Advances in Industry 4.0 and the Industrial Internet of Things

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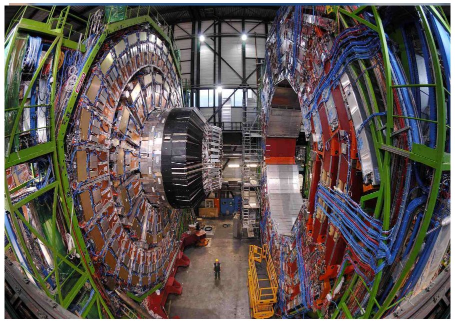
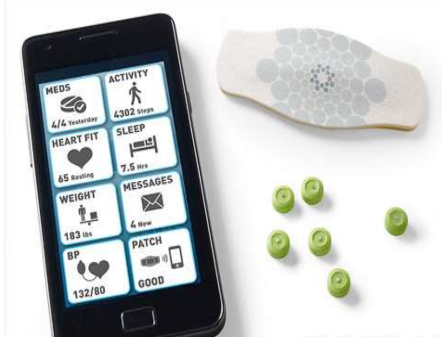
When is the last time you
learned something from a
~~machine~~?
multiple machines?

Industrial IoT is making services and products that learn from (and impact the world via) multiple machines

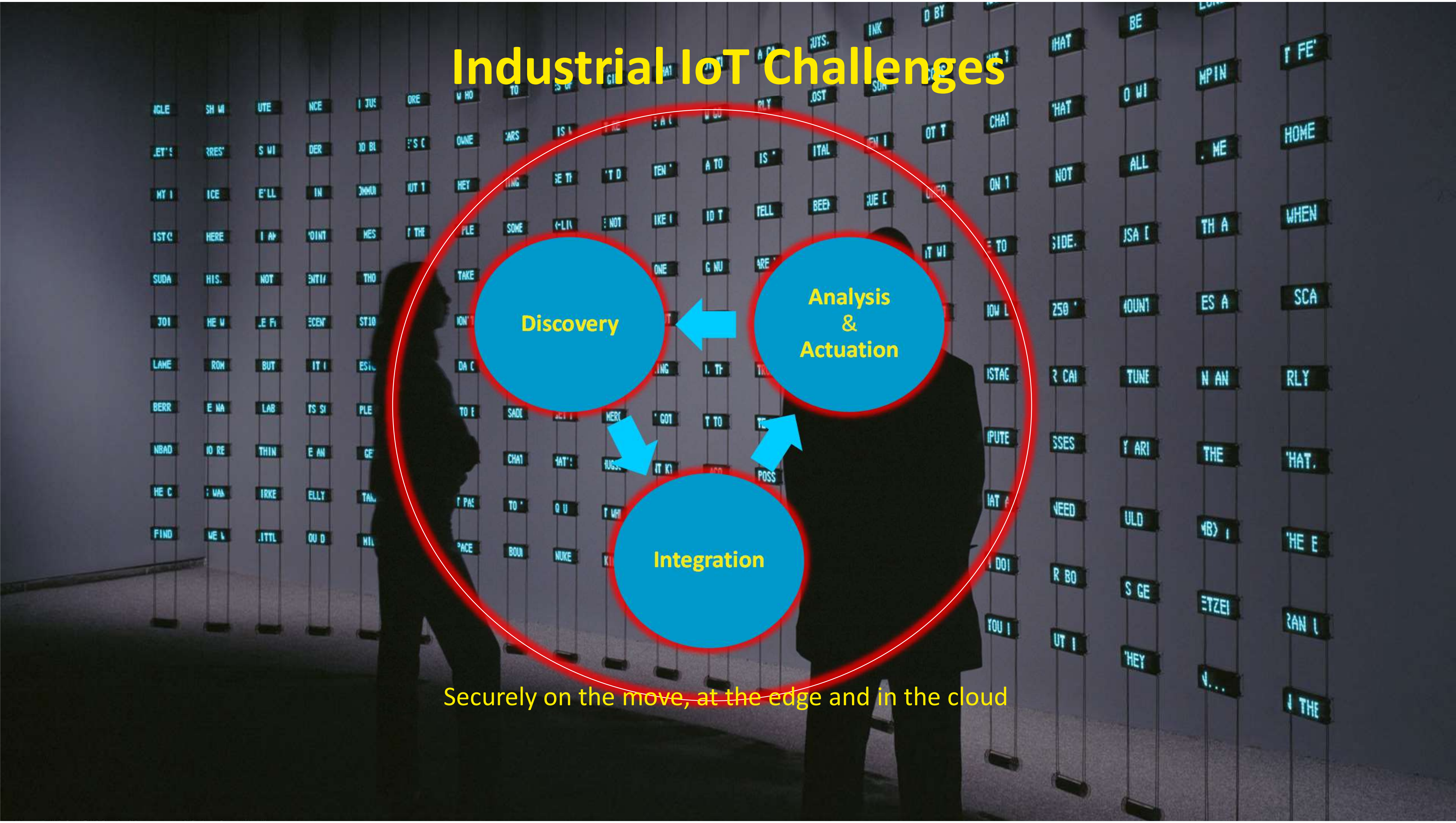
IoT Devices
(from simple sensors to complex machines)





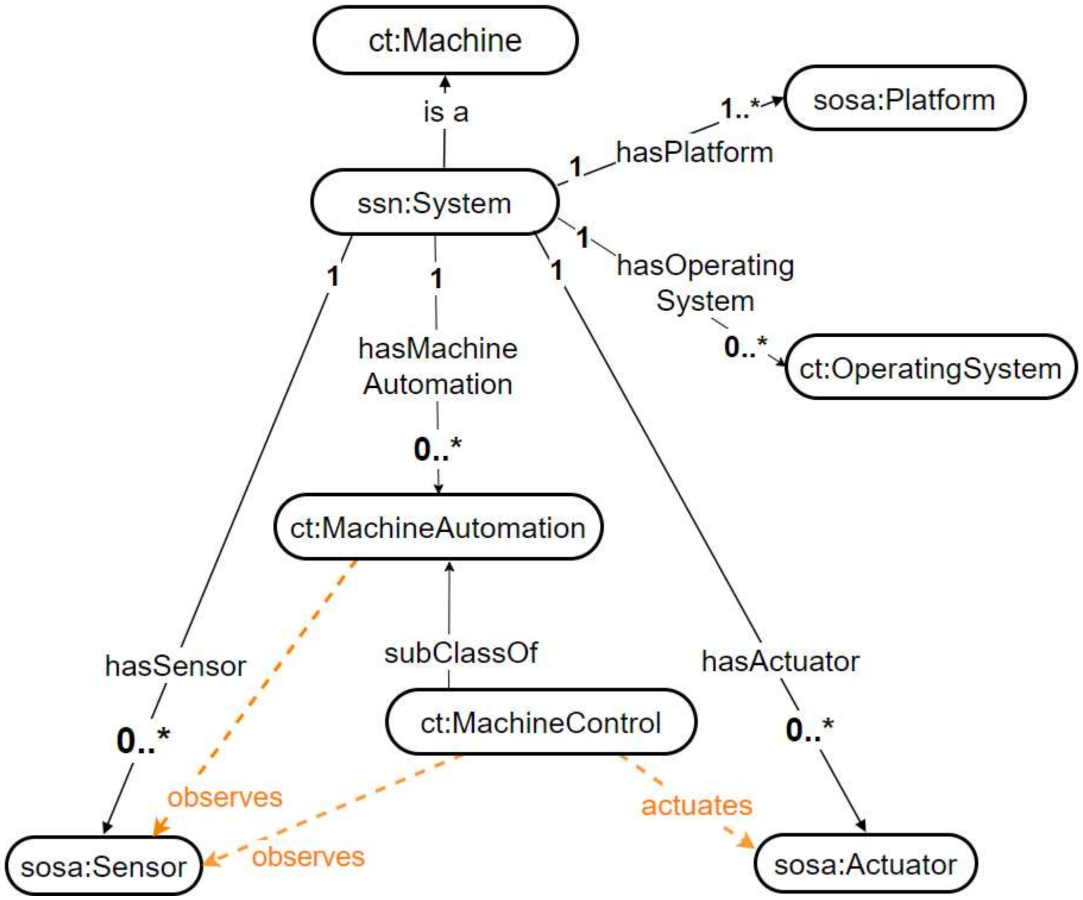
- Sensing the physical world
- Translating and analysing sensor observation
- Receiving setting and incorporating automation
- Actuating and/or interacting

Industrial IoT Challenges



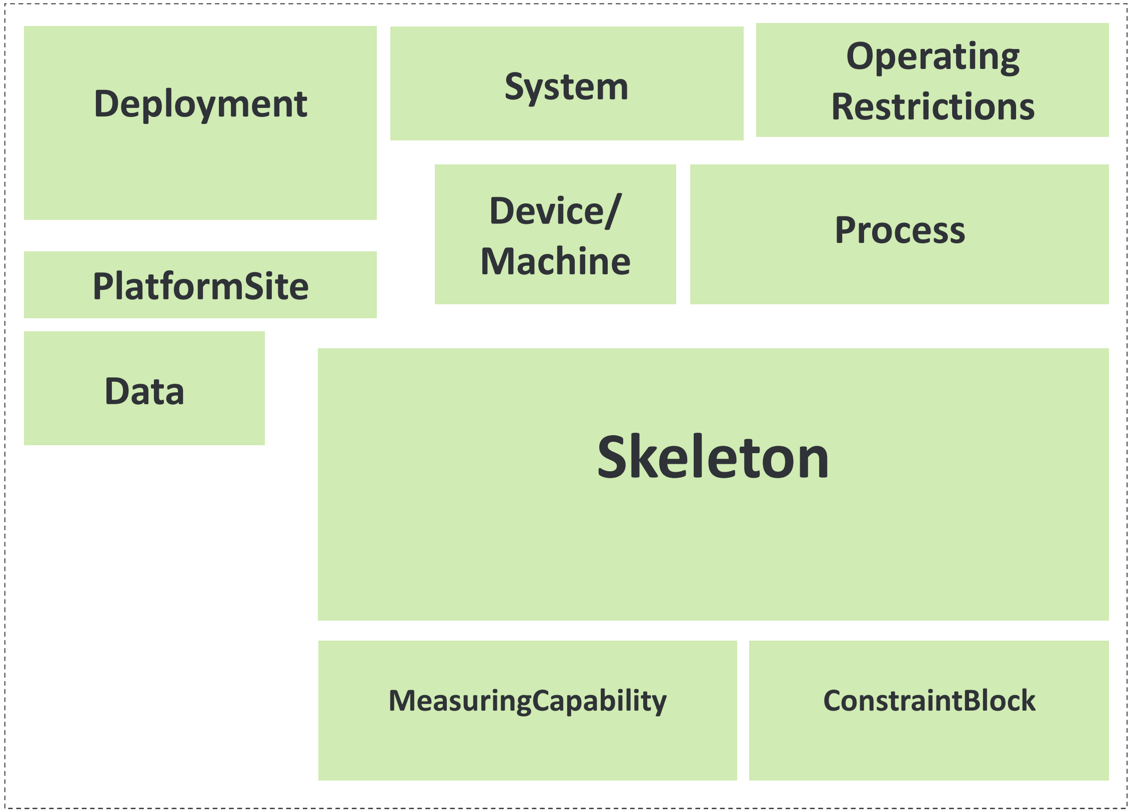
Securely on the move, at the edge and in the cloud

IoT Device Discovery & Integration



The SOSA/SSN Ontology: A Joint W3C and OGC Standard for describing Sensors, Observations, Actuation, and Sampling

Consist of several ontology modules



The SSN ontology can be focused on:

- A sensor perspective, with a focus on what senses, how it senses, and what is sensed
- A data or observation perspective, with a focus on observations and related metadata
- A system perspective, with a focus on systems of sensors, or
- A feature and property perspective, with a focus on features, properties of them, and what can sense those properties

http://www.semantic-web-journal.net/content/sosassn-ontology-joint-w3c-and-ogc-standard-specifying-semantics-sensors-observations

Advancing Sensor Discovery and Integration

- **Automatic classification of IoT Devices based on IoT data streams**
  - F. Montori, K. Liao, P.P. Jayaraman, L. Bononi, T. Sellis and D. Georgakopoulos, “Classification and Annotation of Open Internet of Things Datastreams”, Web Information Systems Engineering (WISE 2018), Dubai UAE, November 2018
  - F. Montori, P.P. Jayaraman, A. Yavari, A. Hassani, D. Georgakopoulos , ”The Curse of Sensing: Survey of Techiques and Challenges to Cope with Sparce and Dense Data in Mobile Crowd Sensing for Internet of Things”, Pervasive and Mobile Computing, Elsevier, July 2018.
- **Global IoT device discovery and integration marketplace**
- **Digital Twins for complex machines**

SenShaMart: A Trusted IoT Marketplace for Sharing IoT Devices and their data

- Improve IoT application development efficiency and cost-effectiveness via enabling:
  - Sharing and reuse of existing IoT devices owned and maintained by different providers
  - Deployment of new IoT devices that is supported by a revenue generation scheme for their providers
- Establish trust worthiness via IoT-ownership that ensures that device discovery is not controlled by any individual or organization
- Provide the scalability needed for achieving global IoT device discovery

Dawod, D. Georgakopoulos, P.P Jayaraman and A. Nirmalathas, “An IoT-owned Service for Global IoT Device Discovery, Integration and (Re)use”, In Proceedings of IEEE 2020 International Conference on Service Computing (IEEE SCC), Beijing, China, October 2020.

D. Georgakopoulos, P.P. Jayaraman, A. Dawod, "SenShaMart: A Trusted IoT Marketplace for Sensor Sharing", In Proc. of the 2020 IEEE 6th International Conference on Collaboration and Internet Computing (CIC), Dec. 2020. DOI: 10.1109/CIC50333.2020.00012

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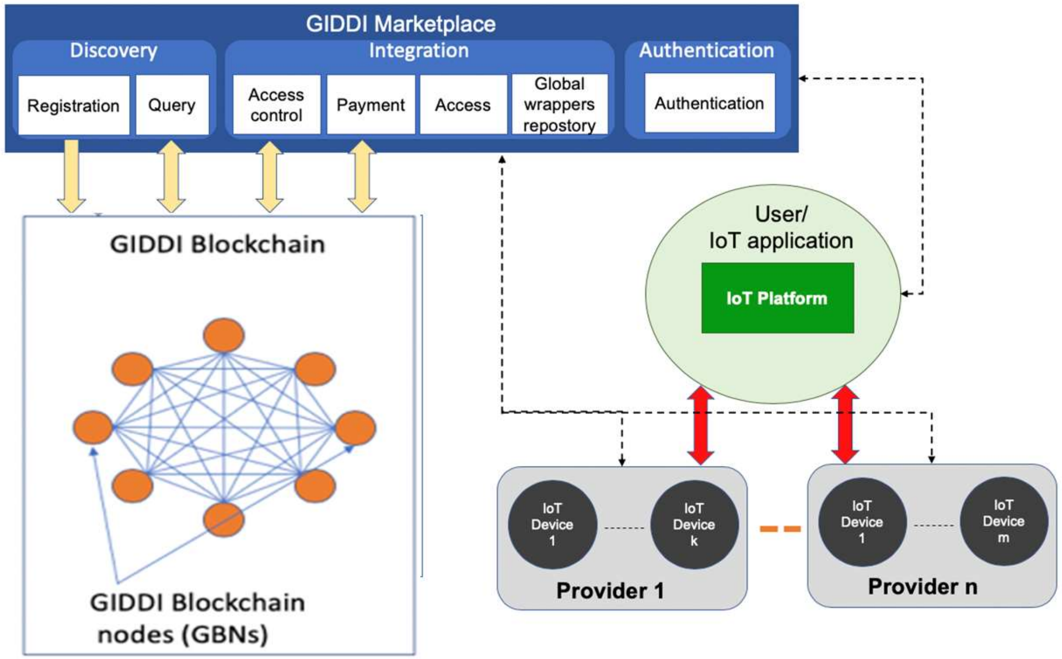
Global IoT Device Discovery and Integration (GIDI)



GIDDI Sensor Provider Blockchain

- Public, decentralized, and semantic ledger, utilizes SSN/SOSA for describing IoT devices
- Contains an RDF triple store for managing semantic IoT device/data descriptions

GIDI Services

- Allows renting/selling use of third party IoT devices and their data
- Supports IoT device registration for IoT device providers
- Provides IoT device and data discovery
- Provides integration and payment for IoT devices/data
- Provides IoT device authentication and access control

Dawod, D. Georgakopoulos, P.P Jayaraman and A. Nirmalathas, "An IoT-owned Service for Global IoT Device Discovery, Integration and (Re)use", In Proceedings of IEEE 2020 International Conference on Service Computing (IEEE SCC), Beijing, China, October 2020.

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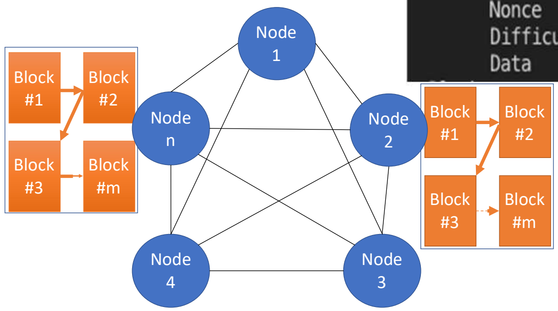
Sensor Provider Blockchain Implementation

- Description of IoT devices and their data is based on extended SSN, e.g., to allow for IoT device owner and location description
- IoT Device metadata are stored in RDF
- IoT device metadata can be queried via SPARQL
- Automatic SDK generation for IoT devices and wrapper invocation via URI metadata stored in the blockchain
- Blockchain-based payment and access control for IoT device use
- Transactions across all above

ID:
Geo:
URI:
Permission:
Org Owner:
Prsn Owner:
Hash:
SSN
Metadata:

```
Block -
        Timestamp : 1543191365951
        Last Hash : f1r57-h45h
        Hash      : 00000feb1f
        Nonce     : 344867
        Difficulty: 5
        Data      : IoTsensor 0
Block -
        Timestamp : 1543191366876
        Last Hash : 00000feb1f
        Hash      : 0000009bf0
        Nonce     : 81910
        Difficulty: 6
        Data      : IoTsensor 1
Block -
        Timestamp : 1543191430649
        Last Hash : 0000009bf0
        Hash      : 00000fdca8
        Nonce     : 5107404
        Difficulty: 5
        Data      : IoTsensor 2
Block -
        Timestamp : 1543191480755
        Last Hash : 00000fdca8
        Hash      : 00005c2283
        Nonce     : 3563038
        Difficulty: 4
        Data      : IoTsensor 3
```

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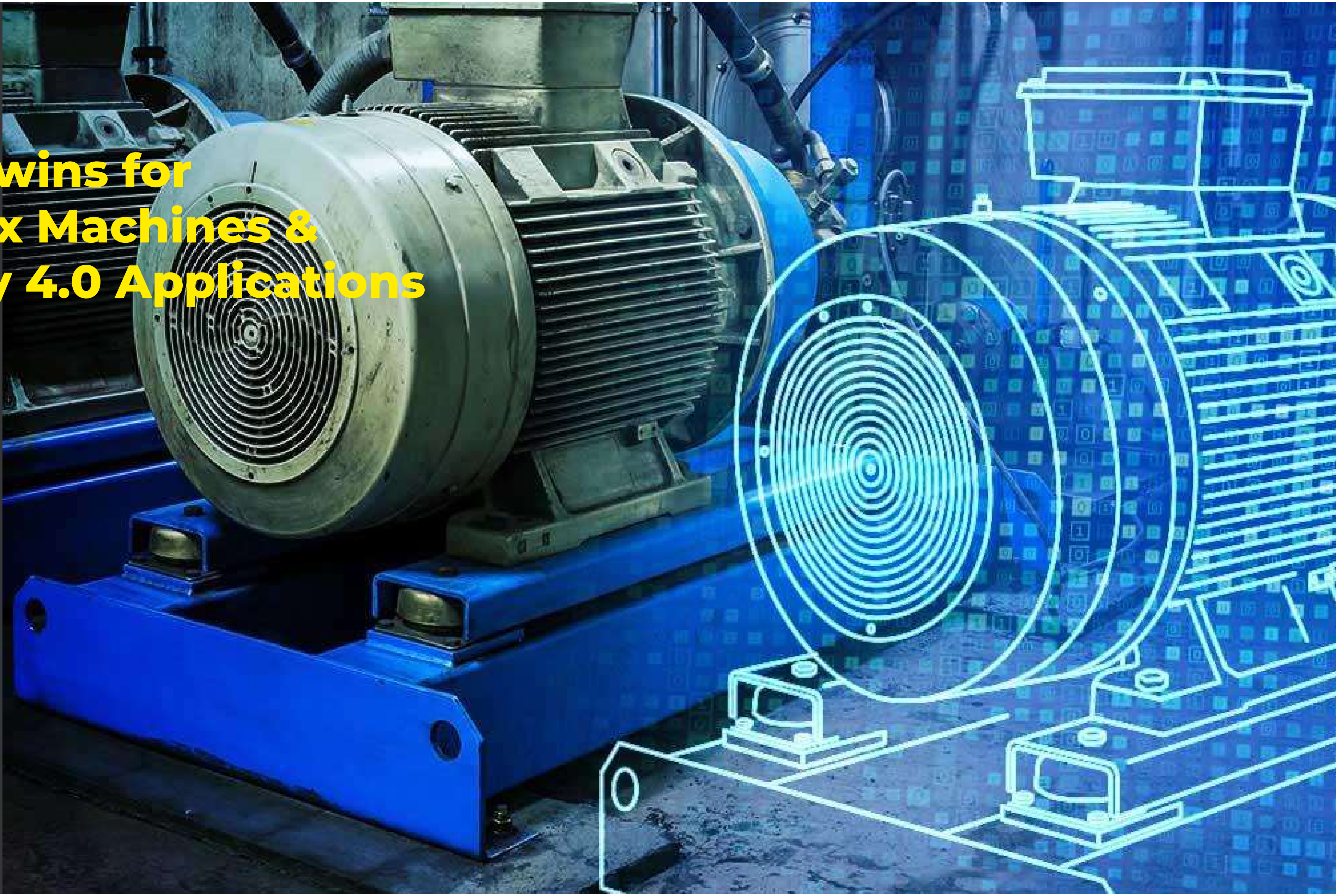
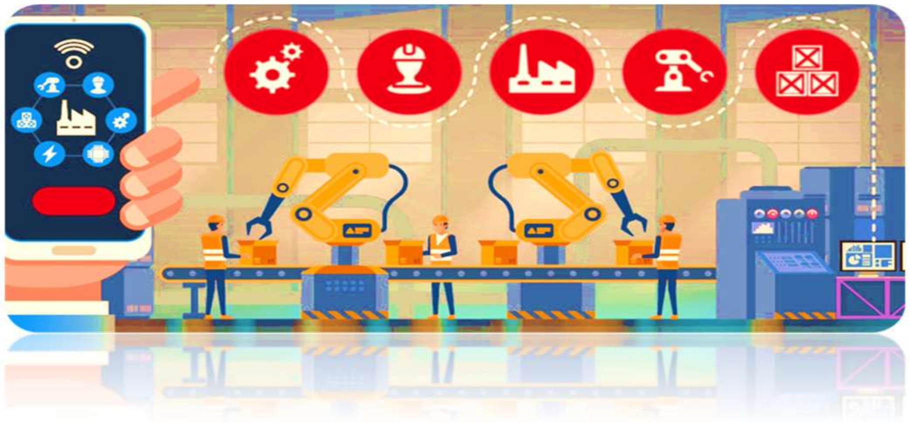
            }
```

Cyber Twins for Complex Machines & Industry 4.0 Applications



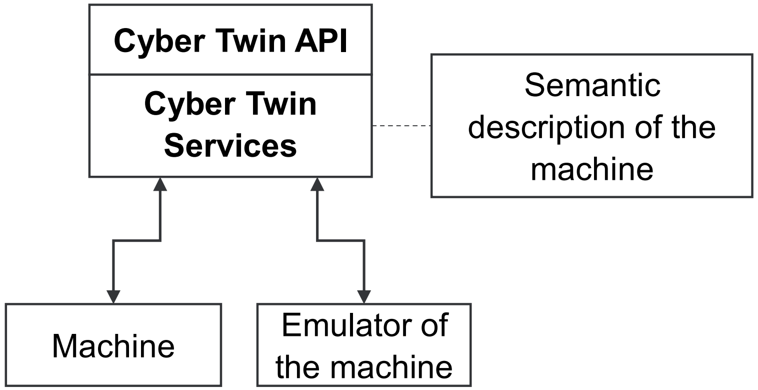
Industry 4.0 application development challenges



- **Sample aims of Industry 4.0 applications**
  - Increase production automation
  - Improve production efficiency
  - Enhance product consistency/quality
  - Better sustainability
  - Perform predictive maintenance
  - Facilitate worker training

- The development of Industry 4.0 applications that utilize complex machines is both **costly** and **time-consuming** due to the limited support of IoT platforms in describing, integrating, testing complex industrial machines, including:
  - Lack of standards for modelling complex machines
  - Limited support for efficient machine integration and testing
  - No support for porting Industry 4.0 applications in different machines and plants without significant rework
    - Azure IoT allows simulating complex machines by coding their behavior, but this is costly, time-consuming and require knowledge of the machine's control functions and related input and output data

Cyber Twins (CTs) for efficient Industry 4.0 application development and testing



Cyber Twin of a machine

A Cyber Twin represents a machine in cyberspace. Each CT includes:

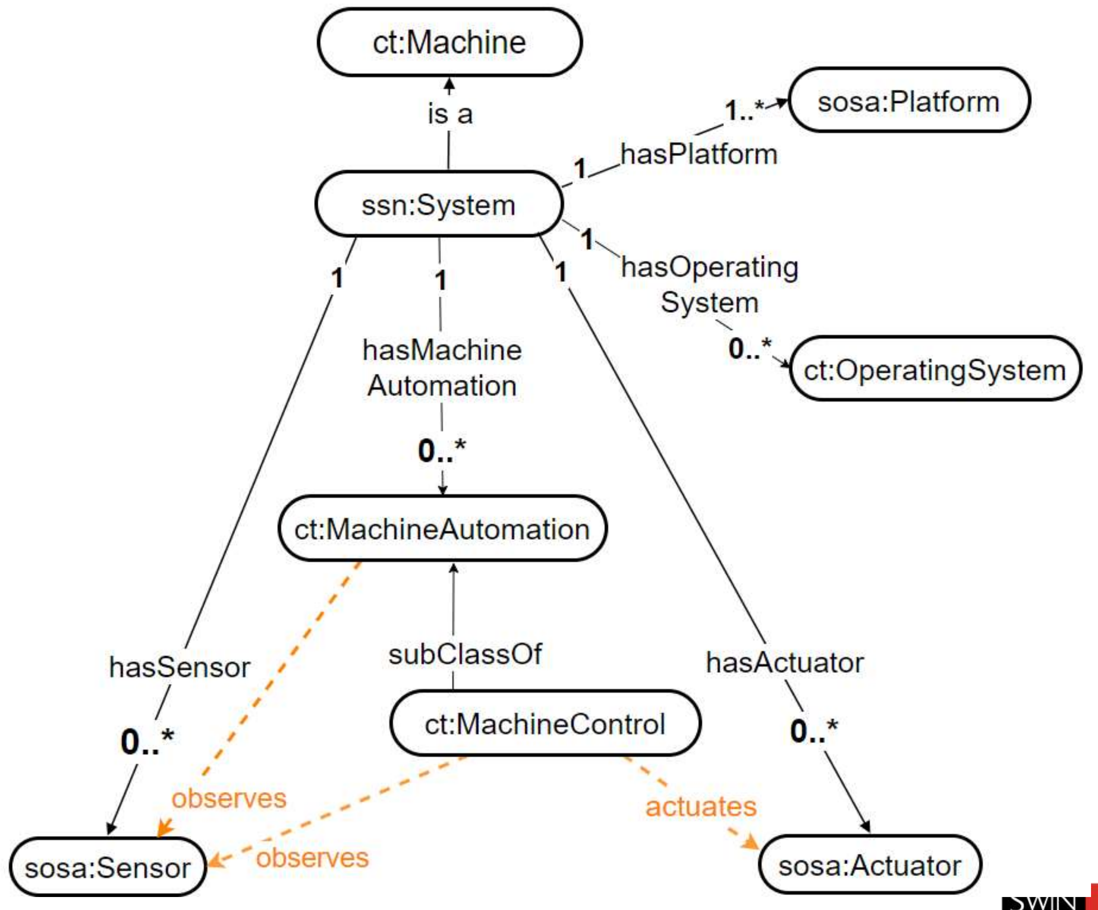
- A semantic model of the machine it represents
- An emulator or simulator of the machine it represents
- Services allowing Industry 4.0 application to:
  1) Connect with the CT
  2) Query the CT''s model
  3) Integrate the CT in an Industry 4.0 application
  4) Allow Industry 4.0 applications to apply machine setting via the CT, sense and actuate though the machine via the CT, interact with the CT-provided emulator and switch between these on demand

D. Bamunuarachchi, D. Georgakopoulos, P.P Jayaraman, A. Banerjee, "A Framework for Enabling Cyber-Twins based Industry 4.0 Application Development", In Proc. of the 2020 IEEE International Conference on Services Computing (SCC), September 2021

CT Ontology for Semantically Describing Complex Machines

Machine classification	Classification conditions
Simple Machine	Sensors + Actuators = 1 **AND** Platforms = 1 **AND** MachineAutomations = 0
Complex Machine	Sensors + Actuators > 1 **AND** Platforms > 0 **AND** MachineAutomations > 0

Conditions for differentiating between simple and complex machines



CT ontology for modelling machines

D. Bamunuarachchi, D. Georgakopoulos, P.P Jayaraman, A. Banerjee, "A Framework for Enabling Cyber-Twins based Industry 4.0 Application Development", In Proc. of the 2020 IEEE International Conference on Services Computing (SCC), September 2021

CT Ontology-based Model of a Simple Machine

- A predictive maintenance application developed for a soft drink bottling plant needs to monitor the glue temperature data produced by an adhesive melting machine to predict the packaging issues caused by glue temperature drops.

- The adhesive melting machine has a glue temperature sensing thermistor. The machine produces the glue temperature as the machine output.

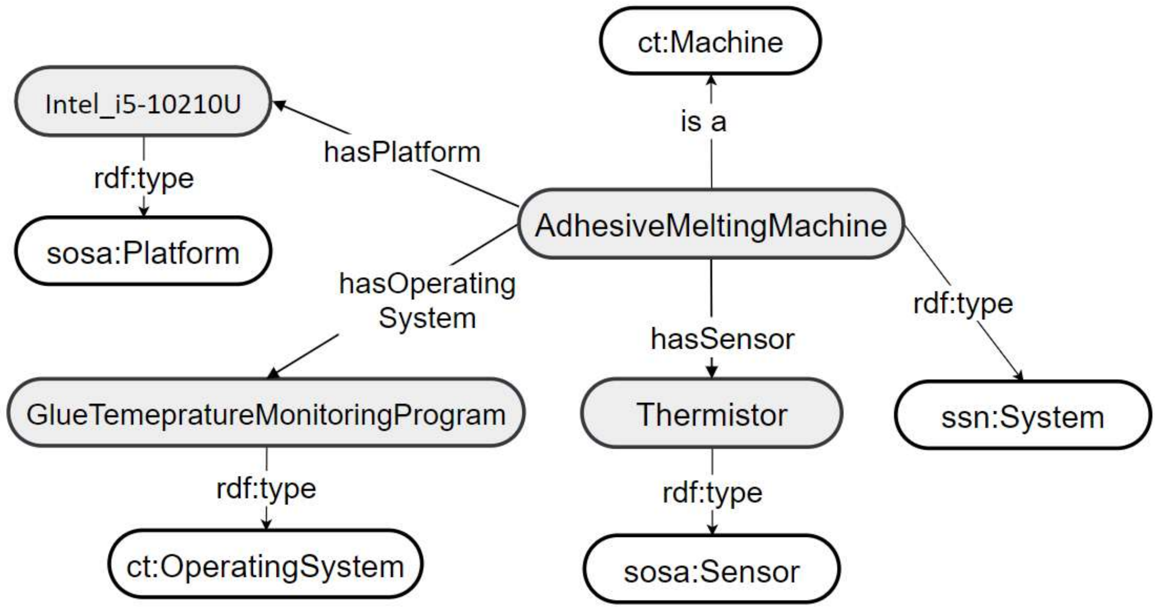


Figure 3 : CT ontology-based model of a simple adhesive melting machine

D. Bamunuarachchi, A. Banerjee, P.P. Jayaraman, D. Georgakopoulos, "Cyber twins supporting industry 4.0 application development", In Proceedings of the *18th International Conference on Advances in Mobile Computing & Multimedia (MOMM)*, November 2020

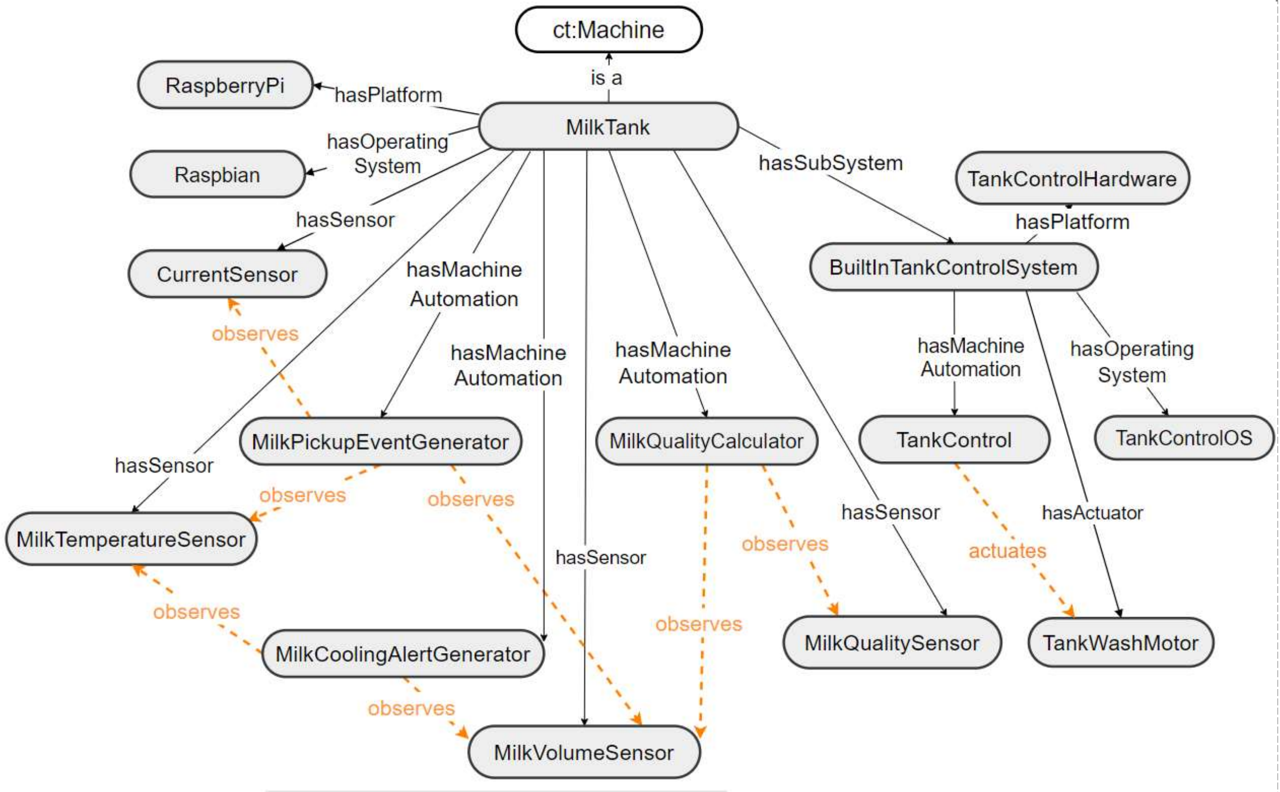
CT Ontology-based Model of a Complex Machine

- A milk monitoring application developed for milk suppliers needs to utilize machine outputs produced by a milk tank machine.

- The milk tank consists of milk quality, milk quantity, milk temperature and current sensors connected to a Raspberry Pi platform. The tank also has a built in control system that actuates the tank wash motor.

Machine Inputs	Machine Outputs
Truck arrival events	Milk Temperature Milk Quantity Milk Quality Milk Temperature Alerts Milk Pickup Events Milk Cooling Alerts

Machine inputs and outputs produced and consumed by the milk tank



CT ontology-based model of a milk tank machine

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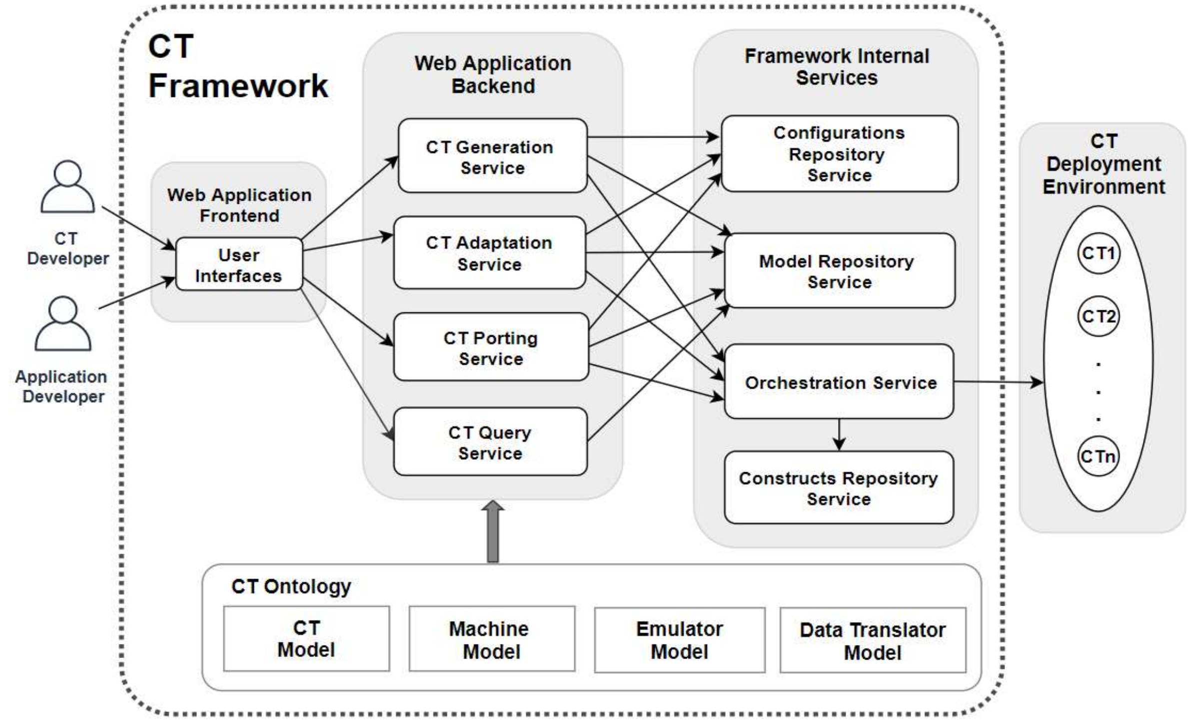
High-Level Architecture of the CT Framework

- The CT framework provides **constructs**, which are a collection of components (including machine data connectors, application data connectors, emulators, data translators) used for formulating CTs.
- **CT generation:** Based on the (CT ontology-based) semantic description of a machine, the service determines the constructs needed for the CT. It deploy the related constructs that comprises the CT using the framework internal services to establish the connection with the machine.
- **CT adaptation:** The service provides a list of semantically compatible data translators for a selected CT to the application developer. Based on the application developer's selection the service picks the constructs of the related data translators and updates the CT by deploying them.
- **CT porting:** Based on the semantic description of the new machine uploaded by the CT developer, the service updates the connectivity configurations and constructs that comprises the CT to connect to the new machine.
- **CT querying:** The service provide the CTs that match the given machine identification and the filtering criteria based on the available semantic descriptions of the CTs



High-level architecture of the CT Framework

D. Bamunuarachchi, A. Banerjee, P.P. Jayaraman, D. Georgakopoulos, "A Cyber Twins Approach to Supporting Industry 4.0 Application Development", 18th International Conference on Advances in Mobile Computing & Multimedia (MoMM2020), 2020.

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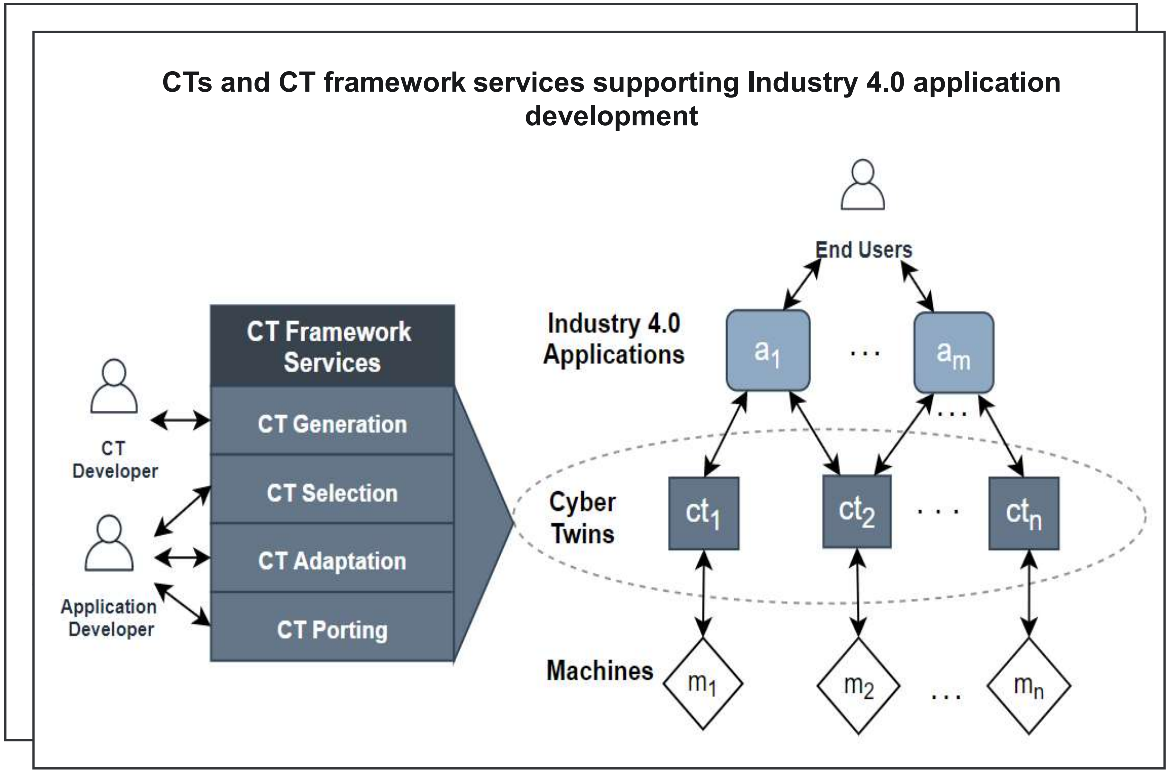
Using CTs in Industry 4.0 Application Development

- **CT developers** use the framework to develop CTs for machines
- Industry 4.0 **Application developers** use the framework to find the available CTs and use them in the applications they are developing
- Industry 4.0 **Application end users** (e.g., plant operators) interact with the Industry 4.0 applications
- The framework currently provides services for **generating, selecting, adapting, and porting** CTs for complex machines
- A CT represents a machine in cyberspace. It include a model that describe the machine and provide services for **applying machine settings** and **getting machine data**, as well as **simulating/emulating the machine** to support the efficient development of Industry 4.0 applications that utilize the machine

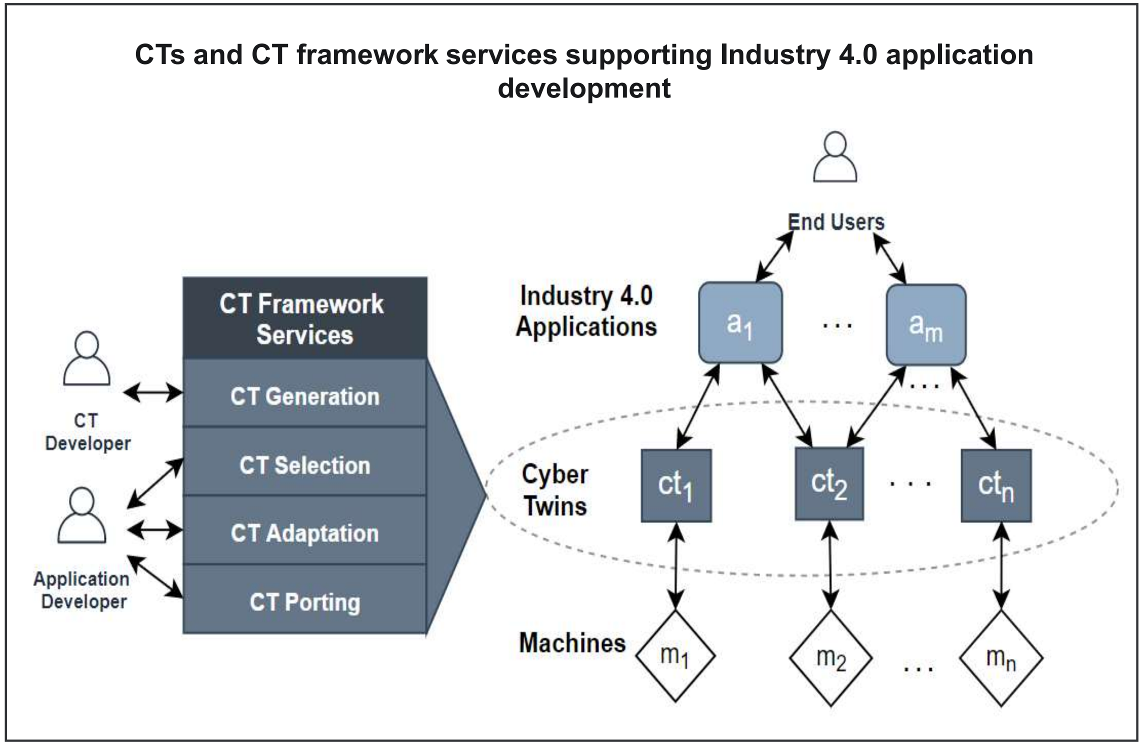


D. Bamunuarachchi, D. Georgakopoulos, P.P Jayaraman, A. Banerjee, "A Framework for Enabling Cyber-Twins based Industry 4.0 Application Development", In Proc. of the 2020 IEEE International Conference on Services Computing (SCC), September 2021

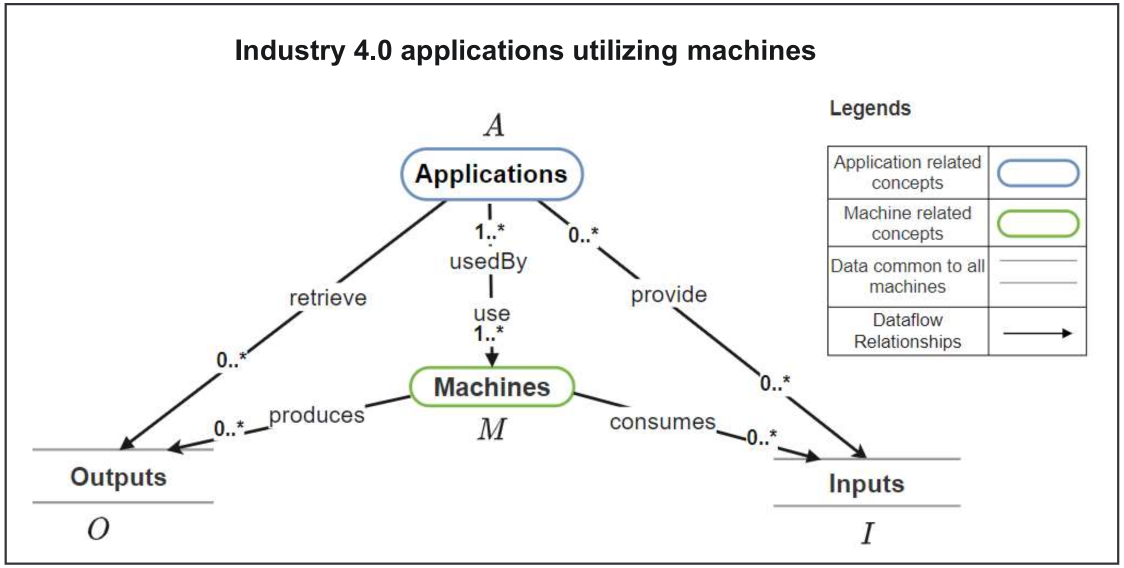
Using CTs in Industry 4.0 Application Development

To develop an Industry 4.0 application, replace machine(s) used by the application, or port the application in a different plants, the developer performs the following steps:

1. Selects the CTs of the machines
2. Integrates the CTs of the machines, and their data with the application
3. Develops the application functionality and test the application by using machine emulators and/or simulators via the CTs
4. When testing using the machine simulators/emulators is completed, sets the CTs to use the actual machines
5. Repeats step 1-3 until the application passes testing while the CTs use the actual machines



Modelling Industry 4.0 Application development Cost



Notation	Description
A	Set of applications in the environment ($a_l \in A$)
M	Set of machines in the environment ($m_j \in M$)
M^l	Set of machines that are utilized by a_l ($M^l \subset M$)
$Cost_{Total}(a_l)$	The total cost of developing a_l
$Cost_{select}(M^l, a_l)$	Cost of selecting M^l, for developing a_l
$Cost_{int}(M^l, a_l)$	Cost of integrating M^l and their data to develop a_l
$Cost_{dt}(M^l, a_l)$	Cost of developing and testing a_l using M^l

Total cost of developing an Industry 4.0 application,

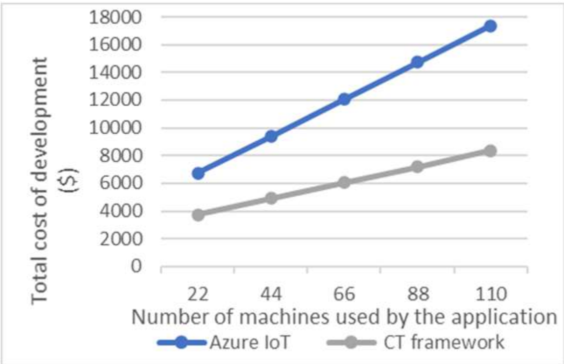
$$Cost_{Total}(a_l) = Cost_{select}(M^l, a_l) + Cost_{int}(M^l, a_l) + Cost_{dt}(M^l, a_l)$$

D. Bamunuarachchi, D. Georgakopoulos, P.P Jayaraman, A. Banerjee, "A Framework for Enabling Cyber-Twins based Industry 4.0 Application Development", In Proc. of the 2020 IEEE International Conference on Services Computing (SCC), September 2021

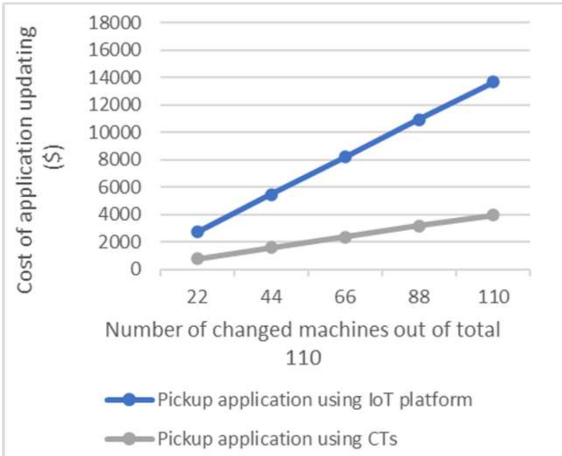
The Costs of Industry 4.0 Application Development and Porting

Comparison of the developing and porting cost of an Industry 4.0 milk supply monitoring application in Azure IoT and the CT framework

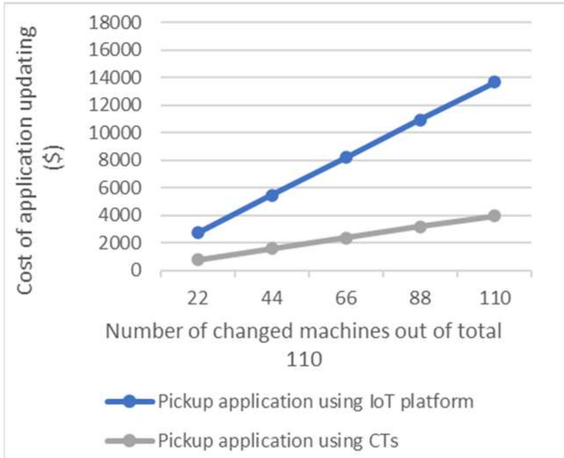
A. New application development cost wrt. No. of machines used by the application.



B. Application update cost wrt. No. of machines changed/replaced.



C. Application porting cost wrt. No. of machines used by the application



The CT Framework significantly reducers the cost of developing and porting this Industry 4.0 application when this is used instead of Azure IoT

D. Bamunuarachchi, D. Georgakopoulos, P.P Jayaraman, A. Banerjee, "A Framework for Enabling Cyber-Twins based Industry 4.0 Application Development", In Proc. of the 2020 IEEE International Conference on Services Computing (SCC), September 2021

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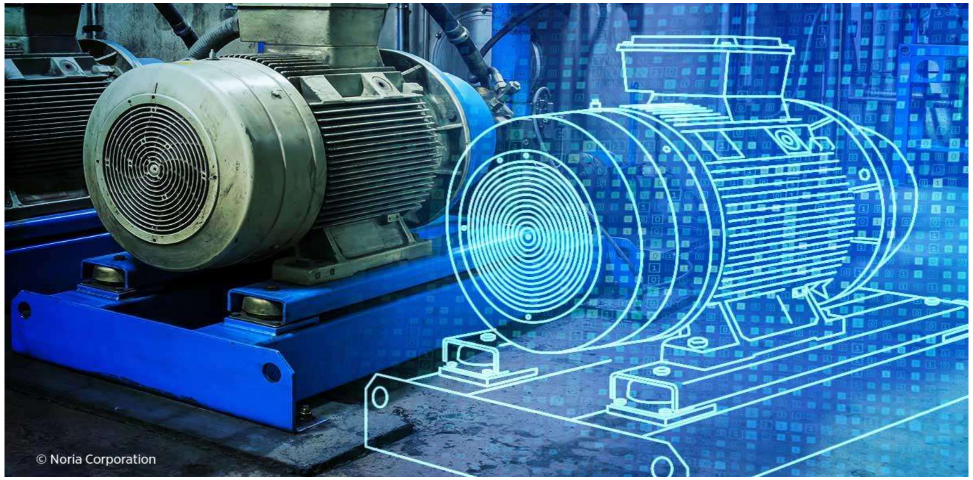
Benefits of Cyber Twins



- Improved **cost-effectiveness** and **efficiency** as well as **reduced programming effort** in Industry 4.0 application development
- Reduced effort for application testing and improved **reliability** in Industry 4.0 applications
- Improved **portability** of the Industry 4.0 applications across the manufacturing plants
- Improved **adaptability** of the Industry 4.0 applications to change of machines, workers, and products
- Enable making rapid improvements in the manufacturing plants by supporting the efficient introduction and testing of novel solutions
- Improved portability would result in the elimination of the cost of developing multiple siloed solutions for different plants

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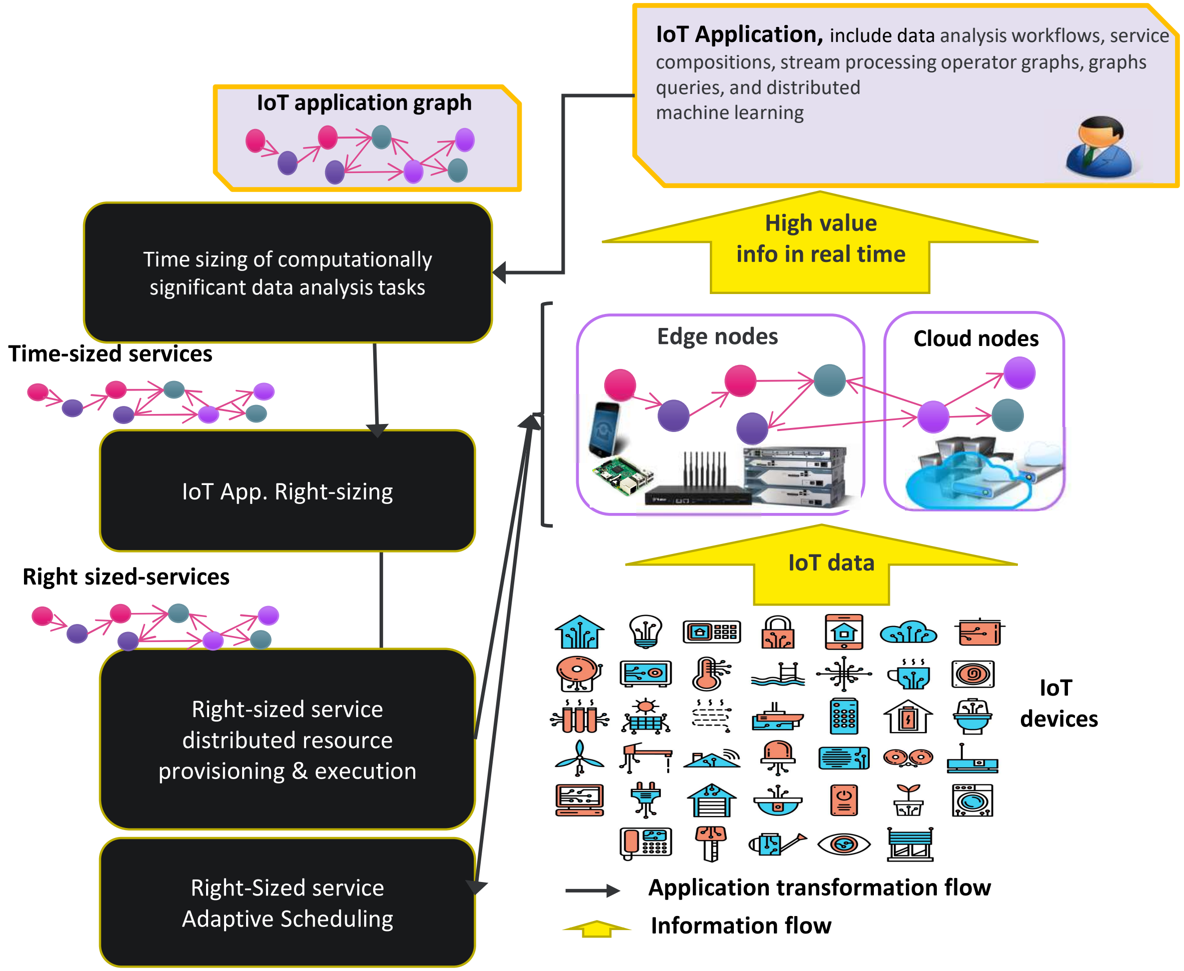
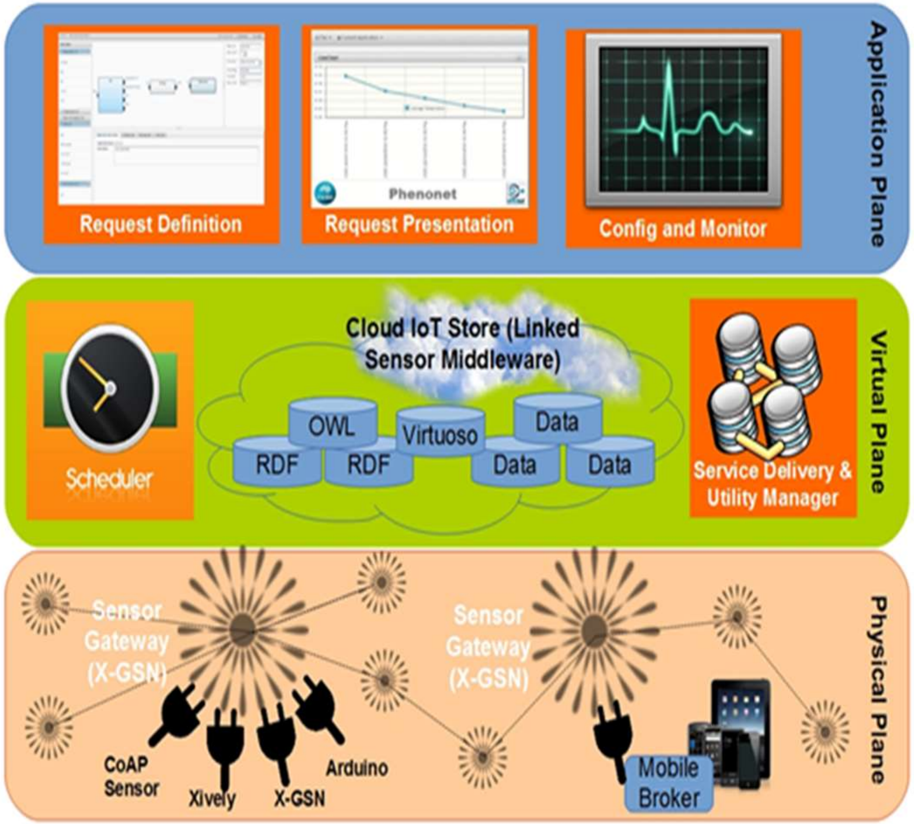
Sample Industry 4.0/Industrial IoT Applications form Industry Projects



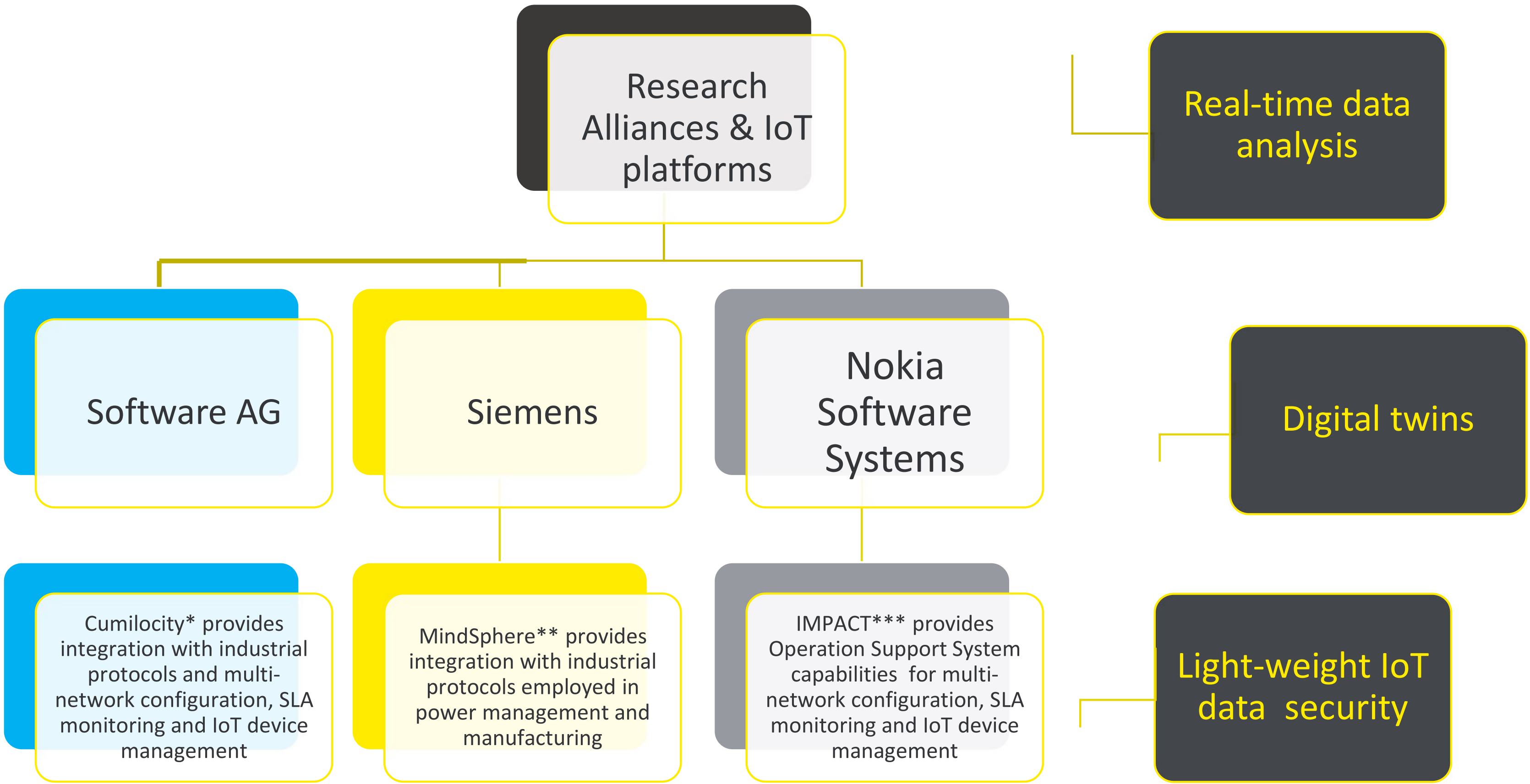
Open IoT Legacy

- **OpenIoT supports semantic-based sensor and IoT data integration in the cloud**
  - W3C SSN ontology
- **Open IoT cloud services:**
  - Sensor discovery & integration
  - Senor data integration
  - Sensor data analysis services (e.g., SPARQL, R)
- **Open Source: [https://github.com/OpenIot Org/openiot](https://github.com/OpenIotOrg/openiot)**

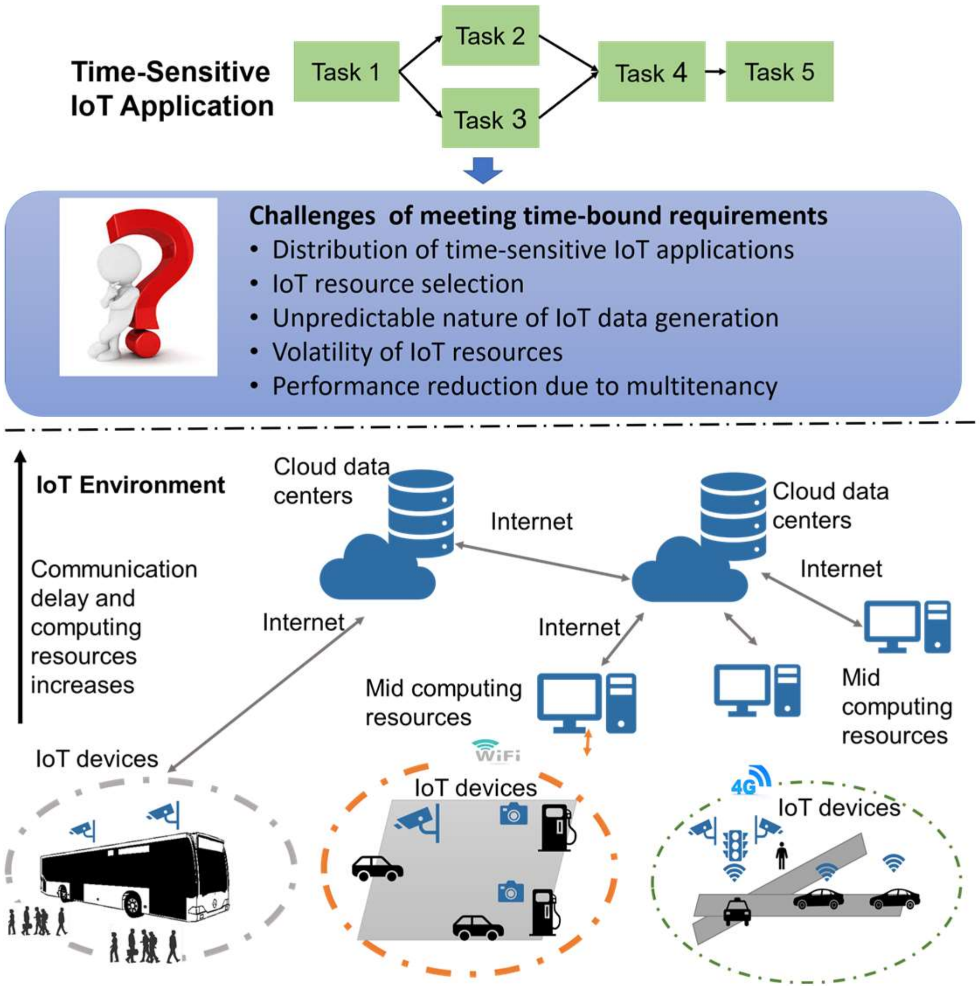


2013 OPEN SOURCE ROOKIE OF THE YEAR BLACKDUCK

Blades for IoT Platforms



Meeting time-bound requirements of time-sensitive IoT applications



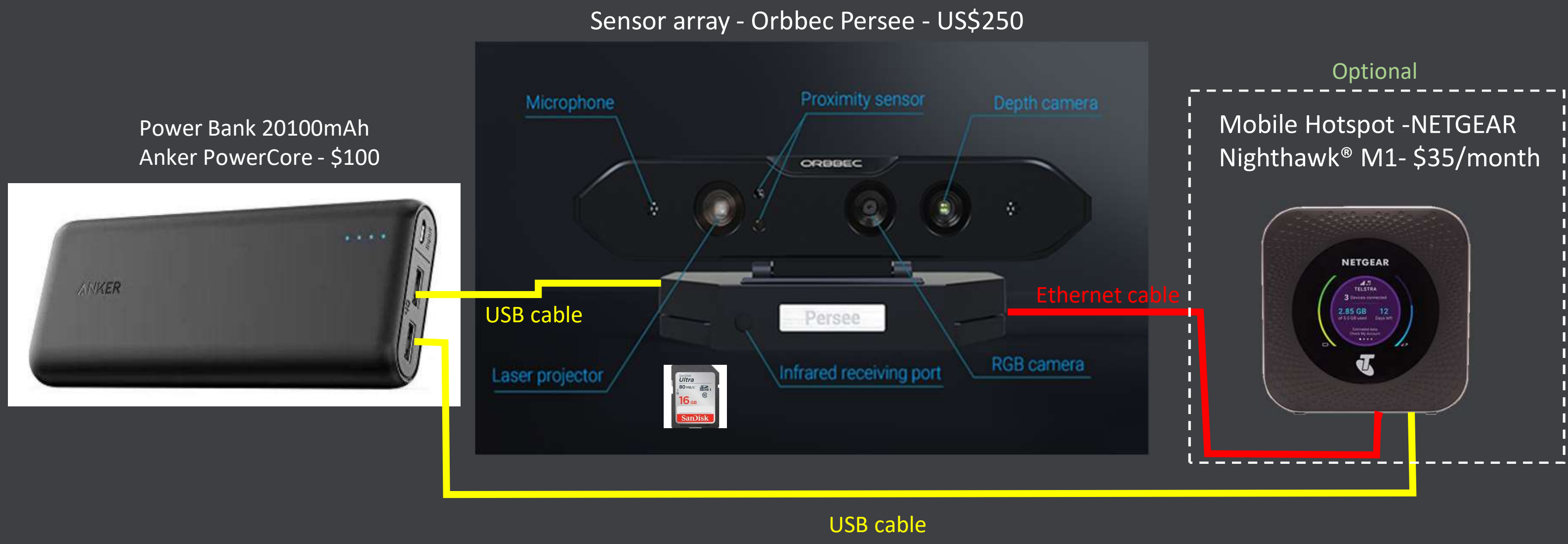
- The results of time-sensitive IoT *(TS-IoT)* applications must be produced within a specific time-bound to be useful

  e.g. : A vehicle accident prediction application must analyse IoT data collected from traffic and on-board cameras and sensors, predict a possible accident and prevent the accident by informing the corresponding driver in near real-time (e.g. within a 30ms time bound)

- TS-IoT applications are currently executed in distributed IoT environments which comprises of various computing and network resources.
- Meeting the time-bound requirements of TS-IoT applications is challenging due to the volatile and heterogenous nature of IoT environment, and the application-specific requirements of TS-IoT applications.

Depth sensor-based IoT devices use to count passengers

Transport Sydney Trains

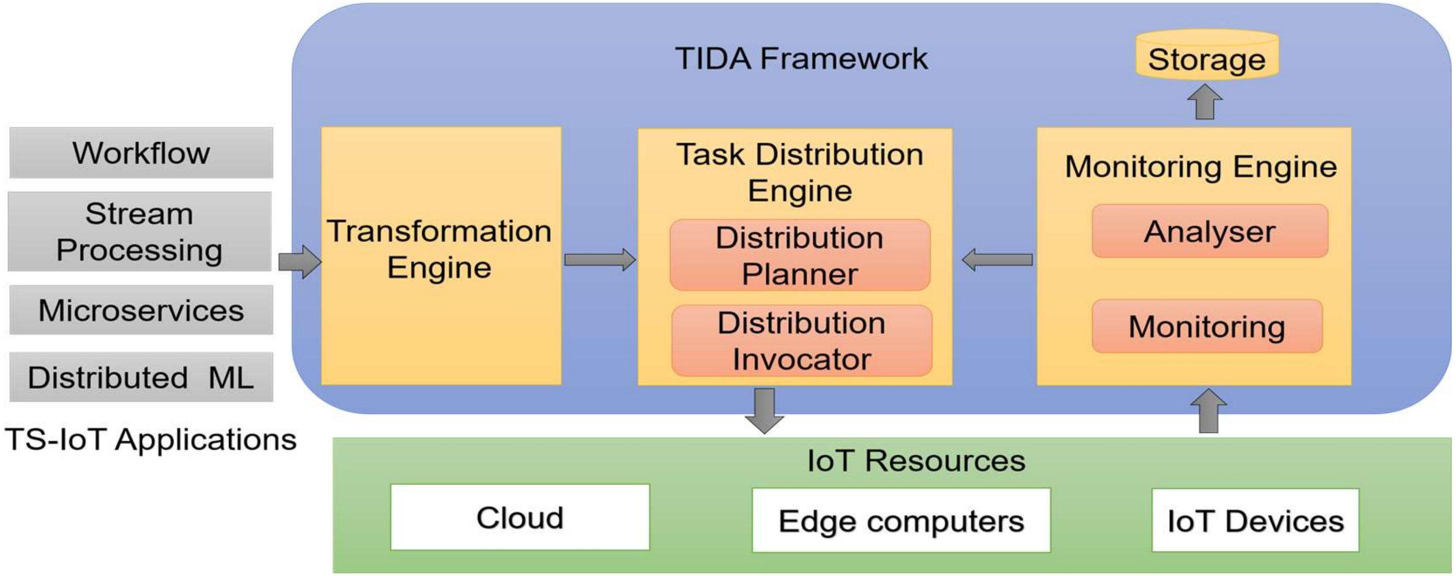


Depth data analysis for counting passengers

Summary	Mean accuracy	Lowest accuracy	First quartile	Median	Third quartile
Percent	76.01%	0%	63.87%	68.6%	83.06%

Moser, C. McCarthy, P.P. Jayaraman, H. Ghaderi, H. Dia, R. Li, M. Simmons, U. Mehmood, A.M. Tan, Y. Weizman, A. Yavari, D. Georgakopoulos, F.K. Fuss, "A Methodology for Empirically Evaluating Passenger Counting Technologies in Public Transport", In Proceeding of *Australasian Transport Research Forum*, Canberra, Australia, Oct. 2019

Time-Sensitive IoT Data Analysis Framework (TIDA Framework)



- Distributes and schedules IoT data analysis tasks across the available IoT devices, mid and cloud resources
- Continuously monitors the time-related performance of distributed data analysis tasks
- Dynamically migrates tasks from cloud to edges and edges to devices to meet the time-bounds of IoT applications
- Approximates data analysis tasks
- Open source platform for time-bound IoT data analysis
- Uses Microsoft's Orleans Actor-based system

H. Korala, D. Georgakopoulos, P.P. Jayaraman, A. Yavari, "A Time-Sensitive IoT Data Analysis Framework", In Proceedings of the *54th Hawaii International Conference on System Sciences*, January 2021

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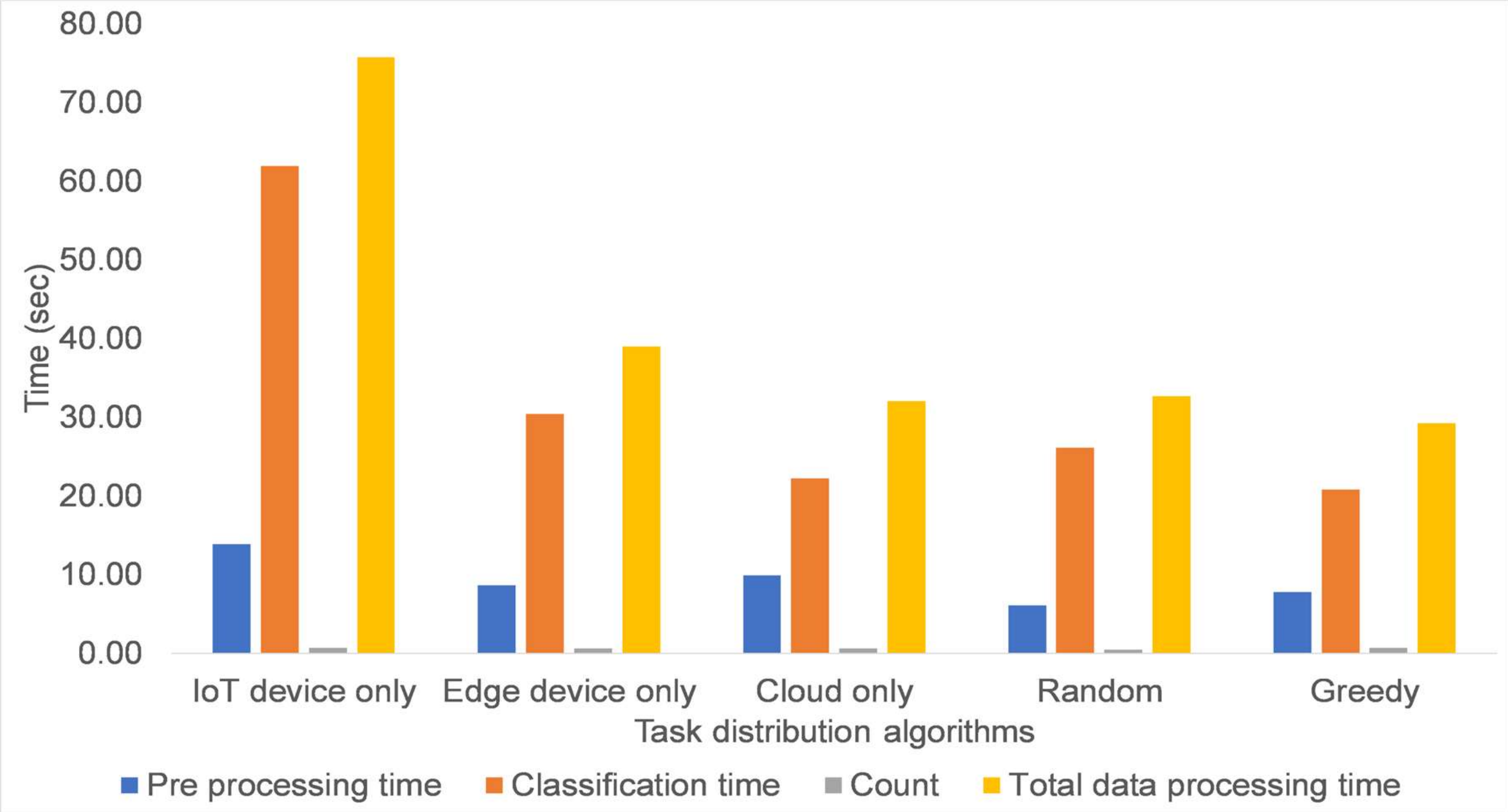
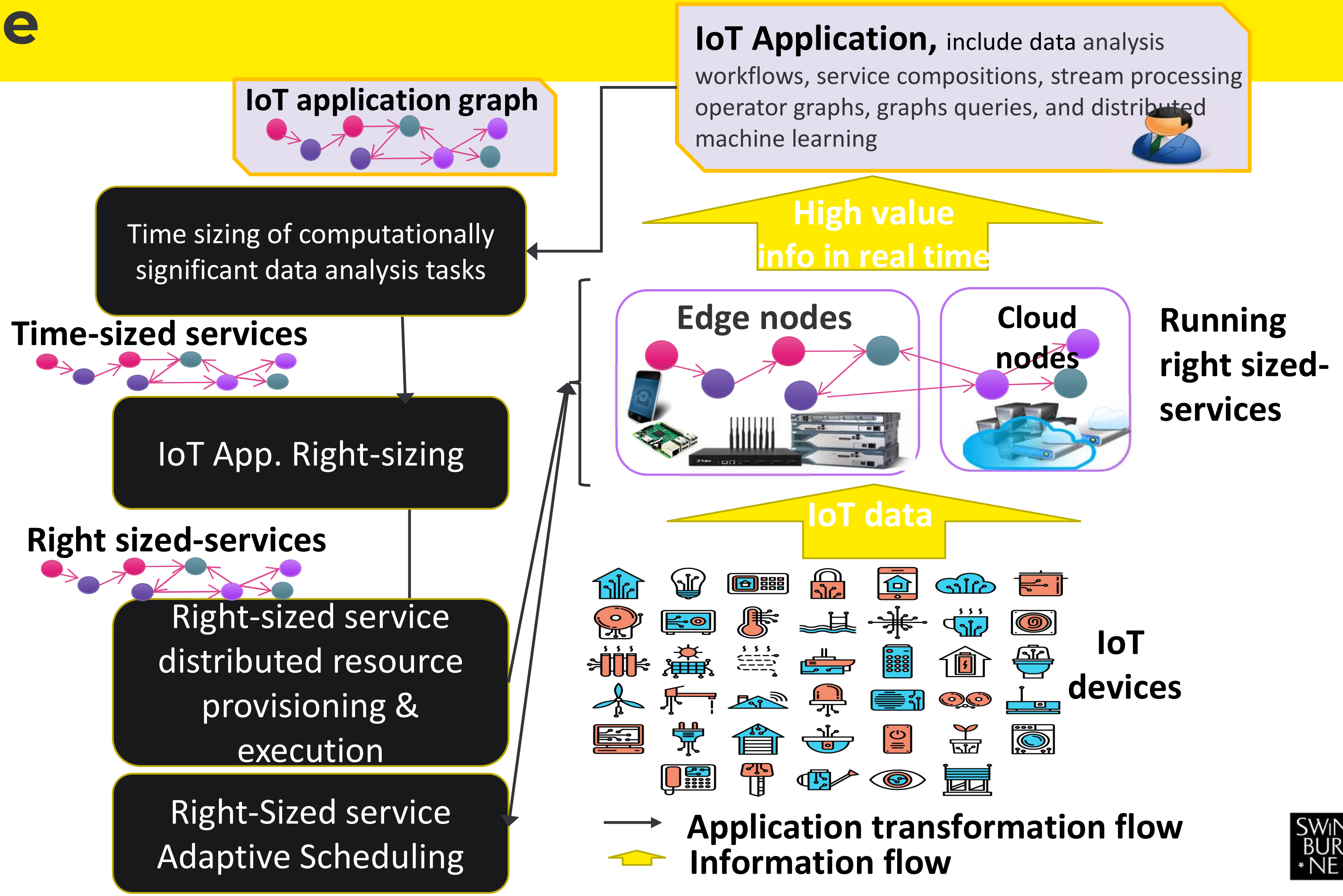
TIDA data processing times for Greedy Task distribution algorithm

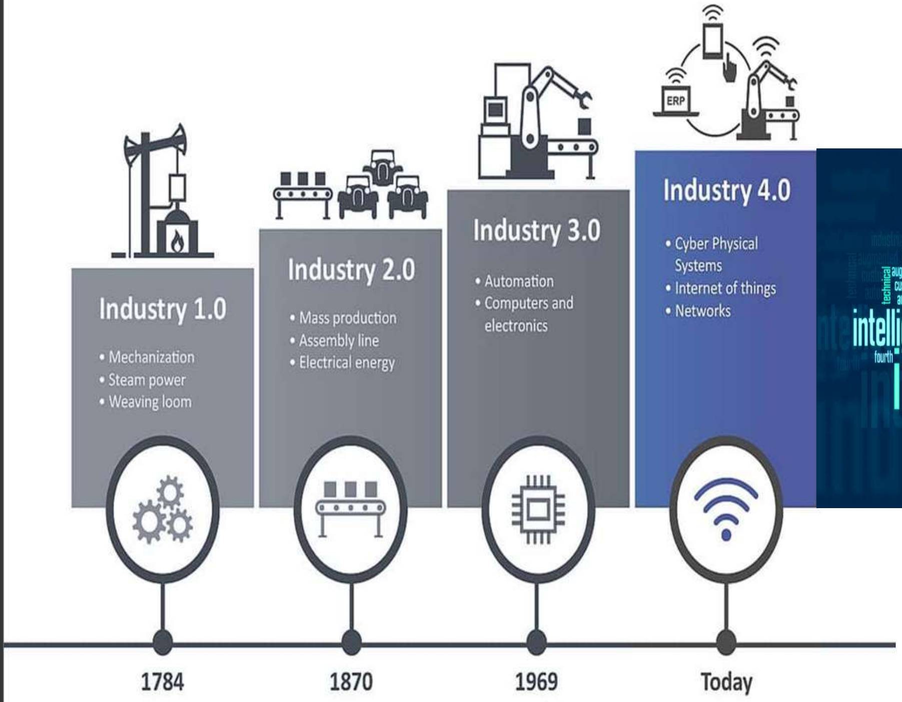


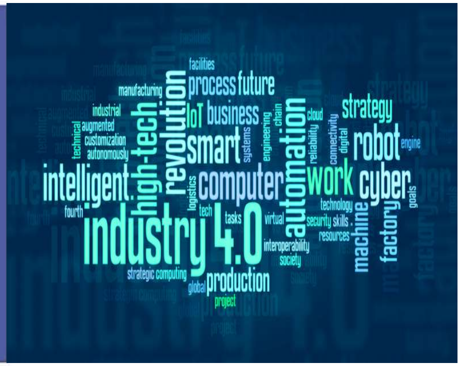
H. Korala, P.P. Jayaraman, A. Yavari, D. Georgakopoulos. "APOLLO: a platform for experimental analysis of time sensitive multimedia IoT applications", In Proc. of the *18th International Conference on Advances in Mobile Computing and Multimedia (MoMM '20)*, November 2020

Time-sensitive IoT application processing lifecycle



Industry 4.0/Industrial IoT Applications





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Some of our industry partners

Australian Government Department of Industry, Innovation and Science | Business Cooperative Research Centres Program

OPTUS yes

Australian Government Department of Defence Defence Science and Technology Group

Asahi ASAHI GROUP

AMGC ADVANCED MANUFACTURING GROWTH CENTRE LTD

Quickstep

software AG

TELSTRA

Fill

AMPC AUSTRALIAN MEAT PROCESSOR CORPORATION

Australian Government IP Australia

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Bega

Australian Country Choice

iMOVECRC

PLATAINE® people-smart automation

Asta® Trusted with IT

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Australian Government Australian Transaction Reports and Analysis Centre

ARENA 2036

wipro

Transport Sydney Trains

NCMC

JBS

Hydro Tasmania

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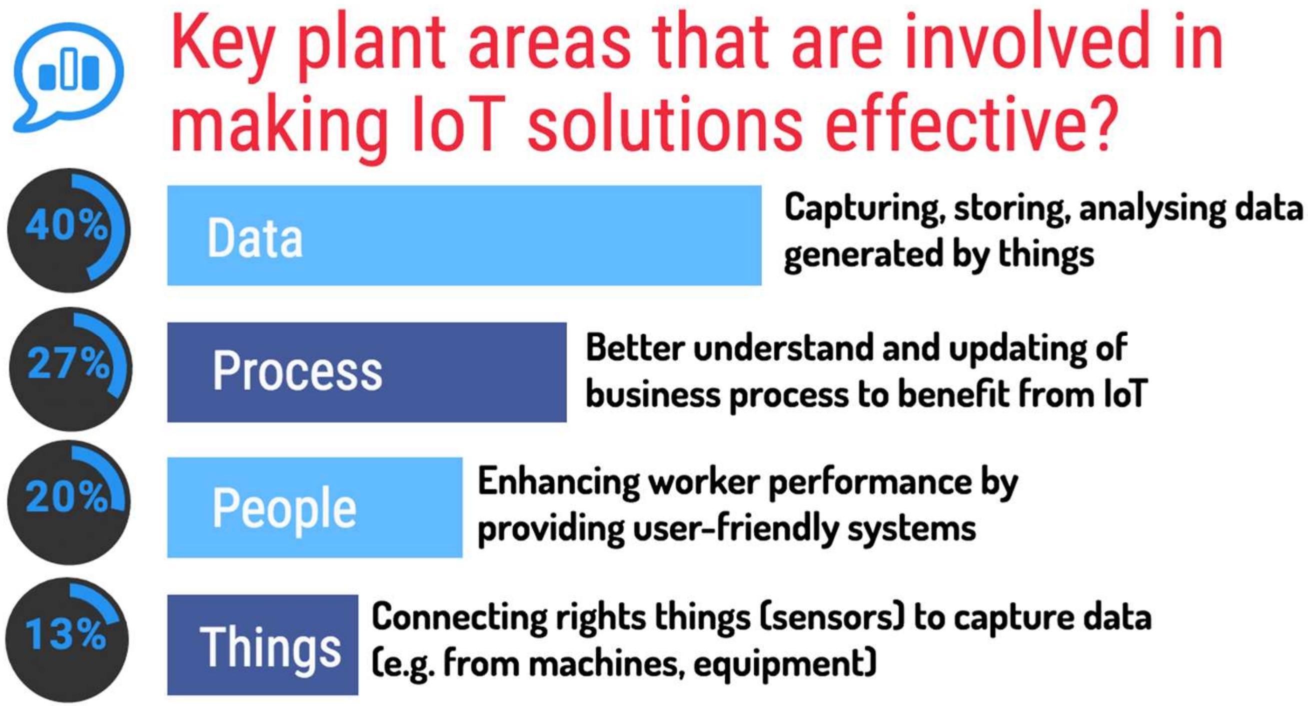
What makes Industrial IoT solutions effective?

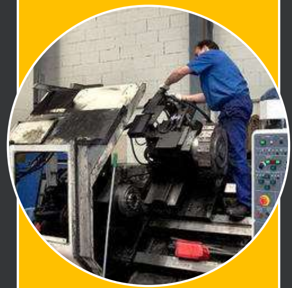
IoT Value in Manufacturing



"Leading Tools Manufacturer Transforms Operations with IoT" (Black and Decker case study 2016)
http://www.cisco.com/c/dam/en_us/solutions/industries/docs/manufacturing/c36-732293-00-stanley-cs.pdf

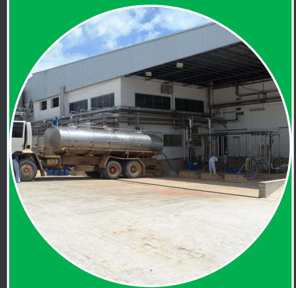
Improving Plant Productivity, Product Quality and Supply Chain Efficiency

Improve worker productivity



Reduce Unscheduled Machine Maintenance

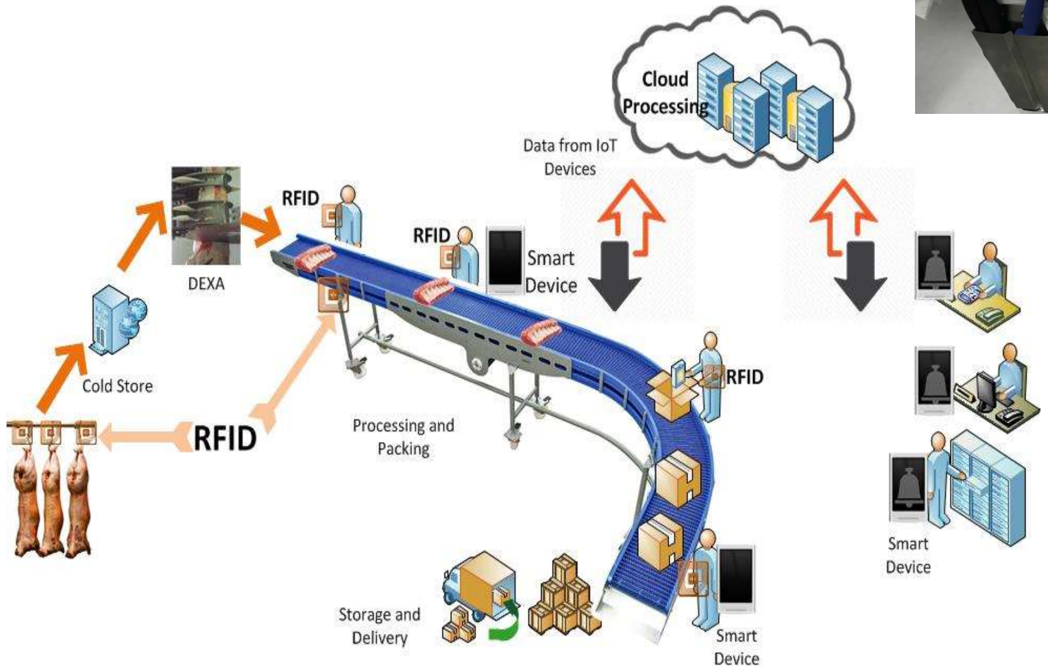
Improve Product Quality



Enhance just- in-time supply chain efficiency

Measuring and improving worker productivity Meat processing

- Track workers in the production line via wearable IoT devices and measure their productivity
- Track and measure yield per worker
- Compute yield KPI's in real time and deliver related alerts to supervisors via any device, anywhere



IoT-based Monitoring of Worker Productivity

AUSTRALIAN COUNTRY Choice

AMPC

AUSTRALIAN MEAT PROCESSOR CORPORATION

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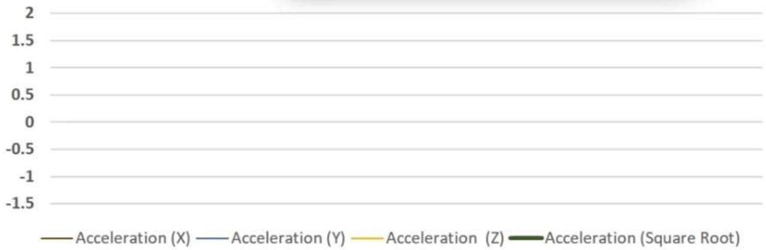

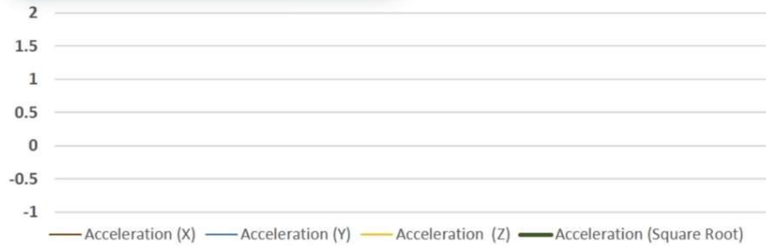

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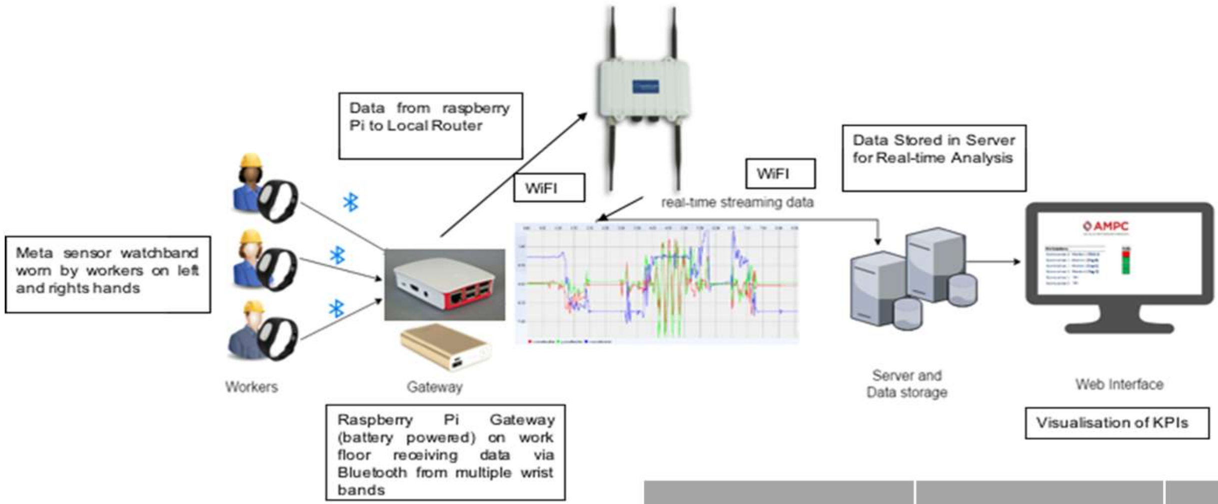
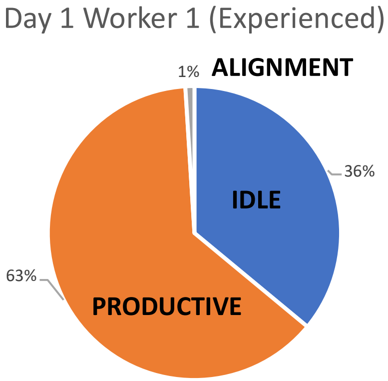
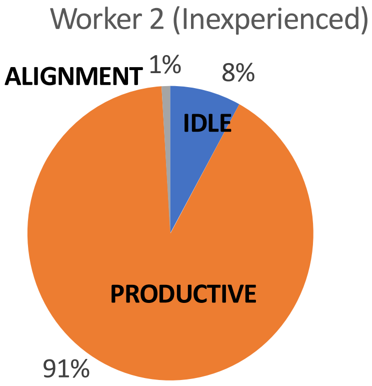
Measuring and Improving Worker Productivity
IoT system and Solution

- Trialed in a major meat processing plant
- IoT solution payback in 0.4 years
- IoT solution provides a significant improvement in plant productivity







	Worker 1 (Experienced)	Worker 2 (Inexperienced)
Idle Time	36%	8%
Productive Time	63%	91%
Alignment Time	1%	1%
Active States	49	30

Activity Recognition

- Vector machine-based models
- Random tree models
- Training a major research issue
  - Expert-based model training
  - Productivity-based model training
  - Personalising training

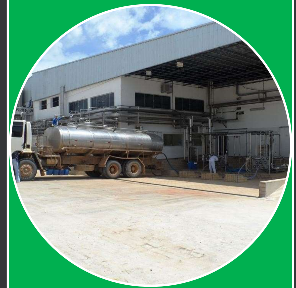
Thanks to machine-learning algorithms,
the robot apocalypse was short-lived.

Improving Plant Productivity, Product Quality and Supply Chain Efficiency

Improve worker productivity

Reduce Unscheduled Machine Maintenance

Improve Product Quality



Enhance just- in-time supply chain efficiency

Measuring and Improving Plant Productivity Preventing Unscheduled Maintenance

- Improve plant productivity through the reduction of unplanned downtime
- Approach involves combined manufacturing process and machine data modelling, capture, and analysis

Machine Selection and FMEA → Detailed Process Capture → Data Model Development (Process and Machine level) / Analytical Validation of Machine Selection → Data Capture → Development of Predictive Tool → Evaluation, Gap Analysis, and Iteration

Objective: Improve plant machine efficiency, e.g., from 65% to 85%

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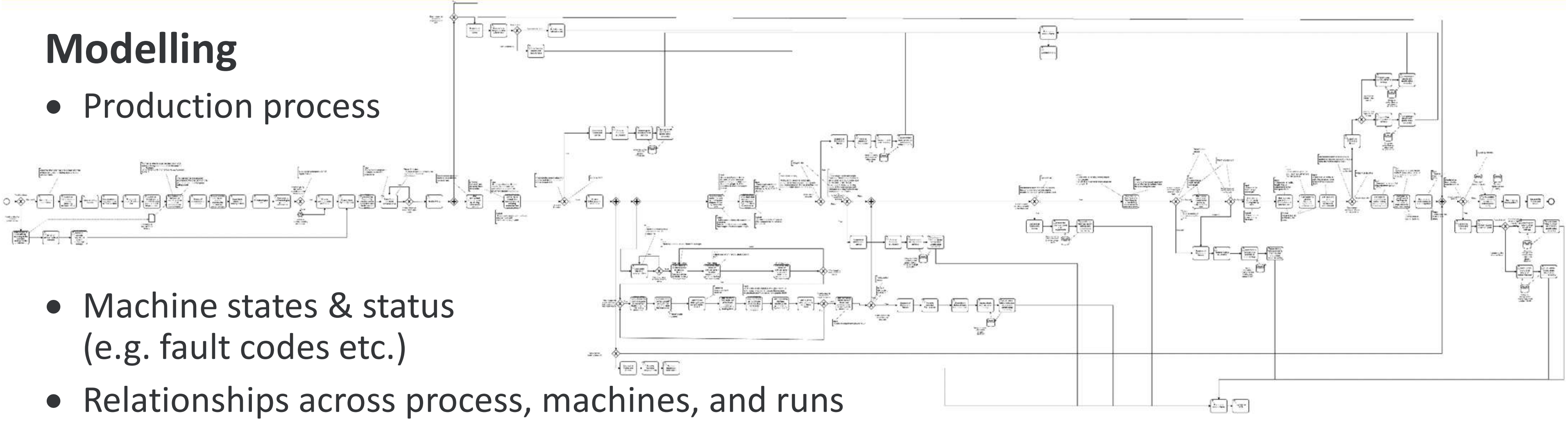
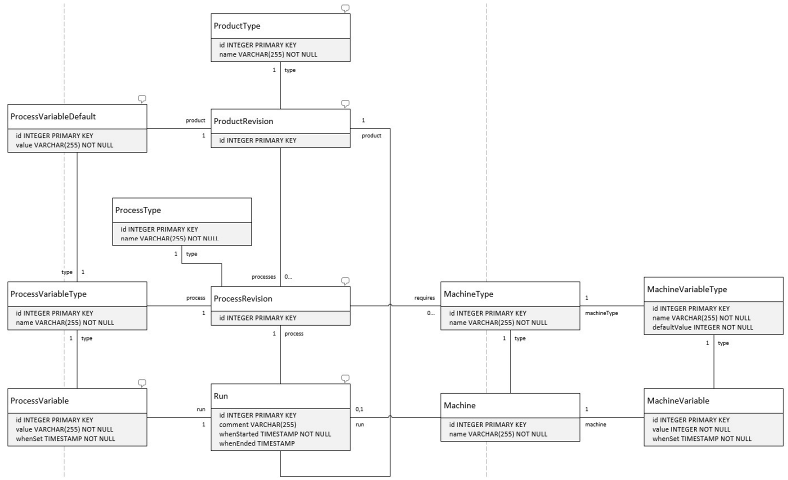
Measuring and Improving Plant Productivity Predictive Analytics Modeling and Data capture

Modelling

- Production process



- Machine states & status (e.g. fault codes etc.)
- Relationships across process, machines, and runs



Data Capture

- Process/run information
- Machine information (e.g. fault codes etc.)
- Production run-based relationships of this information

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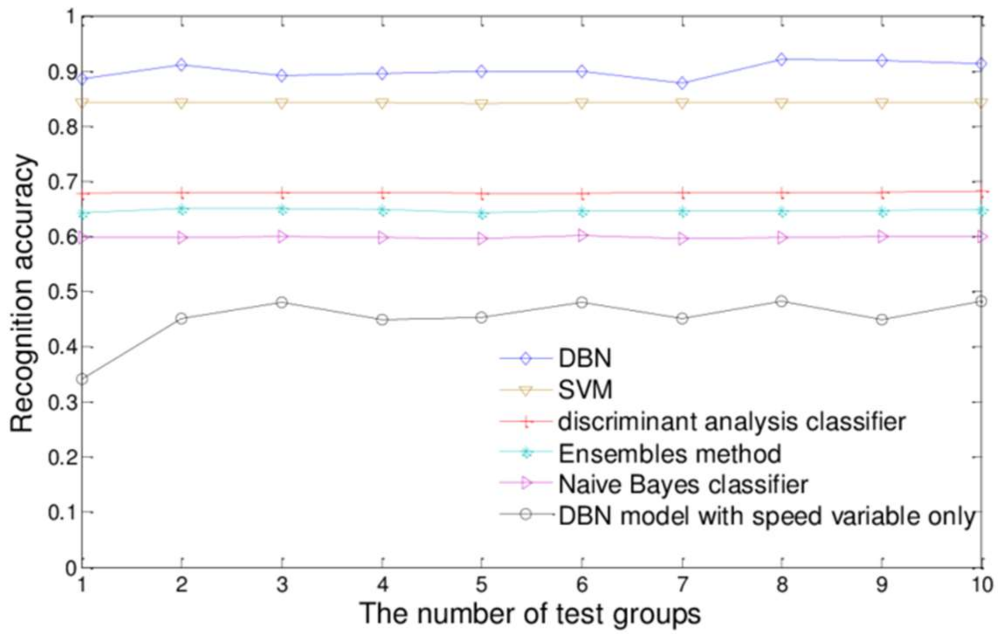
Predictive Machine Data Analysis

- Bayesian analysis identifies which machines are responsible for most unplanned downtime
- Performing more detailed data collection from these machines
- Predictive data analysis utilises a statistical and Markov chain-based models to predict unplanned production stoppages using production run data collected over a period of months

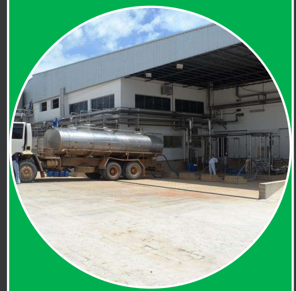


Improving Plant Productivity, Product Quality and Supply Chain Efficiency

Improve worker productivity

Reduce Unscheduled Machine Maintenance

Improve Product Consistency/ Quality



Enhance just- in-time supply chain efficiency

Industry 4.0 solution for reducing variation in Vegemite (yeast) production

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The Vegemite product variation problem

Low yeast product consistency
due to:

- Variation in raw materials
- Plant machine settings
- Operator actions

Problems:

- Low plant productivity
- High energy consumption
- High reliance to monitoring
  and intervention by the plant operators

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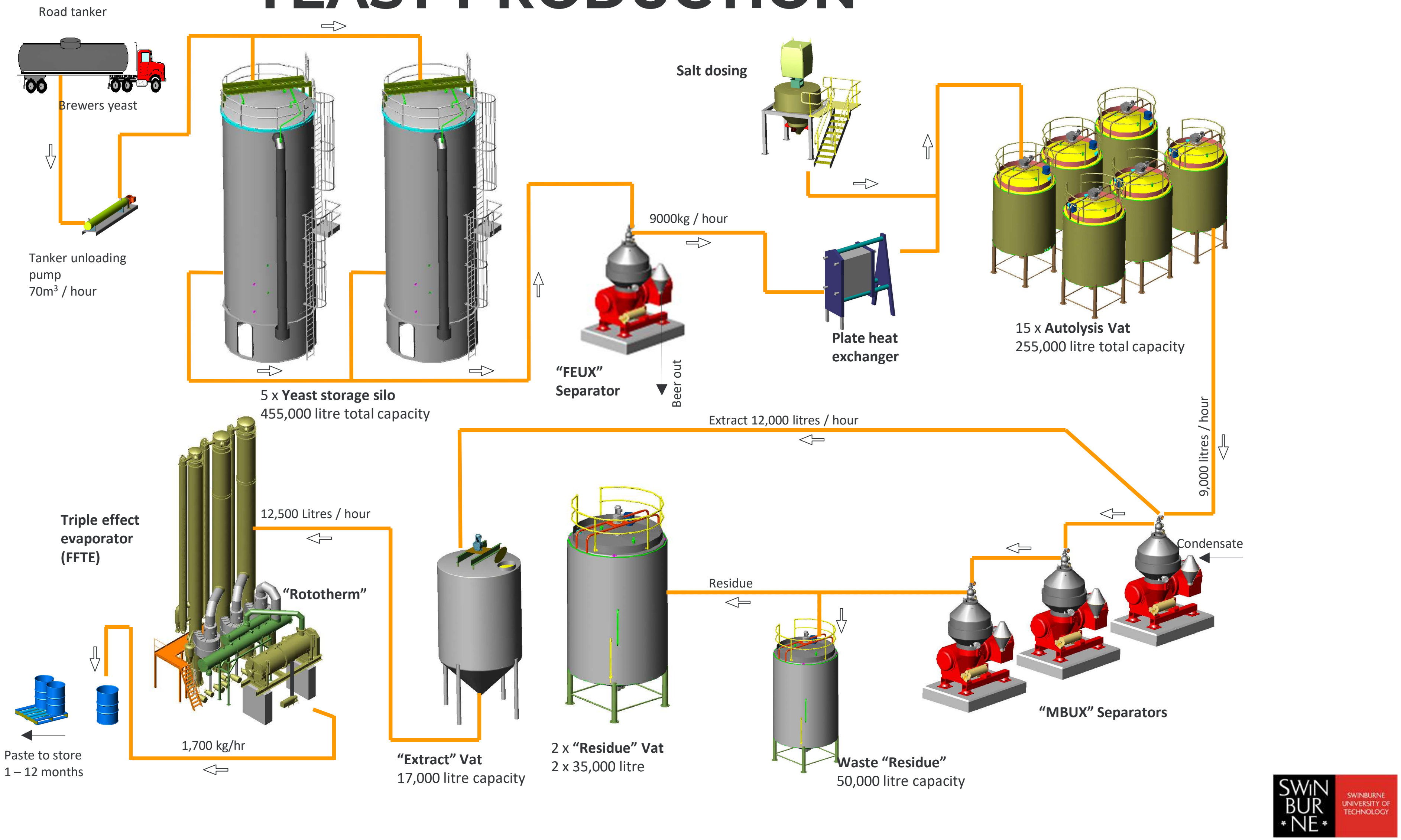
YEAST PRODUCTION



Project aims

Devising and in-plant trialling an Industry 4.0 Application that will eliminate Vegemite product variation (ensure that this yeast-based product contains 61-63% solids)

1. Determine appropriate evaporator machine settings and related operator actions to ensure the presence of 61-63% solids in the yeast product
2. Improve plant productivity by standardising the start-up and shut down processes, machine settings, and operator actions that reduce the waste and re-processing of the yeast product
3. Enable data-driven automation of the Vegemite production

Vegemite plan data collection

- **Data collected**
  - 1.83 GB machine data, production data and yeast paste quality data
  - July 2019 – June 2020
- **Existing Vegemite plan production performance form collected data**
  - **43%** efficiency (43% of production runs produced 61 – 63% solids in the yeast paste)
  - Computed from yeast quality that was automatically collected form the refractometer
- **Data annotation for predictive model training**
  - **Performed by the plant operation after each production run**

VegQR Solution for ensuring Vegemite product consistency

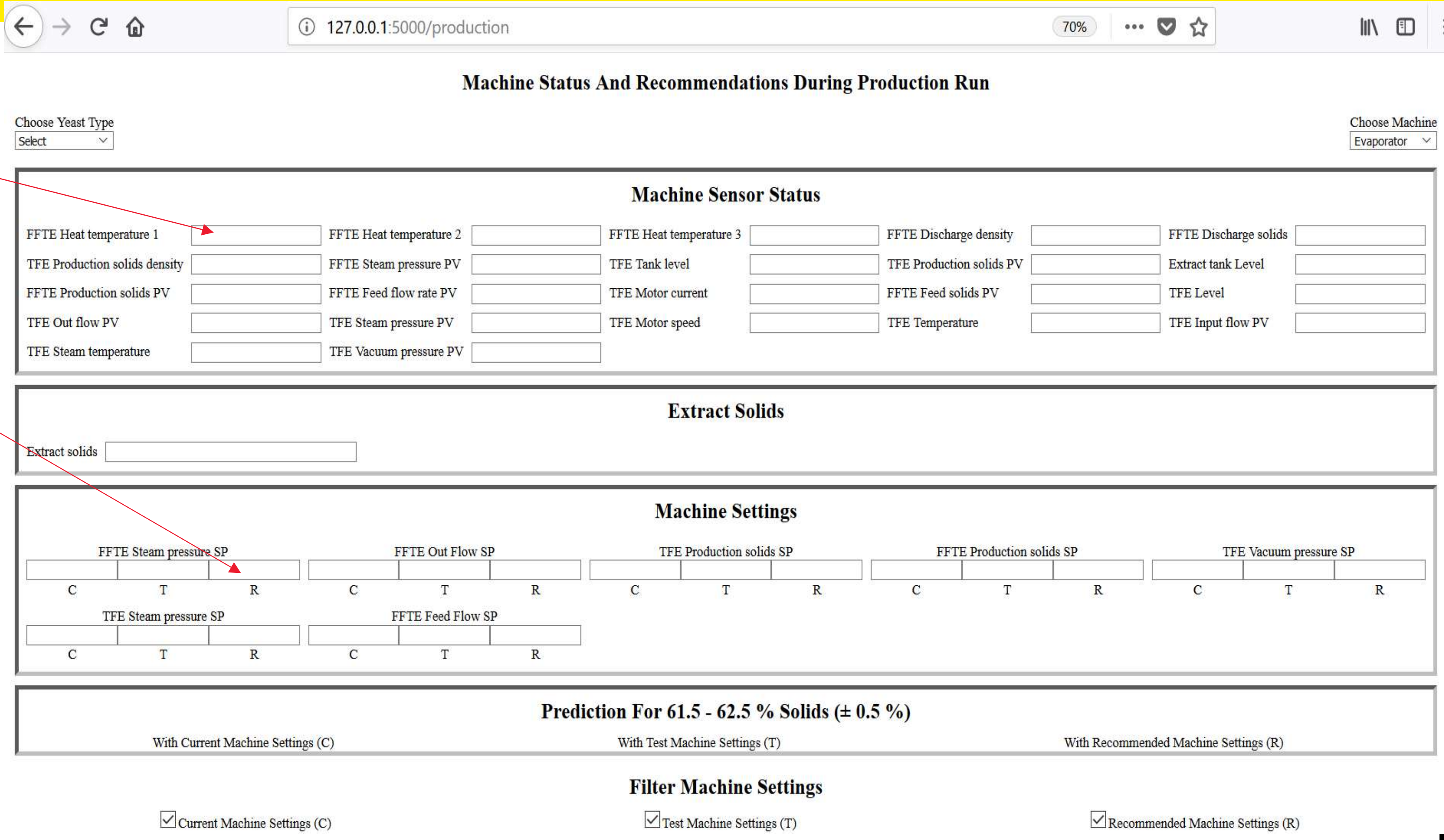
Device VegQR – an Industry 4.0/Industrial IoT application that in real time will:

1. Predict the consistency of the Vegemite product during production by considering:
   - Raw yeast seasonal variation and quality
   - Plant machine setting
   - Machine sensor data
2. Recommend plant machine settings that will achieve the required product consistency
3. Allow plant operators to formulate "what if" scenarios involving alternative settings and predict expected production outcomes
4. Interact directly with the plant PLCs to get the above information and potentially fully automate production

VegQR interface for production

Displays current machine sensor data

Machine settings recommendations are provided based on both machine sensor status and current machine settings



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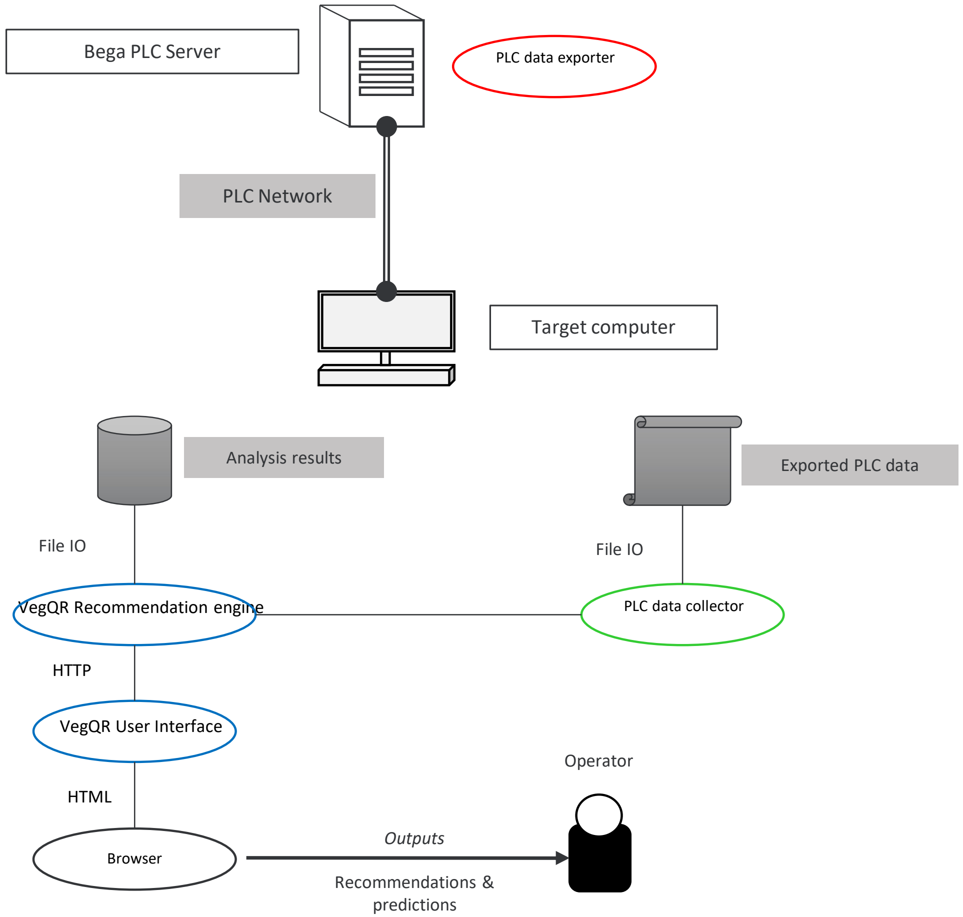
VegQR Industry 4.0/Industrial IoT Application



- PLC data exporter(s) run on PLC server(s) and periodically collect and send data collected form the PLCs to the VegQR (target) computer
  - Format of exported PLC data is as a comma-separated-values (CSV) file
  - PLC data is exported every 3 seconds
- PLC data collector runs on the target computer and periodically reads the exported PLC data and updates the VegQR application
- VegQR application runs on the target computer and generates recommendations using the latest PLC data

VegQR trial

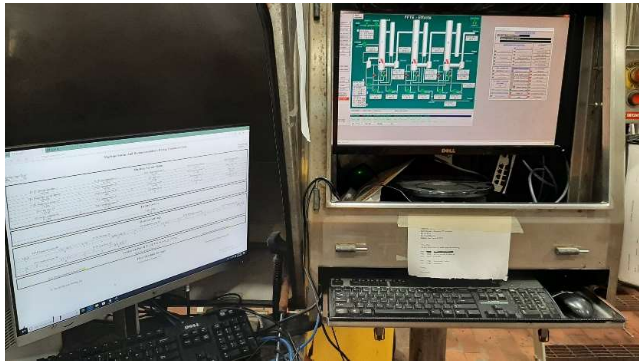
1. **Conducted operator training, usability assessment and related tool improvements**

- VegQR training and usability assessment conducted with multiple operators
- Enhancements were made to VegQR user interface based on operator feedback

2. **Performed VegQR model training/configuration**

- Assessed alternative configurations of VegQR machine learning model (using only start-up data as opposed to data from entire production runs)
- Selected the default VegQR machine learning model as most suitable for the trial

3. **Applied VegQR-provided recommendations in multiple live production runs involving multiple operators**



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VegQR result in improving product consistency and corresponding plat efficiency

Main VegQR trial outcomes:

- **60% product consistency and plant efficiency (or 17% improvement over the existing 43%)** in producing yeast paste quality in the **61 – 63**% solids range
- **100% consistency and plant efficiency in producing** yeast paste quality in the **61 – 63.5%** % solids range

Trial date	Yeast type	Time to build solids	Percentage solids	VegQR prediction
17/11/2020	BRD	1 hr 15 mins	62.1	VegQR predicted \`target solids\` (61-63%) will be achieved
14/1/2021	BRN	1 hr	61.9	VegQR predicted \`target solids\` (61-63%) will be achieved
19/1/2021	FMX	1 hr 20 mins	63.3	VegQR predicted \`high solids\` (>63%) will be achieved
21/1/2021	BRD	1 hr	61.9	VegQR predicted \`target solids\` (61-63%) will be achieved
9/2/2021	FMX	1 hr	63.5	VegQR predicted \`high solids\` (>63%) will be achieved

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Industry 4.0 solution for
reducing variation in
recycled steel production

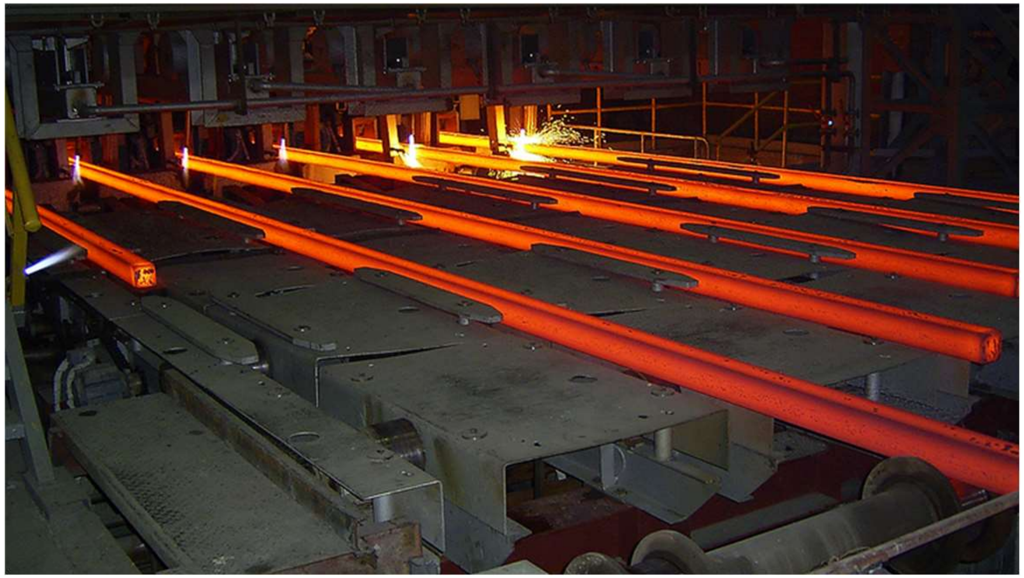
The recycled steel product variation problem

Low billet quality/consistency
due to:

- Variation in recycled steel (raw material comes for crashed vehicles)
- Plant machine settings
- Operator actions

Problems:

- Low plant productivity due to reprocessing
- High energy consumption
- High reliance to monitoring
  and intervention by the plant operators



Improving curing in high-volume manufacturing of lightweight composites

Objectives

- Monitoring and improving curing process
- Monitoring and improving product quality

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Australian Government | Business business.gov.au

Sensor-based monitoring of the curing of carbon composites

Real-time monitor of production defects

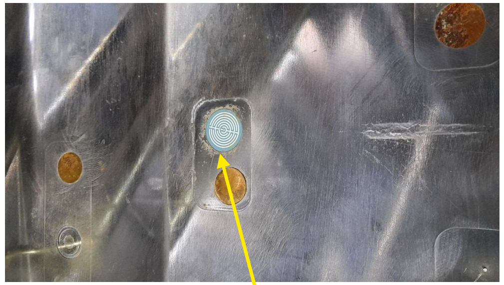
Existing Sensors

- **Pressure sensors** monitor level of filling of cavity based on cavity pressure
- **Temperature sensors** monitor material temperature during the process
- Monitoring is not based on actual material behaviour during curing, which is the cross-linking reaction

New dielectric sensors and data analysis

- Material placed in contact with dielectric sensor
- **Dielectric sensors** measures dielectric loss factor, based on which the ion viscosity of the material is calculated

Dielectric sensor



Sensor installation in a frame

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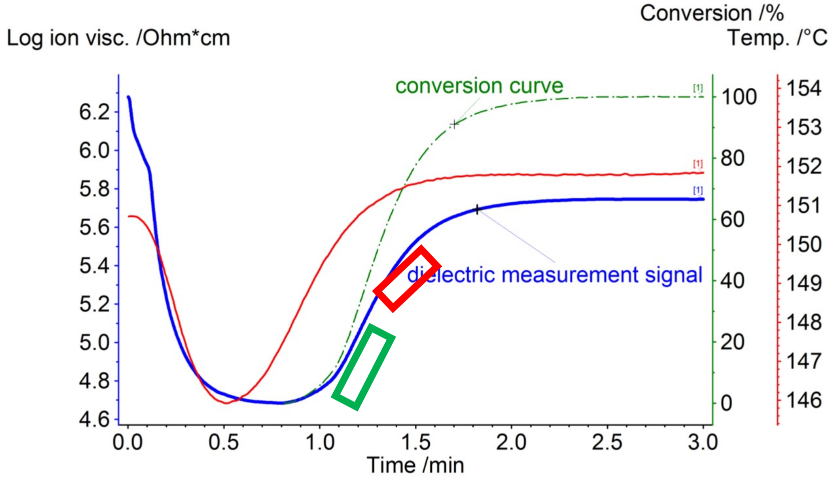
Defect detection vs defect prediction

Existing defect detection – an engineering solution

- Calculate ion viscosity (blue) and temperature (red) of material in conjunction with progress of cure process (green)
- Detect defects is based on known threshold windows, (shown as rectangular boxes)
- Process is stopped if window is breached

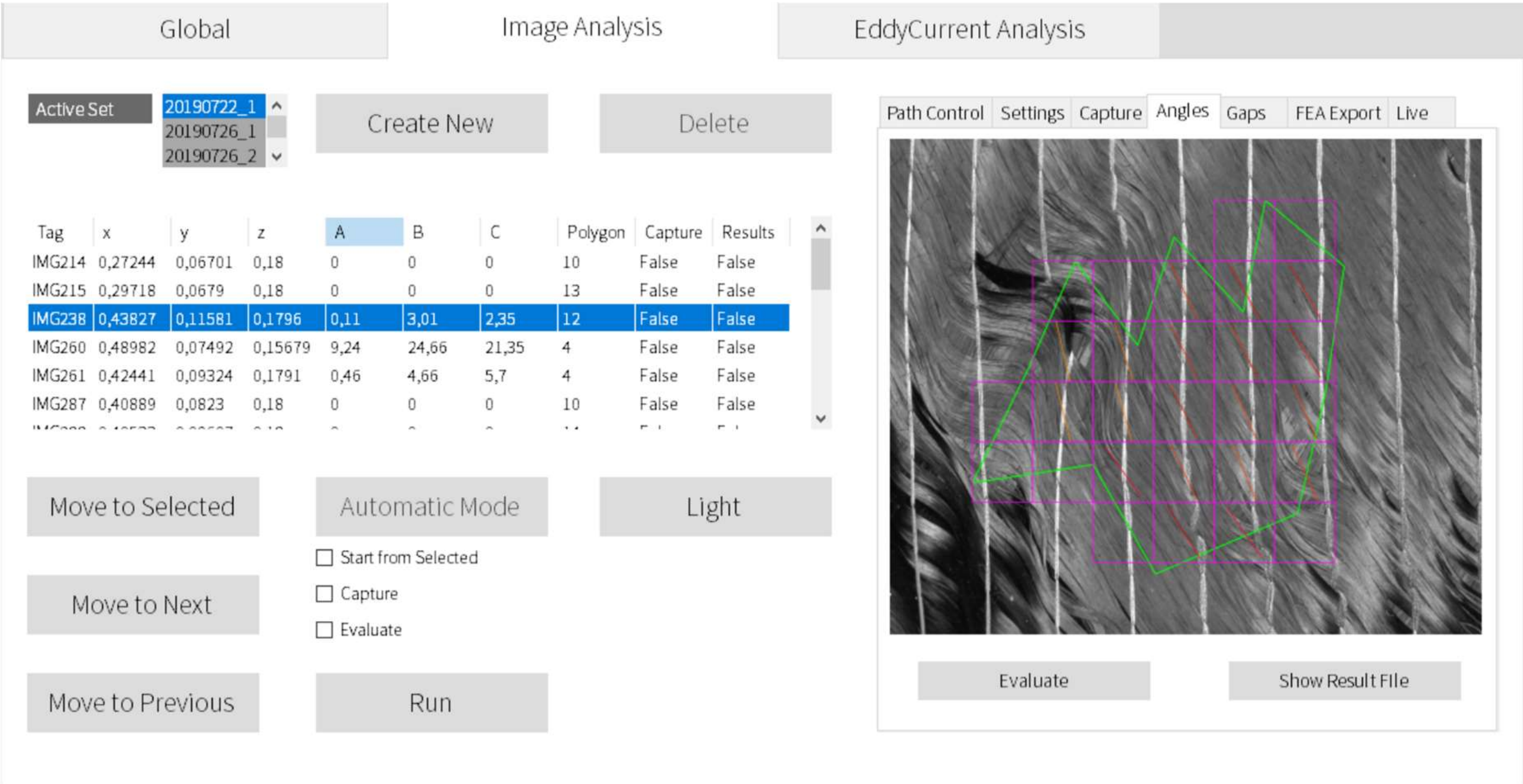
Proposed defect prediction – a smart data driven machine learning model-based solution

- Machine learning model predicts curing outcomes in real time
- Machine setting are adjusted to ensure perfect curing (no threshold windows)

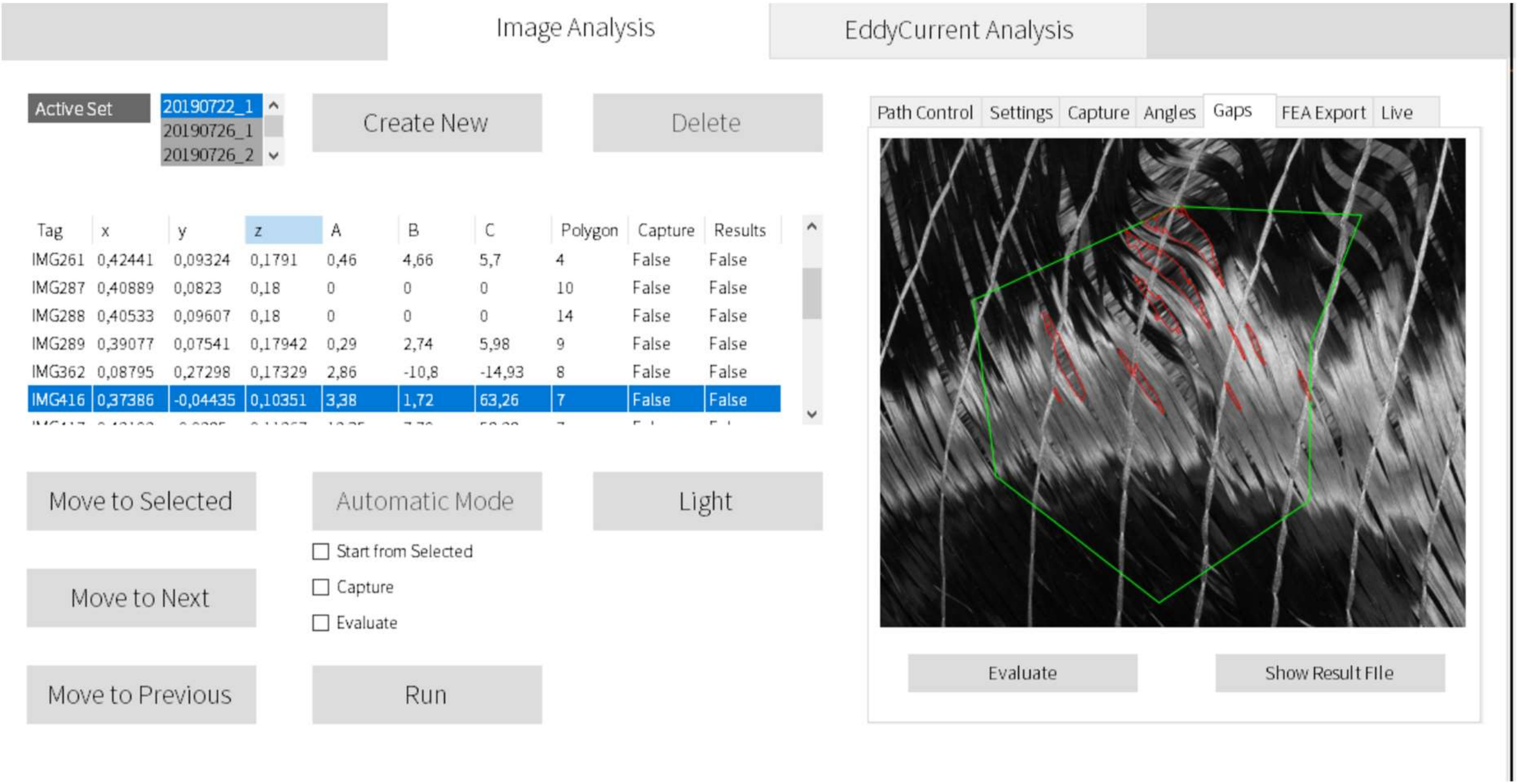


Source: https://ta-netzsch.com/process-automation-for-composites

Model training via camera-based gap evaluation



Model training via camera-based via angle evaluation

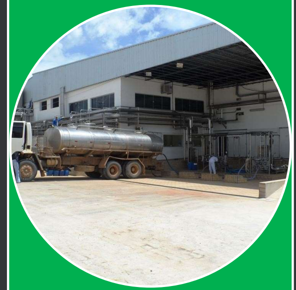


Improving Plant Productivity, Product Quality and Supply Chain Efficiency

Improve worker productivity

Reduce Unscheduled Machine Maintenance

Improve Product Quality



Enhance just- in-time supply chain efficiency

Live Inbound Milk Supply Chain Monitoring

Harvests the following measurements across the supply chain

- Milk quantity, temperature, quality (% of protein and fat)
- Truck arrivals/departures and tank wash events
- Environmental conditions

Incorporates 250 IoT devices deployed in 100 dairy farms and 40 trucks

- Novel milk quality sensors
- COTS sensors, microcontrollers, NB-IoT cards, power supplies, backup batteries
- Milk-safe enclosures specifically designed for milk monitoring

Provides Real-time milk pick-up logistics & Highly accurate milk forecasting

- Apps supports viewing all supply chain information and related alerting

Australian Government
Department of Industry, Innovation and Science
Business Cooperative Research Centres Program
Bega
software AG
OPTUS yes
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Live Inbound Milk Supply Chain

Objectives

- Real-time milk and pick up monitoring
- Real-time milk pick-up logistics
- Highly accurate milk forecasting
- Just-in-time milk delivery to processing plants

CT sensor

Milk quantity, temperatre & quality sensors

Environmental temperature & humidity sensors

Tracking sensors

Australian Government
Department of Industry, Innovation and Science

Business Cooperative Research Centres Program

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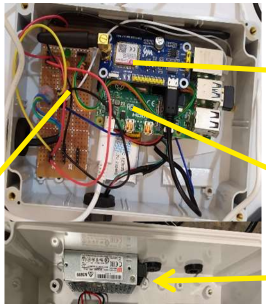
Milk quality, quantity and temperature monitoring

Sensor cables gland

SD Card

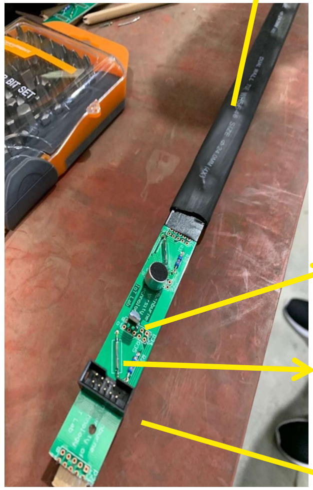


NB-IoT Communication Module

Raspberry Pi Sensor Platform

Power Supply AC to DC Converter

Heat shrink to protect the PCB and reed sensors



Temperature sensor

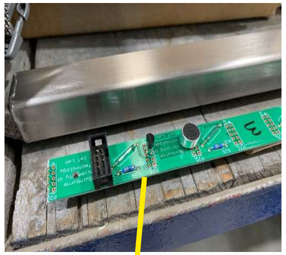
Reed sensor

PCB connector

Float with a magnet inside

Sensor cables

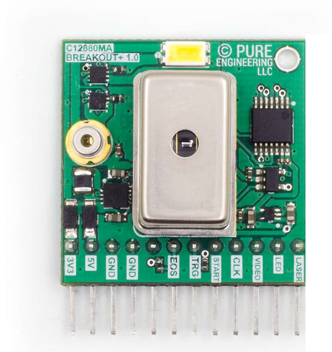
Sensor enclosure to be installed inside the vat

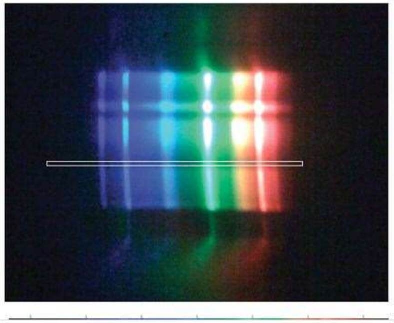


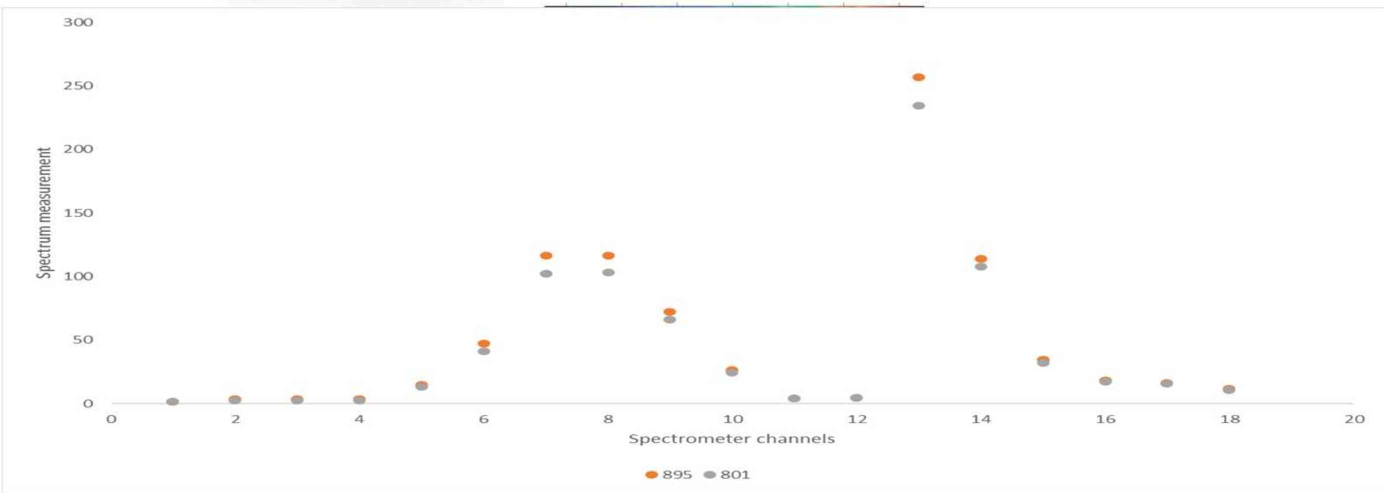
PCB is installed inside the enclosure

Novel Milk Quality Sensors

- **Arduino-based spectrometer (Hamamatsu)**
- **3 LEDs**
  - One visible light LED and two infrared LEDs
- **Machine learning milk classifier**
- **Ground truth**
  - 2000 milk samples
  - Lab test reports







Spectrum measurements from 2 samples: fat (4-10) and protein (13-18)

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Swinburne's Industry 4.0 Program

Industrial IoT (IIoT)

- Data acquisition and integration
- Data analysis and actuation
- Cloud, edge and device computing
- Sensor/actuator networking, security and mobility
- IIoT platforms

Cyber-Physical Machines, Processes, Humans, Products (Cyber Twins)

- Machine, process, human and product (MPHP) modeling and simulation
- MPHP monitoring, performance, health and safety
- Self-adjustment and self-optimization
- Sensor/actuator/machine design and development
- Human and machine integration including wearables

Manufacturing Solution Development and Optimization (DevelOpt)

- Solution development methodologies, techniques, and forums
- Advanced process control
- Improving productivity, product quality and safety
- Reducing energy consumption and waste
- Fine-tuning supply chains

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IoT Lab

swinburne.edu.au/digital-capability-platform/our-labs/the-internet-of-things-lab/


Farming


Manufacturing


Cities


Energy


Marketing


Health

- We addresses important challenges in our industries, cities, farms, hospitals, homes, retail chains, personal lives and our society.
- Securely, and in real time, we collect, integrate and analyse data from millions of internet-connected devices that range from sensors, cameras, phones and wearables, to smart meters, vehicles, medication pills, and industrial machines.
- We develop innovative IoT-based solutions for industries and governments.

IoT Lab Capabilities

- **Development of IoT devices and collaborative robots** that provide and use information from the IoT ecosystem
- **Discovery and integration of IoT devices and their data** permitting the use of any machine or IoT devices that have been deployed including IoT devices owned and controlled by others
- **Real-time IoT data analysis on the cloud, at the edge, and on the move** including personalisation and contextualisation of IoT data
- **IoT Security and privacy for IoT devices** with limited computing resource and connectivity
- **IoT Actuation and Automation** via people, IoT devices and robots, and process-based automation
- **Lower-power and longer-range IoT networking** for IoT devices
- **Wearable IoT devices and systems**
- **Human performance, human/IoT integration, and IoT information visualisation**

Thank You!

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