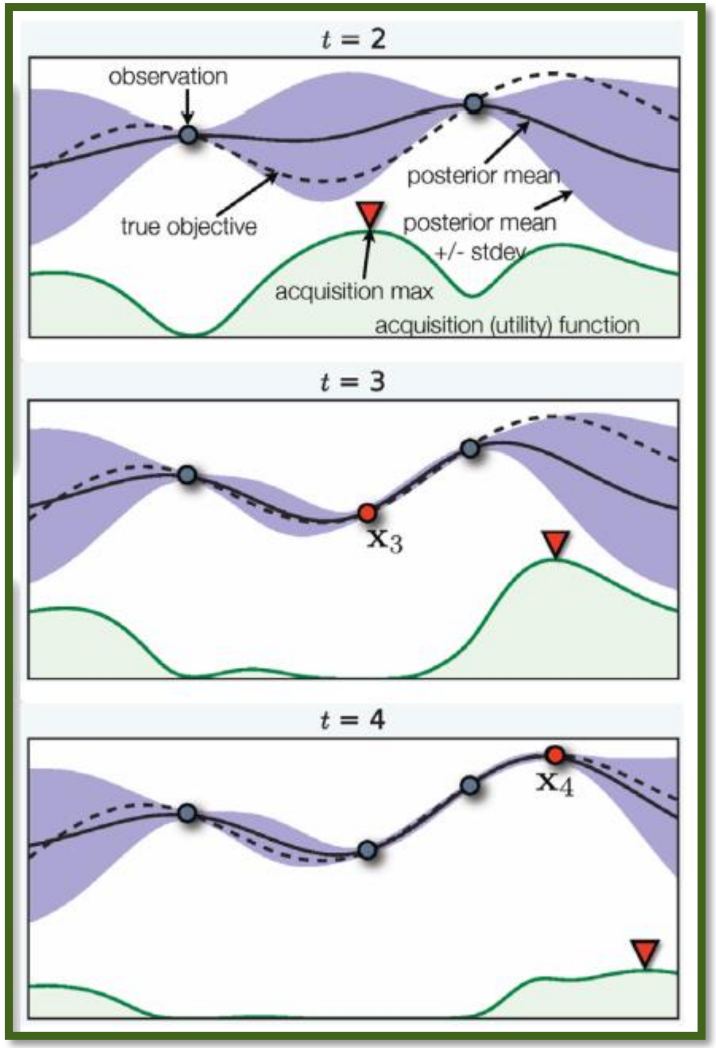
Automatic selection of optimal parameter values is possible using the **AI optimization method** Sequential Model-based Algorithm Configuration (**SMAC**).

Sequential Model-based Algorithm Configuration (SMAC)

An optimization method based on a **search space model** that uses a sequential strategy that enables model refinement during the optimization process and adaptive sampling to balance search space exploration and model exploitation.

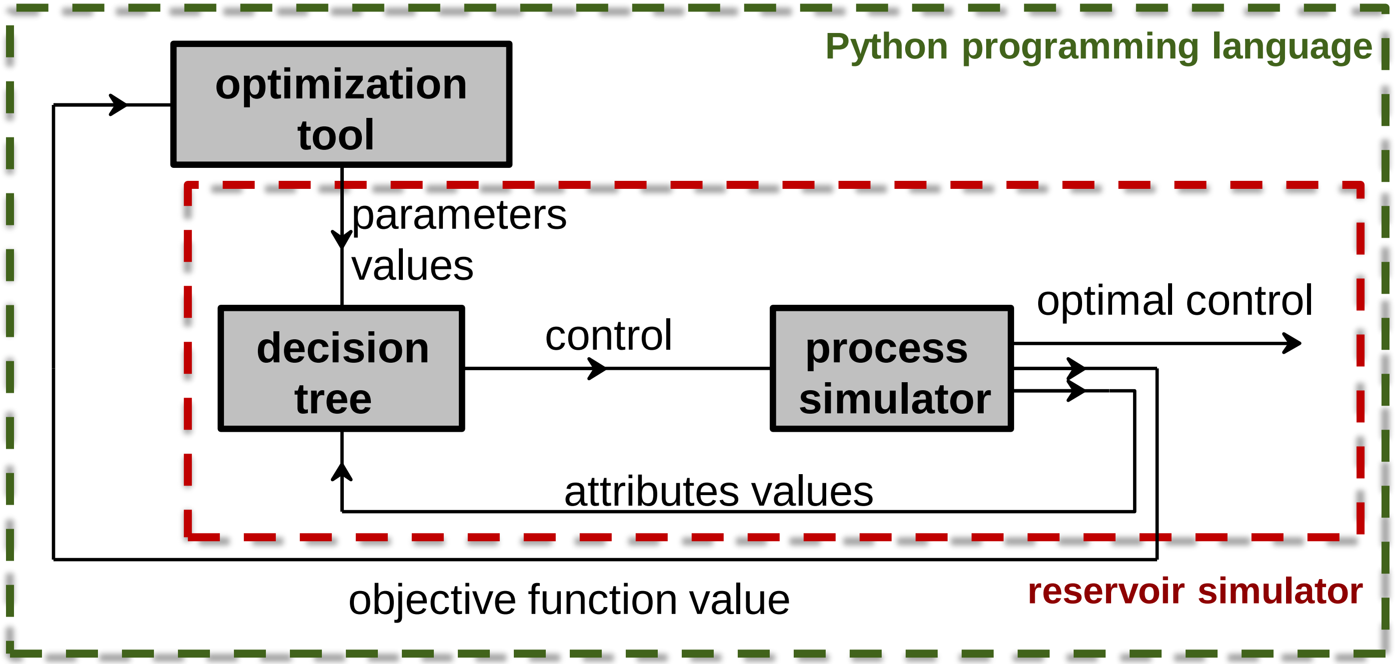
Algorithm 1: SMAC
Input: Algorithm A with parameter configuration space Θ; cost function f
Output: Optimized parameter configuration

$[H, \theta_{init}] = Initialize(\Theta);$
repeat
  M ← FitModel(H); ▻ Random forest: $\Theta \times R^m \to R$
  $\theta^* \leftarrow \mathrm{argmax}_\theta\, Q\,(\theta, M);$ ▻ Expected improvement
  Evaluate(f(θ^*)); ▻ Expensive step
  H ← H ∪ $\left(\theta^*, f(\theta^*)\right);$
until TerminationCriterion()
return $\theta^* \leftarrow \mathrm{argmin}_{\theta \in \Theta}\, E\left(f(\theta)\right)$



Intelligent control optimization algorithm

In the proposed solution, at **each time step** of the simulation, control is defined based on a **parameterized decision tree** configured using the **SMAC optimization method**.



The developed algorithm provides a **self-improving automatic control** of the analyzed process.

Exemplary application – Optimal control of Underground Gas Storage (UGS)

The purpose of the optimal control of underground gas storage is to determine the **control policy** that will **maximize the total amount of energy** that can be obtained from gas extracted during the production cycle.

Energy produced from a single well

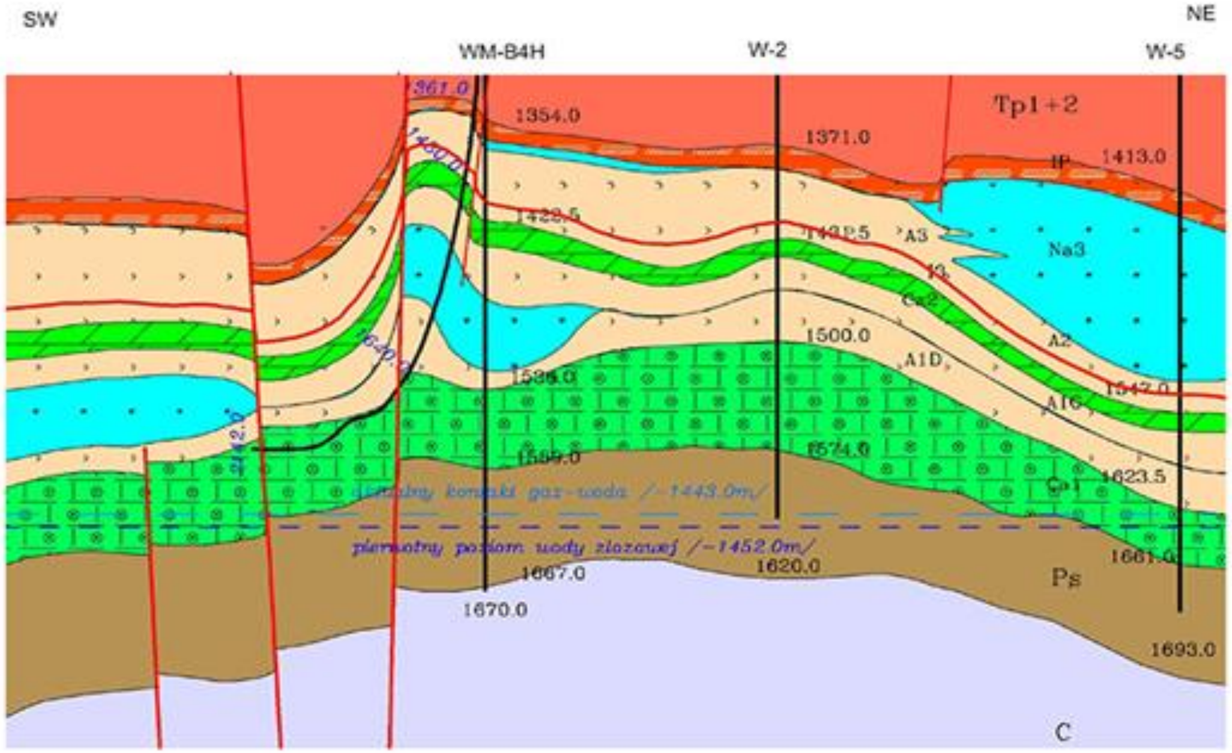
$$E_k(\boldsymbol{u}) = \sum_{n=1}^{T} \left(\sum_{i=1}^{N} C_i \, y_{i,n,k} \, u_{n,k} \right)$$

Objective function – total energy

$$J(\boldsymbol{u}) = \sum_{k=1}^{W} E_k(\boldsymbol{u})$$

Optimal control problem

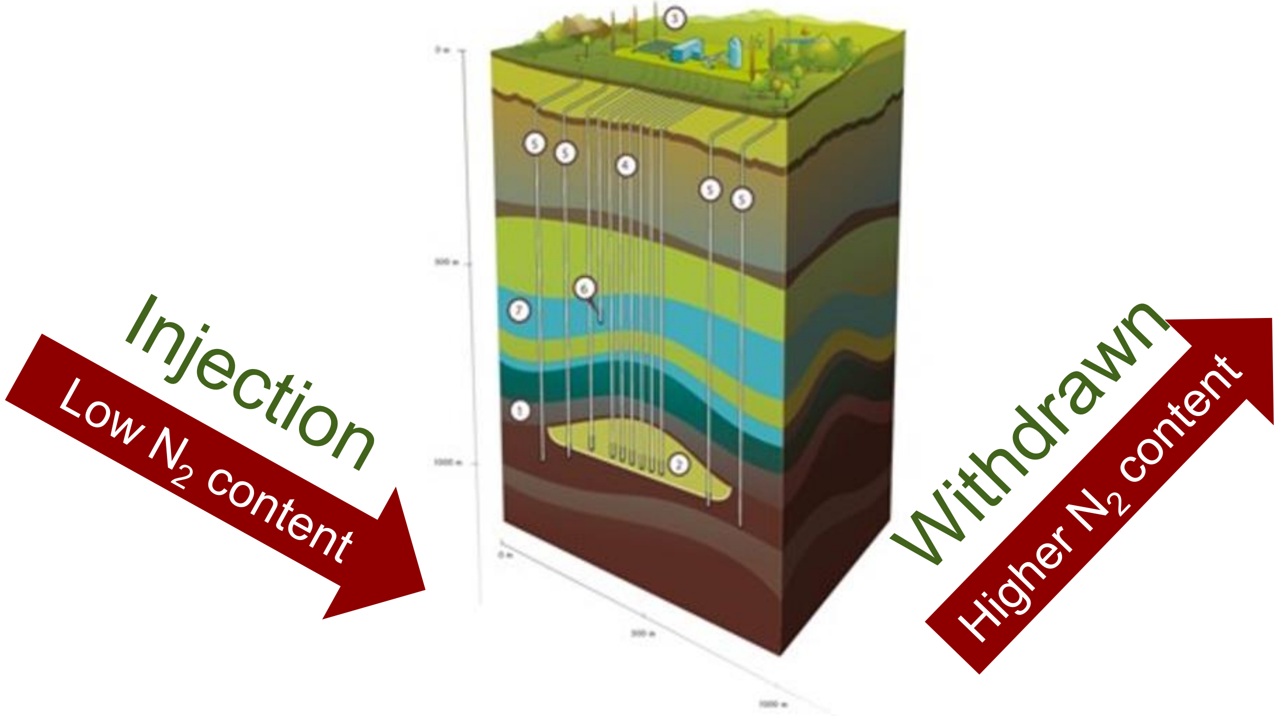
$$J(\hat{\boldsymbol{u}}) = \max_{\boldsymbol{u}} J(\boldsymbol{u})$$



Maximizing energy efficiency of UGS

As an example, the problem of **mixing of high-methane injected gas with nitrogen-rich native gas** has been considered.

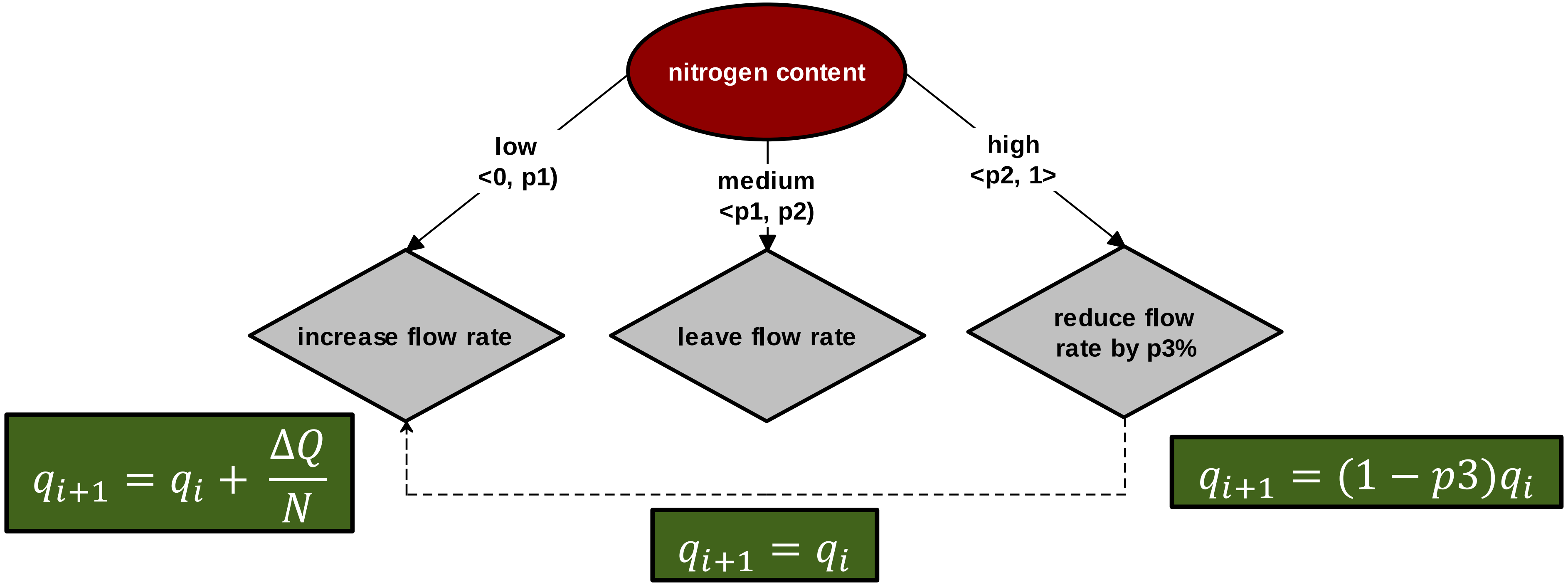
Component	Native gas mole fraction	Injected gas mole fraction
Nitrogen	0.29	0.01-0.03
Methane	0.70	0.96-0.985
…	…	…



In order to illustrate the effectiveness of the proposed solution, it has been tested on **a single historical cycle**.

Developed parametrized decision tree

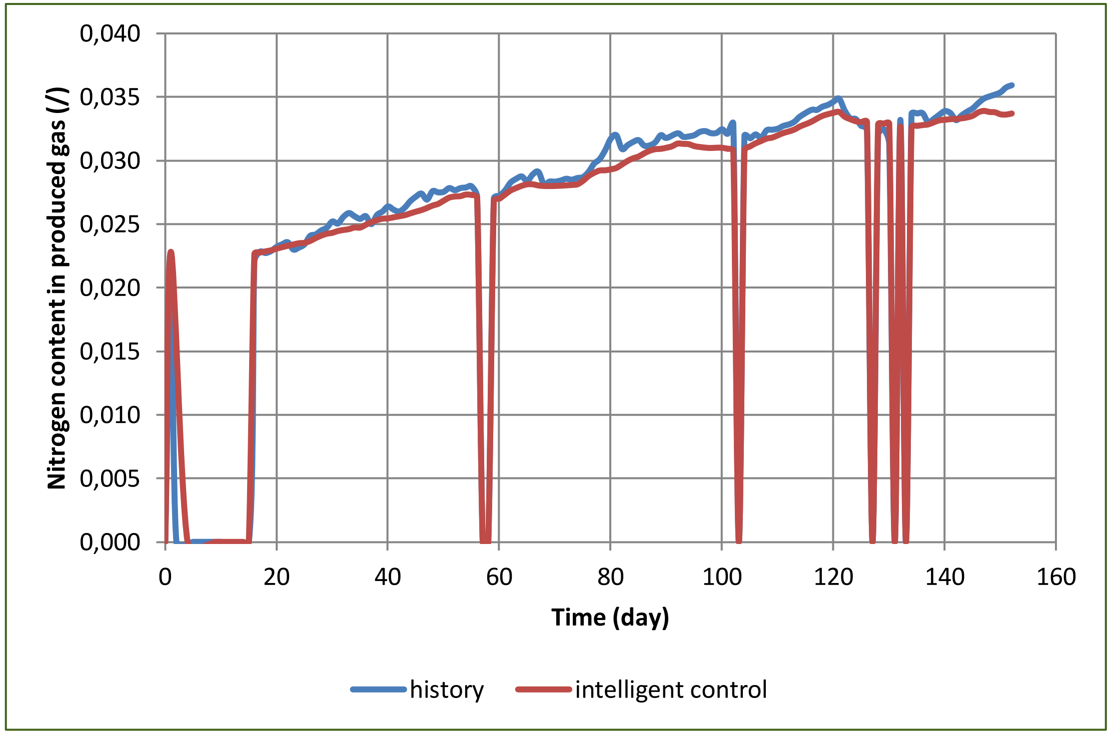
In each time step well rates are automatically updated according to the developed decision scheme.

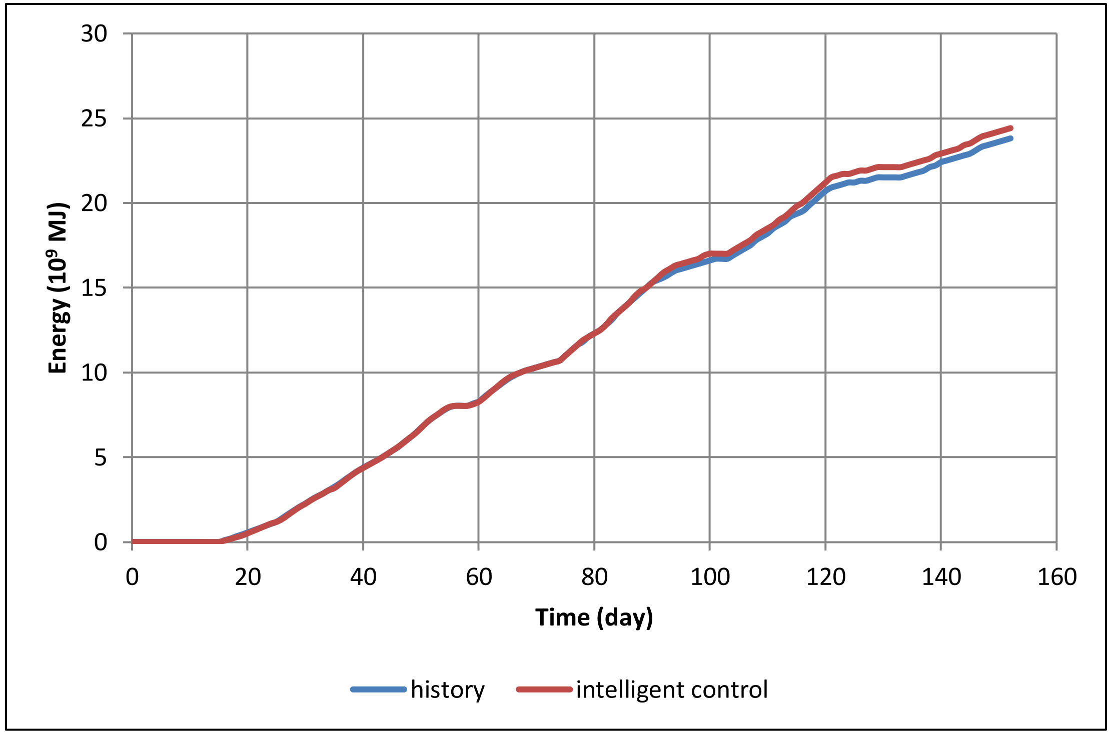


The value of how to **reduce the production rate** of wells with high nitrogen content and limit values **separating well groups** were **parameterized** in order to **optimize** the gas withdrawn process.

Optimization results

The proposed control determination algorithm returned process parameters to **0.0212, 0.0347 and 0.4902** for p1, p2, p3, respectively.



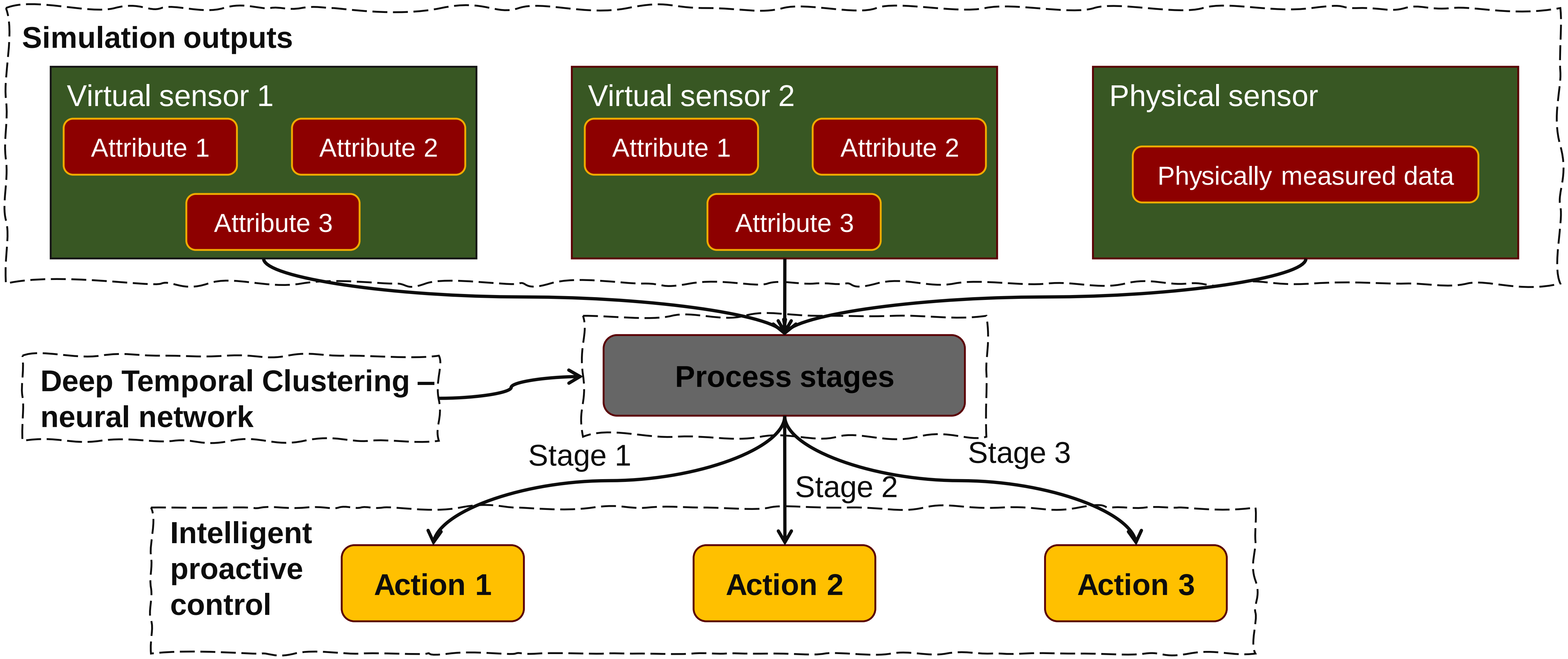


As a result **the energy efficiency of the storage increased by 2.4% (3,8 mln $)** without any extra investment. The developed method allowed a **rapid increase of the objective function** – only 80 iterations.

Proactive process control using virtual sensors

Proposed proactive solution

The idea is to analyze parameters measured by the **virtual sensors** and automatically determine **process control** based on the process stage.

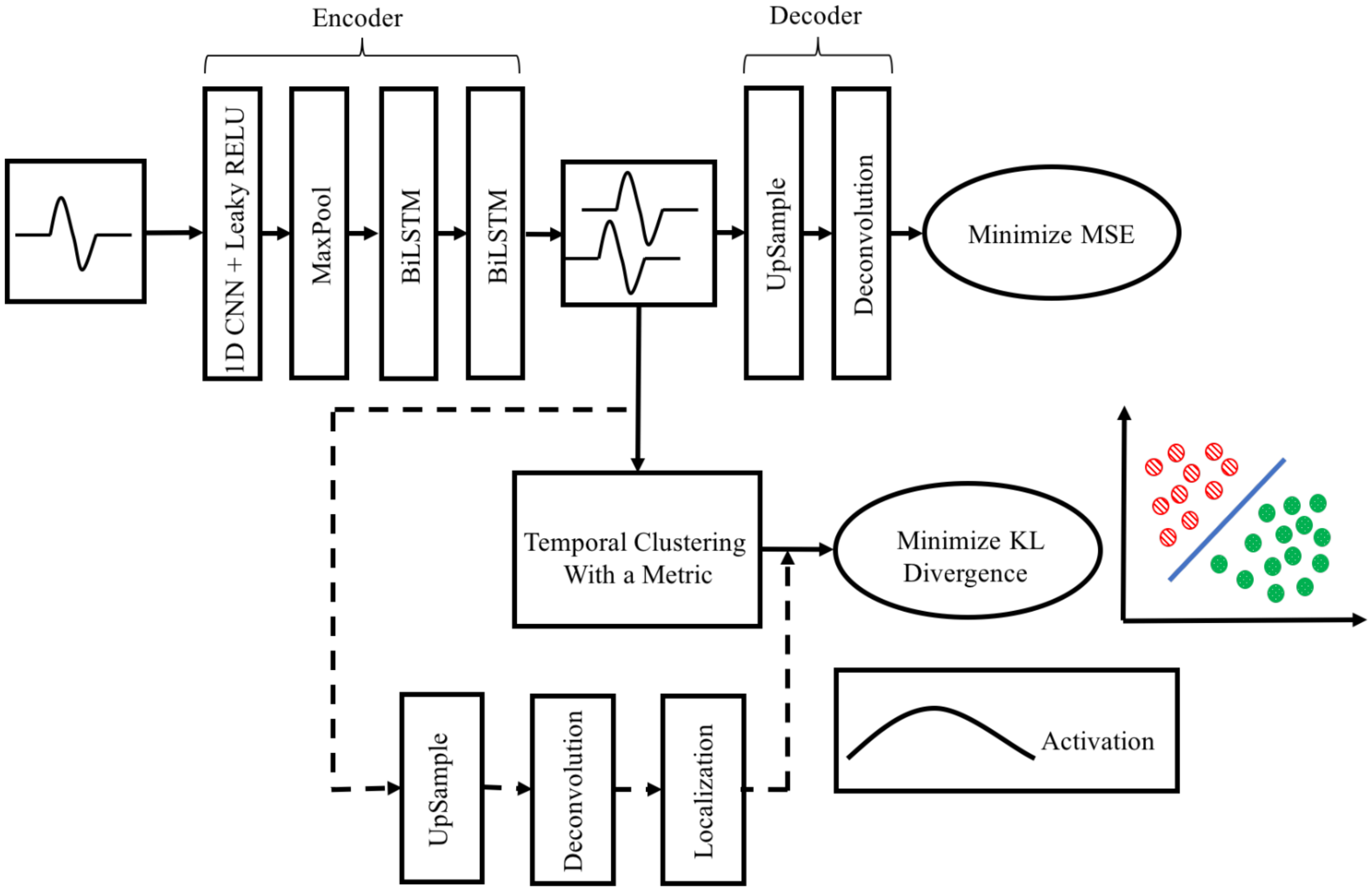


Deep Temporal Clustering (DTC)

The DTC algorithm uncover the **latent dimension** along which the temporal unlabeled data **split into classes**.

DTC utilizes an **autoencoder** for temporal dimensionality reduction and a **novel temporal clustering layer** for cluster assignment.

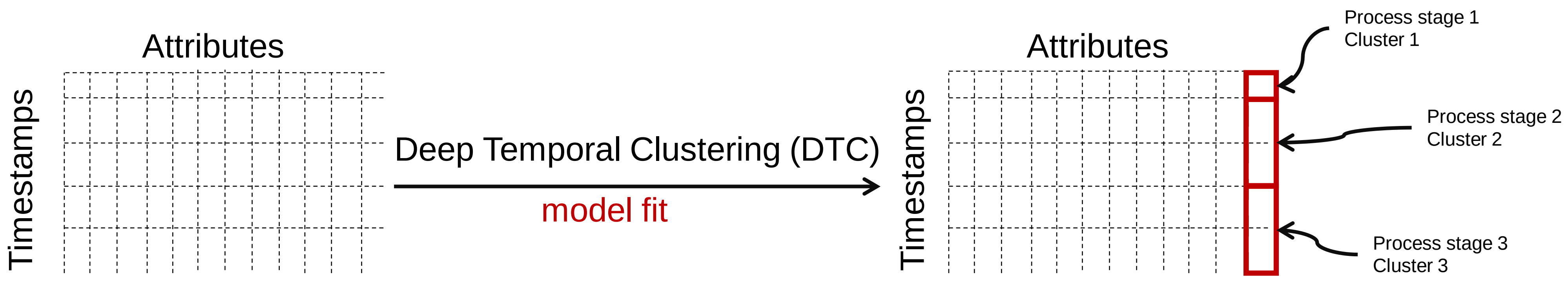
Then it **jointly optimizes** the clustering objective and the dimensionality reduction objective.



Artificial intelligence based proactive control algorithm – offline stage

The proposed algorithm is composed of two stages: **offline** learning process and **online** production stage assignment.

Offline stage

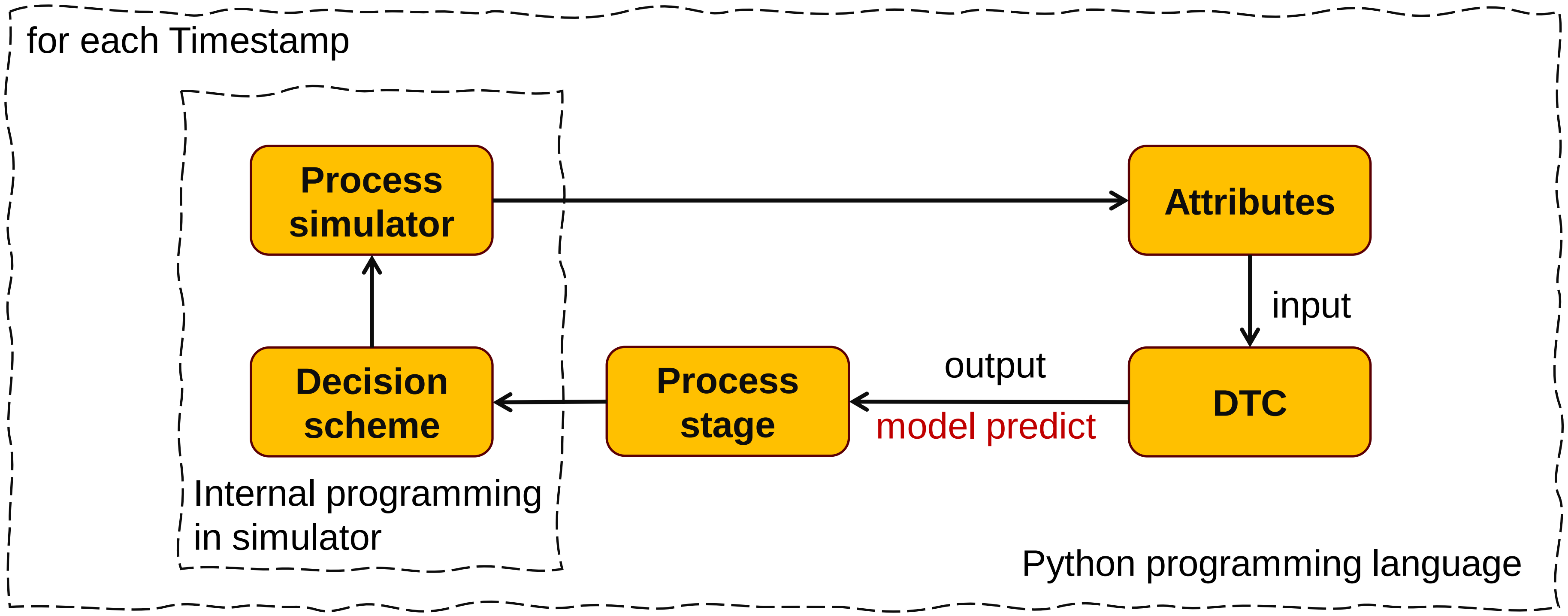


During the learning process (offline stage), the DTC algorithm **learns to detect the process stage** based on **historical values** of virtual sensors and physically measured attributes.

Artificial intelligence based proactive control algorithm – online stage

The proposed algorithm analyses process behavior and changes strategy **in each time step** to optimize the process.

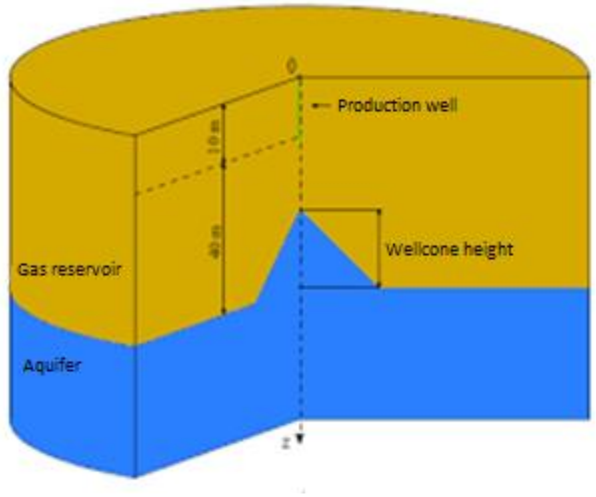
Online stage

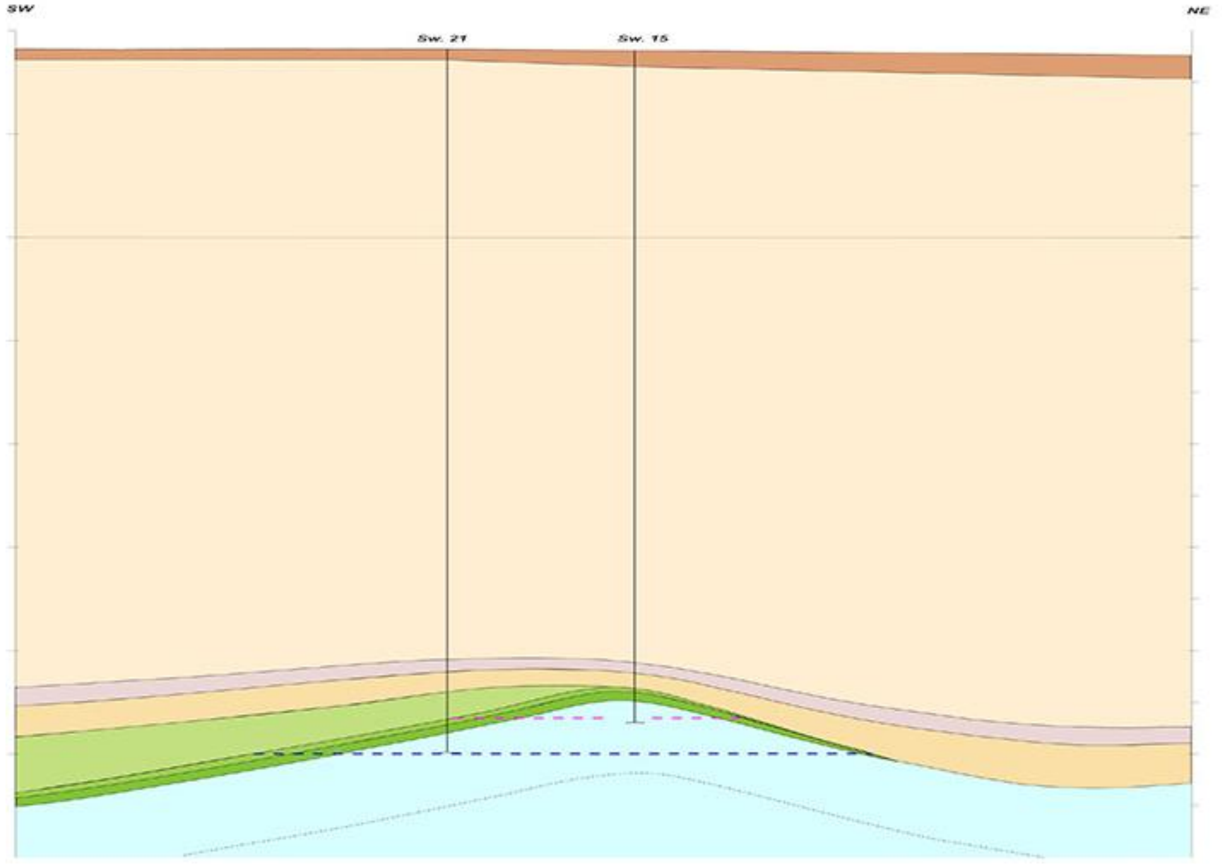


The **actions** programmed according to **virtual active sensors** measurements yield **automatic self-modifying strategy** of process control.

Exemplary application – Optimal control of Gas Wells Conning Water

Water coning refers to the **upward movement of water** in the vicinity of the production well. It can seriously **affect the productivity of the well**, significantly increase production costs and consequently reduce well's lifespan.





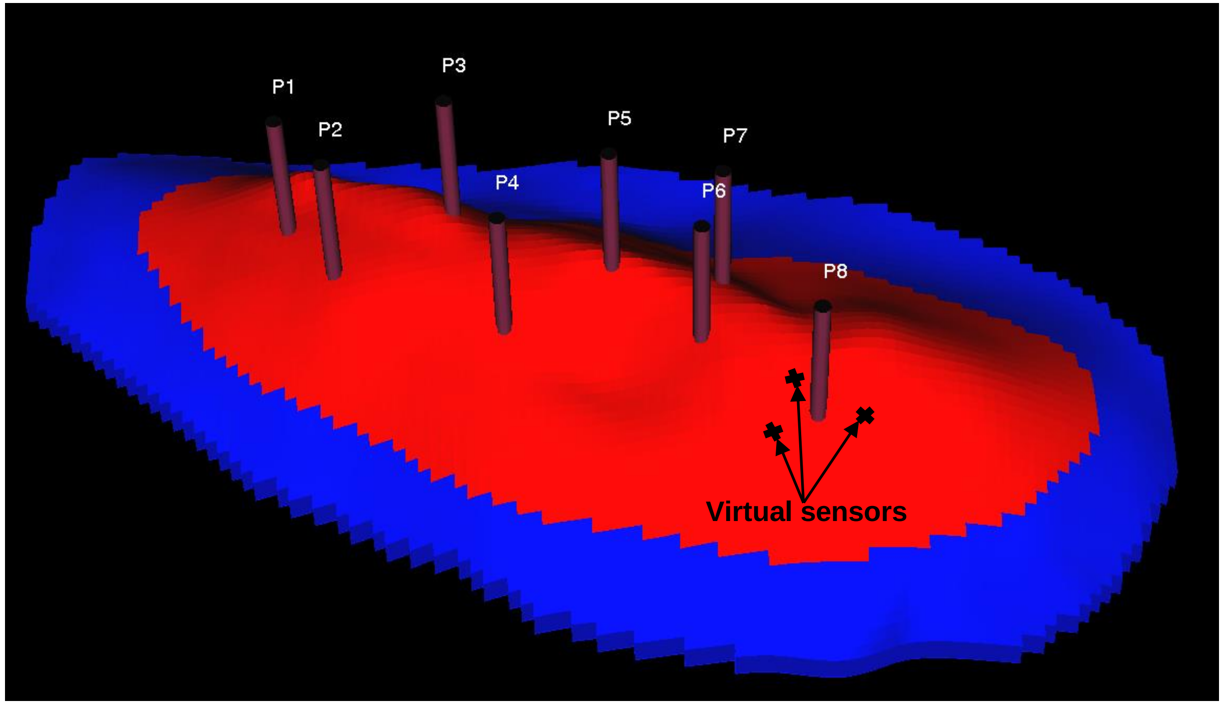
The purpose of the optimal control of gas wells conning water is to determine the **control policy** that will **minimize the total amount of water produced** as a co-product.

$$J(u) = \sum_{n=1}^{T} \sum_{k=1}^{N} q_{w_{kn}}$$

Minimizing water production from the reservoir

The **virtual active sensors,** used for intelligent proactive control, have been located in the vicinity of each production well.

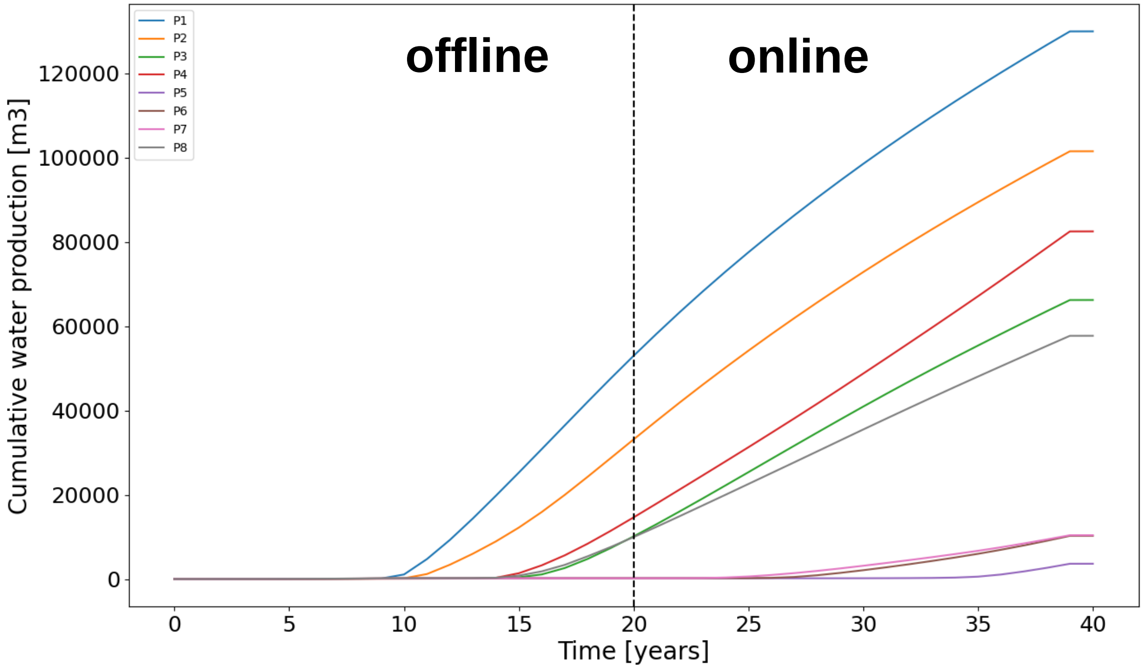
Parameters	Value
Number of wells	8
Number of virtual sensors per well	3
Virtual sensor attributes	Water saturation Pressure
Production well attributes	Gas flow rate Water flow rate

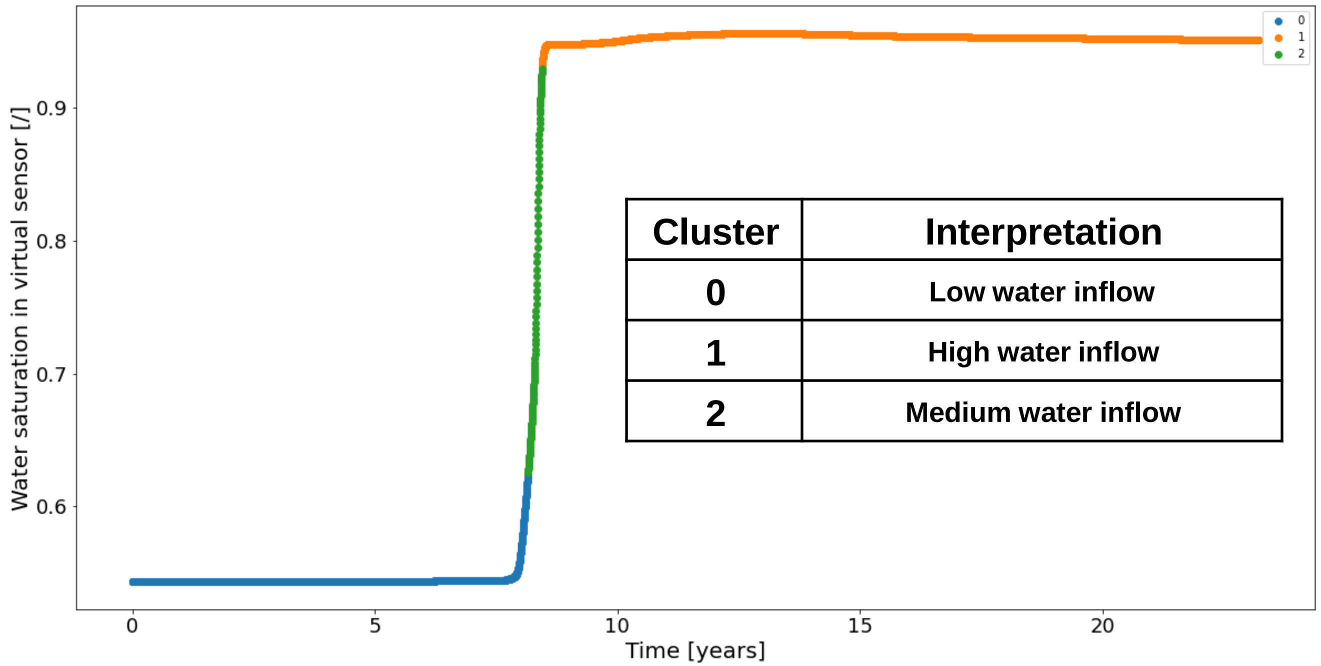


In order to illustrate the effectiveness of the proposed solution, it has been tested on a **historical production period**.

Results of the offline learning process

During the offline stage, the DTC model was trained based on the **multivariable historical data** (8 attributes) for **P1 well** as its reservoir situation is the most difficult considering water production.



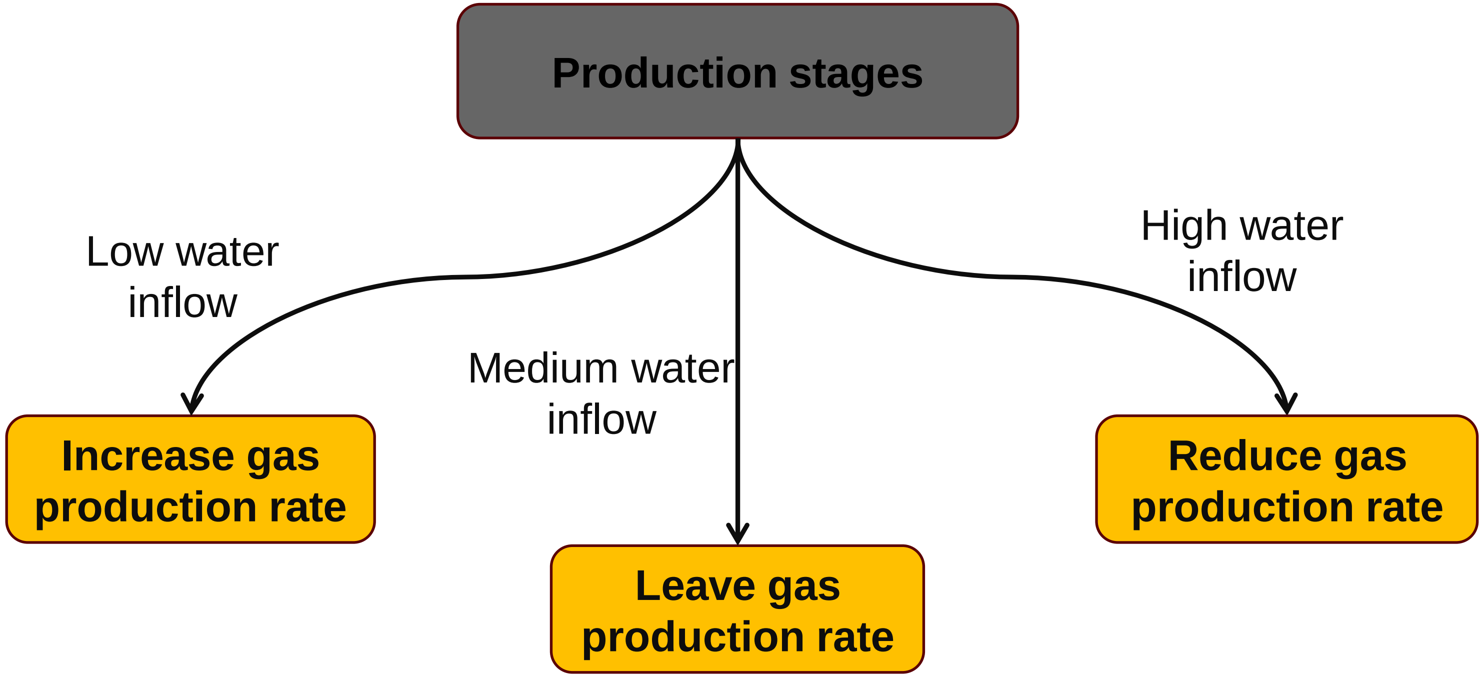


Cluster	Interpretation
0	Low water inflow
1	High water inflow
2	Medium water inflow

Detected clusters were interpreted based on the **expert knowledge** to allow an unambiguous physical interpretation of the proposed **intelligent control** of gas wells conning water.

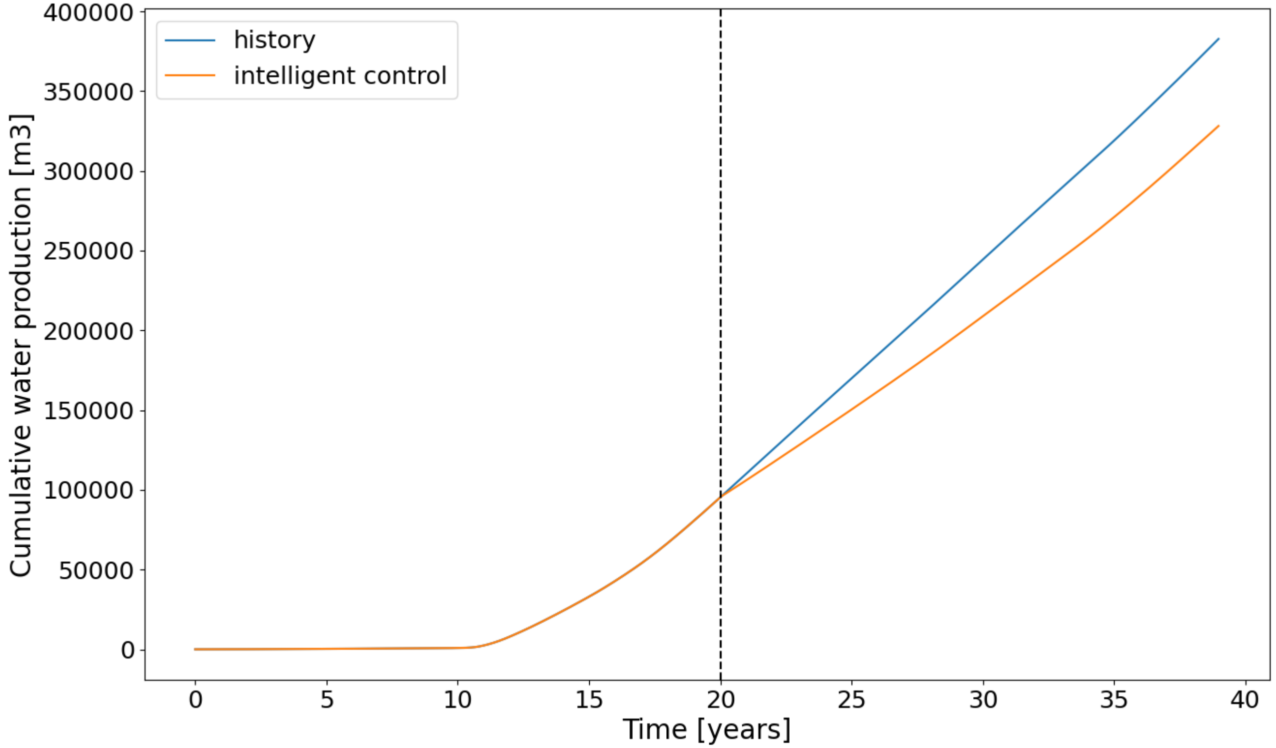
Developed decision scheme

During the online stage, **in each time step**, the production stage of each well is predicted by the trained DTC model. Well rates are automatically updated according to the developed decision scheme.



Modeling results - self-modifying strategy

Smart strategy **reduced the total water production by 15%** comparing with historical data based on the engineering experience. Moreover, intelligent control enabled to keep the cumulative gas production on the same level.

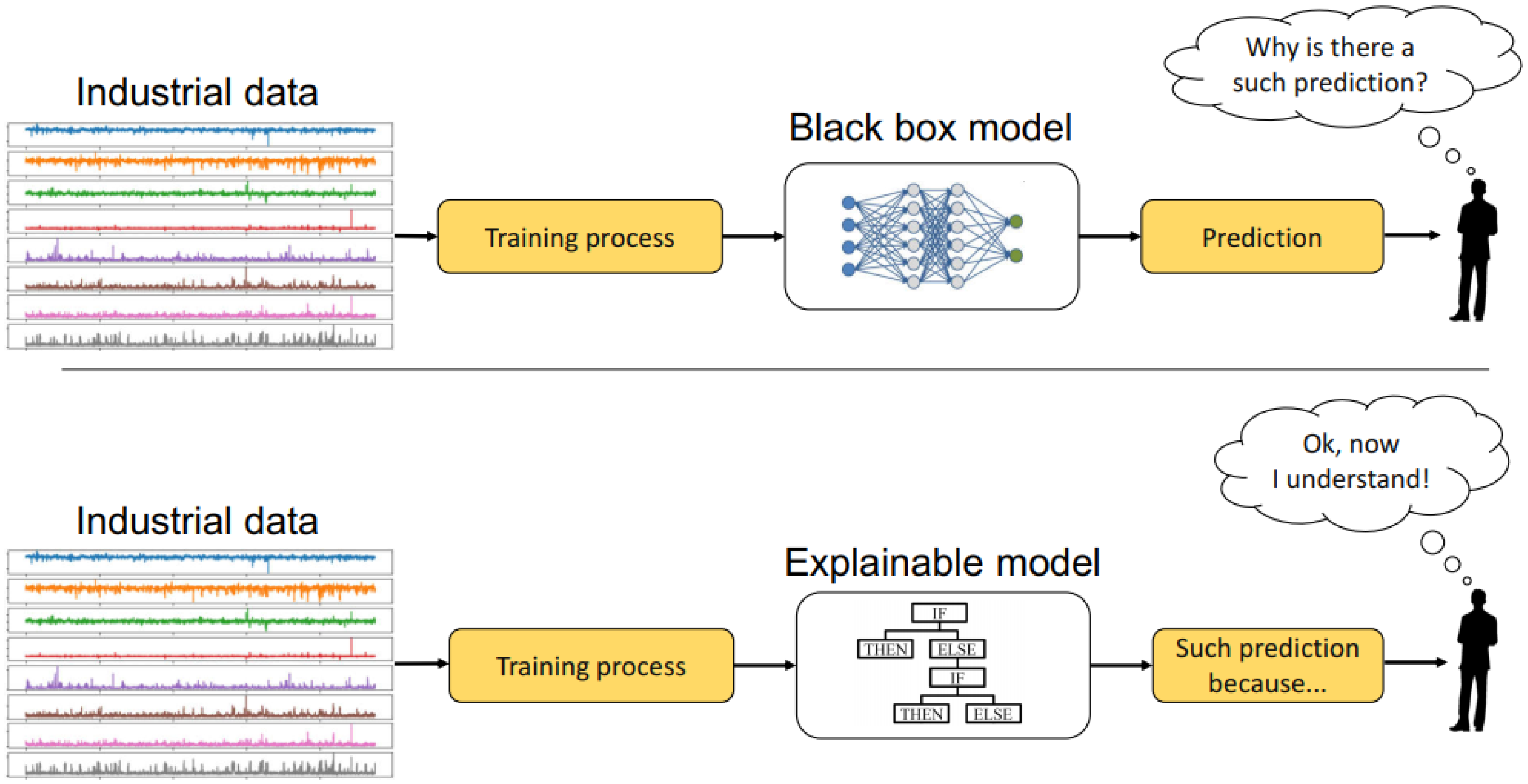


The proposed intelligent control strategy ensures accurate control of water conning phenomenon and helps to increase overall income **without any extra expenditure** as only control is changed.

Explainable proactive process control

Explainable Artificial Intelligence (XAI)

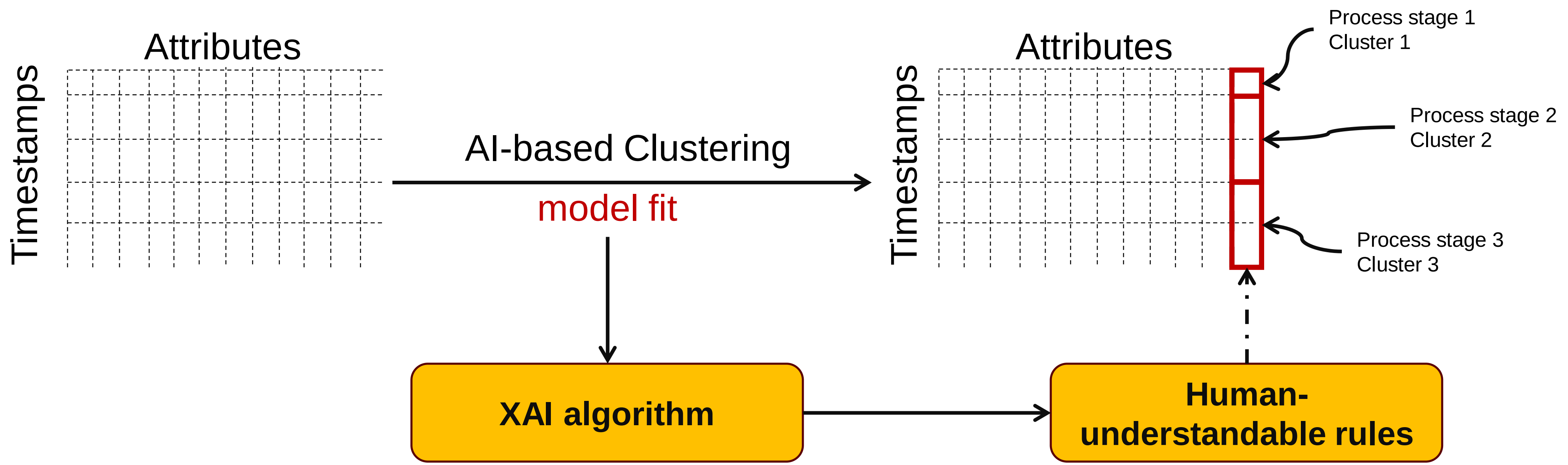
XAI techniques introduce **transparency and intelligibility** into the decision-making process of **AI-based systems**.



Decisions suggested by not interpretable, AI-based models replaced with **human-understandable rules**.

Explainable proactive process control algorithm – offline stage

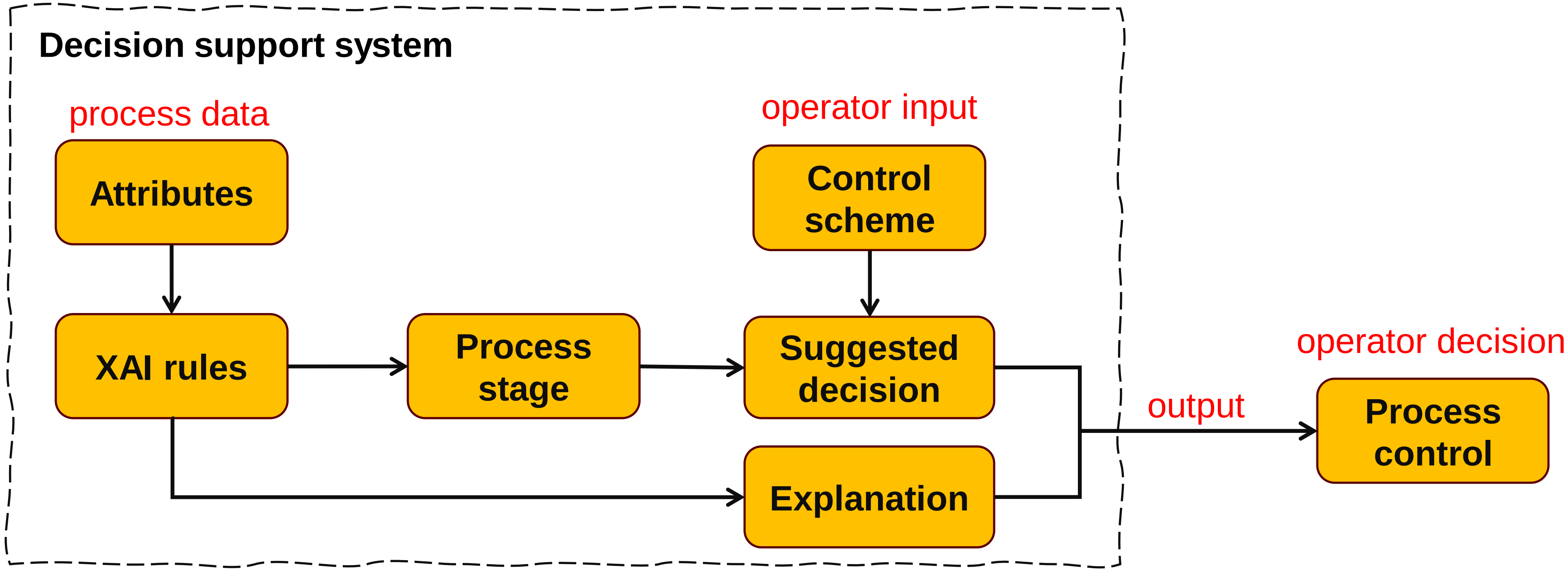
The proposed algorithm is composed of two stages: **offline** learning process and **online** decision support.



During the learning process, the AI-based clustering algorithm **learns to detect the process stage**. Then, XAI algorithm is used to translate results into human-understandable decision rules.

Explainable proactive process control algorithm – online stage

During the online stage, the proposed algorithm analyses process behavior and **automatically suggest changes of control strategy**. In each time step, the process stage is predicted based on trained (XAI) **decision rules**.



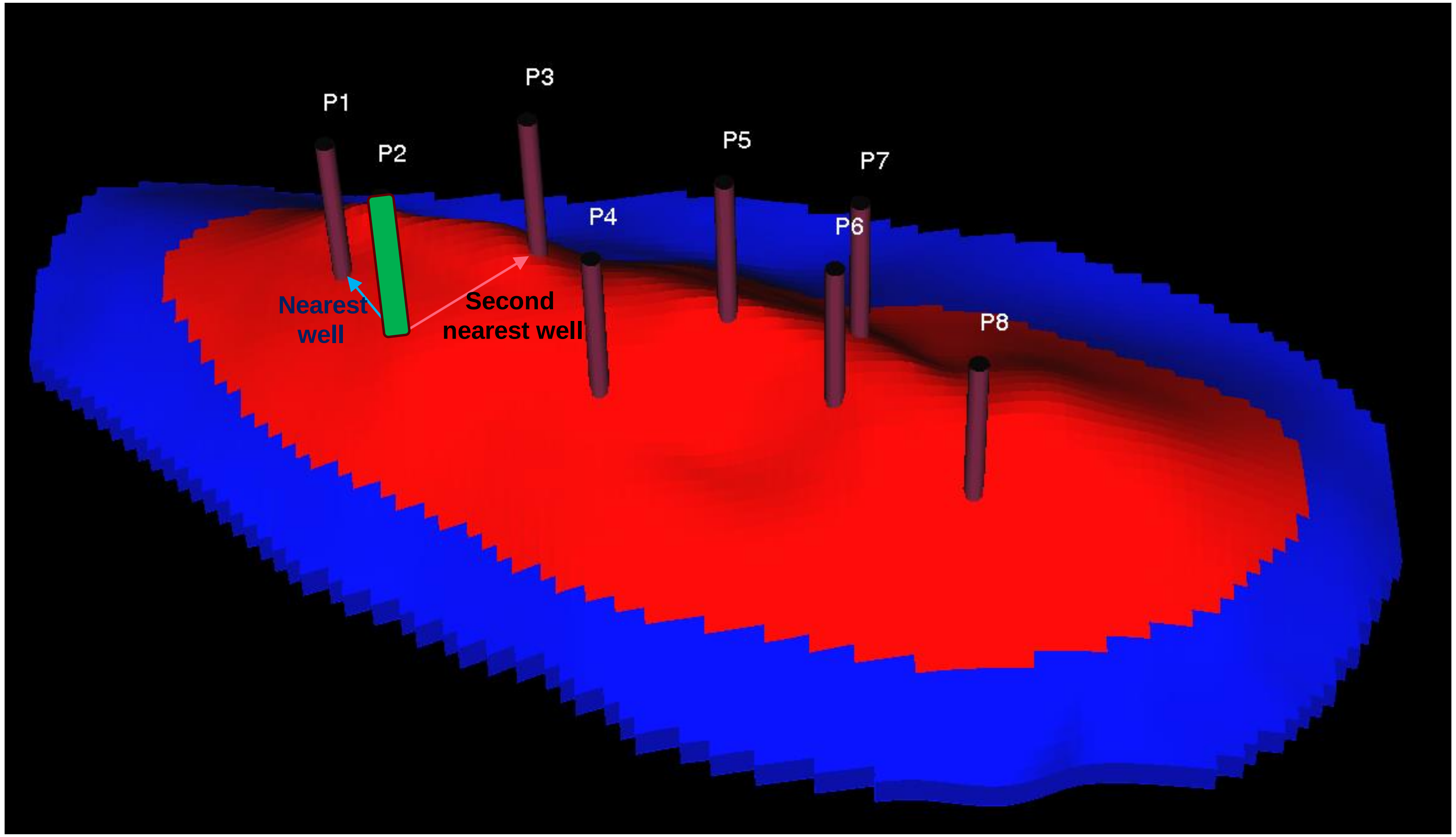
Provided decision support system can be used in **real-time management.**

Exemplary application

The **surrounding wells** for each production well were used for intelligent proactive control.

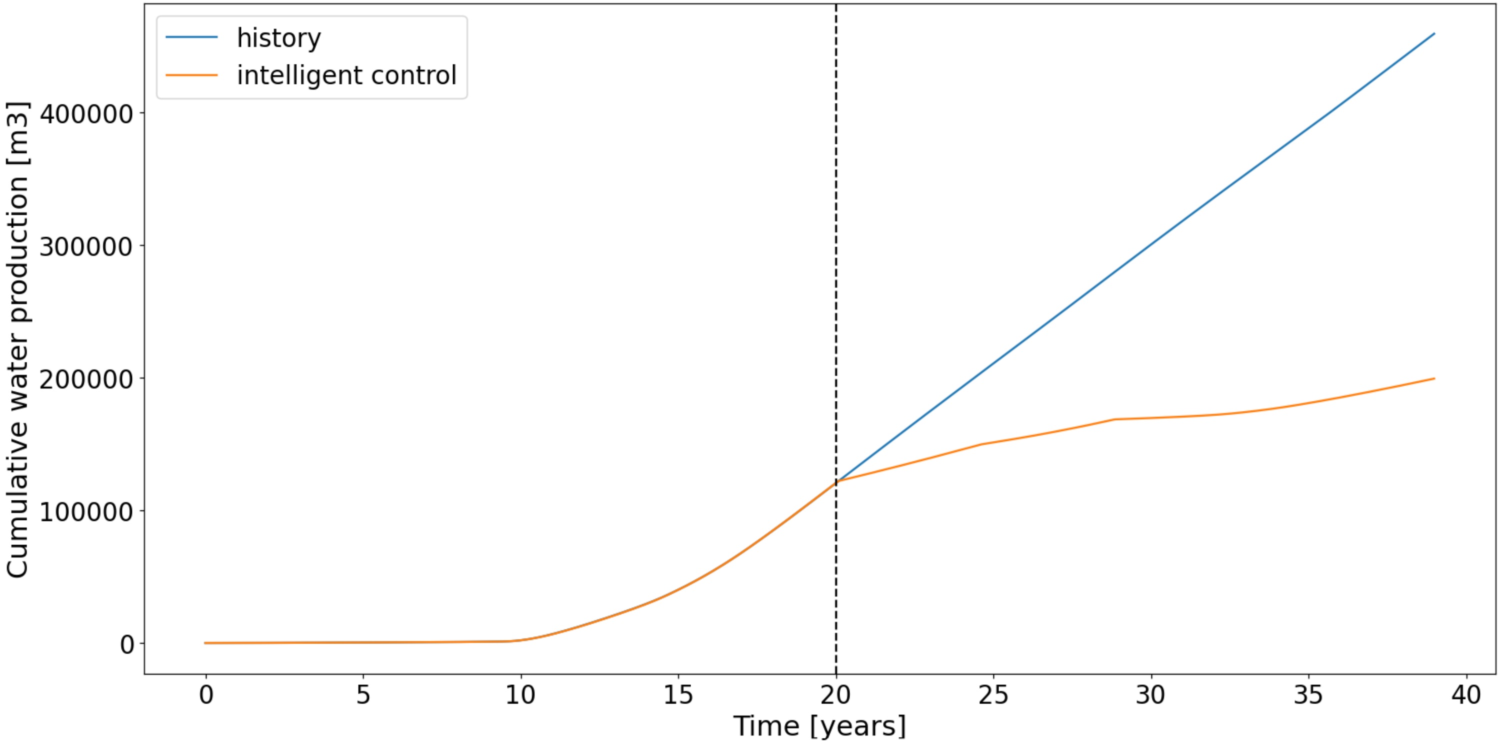
Proposed solution has been tested on a **historical production period**.

Parameters	Value
Number of wells	8
Number of nearest wells per well	2
Well attributes	Water flow rate Water cut Pressure



Modeling results – intelligent contol strategy

Developed decision support system allowed **the total water production to be reduced by 56%** comparing with historical data keeping the cumulative gas production on the same level.



The suggested intelligent control strategy ensures accurate control of water conning phenomenon and helps to increase overall income **without any extra expenditure** as only control is changed.

Conclusions

- The **decision support system** for explainable proactive process control has been proposed

- Developed solution is based on **machine learning methods** enriched with elements of control theory and simulation

- The created algorithm enables **full automation** of the optimal control determination

- Use of **expert knowledge** makes the whole process fully interpretable

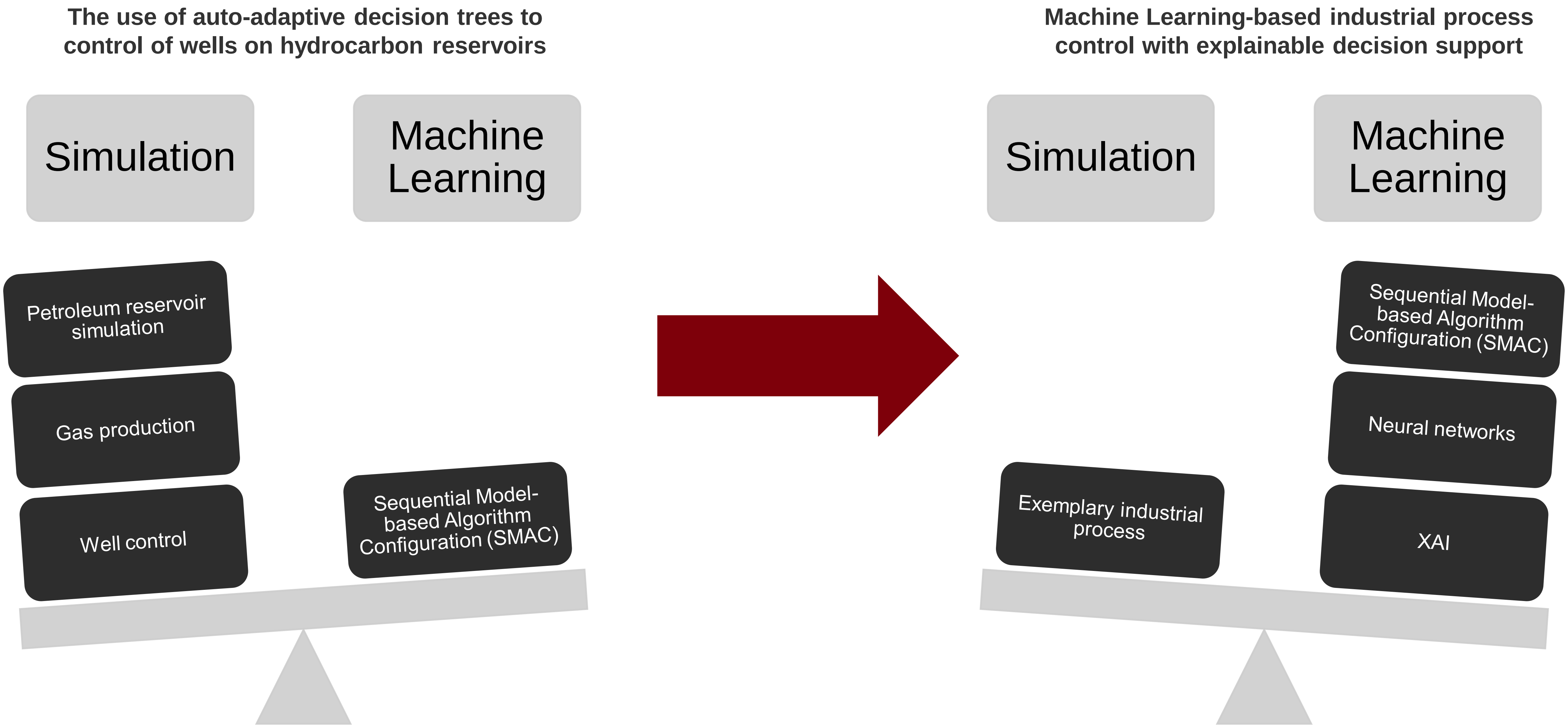
- Use of the Explainable Artificial Intelligence (XAI) techniques makes defined control **more reliable** for the operator

- The created decision support system can be used in **real-time management**

- The developed procedure **can be implemented** to other industrial processes

Plans

Concept generalization

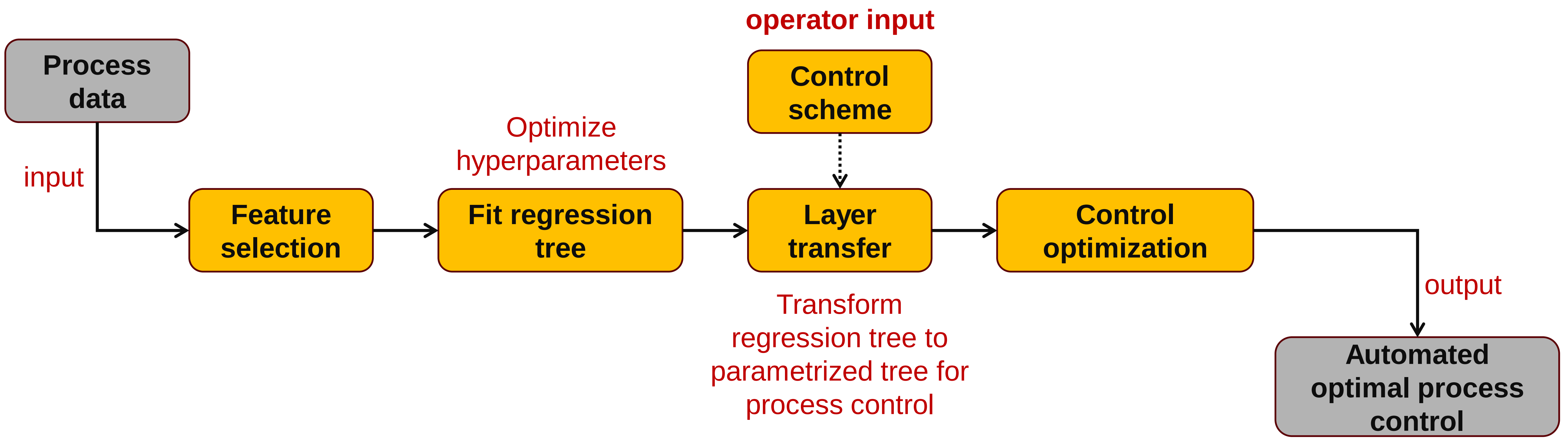


Automated generation of the decision tree for process control

Layer transfer concept

Layer transfer concept

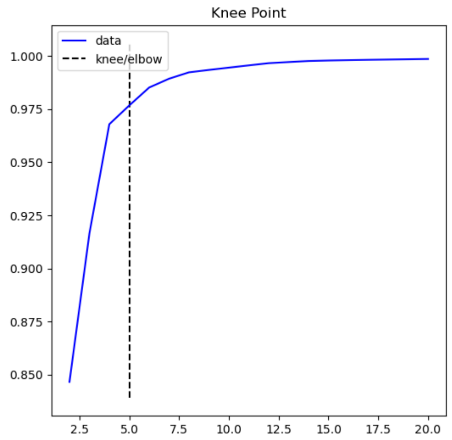
The proposed idea is to **replace the leaves** of the regression tree defining how the parameters affect the target **with control actions** to be taken. These actions are then parameterized and optimized to automatically generate a control scheme that defines optimal process control.

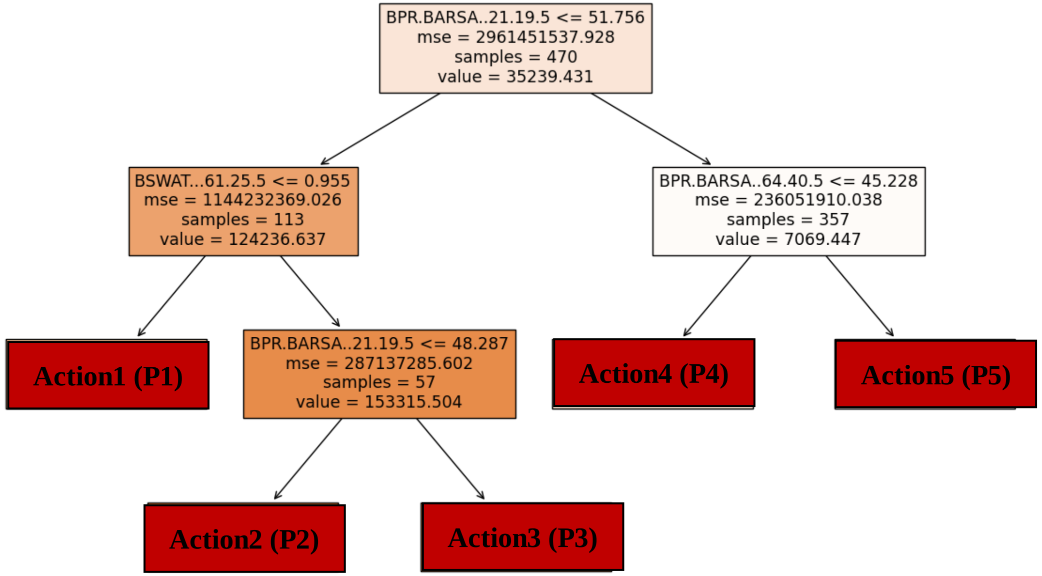


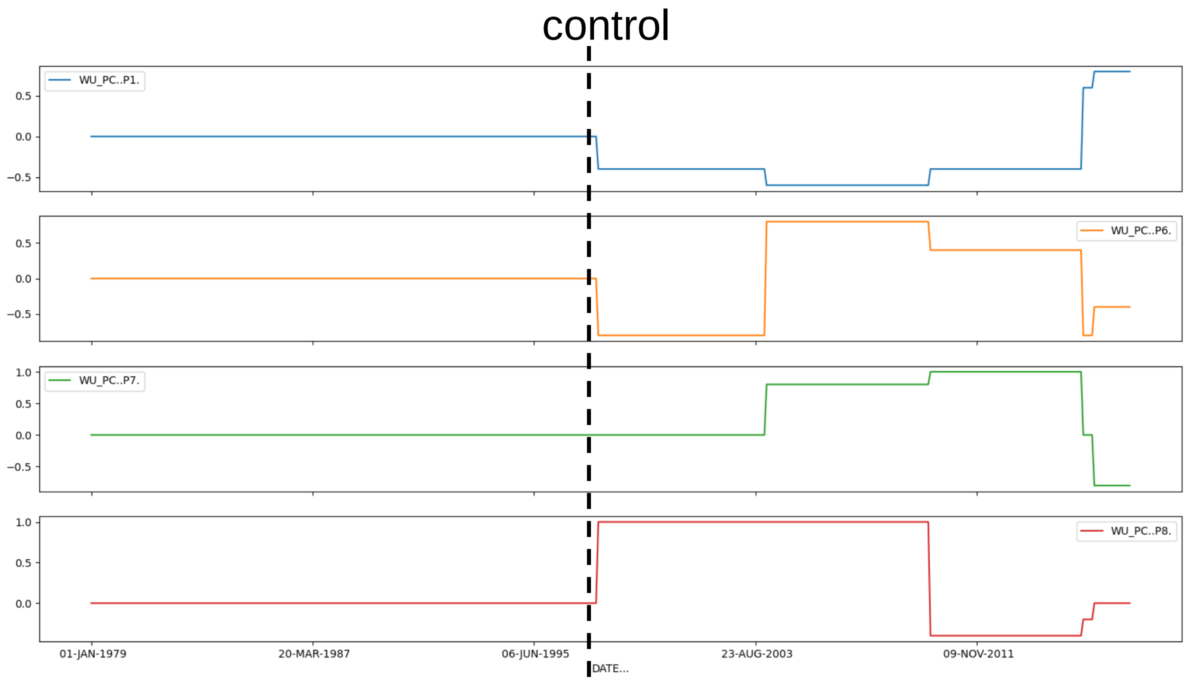
To make the control scheme understandable to the operator, the hyperparameters of the regression tree are chosen to strike a **balance between precision and complexity**.

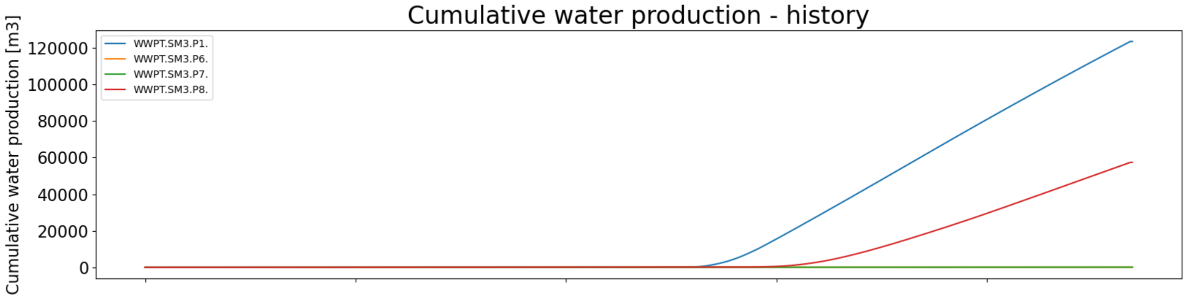
Exemplary application

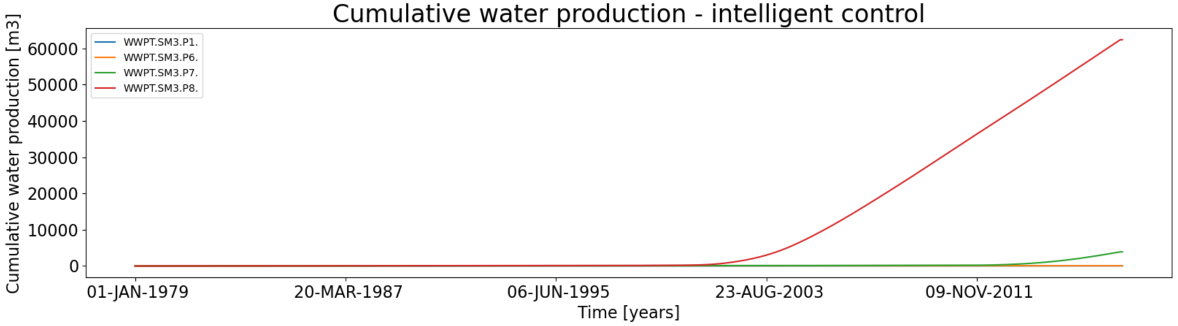
Easily understandable control scheme helped to improve the process control and reduce water production.











Questions?