FC. Machine learning technique for flooding control

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- ASTRA SMS (in-house development) Rotating equipment monitoring
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Process control and computer modeling

- DW (Digital Workover) and DLS (Digital Logistics Support) - in-house development for automated control of workover and logistics
- APC - Advanced Process Control
- Modeling the processes for the development of production facilities digital twins or simulators for process operators

Life cycle management of submersible equipment

- Remote monitoring centers for ESP submersible equipment
- Ecosystem of CycleOp products (in-house development)

CycleOp Ecosystem

1. Well operation model
2. Selection of main artificial lift methods of oil and gas production
3. Digital warranty certificate
4. Anomaly detector and failure prediction

Challenges in developing brownfields that FC can solve

01 Suboptimal efficiency factor per unit of injected water

02 Suboptimal efficiency factor per unit of produced fluid

03 Lack of prompt handling of vast amounts of unstructured data

04 Numerous time-consuming routine tasks

05 Unavailability of tools to set the operating conditions for injection well modes with due regards to interference

06 No uniform methodology to optimize injection with due regards to well interference and risks of water cut

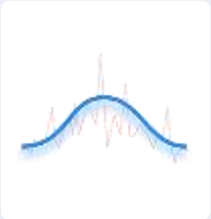
FC capabilities

- Then the latest 5-year history of daily well operation is analyzed
- The next step is the definition of well interference factors and formation of intervals that have the same fluid dynamics
- Each neural network for the dedicated interval has its own development and training
- Calculation of suitable injection modes under any restriction scenario
- The calculations assume the function of minimizing water cut and maximizing oil production
- Lower rates of unproductive injection, without loss of oil production
- Optimal redistribution of existing injection rates, with increased oil production

Algorithm flowchart

Source raw data

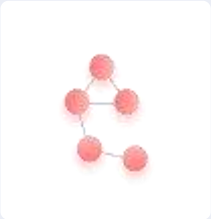
Data filtering and recovery



Computerized data

01

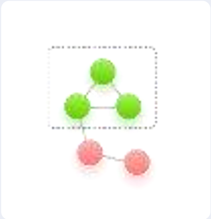
Searching hydrodynamic well-to-well interference coefficients



Graph of well interference

02

Identifying groups of wells that have the maximum interference, scaling down the task



Well clusters

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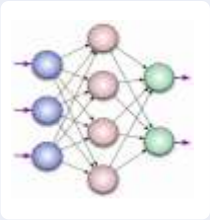
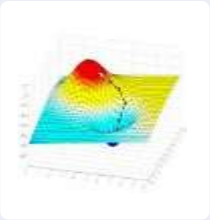
Building neural network-based proxy models of each well cluster to predict well production rate



Trained neural network

04

Solving inverse optimization problem



Best possible well operation modes

05

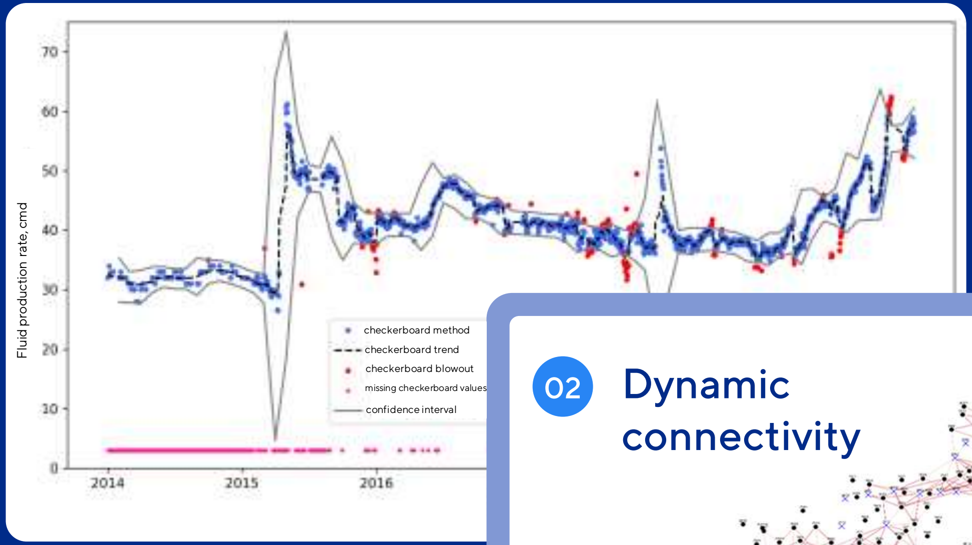
Best possible operation modes for injection wells

06

Implementation schedule

07

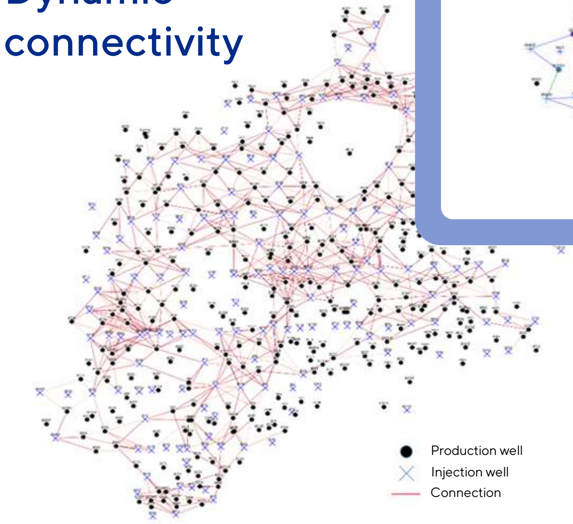
Computational kernel architecture



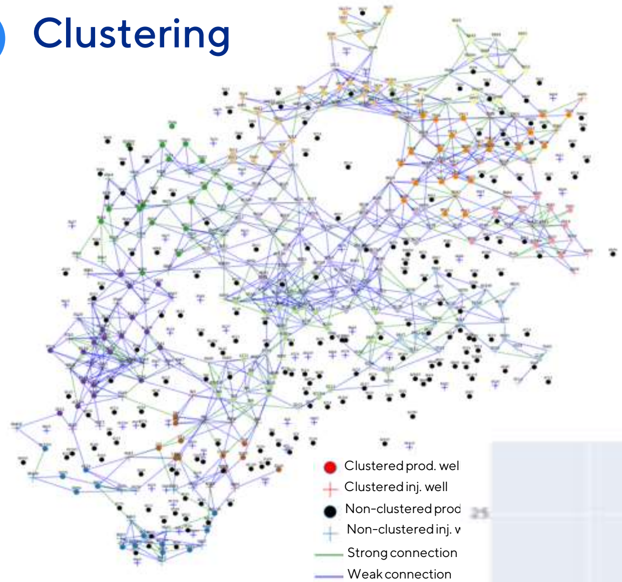
01

Data filtering and recovery

02 Dynamic connectivity



03 Clustering



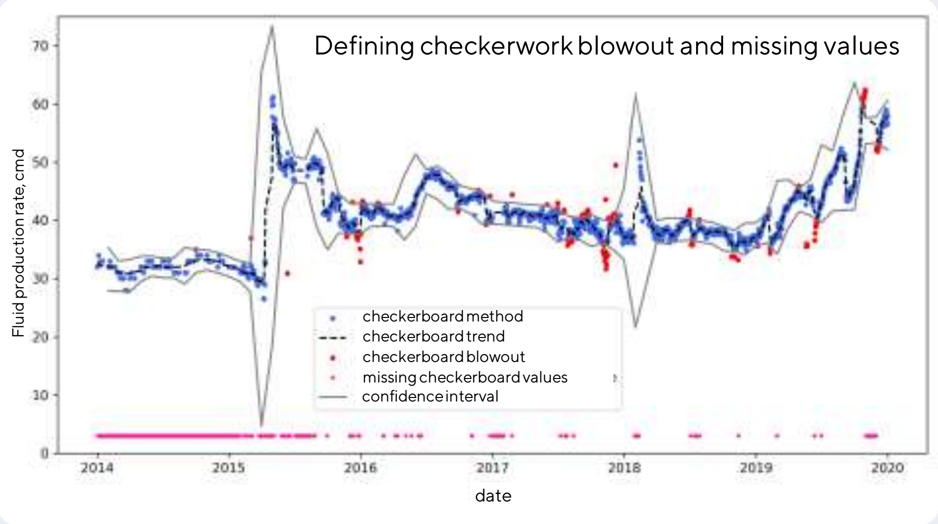
04 Training and adaptation of proxy models

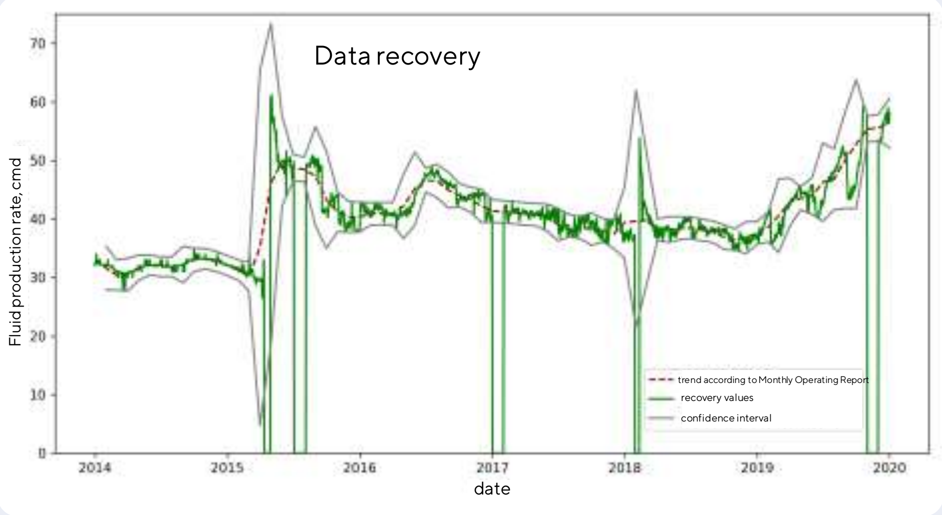
Data filtering and recovery

Obtained on the basis of monthly and daily data, the continuous dataset of fluid and oil production rates, as well as injectivity for the given period (of at least 5 years) is as follows:

- Monthly data, i.e. process flow pattern, is used to build the trend and the confidence interval
- Daily data, i.e. using the checkerboard method, is used to obtain the final dataset, which, if unavailable or excluded, gets replaced by the trend
- The confidence interval depends on how much the approved operating modes vary

Case study of data recovery for fluid production rate





Dynamic interference coefficients between wells

Definition of dynamic interference coefficients between wells

$$\dot{\boldsymbol{q}}_i(t) = \sum_{k=1}^{n} a_{ik}\boldsymbol{q}_{\boldsymbol{k}}(t - t_{ik\ lag1}) + \sum_{j=1}^{m} b_{ij}\boldsymbol{i}_{\boldsymbol{j}}(t - t_{ij\ lag2}),$$

$\boldsymbol{q}_i\ (t)$ — Production rate of producing well No. i at time t

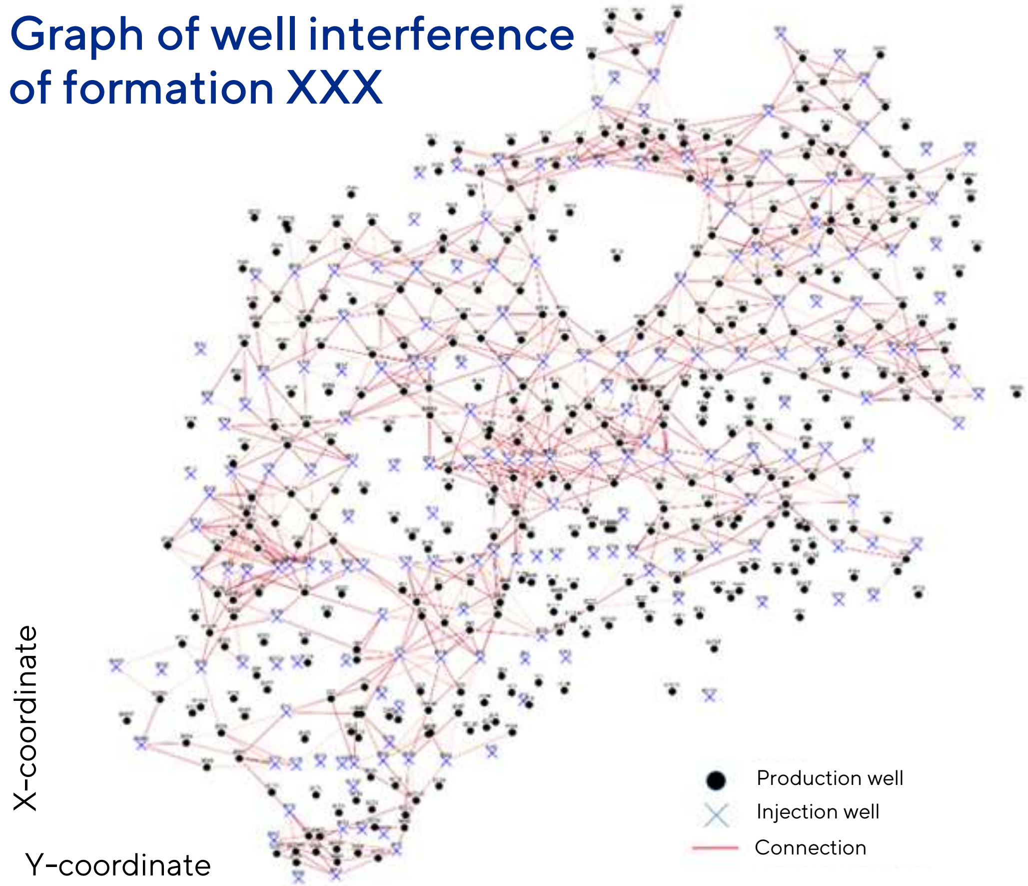
$\boldsymbol{q}_k\ (t)$ — Production rate k

$\boldsymbol{i}_j\ (t)$ — Injectivity j

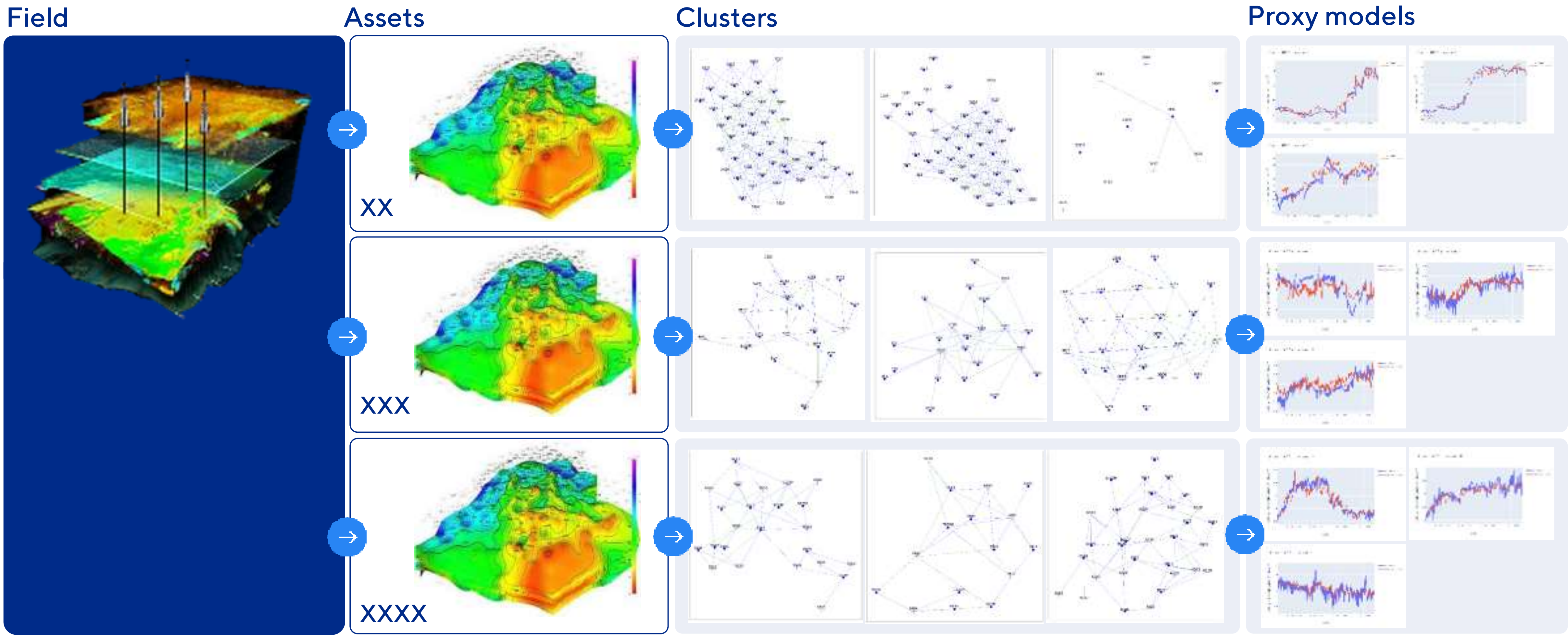
$\boldsymbol{t}_{ik\ lag}$ $\boldsymbol{t}_{ij\ lag}$ — Time of delay in well-to-well connection defined according to field data dynamics

This allowed for the well connectivity matrix, which can be interpreted as a weighted connectivity graph, where wells are the peaks and interference coefficients are the edges

Graph of well interference of formation XXX



Downsizing strategy for development of proxy models

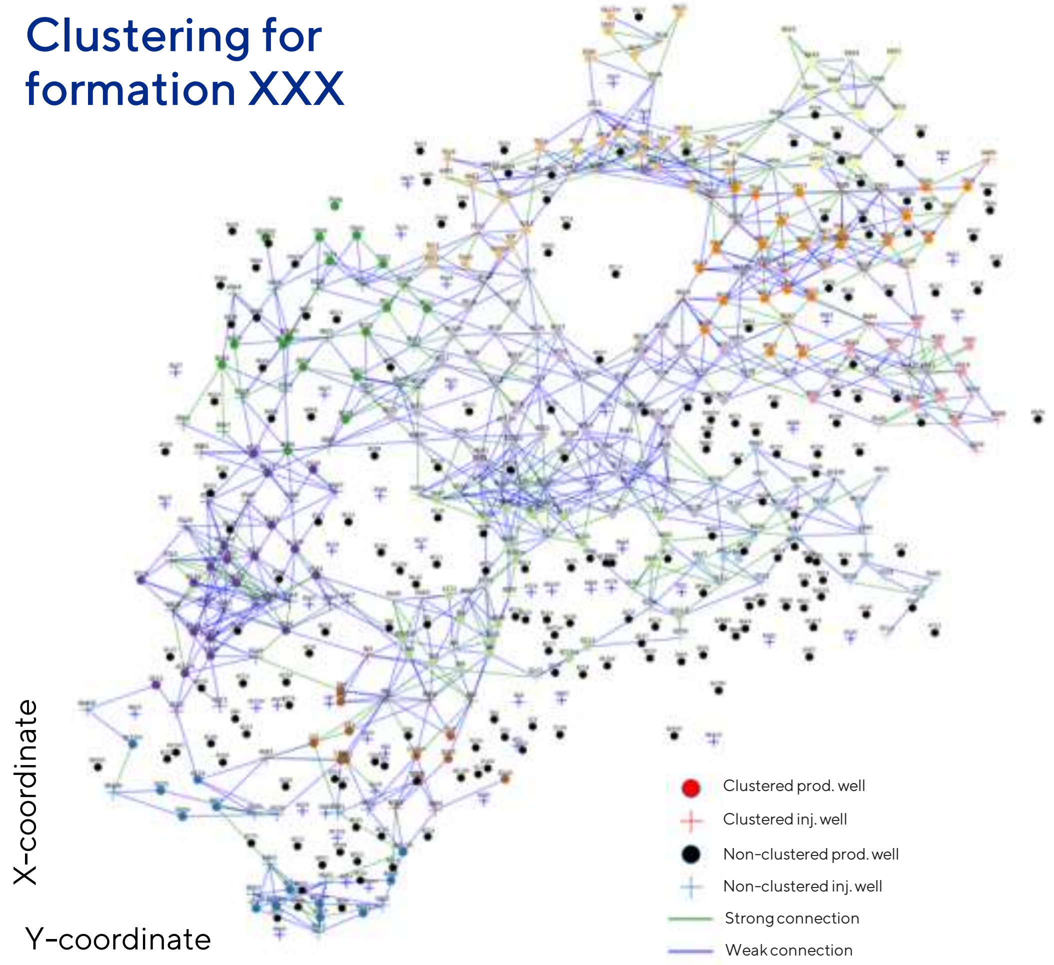


Clustering of target assets

Interference coefficient matrix

- Given that the matrix of interference coefficients is a weighted connected graph, it is possible to treat the task of clustering as the task of splitting the graph into interference components, which are actually clusters
- For this purpose, spectral clustering was used. Such technique partitions interference components of the connected graph by finding minimum cut sets of the graph, i.e. wells that have maximum interference or hydro-dynamic connection become part of the cluster
- The cluster edges follow the boundaries of geological and physical variability of reservoir rocks

Clustering for formation XXX



Proxy modeling module. Proxy model variability

Input parameters of proxy model → **Output parameters of proxy model**

Injectivity of wells → Target function developed

The module of proxy modeling uses neural networks to facilitate the generation of various loss functions for their subsequent optimization, such as:

- Fluid production rate by cluster
- Oil production rate by cluster
- Non-linear combination of oil production rate and water cut is such that its maximization implies increasing oil production rate while decreasing water cut (minimax optimization)

Learning strategy

1. Training of the neural network for each cluster is based on continuous recovery data that is obtained daily.
2. The original sample is divided into training and test samples according to the Pareto principle (80/20 Rule).

Example of neural network training for Cluster 1 of Asset XXX in terms of oil production rate and water cut

Solving optimization problem

Search for solution

The optimization problem of maximizing fluid production rates based on injectivity modes of injection wells is stated as follows:

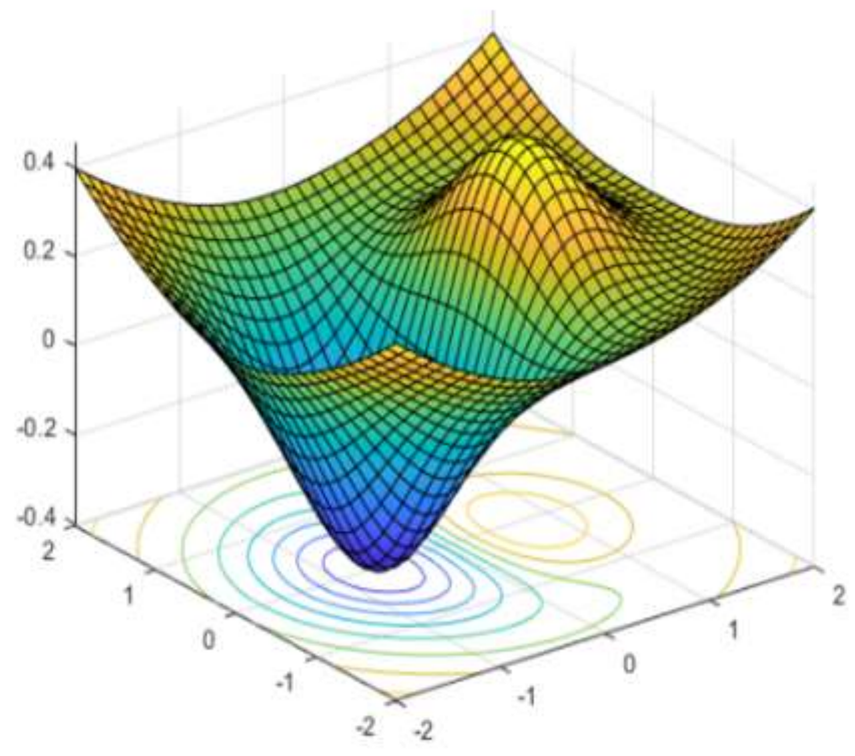
$$\boldsymbol{q}(\boldsymbol{i}(t)) \rightarrow max$$
$$c_j(x) = 0, j \in E$$
$$c_j(x) \geqslant 0, j \in I$$
$$lb_i \leq x_i \leq ub_i, i = 1, \dots, N$$

$\boldsymbol{q}(t)$ — Production well flow by cluster

$\boldsymbol{i}(t) = (\boldsymbol{i}_1(t), \dots, \boldsymbol{i}_N(t))$ — m-dimensional flow vector of injection wells

E and I — Sets of indices of equations that describe restrictions as equalities or inequalities

$[lb_i, ub_i]$ — Sets of lower and upper limits for the domain of the function



Solving optimization problem. Generating constraints model

Restrictions for the domain of the function

$[0, I_{maxi}]$

I_{maxi} — Injection well restrictions based on maximum injectivity in history

Constraints for target function (group constraints)

$\Sigma_i^m I_i \leq I_{gr\_max}$

I_{gr_max} — Maximum allowable injection by cluster

$$\begin{cases} \sum_i^m I_i \geqslant I_{min\_gr} & \text{Where } I_{min\_gr} = \sum_i^m I_i, \text{ if } K_{total} \leq 1 \\ \sum_i^m I_i \geqslant I_{min\_gr} & \text{Where } I_{min\_gr} = 1/K_{total} \sum_i^m I_i, \text{ if } K_{total} > 1 \end{cases}$$

$K_{total} = \Sigma_i^N Q_{total\_i} / \Sigma_i^m I_{total\_i}$ — Cumulative compensation factor by cluster

I_{gr_min} — Maximum allowable injection by cluster

Model proxy optimization strategy

Optimization scenarios for different models of injectivity restrictions

- **Scenario I**
  Conservative optimization if the confidence interval of allowable values [$\varepsilon\_l;\varepsilon\_h$] for injectivity rates falls within the range [0.85;1.15], which is +/-15% of the existing operating mode

- **Scenario II**
  Optimization based on maximum injectivity in history and cluster group restrictions.
  In other words, the upper limit for injection wells is the maximum injection in history

- **Scenario III**
  Optimization based on existing group injectivity.
  In other words, the upper limit for a group of injection wells is the existing injection. Consequently, there will be only redistribution of injection between various wells, without any increase

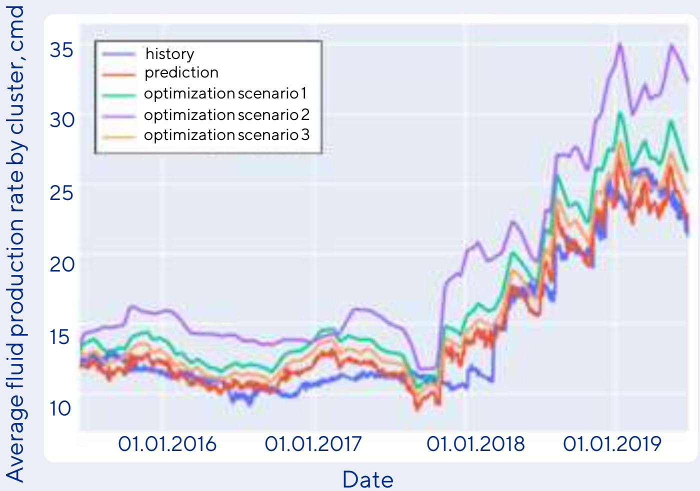
- It is possible to assume any change in injection rate.

✓ The optimization of the proxy model of oil production rate versus well injectivity aimed to maximize oil production rate by cluster and minimize water cut

✓ The result of the optimization is the recommended injectivity rate for each time interval, which maximizes oil production rate by cluster

✓ The effect from optimization was tested using hydrodynamic models as of the date of the latest adaptation.

Example of proxy model optimization for Cluster 1 of Asset XXXX



Solving optimization problem

The outcomes of predictive optimization models were compared to the base case predictive model

Forecast period: 1 year in geological and hydrodynamic model

Example of computing optimal modes for Cluster 1 of Asset XXXX

Injection wells	Existing injectivity, cmd	Recommended mode		
		Scenario 1	Scenario 2	Scenario 3
0001	89.68	98.37	92.69	107.36
0002	31.16	28.14	18.93	18.76
0003	29.29	32.44	29.61	38.99
0004	0.00	0.00	0.00	0.00
0005	119.34	131.93	85.63	107.05
0006	175.58	192.69	172.59	152.85
0007	34.22	37.37	34.58	41.95
0008	103.27	92.60	117.47	92.20
0009	186.72	208.15	176.72	138.21
0010	209.24	230.09	169.54	246.47
0011	54.25	60.03	56.03	70.33
0012	142.81	157.24	121.62	161.49
0013	196.55	215.33	186.47	112.00
0014	20.81	21.40	24.78	15.44
0015	10.17	11.38	37.73	46.10
0016	57.27	51.40	62.95	64.99
0017	14.35	15.82	19.75	15.83
0018	15.42	16.97	32.10	48.54
0019	34.61	32.64	20.93	33.44
Total by cluster	1,524.75	1,633.99	1,460.12	1,511.99

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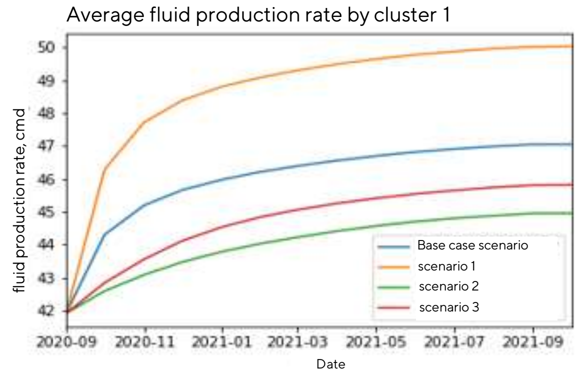
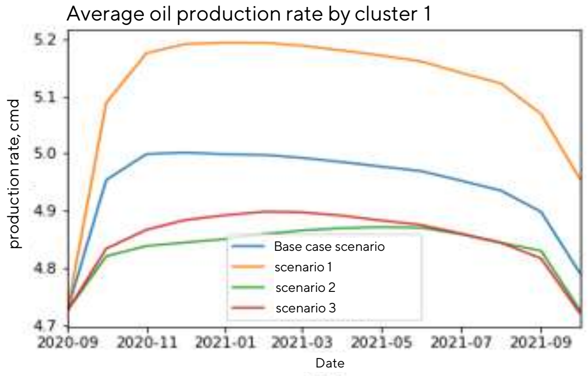
Example of proxy model optimization for Cluster 1 of Asset XXXX.

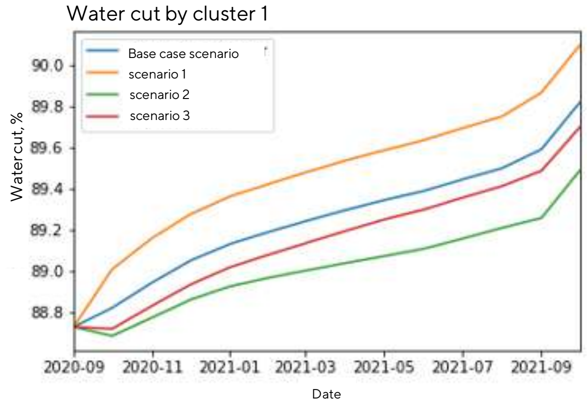
Predictive model outcomes for the cluster for one year	Base case scenario	Scenario 1		Scenario 2		Scenario 3	
		value	gain	value	gain	value	gain
Cumulative fluid production (tc^{m})	637.82	675.48	+5.9%	609.63	-4.4%	619.6	-2.9%
Cumulative oil production (tc^{m})	68.55	71.01	+3.6%	66.95	-2.3%	67.2	-2%
Cumulative injectivity (tc^{m})	602.27	645.43	+7.2%	576.75	-4.2%	597.24	-0.8%
Last-step water cut (%)	89.82	90.09		89.49		89.7	
Cumulative production water cut (%)	89.25	89.49	+0.3%	89.02	-0.3%	88.15	-0.1%

Example of optimization of proxy model for Cluster 2 of Asset XXXX

Predictive model outcomes for the cluster for one year	Base case scenario	Scenario 1		Scenario 2		Scenario 3	
		value	gain	value	gain	value	gain
Cumulative fluid production (tc^{m})	156.3	157.59	+0.8%	164.25	+5.1%	147.59	-5.6%
Cumulative oil production (tc^{m})	16.5	16.46	-0.2%	17.02	+3.2%	16.44	-0.4%
Cumulative injectivity (tc^{m})	369.07	374.75	+1.5%	386.71	+4.8%	369.07	0.0%
Last-step water cut (%)	90.05	90.19		90.2		89.42	
Cumulative production water cut (%)	89.31	89.62	+0.00%	89.7	+0.00%	88.91	-0.00%







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Results of testing algorithms for pilot areas within Western Siberia

Data

The Owner selected one of the XXXX field clusters in Western Siberia as the pilot area.

The activities did not include any well intervention for oil production well stock.

Solution

The taken steps required reasonable expenses: installation and replacement of the nozzle, bottomhole treatment using impellers.

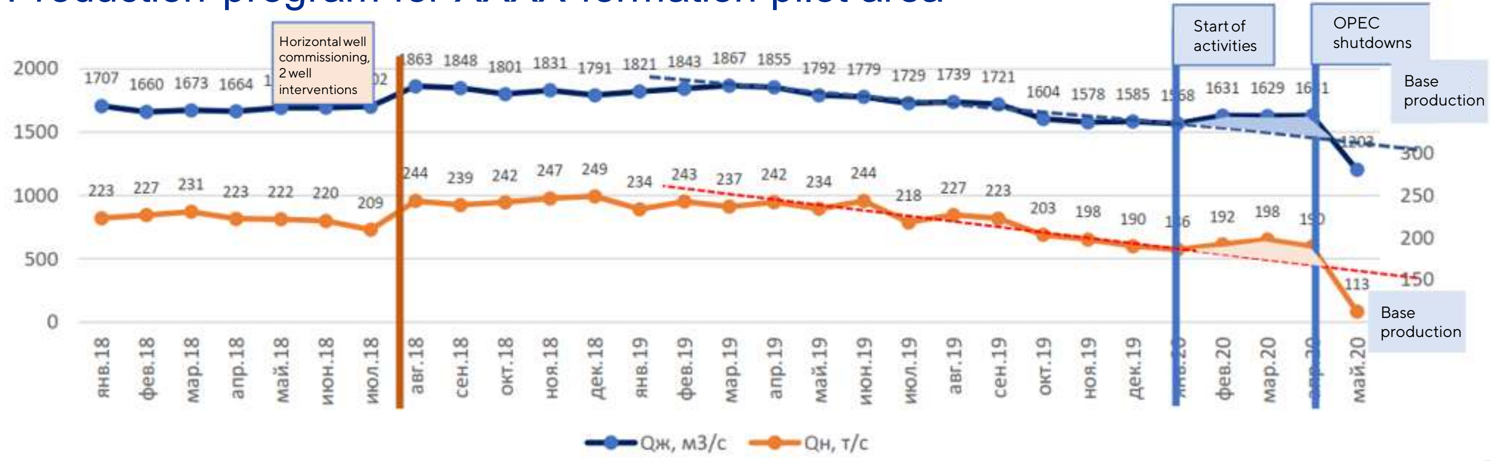
Several wells reached the design conditions after redistributing injection and replacing detectors.

Result

Oil production has been increasing since February, with extra production volume of 1,275 tons by April.
It is estimated that approximately 700–800 tons are conditioned by using physical and chemical methods of enhanced oil recovery (3 cases in October, 1 case in December and 1 case in January)

The effect of neural network optimization is 475–575 tons of oil for 3 months, which is about 30 mln RUB.

Production program for XXXX formation pilot area



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Results of testing algorithms for pilot areas within Western Siberia

Data

The Owner selected two of the XXX field clusters in Western Siberia as the pilot area.

The activities did not include any well intervention for oil production well stock.

Solution

The taken steps required reasonable expenses: installation and replacement of the nozzle, bottomhole treatment using impellers.

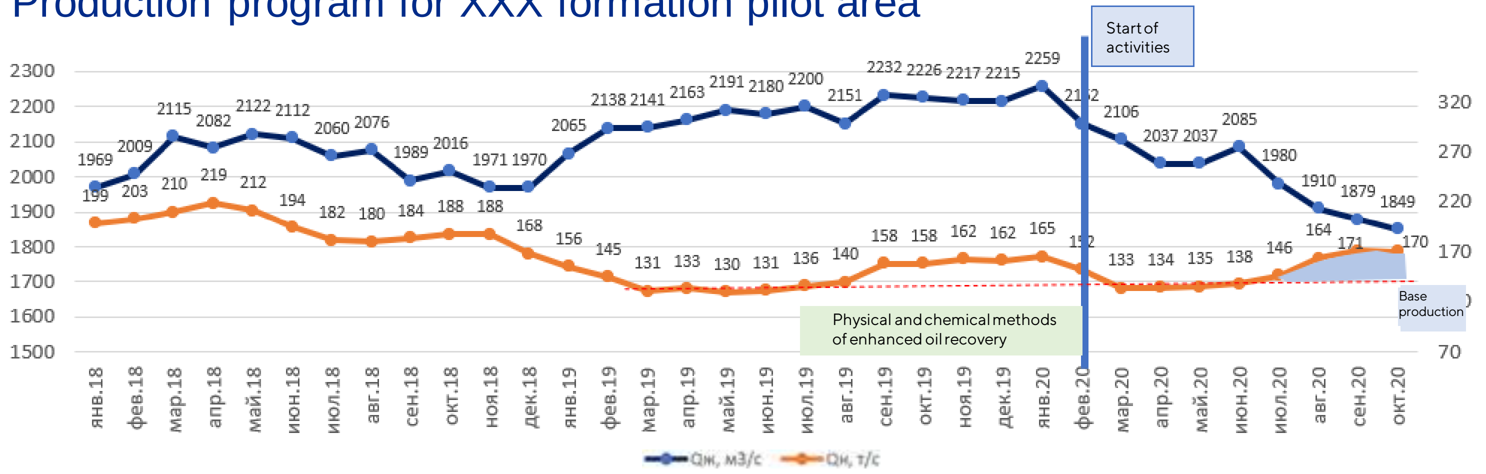
Several wells reached the design conditions after redistributing injection and replacing detectors.

Result

Oil production is decreasing from January to March (because of suspending physical and chemical methods of enhanced oil recovery and the end of the desired effect). There were 8 bottomhole treatments from late July until early January (53% of the stock). Oil production has been stabilizing since April, followed by the steady increase since June.

The estimated effect of neural network optimization is 1,435 tons

Production program for XXX formation pilot area



Conclusions

1. Various approaches to brownfield development management have been analyzed.

2. The flooding control approach using regression models, clustering and neural networks has been proposed.

3. The approach to initial data recovery and filtering has been developed.

4. The model for definition of dynamic interference coefficients between wells with further clustering of the interference graph has been suggested.

5. The neural network architecture for building proxy models reflecting the dependence of the cluster production rate from injection wells has been developed.

6. The optimization problem has been stated and the constraints model for solving the problem has been designed.

7. The optimization module to search for recommended injectivity rates for injection wells has been created.

8. The computational kernel has been designed, which is a flexible tool that facilitates solution of various problems depending on the goals by changing the loss function of the proxy model and using several constraints models.

9. Functionality of flooding control algorithms has been proven by the pilot area of the field in Western Siberia.

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Thank you for your attention!