NASA Apollo 13
NASA Apollo 13
A digital twin is a virtual representation of an object or system helping in decision-making and prediction. It takes in real-time data and keeps track of the lifecycle of the object or system.
Digital Twin of UAV

Control inputs: Actions or decisions that influence the physical asset

Physical State: Parametrized state of the physical asset

Observational data: Available information describing the state of the physical asset

Digital State: Parameters (model inputs) that define the computational models comprising the digital twin

Reward: Quantifies overall performance of the asset-twin system

Quantities of Interest: Quantities describing the asset, estimated via model outputs

Digital Twin of UAV

Digital Twin of UAV

$t = 0$

$p(S_t | S_{t-1})$

$t = t_c = 2$

$p(D_t | D_{t-1})$

Willcox K. et al., Predictive Digital Twins, CIS Digital Twin Days, 2021
Graph represents joint probability distribution: $p\left(D_0, ..., D_{t_p}, Q_0, ..., Q_{t_p}, R_0, ..., R_{t_p}, U_{t_c+1}, ..., U_{t_p} \mid o_0, ..., o_{t_c}, u_0, ..., u_{t_c}\right)$

Creating and evolving a structural digital twin for an unmanned aerial vehicle

Baseline model $D_b$
- calibrate geometry, $g$
- $U_1$ = “measure geometry”
- $O_1$ = $\hat{y} = [\hat{y}_b, \hat{y}_{root}, \hat{y}_{tip}]$
- $Q_1 = \| E[D_b] - E[D_1|a_1] \|

$D_a$
- calibrate material properties, $e$
- $U_2$ = “load-displacement test”
- $O_2$ = $\{ \hat{f}, \hat{x} \}$
- $Q_2 = k = f/x$
- $R_2 = \text{Var}(D_a) - \text{Var}(D_2|a_1, a_2)$

$D_b$
- calibrate mass and damping, $m, \alpha, \beta$
- $U_3$ = “initial condition test”
- $O_3$ = $\{ \hat{\omega}, \hat{\zeta} \}$
- $Q_3 = [\omega_1, \zeta_1]$
- $R_3 = \| E(Q_3) - \alpha_3 \|

Calibrated digital twin

Dynamic data-driven digital twin
- dynamic estimation of structural health, $z$
- $U_4$ \in \{2g, 3g\}
- $O_4$ = $\{ \epsilon^a \}$
- $Q_4 = \{ \epsilon^a \}$
- $R_4 = [R_{health}^a, R_{control}^a, R_{error}^a]$

Baseline model $D_0$ $D_1$ $c_{\text{root}}$ $c_{\text{tip}}$

**Prior**

- $U_1$ = “measure geometry”
- $O_1 = \hat{g} = [\hat{i}, \hat{c}_{\text{root}}, \hat{c}_{\text{tip}}]$
- $Q_1 = g = [l, c_{\text{root}}, c_{\text{tip}}]$

\[ R_1 = ||E[O_1] - E[O_1|D_1]|| \]

<table>
<thead>
<tr>
<th>$c_{\text{root}}$ [mm]</th>
<th>$c_{\text{tip}}$ [mm]</th>
<th>$l$ [mm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mathcal{N}(435.6, 1.3)$</td>
<td>$\mathcal{N}(261.1, 1.3)$</td>
<td>$\mathcal{N}(1828.8, 1.3)$</td>
</tr>
</tbody>
</table>

**Observation**

- $D_1$
- Posterior estimate

433
260
1828

Willcox K. et al., Predictive Digital Twins, CIS Digital Twin Days, 2021
calibrate mass and damping, $m, \alpha, \beta$

\[ U_3 = \text{“initial condition test”} \]

\[ O_3 = \{ \hat{t}, \hat{\epsilon}(\hat{t}) \} \quad \text{post-process} \quad \{ \omega_i, \zeta_i \} \]

\[ Q_3 = [\omega_i, \zeta_i] \]

\[ R_3 = ||E(Q_3) - o_3|| \]

![Experimental datasets Two mode fit](image)

\[ \begin{array}{cccccccc}
D & c_{ root} & c_{ tip} & l & e & m_{ servo} & \alpha & \beta \\
\hline
\text{Prior information} & N'(435.6, 1.3) & N'(261.1, 1.3) & N'(1828.8, 1.3) & N'(1.0, 0.026) & m_{ servo} + m_{ plate} = 472 & 0 & 0 \\
\text{Posterior estimate} & 433 & 260 & 1828 & 1.0073 (0.0103) & 169.1 (3.3) & 1.030 (0.001) & 7.66 \times 10^{-5} (6.18 \times 10^{-5})
\end{array} \]

- Aircraft undergoes in-flight structural health degradation
- 24 wing-mounted sensors provide noisy strain data
- Digital twin is dynamically updated and used to drive mission re-planning
- Scenarios are simulated in ROS

Digital Twin of Patient

$D_t$: Digital Twin State
Tumor dynamics, mechanics

$U_t$: Control inputs
MRI studies, biopsies, treatment regimens

$S_t$: Physical State
Anatomy & morphology, mechanical & physiological state

$R_t$: Reward
Patient outcomes: treatment efficacy, toxicity

$Q_t$: Observational data
Anatomy, perfusion, permeability, cell density, metabolism

$Q_t$: Quantities of Interest
Distribution of therapies, tumor shape, cell density

Digital Twin of Patient

[true glioma properties]

\[ S_0 \quad MRI_0 \quad O_0 \quad RT_0 \quad D_0 \quad Q_0 \]

\[ \phi(t) = \text{est. cell count} \]

\[ \theta = \text{model parameters} \]

[est. glioma properties]

\[ \frac{d\phi}{dt} = f(\phi; \theta) \]

interTwin overall objective

Co-design and implement the prototype of an interdisciplinary Digital Twin Engine.

Digital Twin Engine

- It is an open-source platform based on open standards.
- It offers the capability to integrate with application-specific Digital Twins.
- Its functional specifications and implementation are based on
  - a co-designed interoperability framework
  - conceptual model of a DT for research - the DTE blueprint architecture.
EGI Foundation as coordinator

Participants, including 1 affiliated entity and 2 associated partners

Consortium at a glance

10 Providers
cloud, HTC, HPC resources and access to Quantum systems

11 Technology providers
delivering the DTE infrastructure and horizontal capabilities

14 Community representants
from 5 scientific areas; requirements and developing DT applications and thematic modules
Collaboration with ECMWF
Demonstrators of data handling across interTwin and DestinE DTs for the Extremes and Climate in production-type configurations.

Collaboration with DestinE
Development of common software architecture concepts that are also applicable to other major DTs initiatives.
Requirements

- **Online Learning**
The DTE shall enable handling stream of data larger than 10MB/s

- **Federated Learning**
The DTE shall be able to transmit/receive data synchronically (at least aperiodically) between different HPC providers

- **Hyperparameter Optimization**
The DTE shall support HPO frameworks (RayTune, etc).

- **Unified access to infrastructure**
  The DTE shall enable homogeneous security and access policies, resource accounting to HPC, HTC and cloud providers

- **Bridge difference in infrastructure needs**
The DTE shall be usable by sciences with vast differences in compute/storage needs
interTwin components

**DT Applications**

DTE Thematic Modules
- Thematic Modules (Environmental Sciences)
- Thematic Modules (Physics Sciences)
- Thematic Modules (Other Sciences)

DTE Core Modules
- Quality Verification
- Workflow composition
  - Big Data analytics
  - AI / ML
  - Data fusion
- Real-time data acquisition and processing

DTE Infrastructure
- Orchestration
- Federated data management
- Quantum
- HPC
- HTC and Cloud
- Data repositories
Digital Twin Engine
Digital Twin Engine (2)
Digital Twin Engine (4)

The DTE core
DT workflow composition

DT developer

Workflow orchestrator
DT workflow composition (2)
DT workflow composition (3)
DT workflow composition (5)
DT workflow composition (6)
DT workflow composition (7)
EMP²: Environmental Modelling and prediction platform

First proof-of-concept of a machine-learning based global environmental model trained on terabytes of observational data

R&D at Juelich SSC: 4x10⁶ GPU hours granted in 2023
Why CERN?

Solve common scientific challenge(s) in high-energy physics and weather/climate science using AI/ML

Model complex, nonlinear phenomena and improve current simulations
Access multi-scale dependencies of a given process
Earth science: eg. better understand convection phenomena
CERN: eg. particle-jet showers reconstruction

Explore potential of unsupervised learning for scientific applications
Extract new information directly from data
Earth science: eg. early detection of extreme events
CERN: eg. anomaly detection

Common Goal:
Develop a proof of concept of representation learning for scientific applications based on observations
Thank you!
References
