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# Addressing 5G Network Management Challenges with Machine Learning

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  Public

# 5G Network Management

## Addressing the challenges

| Ultra Dense Small Cells | Cloudified RAN & Core | Multi-connectivity (MC) | URLLC network service | Multi-service Network |
|---|---|---|---|---|
| Distribution | Centralization | Multi-RAT / layer | Low latency radio, edge cloud | Slices |
| Distributed decisions; Management hierarchy / aggregation | Combined management of physical / virtualized infrastructure | MC-aware, management incl. aggregation of PM/FM data | NM data resolution; prognostic diagnosis; combined network resilience & self-healing | Intra- / inter-slice management; Separation (& sharing) of knowledge; Embedded analytics |

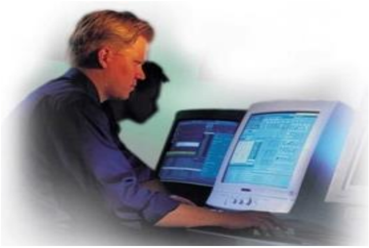
*Flexible VNF re-location / re-configuration*

*„Hybrid“ NM*

# Cognition & Self-Organization

## applied to infrastructure networks ?

**Cellular macro network**
- Tightly planned, infrequent physical topology changes, automated operation
- Single operator
- Single vendor equipment per OAM domain

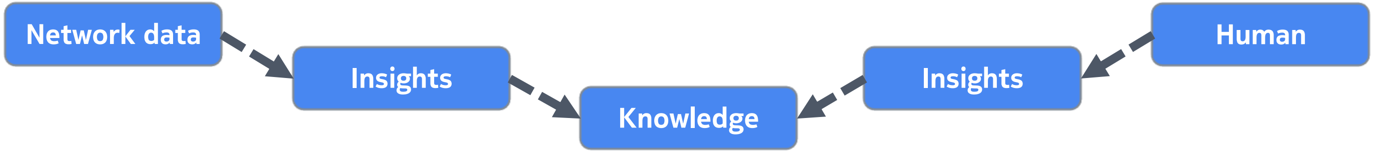


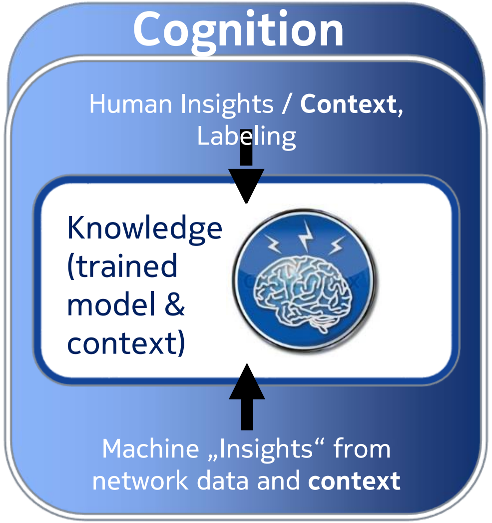
**5G Cellular Heterogeneous Network**
- Some parts only coarsely planned, frequent virtual topology changes, highly automated operation
- Multi-tenant (shared infra)
- Multi-vendor per domain

**Ad-hoc / mesh network**
- Uncoordinated deployment, frequent physical topology changes, autonomous operation
- Only node operator
- Open environment, standardized protocols between nodes

“Self-organization is a process where the organization (constraint, redundancy) of a system spontaneously increases, i.e., without this increase being controlled by the environment or an encompassing or otherwise external system.“ (F. Heylighen, Principia Cybernetica Web, 1997)

# Cognition




„Cognitive Functions“: inputs → ML algorithm / rules → outputs

- Gaining *machine-level insights* from data

**Combining** machine-level insights with human insights

- Closed-loop Cognitive Functions (for specific, frequent tasks)
- Linking to human-level workflows through open-loop functions (for other, more complex tasks)

**Cognition is „the brain“ of the future mobile network business (design, build/commission, operate, de-commission)**

Building knowledge in silos is not sufficient
→ **sharing** knowledge inside an operational domain and across different, related areas

# Machines vs. Humans

MACHINE

Fast number-crunching (e.g., multi-variate KPI data processing)
Keeping a lot of historical information
Executing lots of concurrent low-level tasks / decisions, etc.

***Machine overriding human*** (potential erroneous actions / mis-configuration, easy to detect with the machine-level, fast, concurrent processing)

***Human overriding machine*** (still limited machine intelligence and limited / erroneous instrumentation, easy to detect with human intuition)

HUMAN

Using intuition to make complex decisions under uncertainty (e.g., “low level” root cause diagnosis; expressing high-level targets and tradeoffs)



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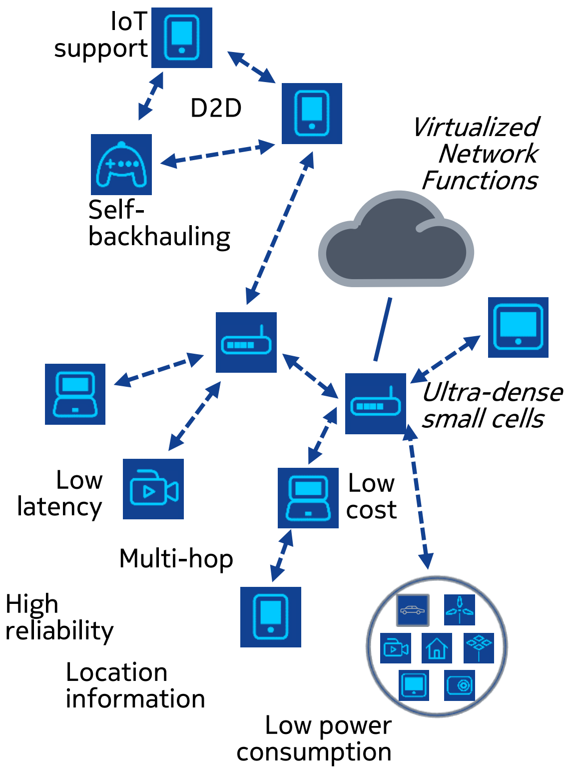
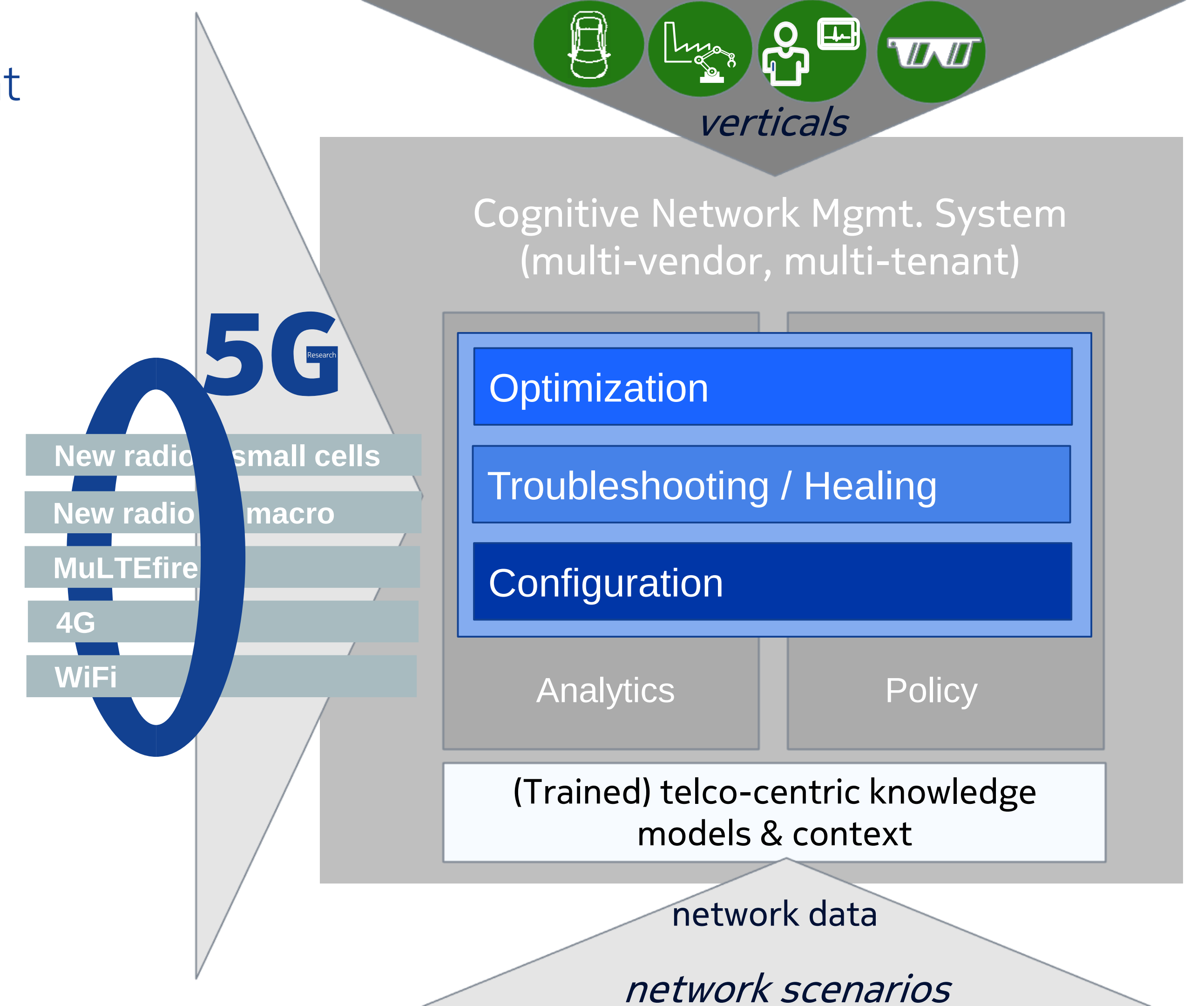
# Machines vs. Humans

**Challenges wrt. Machine intelligence**

- Data uncertainty / incompleteness / volatility / variability:
  - Cell level data (PM, FM, CM) provides only incomplete, system-internal view; mostly treated in isolation
  - Significant changes over time (new NE/cells, new SW releases, …), different deployments
  - System-external information and human operator knowledge is decoupled
- Knowledge transfer from human to machine domain
  - Lack of systematic human-level knowledge management
- Technical applicability
  - Many different AI approaches with different capabilities / constraints
  - Considering analogies in other domains, e.g., rule generation in coordination / verification compared to firewall rules coming from intrusion detection

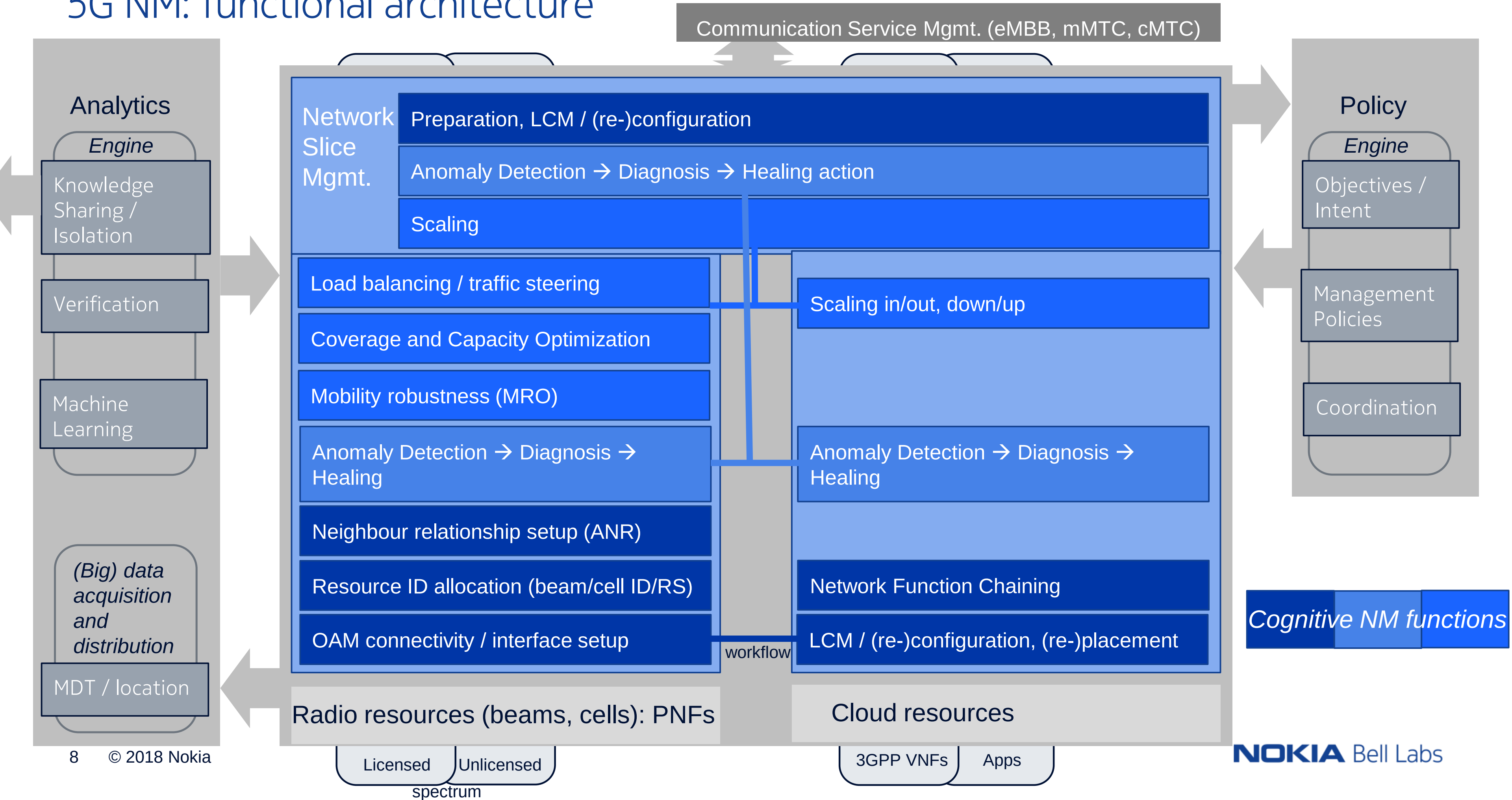
# 5G Network Management



# 5G NM: functional architecture



# Different 5G use case requirements → slice characteristics → set of cognitive functions

| | SMF/Control Plane Capacity | Mobility Frequency | UPF/ Forwarding Capacity | Latency Challenge | Resiliency need |
|---|---|---|---|---|---|
| Smart Meters | MEDIUM | LOW | LOW | LOW | LOW |
| Car to Car | HIGH | HIGH | LOW | HIGH | HIGH |
| Fixed Wireless | LOW | LOW/None | Ultra HIGH | MEDIUM | MEDIUM |
| Consumer Mobility | MEDIUM | HIGH | MEDIUM | MEDIUM | MEDIUM |
| Industrial IoT | LOW | LOW | HIGH | HIGH | HIGH |

*SMF: Session Management Function*

*UPF: User Plane Function*

# Different 5G use case requirements → slice characteristics → set of cognitive functions

| | SMF/Control Plane Capacity | Mobility Frequency | UPF/ Forwarding Capacity | Latency Challenge | Resiliency need |
|---|---|---|---|---|---|
| mMTC | MEDIUM | LOW | LOW | LOW | LOW |
| cMTC / high mobility | HIGH | HIGH | LOW | HIGH | HIGH |
| eMBB / no mobility | LOW | LOW/None | Ultra HIGH | MEDIUM | MEDIUM |
| eMBB | MEDIUM | HIGH | MEDIUM | MEDIUM | MEDIUM |
| cMTC / low mobility | LOW | LOW | HIGH | HIGH | HIGH |

# Different 5G use case requirements → slice characteristics → set of cognitive functions

<table>
<tr><th>→ Radio vs. Cloud resources</th><th>SMF/Control Plane Capacity</th><th>Mobility Frequency</th><th>UPF/ Forwarding Capacity</th><th>Latency Challenge</th><th>Resiliency need</th></tr>
<tr><td>mMTC</td><td rowspan="5">→ Cloud</td><td rowspan="5">→ Radio</td><td rowspan="5">→ Radio & (Edge) Cloud</td><td rowspan="5" colspan="2">→ Radio: Multi-cell coord. & connectivity<br>→ Cloud: Edge Cloud, VNF resiliency</td></tr>
<tr><td>cMTC / high mobility</td></tr>
<tr><td>eMBB / no mobility</td></tr>
<tr><td>eMBB</td></tr>
<tr><td>cMTC / low mobility</td></tr>
</table>

# Cognitive NM functions: inputs → ML algorithm / rules → outputs

| Cognitive NM Function | Examples for applicable ML algorithm |
|---|---|
| Load balancing / traffic steering | Metaheuristics (PSO*) / decision tree |
| Coverage and Capacity Optimization | Reinforcement learning (QL*) |
| Mobility robustness (MRO) | Reinforcement learning (QL*) |
| Scaling in/out, down/up | Reinforcement learning; Graph Neural Nets |
| Anomaly Detection → Diagnosis → Healing | Topic Modeling → MLN* → Utility Theory |
| Network Function Chaining | Metaheuristics (genetic algorithms) |
| LCM / (re-)configuration, (re-)placement | Metaheuristics (harmony search) |
| Neighbour relationship setup (ANR) | n/a (rules) |
| Resource ID allocation (beam/cell ID/RS) | Unsupervised learning (clustering) |
| OAM connectivity / interface setup | n/a (rules) |

* PSO: Particle Swarm Optimization, QL: Q(uality) Learning, MLN: Markov Logic Networks



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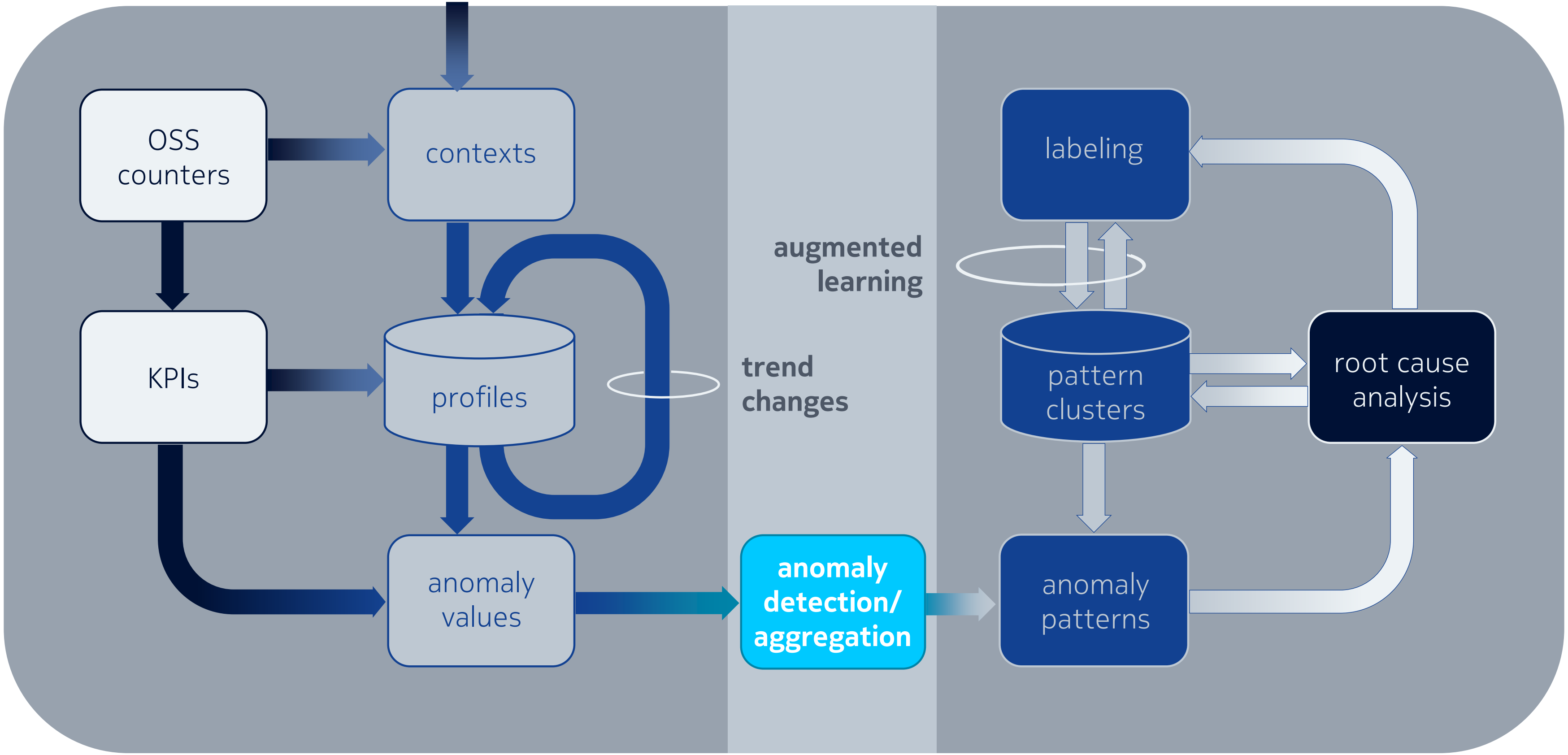
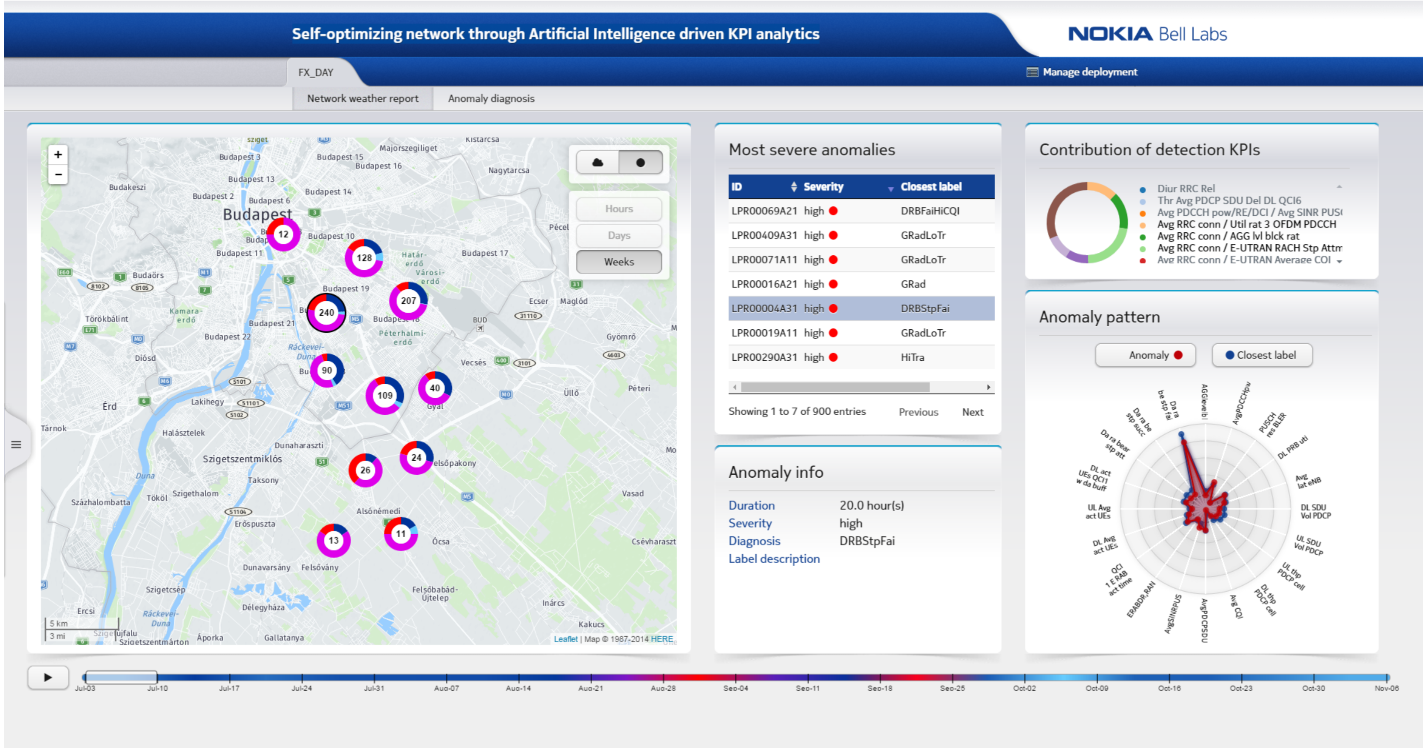
# Example: anomaly detection and diagnosis – overview



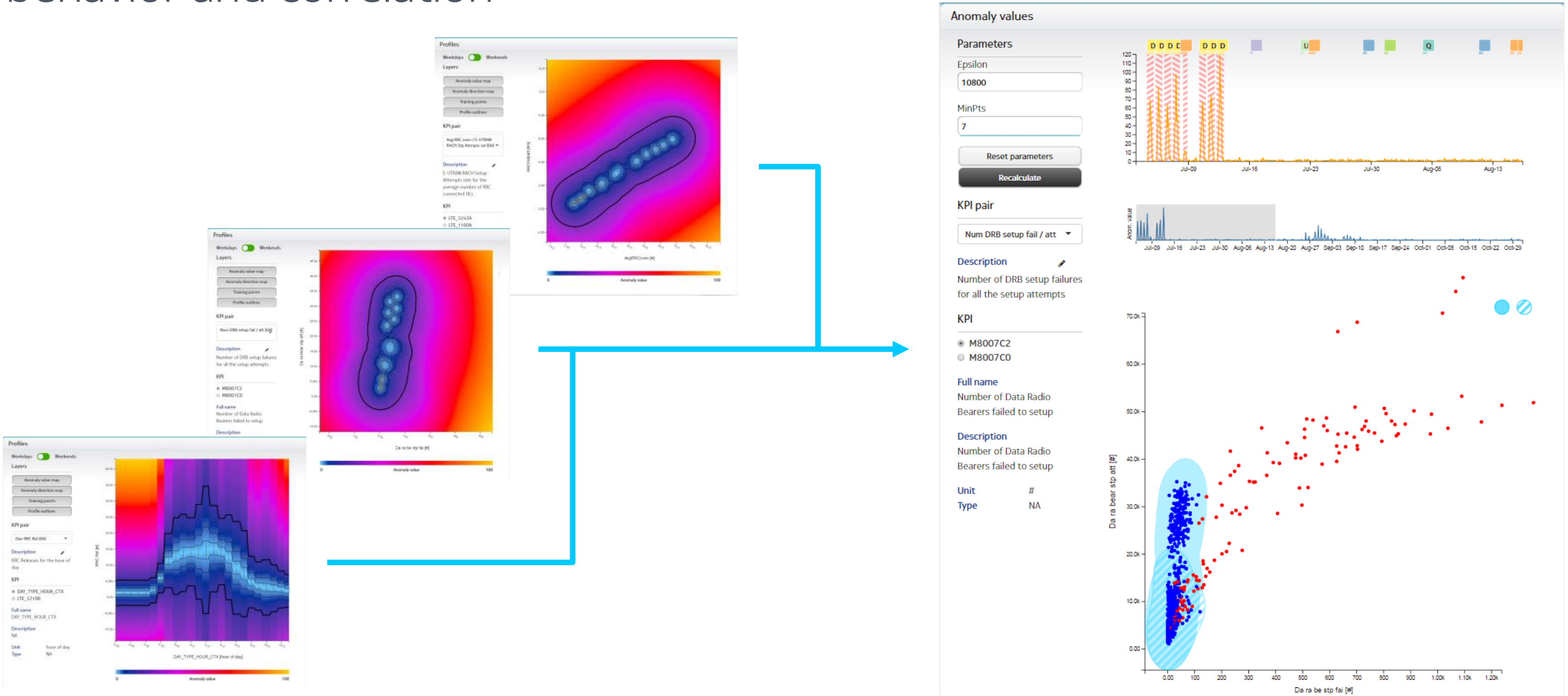
# Network Weather Report

## Overview of network state and diagnosis in spatial and temporal context



# Anomaly detection procedure

## Context-aware learning of normal states, measuring anomalousness in diurnal behavior and correlation



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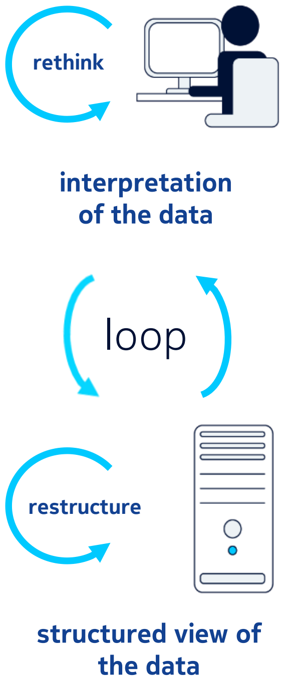
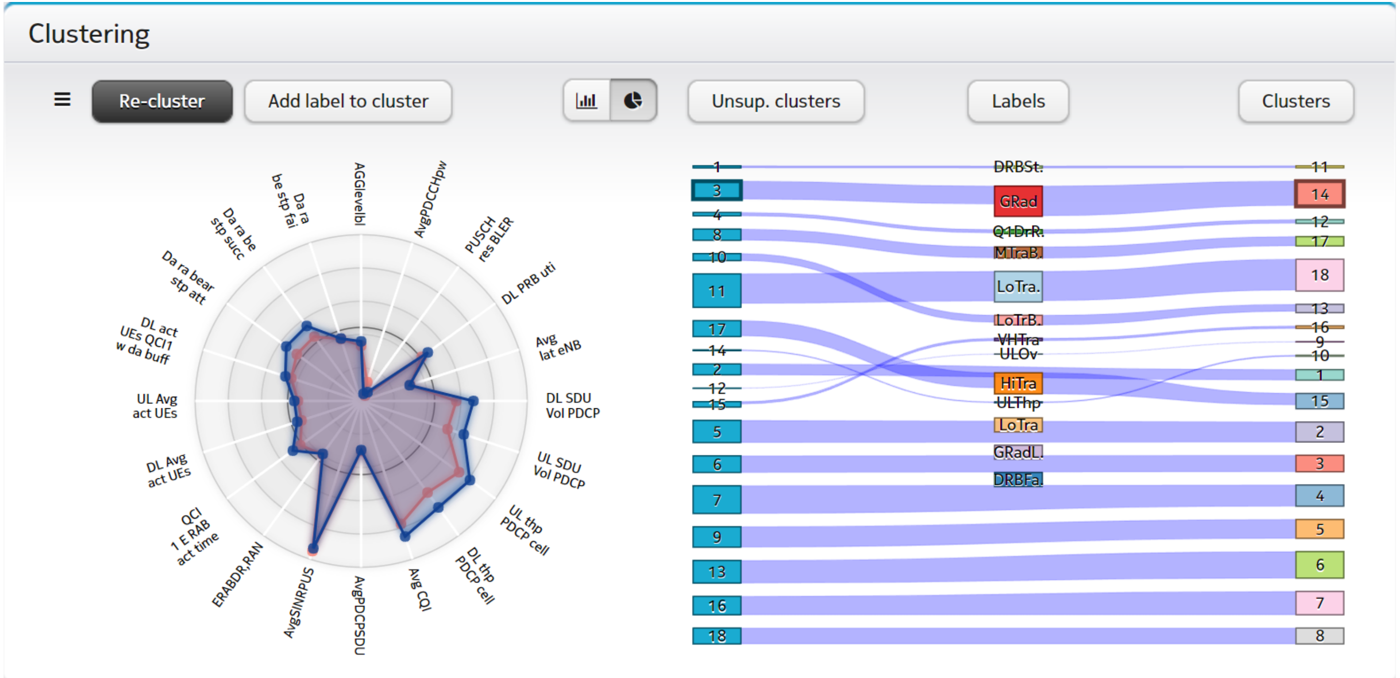
# Augmented diagnosis

## Synergetic exploitation of human-machine capabilities for fast and efficient analysis



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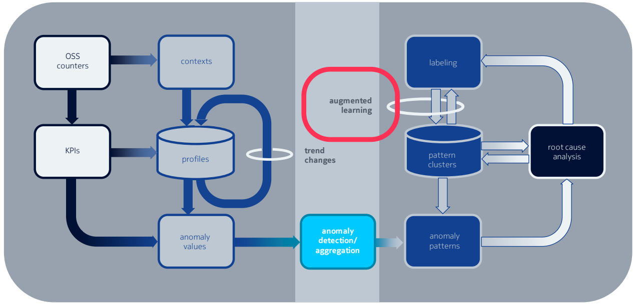
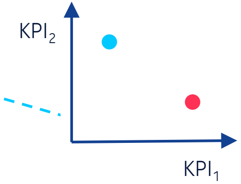
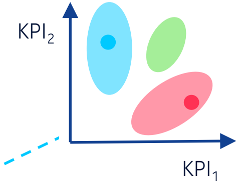
# Augmented diagnosis

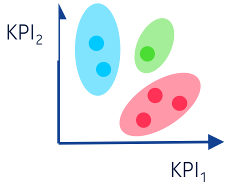



## Human

1. Labels a few examples of the major expected anomaly groups




3. Expands and refines the labeling:
   - Labels the previously unlabeled anomalies in the expected groups
   - Labels the anomalies in the unexpected groups

## Machine

2. Creates a clustering taking the labeled points into account

4. Any newly arriving anomalies can be **automatically labeled** with this information



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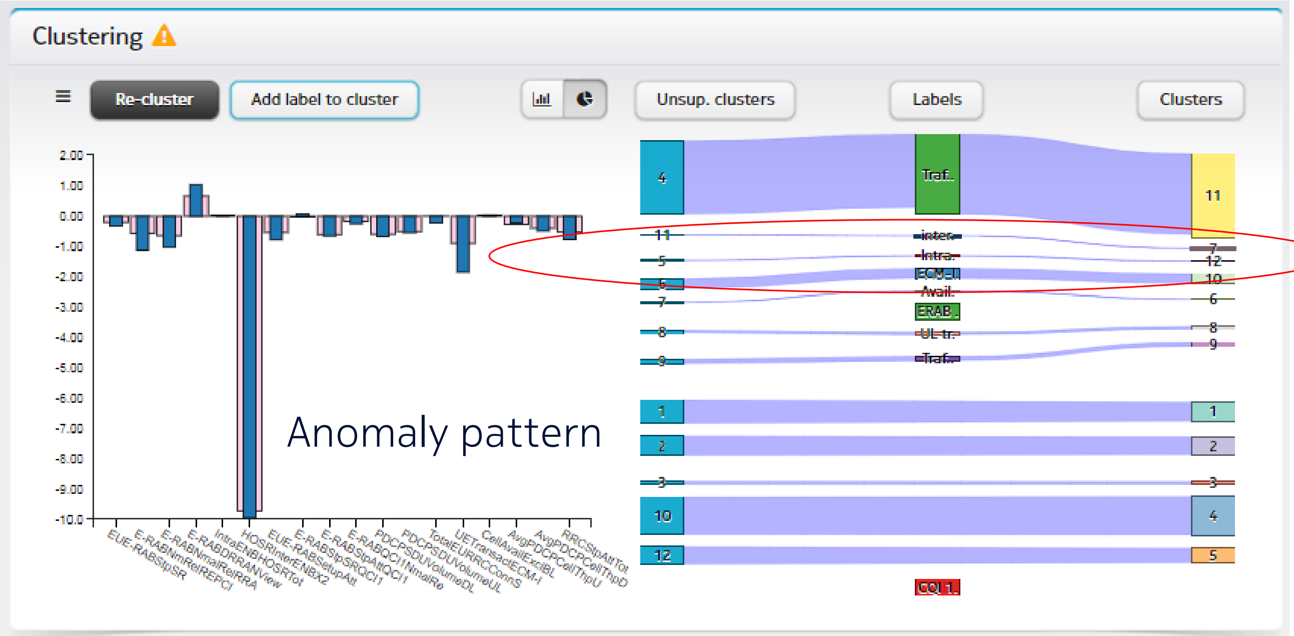
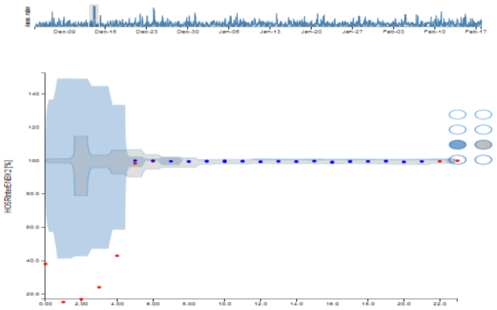
# Use Case Example from a Major Operator

- Augmented learning → new cluster of intra- and inter-eNB Handover problems (distinct classes of anomalies that had not been discovered / analyzed yet)




New identified problem cluster → new „golden configuration“





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# Addressing 5G Network Management Challenges with Machine Learning

## Conclusions

- **5G Network complexity (ultra dense, cloudified, multi-service / -tenant) imposes new operability challenges**
  - **Functional:**
    - per service- / tenant- instrumentation and *dynamic* operation (multiplicity of varying *virtual* network configurations)
    - data: higher resolution of measurements; new external sources / context
    - higher degree of autonomy in management
  - **Architectural:**
    - new building blocks related to slicing management
    - higher degree of distribution, cooperation / coordination and abstraction
- **Cognitive NM functions**
  - Shield the complexity of physical and virtual network functions from higher layers →balancing human and machine decision making
  - Are intra- / inter-slice-aware; sets of CFs are defined per slice type
  - Enable the management of diverse service types in diverse network scenarios

 

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# Addressing 5G Network Management Challenges with Machine Learning

## Conclusions

- **Machine Learning: key enabler to realized Cognitive NM functions → approach:**
  - Matching of key use case characteristics with technology capabilities → selection
  - Anomaly Detection / Diagnosis
    - Holistic PM/FM/CM analysis: leverage the potential of the data, by comprehensive analysis, combine network data with context data
      → high quality detection + basic diagnosis (unsupervised learning)
    - Motivate Network Operations Experts to combine their knowledge with the machine-level → (semi-)supervised learning (augmented diagnosis)
- **Research challenges**
  - 5G URLLC management: instrumentation, prognostic diagnosis
  - Cognitive Function placement
  - Slice management (incl. knowledge sharing & isolation)
  - Management of interworking legacy net(s), 5G (private / public)

TACNET 4.0 Taktiles Internet

 

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# SON + ML = Cognitive Network Management functions

| | SON | Cognitive Network Management |
|---|---|---|
| *Input data* | Structured data; rel. Low spatial and temporal resolution | Structured and unstructured data; both low and high spatial and temporal resolution (real-time, location-annotated) → ***exploit available data to the max; be flexible / robust wrt. the data availability / quality*** |
| *Analysis* | Simple feature extraction (fixed thresholds on raw KPIs) | (Pre-processing of unstructured data)<br>Advanced feature extraction (**training** based on KPI distributions) → ***no configuration of thresholds, deploy → train → operate*** |
| *Diagnosis* | Static: fixed algorithm / ruleset (adaptation time cycle: NE SW update interval: ~months) | Dynamic: probabilistic **reasoning & learning** (adaptation time cycle: rule update interval: ~hours) → ***fast, autonomic adaptation to specific deployment situation*** |
| *Actions* | Single step, simple actions (sometimes circumventing the problem rather than solving it, e.g., cell resets) | Multiple step action **planning**, considering utility; smarter, fine granular actions → ***smarter automated actions taking into account context (cost)*** |
| Management | Technical policies | Business-level policies **(operator objectives / "intent")** → automatically derived technical policies; high-level feedback for **trust**-building (**verification**) |
| Use cases | Simple „replacing" (OPEX-improving, e.g., ANR) and „new" (quality-improving, e.g., MRO/MLB) features | Also complex „new" (e.g., Cell Anomaly Detection), „Integrating" (Coordination, Verification) and „Supporting" (e.g., Cell Degradation Diagnosis, tightly integrated with human-level workflows) features → ***covering a wide(r ) range of use cases*** |

# Example: Cell anomaly detection and diagnosis – ML Algorithms

| Cognitive NM Function | Examples for applicable ML algorithm |
| --- | --- |
| Input selection | Genetic algorithms, PCA |
| Multi-dimensional non-normally distributed profiling | Clustering: k-NN, SOM, GNG |
| Anomaly level calculation | Multi-dimensional probabilistic distributions |
| Anomaly event aggregation | DBSCAN |
| Diagnosis | Decision theory, rulebases, different distance measures: Mahalanobis, Kullback-Leibler divergence or Hellinger |
| Augmented learning | Active learning, DBSCAN, k-NN |

 