Data Augmentation for Intelligent Contingency Management Using Generative Adversarial Neural Networks

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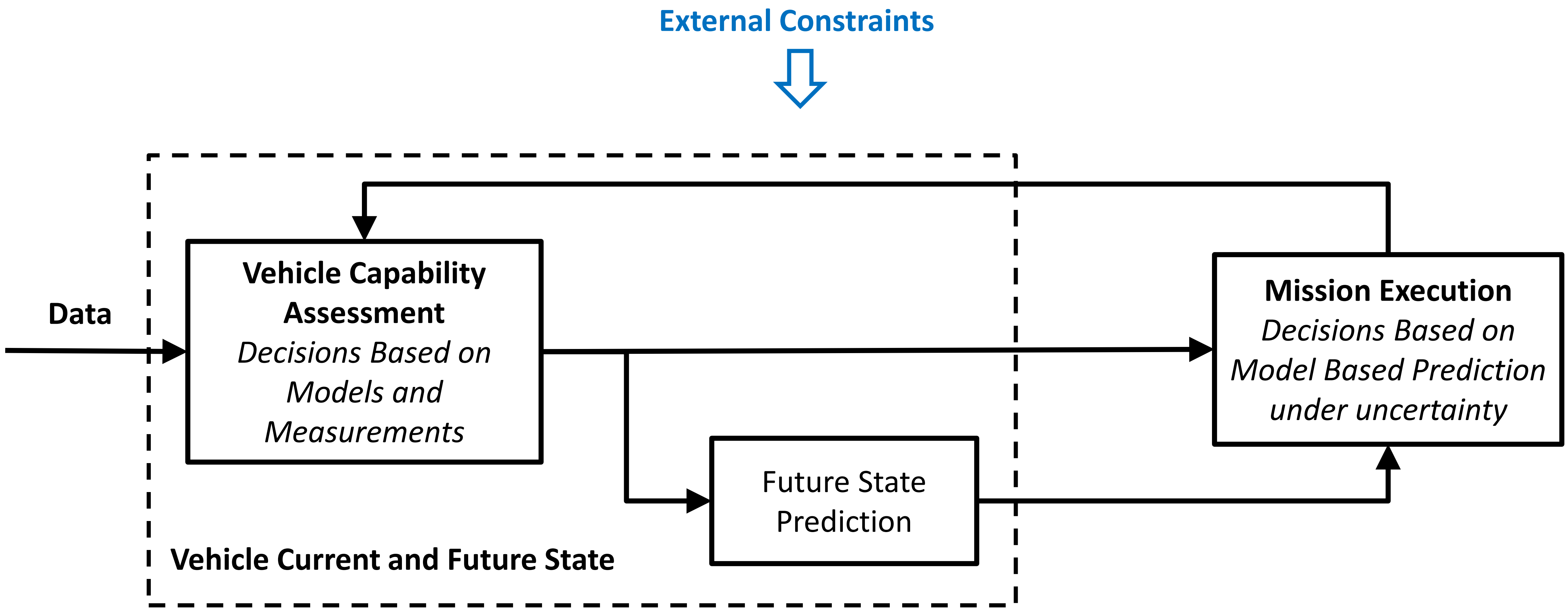
Overview



High level architecture

* I. M. Gregory *et al.*, “Intelligent contingency management for urban air mobility,” in *AIAA Scitech 2021 Forum*, 2021.

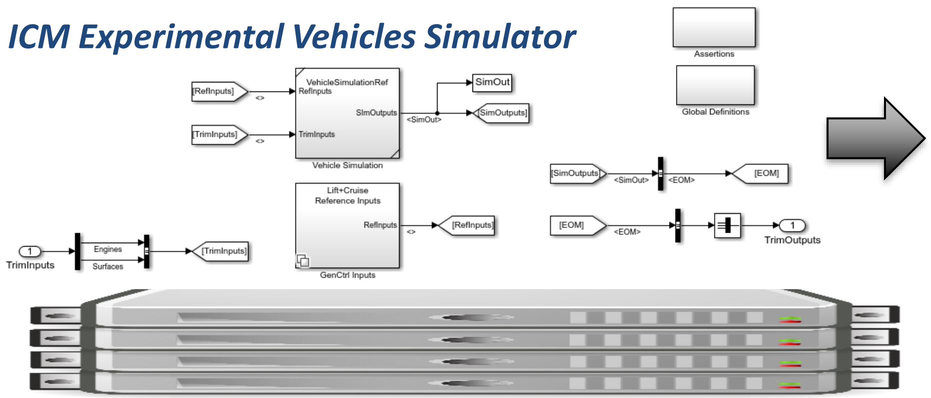
Our Infrastructure

ICM – Environment for Autonomous Decision-Making and Machine Learning for UAM eVTOL

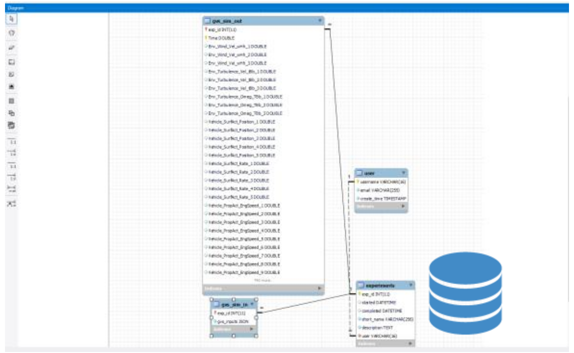
- Mechanisms for choosing appropriate neural network architectures for specific aero use cases
  - Campbell, N. H., Grauer, J. A., & Gregory, I. M. (2021, March). Use of Design of Experiments in Determining Neural Network Architectures for Loss of Control Detection. In 2021 IEEE Aerospace Conference (50100) (pp. 1-20). IEEE.
- Infer state change from measurements of a trained variational autoencoder (CVAE)
  - Campbell, N. H., Grauer, J. A., & Gregory, I. M. (2021). Loss of Control Detection for Commercial Transport Aircraft Using Conditional Variational Autoencoders. In AIAA SciTech 2021 Forum (p. 0778).
- Analysis tools and techniques for Vehicle Capability Assessment
  - Grauer, J. A., Campbell, N. H., Acheson, M. J., & Gregory, I. M. (2021). Dynamic Vehicle Assessment for Intelligent Contingency Management of Urban Air Mobility Vehicles. In AIAA SciTech 2021 Forum (p. 1001).
- Machine learning Models for Failure Analysis (Future Publication)
  - Initial application to propulsor control effectiveness degradation

Lift+Cruise Vehicle Model

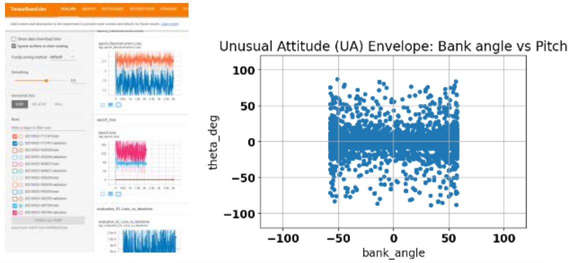
ICM Experimental Vehicles Simulator



Batch Simulation and Data Collection



ICM Database



Machine Learning & Data Viz

Visual Assessment

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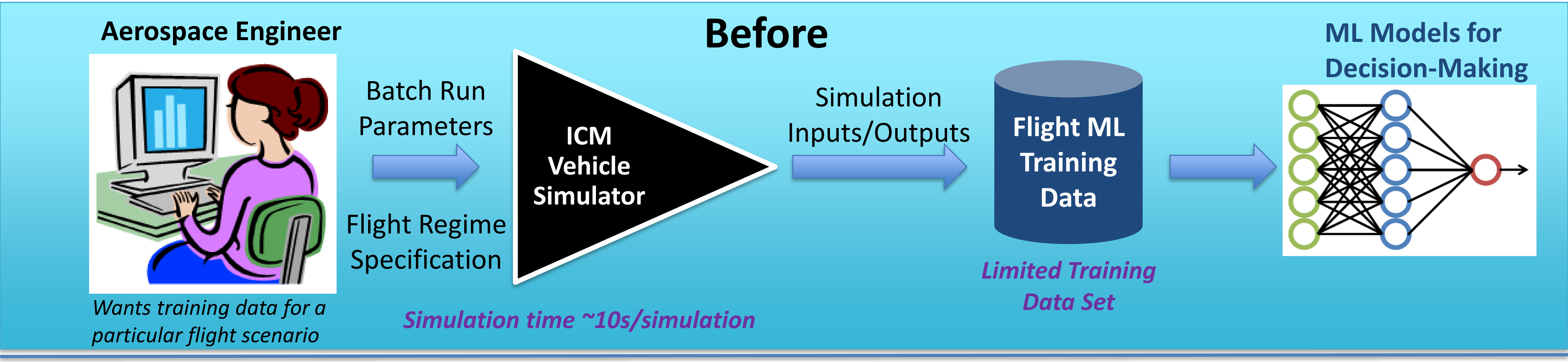
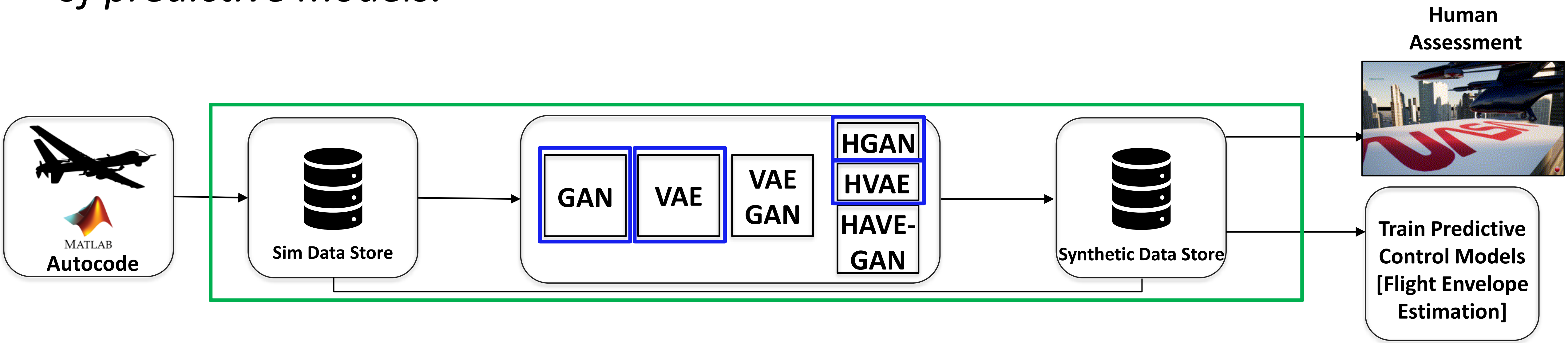
Problem



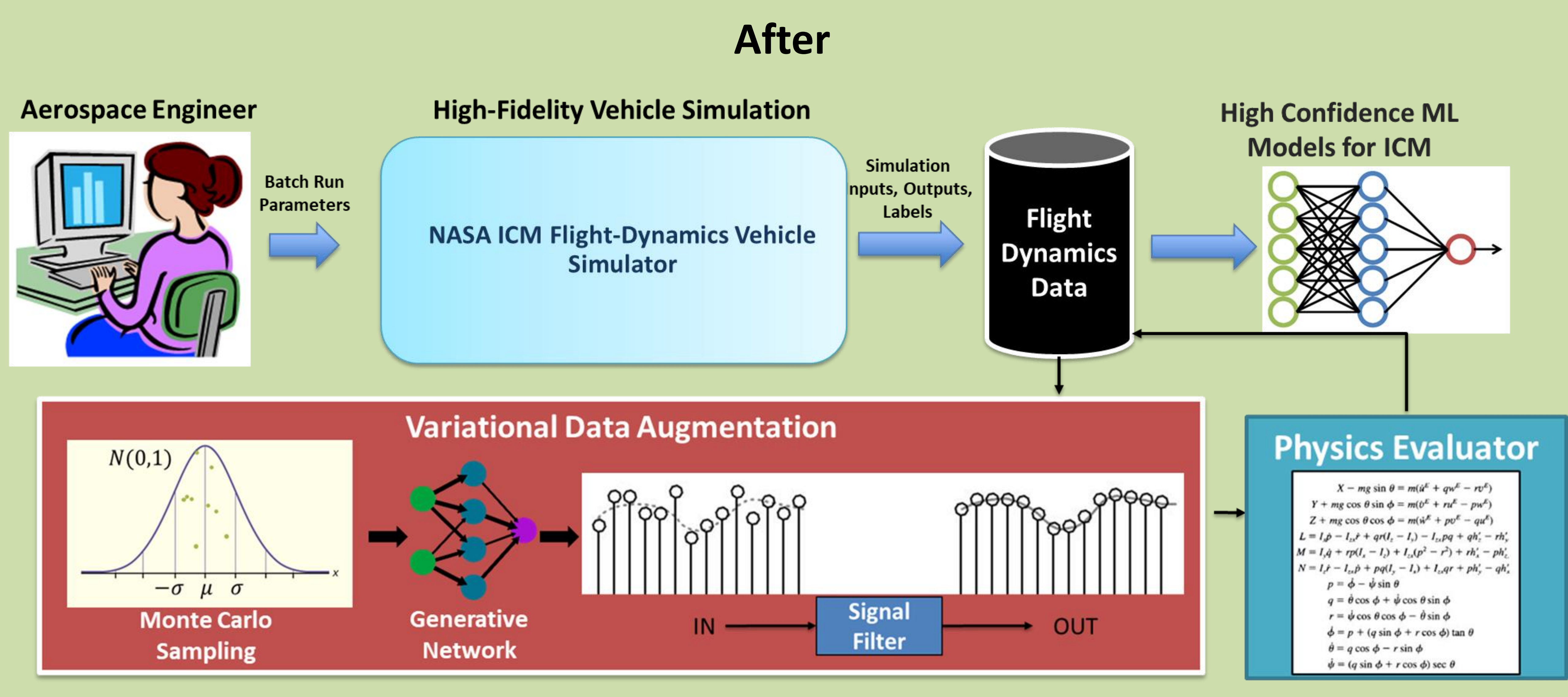
The problem that this research addresses is that the data size and richness necessary for practical aerospace artificial intelligence models can not be sufficiently produced through high-fidelity simulation.

Approach

Train Generative Machine Learning models to synthesize data based on specific flight regimes or scenarios and develop a mapping for future training of predictive models.



Concept of Operations



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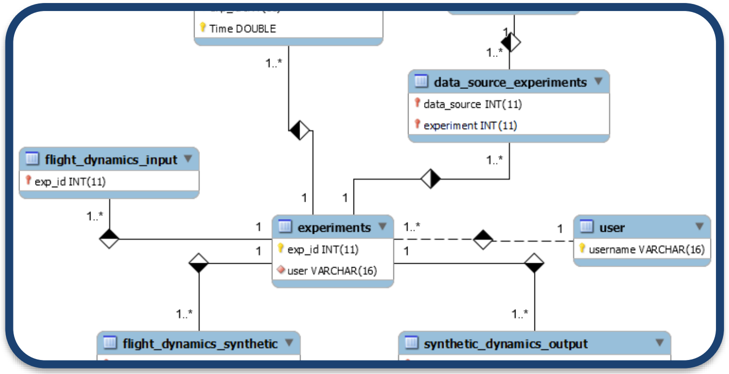
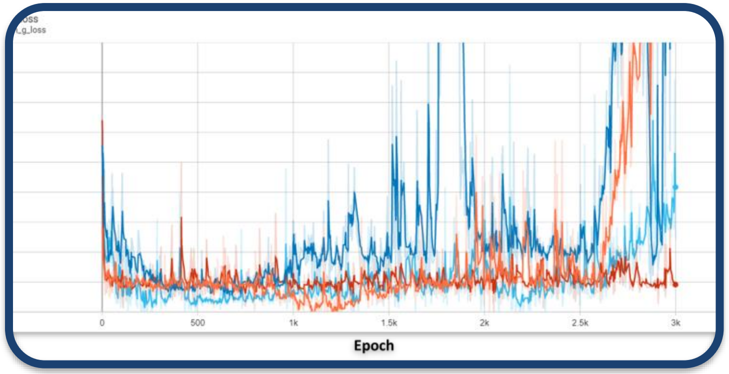
Enabling Tools and Technologies





$$
\begin{aligned}
Y + mg\cos\theta\sin\phi &= m(\dot{v}^E + ru^E - pw^E) && (b) \quad (4.7,1)\\
Z + mg\cos\theta\cos\phi &= m(\dot{w}^E + pv^E - qu^E) && (c)\\
L &= I_x\dot{p} - I_{zx}\dot{r} + qr(I_z - I_y) - I_{zx}pq + qh'_z - rh'_y && (a)\\
M &= I_y\dot{q} + rp(I_x - I_z) + I_{zx}(p^2 - r^2) + rh'_x - ph'_z && (b) \quad (4.7,2)\\
N &= I_z\dot{r} - I_{zx}\dot{p} + pq(I_y - I_x) + I_{zx}qr + ph'_y - qh'_x && (c)\\
p &= \dot{\phi} - \dot{\psi}\sin\theta && (a)\\
q &= \dot{\theta}\cos\phi + \dot{\psi}\cos\theta\sin\phi && (b)\\
r &= \dot{\psi}\cos\theta\cos\phi - \dot{\theta}\sin\phi && (c)\\
\dot{\phi} &= p + (q\sin\phi + r\cos\phi)\tan\theta && (d) \quad (4.7,3)
\end{aligned}
$$

Database Optimization

- Relational Database Design
- Optimized Indexing and Querying
- Relational JSON Querying

Generative Artificial Intelligence

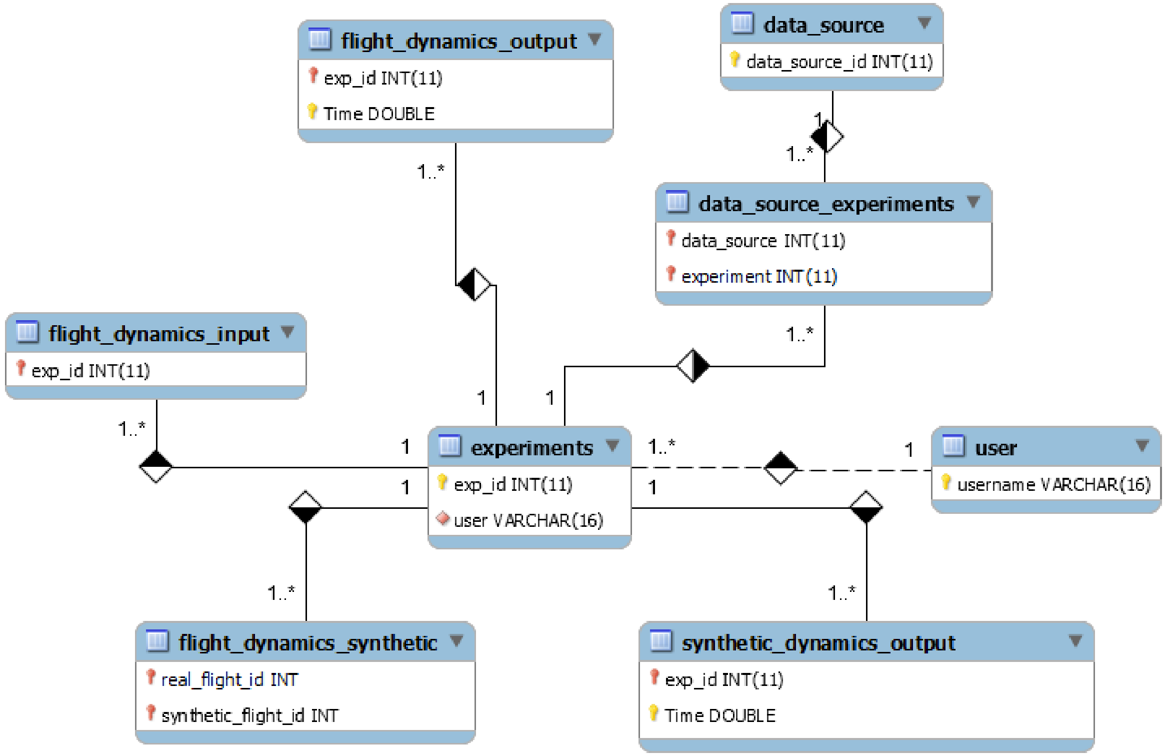
- Generative Adversarial Networks (GAN)
- Physics-Informed Learning
- Biased machine learning

Algorithmic Physical Evaluation

- Kinematic Consistency Checking
- Rotation Spline Generators
- 6DOF EOM

Methods: Database for Variational Data Augmentation

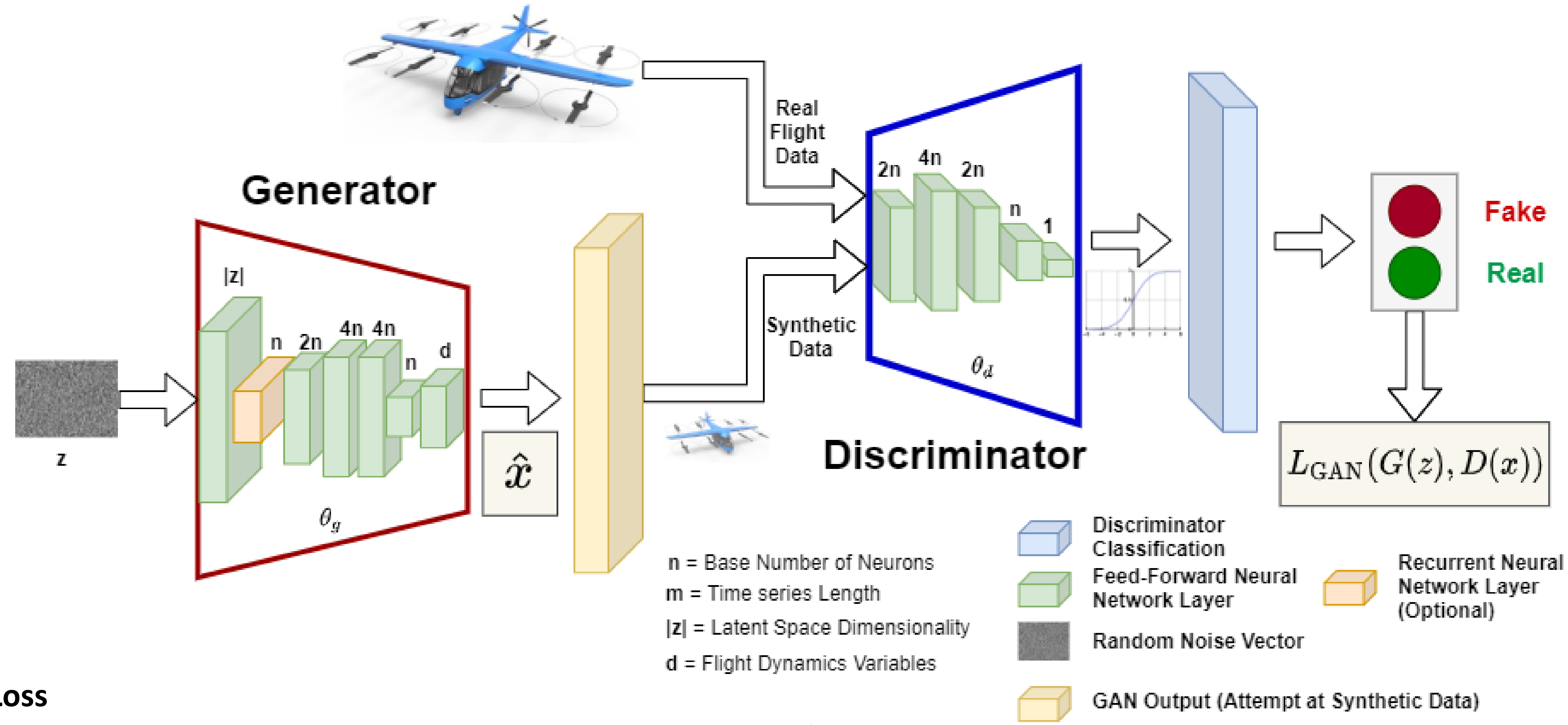
Relational Database Solution for Time Series Data



Requirement - *Solution*

- **Minimize I/O and query costs** by *indexing on key flight parameters*
- **Minimize storage requirements for 486 flight simulation output variables** by *storing normalizing metadata tables and storing time series in flat tables*
- **Query flights and subsets of flights with specific characteristics** by *storing metadata as MySQL JSON data type*
- **Maintain a mapping between simulated and augmented flight data** by *using a MySQL mapping table and foreign keys for real and synthetic data*

Methods: Basic Generative Adversarial Network



Loss

$$L_{\mathrm{GAN}}(G(z), D(x)) = \mathbb{E}_{x\sim P(x)}\left[\log D(x)\right] + \mathbb{E}_{z\sim P(z)}\left[\log(1 - D(G(z))\right]^2$$

Optimization (Adam)

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{\hat{v}} + \epsilon} \cdot \hat{\mu}, \quad \hat{\mu}_t = \frac{\mu_t}{1-\beta_1^t} \quad \mu_t = \beta_1 \mu_{t-1} + (1-\beta_1)\frac{\partial L}{\partial w_t}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t}, \quad v_t = \beta_2 v_{t-1} + (1-\beta_2)\left[\frac{\partial L}{\partial w_t}\right]^2$$

Methods: Physics-Evaluation of Generated Data

6-Degrees of Freedom Equations of Motion:

Rates of rotation of the Euler Angles

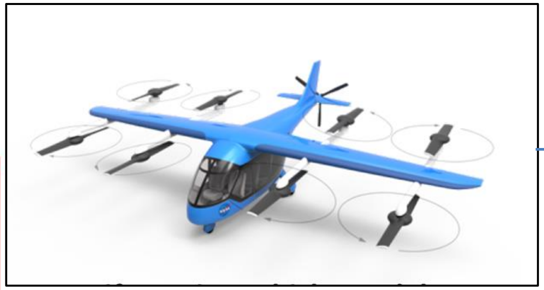
$$
\begin{aligned}
X - mg\sin\theta &= m(\dot{u}^E + qw^E - rv^E) && (a)\\
Y + mg\cos\theta\sin\phi &= m(\dot{v}^E + ru^E - pw^E) && (b) \quad (4.7,1)\\
Z + mg\cos\theta\cos\phi &= m(\dot{w}^E + pv^E - qu^E) && (c)
\end{aligned}
$$

$$
\begin{aligned}
L &= I_x\dot{p} - I_{zx}\dot{r} + qr(I_z - I_y) - I_{zx}pq + qh'_z - rh'_y && (a)\\
M &= I_y\dot{q} + rp(I_x - I_z) + I_{zx}(p^2 - r^2) + rh'_x - ph'_z && (b) \quad (4.7,2)\\
N &= I_z\dot{r} - I_{zx}\dot{p} + pq(I_y - I_x) + I_{zx}qr + ph'_y - qh'_x && (c)
\end{aligned}
$$

$$
\begin{aligned}
p &= \dot{\phi} - \dot{\psi}\sin\theta && (a)\\
q &= \dot{\theta}\cos\phi + \dot{\psi}\cos\theta\sin\phi && (b)\\
r &= \dot{\psi}\cos\theta\cos\phi - \dot{\theta}\sin\phi && (c)\\
\dot{\phi} &= p + (q\sin\phi + r\cos\phi)\tan\theta && (d) \quad (4.7,3)\\
\dot{\theta} &= q\cos\phi - r\sin\phi && (e)\\
\dot{\psi} &= (q\sin\phi + r\cos\phi)\sec\theta && (f)
\end{aligned}
$$

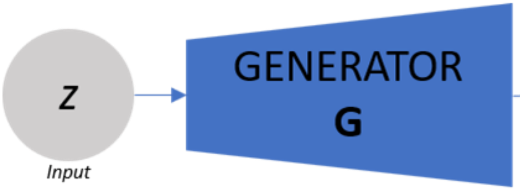
(ψ, θ, ϕ) Euler angles, radians
(p, q, r) scalar components of $\boldsymbol{\omega}$, radians/sec in F_B

Reference Text:
Dynamics of Flight Stability and Control by BERNARD ETKIN & LLOYD DUFF REID



ICM Simulation Flight Dynamics Data

V	α	β	γ	p
q	r	ϕ	ψ	θ



Synthetic Data

$\hat{V}$	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{p}$
$\hat{q}$	$\hat{r}$	$\hat{\phi}$	$\hat{\psi}$	$\hat{\theta}$

$$error = \begin{bmatrix}\epsilon_p & \epsilon_q & \epsilon_r & \epsilon_u & \epsilon_v & \epsilon_w & \epsilon_\alpha & \epsilon_\beta & \epsilon_\gamma\end{bmatrix}$$

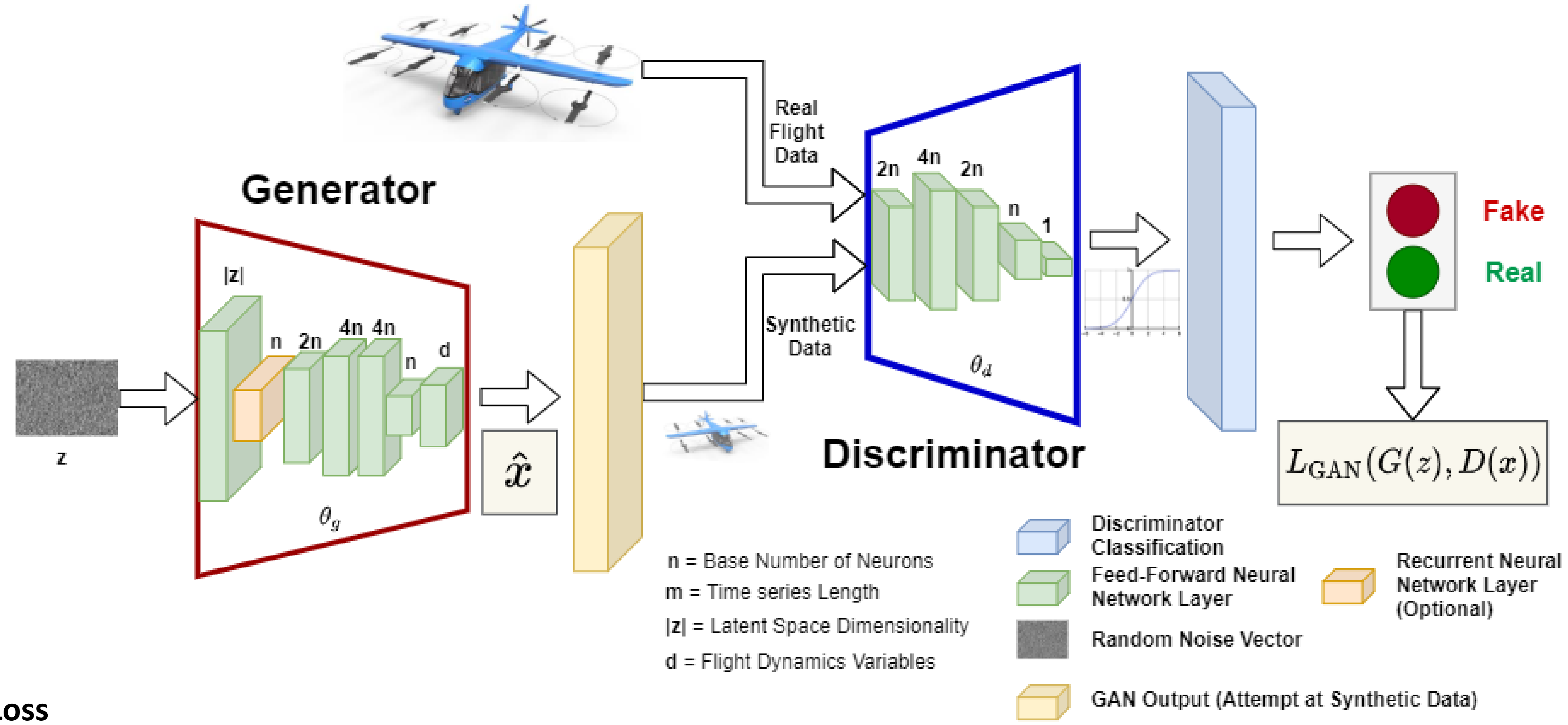
$$\epsilon_p = \left(\dot{\phi} - \dot{\hat{\phi}}\right)^2 \qquad \epsilon_u = \left(u - \frac{w}{\tan\alpha}\right)^2 \qquad \epsilon_\alpha = \left(\alpha - \tan^{-1}\frac{w}{u}\right)^2$$

$$\epsilon_q = \left(\dot{\theta} - \dot{\hat{\theta}}\right)^2 \qquad \epsilon_v = \left(v - \sqrt{V^2 - u^2 - w^2}\right)^2 \qquad \epsilon_\beta = \left(\beta - \sin^{-1}\frac{v}{V}\right)^2$$

$$\epsilon_r = \left(\dot{\psi} - \dot{\hat{\psi}}\right)^2 \qquad \epsilon_w = (w - u\tan\alpha) \qquad \epsilon_\gamma = (\gamma - (\theta - \alpha))^2$$

$\begin{bmatrix}\dot{\hat{\phi}} & \dot{\hat{\theta}} & \dot{\hat{\psi}}\end{bmatrix} = f(\phi, \theta, \psi)$ where f is a cubic interpolation spline and $V^2 = \sqrt{u^2 + v^2 + w^2}$

Constrained Generative Adversarial Network



Loss

$$L_{\mathrm{GAN}}(G(z), D(x)) = \mathbb{E}_{x\sim P(x)}\left[\log D(x)\right] + \mathbb{E}_{z\sim P(z)}\left[\log(1 - D(G(z))\right]^2$$

Optimization (Adam)

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{\hat{v}} + \epsilon} \cdot \hat{\mu}, \quad \hat{\mu}_t = \frac{\mu_t}{1-\beta_1^t} \quad \mu_t = \beta_1 \mu_{t-1} + (1-\beta_1)\frac{\partial L}{\partial w_t}$$

$$\hat{v}_t = \frac{\nu_t}{1-\beta_2^t}, \quad \nu_t = \beta_2 \nu_{t-1} + (1-\beta_2)\left[\frac{\partial L}{\partial w_t}\right]^2$$

$$L(G(z), D(x)) = \begin{bmatrix} L_{GAN}\left(G(z), D(x)\right) & & \\ \|\epsilon_p & \epsilon_q & \epsilon_r\|_1 \\ \|\epsilon_u & \epsilon_v & \epsilon_w\|_1 \\ \|\epsilon_\alpha & \epsilon_\beta & \epsilon_\gamma\|_1 \end{bmatrix} / N$$

Experimental Setup

Focus on Flight Dynamics:

$$X = \begin{bmatrix} u \\ v \\ w \\ \phi \\ \theta \\ \psi \\ p \\ q \\ r \end{bmatrix} \quad \begin{matrix} \text{Translational Velocities} \\ m/s \\ \text{Euler Angles} \\ deg \\ \text{Angular Rates} \\ deg/s \end{matrix} \quad \text{and} \quad \delta = \begin{bmatrix} \delta_\mathrm{e} \\ \delta_\mathrm{a} \\ \delta_\mathrm{r} \end{bmatrix} \quad \begin{matrix} \text{Elevator} \\ \text{Aileron} \\ \text{Rudder} \end{matrix}$$

NASA AirSTAR T-2

$$X_{\mathrm{AirSTAR}} = \begin{bmatrix} V & \alpha & \beta & \gamma & p & q & r & \phi & \theta & \psi \end{bmatrix}$$

Lift+Cruise Model

$$X_{\mathrm{L+C}} = \begin{bmatrix} u & v & w & V & \alpha & \beta & \gamma & p & q & r & \phi & \theta & \psi \end{bmatrix}$$

$$X_{\mathrm{L+C}_\delta} = \begin{bmatrix} u & v & w & V & \alpha & \beta & \gamma & p & q & r & \phi & \theta & \psi & \delta_\mathrm{e} & \delta_\mathrm{a} & \delta_\mathrm{r} \end{bmatrix}$$

Experimental Setup

Experimental Factors

Flight Regime	Loss Function	RNN Layer	Include Commands
Linear	Baseline (Vanilla)	None	No
ORCA	Physics-Constrained	GRU	Yes

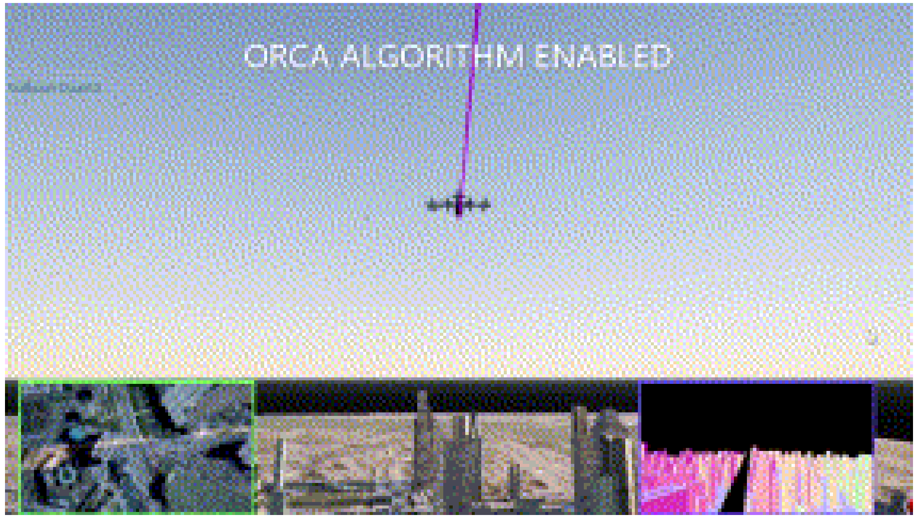
Experimental Outcomes

$$error = \begin{bmatrix} \underset{rad}{\epsilon_p} & \underset{rad}{\epsilon_q} & \underset{rad}{\epsilon_r} & \underset{m/s}{\epsilon_u} & \underset{m/s}{\epsilon_v} & \underset{m/s}{\epsilon_w} & \underset{rad}{\epsilon_\alpha} & \underset{rad}{\epsilon_\beta} & \underset{rad}{\epsilon_\gamma} \end{bmatrix}$$

- Validate methodology on two flight regimes: **Linear** and **Optimal Reciprocal Collision Avoidance (ORCA)**
- Instantiated all generator networks with a **bias vector** of flight state means
- Generated 10,000 flights and smoothed with **Savitzky–Golay filter**

Vehicle	# Flights	Avg Time(s)
AirSTAR	47	1000
Lift+Cruise – Linear	27	45
Lift+Cruise – ORCA	37	100

Linear



ORCA

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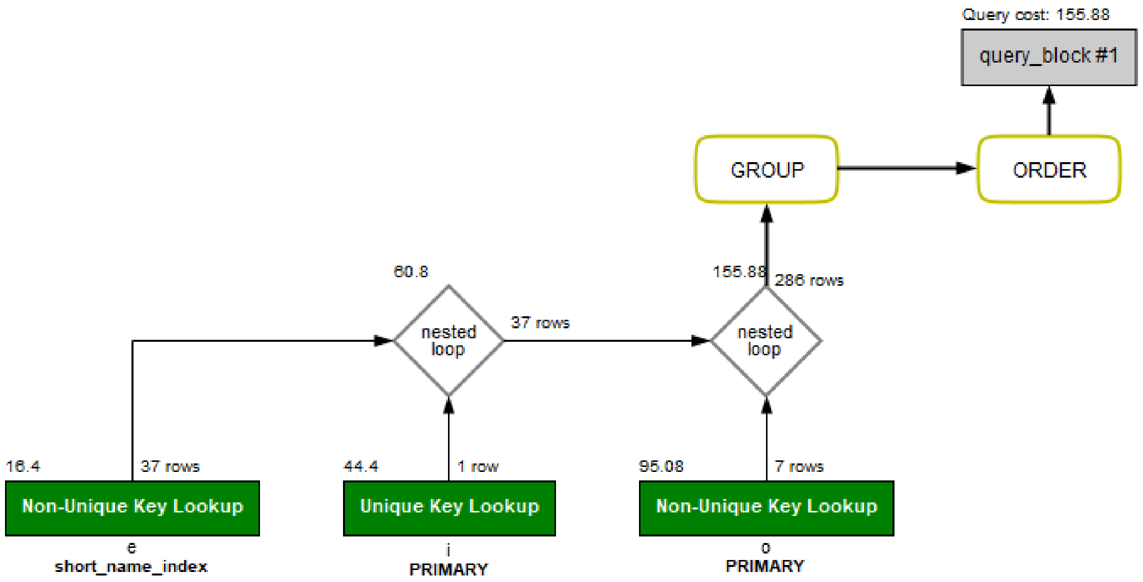
Results

MySQL Database Storage

```
SELECT e.exp_id as exp_id, e.short_name as short_name, e.description, (MAX(Time)-MIN(Time
    ↪ )) AS num_seconds, COUNT(Time) AS num_observations, i.flight_dynamics_inputs->'$.
    ↪ case' as flight_regime, i.flight_dynamics_inputs->'$.trajFile' AS trajectory_file,
    ↪  i.flight_dynamics_inputs->'$.vehicleType' AS vehicle, i.flight_dynamics_inputs->'
    ↪ $.SwitcheTurbulenceOn' AS turbulence, i.flight_dynamics_inputs->'$.fmType' AS
    ↪ fmType
FROM experiments e INNER JOIN flight_dynamics_outputs o ON e.exp_id=o.exp_id INNER JOIN
    ↪ flight_dynamics_inputs i ON e.exp_id=i.exp_id
WHERE short_name='ORCA' GROUP BY exp_id HAVING num_observations < 900 AND turbulence = 0
ORDER BY exp_id
```

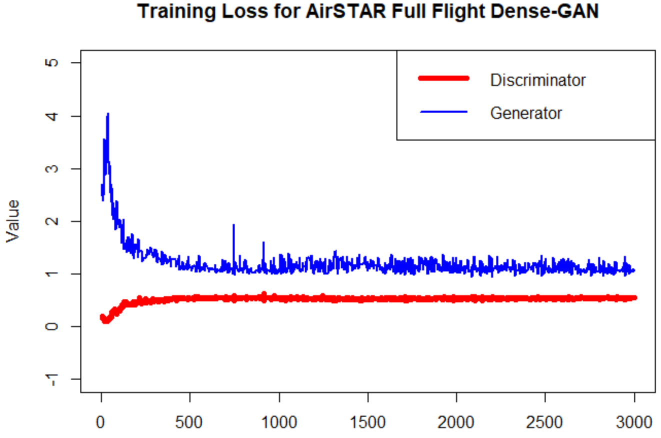


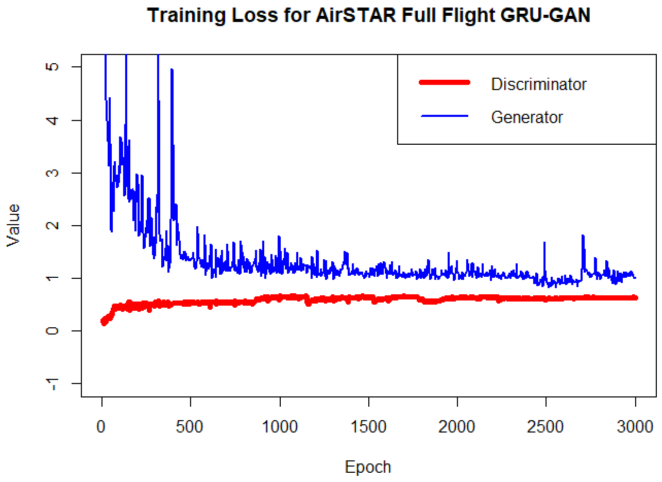
Validated all queries needed for experiment required sub-second range:

- Flight Metadata Queries: **~10ms**
- Flight Time Series Queries: **~10ms** (for 100s of observations)

Results: AirSTAR

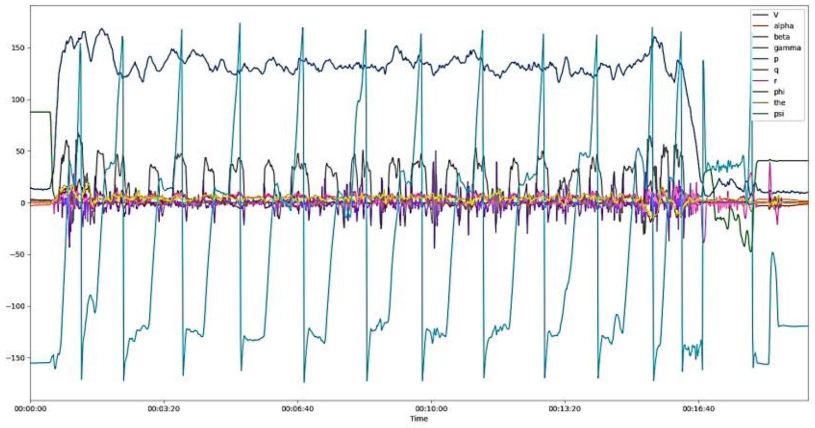
Training



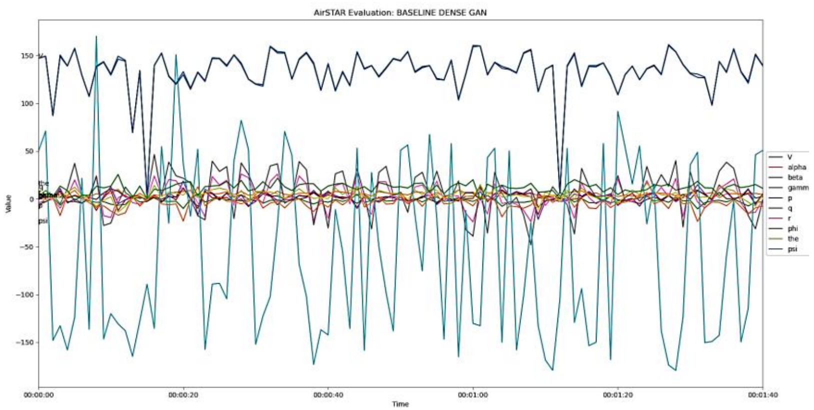


Mimics Loss-of-Control Features

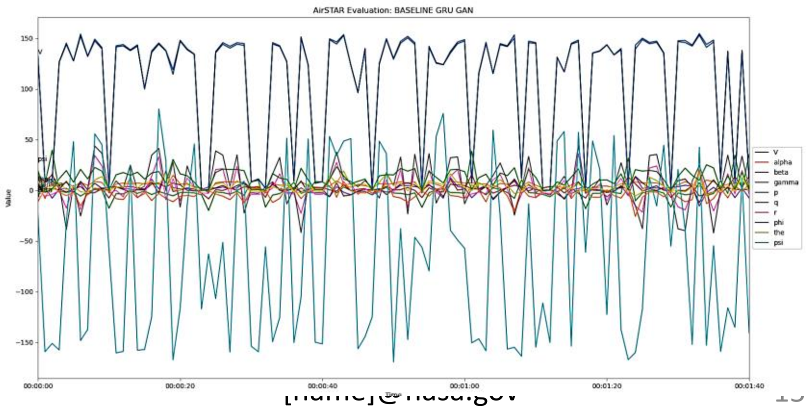
Original Data (Single Flight)



Generated Data



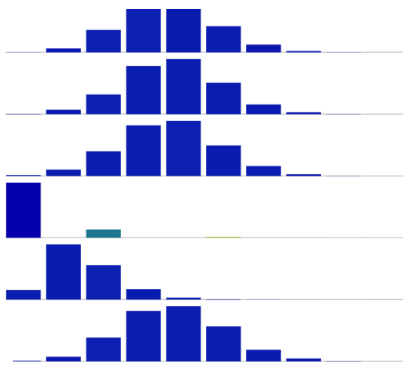
Dense-GAN



GRU-GAN

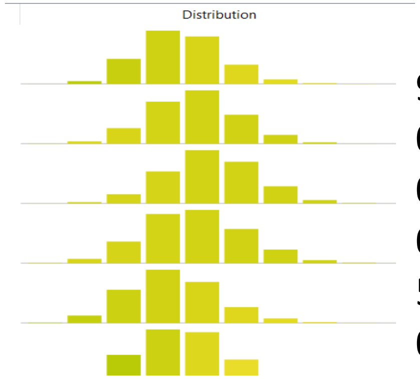
Evaluation

Dense



	Mean	$C_v = \frac{\sigma}{\mu}$
ϵ_p	0.012	0.07
ϵ_q	0.015	0.05
ϵ_r	0.048	0.0367
ϵ_α	1.6E-3	3.3E-17
ϵ_β	2.34E-18	5.97E-19
ϵ_v	0.0117	0.0094

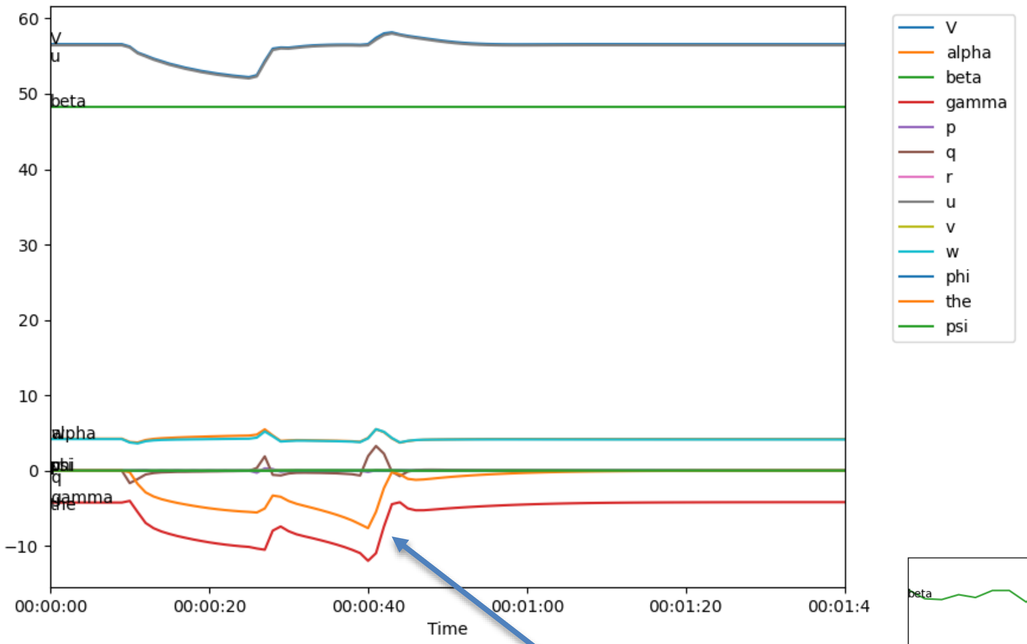
GRU



	Mean	$C_v = \frac{\sigma}{\mu}$
ϵ_p	9.5E-3	0.064
ϵ_q	0.011	0.056
ϵ_r	0.058	0.042
ϵ_α	0.28	0.189
ϵ_β	5.28E-17	-------
ϵ_γ	0.022	0.0567

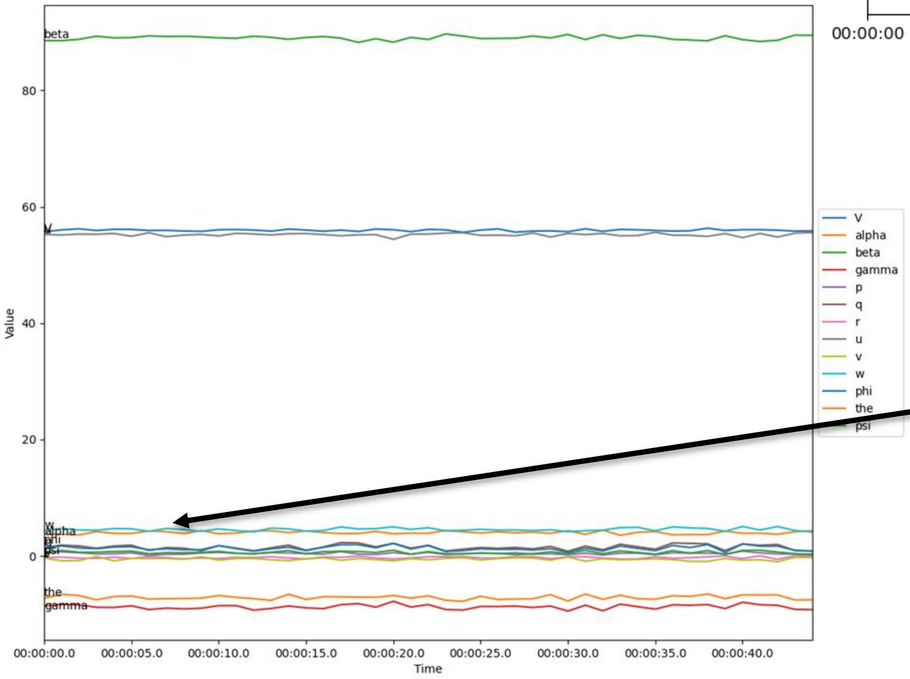
Results: Lift+Cruise for ORCA Flights

ICM Simulator Flight: ORCA



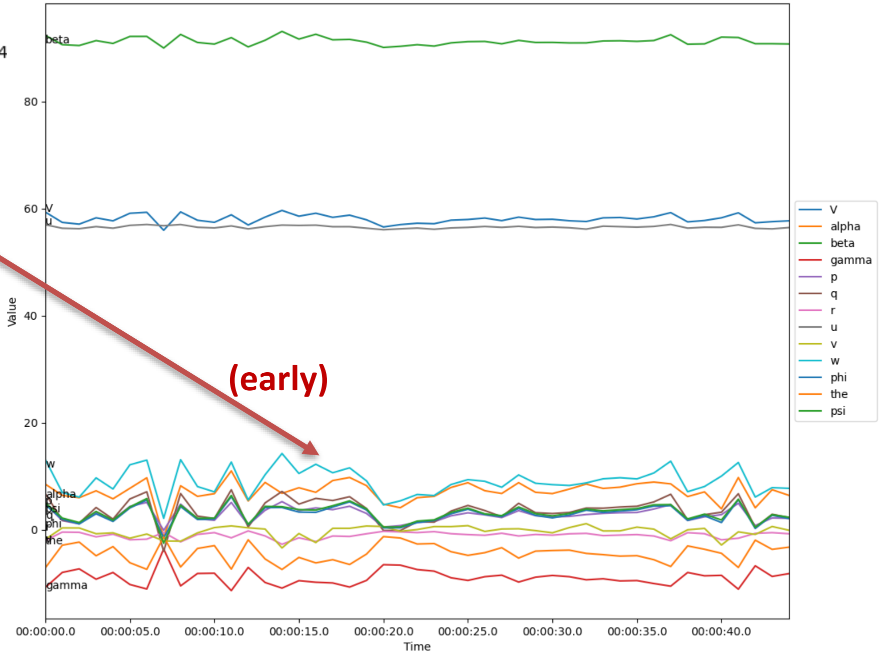
ORCA Maneuver

Generated Flight: ORCA, CONSTRAINED, DENSE



Not captured well

Generated Flight: ORCA, CONSTRAINED, GRU



(early)

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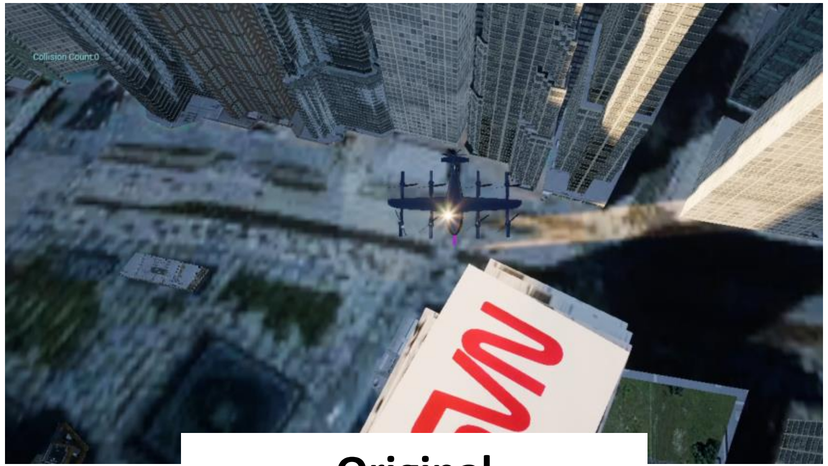
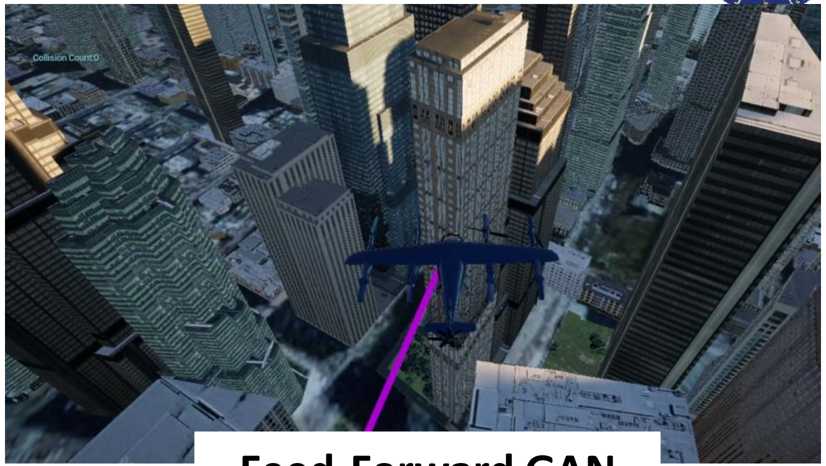
Results: Lift+Cruise for Linear Flights

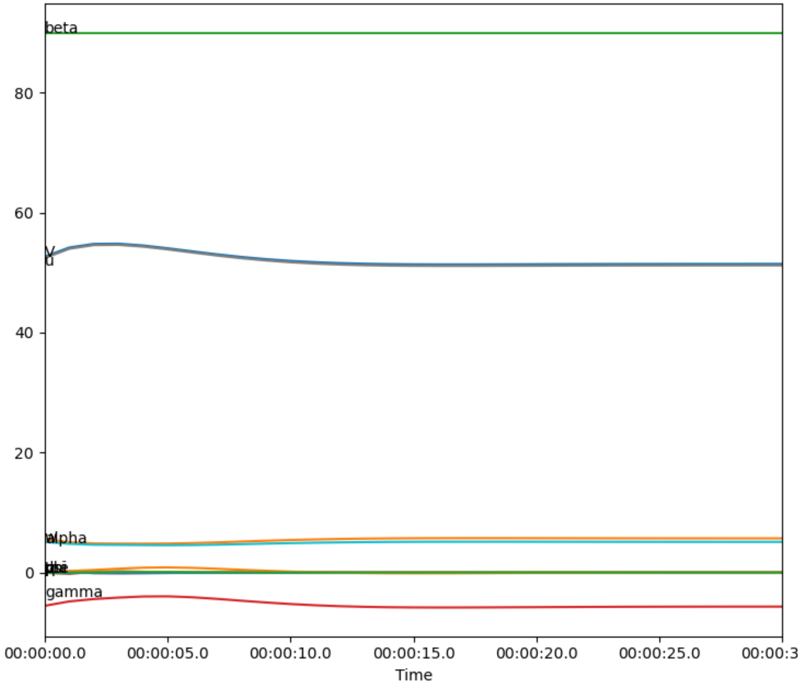
GRU-GAN

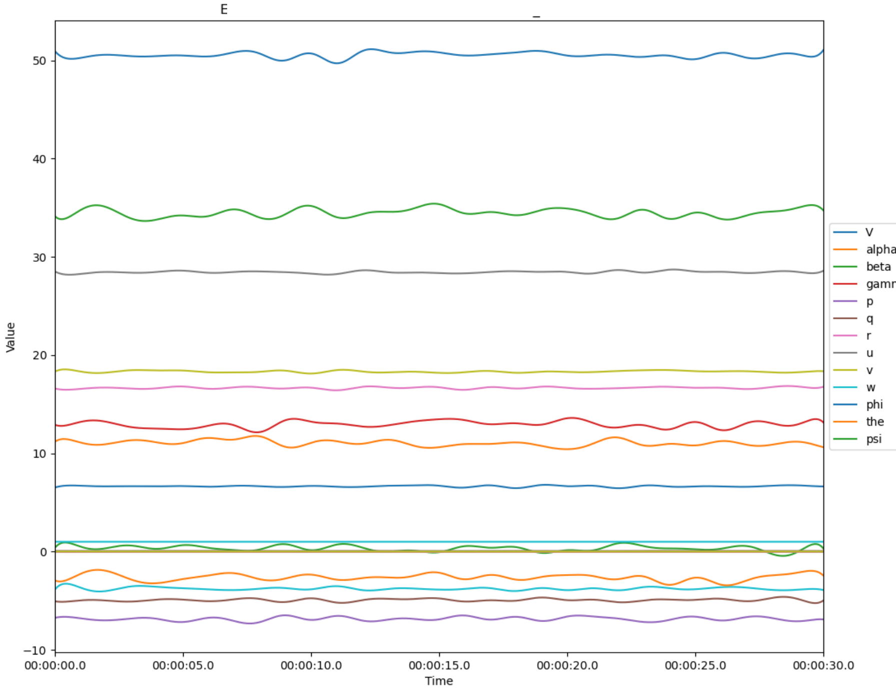


Original

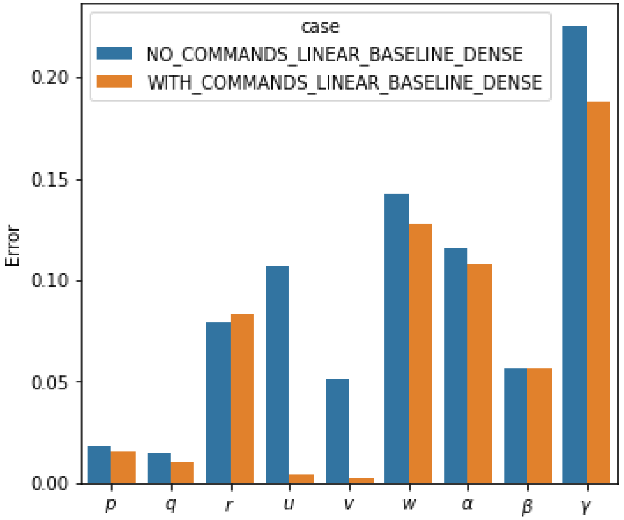


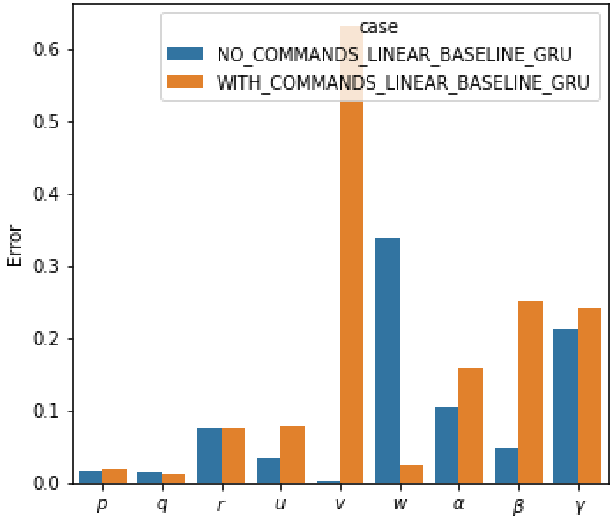
Feed-Forward GAN

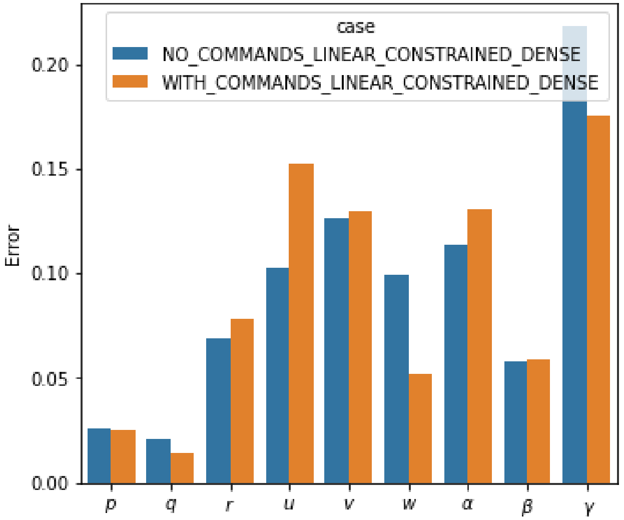


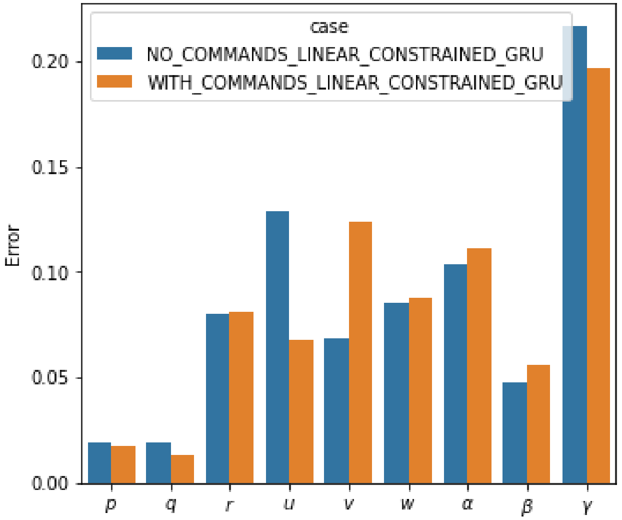


EoM and Performance Evaluation

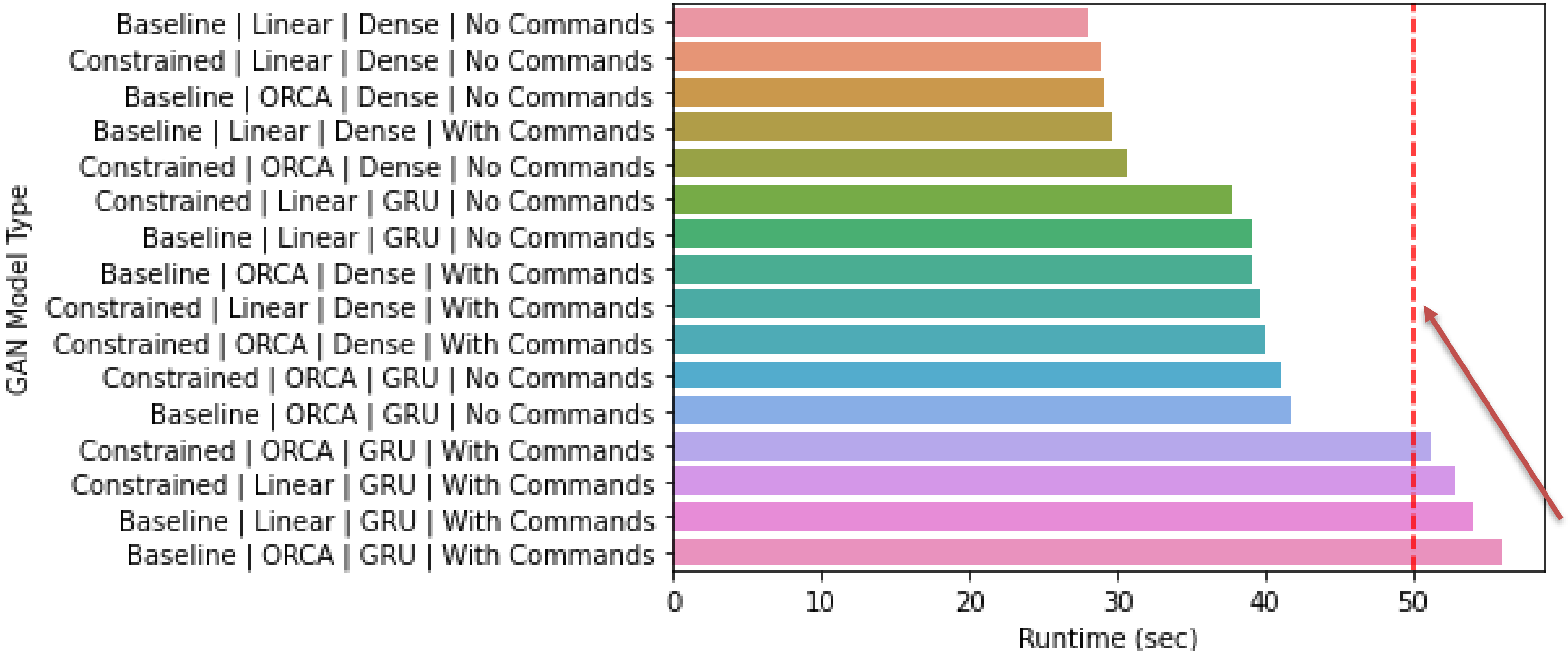








Total Time for Generating 10,000 Flights



AVERAGE Time for ICM Simulation of 1 Flight

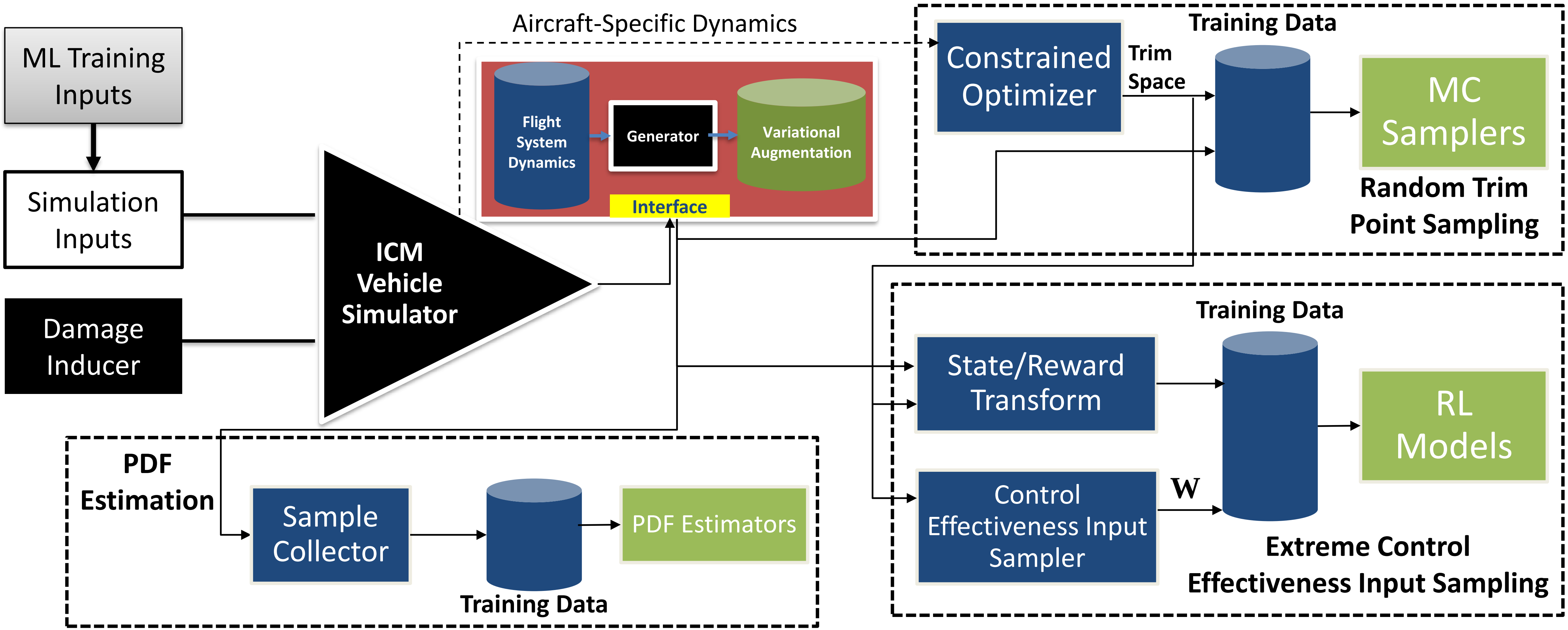
Results

- Including the commands alone did not reliably improve error
- Introducing a bias vector allowed quick convergence during training
- Including either GRU or constrained networks (or both) increase necessary training times

Next Steps

- Run simulations beyond just linear and ORCA flight regimes, including vehicle failure scenarios
- Investigate additional canonical equations of motion that are incorporated into the ICM Vehicle Dynamics Simulator (Forces, Moments, relationships with Controls)
  - Optimize calculation of kinematic consistency checks
- Explore other methods of attaching the physics values to the loss function
  - Include Hamiltonian constraints described in evaluation and loss function

Vision



*Original presented in: Grauer, J. A., Campbell, N. H., Acheson, M. J., & Gregory, I. M. (2021). Dynamic Vehicle Assessment for Intelligent Contingency Management of Urban Air Mobility Vehicles. In AIAA Scitech 2021 Forum (p. 1001).

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