Improving Air Traffic Management operations with machine learning collaboration on private data sets: discussion of use cases of interest for the ATM stakeholders

(The SESAR AICHAIN Solution)

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Project site: www.aichain-h2020.eu

Project partners: SITA FOR AIRCRAFT, EUROCONTROL, NOMMON, SCALEOUT, SWISS

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SESAR 2020 Exploratory Research project addressing call topic SESAR-ER4-2019 - Digital Information Management (DIM).

Full project title: ***A platform for privacy-preserving Federated Machine Learning using Blockchain to enable Operational Improvements in ATM***

This project has received funding from the SESAR Joint Undertaking (JU) under grant agreement No 894162. The JU receives support from the European Union's Horizon 2020 research and innovation programme and the SESAR JU members other than the Union.

Purpose of the meeting

1. To present a solution that enables **privacy-preserving machine learning collaboration on private data sets to enable operational improvements in ATM** (based on the results from SESAR ER4 project AICHAIN).

2. To **identify use cases of your interest** that could be enabled with AICHAIN (the solution can be applied in many use cases)

Session agenda

10’ Participants presentation (& initial Q&A)

30’ AICHAIN Solution presentation

20’ Open Q&A on the AICHAIN Solution

60’ Use cases discussion

Participants presentation

Opening questions :
What is your interest in this workshop?
Tentative ideas of use cases interest?

Co-funded by the European Union

sesar JOINT UNDERTAKING

AICHAIN

The AICHAIN Solution presentation

Context and Motivation,

The AICHAIN Solution architecture,

The Governance and Incentives Framework,

The AICHAIN technology demonstrator,

Experimental results with two ATM research use cases

Co-funded by the European Union

The AICHAIN Solution Context and Motivation

AICHAIN Solution context and motivation

There is a need to enable **access to private data** to enable higher levels of **automation** and **performance** in ATM

Privacy-preserving machine learning collaboration on private data sets to enable operational improvements in ATM

Digitalisation
in Aviation & Air Traffic Management (ATM)

Enables

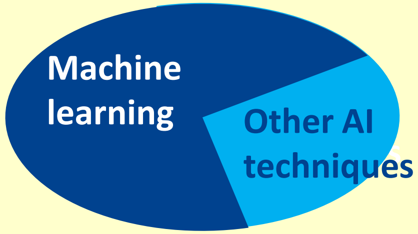
More Operational Data

Sharable Data

Private Data (non-sharable)

Enables

***Artificial Intelligence** in Aviation*



***Machine learning** will play a key role to foster the needed levels of automation*

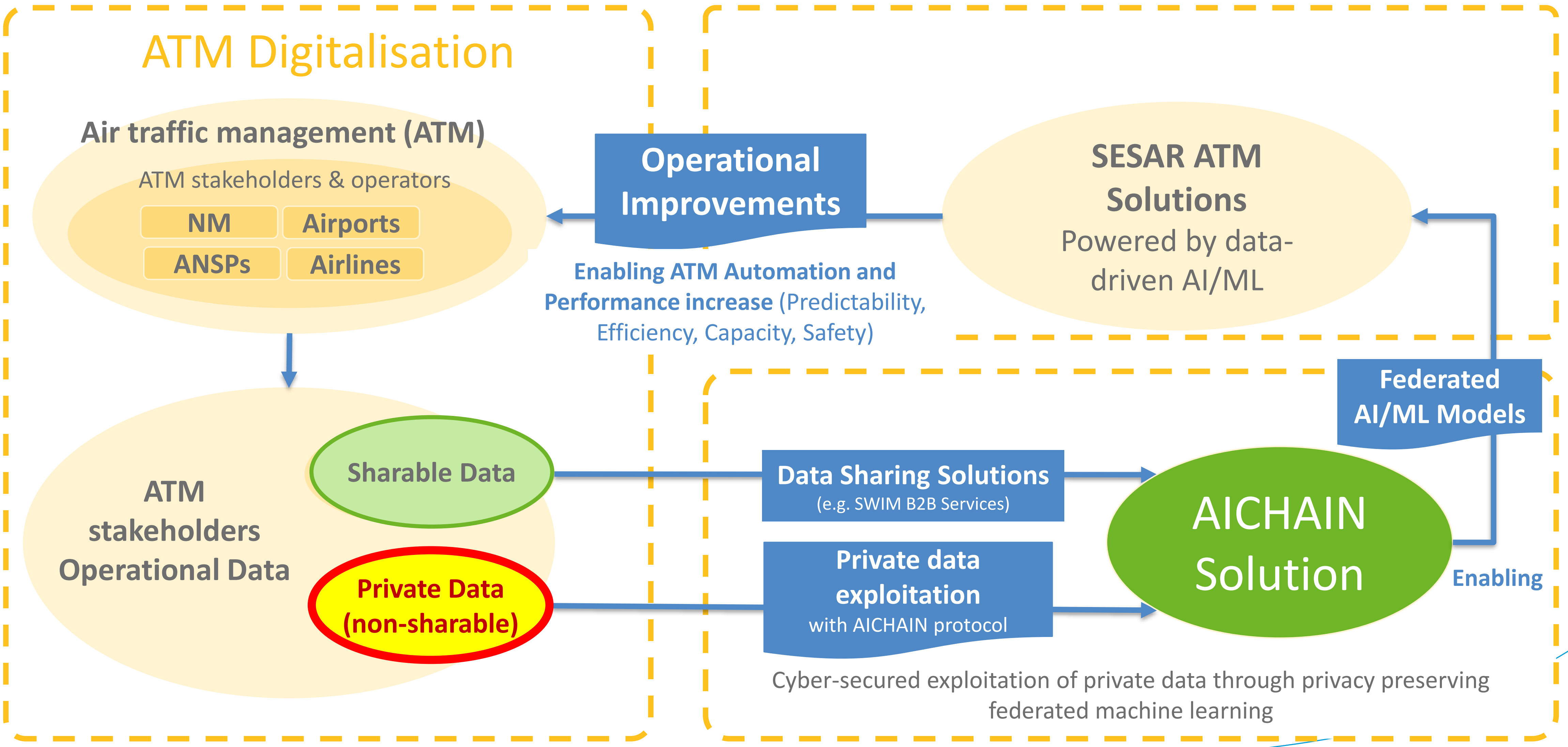
Enables

***Automation** in future ATM: three foreseen scenarios*

ATM Automation Scenarios		
Scenario 1: Locally optimised	Scenario 2: Holistic cognitive	Scenario 3: Autonomous ATM

ATM Operational Improvements

The AICHAIN Solution as a new SESAR technology enabler for ATM operational improvements



The AICHAIN Solution Architecture

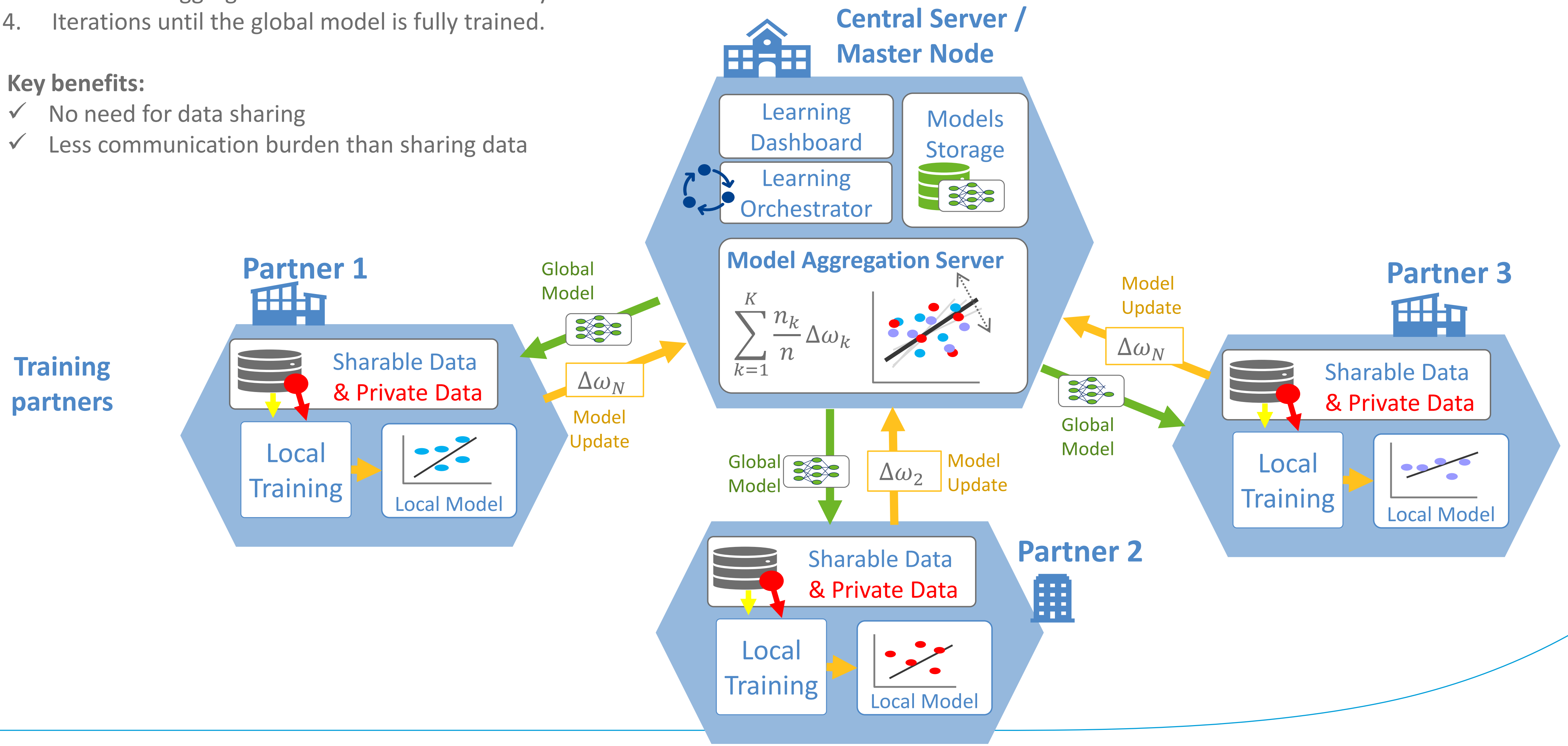
The Federated Learning concept

PROCESS WORK FLOW:

1. The master distributes the most updated version of a global model.
2. Each node trains the model locally with private data and uploads the model update to the server.
3. The server aggregates all the sub-models locally trained.
4. Iterations until the global model is fully trained.

Key benefits:

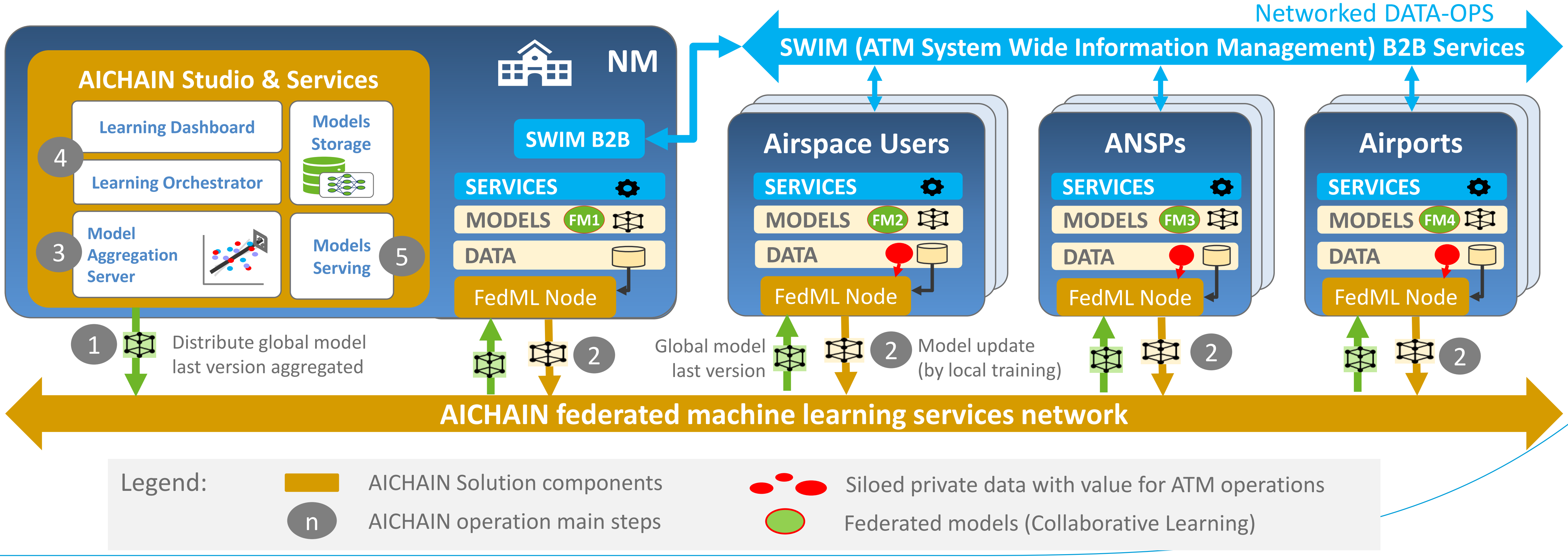
✓ No need for data sharing
✓ Less communication burden than sharing data



AICHAIN Solution in ATM : Context and relation with SWIM

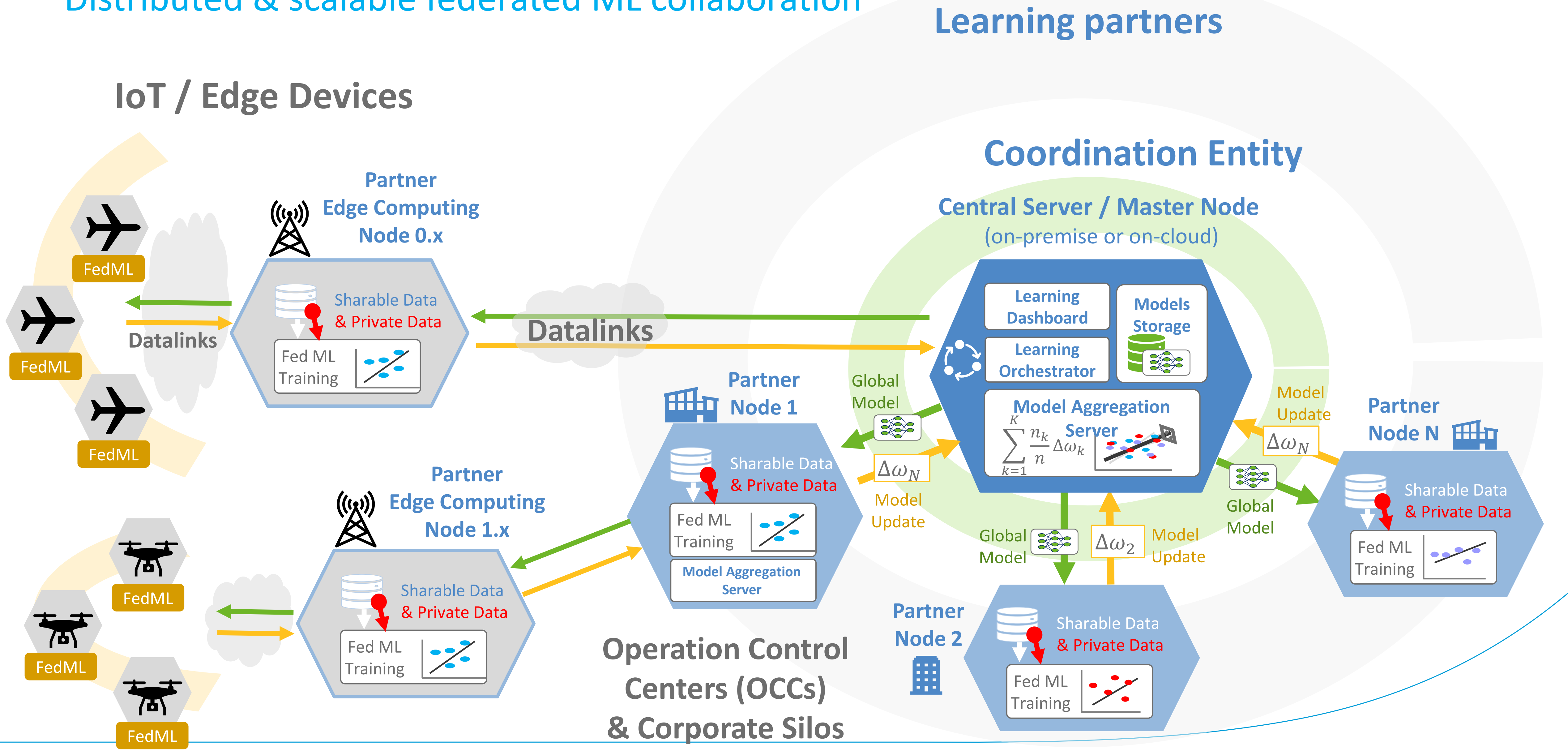
Data and Information Management infrastructures in ATM

- AICHAIN is proposed to enable privacy-preserving federated machine learning collaboration (PPFML)
- ATM USERS & STAKEHOLDERS become Machine Learning Partners (Nodes) using AICHAIN.
- This is a complementary function to SWIM B2B data-sharing services.
- Integrated with SWIM Data network to enable and harmonise implementation of AICHAIN governance
- Diagram shows a deployment example with NM as coordination entity. Other deployments settings are possible depending on use case.



The AICHAIN Solution in ATM:

Distributed & scalable federated ML collaboration

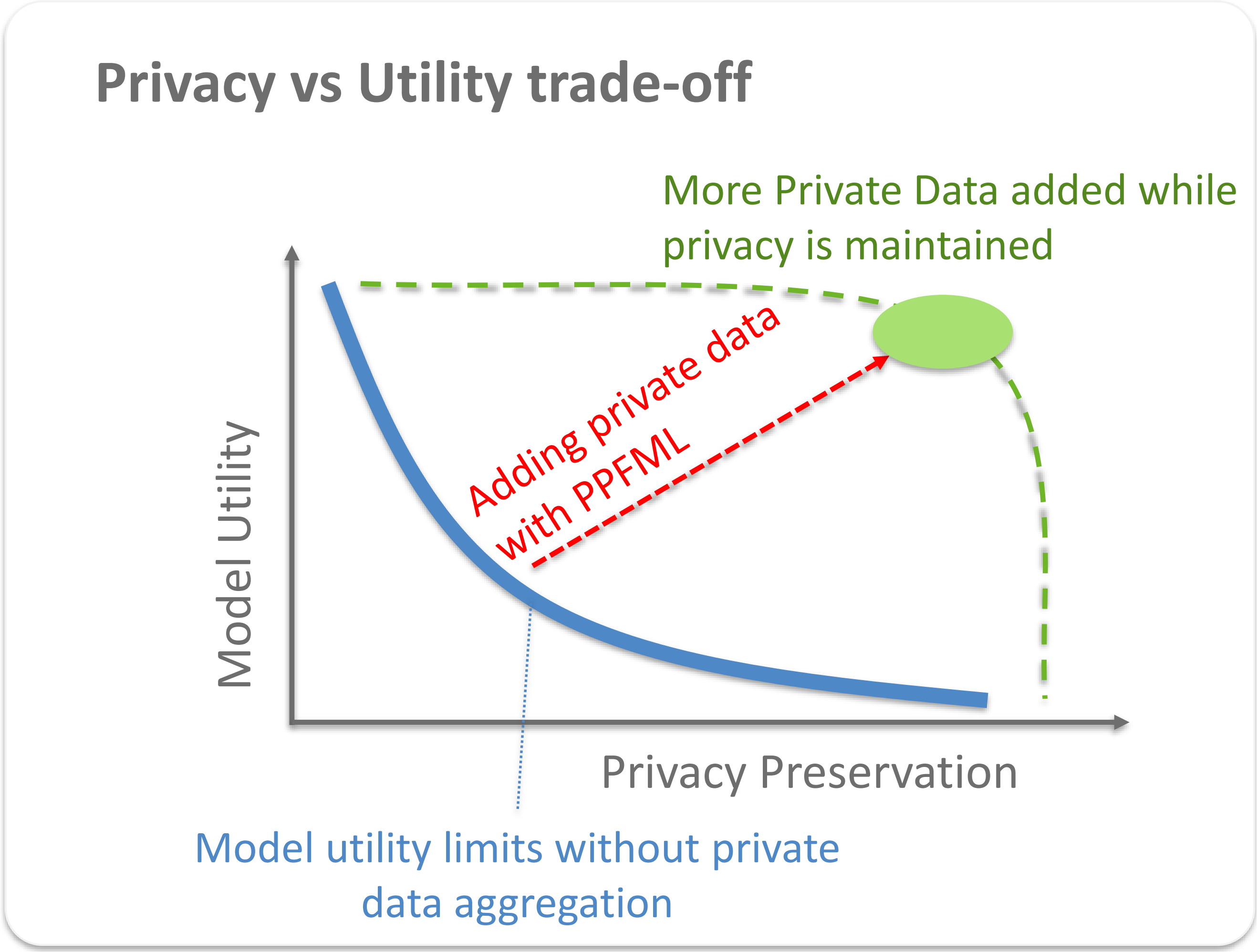


Comparing Machine learning based on Data Sharing versus Machine Learning Federated

	Data Sharing based Machine Learning (moving data)	Federated Machine Learning (moving models)
Privacy and cyber-security protection	Difficult	Easier
Communication & computation efficiency	Heavier	Lighter
Model performance (utility)	Limited	Higher
Deployment complexity	High	High

The Privacy vs Utility trade-off

when building machine learning models with privacy preservation constraints



Federated Learning enables to maximise the utility and the privacy when building ML models

The AICHAIN Solution: Federated Learning enhanced with Blockchain-based Governance and Incentives

AICHAIN Solution

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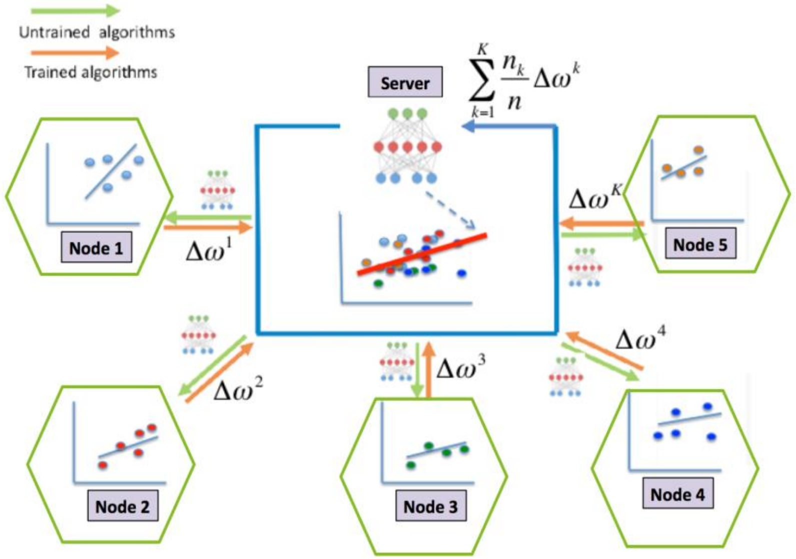
Federated Machine Learning

(Non-shareable data exploitation for AI with privacy-preserving ML techniques that do not involve data sharing)



+

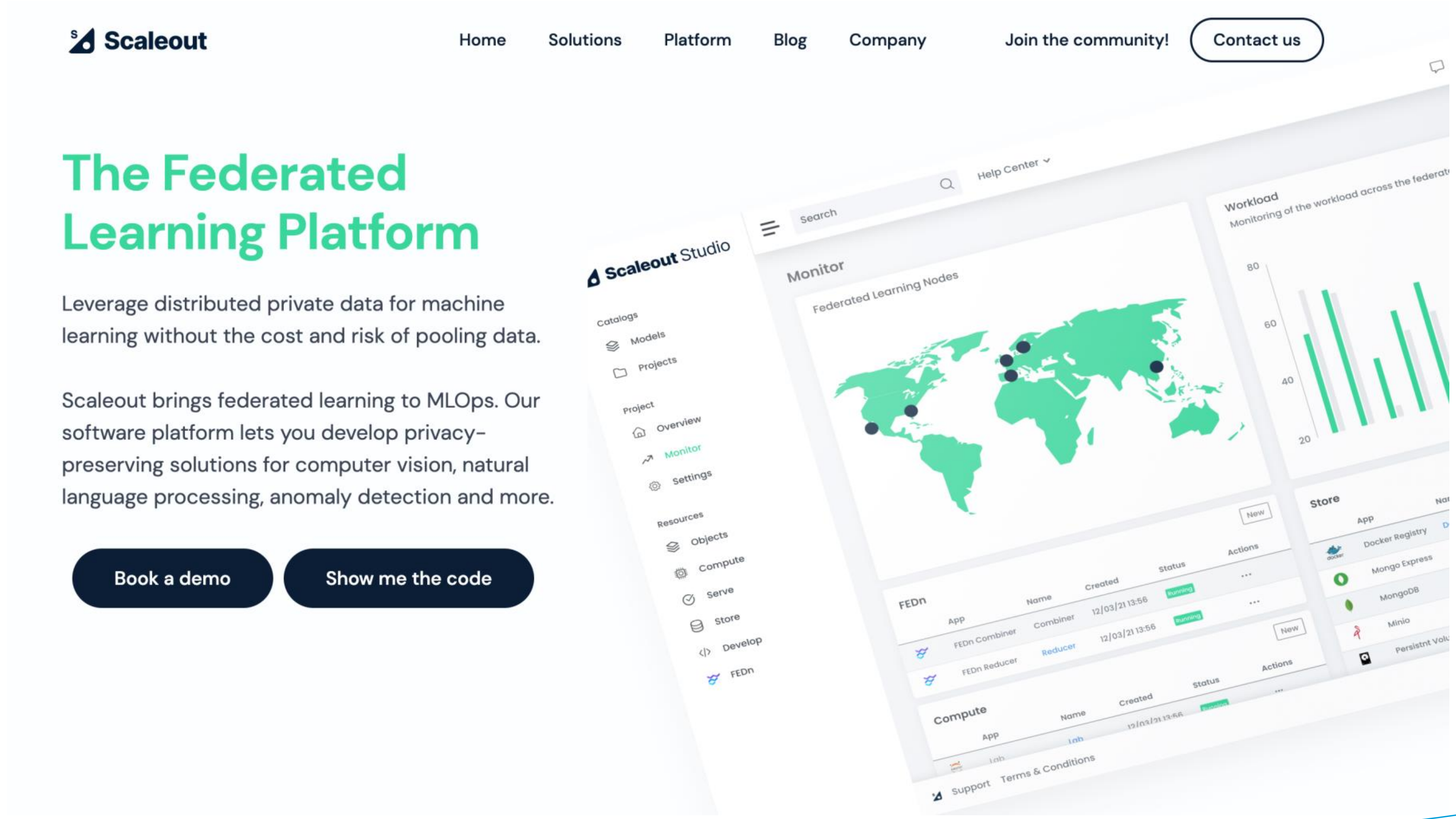
Blockchain-based Governance & Incentives

(with distributed ledgers, smart contracts and tokens)

The AICHAIN Solution technology demonstrator & experimental platform

The AICHAIN Solution technology demonstrator & experimental platform

Based on the Scaleout Systems technology https://scaleoutsystems.com



The AICHAIN Solution technology demonstrator & experimental platform : Architecture

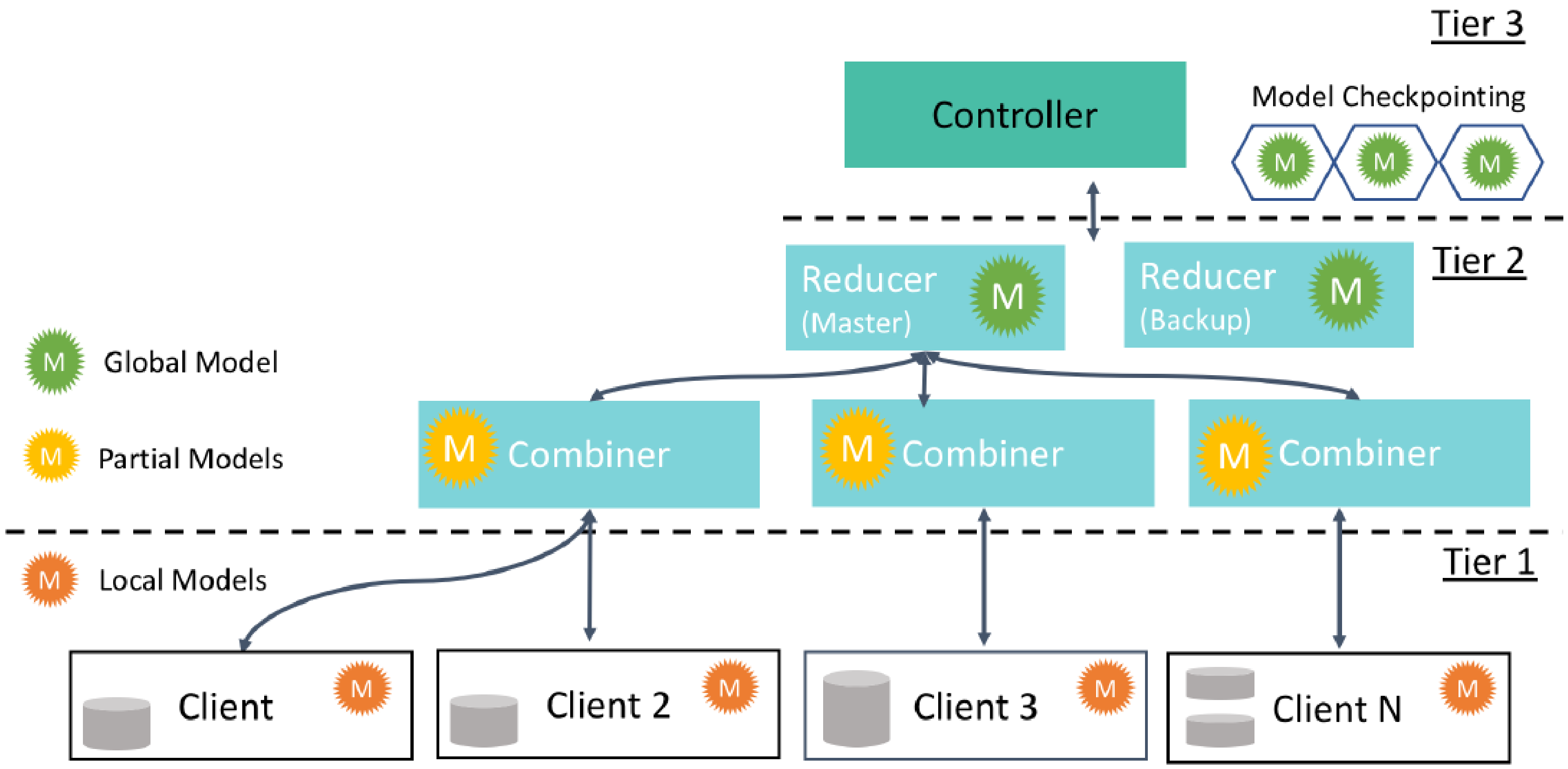
Tier 3 (Control Management) - services

- Monitoring
- Service discovery
- Model checkpointing
- ….

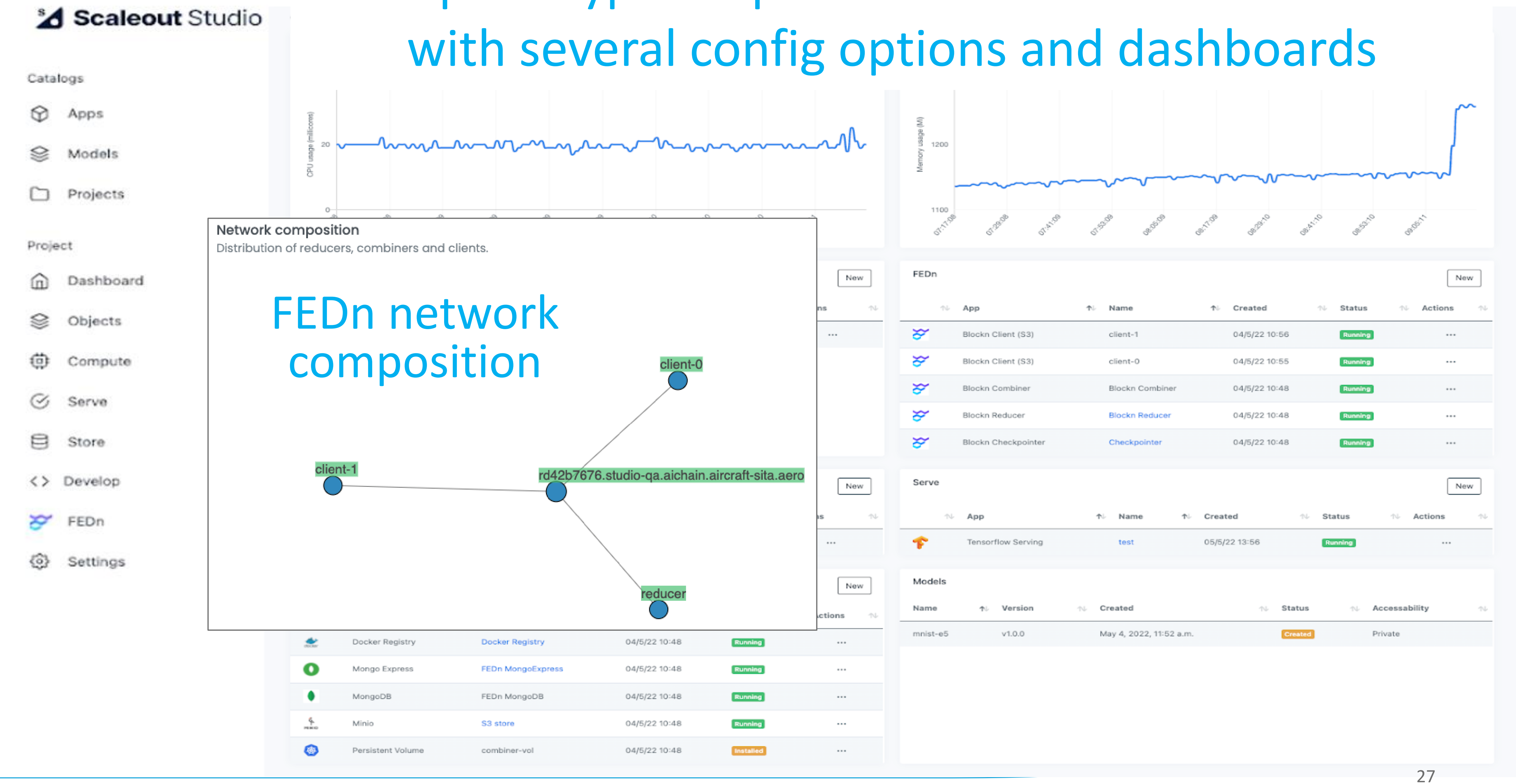
Tier 2 (Combiners & Reducer)- model aggregation

- Combiner - responsible of load balancing and partial model aggregation
- Reducer -

Tier 1 (Clients) - geographically distributed clients



The prototype is operated via a website interface with several config options and dashboards



Proof of model training with distributed clients

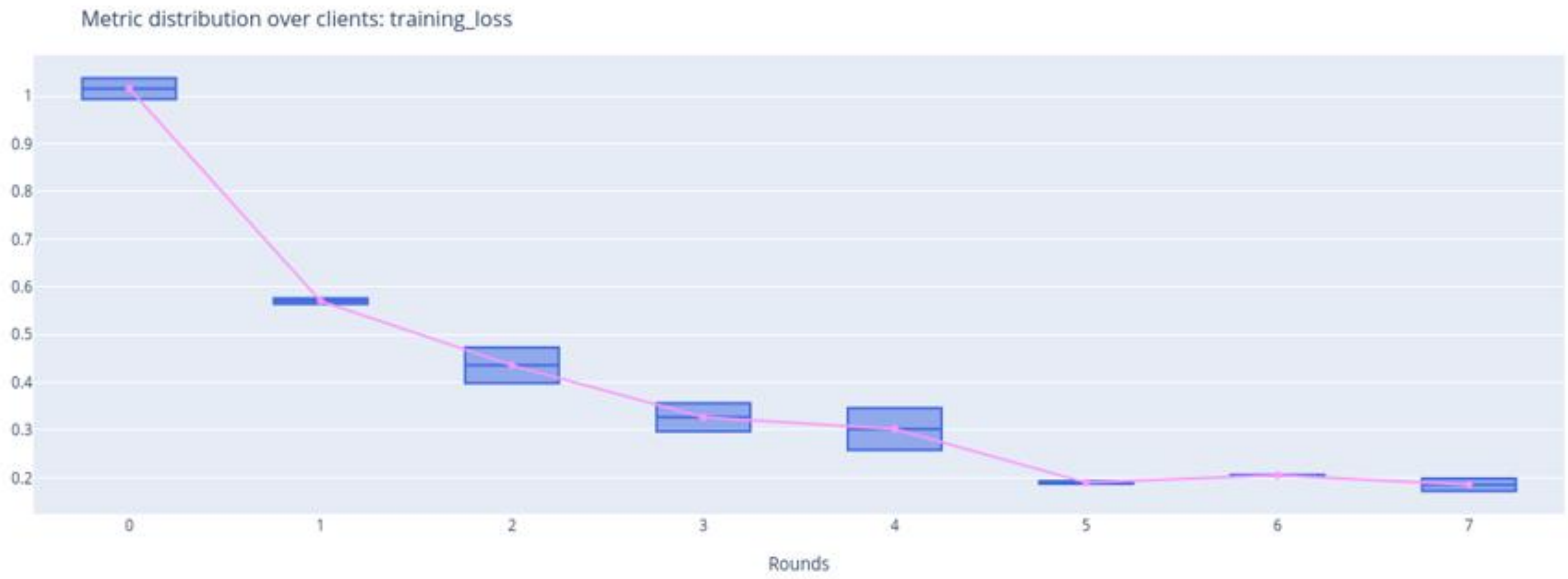
The plots show the following:

- Federated model training loss
- Global model accuracy in each round
- Aggregated client profile and training time distribution

Model evaluation

Distribution over clients

Metric training_loss



Model evaluation

Client average metrics

Model Id

Accuracy

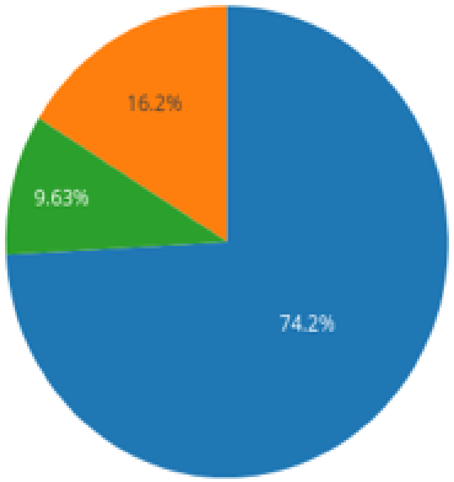
Summary: mean metrics

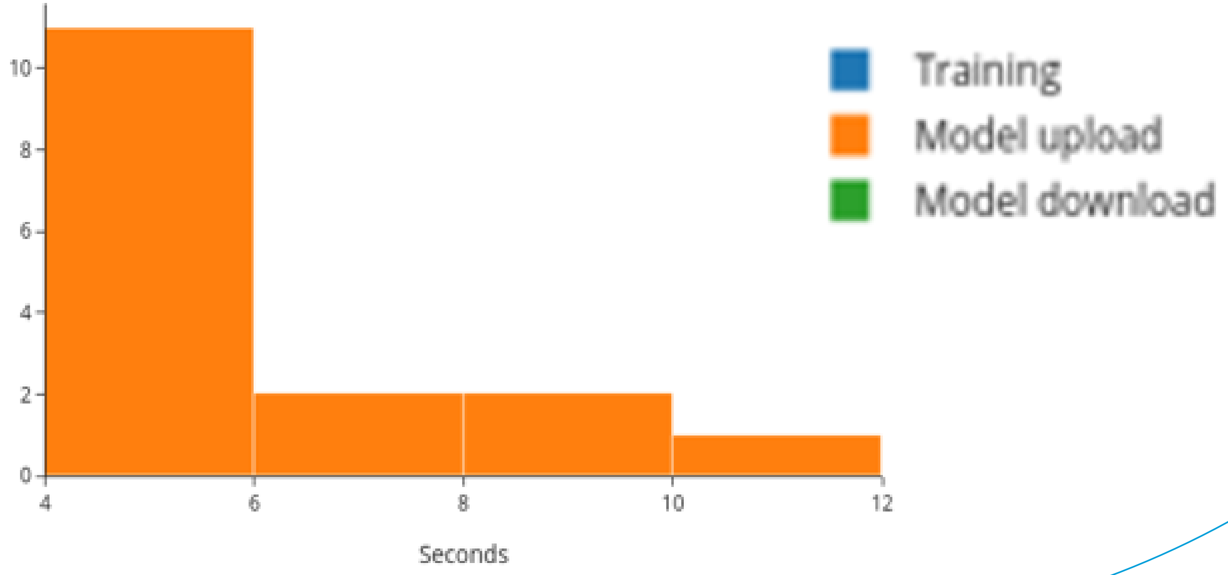
Model ID	training_loss	training_accuracy	test_loss	test_accuracy
252837f8-edd8-4e73-89a0-e20e60c4cc9c	0.18521447479724884	0.9491666555404663	0.161325141787529	0.949999988079071
47e70638-7d49-4c9d-8219-f33bd4d6a8bc	0.2052280157804489	0.9474999904632568	0.19198347628116608	0.949999988079071
dfefc10b-56c8-4d21-a4ad-228546858268	0.1897175833582878	0.9441666603088379	0.21228180825710297	0.949999988079071
e1352d75-f8a1-4d23-829d-224b91954b68	0.3021675795316696	0.9116666615009308	0.283580020070076	0.9199999868869781
7c8b05cc-1742-4d30-80c6-e9ec659beedc	0.3267817050218582	0.9124999940395355	0.31600311398506165	0.9050000011920929
4ecf55dd-3135-45ad-a33d-15de14a63d78	0.4355725198984146	0.8891666531562805	0.48843222856521606	0.8599999845027924
23442aa5-a209-4014-9bd7-b5c2f785af08	0.5701746046543121	0.8333333134651184	0.49499398469924927	0.8700000047683716
fd7ee50d-a0e5-45e1-a272-c8f801c4fdff	1.015582650899887	0.7450000047683716	0.9210501313209534	0.8199999928474426

Communication-Computation performance monitoring

Aggregated client profile and training time distribution

Total mean client processing time: 8.51778195798397





Model serving and inference

1) List of available models

Models

Delete models [11]

Model Id	Date
initial_model.npz	2022-05-04 10:52:42.059210
d075ab98-95c4-4aa2-adc9-c3593db518c9	2022-05-04 10:58:11.053704
f4b55cab-b287-4173-ac0a-522ffbea4721	2022-05-04 10:58:27.000986
bf8c90ad-b82c-44c3-ad9f-3ed9874dcc0a	2022-05-04 10:58:40.162517

2) Model platforms available:

TensorFlow serving, MLFlow serving, PyTorch serving

Serve

App	Name		State	Created		
Tensorflow Serving	test	Open	Running	May 5, 2022, 1:56 p.m.		Publish

Tensorflow Serving
Create

PyTorch Serve
Create

MLFlow Serve
Create

Dash App
Create

Python Model Deployment
Create

3) Using the model (model serving)

```
[3]: samples = X[0:2][::].tolist()
     inp = {'inputs': samples}
```

Serving endpoints

```
[6]: # Edit the endpoint url to your served endpoint
     service = "http://r8340e651:80/v1/models/models"
     endpoint = service+':predict'
     model_info = requests.get(service)
     prediction = requests.post(endpoint, json=inp)
```

```
[7]: #Model info
     model_info.json()
```

```
[7]: {'model_version_status': [{'version': '1',
        'state': 'AVAILABLE',
        'status': {'error_code': 'OK', 'error_message': ''}}]}
```

```
[8]: #Prediction
     prediction.json()
```

```
[8]: {'outputs': [[1.27690907e-06,
        1.94565791e-06,
        1.40191821e-06,
        0.00240362016,
        1.823269e-08,
        0.997521222,
        3.39700335e-07,
        5.01548038e-06,
        6.49111098e-05,
        2.76874033e-07],
       [0.999993443,
        2.61303654e-08,
        1.32278751e-06,
        9.83337486e-07,
        2.61141366e-07,
        8.30120399e-08,
        6.32575677e-07,
        3.33535382e-07,
        4.47301858e-07,
        2.49934078e-06]]}
```

```
[ ]:
```

Experimental results from two ATM use cases

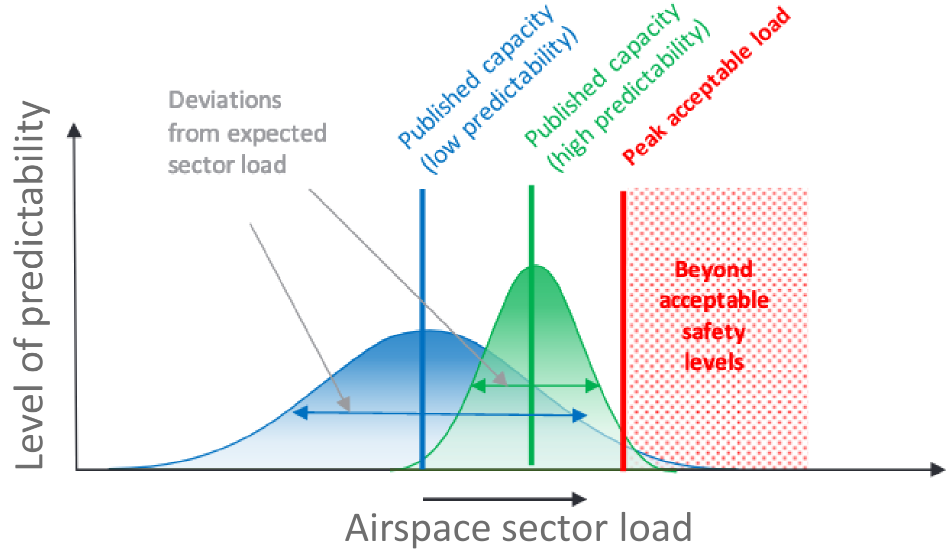
UC1: Improving Take-off time prediction

UC2: Improving 2D Route-selection prediction

Experimental results from two use cases

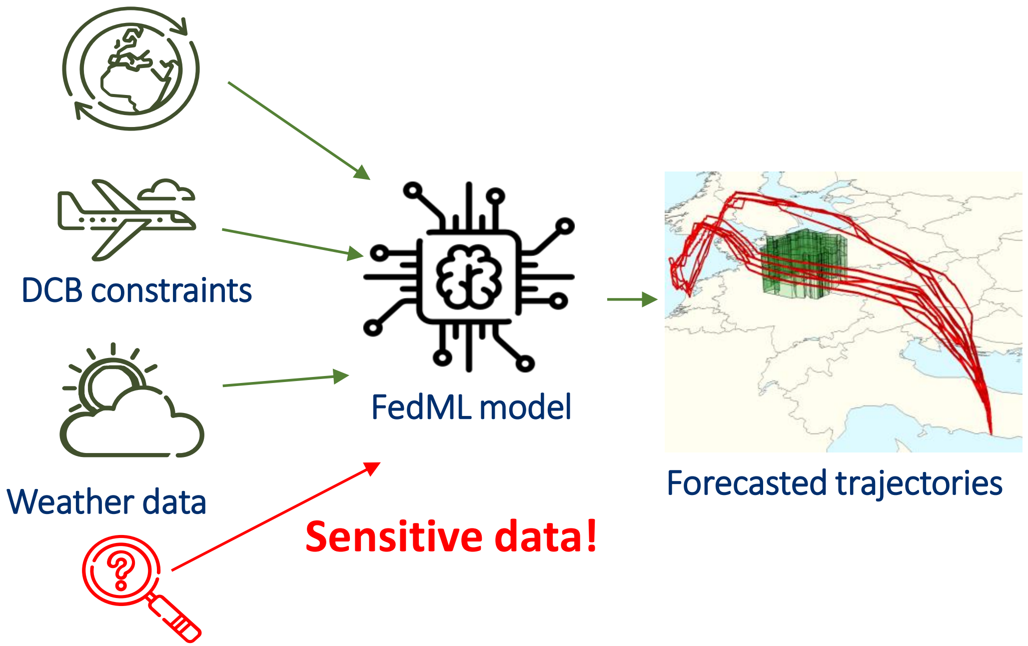
Two baseline models have been enhanced with private data

UC1: Improving Take-off time prediction



Uncertainty reduction in departure time ▶ Reduction of capacity buffers

UC2: Improving 2D Route-selection prediction



Throughput at sectors can be increased if traffic is more predictable

Benefits: less congestion and less delay costs

UC1: Improving Take-off time prediction

Features:

Simplified version of the model at MUAC

NM features

EVENT
EVENTCLASS
FLTSTATE
ADEP
ADES
ARCTYP
IRULES
RDYSTATE
TAXITIME
AOARCID
FLTTYP
DEPAPTYPE
CDMSTATUS
AOOPR
ATFMDELAY
IFPSDISCREPANCY_REG
IFPSDISCREPANCY_ARCTYP
IFPSDISCREPANCY_OBT
DEPSTATUS
ADESOLD
RWY
FLIGHT_DURATION
EOBT_IFP_TO_EOBT
ADEPETO_IFP_TO_ADEPETO
IOBT_TO_EOBT
TIMESTAMP_IFP_TO_TIMESTAMP
TIMESTAMP_TO_ADEPETO
TIMESTAMP_TO_EOBT
TIMESTAMP_TO_TSAT
TIMESTAMP_TO_TOBT
TIME_FROM_REG_CHANGE
TURNAROUND_LEG
FLIGHT_DURATION_LEG
TIMESTAMP_TO_TA_LEG
ADEPETO_IFP_TO_ADEPETO_LEG
EOBT_IFP_TO_EOBT_LEG
TIMESTAMP_LEG_TO_TIMESTAMP
EVENT_LEG
AOOPR_LEG
FLTSTATE_LEG
ADEP_LEG
AOARCID_LEG
FLTTYP_LEG
HOUR
MONTH
DAY

SWISS features

- PAX_BOARDING_STATUS
- DEPARTURE_GATE
- SWISS_EXIT
- SWISS_EXOT
- SWISS_TURNAROUND_LEG
- DEPARTURE_GATE_ASSIGNED
- CREWHADTAILCHANGEPREVIOUS
- CREWCONNECTIONTIMEPREVIOUSFLIGHTSCHEDULED
- CREWCONNECTIONTIMEPREVIOUSFLIGHTACTUAL
- OCCUPATION
- PREDINPAX_GX
- SCDOUTPAX_GX
- SCDINPAX_GX
- SWISS_RWYNUM
- SWISS_RWYSPEC
- NUMPAXBOOKED
- NUMPAXFLOWN
- AIRCRAFTCAPACITY
- SWISS_TIMESTAMP_TO_TIMESTAMP
- SWISS_EOBT_TO_EOBT
- SWISS_ETOT_TO_ETOT
- SWISS_EOBT_TO_SOBT
- SWISS_TIMESTAMP_TO_ALL_DOORS_CLOSED

SWISS airline kindly provided a dataset with the private features needed for a subset of their flights

- **Objective of the regression model**: to optimise the ETOT calculated by the current system without ML models (the ML model computes the difference between the current ETOT and the actual take-off time)

UC2: Improving 2D Route-selection prediction

Features:

Private features available in the experiments

Private feature approximated

Variable Name	Description
Airline TOW	**Measured Take-Off weight by the airline of each flight**
Connecting passengers	**Number of passengers that have a flight connection in the destination airport**
DoW	The day of week of the flight codified accordingly
Flight Time	The ETOT hour of the flight
DoY	The day of year the flight takes place in
Longitude diff	Geodesic longitudinal separation between origin and destination
Latitude diff	Geodesic latitudinal separation between origin and destination
Airport population	Population density of the Origin/Destination surroundings areas
Airport GDP	Gross Domestic product of the Origin/Destination surroundings areas
Daily flights	Number of flights for each od pair and day
Airline market share	Airline's flight share for each od pair and day

Variable Name	Description
Route length	The length in kilometres of a given route
Wind length	Length of the route in kilometres adjusting the effect of the along wind
Charges	The charges paid for the current route for a given aircraft
Fuel cost	**Estimation of the cost of fuel for each given route**
Direct costs	Sum of the fuel and charges costs
CAPE	Used as a storm proxy
K-index	Weather metric that approximates the probability of a thunderstorm to happen
Humidity	The relative humidity observed along the route, that is a requisite for thunderstorms to occur
Local wind at origin/ destination	Variable that measures how aligned and in what value local wind at the airport is
Military zones	The route crosses a closed military zone, not use as a feature but to discard routes
Regulations	The duration of the regulation affecting the route

Experimental results from the two use cases
Model performance improvements observed:

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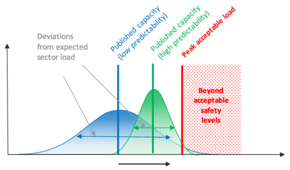
UC1: Improving Take-off time prediction



Absolute error of the predictions on the test set

	ETFMS (legacy)	NM data (baseline)	NM+SWISS (solution)
Mean	10,5	9,3	9,0

+11.4%

+14.3%

Relative improvement: 14.3/11.4 = +25%

UC2: Improving 2D Route-selection prediction

Accuracy of the predictions on the test set

	Most flown (non-ML)	NM data (baseline)	NM+SWISS (solution)
Mean	0,87	0.95	0.954

+9.2%

+9.6%

Relative improvement: 9.6/9.2 = +4%

Note: there is still room for improvement, either fine-tuning the model and/or adding more data

UC1: feature importance analysis

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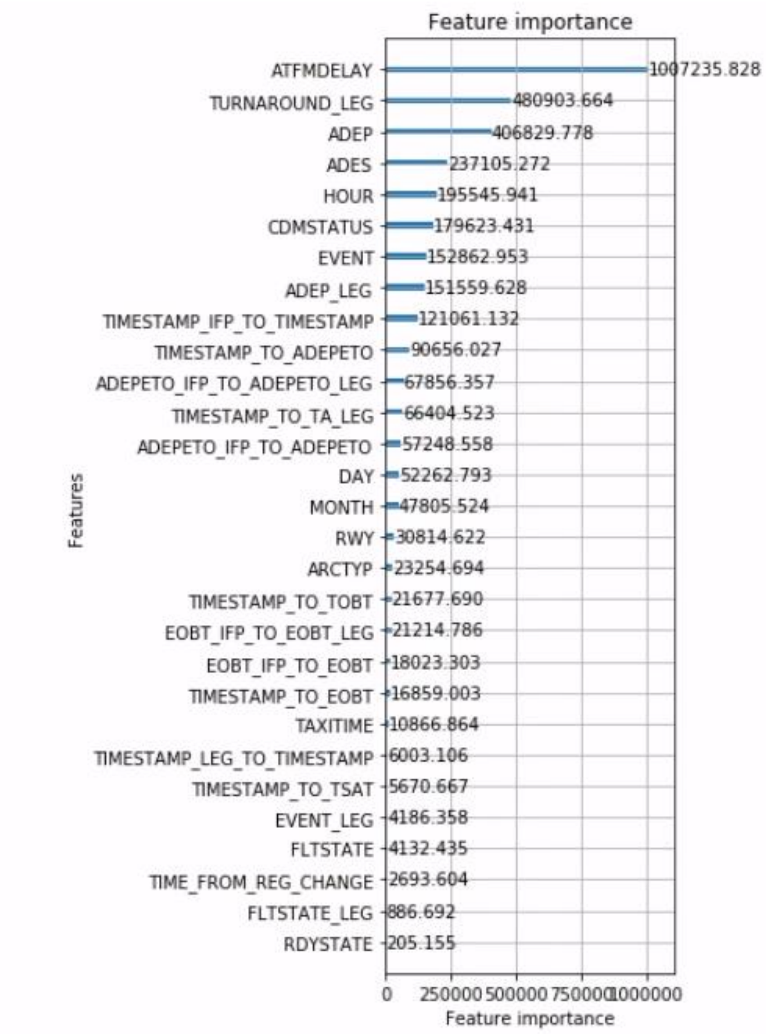
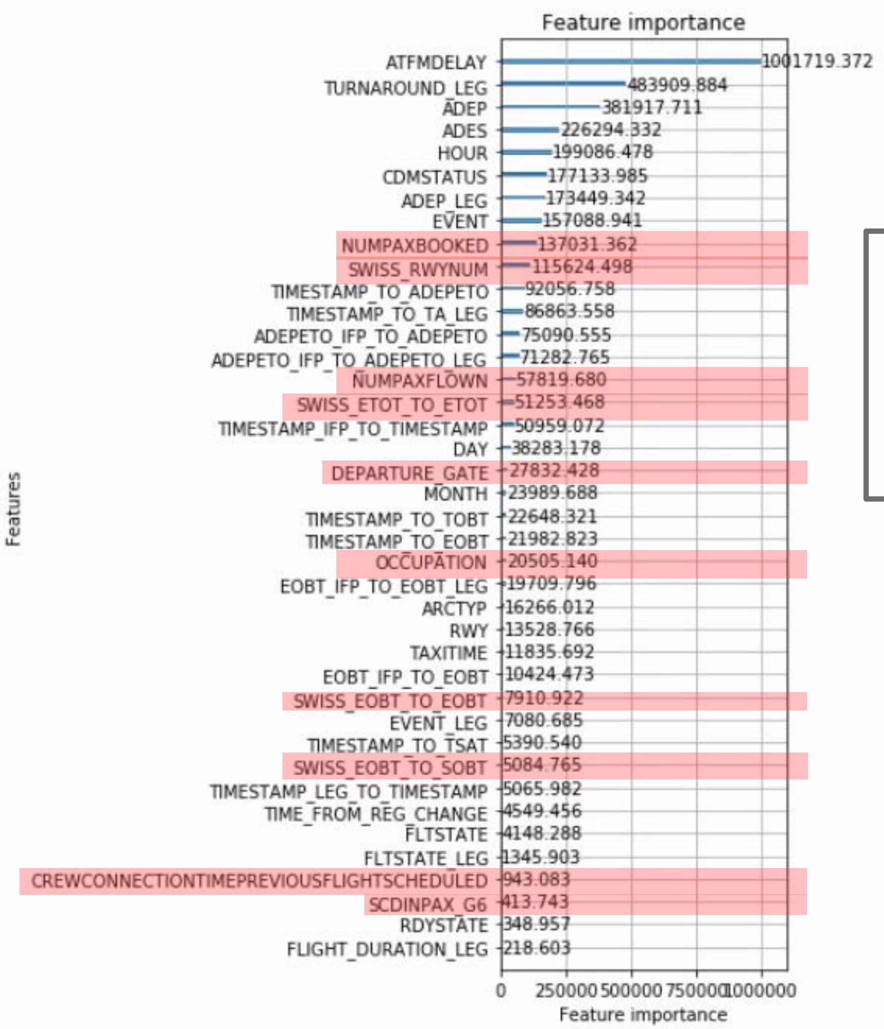
Non-augmented vs augmented models

Non-augmented model (NM data)



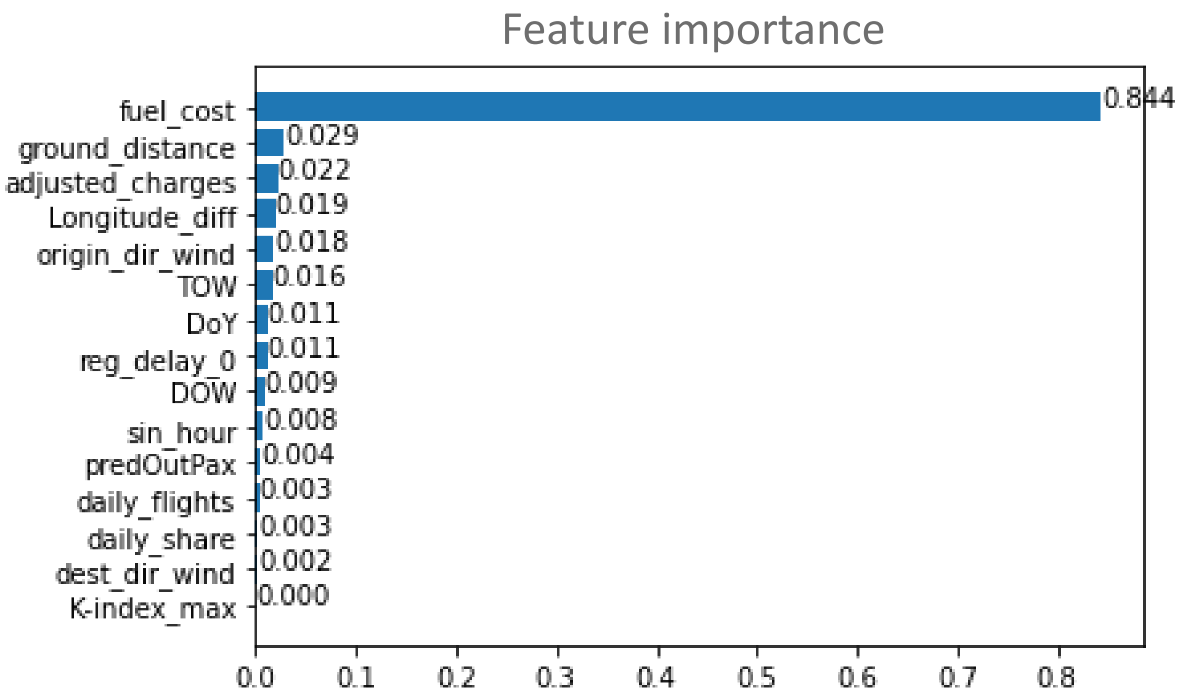
Augmented model (NM+SWISS data)



Private features (in red) do improve the model performance

UC2: feature importance analysis

Augmented model (NM+SWISS data)



The most important feature in this use case is the fuel cost, which is considered private data.

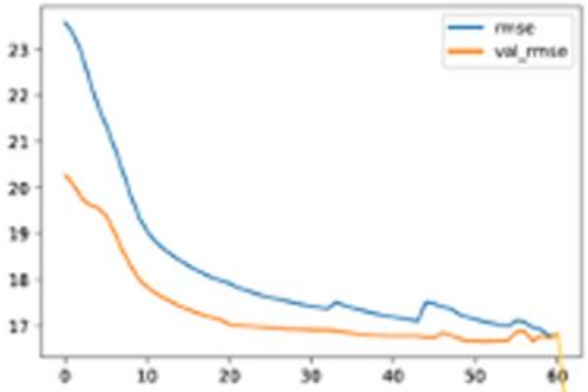
Some models' performance can be highly dependent on private features

Note: in our experiments the fuel cost was approximated because the actual fuel cost was considered too private by the airline owner! It is expected that using the actual cost through federation the model performance could improve significantly, due to the importance of such feature in this model.

Federated machine learning exploits the value of private datasets

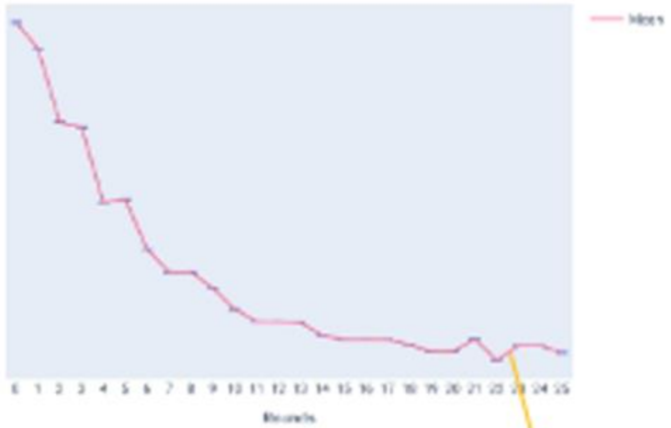
Non-federated vs federated models

Augmented model (V1)



val_rmse: 16.81

Federated augmented model (V2)



val_rmse: 16.93

same model performance

(root mean square error metric)

Conclusion: federated learning can exploit all the value from the private datasets while privacy is preserved (i.e. the augmented model could be built through federation without sharing the private data).

Discussion of use cases of your interest

which could be enabled with AICHAIN Solution
(it can be applied in many use cases)

Co-funded by the European Union

AICHAIN solution: many potential use cases

The AICHAIN Solution is proposed as a new SESAR Solution of type technology enabler.

It can be applied transversally, i.e. in many use cases

1 **VERTICAL dimension** : Multiple applications and use cases

2 **HORIZONTAL dimension:** New SESAR Technology Enabler Proposal

Two use cases researched in the project

UC1 | UC2 | Other Use Case(s) | Other Use Case(s) | Other Use Case(s)

AICHAIN Solution - Technological Enabler

A privacy-preserving Federated Machine Learning platform enhanced with Blockchain-based Governance & Incentives mechanisms

Explored in the project:

- **UC1: Improving Estimated Take off Time**
- **UC2: Improving ATM AU´s 2D Route prediction**

Other use-cases possible:

- **Curfew management**
- **Flight efficiency indicators for ATC and ATFM**
- **Inter modality – Cargo-Drone Hub operation improvements**
- **Inter modality – End-to-end passenger journey operational improvements**
- **Other**

Is there any use case of your interest? Let's talk about that!

Discussion of use cases of your interest

1.	Do you think privacy-preserving machine learning is needed in ATM?		[A] Agree, [B] Partially agree [C] Disagree, [D] Not sure I don´t know

Discussion of use cases of your interest

2.	Do you have or foresee to have machine learning solutions in your organisation?		[A] Yes, one or several [B] No, but considering [C] No [D] Not sure I don´t know

Discussion of use cases of your interest

3.	Do you think private data from other ATM actors could bring benefits to your own operations (i.e. your own ML model based solutions)?		[A] Agree [B] Partially agree [C] Disagree [D] Not sure I don´t know

Discussion of use cases of your interest

4.	Do you think private data from other ATM actors could bring benefits to common service? Would your organisation collaborate with private data in the development of ML models of common interest (e.g. UC1)?		[A] Yes [B] Yes, but with a clear business case / return on investment [C] No, due to cyber-security concerns [D] No, others…

Discussion of use cases of your interest

5.	Would your organisation collaborate with private data in the development of ML models of other's interest (e.g. to improve a particular process in an airport that you don't use)?		[A] Yes [B] Yes, but with a clear business case / return on investment [C] No, due to cyber-security concerns [D] No, others...

AICHAIN solution: many potential use cases

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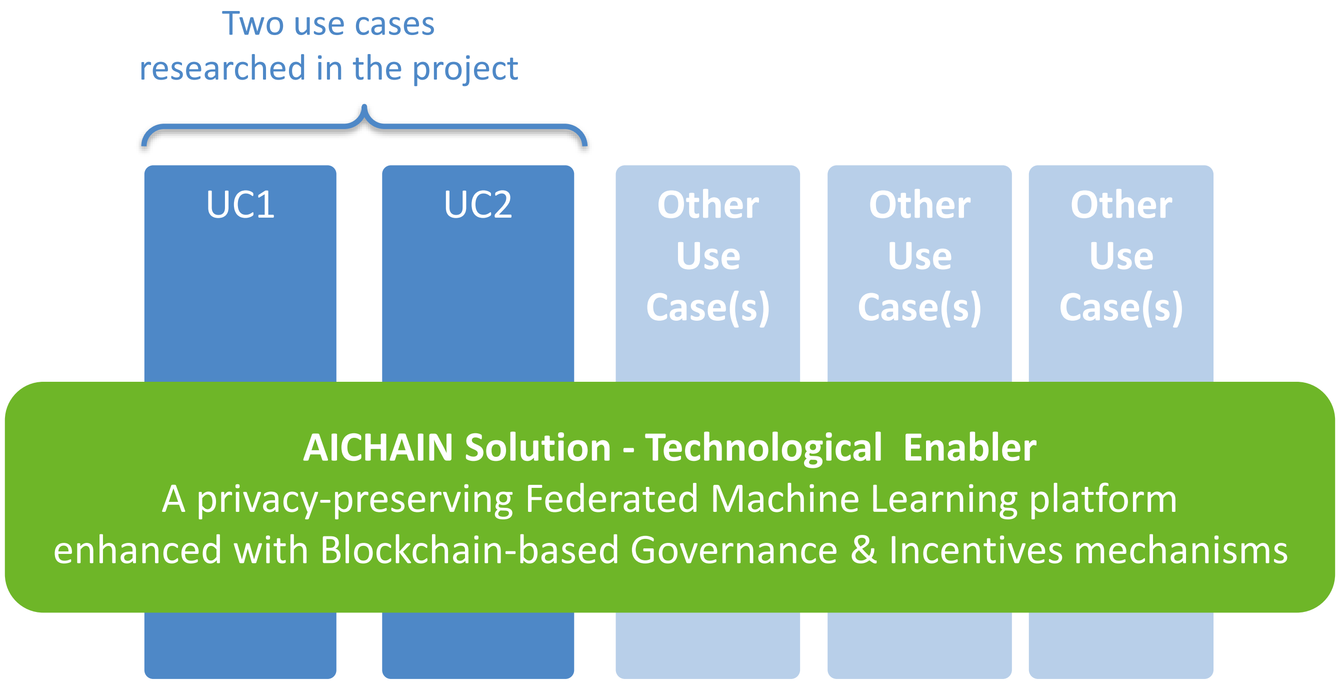

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The AICHAIN Solution:

Improving Air Traffic Management with machine learning collaboration on private data sets

Project site: www.aichain-h2020.eu

Project partners: SITA FOR AIRCRAFT, EUROCONTROL, NOMMON, SCALEOUT, SWISS

Coordinator contact: Javier.busto@sita.aero

SESAR 2020 Exploratory Research project addressing call topic SESAR-ER4-2019 - Digital Information Management (DIM)
Full project title: ***A platform for privacy-preserving Federated Machine Learning using Blockchain to enable Operational Improvements in ATM***

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