

Summer school on sensor fusion – SUT, Gliwice, Poland

20-25.07.2026

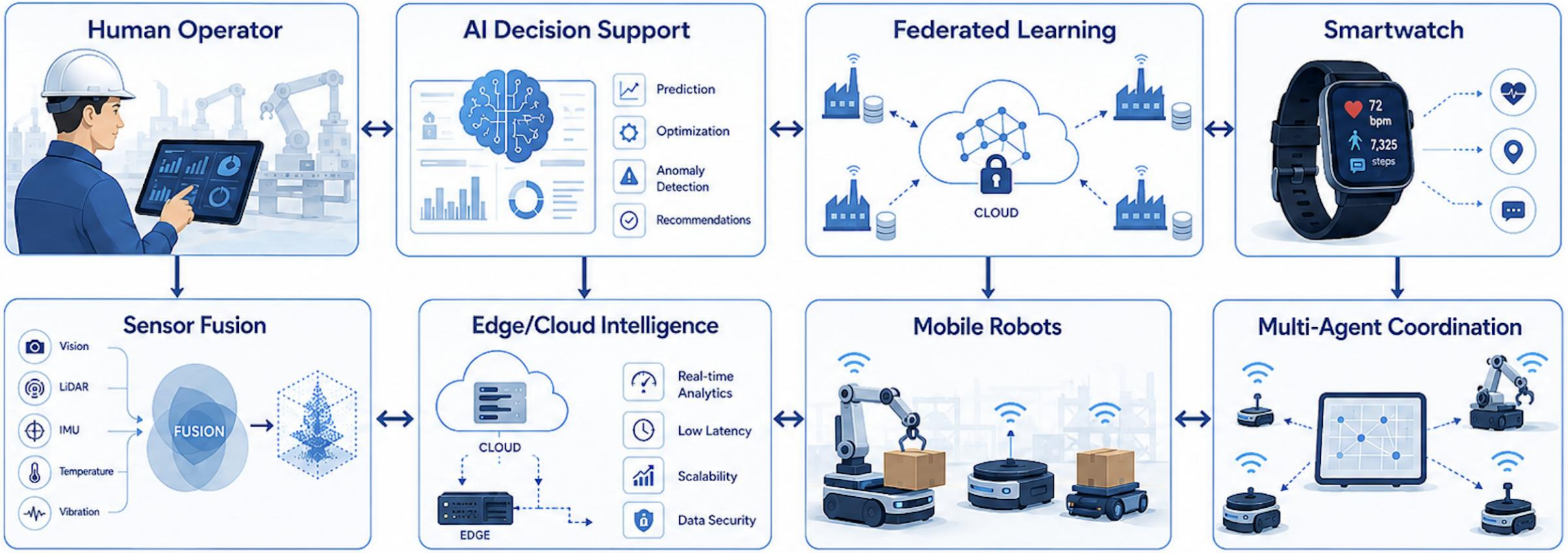
HUMAN-CENTRIC SENSOR FUSION AND FEDERATED LEARNING FOR ENERGY-AWARE MULTI-AGENT CONTROL OF INDUSTRIAL MOBILE ROBOTS

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AGENDA

1. Safe multi-AGV control in human environments (Industry 5.0)
2. Multimodal sensor fusion (robots + humans + context)
3. Human-centric fusion for adaptive decision-making
4. Federated learning for privacy-preserving distributed training
5. End-to-end fusion pipeline (sensing, cleaning, features, learning)
6. Core models: HAR, battery, wireless prediction
7. Fusion-driven constraint generation for planning
8. Multi-agent federated path planning
9. Results: improved safety, energy efficiency, scalability

INDUSTRY 5.0


Human Operator
AI Decision Support
Prediction
Optimization
Anomaly Detection
Recommendations
Federated Learning
CLOUD
Smartwatch
72 bpm
7,325 steps
Sensor Fusion
Vision
LiDAR
IMU
Temperature
Vibration
FUSION
Edge/Cloud Intelligence
CLOUD
EDGE
Real-time Analytics
Low Latency
Scalability
Data Security
Mobile Robots
Multi-Agent Coordination


Energy-Aware Industrial Tasks
Energy Optimization
Task Scheduling
Sustainability
Performance Balance

PROBLEM STATEMENT

Real-world industrial environments bring complex challenges for multi-agent robot systems operating alongside humans.



Many AGVs operate together

High traffic density leads to complex interactions and risk of collisions.

Humans work and move nearby

Safety and comfort of workers must be always guaranteed.

Battery status constantly changes

Uncertain energy levels affect task execution and mission reliability.

Wireless connectivity is unstable

Intermittent communication causes delays, data loss and coordination issues.

Personnel data cannot be centralized

Privacy regulations prohibit central collection of human-related data.

These challenges require a human-centric, privacy-preserving, and energy-aware solution for robust multi-agent control in dynamic industrial environments.

SENSOR FUSION

AGV:

- Battery sensors (voltage, current, SOC)
- IMU (accelerometer, gyroscope)
- WiFi signal strength / connectivity metrics
- OPC UA industrial communication data
- Odometry (wheel encoders / motion tracking)

Human:

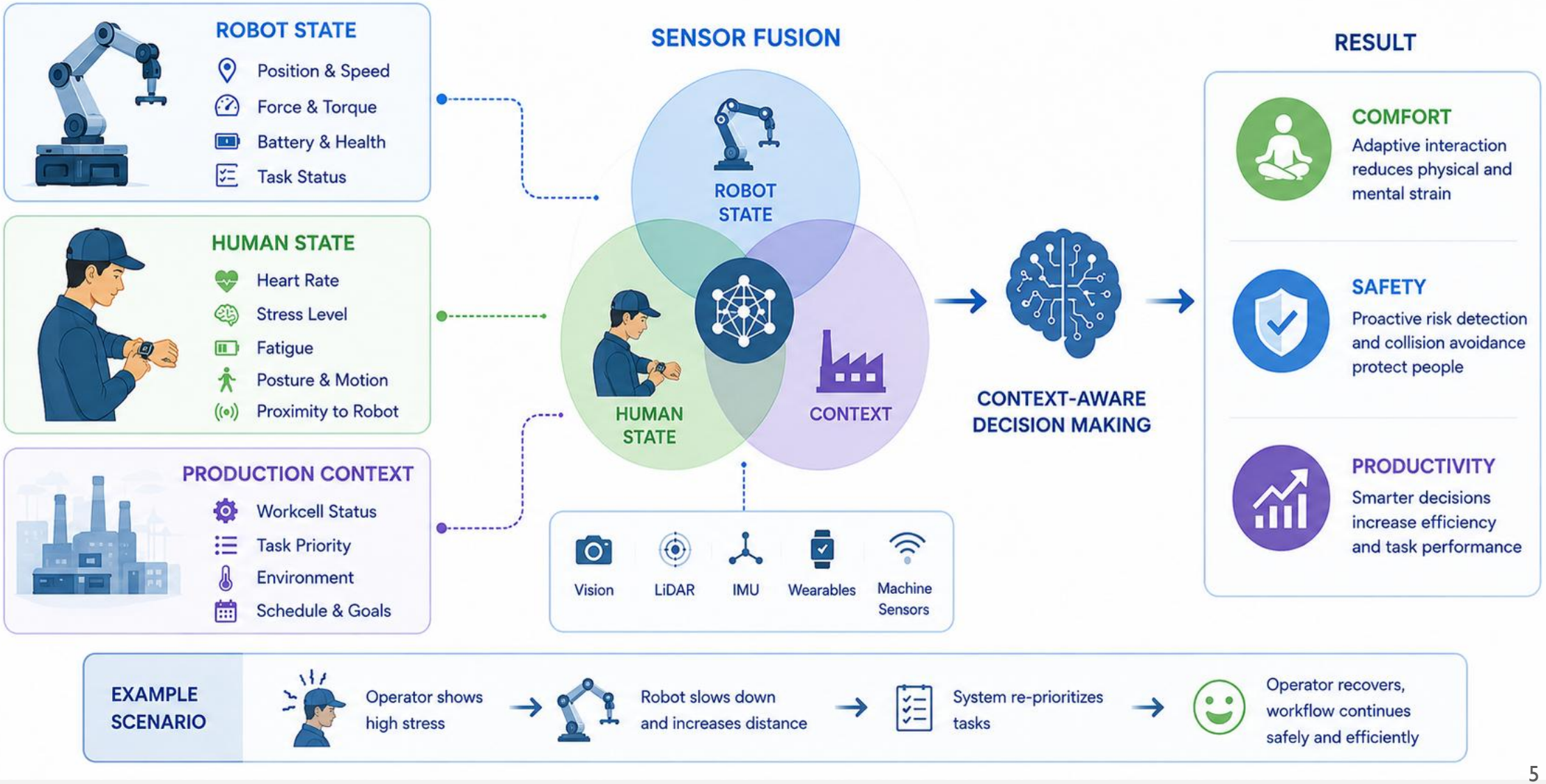
- Accelerometer (motion patterns)
- Gyroscope (orientation / activity)
- PPG (heart rate, physiological signals)
- Smartphone context (location, app usage, activity state)

Why combine them?

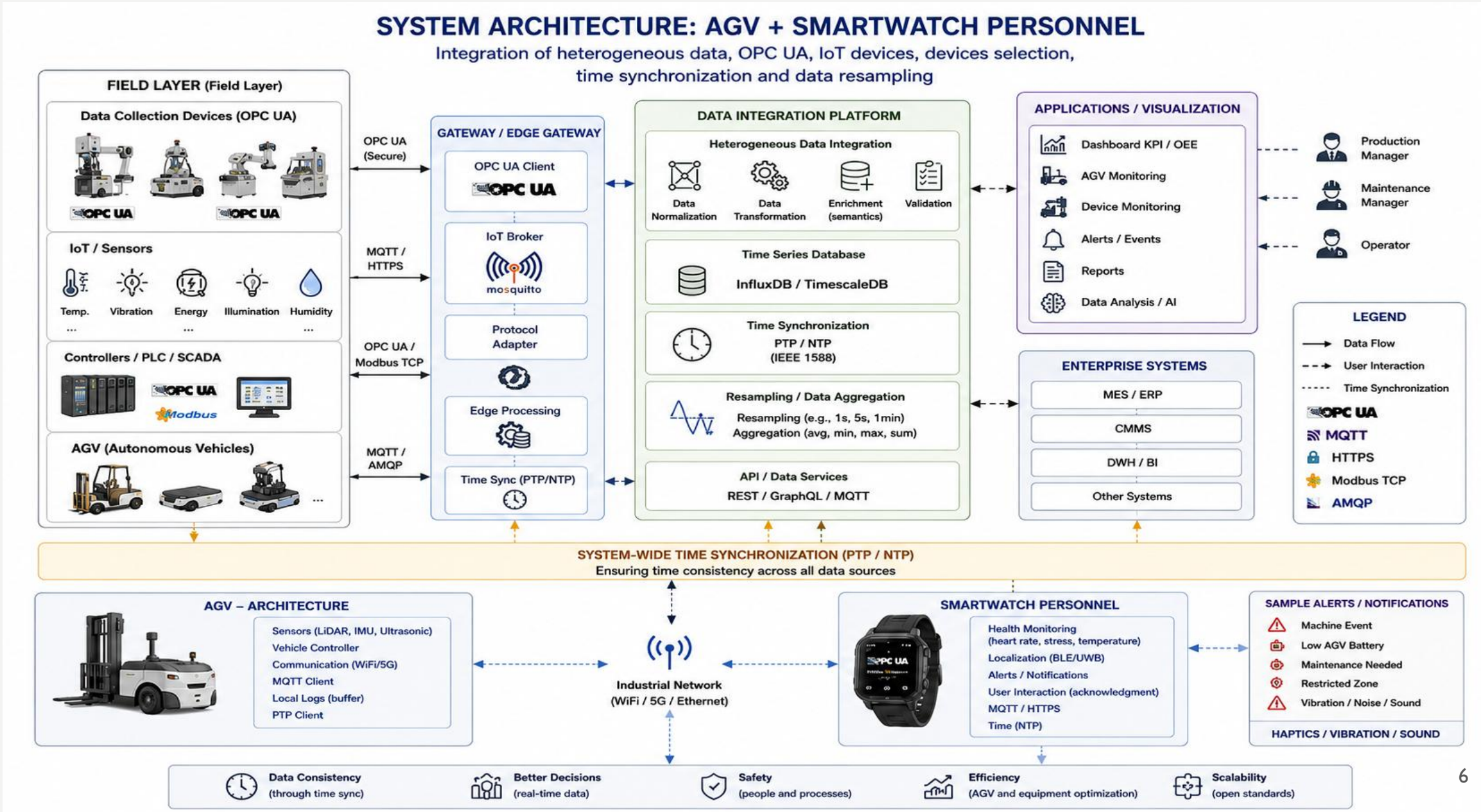
- Reduces uncertainty from single-sensor noise
- Enables cross-validation between physical and behavioral signals
- Improves anomaly detection (machine + human interaction context)
- Supports predictive maintenance + human-aware robotics

HUMAN-CENTRIC SENSOR FUSION

Integrating robot state, human state, and production context for context-aware decisions

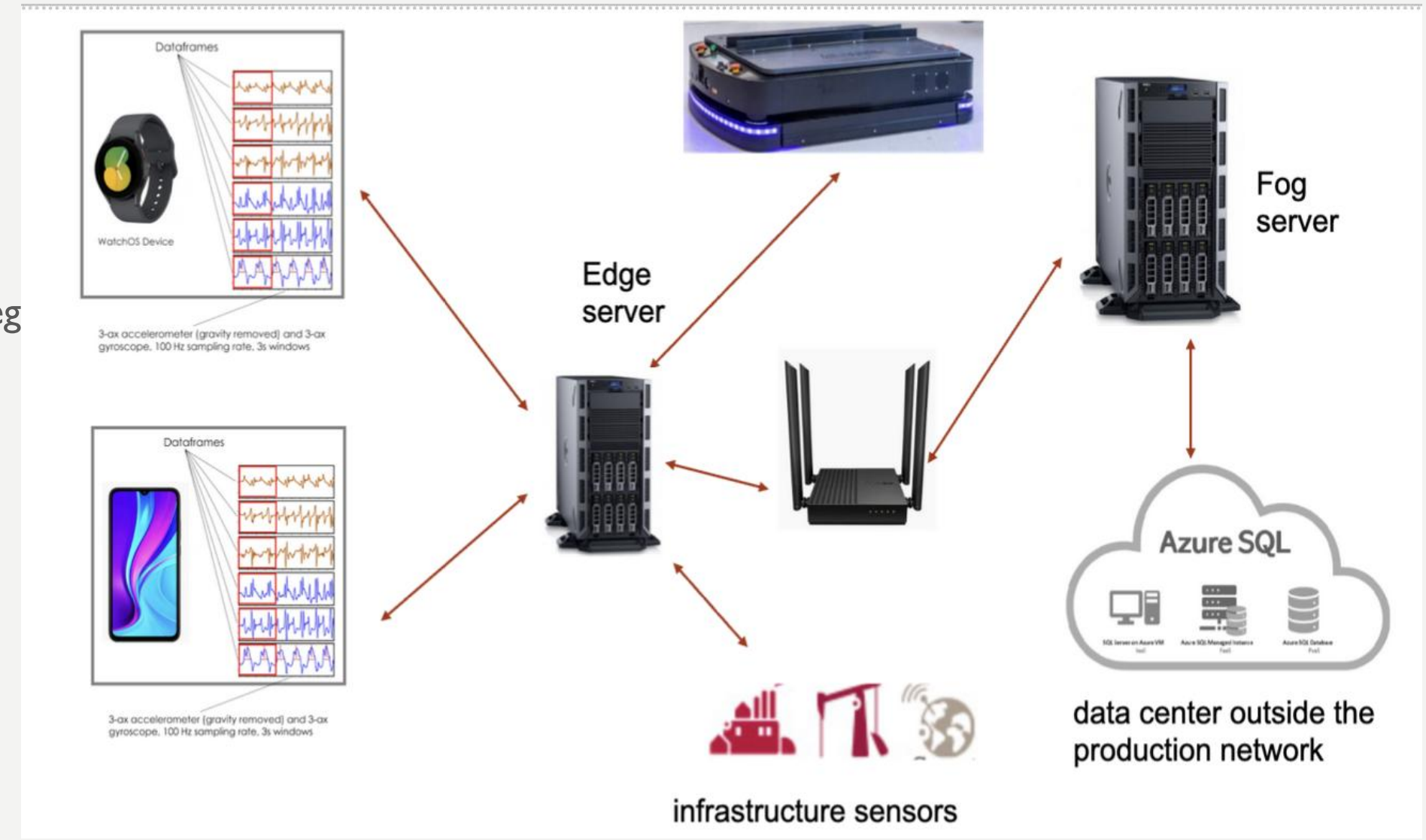


HETEROGENEOUS DATA INTEGRATION, OPC UA, IOT, ELECTIVE DEVICES, TIME SYNCHRONIZATION AND DATA RESAMPLING



DECENTRALIZED DATA COLLECTION IN FEDERATED LEARNING

- edge–fog–cloud
- multi-level aggreg
- privacy



GLOBAL-LOCAL-CENTRALIZED FEDERATED LEARNING ARCHITECTURE

Edge – local client training.
Fog – indirect model aggregation from client groups.
Cloud – global model aggregation from fog nodes.

Local Training (Edge)

$$w_i^{t+1} = w_i^t - \eta \nabla F_i(w_i^t)$$

Fog Aggregation

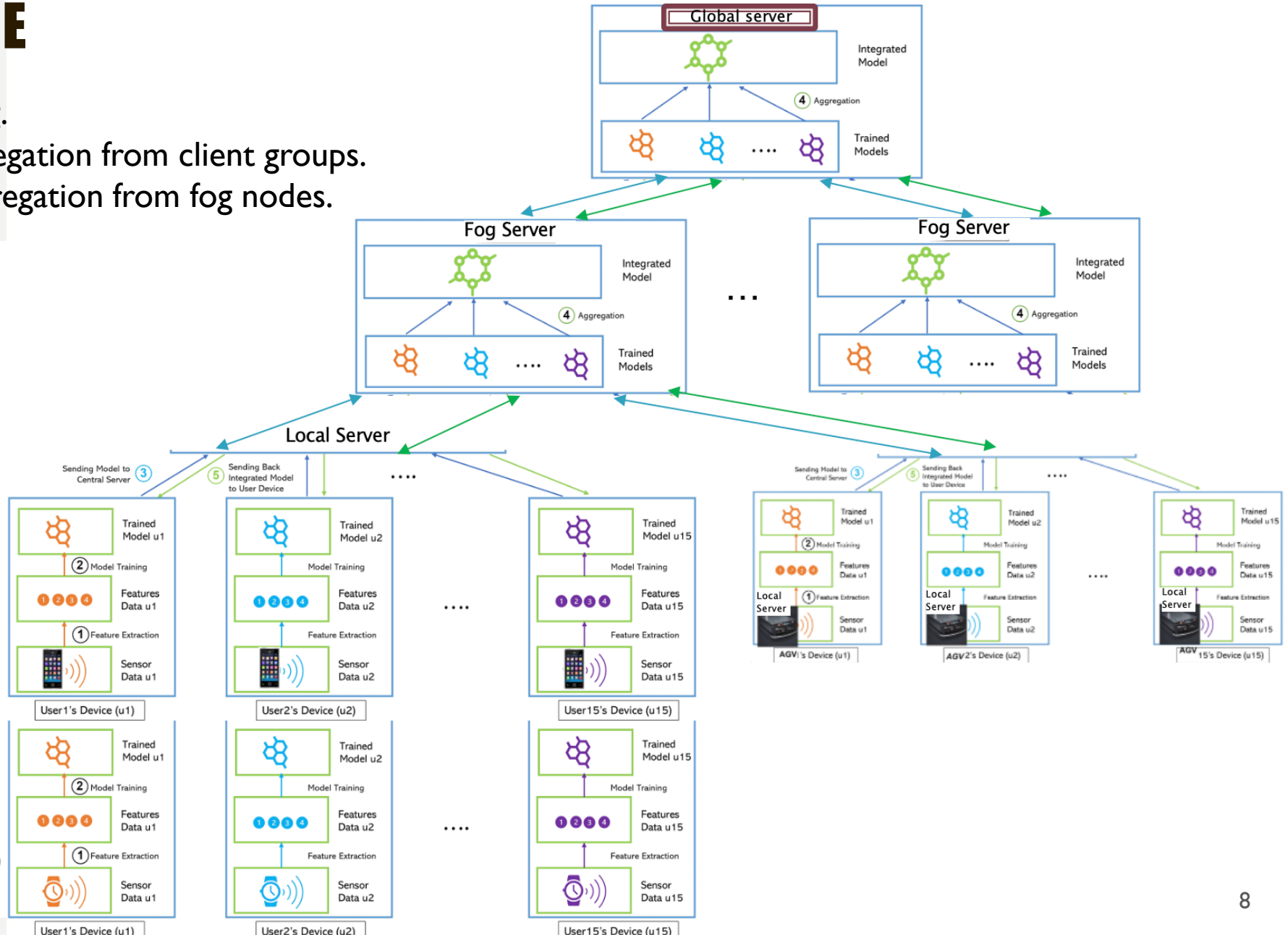
$$w_j^{t+1} = \sum_{i \in S_j} \frac{n_i}{N_j} w_i^{t+1}, \qquad N_j = \sum_{i \in S_j} n_i$$

Cloud Aggregation

$$w_G^{t+1} = \sum_{j=1}^{M} \frac{N_j}{N} w_j^{t+1}, \qquad N = \sum_{j=1}^{M} N_j$$

Global Objective

$$F(w) = \sum_{i=1}^{K} \frac{n_i}{N} F_i(w), \qquad w^* = \arg\min_w F(w)$$



DATA FUSION PIPELINE



SENSOR DATA PREPROCESSING

Interpolation
- Missing-value recovery
- Time-series reconstruction

Signal smoothing
- Moving Average
- Exponential Smoothing
- LOWESS

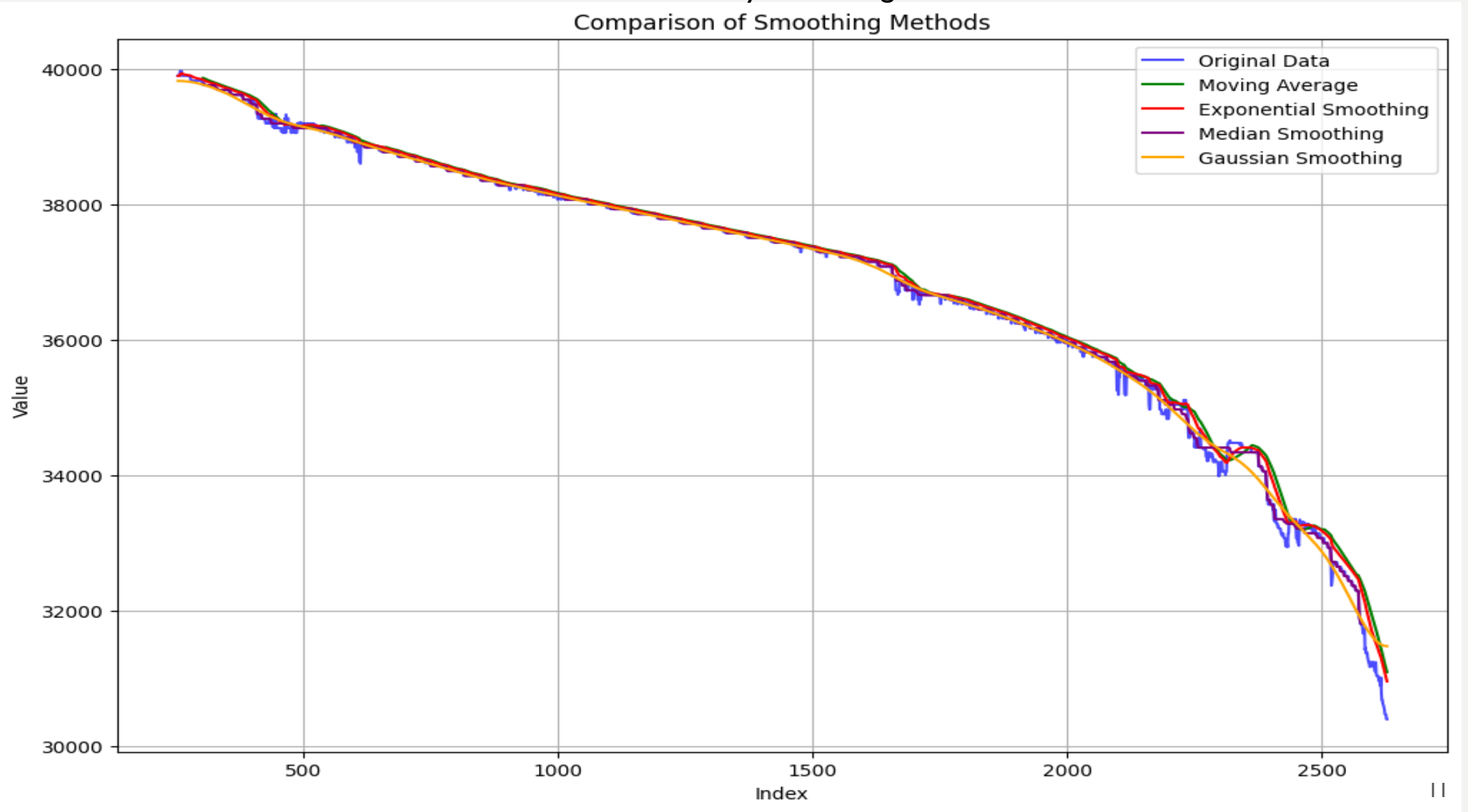
Filtering
- Kalman filter
- Wiener filter

Anomaly detection
- Statistical methods
- Machine learning detectors

Adaptive consensus cleaning
- Multiple lightweight detectors
- Local consensus
- Federated data quality improvement

AGV SIGNAL SMOOTHING

AGV Battery cell voltage

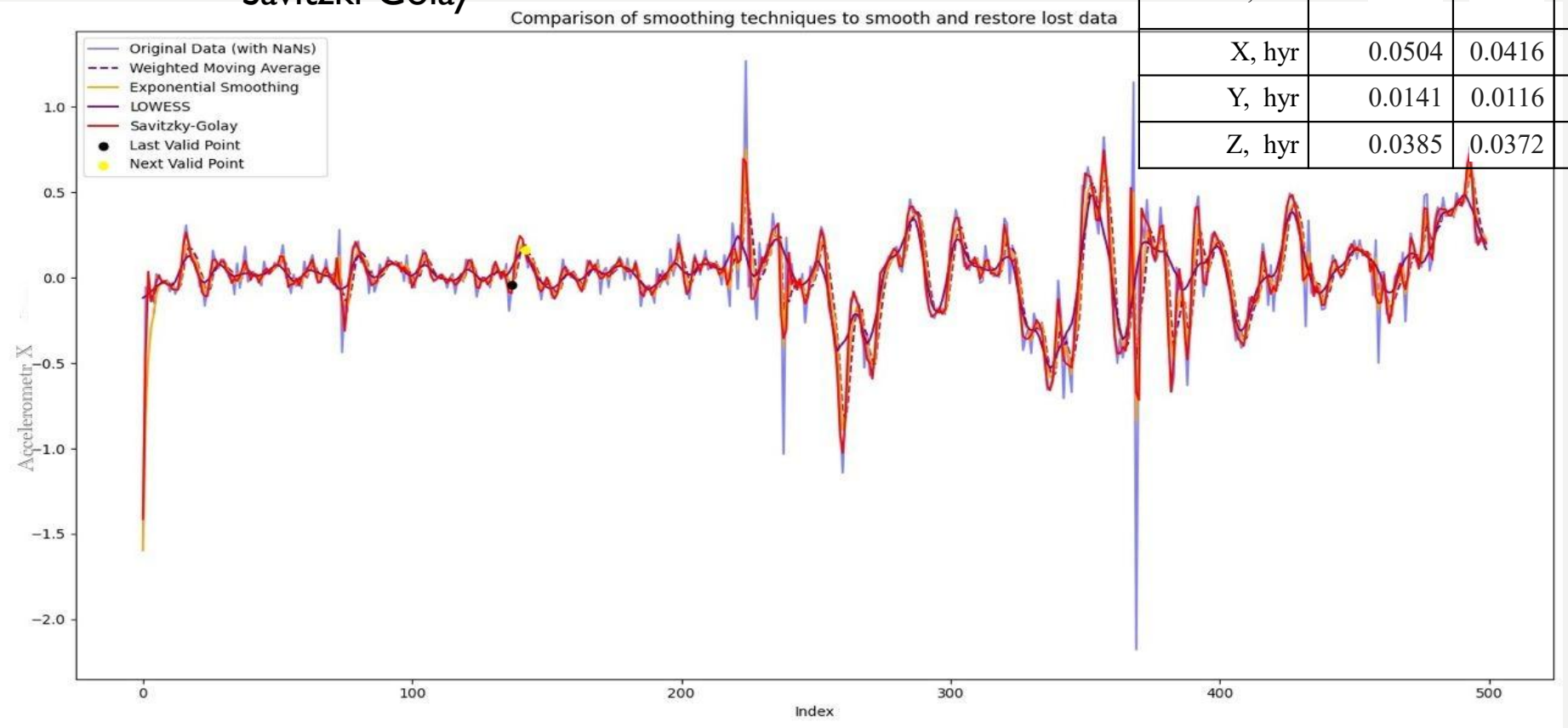


SMOOTHING OF SIGNALS RECEIVED FROM WEARABLE DEVICES

Filtering three-axis accelerometer and gyroscope data from staff smartwatches

- Weighted moving average
- Exponential Smoothing
- LOWESS
- Savitzki-Golay

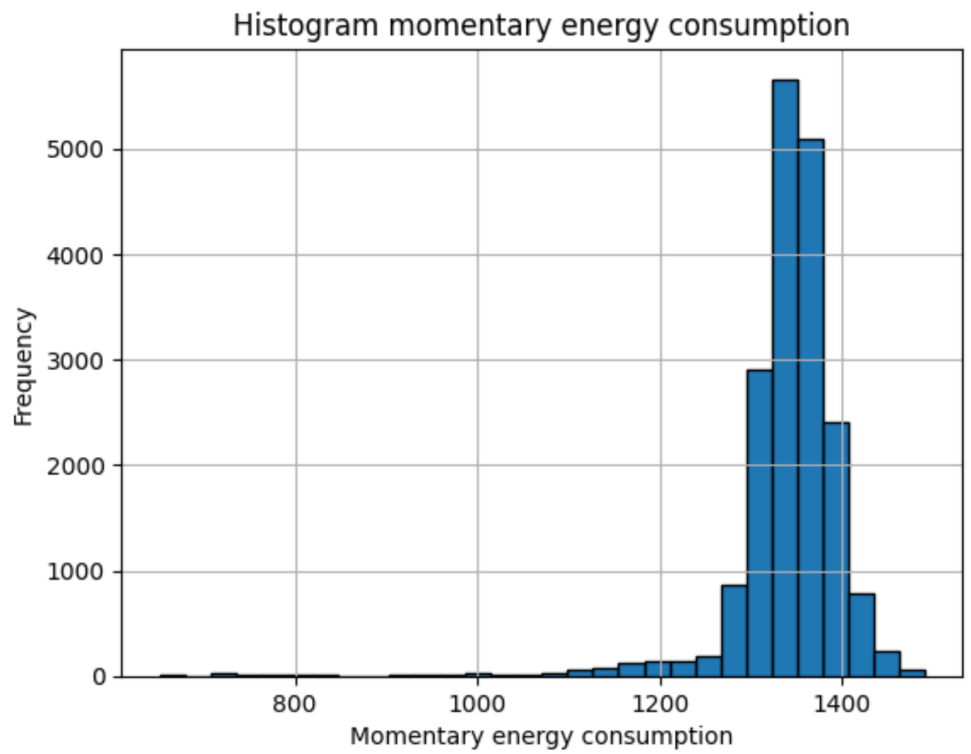
deviation	oryg. data	MA	WMA	ES	LOWESS	SG
X, axe	0.2824	0.2021	0.2086	0.2291	0.1795	0.2477
Y, axe	0.5635	0.4323	0.4472	0.4618	0.4284	0.5160
Z, axe	1.0584	0.5361	0.5248	1.1328	0.4430	0.9993
X, hyr	0.2244	0.2040	0.2073	0.2074	0.2143	0.2225
Y, hyr	0.1189	0.1076	0.1103	0.1095	0.1130	0.1182
Z, hyr	0.1962	0.1929	0.1934	0.1897	0.1913	0.1964
deviation	oryg. data	MA	WMA	ES	LOWESS	SG
X, axe	0.0798	0.0408	0.0435	0.0525	0.0322	0.0613
Y, axe	0.3175	0.1869	0.2000	0.2133	0.1835	0.2662
Z, axe	1.1203	0.2874	0.2754	1.2832	0.1962	0.9987
X, hyr	0.0504	0.0416	0.0430	0.0430	0.0459	0.0495
Y, hyr	0.0141	0.0116	0.0122	0.0120	0.0128	0.0140
Z, hyr	0.0385	0.0372	0.0374	0.0360	0.0366	0.0386

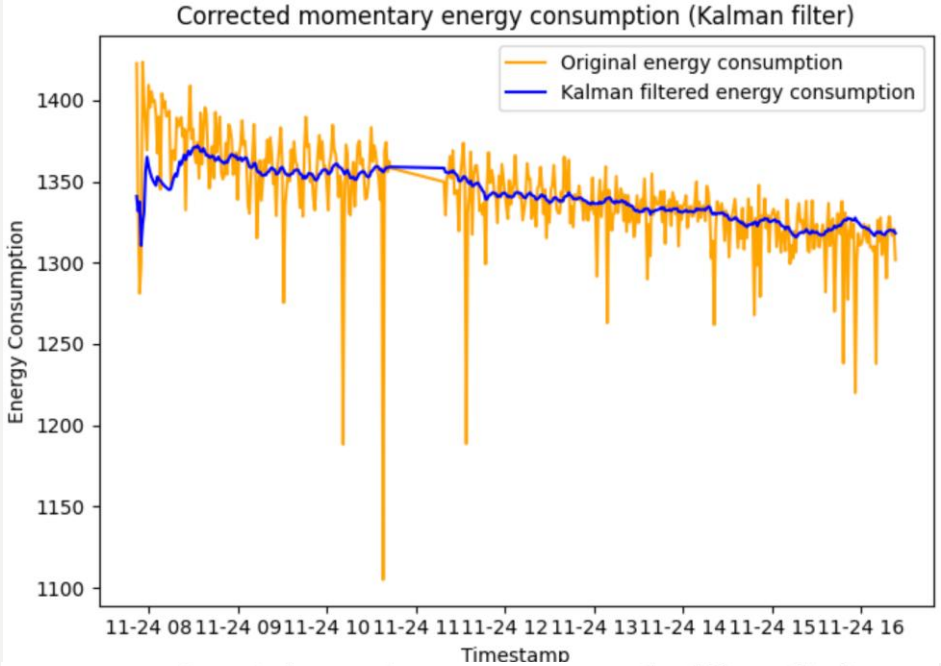


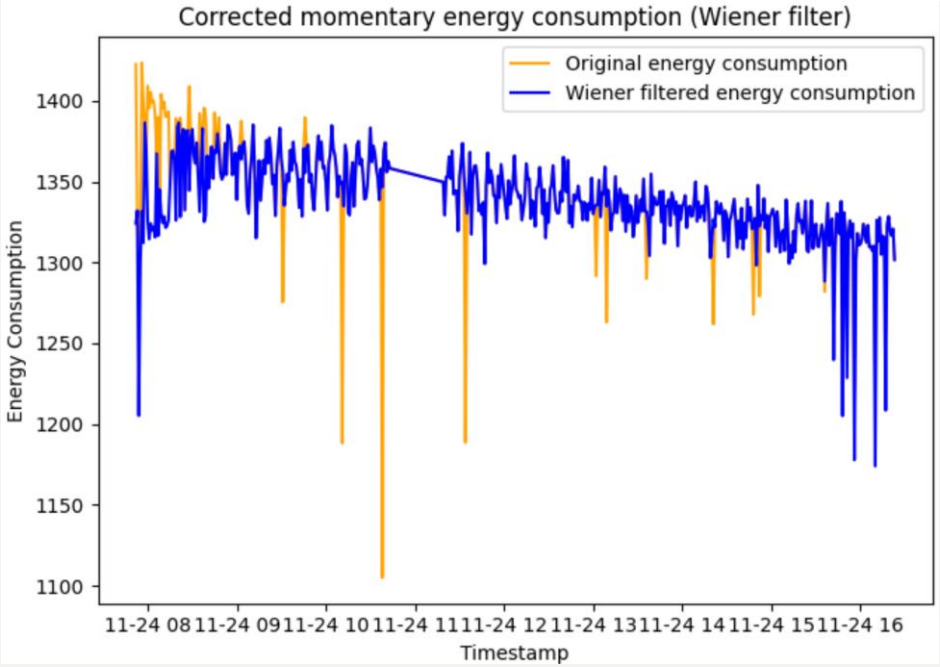
AGV SIGNAL FILTERING

Filtering instantaneous energy consumption data

- Weighted moving average
- Kalman
- Winner







AGV ANOMALY DETECTION

$$MA(t) = \frac{1}{w} \sum_{i=t-w+1}^{t} x(i)$$

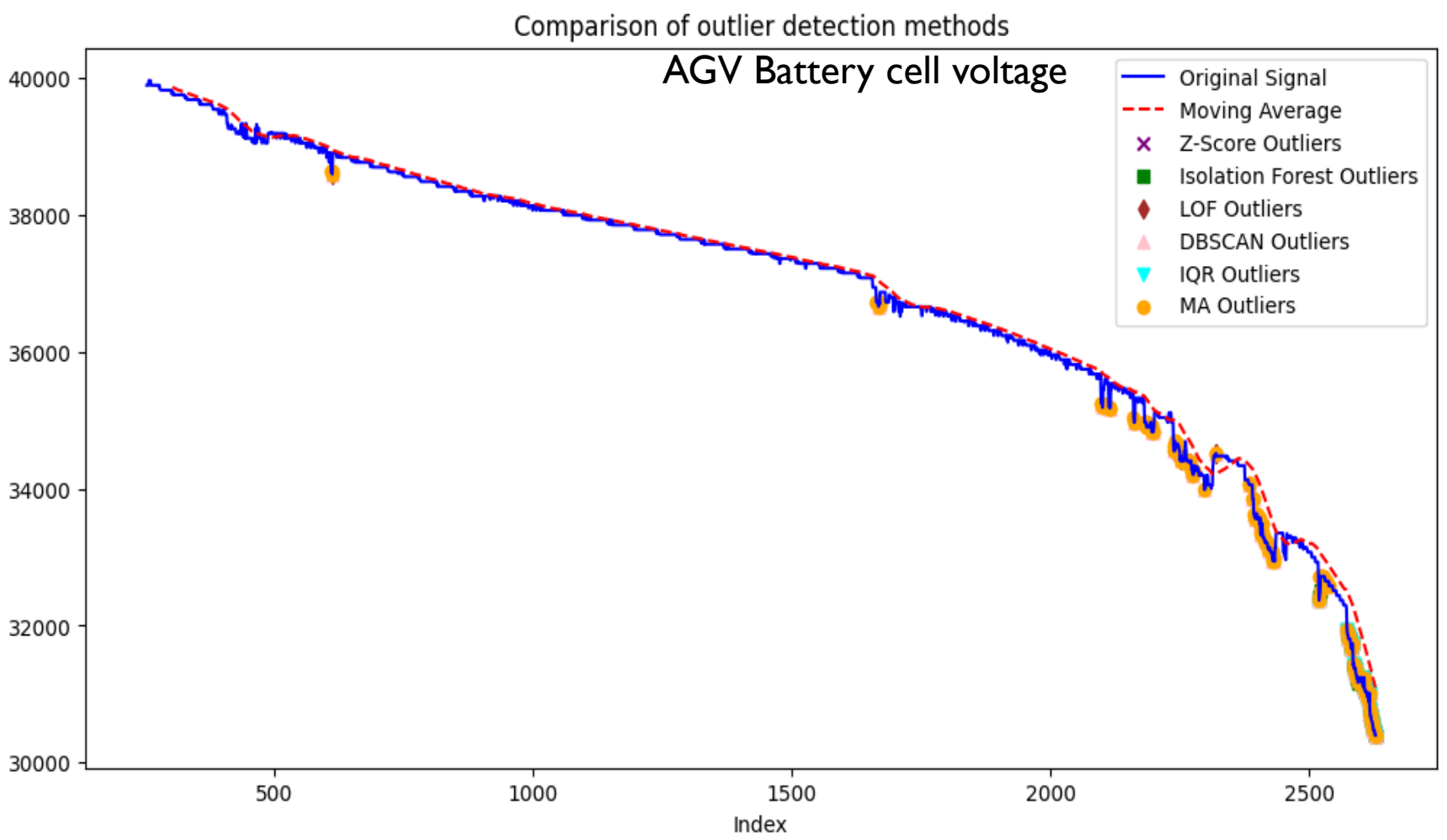
$$D(t) = |x(t) - MA(t)|$$

$$\sigma_D = \text{std}(D)$$

$$T = k \cdot \sigma_D$$

$$y(t) = \{\, 1 \,, D(t) > T$$

$$0, \;\; \text{D(t)} \leq T$$

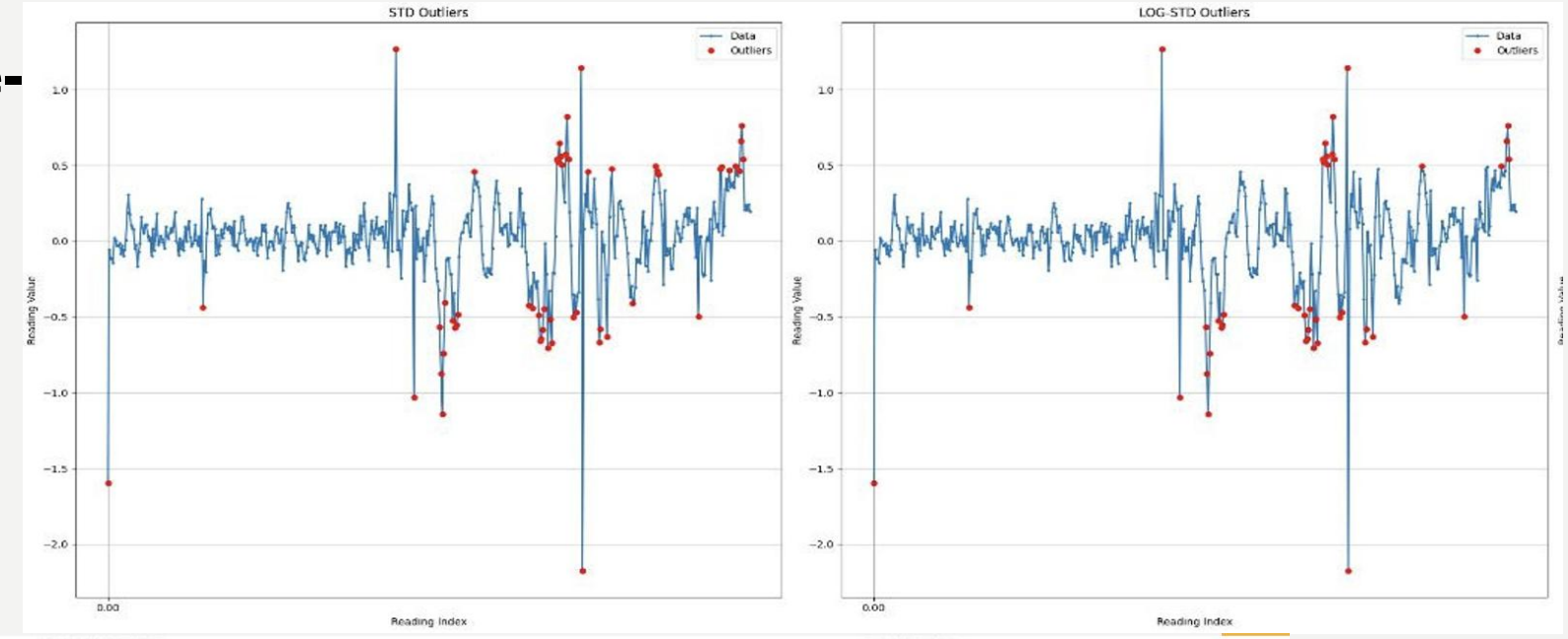


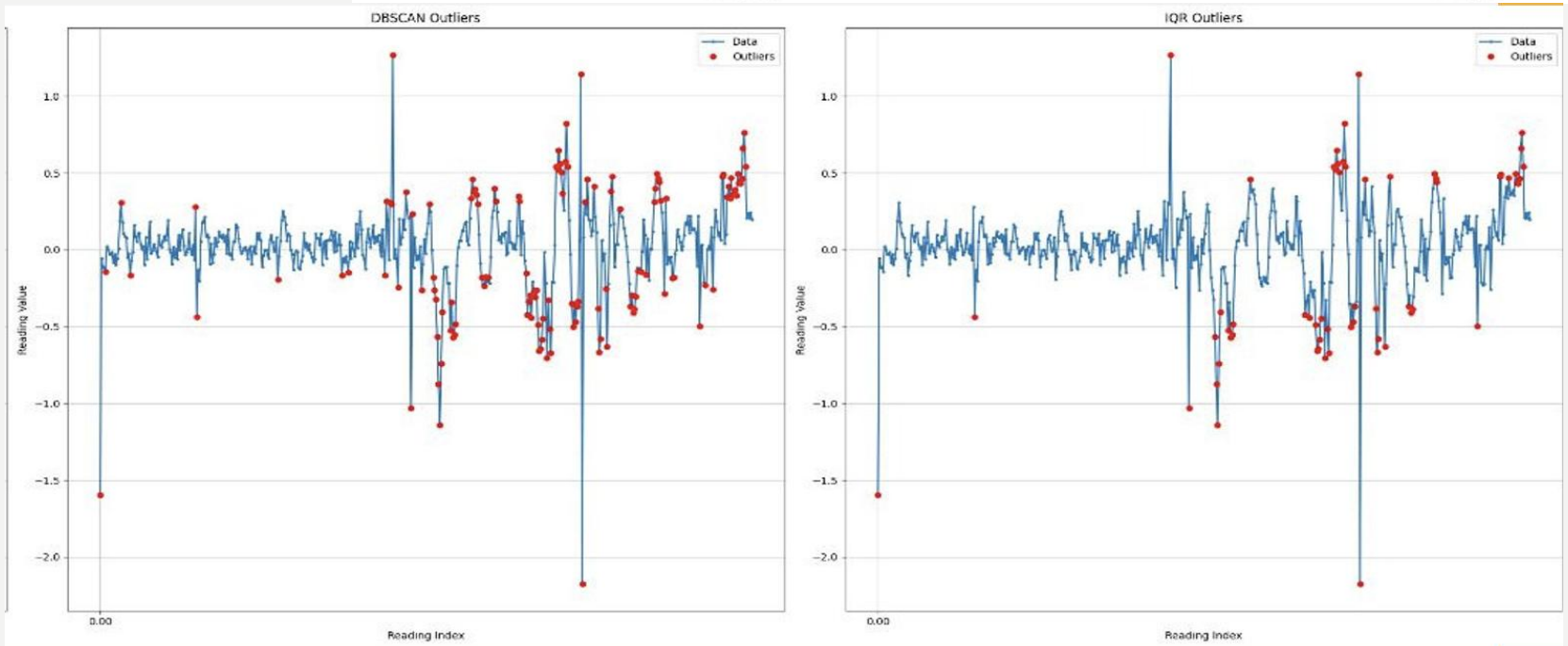
- $x(t)$ — time series valu
- w — moving average window size
- $D(t)$ — deviation from local trend
- k — threshold coefficient (parameter "threshold")
- $y(t)$ — anomaly label

WEARABLE ANOMALY DETECTION

Finding outliers in three-axis accelerometer and gyroscope data from staff smartwatches

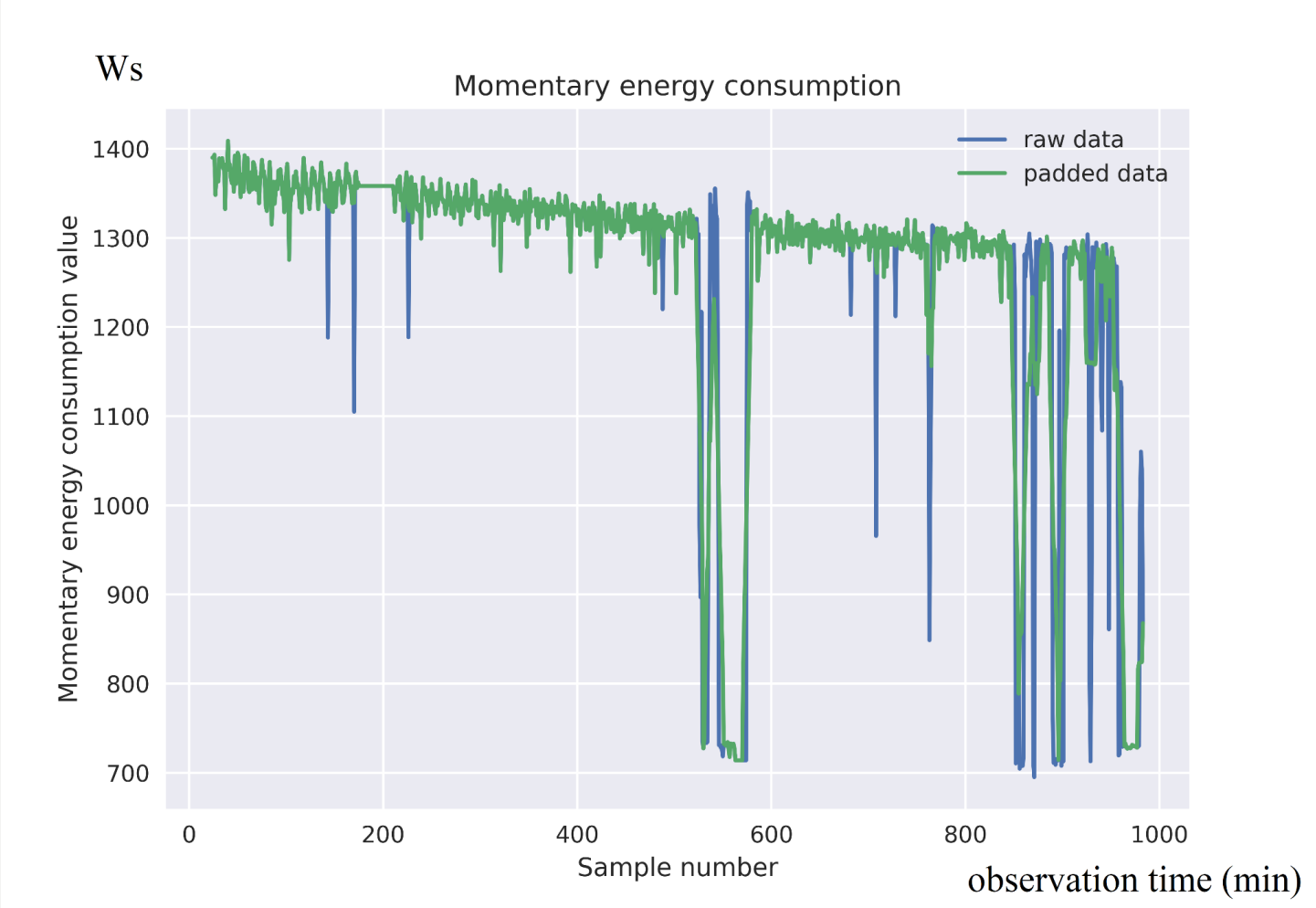
- STD
- LOG-STD
- DBSCAN
- IQR





VARIANCE ANALYSIS USED TO DETECT AND SUPPLEMENT PARTIALLY MISSING DATA BASED ON VARIANCE ANALYSIS

$\sigma = 1.5$ and time window duration 12, using the moving average method.



ADAPTIVE CONSENSUS-WEIGHTED FRAMEWORK FOR TIME SERIES ANOMALY CORRECTION IN FEDERATED AGV SYSTEMS

$$w_{c,m} = \frac{\frac{1}{\mathrm{MAE}_{c,m} + \varepsilon}}{\sum_{m'} \frac{1}{\mathrm{MAE}_{c,m'} + \varepsilon}},$$

$$S_i = \sum_{m \in \text{methods}} \mathbf{1}_{\text{anom}_m(i)} \cdot w_{c,m},$$

$$\text{is_outlier}_i = \begin{cases} 1, & \text{if } S_i \geq \theta, \\ 0, & \text{else.} \end{cases}$$

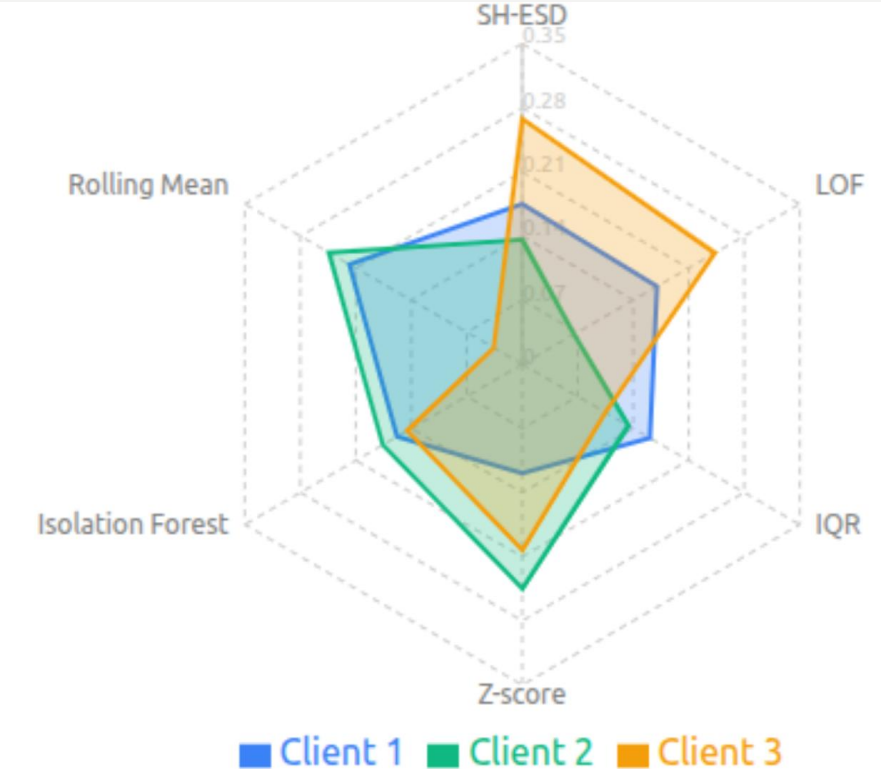
$$w_m^{(0)} = \frac{1}{|M|}$$

$$V_i = \sum_{m \in M} w_m \cdot d_{i,m},$$

$$\text{is_outlier}_i = \begin{cases} 1, & \text{if } V_i \geq T, \\ 0, & \text{else.} \end{cases}$$

$$\mathrm{MAE}_m = \frac{1}{N} \sum_{i=1}^{N} \left| y_i - \hat{y}_i^{(m)} \right|.$$

$$\tilde{w}_m = \frac{1}{\mathrm{MAE}_m + \varepsilon}; \qquad w_m^{\text{new}} = \frac{\tilde{w}_m}{\sum_{k \in M} \tilde{w}_k}$$

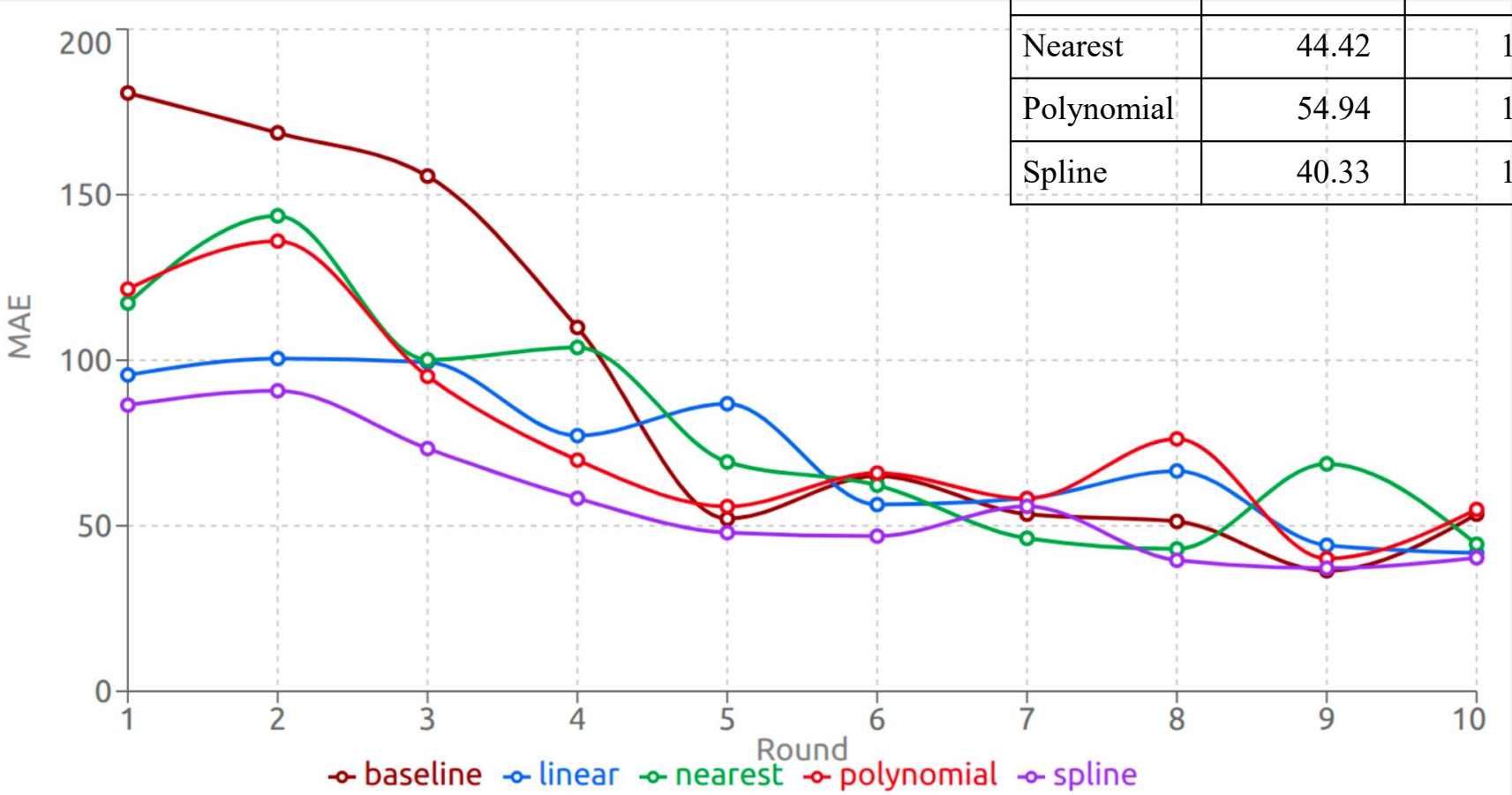


Method	Client 1	Client 2	Client 3
SH-ESD	0.175	0.136	0.268
LOF	0.170	0.065	0.243
IQR	0.161	0.134	0.105
Z-score	0.119	0.245	0.203
Isolation Forest	0.158	0.176	0.145
Rolling Mean	0.218	0.244	0.036

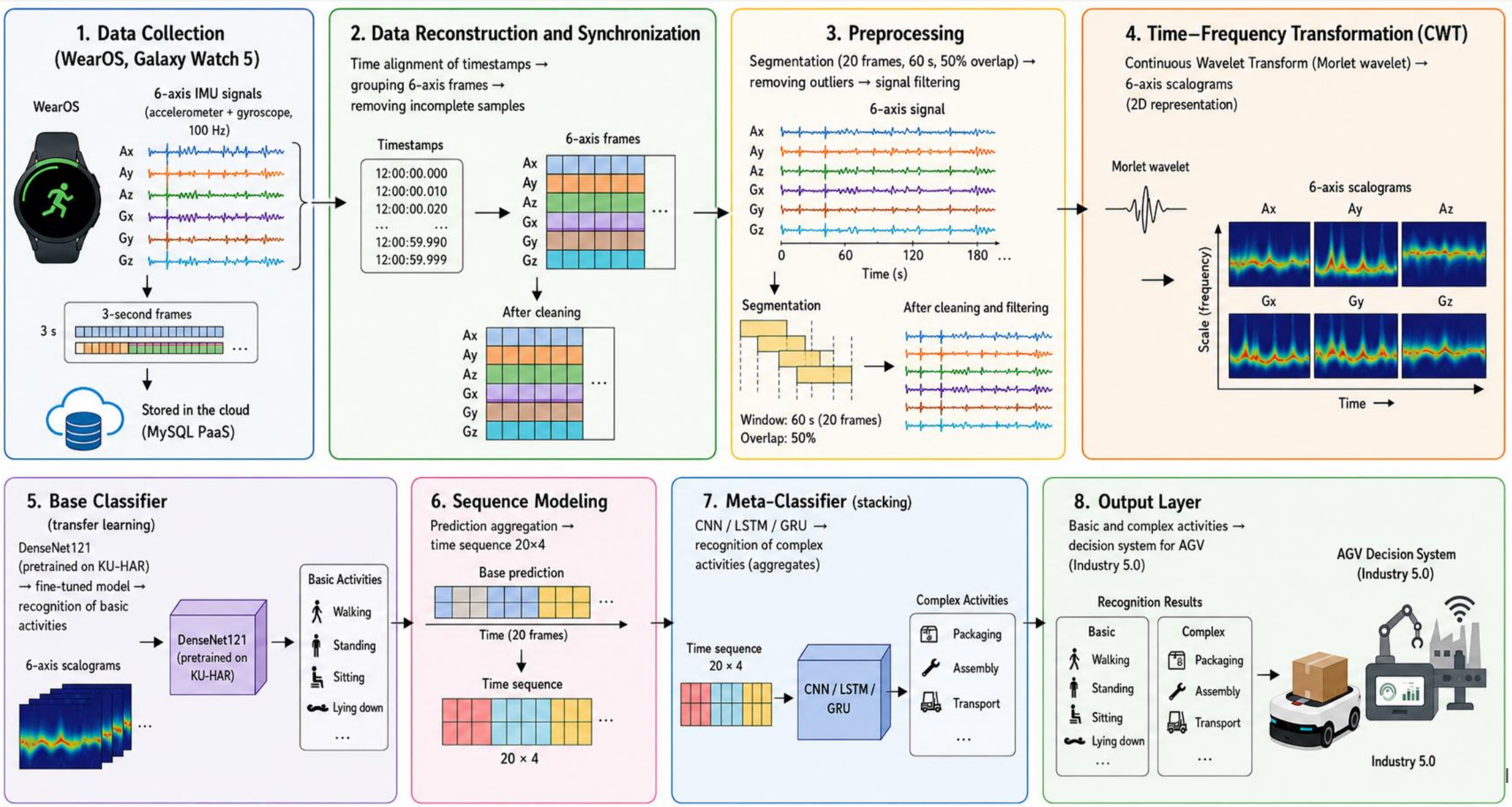
COMPARISON OF THE EFFICIENCY OF INTERPOLATION METHODS IN FL EMULATION.

Global MAE in UF rounds for each interpolation method

Metoda	MAE	MAPE(%)	RMSE	R^2
Baseline	53.47	13.91	161.39	0.9978
Linear	41.78	10.52	180.05	0.9972
Nearest	44.42	11.18	174.87	0.9974
Polynomial	54.94	13.79	198.67	0.9966
Spline	40.33	10.03	182.92	0.9971



HUMAN LOCALIZATION, TRAJECTORY PREDICTION, AND ACTIVITY RECOGNITION



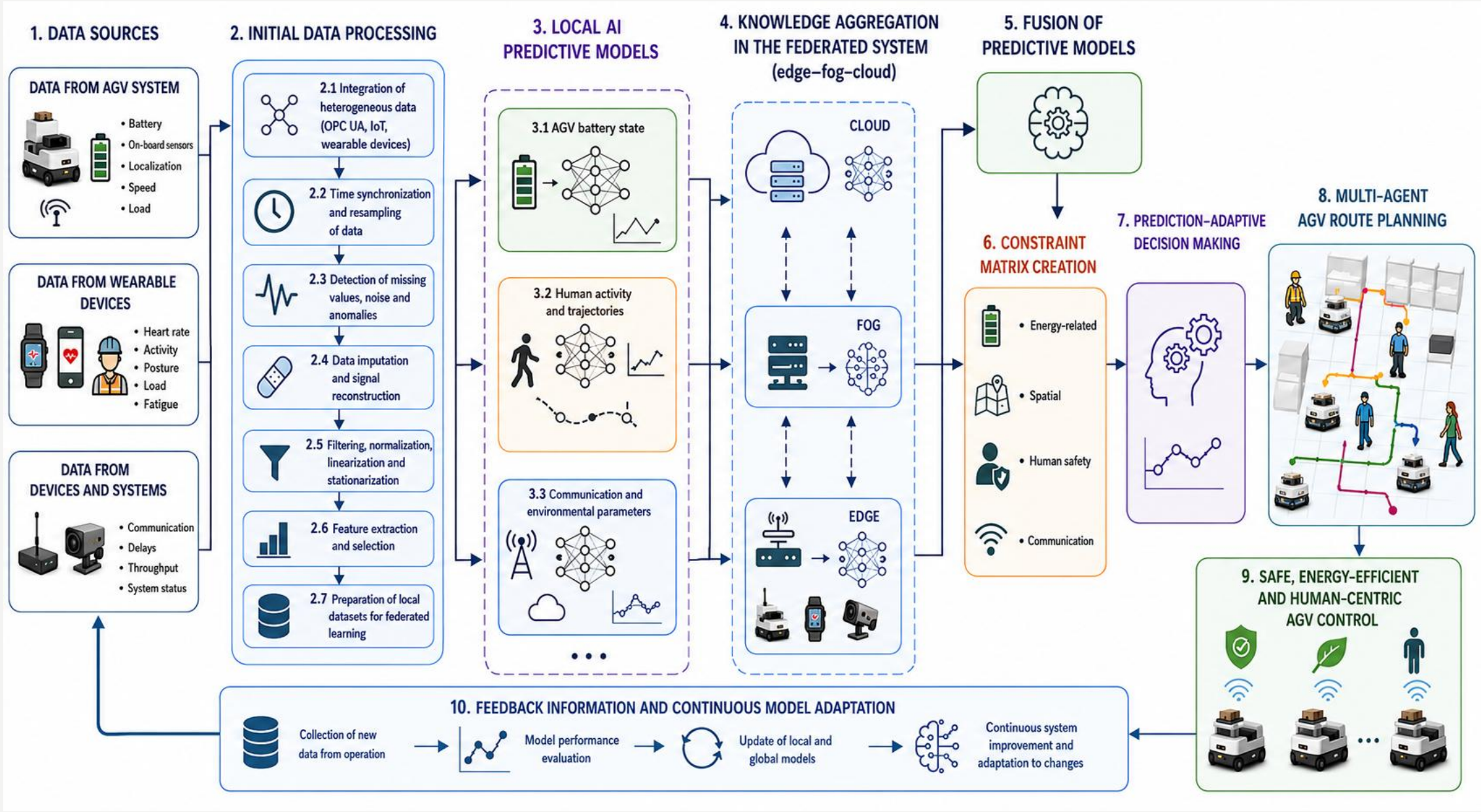
RESULTS RECOGNITION OF COMPLEX ACTIVITY ON THE TEST SUBSET (BASIC CLASSIFIER)

Classifier	Mex. Hat 32	Mex. Hat 64	Mex. Hat 128	Mex. Hat 256	Morlet 32	Morlet 64	Morlet 128	Morlet 256
ResNet50	96.21	95.79	96.06	96.27	94.06	95.47	96.15	96.71
ResNet101	95.84	96.13	96.32	96.31	94.46	95.79	96.15	96.90
ResNet152	95.78	96.11	96.45	96.63	92.77	95.18	96.24	96.63
Xception	–	–	97.33	97.29	–	–	96.93	97.16
InceptionV3	–	–	95.81	95.49	–	–	96.34	96.40
InceptionResNetV2	–	–	95.81	95.58	–	–	96.48	96.32
DenseNet121	97.27	96.96	97.11	97.24	95.81	96.82	96.87	**97.48**
DenseNet169	97.16	96.95	97.04	97.03	95.52	96.68	96.84	97.41
DenseNet201	97.03	96.77	97.00	96.85	95.66	96.85	96.85	97.24

RESULTS OF COMPLEX ACTIVITY RECOGNITION ON THE TEST SUBSET (META-CLASSIFIER)

Classifier	Accuracy	Precision	Recall	AUC	F1-score
CNN	87.50%	87.43%	87.50%	92.40%	87.44%
Single-layer LSTM	69.44%	71.42%	69.44%	76.93%	69.96%
Multi-layer LSTM	72.22%	72.75%	72.22%	78.70%	72.43%
Single-layer BiLSTM	72.22%	75.04%	72.22%	78.43%	72.75%
Multi-layer BiLSTM	73.61%	74.42%	73.61%	78.76%	73.89%
Single-layer GRU	72.22%	76.08%	72.22%	79.74%	72.77%
Multi-layer GRU	72.22%	72.22%	72.22%	80.84%	72.22%
Single-layer BiGRU	72.22%	75.04%	72.22%	77.93%	72.75%
Multi-layer BiGRU	73.61%	76.92%	73.61%	80.84%	74.13%

HUMAN-CENTRIC PREDICTIVE-ADAPTIVE CONTROL OF MULTI-AGENT AGV SYSTEMS IN INDUSTRY 5.0



BATTERY HEALTH PREDICTION MODELS

Long-Term AGV Battery Voltage Prediction with Correlation-Based Feature Reduction

Pearson correlation

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Spearman correlation

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)}$$

Random Forest feature importance

$$FI(f) = \frac{1}{T}\sum_{t=1}^{T}\sum_{v \in V_f} \Delta I(v)$$

Feature selection criterion

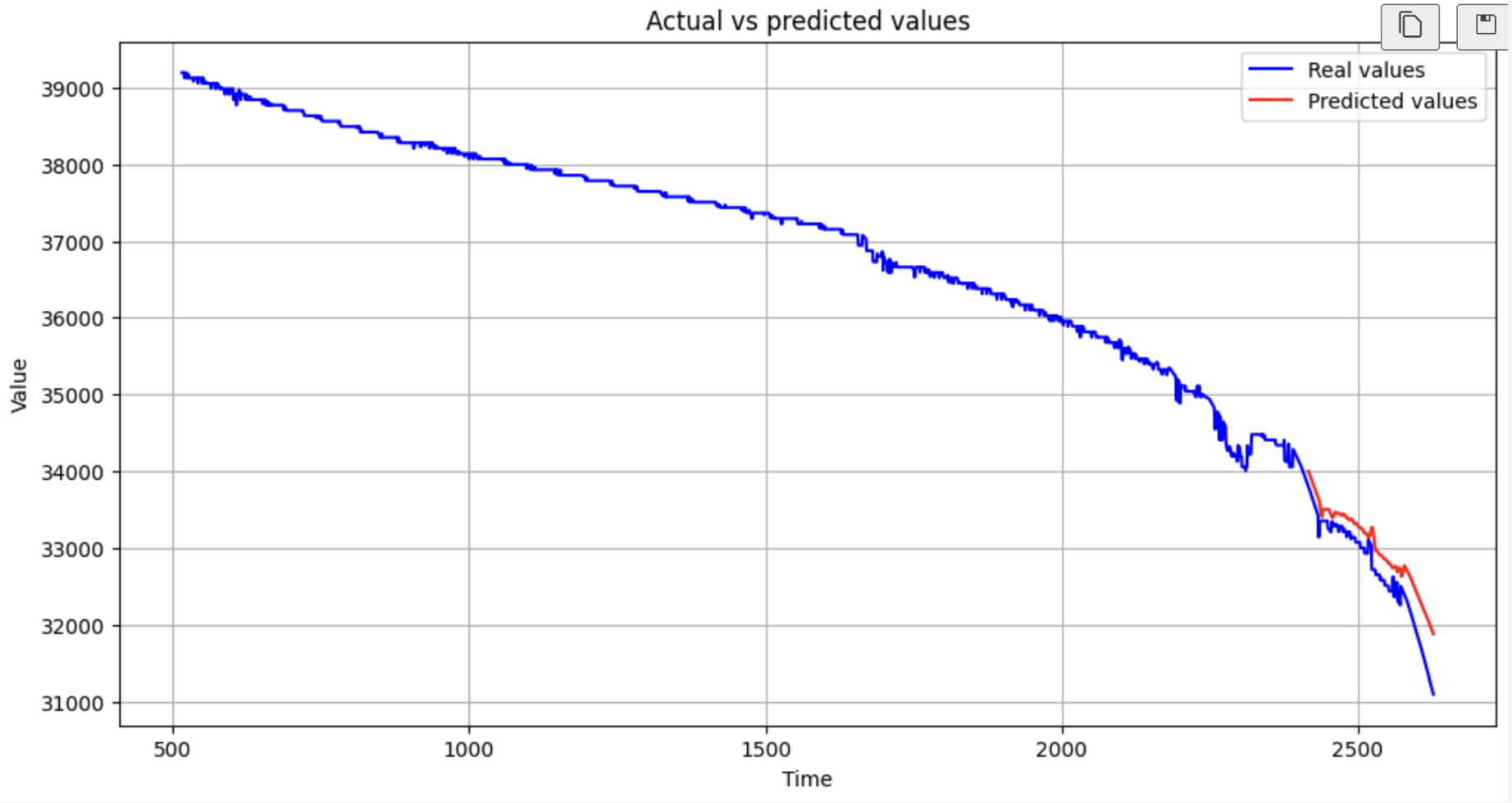
$$|r_{ij}| > \tau \quad \wedge \quad FI(f_i) > FI(f_j)$$

The prediction results of the proposed method and the maximum number of features using the Random Forest method

Method	MAPE	RMSE	MSPE	RMSPE	MBE	ME	R^2	Min.
Pearson correlation	0.05	181049.1	0.01	6.65	57404.7	820493.9	0.99	10.8
Spearman correlation	0.11	347839.3	0.022	14.76	93009.5	1215717.9	0.99	10.22
Kendall	0.46	452789.9	1.04	101.98	222501.6	1281451.9	0.99	10.1
Random Forest	1.825e+20	3076850.18	2.141e+30	1.46e+17	822869.3	14596494.25	0.66	62.2

LONG-TERM AGV BATTERY VOLTAGE PREDICTION

Anomaly Detection → Data Filtering → Sliding-Window LSTM Forecasting




```
MAE: 303.77
MAE (%): 0.93
MSE: 119186.96
MSE (%): 364.15
RMSE: 345.23
RMSE (%): 1.05
R²: 0.71
```

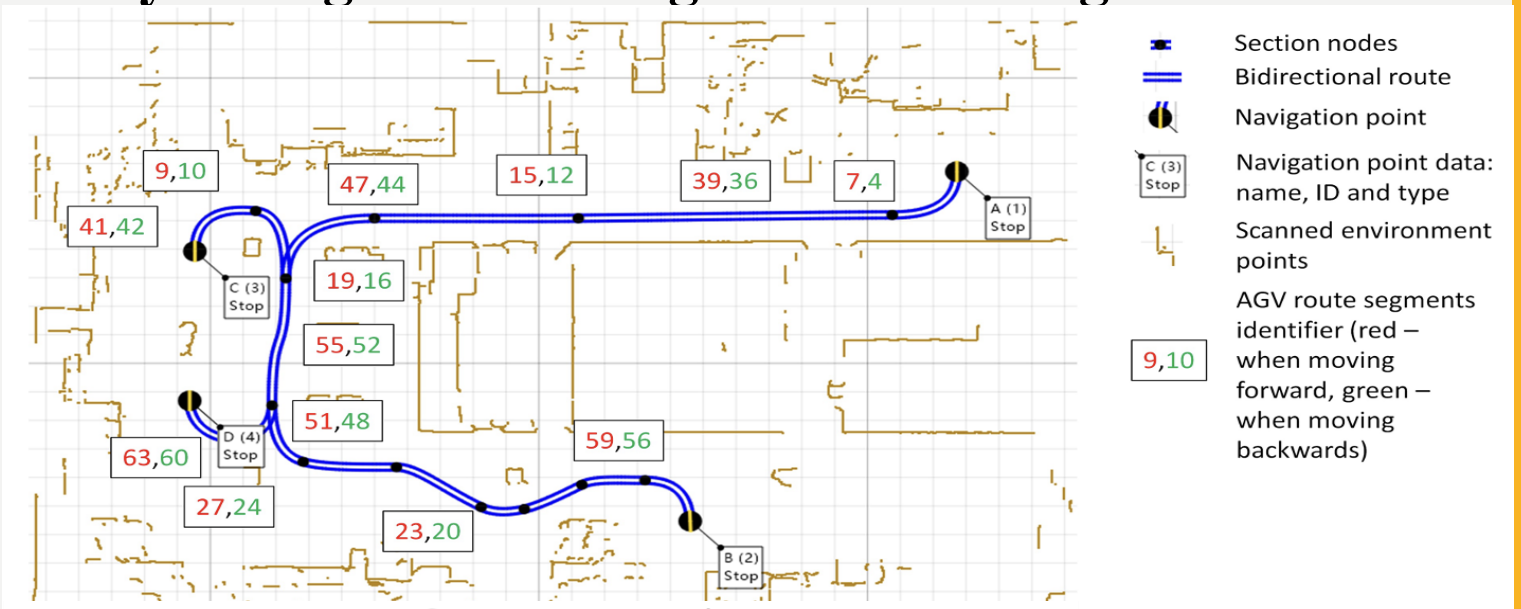
MULTIMODAL BATTERY STATE ESTIMATION AND ENERGY PREDICTION

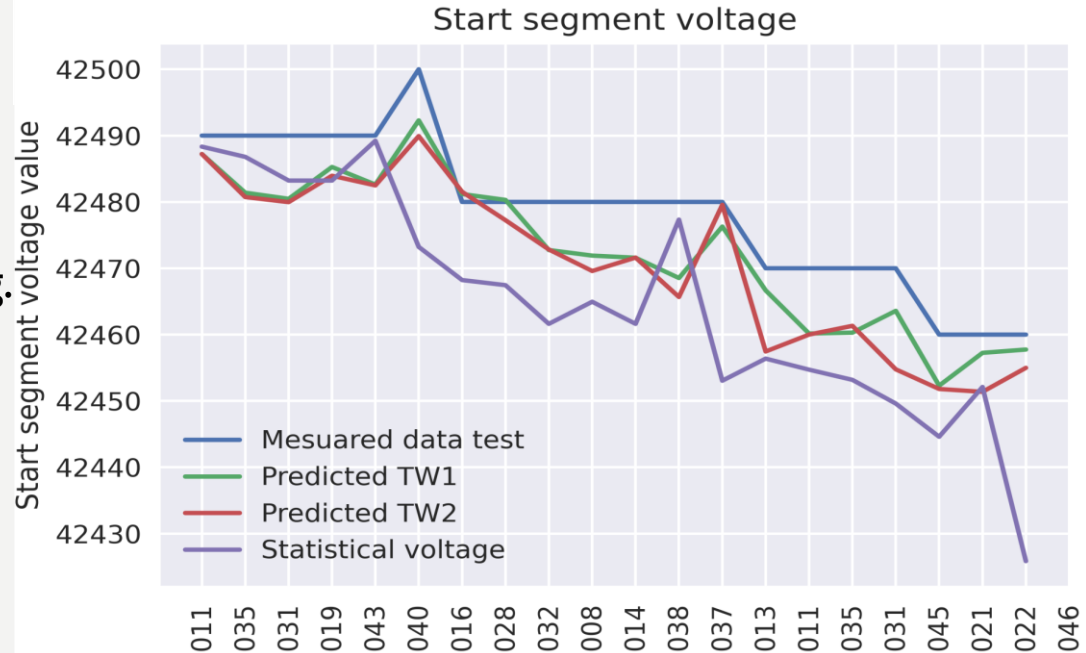
Medium and short-term battery voltage forecasting in AGVs using RNN

Feature Selection

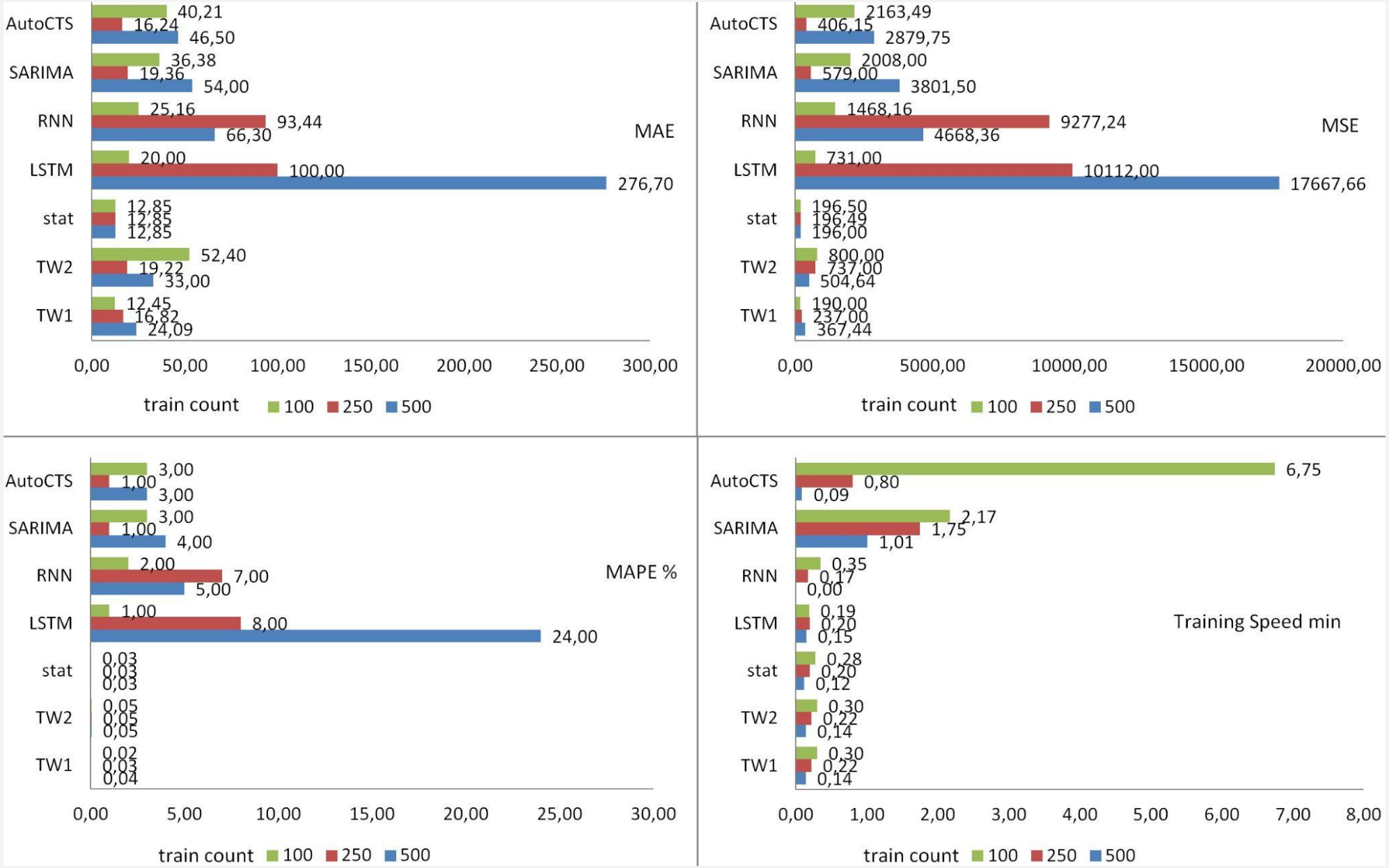
- Segment
- Quantity
- Duration
- Voltage Delta
- Volume

TW1 – segmented forecasting based on raw data.
TW2 – segmented forecasting based on data after intelligent processing.
stat – statistically averaged values for segments.





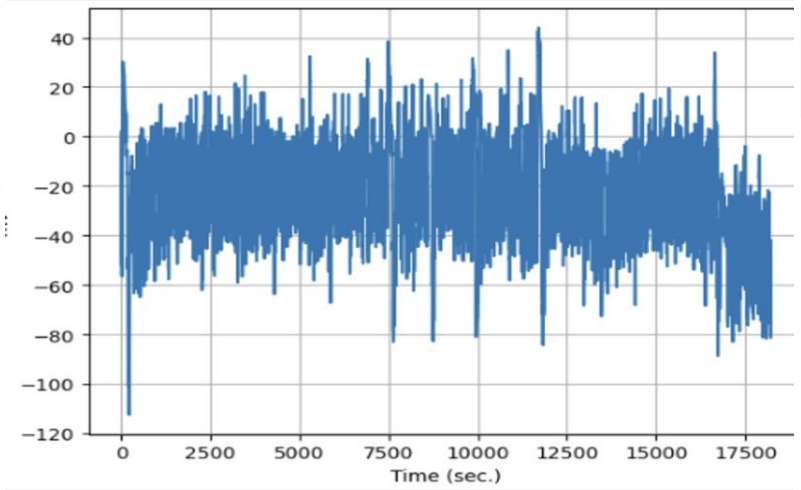
COMPARISON OF FORECAST RESULTS



BATTERY STATUS FORECASTING MODELS

Long-Term Battery Voltage Forecasting in AGV Systems

AGV Data
↓
Stationarity Analysis
↓
MA / WMA / ES / LR / LOWESS
↓
Centralized Signal
↓
Normalization
↓
RNN
↓
Forecasting
↓
MAPE, RMSE, R^2



simple_rnn_input	input:	[(None, None, 1)]
InputLayer	output:	[(None, None, 1)]

simple_rnn	input:	(None, None, 1)
SimpleRNN	output:	(None, 12)

dense	input:	(None, 12)
Dense	output:	(None, 1)

The centered signal became stationary.
Dickey-Fuller test
ADF statistic: -13.014769; p-value: 0.000000;
critical values: 1%: -3.431; 5%: -2.862; 10%: -2.567.

BATTERY STATUS FORECASTING MODELS

Results of short-term battery voltage forecasting in AGV vehicle systems

Errors	Moving average.	Weighted moving average	Exponential smoothing	Smoothing with local regression	Lowess smoothing
MAPE	0.002	0.002	0.002	0.004	**0.002**
RMSE	146.589	151.823	141.481	237.103	**124.239**
MSPE	1.15e-05	1.24e-05	1.08e-05	3.01e-05	**8.29e-06**
RMSPE	0.339	0.352	0.328	0.548	**0.288**
MFE	-90.164	-97.213	-83.907	-156.679	**-68.393**
SEBIAS	-330362	-358132	-309115	-577209	**-251961**
ME	461.821	479.169	455.665	664.735	**419.703**

WIRELESS SIGNAL PREDICTION

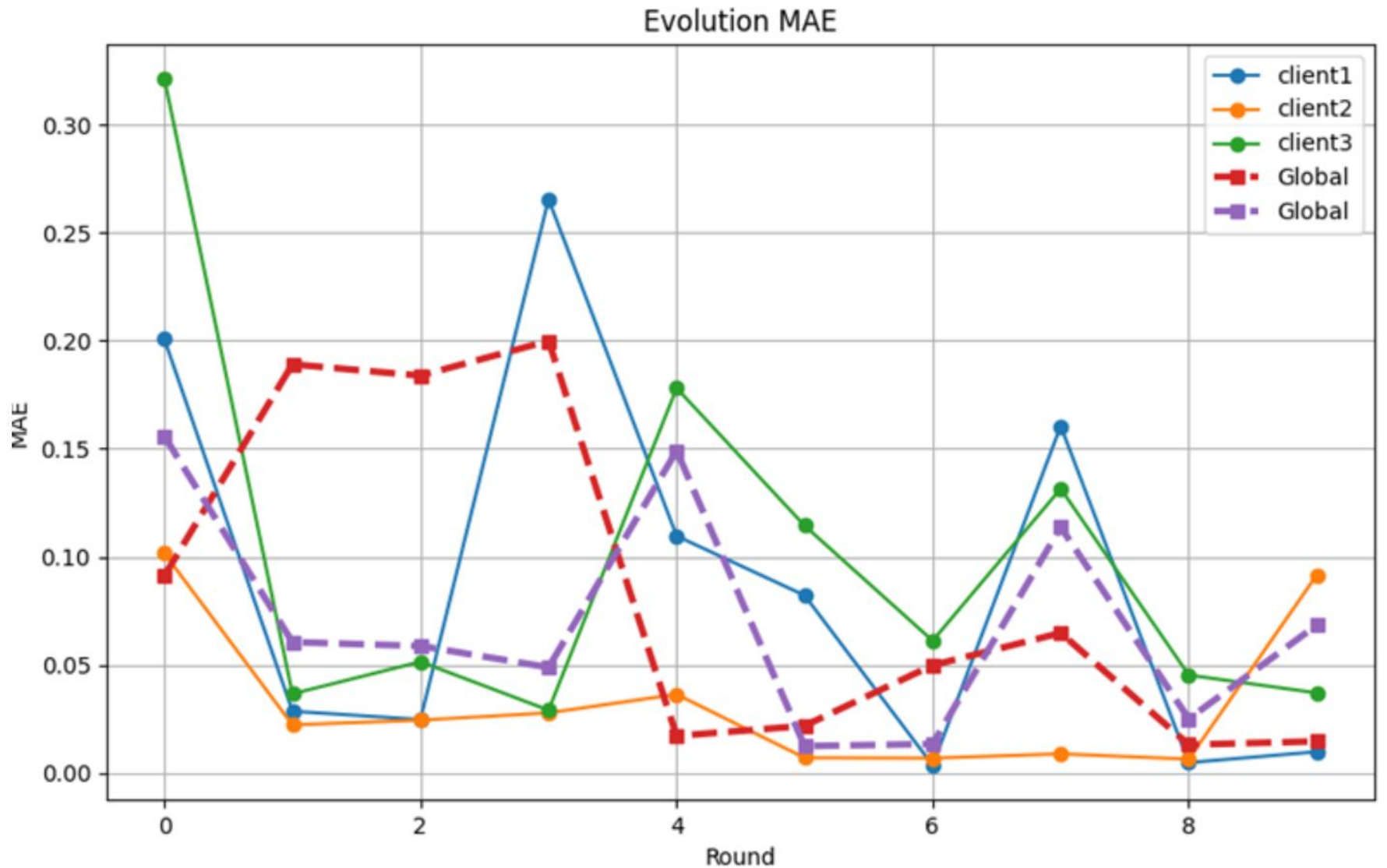


RESULTS OF COMMUNICATION AND ENVIRONMENT PARAMETERS

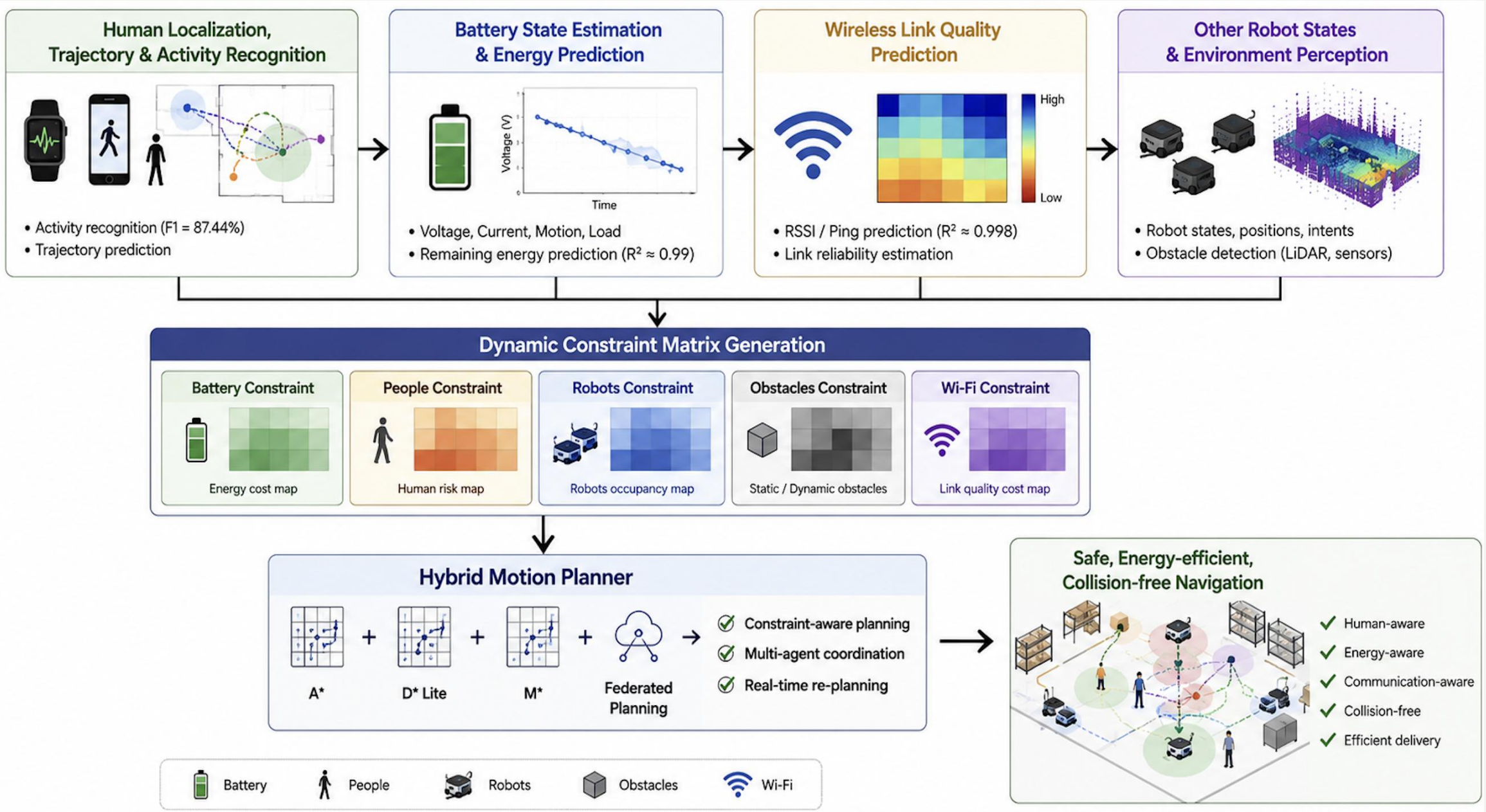
MAE, RMSE I R^2 DLA KLIENTÓW I MODELU GLOBALNEGO W CIĄGU 10 RUND SZKOLEŃ FEDERACYJNYCH

Round	C1 MAE	C1 RMSE	C1 R^2	C2 MAE	C2 RMSE	C2 R^2	C3 MAE	C3 RMSE	C3 R^2	Global MAE	Global RMSE	Global R^2
1	0.201	0.295	0.992	0.102	0.316	0.996	0.321	0.581	0.976	0.156	0.350	0.996
2	0.029	0.139	0.997	0.022	0.220	0.998	0.037	0.350	0.992	0.061	0.256	0.998
3	0.025	0.134	0.998	0.024	0.175	0.999	0.051	0.345	0.993	0.059	0.250	0.998
4	0.265	0.340	0.906	0.028	0.161	0.999	0.029	0.342	0.993	0.049	0.249	0.998
5	0.110	0.178	0.996	0.036	0.156	0.999	0.178	0.382	0.991	0.149	0.283	0.997
6	0.082	0.155	0.994	0.007	0.149	0.999	0.114	0.361	0.992	0.013	0.244	0.998
7	0.004	0.131	0.999	0.007	0.149	0.999	0.061	0.345	0.993	0.013	0.244	0.998
8	0.160	0.220	0.975	0.009	0.149	0.999	0.132	0.364	0.992	0.114	0.270	0.997
9	0.005	0.131	0.999	0.006	0.149	0.999	0.045	0.342	0.993	0.025	0.245	0.998
10	0.010	0.132	0.999	0.092	0.190	0.995	0.037	0.342	0.993	0.068	0.253	0.998
AVG	**0.089**	**0.186**	**0.985**	**0.033**	**0.181**	**0.998**	**0.101**	**0.376**	**0.991**	**0.071**	**0.264**	**0.998**

RESULTS OF COMMUNICATION AND ENVIRONMENT PARAMETERS

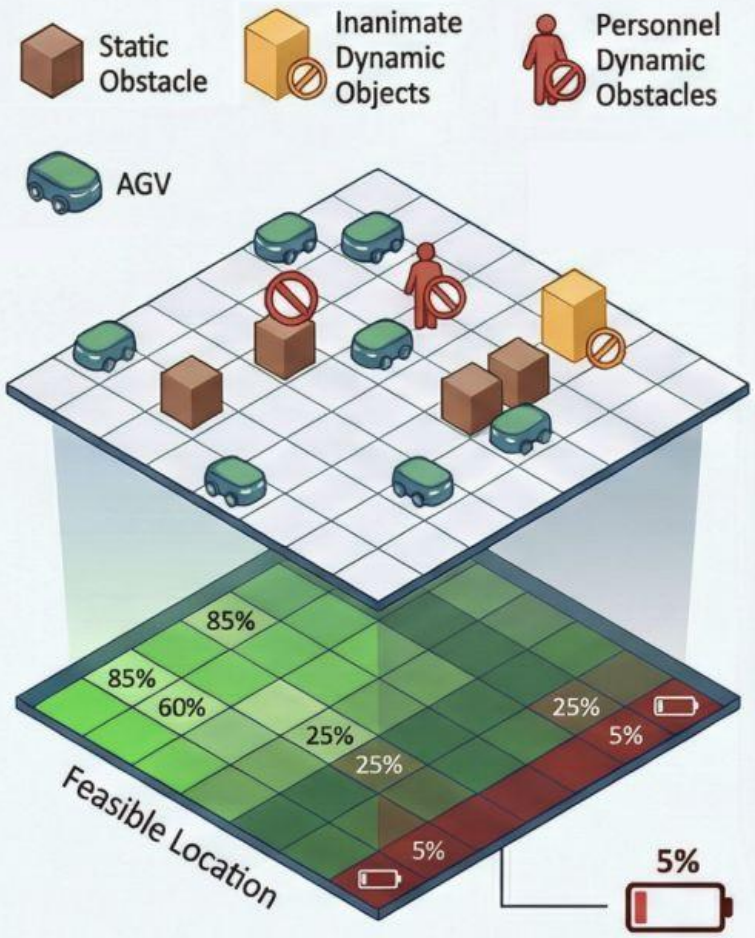


SENSOR FUSION FOR DECISION MAKING



Energy-Aware Spatio-Temporal Multi-Agent Route Planning for AGVs

Environment & Inputs



Battery Residual Charge Matrix B[i,j]

A novel environment model that embeds cell-level energy feasibility into the route map.

Hybrid Algorithm Scheme

Hybrid A*–D* Lite–M* Scheme

A* Global Pathfinding

D* Lite Online Replanning

M* Multi-Agent Conflict Resolution

Generalized Dynamic Cost Function

Energy Consumption — Energy(c)

Travel Time — Time(t)

Safety (Personnel vs. Inanimate Obstacles) — Safety(s)

→ Total Cost Equation

Unifies energy consumption, travel time, and safety into a single cost equation.

Results & Contributions

Energy-Constrained Replanning

Low-SoC agents are automatically stopped or rerouted to ensure operational continuity.

Dynamic Obstacle Management

Successfully differentiates between human personnel (prohibited passage) and inanimate objects (penalty-based passage).

Grid: 10 x 10 cells with static & dynamic obstacles

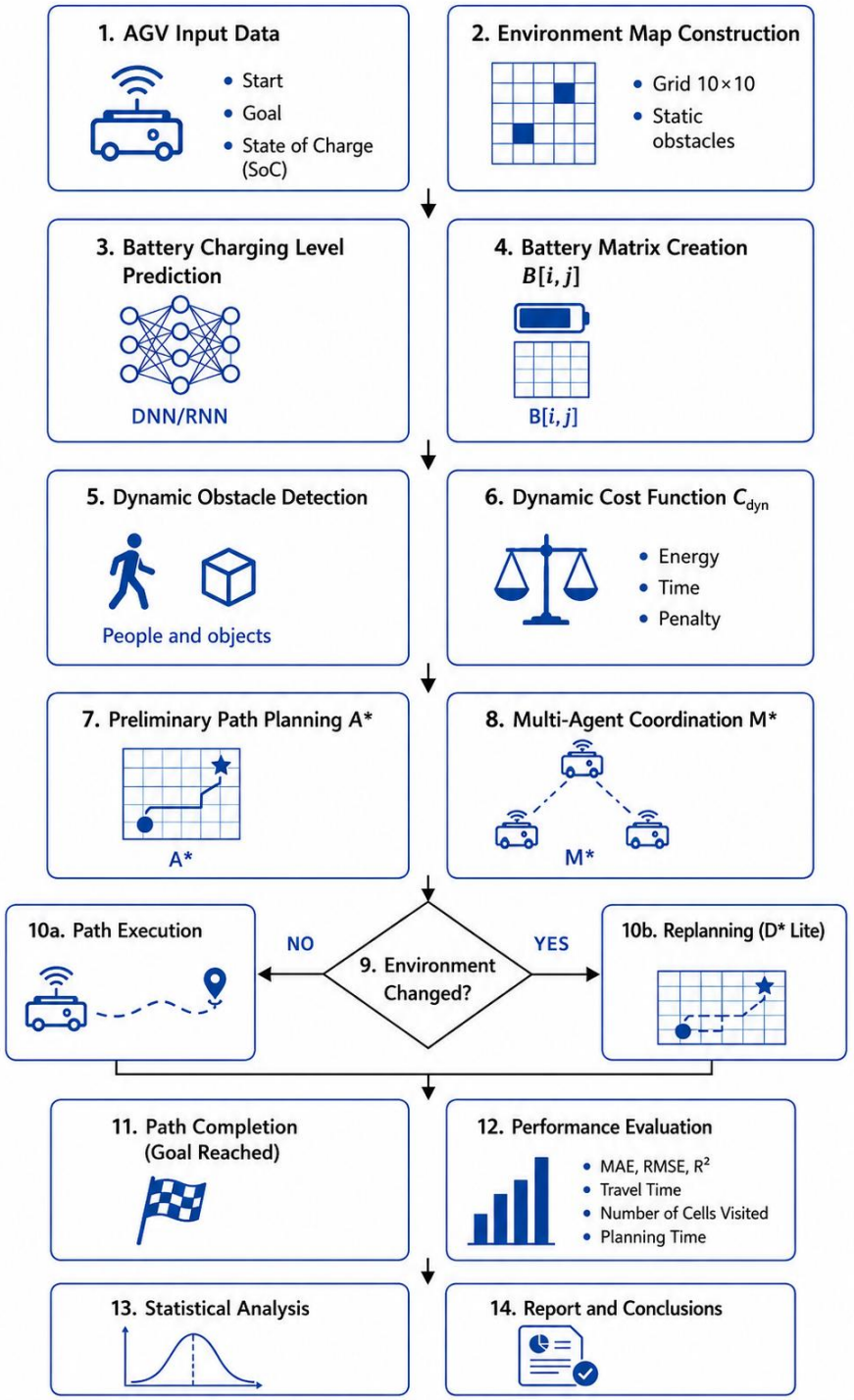
Agents: 3 AGVs with individual start/goal positions

Battery: Initial SoC per agent, B_min threshold

Algorithm Comparison (Table 2)

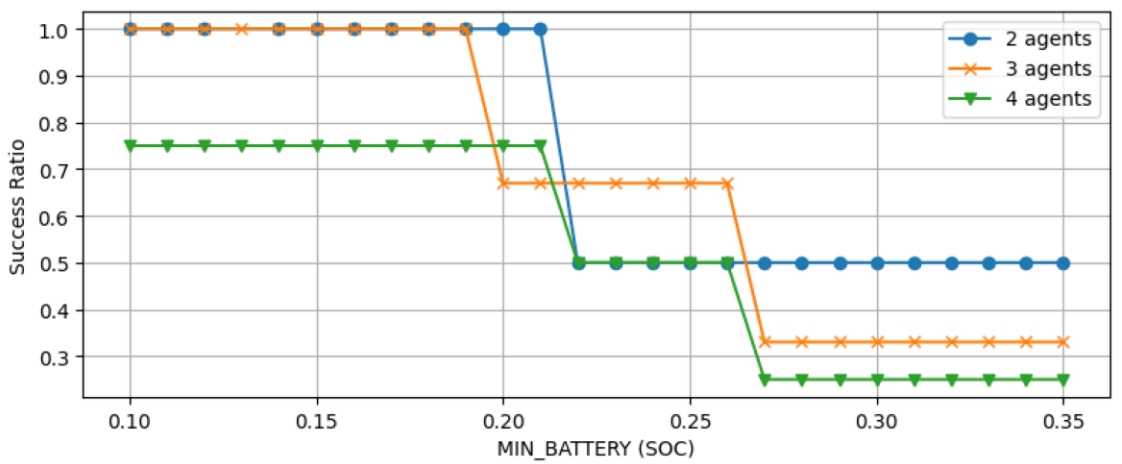
Method	Goals	Cells passed	Cells considered
Proposed hybrid	**3/3**	**31**	**242**
A*	3/3	33	386
Cooperative A*	3/3	33	394
D* Lite	3/3	35	119
M*	2/3	22	59*

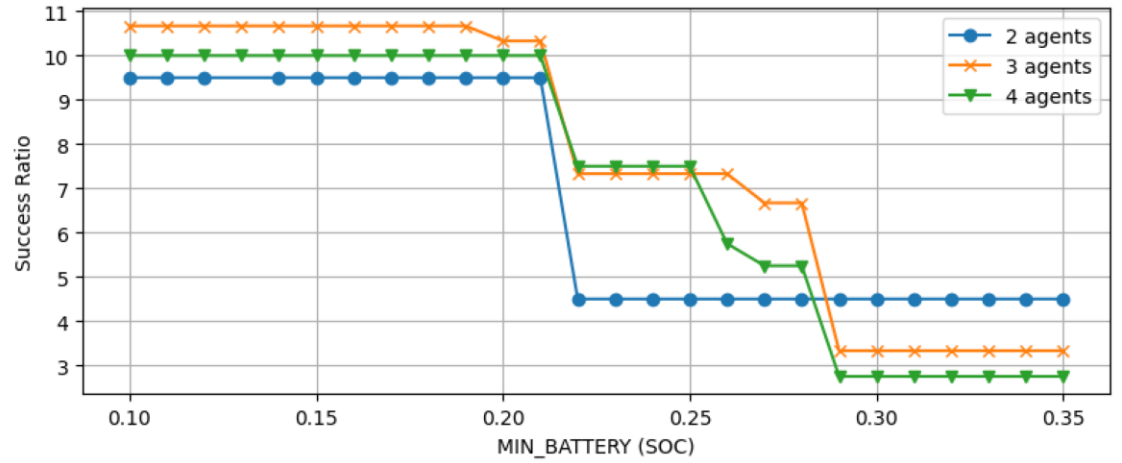
M: Agent 2 failed; proposed = shortest + all goals

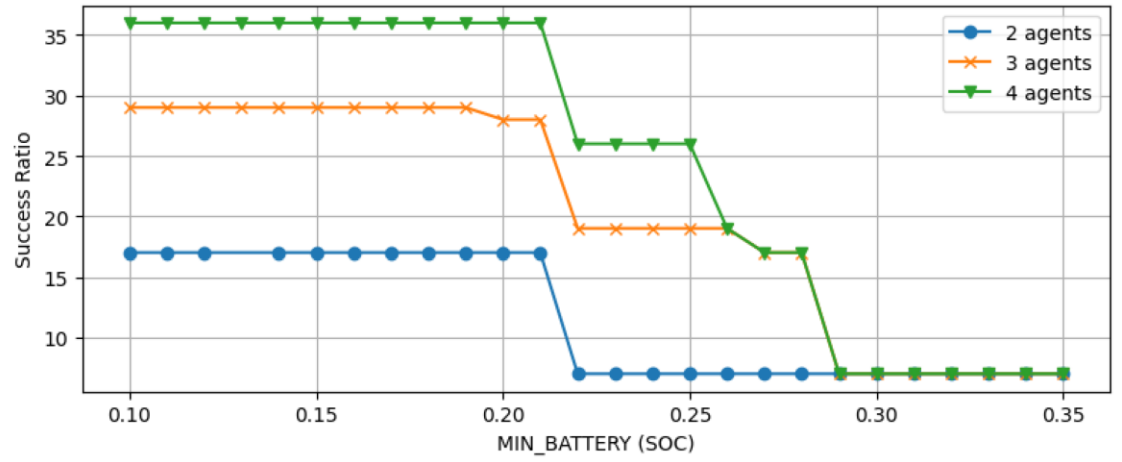


RESULTS OF THE COMPARISON OF DIFFERENT METHODS FOR FINDING THE SHORTEST PATHS WITH CONSTRAINTS

Metod	Agent	Number of cells transmitted	The number of cells to be considered in order
Proposed	1	8	61
Proposed	2	11	84
Proposed	3	12	97
A*	1	8	118
A*	2	11	74
A*	3	14	194
Cooperative method A*	1	8	126
Cooperative method A*	2	11	74
Cooperative method A*	3	14	194
M*	1	8	25
M*	2	2	None
M*	3	12	34
D* Lite	1	10	67
D* Lite	2	11	19
D* Lite	3	14	33

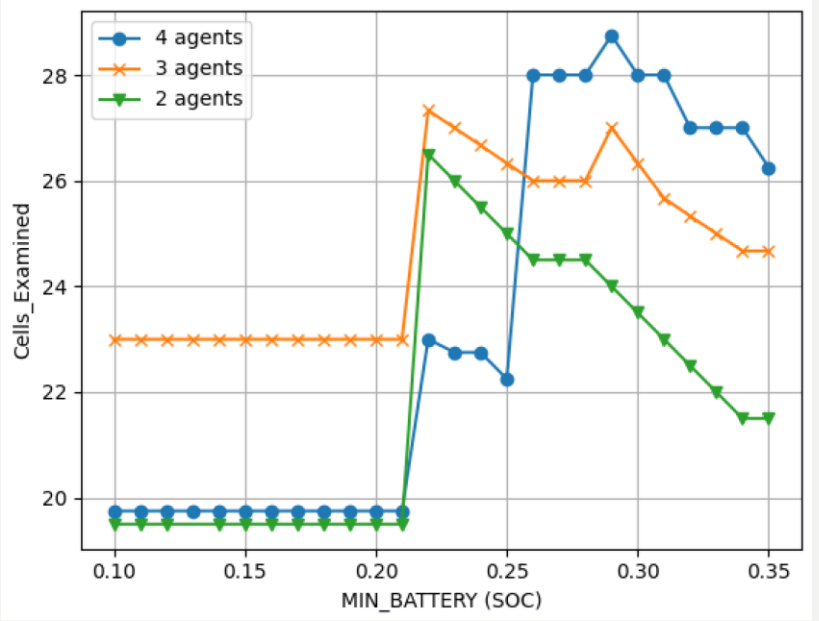






The impact of the minimum SoC threshold on the parameters of performance of path planning: average length of path, number of tested cells and time of planning.

Dependence of the number of tested cells on the minimum SoC threshold



AGV RELIABILITY ANALYSIS

1 AGV SYSTEM DEFINITION



- Define the goal of the analysis
- Identify all components
- Classify components as critical and non-critical

2 SYSTEM STRUCTURE

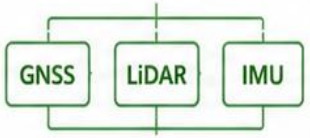
Series components (critical)



Accumulator – Programming – Drive control – Steering system

$$R_{sz}(t) = \prod_{i=1}^{n_s} R_i(t)$$

Parallel components (redundant)



$$R_p(t) = 1 - \prod_{j=1}^{n_r} [1 - R_j(t)]$$

3 RELIABILITY MODELING OF COMPONENTS

Exponential distribution

$$R(t) = e^{-\lambda t}$$

$$f(t) = \lambda e^{-\lambda t}$$

$$\lambda(t) = \lambda$$

Weibull distribution

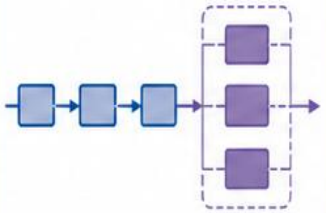
$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}$$

η – scale parameter
β – shape parameter

4 AGV SYSTEM OVERALL RELIABILITY



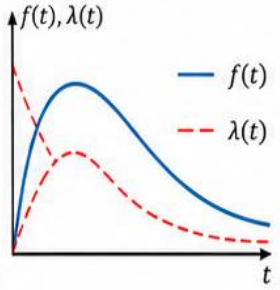
$$R_{AGV}(t) = R_{sz}(t) \cdot R_p(t)$$

$$Q_{AGV}(t) = 1 - R_{AGV}(t)$$

$$P(t) = R_{AGV}(t)$$

$R_{AGV}(t)$ – reliability of the AGV system
$Q_{AGV}(t)$ – probability of failure
$P(t)$ – probability of error-free operation

5 AVAILABILITY ANALYSIS



$$f(t) = \frac{dR(t)}{dt}$$

$$\lambda(t) = \frac{f(t)}{R(t)}$$

$f(t)$ – probability density function of time to failure
$\lambda(t)$ – failure intensity (hazard rate)

6 RELIABILITY INDICATORS EVALUATION



MTTF – Mean Time To Failure

$$MTTF = \int_0^{\infty} R(t)\,dt$$

Other indicators:

- MTBF – Mean Time Between Failures
- Availability $A(t) = \frac{MTTF}{MTTF + MTTR}$
- Probability of system readiness

7 CONCLUSIONS AND SYSTEM IMPROVEMENT

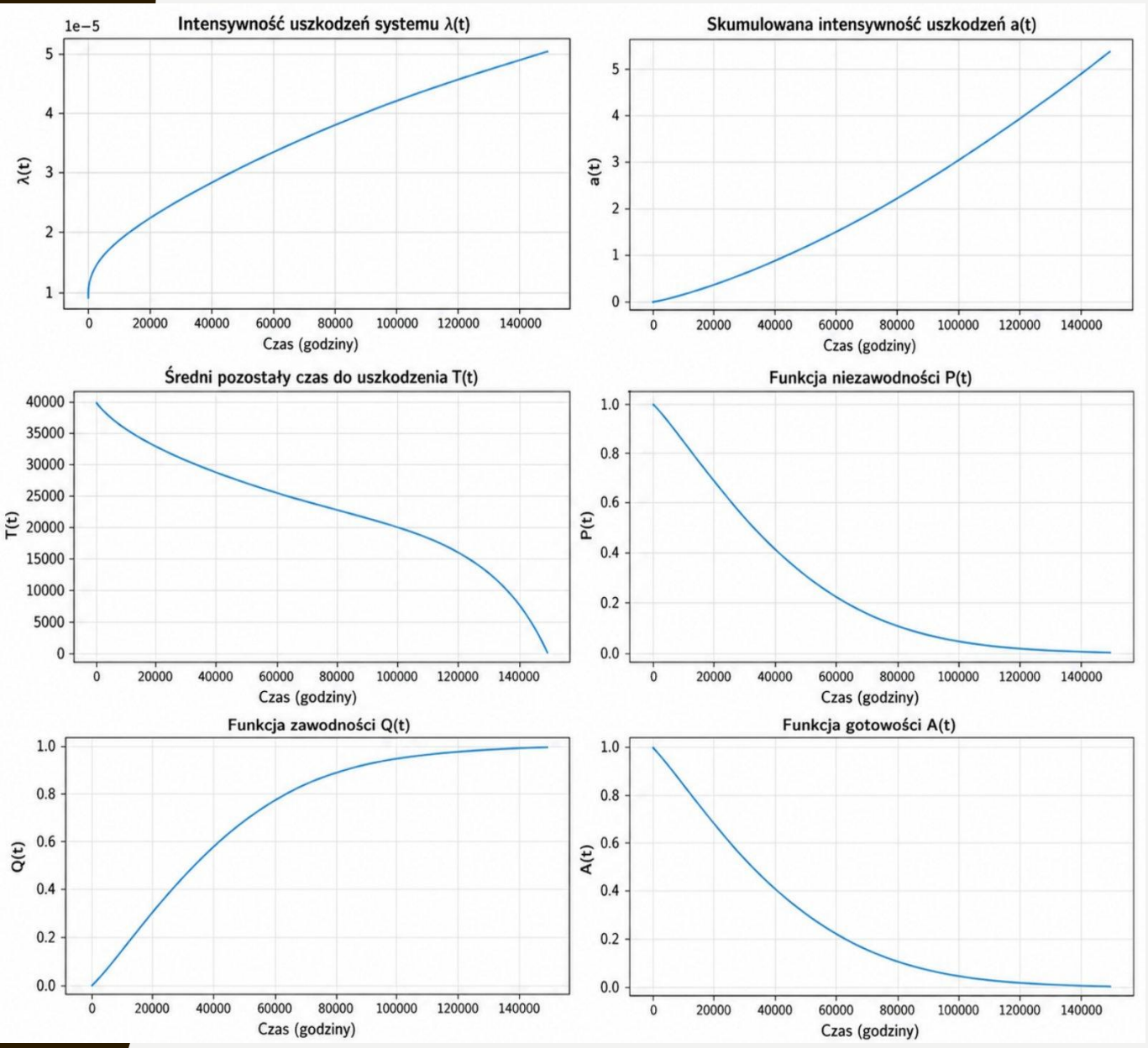


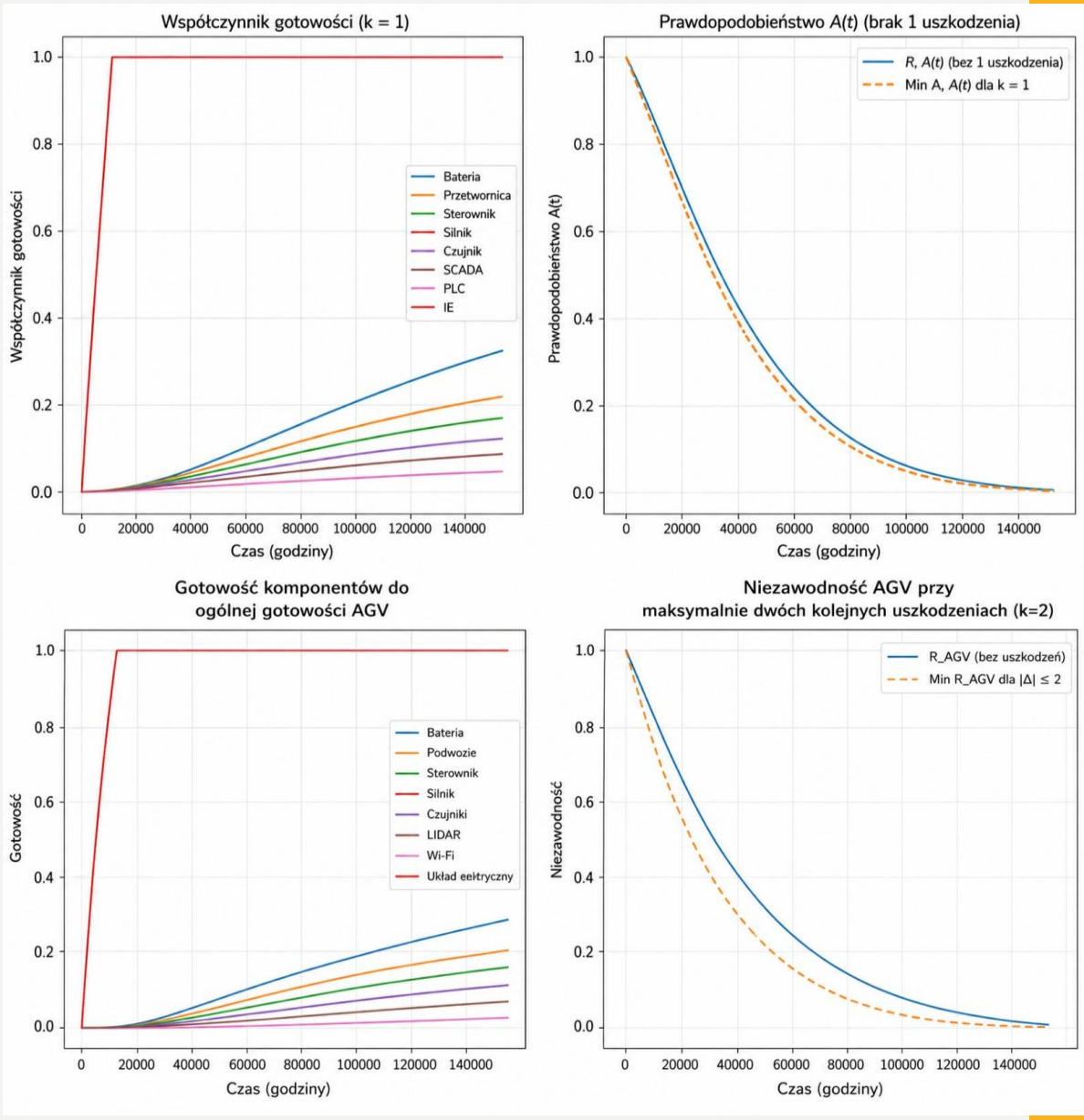
- Identify critical components
- Optimize structure (series/parallel, redundancy)
- Select components with higher reliability (η, β, λ)
- Plan maintenance and replacements
- Improve reliability algorithms

LEGEND

$R(t)$	– reliability (probability of error-free operation up to time t)	$R_{sz}(t)$	– reliability of the series part	λ	– constant failure rate (exponential distribution)
$Q(t)$	– probability of failure up to time t	$R_p(t)$	– reliability of the parallel part	n_s	– number of components in the series structure
$f(t)$	– probability density function	$R_{AGV}(t)$	– reliability of the AGV system	n_r	– number of components in the parallel structure
$\lambda(t)$	– failure intensity (hazard rate)	η	– scale parameter of the Weibull distribution	$MTTF$	– Mean Time To Failure (mean time to failure)
		β	– shape parameter of the Weibull distribution	$MTTR$	– Mean Time To Repair (mean time to repair)

AGV RELIABILITY ANALYSIS RESULTS





IMPACT OF SUBSYSTEM CONFIGURATION ON OVERALL AGV RELIABILITY

1 DATA COLLECTION ON COMPONENTS

- Identification of components
- Determination of connector type (series / parallel)
- Collection of reliability data (MTTF, *shape k*, *scale λ*)

2 MODELING OF COMPONENT RELIABILITY

Weibull distribution:

$$R(t) = e^{-(t/\eta)^k}$$

$$f(t) = \frac{k}{\eta}\left(\frac{t}{\eta}\right)^{k-1} \cdot e^{-(t/\eta)^k}$$

$$\lambda(t) = \frac{k}{\eta}\left(\frac{t}{\eta}\right)^{k-1}.$$

Exponential distribution:

$$R(t) = e^{-\lambda t}$$

$$f(t) = \lambda e^{-\lambda t}$$

$$\lambda(t) = \lambda$$

$$MTTF = \int_0^\infty R(t)\,dt$$

3 MODELING OF MRP PLATFORM STRUCTURE

Series structure:

$$R_{series}(t) = \prod_{i=1}^{n} R_i(t)$$

Parallel structure:

$$R_{parallel}(t) = 1 - \prod_{i=1}^{n}[1 - R_i(t)]$$

Series-parallel structure:

$$R_{sys}(t) = R_{series}(t) \times R_{parallel}(t)$$

4 RELIABILITY INDICATORS CALCULATION

System MTTF:

$$MTTF_{sys} = \int_0^\infty R_{sys}(t)\,dt$$

Failure intensity (hazard rate):

$$\lambda_{sys}(t) = -\frac{d}{dt}\ln\left(R_{sys}(t)\right)$$

Probability of failure at time t:

$$R_{sys}(t)$$

Probability of no failure (availability):

$$F_{sys}(t) = 1 - R_{sys}(t)$$

5 ROBUSTNESS AND SURVIVABILITY MODELING (m out of n)

A system is considered operational if at least m out of n platforms are operational.

$$R_{m\ out\ of\ n}(t) = \sum_{i=m}^{n}\binom{n}{i}[R_p(t)]^i[1 - R_p(t)]^{n-i}$$

where:

$R_p(t)$ – reliability of a single platform

n – number of platforms in the system

m – minimum number of operational platforms required

6 RESULTS ANALYSIS AND VISUALIZATION

- Plots: $R(t)$, $\lambda(t)$, $F(t)$
- Component sensitivity analysis:

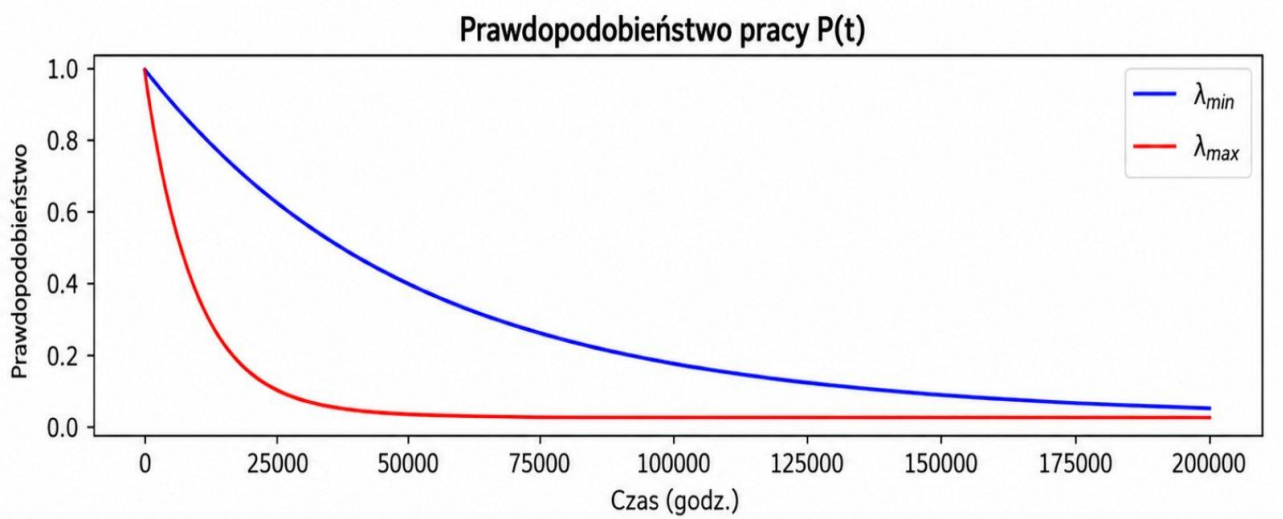
$$S_i(t) = \frac{\partial R_{sys}(t)}{\partial R_i(t)} \cdot \frac{R_i(t)}{R_{sys}(t)}$$

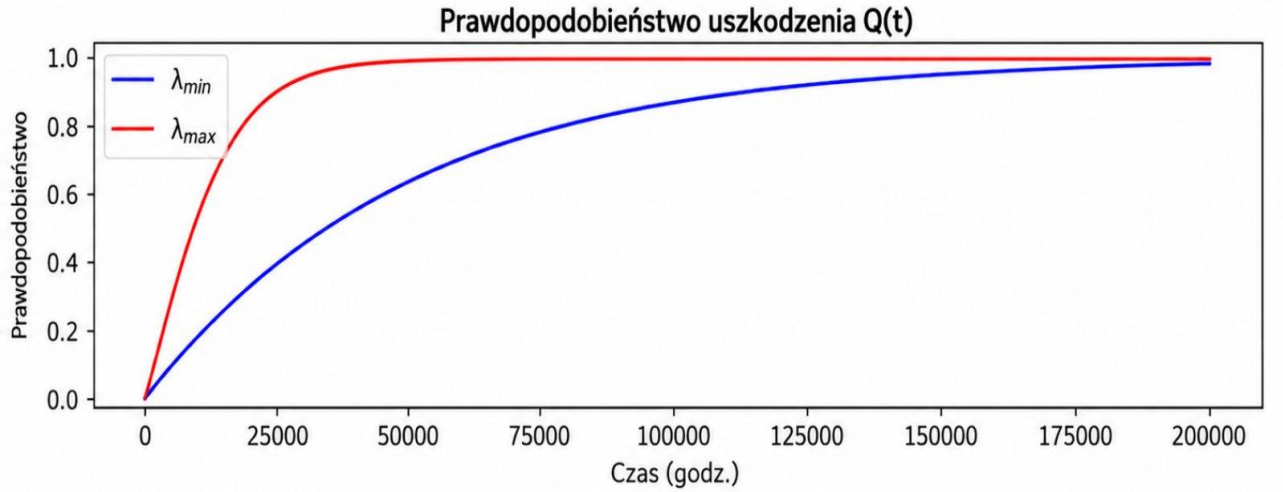
- Failure scenarios
- Design and operational recommendations

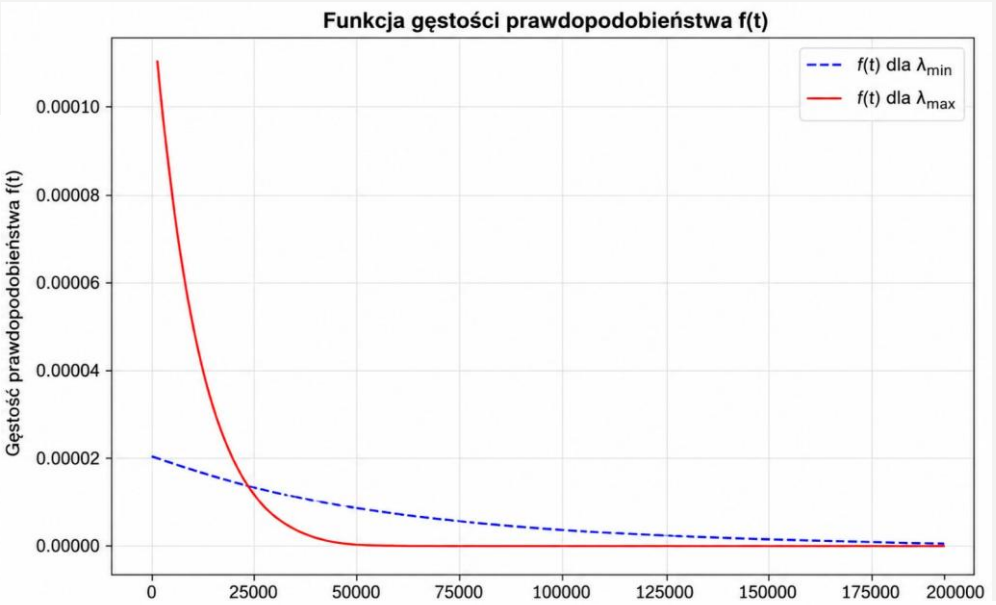
Notation:

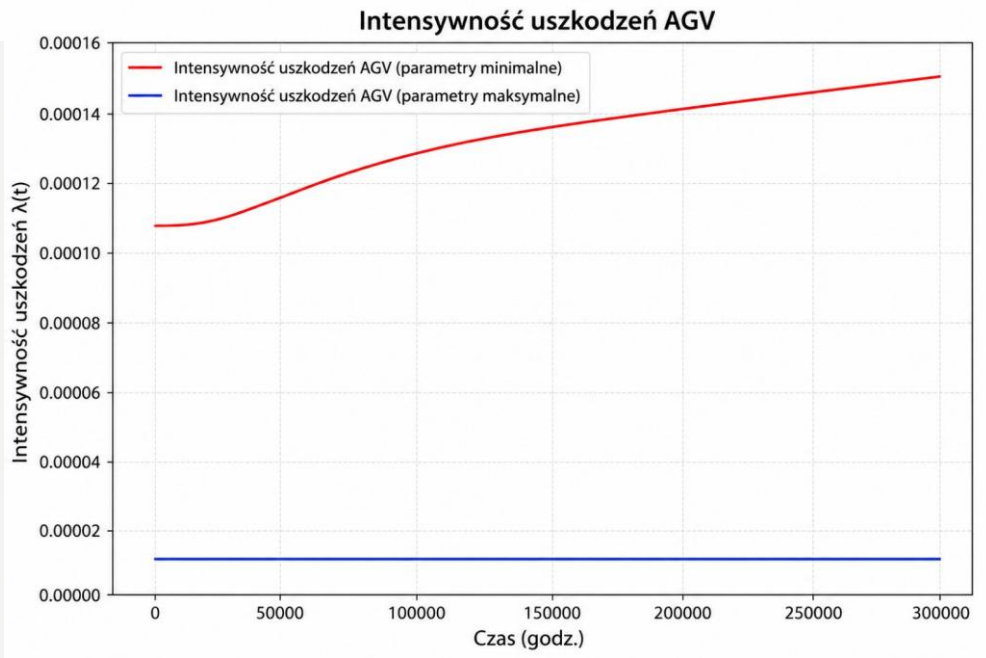
$R(t)$ – reliability function
$F(t)$ – cumulative distribution function (CDF)
$f(t)$ – probability density function (PDF)
$\lambda(t)$ – failure intensity (hazard rate)
$MTTF$ – Mean Time To Failure
k – shape parameter of the Weibull distribution
η – scale parameter of the Weibull distribution
λ – failure rate (exponential distribution)
n – number of platforms in the system
m – minimum number of operational platforms required
$R_p(t)$ – reliability of a single platform
$S_i(t)$ – sensitivity of the i-th component

RESULT OF THE IMPACT OF SUBSYSTEM CONFIGURATION ON OVERALL AGV RELIABILITY



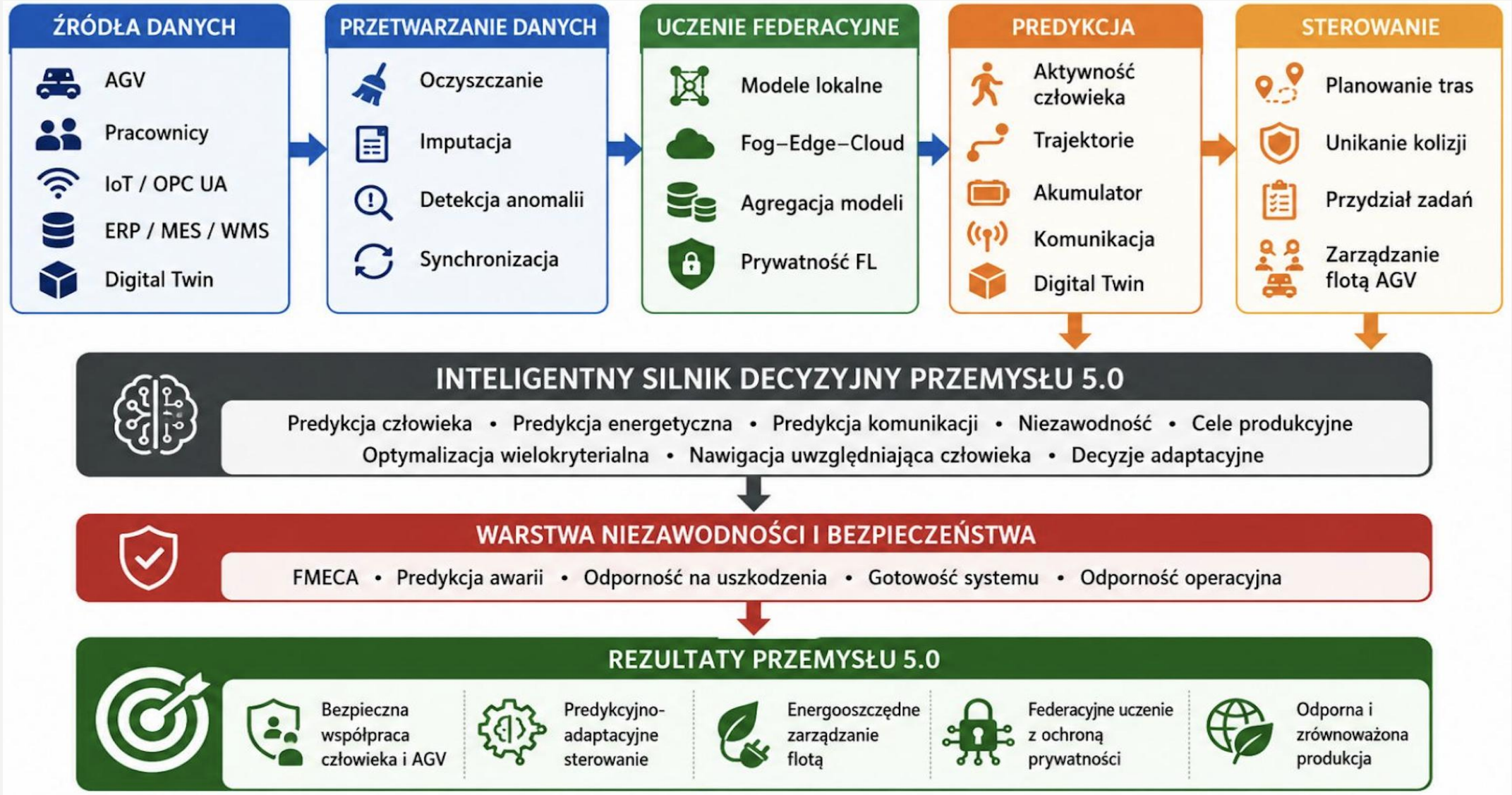






INTEGRATED SYSTEM FRAMEWORK (FINAL SYSTEM)

enables intelligent, safe and adaptive AGV control, taking into account the human as an active element of the system, while optimizing energy consumption and meeting real-time constraints, while maintaining safety requirements and ethical principles of human-machine interaction



MAIN CONTRIBUTIONS

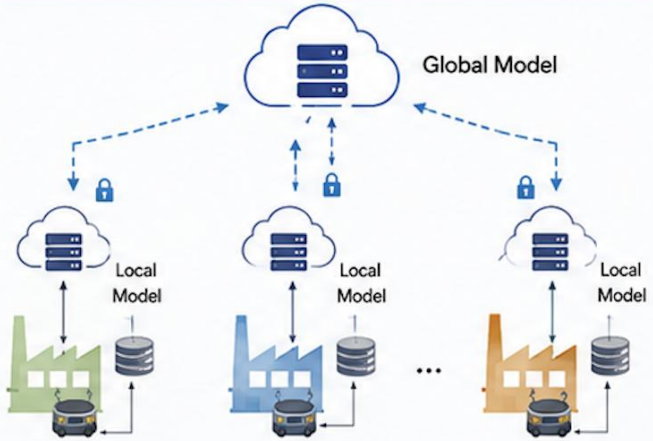
1 Human-Centric Sensor Fusion



The human becomes an integral part of the control system

- Human safety improvement
- Accurate localization & trajectory prediction
- Activity awareness
- Better human-robot interaction

2 Federated Learning



Benefits

- **Privacy Preservation**: Raw data never leaves local devices
- **Scalability**: Supports many robots, sites and users

3 Energy-Aware Multi-Agent Planning



- Energy constraints
- People safety
- Multi-robot coordination
- Obstacle avoidance
- Wi-Fi reliability

Outcomes

- Safe and reliable routes
- Lower energy consumption
- Less downtime, higher productivity

Impact: Bringing human awareness, data privacy, and energy efficiency together for the next generation of industrial mobile robot systems.

PUBLICATION MAP & ACHIEVEMENT

Transfer Learning Approach for Human Activity Recognition Based on Continuous Wavelet Transform Pavliuk, Olena, Mishchuk, Myroslav,Strauss, Christine AlgorithmsOpen source preview, 2023, 16(2), 77 Hybrid machine learning technologies for predicting comprehensive activities of industrial personnel using smartwatch data/ O. M. Pavliuk et al. Radio Electronics, Computer Science, Control. 2025. No. 3. P. 96–111.	1.Human Activity Recognition & Movement / Trajectory Prediction – integration of humans with the AGV system
A Novel Methodology Based on a Deep Neural Network and Data Mining for Predicting the Segmental Voltage Drop in Automated Guided Vehicle Battery Cells Pavliuk, Olena,Cupek, Rafał,Stęclik, Tomasz,Medykovsky, Mykola,Drewniak, Marek Electronics (Switzerland)Open source preview, 2023, 12(22), 4636	Prediction of AGV battery condition and discharge
Federated Learning for Wireless Communication Prediction - The Use Case of Internal Logistic System Based on AGV Smołka, Ireneusz,Pavliuk, Olena,Cupek, Rafał,Musiał, Jakub Proceedings of the IEEE International Conference on Big Data, BigDataOpen source preview, 2025, (2025), pp. 4055–4062	Federated Learning for Wireless AGV Communications
Iterative Weighted-Voting Approach for Adaptive Time-Series Anomaly Correction in Federated AGV Systems Pavliuk, Olena,Mishchuk, Myroslav Proceedings of the IEEE International Conference on Big Data, BigDataOpen source preview, 2025, (2025), pp. 4028–4035	Adaptive anomaly detection and correction in federated systems
Energy-Aware Spatio-Temporal Multi-Agent Route Planning for AGVs Pavliuk, Olena,Mishchuk, Myroslav Applied Sciences (Switzerland)Open source preview, 2026, 16(6), 3060	Energy-efficient route planning and AGV coordination

PROSPECTS FOR FURTHER RESEARCH

- Development of edge AI architectures for real-time AGV systems with limited computational resources.
- Increasing system resilience to signal degradation and sensor failures.
- Adaptive management of computational and communication resources in AGV systems.
- Integration of Explainable Artificial Intelligence for transparent and trustworthy decision making.
- Autonomous cooperation of multi-agent AGV systems using AI.
- Integration of digital twins for AGV simulation and optimization.

Thank you for your attention :)