

# Digital Twins

CPS and IoT Security

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# What is a Digital Twin



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- A digital twin is a virtual model designed to accurately reflect a physical object
- “machines (physical and/or virtual) or computer-based models that are simulating, emulating, mirroring or twinning the life of a physical entity”
- We create a counterpart digital representation of an object to fully characterize its behavior
- The model we create is outfitted with various sensors related to vital areas of its functionality





- All these sensors produce data about the different aspects of the physical object
  - Energy output, temperature, weather conditions,...
- The data is relayed to a processing system and applied to the digital copy
- The model informed with such data can be used to run simulations, study performance issues, generate improvements, study cybersecurity aspects



- Both DT and simulation use digital models to create a replica of a system's process, however
  - Simulations replicates a particular process
  - A DT replicates multiple processes and their interaction
- A DT thus provides way more features for the environment under study
- Furthermore, a DT usually operates on real-time data from sensors
- The DT virtual environment (virtual machines, containers, virtual networks) then creates a new flow of information by processing the real-time data



- A DT comprises three main spaces
- **Physical space:** comprising real world devices such as sensors, actuators, and controllers (OT)
- **Digital space:** digital framework capable of simulating physical assets and their states, conditions, and configurations to make decisions on the physical space
- **Communication space:** creates the connection between the digital and the physical spaces



- It is important to establish bidirectional interfaces in DTs
- *Digital thread* between physical space and digital space: the data from the physical space is processed by the digital space, which creates new useful information that can be sent back to the physical space
- Example: a DT synchronizes its models with respect to its physical counterpart to guarantee consistency in the production process (contextual parameters such as humidity, temperature, pressure)



- We can abstract the functionalities of a DT by considering four layers
- **Layer 1: data dissemination and acquisition**, which captures the dynamics of the physical space and prepares instructions for physical assets
- **Layer 2: data management and synchronization**, which handles multi-source data to pass to layer 3, network management, and synchronization services



- **Layer 3: data modeling and additional services**, which specifies digital models for shapes, behaviors, states and creates services such as monitoring, cybersecurity, and diagnostic
- **Layer 4: data visualization and accessibility**, which provides means for users, entities and processes to visualize the simulation results from the digital models and enable decisions on this basis
- The fundamental difference between layers is in the level of data they consider: from physical to digital model results

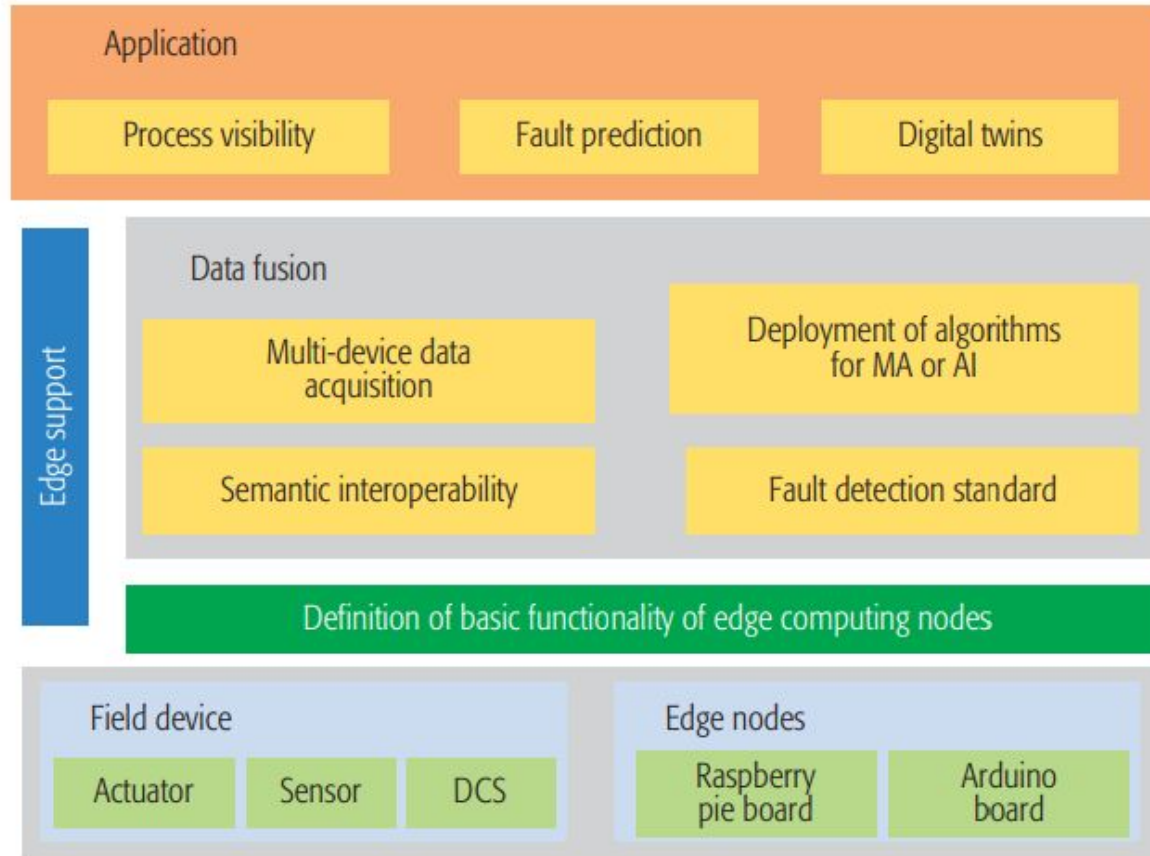




- A fundamental requirement of DTs is to keep the physical space and the digital space synchronized
- In case of a variation not recorded or inconsistent, the whole DT model may significantly deviate from the true world and can thus provide useless (or misleading) information
- Therefore, we should handle the complexities of the system in terms of infrastructure, communication, computation and storage



- We need to take into account the currently available computing infrastructures to guarantee inter-layer synchronization
- We want to optimize the deployment of digital models and their processing during simulation
- Combined use of edge and fog computing: intensive operations can be executed by powerful devices, while less intensive tasks can be executed on resource limited edge devices





- We can identify three classes of overhead: communication, computation and storage
- Communication: layer 1 needs to consider many different protocols (TCP, Modbus, MQTT) which may however not be efficient
- Computation: volume of data produced by virtual assets, information collected from layer 1 elements, complexity of ML techniques (if any)
- Storage overhead: apply alternative techniques such as distributed file storage systems, non-relational database, redundant SQL servers,...

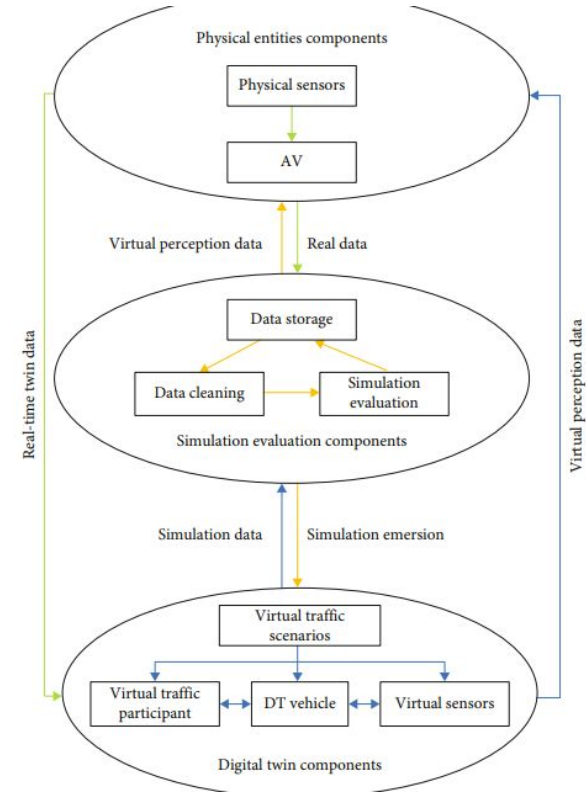


- Let's design a digital twin for an autonomous vehicle
- We need physical components, data processing and evaluation components, and a digital replica of the autonomous vehicle
- The digital twin component generates virtual perception data to send back to the physical entity components
- The AV implements decision making and control based on the received data

# Use Case: Autonomous Driving



- We use real sensor devices to capture physical data and use it to implement the digitalization process from physical to digital space
- We let a real device (equipped with a controller) running over a real-testbed and collect measurements such as position, attitude, fault,...
- Data is transmitted in real-time to the DT via network communication and to the data processing and evaluation components for data storage
- The controller receives the virtual perception information generated by the DT and make decision and control via real test filed and real vehicle actuators to gain insights





- The components are digital descriptions of certain historical moments of current real-time state in physical entity components
- The DT and AV exchange real time data and need to maintain updated information to have the DT in line with what is actually happening to the AV
- The DT components can provide repeatable and extreme simulation test scenarios, such that the virtual sensors can sense such extreme information
- The DT is also used as a visualization module

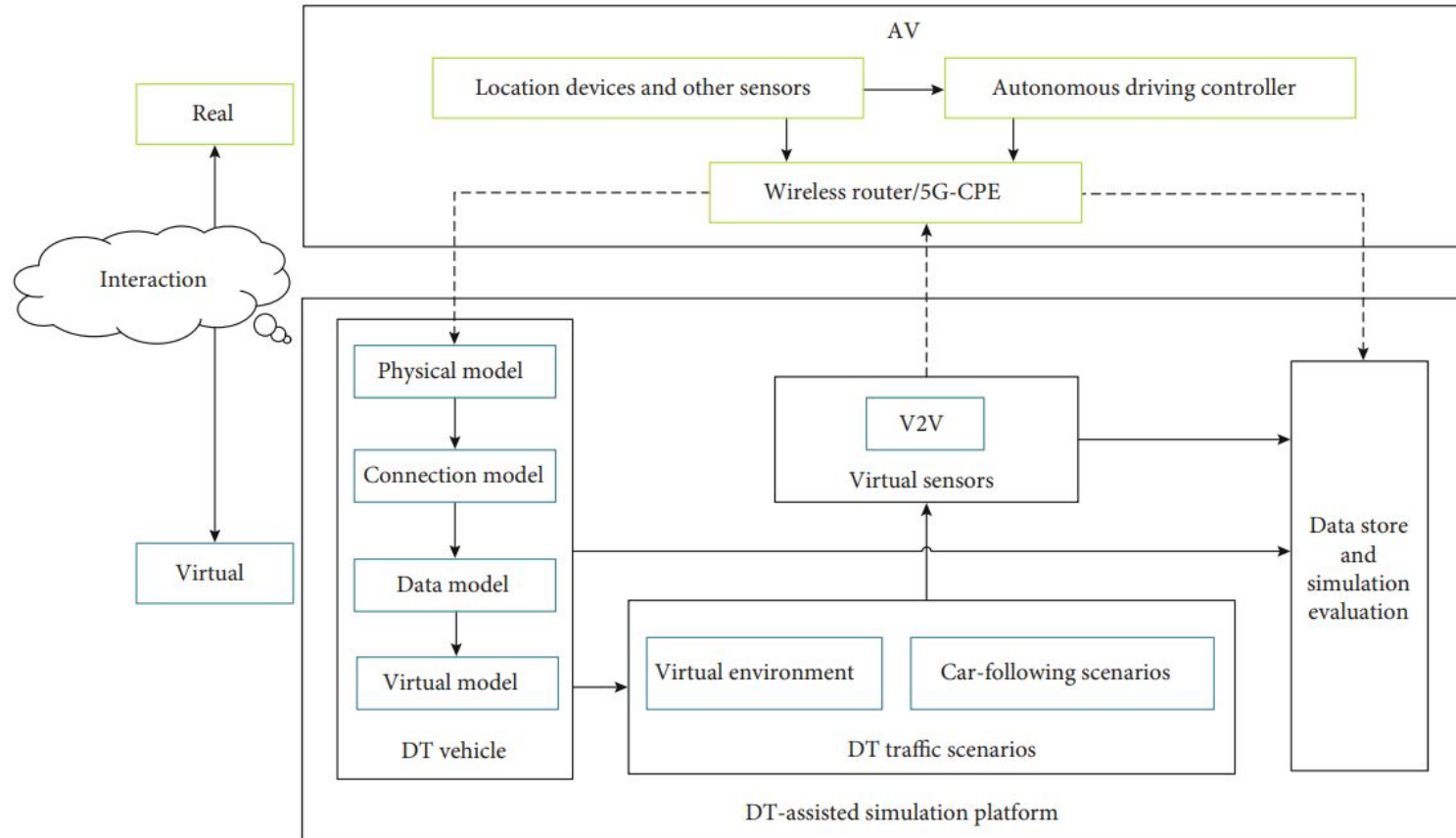
# DT Components



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- The DT is divided into two parts: the virtual environment and the car-following scenarios
- The virtual environment needs to reflect the characteristics of a real environment from various aspects (very high accuracy)
- We use software for modeling of 3D environment (e.g., of a city)
- Very high accuracy means: gathering information from satellites on elevation data, vectorize data and model the city based on them, high definition render pipeline, import traffic scenarios



- The AV replica in the DT can be divided into four levels: physical model, connection model, data model, and virtual model
- The physical model of the DT vehicle is defined to describe the motion characteristics of the AV to be tested
- The connection model of the DT vehicle realizes the synchronization between the AV to be tested and the DT vehicle
- The data model drives the virtual model to keep in sync with the behavior of the physical AV to be tested
- Virtual model is the visual model of the AV to be tested



- This component receives real-time data from the DT and the physical entities for storage and mining
- It can perform simulation evaluation based on the real-time data fed back
- The simulation results are stored in this components which can realize the rapid reproduction of dangerous accident scenarios and key simulation test processes



- We can use a DT to test breaking strategies of AVs without crashing cars
- In this case, we consider a platooning scenario, where a vehicle follows a platoon leader that suddenly breaks
- Time To Collision (TTC) represents the time it takes for the following vehicle to collide with the leading vehicle from the current state of motion
- We use this to verify the effectiveness of the model and policy

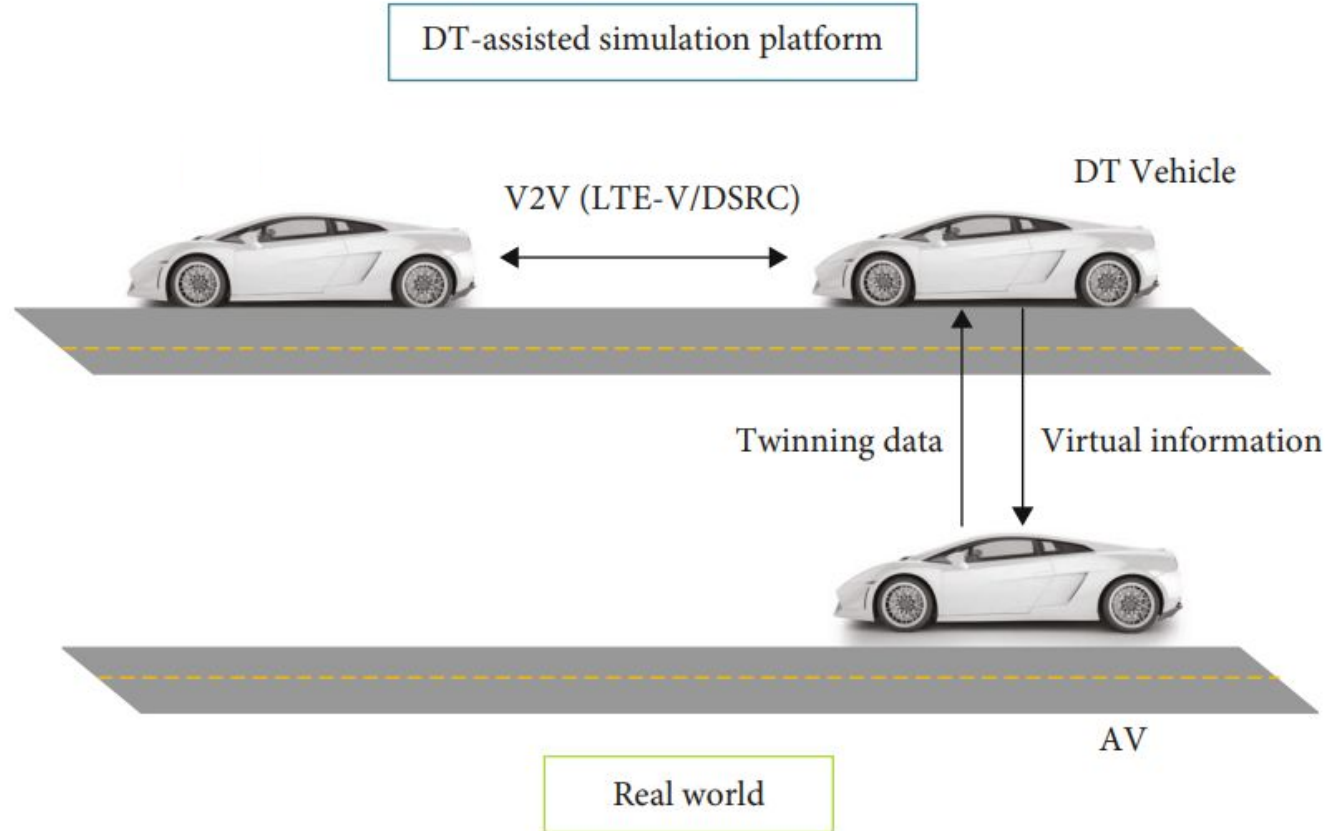
# Car-Following Scenario



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- The rear vehicle is represented by the DT which is a replica of the real AV and maintain a real-time information exchange
- We assume they use V2V communication, implemented via the DT communication module
- The DT vehicle sends the real-time virtual perception information obtained from the Preceding Vehicle (PV) to the AV in the physical world
- PV have four random motion states, that is stationary, accelerated motion, uniform motion, and decelerated motion



- The DT vehicle receives the speed, acceleration, and position information of PV through V2V
- Calculates the distance information between the two vehicles according to the position of the DT vehicle
- Acceleration and speed information of the two vehicles, as well as the distance between the two vehicles and the safe distance, and the TTC are calculated by collision avoidance strategies



- We can implement a collision avoidance strategy and test whether it works in different conditions thanks to the DT
- Implement the strategy and make the leader vehicle behave such that a collision would occur
- Run the AV based on the data obtained from the DT emulation
- Check whether there is a crash in the DT simulation





- “what the physical asset projects must be equivalent to what its digital counterpart interprets and shows”
- We can use semantic description of languages to encode digital assets (ontology-based models) to avoid creating contradictory realities
- Interpret and derive conclusions at different granularity levels
- Related to consistency we can identify two sub requirements: fidelity and granularity



- While most of the DT available are used for maintenance, optimization, and simulation of CPS, DTs can also be used to increase security and safety
- A DT can run in parallel to a CPS to perform security and safety analysis while during operation
- This can be used to minimize the risk of security problems in the real domain, verifying whether a predefined action could bring to damages by looking at the digital domain
- State replication approach, Kalman filter

- We consider a program  $P$  being a finite-state machine defined by a tuple  $P := (X, x_0, U, Y, \delta, \lambda)$ , where  $X$  is the finite set of states,  $x_0 \in X$  denotes the initial state,  $U := \{u_0, u_1, \dots, u_{k-1}\}$  is the set of inputs,  $Y := \{y_0, y_1, \dots, y_{m-1}\}$  is the finite set of outputs,  $\delta: X \times U \rightarrow X$  is the transition function, and  $\lambda: X \times U \rightarrow Y$  is the output function
- The DT runs a program  $\hat{P}$  that is functionally identical to the main one
- Thus,  $\delta(x, u) = \hat{\delta}(\hat{x}, \hat{u}) \Leftrightarrow x' = \hat{x}'$  provided that  $(x = \hat{x}) \wedge (u = \hat{u})$
- $U^*$  and  $Y^*$  denote the set of all devices' possible inputs and outputs, respectively

- We define the set  $S$  of stimuli, representing the roots of subsequent inputs corresponding to one DT (sensors values or HMI commands)

$$S := \{z \in \hat{U} \mid z \in U \wedge z \notin Y^*\}$$

- $\hat{U}$  is the set of inputs of a DT, with  $S \subset \hat{U}$  and  $\hat{U}$  may contain elements of  $\hat{Y}^*$  as well as inputs from users interacting with the DT
- We want to *replicate* stimuli, i.e., repeat the same stimulus  $s$  from the physical environment on a DT such that it leads to an identical program state  $x$



- We want to *replicate* stimuli, i.e., repeat the same stimulus  $s$  from the physical environment on a DT such that it leads to an identical program state  $x$
- If any member of  $S$  would not satisfy the right operand of the logical conjunction  $z \in U \wedge z \notin Y^*$ , then the DT may receive the same input twice
- if such a stimulus is erroneously replicated, then the DT receives the stimulus in addition to an input that was a prior output



- Continuously polling for state changes represent an active monitoring approach that might be used to capture x
- However this comes with drawbacks
- Monitoring all devices requires huge communication overhead that might impact on real-time communications
- The impact is also on devices, not only networks
- An attacker might tamper the response of a poll request



- We implement a passive approach, where we track down the trigger of a state
- Objective is to understand which  $u$  constitutes a stimulus so that it can be fed to the transition function of the DT
- We look for stimuli coming from sources that are already available in the system to avoid adding any type of overhead
- We use devices that are already part of the CPS



- Devices that are located in the CPS receive an input  $u$  that might trigger a state transition such that  $\delta(x, u) = x'$
- Consider an input  $u$  to PLC causing a state transition defined by the control logic
- Since  $u$  must be considered as a determining factor that drives the state transition, it can be directly fed to the PLC's DT provided that  $u=s$
- However more complicated state transitions might lead to problems if, for instance, it is not possible to distinguish  $u$  from  $s$





- To solve the aforementioned challenges, we use the specification of the CPS to identify stimuli
- Let us define the partial function  $f$  that maps the stimuli indices  $I$  to stimuli of all DTs  $S^*$ , i.e.,  $f: U^* \cup Y^* \rightarrow S^*$
- Then  $I$  is defined as  $I := \{j \in U^* \cup Y^* \mid f(j) \in S^*\}$
- We then observe  $j$  and check whether it belongs to  $I$
- Since  $j$  belongs to  $I$  if and only if  $f(j)$  is defined, the value  $f(j)$  is fed to the respective DT provided that  $j$  is indeed in the set  $I$



- Consider a packaging line managed by a HMI that communicates with a PLC to control a conveyor belt
- External influences can be inferred by examining the associated role of components
- The HMI receives inputs from users and, since this is a root of subsequent actions, these can be classified as stimuli for the DT of the HMI
- However, since no input detection mechanism has been implemented, it is not easy to observe the existence of a user input



- A user input generates an output in the format of a request (e.g., Modbus) making  $x$  indirectly observable by passively monitoring the network traffic to capture outputs of the HMI
- We can create  $f$  based on the specified logical network
  - Extract information on how devices communicate (including details on the used protocol)
  - Identify source and destination of packets and which program variable they affect
  - If an output  $y$  of the HMI has been classified as an outcome of a stimulus,  $f$  is defined



- Assuming that the specification of the CPS correctly describes the correct behavior and that each DT follows the state of its physical counterpart, a divergence between the two worlds should be detectable
- Comparing the inputs and outputs of the physical environment with those of the virtual one reveal either device faults or malicious activity
- Thus, the IDS processes elements of the sets  $U^*, Y^*, \hat{U}^*, \hat{Y}^*$



- The comparison between  $p \in U^* \cup Y^*$  and  $v \in \hat{U}^* \cup \hat{Y}^*$  relies on predefined features
- For instance, network traffic can be compared based on source and destination MAC addresses, source and destination IP addresses, Modbus TCP/IP ADUs
- If there is a mismatch in one of these features, the IDS raises an alarm
- The feature selection process has a huge impact on IDS's performance



- Let us consider an industrial control system, where different types of controllers regulate the production process
- We assume a DT for this system is deployed in the cloud, and there exists a connection between the two
- Such a connection creates possibilities for attacks besides those that already exist in the control system
- We want to develop an IDS able to detect both types of attacks

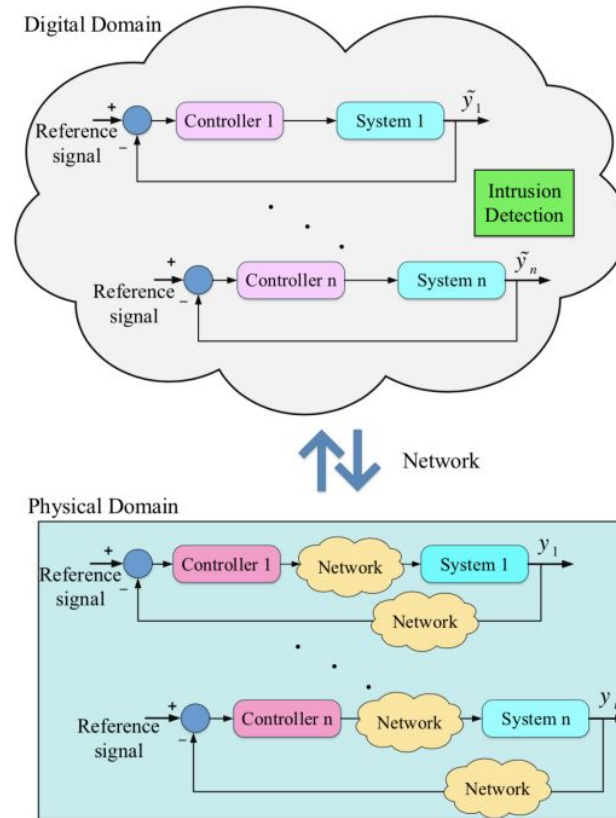
# Kalman Filter-Based State Estimation



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- Scaling attack: the measurement signal is manipulated via a scaling parameter during an attack period

$$y^*(t) = \begin{cases} y(t) & \text{for } t \notin \tau_a \\ (1 + \lambda_s) \cdot y(t) & \text{for } t \in \tau_a \end{cases}$$

- Ramp attack: add a ramp signal to the actual measurement signal

$$y^*(t) = \begin{cases} y(t) & \text{for } t \notin \tau_a \\ y(t) + \lambda_r \cdot t & \text{for } t \in \tau_a \end{cases}$$





- A Kalman filter is an algorithm that uses a series of noisy time measurements to produce an estimate of unknown variables that tend to be more accurate than those based on a single measurement
- For each time frame, it estimates the joint probability distribution
- Two phases:
  - Prediction phase: the algorithm produces estimates of the current state variables
  - Update phase: Once the next observation is available, update estimates via weighted average with more weight being given to estimates with greater certainty



- We use a Kalman filter to estimate the correct signals in the system by using inputs and outputs of the system
- We treat attacks as noisy components, which can be removed by the Kalman filter and therefore indicate change of behaviors
- We assume that there exists a simulated model of the real system that has been obtained easily by system identification algorithms
- Necessary to create an observable realization of this model to generate an observable state-space model

- We model our system as

$$\begin{aligned}x_{k+1} &= Ax_k + Bu_k + Gw_k & w &\rightarrow N(0, Q) \\ y_k &= Cx_k + Fv_k & v &\rightarrow N(0, R)\end{aligned}$$

- Where  $x$  is the state vector,  $y$  is the output signal measured by sensors,  $u$  is the input signal generated by the controller,  $w$  is the process noise, and  $v$  is the measurement noise

- Time update part

$$1) \quad \hat{x}_{k|k-1} = A_k \hat{x}_{k-1|k-1} + B_k u_k$$

$$2) \quad P_{k|k-1} = G_{k-1} Q_{k-1} G_{k-1}^T + A_{k-1} P_{k-1|k-1} A_{k-1}^T$$

- Measurement update

$$3) \quad K_k = P_{k|k-1} C_k^T (C_k P_{k|k-1} C_k^T + F_k R_k F_k^T)^{-1}$$

$$4) \quad \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (y_k - C_k \hat{x}_{k|k-1})$$

$$5) \quad P_{k|k} = (I - K_k C_k) P_{k|k-1}$$

- Time update part

$$1) \quad \hat{x}_{k|k-1} = A_k \hat{x}_{k-1|k-1} + B_k u_k$$

**Predicted  
state**

**Predicted  
covariance**

$$2) \quad P_{k|k-1} = G_{k-1} Q_{k-1} G_{k-1}^T + A_{k-1} P_{k-1|k-1} A_{k-1}^T$$

- Measurement update

**Kalman Gain**

$$3) \quad K_k = P_{k|k-1} C_k^T (C_k P_{k|k-1} C_k^T + F_k R_k F_k^T)^{-1}$$

**Updated state  
estimate**

$$4) \quad \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (y_k - C_k \hat{x}_{k|k-1})$$

**Updated covariance  
estimate**

$$5) \quad P_{k|k} = (I - K_k C_k) P_{k|k-1}$$



- Kalman filter requires the knowledge of the noise covariance matrices  $Q$  and  $R$
- We can estimate them from the process and use methodologies such as particle swarm optimization to find the optimal estimation
- Using our designed filter, we can estimate the state variable  $x$  and consequently the system output as  $\hat{y}_k = C\hat{x}_k$
- The residual signal is given by the difference between the estimate signal and the output signal  $r_k = \tilde{y}_k - \hat{y}_k$

- We use a detector to distinguish attack from noise and detect the occurrence of attacks
- Helps to make the effects of attacks and noises on the signal more prominent, filter impacts of noises, and prevent false alarms

$$h_k = \sup_{k-k_0 < i < k} |r_i|, \quad \begin{cases} H_0 : & \text{if } h_k \leq \text{threshold} \\ H_1 : & \text{if } h_k > \text{threshold} \end{cases}$$

- Based on 68-95-99.7 rule, in a Gaussian distribution, 68.27%, 95.45%, and 99.73% of the values lie within one, two, and three standard deviations of the mean, respectively



- DTs must be considered as critical systems
- We must care about CIA triad
- But we should also care about privacy issues of entities and localization of assets
- We consider two types of attack surfaces:
  - Physical, comprising attacks against access endpoints, CPS and IoT devices, communication infrastructure and facilities
  - Digital, comprising exploits against software, components for computing, and information systems