Towards Sustainable and Efficient Healthcare Facilities:

The Role of Automation and Intelligent Control Systems

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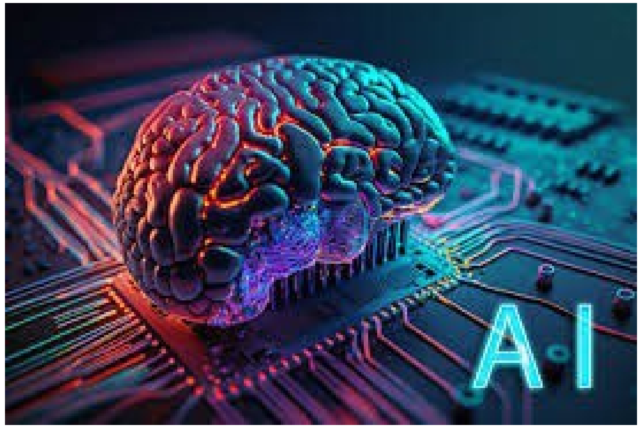
Intro

- Ensuring sustainable access to clean energy and water is essential for public health and aligns with UN goals 3, 6, 7, 11 and 13.
- In the UK, healthcare facilities are major consumers of both, contributing significantly to environmental impact. Improving efficiency in energy and water use is vital for sustainability and cost savings.
- Advancing technologies—particularly intelligent building management systems, IoT, cloud-based tools, and AI-driven optimisation—are delivering measurable improvements in reducing waste, emissions, and resource use. This talk will take a deeper dive into progress and opportunities in these areas.



- Motivation: Net Zero, Sustainability and Digitalisation
- Net Zero Innovation & NZIIC
- Deeper Dive into Digital and AI (CNNs, SNNs, LLMs, … etc)
- Examples:
  - Smart Infrastructure
  - Smart Manufacturing
  - Smart Refuelling
  - Smart Recycling
- Final Thoughts

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Sustainability and Net Zero: Why?

- Energy is fundamental to grow and sustain life on earth.
- But we can also see conflict over territory and dwindling fuel resources, geopolitical upheaval, rising global temperatures, with increasingly **dense toxic smog around cities,** more frequent occurrence of **extreme weather events** and **rising toxic waste problems**;
- There are abundances (of food, clothing, plastics …) in the developed world, with significant shortfalls in the less developed world.
- These are some of the rising **costs and problems** associated with our traditional ways of life in the last centuries: positive change is needed.

Where do we want to Go?

- There are 17 UN Sustainable Development Goals:
- End poverty, hunger and discrimination
- **Sustainable and Clean Energy**, Food & Water Resources and Sanitation
- Towards an equitable Society
- Access to well-paid, decent work
- Access to Good Education
- **Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation**
- **Climate Action**

Re-Industrialise for a Smarter, Cleaner World

Net Zero Timeline

1997: UK Signs Kyoto Protocol
Commitment to 12.5% CO_2 emissions reductions from 1990 levels by 2012

2005: Kyoto Protocol Comes into Force
Commitment to 12.5% CO_2 reduction from 1990 levels by 2012

2008: UK Climate Change Act
Commitment to 80% reduction in CO_2 levels by 2050

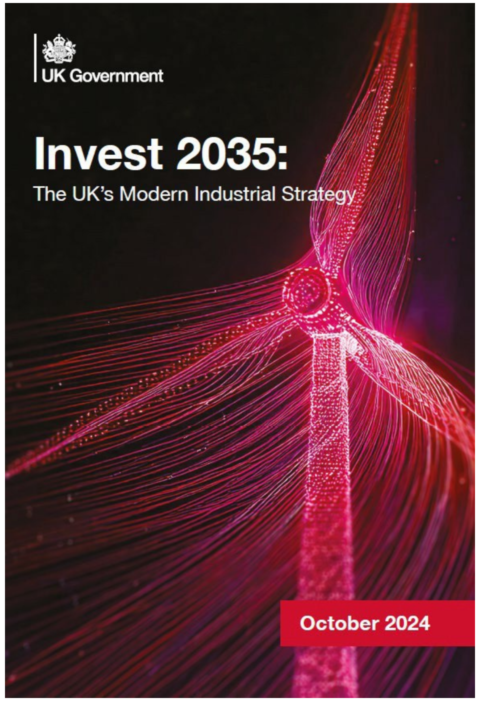
2012: UK Meets Kyoto Protocol Targets
18.5% CO_2 emissions reductions between 1990 and 2012

2012: UK Signs 2nd Kyoto Protocol
Commitment to 19% CO_2 emissions reductions by 2020

2015: Paris Agreement Signed by UK
Global temperatures aimed to be kept below 2°, with target 1.5°

2019: UK Climate Change Act Revised
Revised Commitment to 100% reduction in CO_2 levels by 2050 (Net Zero)

2020: UK Meets 2nd Kyoto Protocol Targets
2nd Protocol remains unratified, Paris agreement favoured



Net Zero: Innovation

In June 2019, the Government amended the Climate Change Act from 80% to 100% GHG emissions reduction – or Net Zero – by 2050.

Because of the need for **greater intermittent renewable penetration**, Net Zero pathways have a greater requirement for system balancing. This can be achieved through supply side flexibility, **demand side flexibility** and **energy storage** in various forms.

"**Decarbonising heat** will rely on deep retrofits for millions of homes and some mixture of **electric heat pumps**, **hydrogen boilers** and district heating depending on local circumstances.

"**Decarbonising industry and transportation** will rely on **carbon capture**, **hydrogen and other alternative fuels**, and **electrification** depending on local circumstances.

Eliminating emissions from buildings is one of the most difficult challenges facing the energy sector and requires significant technological and behavioural innovation."

Teesside University & NZIIC

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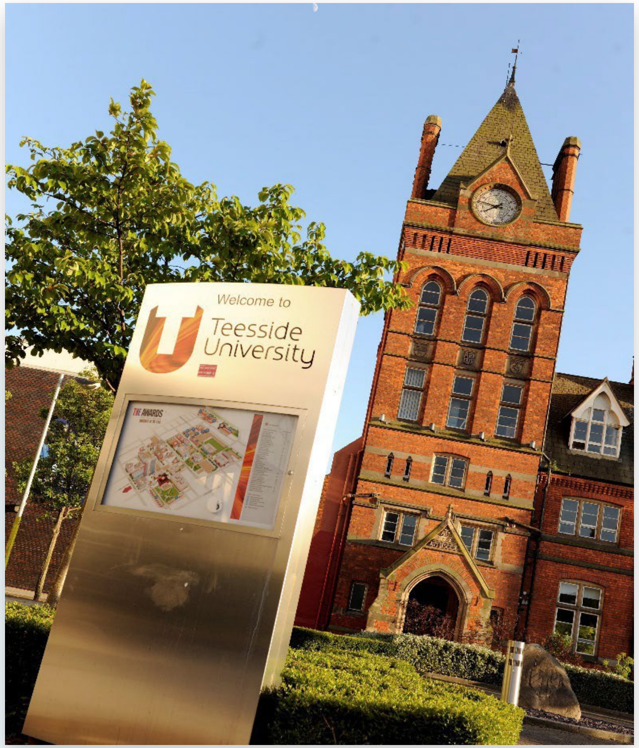
- Teesside University is a public university with its main campus in Middlesbrough, North Yorkshire in North East England.
- In June 2023 a new £13M Net Zero Industry Innovation Centre was opened, to help meet the needs of decarbonisation of our local industry cluster.
- The UK (and currently World's) Largest CCUS Project is underway. We also have the UK's largest Hydrogen Hub
- Largest growing Net Zero industry base and innovation zone in UK, and the fastest growing regional digital sector in UK.



Digitalization: A Net Zero Enabler

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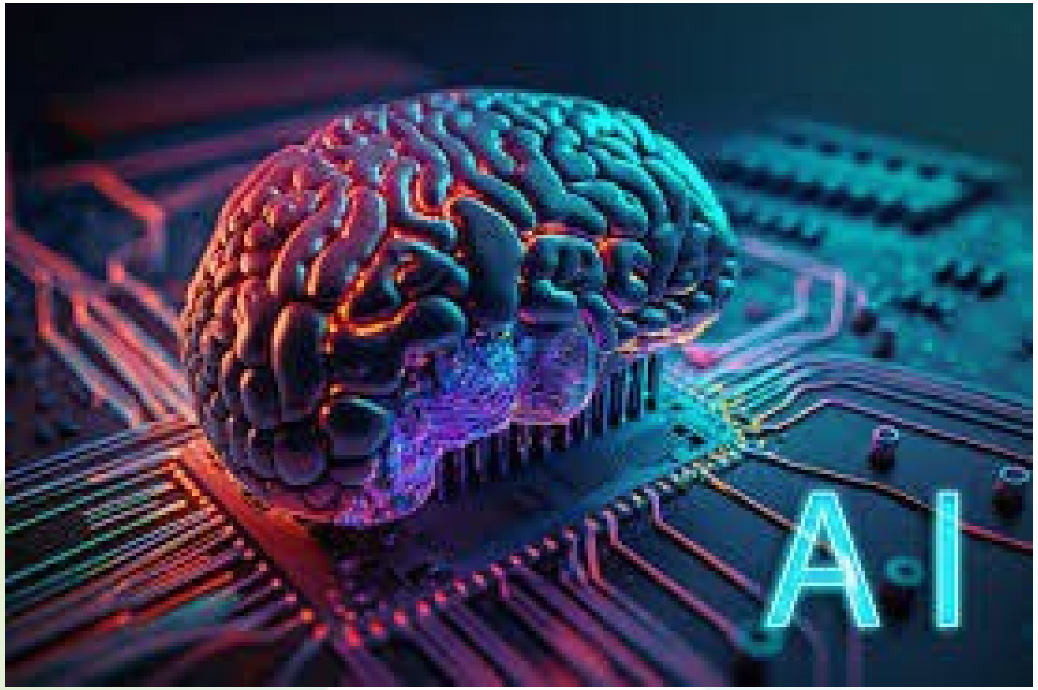
3IR (Digital Revolution) + Infrastructure Digitization = Big Data! + A.I. =

Microprocessors
Automation / Robotics
Flexible Manufacturing
Internet

4G / 5G / 6G / IoT /
WEB 3.0 / IPv6 / Diffserv /
TSN / IPSEC / Cybersecurity
/ DLT / Blockchain

(Deep) Machine Learning
Advanced Mathematics/Statistics
Predictive Analytics
Optimization / Decision Support
Generative AI / LLMs

AI & Automation

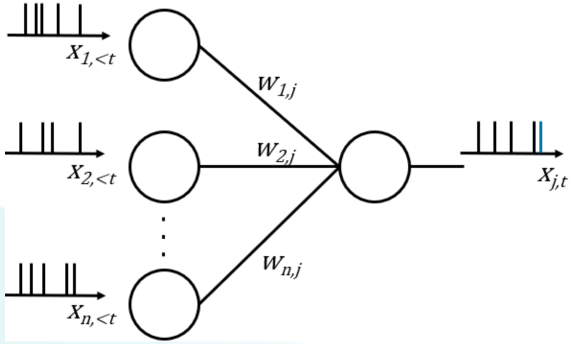


"Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think and learn like humans. These systems can perform tasks that typically require human intelligence, such as learning, problem-solving, perception, and decision-making.

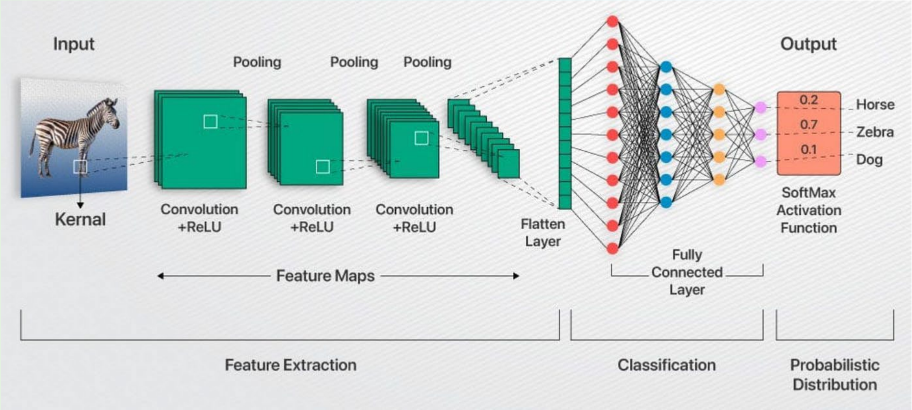
AI encompasses a wide range of technologies, including machine learning, natural language processing, and computer vision, and is used in various applications, from personal assistants to self-driving cars."

Modern AI

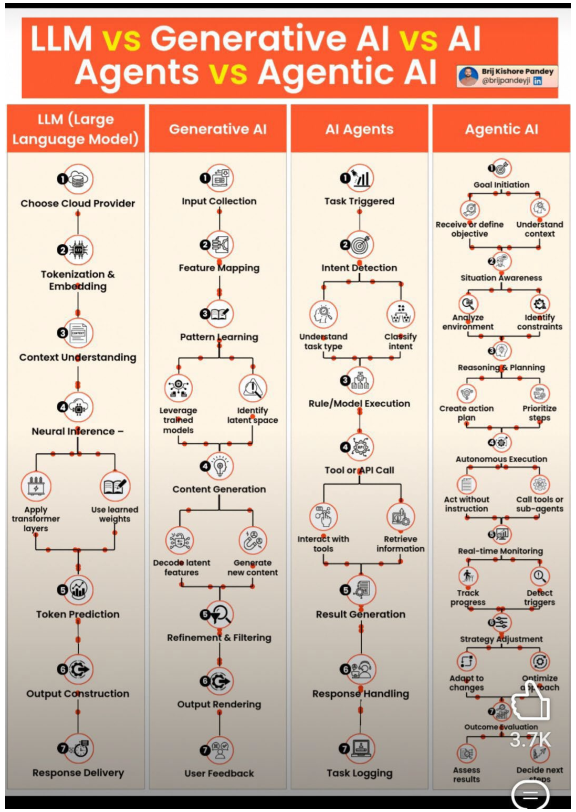
LLM
LARGE LANGUAGE MODEL



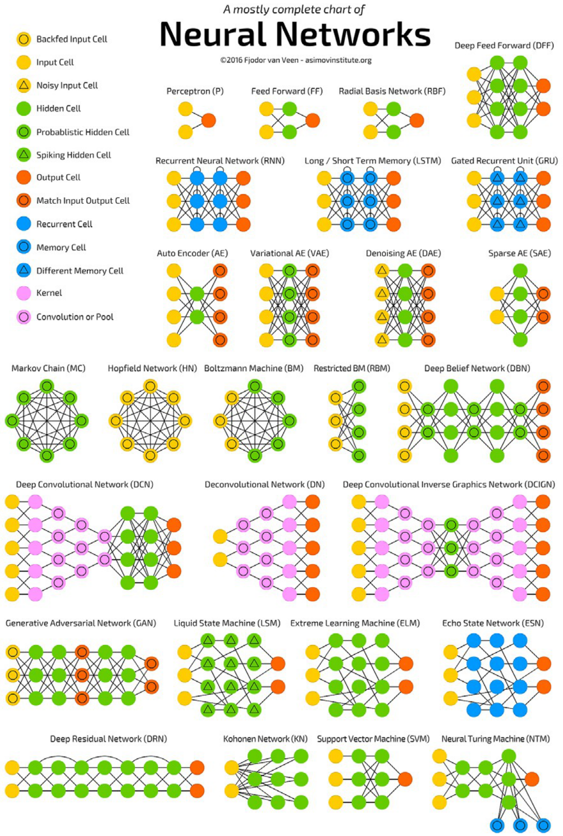
$X_{1,<t}$
$X_{2,<t}$
$X_{n,<t}$
$W_{1,j}$
$W_{2,j}$
$W_{n,j}$
$X_{j,t}$



Input
Kernal
Pooling
Pooling
Pooling
Convolution +ReLU
Convolution +ReLU
Convolution +ReLU
Flatten Layer
Fully Connected Layer
Output
0.2
0.7
0.1
Horse
Zebra
Dog
SoftMax Activation Function
Feature Maps
Feature Extraction
Classification
Probabilistic Distribution



LLM vs Generative AI vs AI Agents vs Agentic AI
Brij Kishore Pandey
LLM (Large Language Model)
Generative AI
AI Agents
Agentic AI
Choose Cloud Provider
Tokenization & Embedding
Context Understanding
Neural Inference
Apply transformer layers
Use learned weights
Token Prediction
Output Construction
Response Delivery
Input Collection
Feature Mapping
Pattern Learning
Leverage trained models
Identify latent space
Content Generation
Decode latent features
Generate new content
Refinement & Filtering
Output Rendering
User Feedback
Task Triggered
Intent Detection
Understand task type
Classify intent
Rule/Model Execution
Tool or API Call
Interact with tools
Retrieve information
Result Generation
Response Handling
Task Logging
Goal Initiation
Receive or define objective
Understand context
Situation Awareness
Analyze environment
Identify constraints
Reasoning & Planning
Create action plan
Prioritize steps
Autonomous Execution
Act without instruction
Call tools or sub-agents
Real-time Monitoring
Track progress
Detect triggers
Strategy Adjustment
Adapt to changes
Outcome Evaluation
Assess results
Decide next steps
3.7K



A mostly complete chart of
Neural Networks
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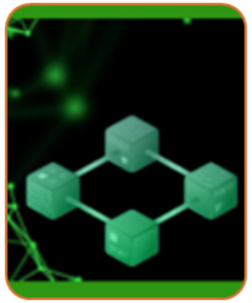
Backfed Input Cell
Input Cell
Noisy Input Cell
Hidden Cell
Probablistic Hidden Cell
Spiking Hidden Cell
Output Cell
Match Input Output Cell
Recurrent Cell
Memory Cell
Different Memory Cell
Kernel
Convolution or Pool
Perceptron (P)
Feed Forward (FF)
Radial Basis Network (RBF)
Deep Feed Forward (DFF)
Recurrent Neural Network (RNN)
Long / Short Term Memory (LSTM)
Gated Recurrent Unit (GRU)
Auto Encoder (AE)
Variational AE (VAE)
Denoising AE (DAE)
Sparse AE (SAE)
Markov Chain (MC)
Hopfield Network (HN)
Boltzmann Machine (BM)
Restricted BM (RBM)
Deep Belief Network (DBN)
Deep Convolutional Network (DCN)
Deconvolutional Network (DN)
Deep Convolutional Inverse Graphics Network (DCIGN)
Generative Adversarial Network (GAN)
Liquid State Machine (LSM)
Extreme Learning Machine (ELM)
Echo State Network (ESN)
Deep Residual Network (DRN)
Kohonen Network (KN)
Support Vector Machine (SVM)
Neural Turing Machine (NTM)

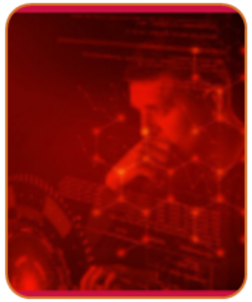
Powering Future Industries: Smart Energy

Blockchain



- Smart Energy Contracts and Balancing Services, Energy Trading
- Data visibility & control, DLT
- Improved custody trail & traceability
- Atomic settlement for transactions

Big Data & Artificial Intelligence



- Energy analytics and forecasting
- Quantifying and Trading Emissions
- Economic dispatch and balancing
- De-risking trade finance access

Internet of Things

- Tracking and monitoring supply, demand and environmental variables
- RPA for Renewables Integration, Demand response and VPPs
- Digital Twinning and User Interaction

Digital Identity / Cryptography

- Secure Electronic Documentation
- Trusted Energy Value Chain Visibility
- Secure and private Energy Trading
- Intrusion detection and authentication

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Smart Infrastructure

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Smart Apps for Building Energy Control

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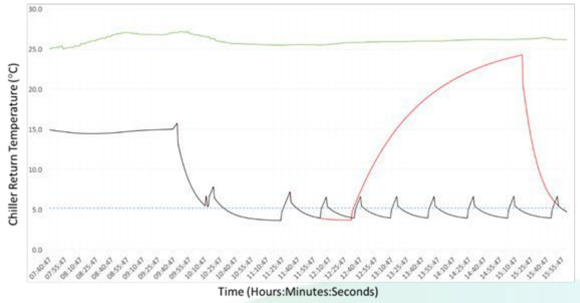
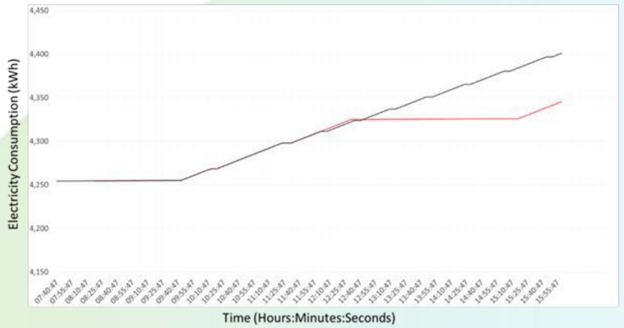
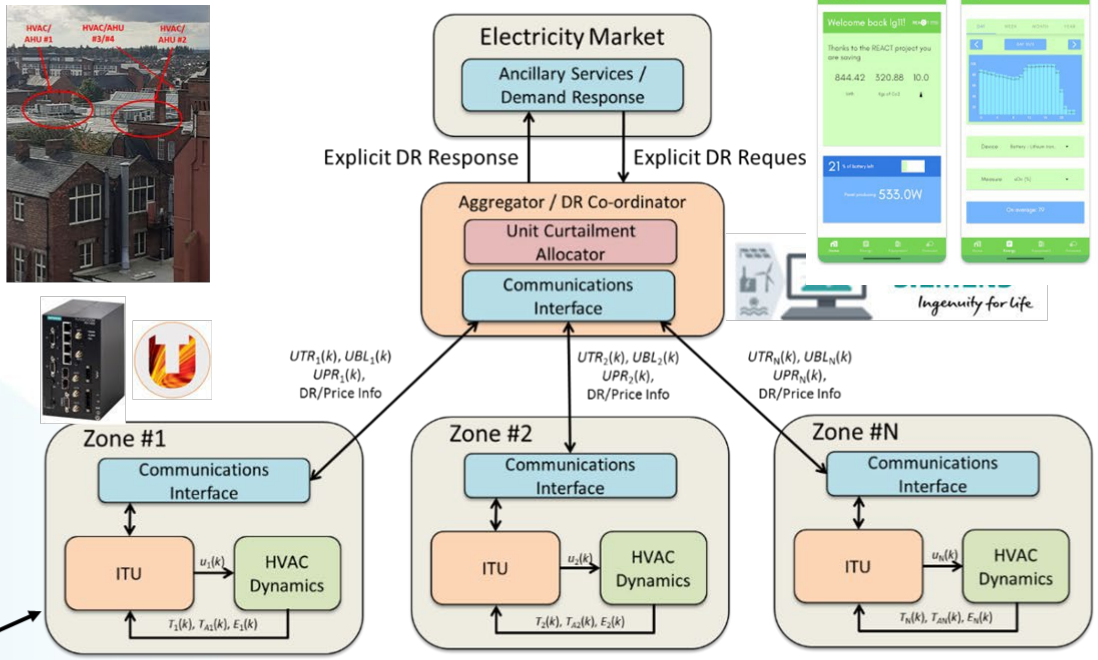
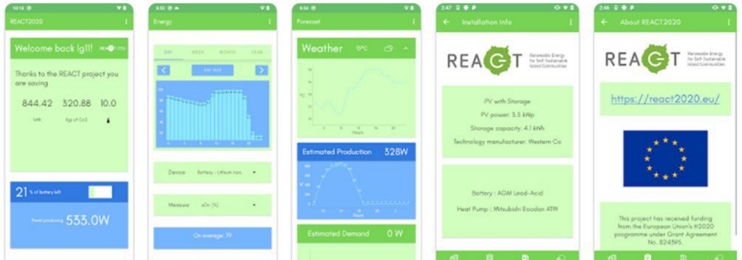




REACT

$$J_N(x_N) = g_N(x_N);$$
$$k = N-1, N-2, \ldots, 1, 0:$$
$$J_k(x_k) = \min_{u_k \in U_k(x_k)} \{g_k(x_k, u_k) + J_{k+1}(f_k(x_k, u_k))\};$$





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Horizon 2020
European Union Funding
for Research & Innovation

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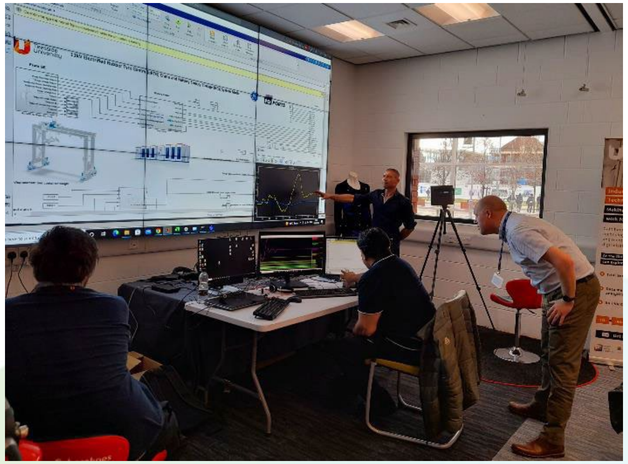
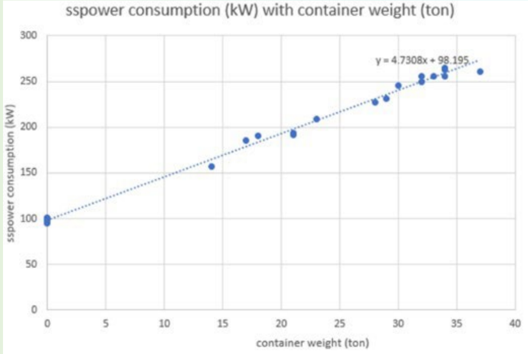
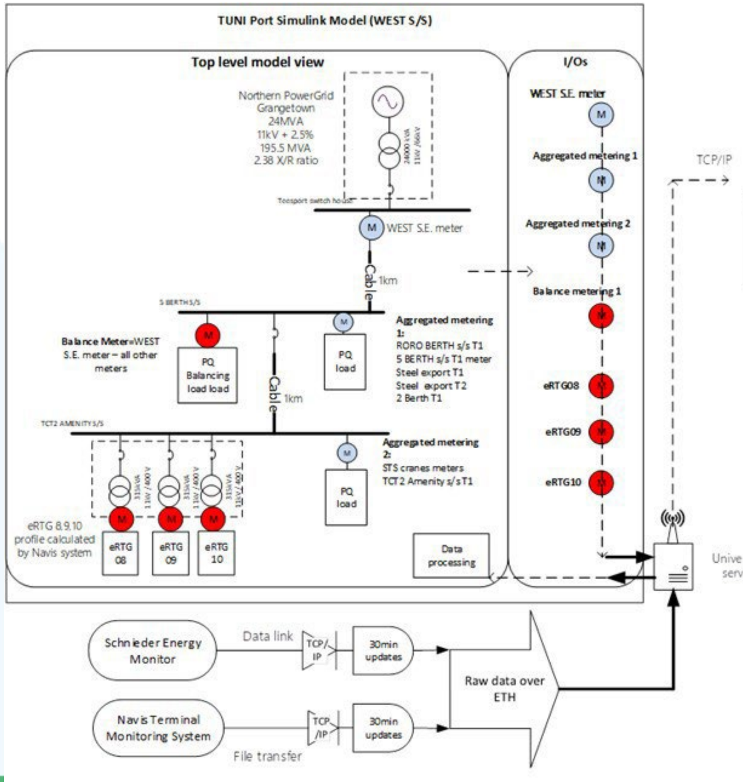
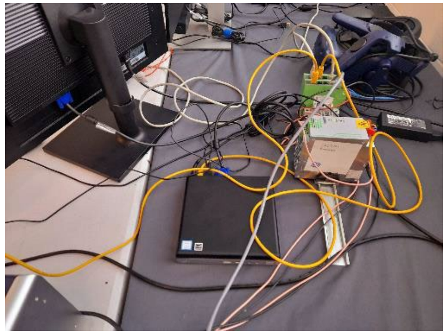
Smart Marine Infrastructure

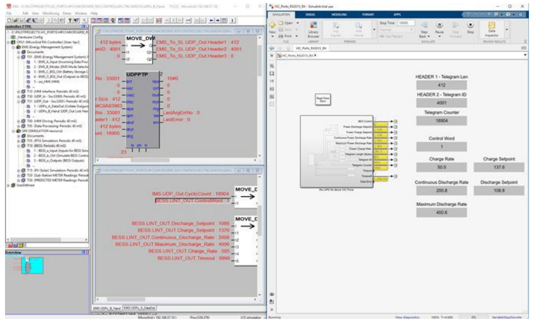
$$P_H(t) = k(J_H(t)) * J_H(t) * \sqrt{M_c(t)}$$

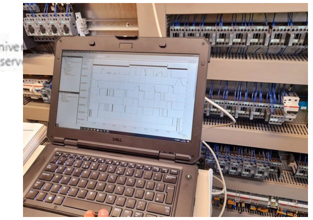












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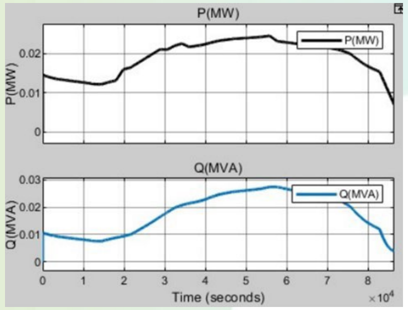
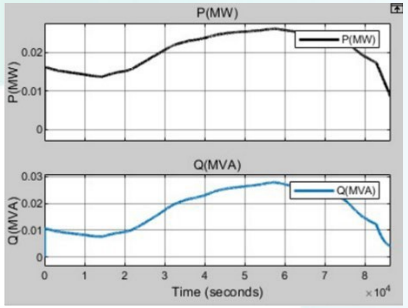
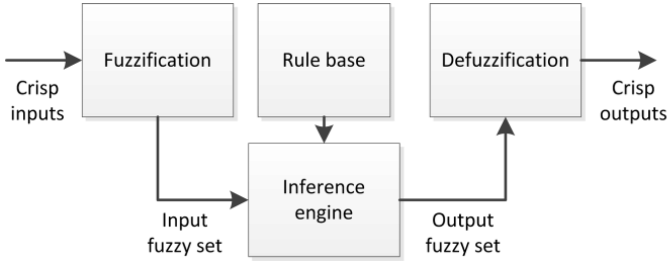
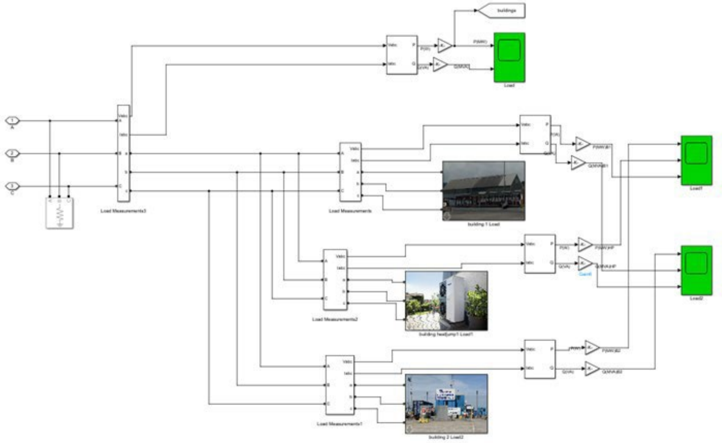
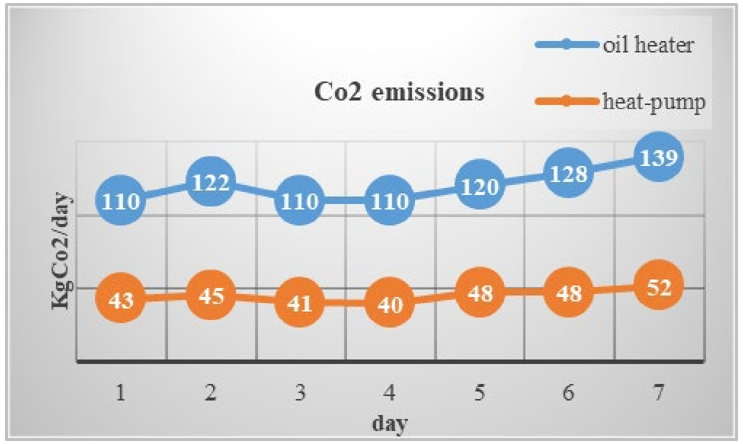
Smart Marine Infrastructure











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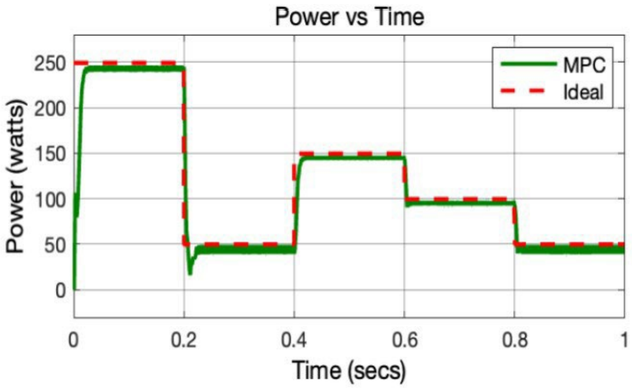
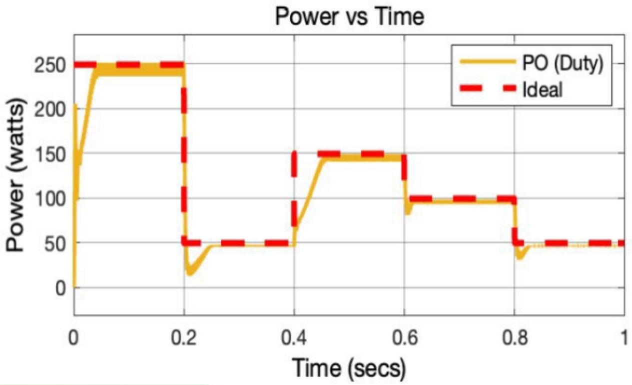
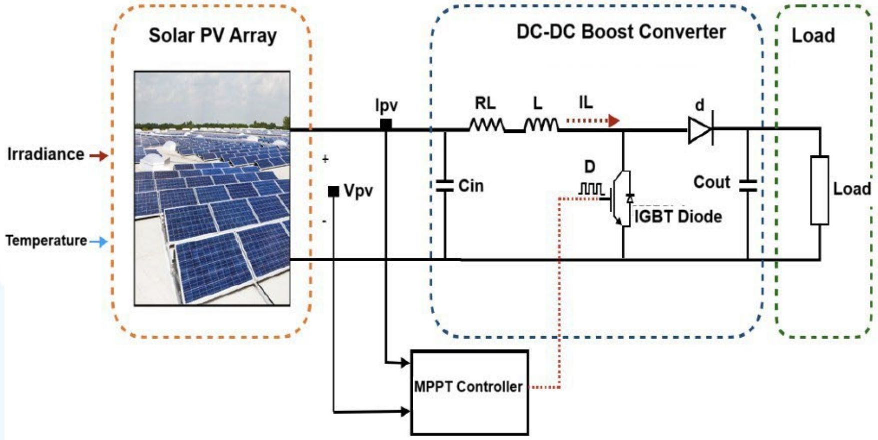
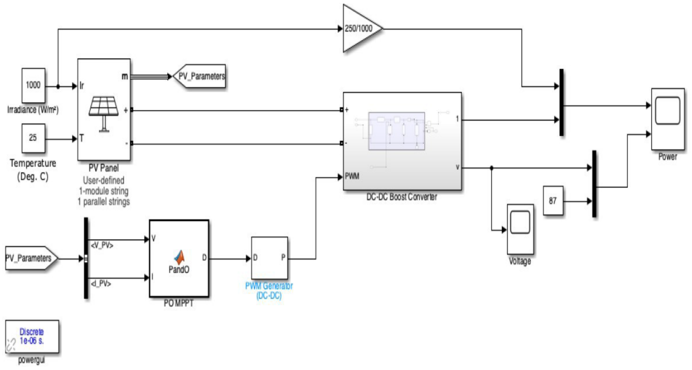
Smart Solar Integration









Performance Analysis of Model Predictive Control and Perturb & Observe MPPT for Solar PV Systems

Rajitha Wattegama[1,*], Michael Short[1], Geetika Aggarwal[1] and Raj Naidoo[2]

[1]School of Computing, Engineering and Digital Technology, Teesside University, U.K.

[2]EDepartment of Electrical, Electronic and Computer Engineering, University of Pretoria, S.A.

***Abstract*—The efficiency of solar PV systems is significantly affected by environmental variations, requiring robust Maximum Power Point Tracking (MPPT) techniques to ensure operational efficiency. Conventionally deployed methods, such as Perturb & Observe (P&O), typically suffer from steady-state oscillations and slow dynamic responses, leading to power losses. To address these challenges, this study investigates the potential of a novel hybrid predictive control strategy to enhance P&O-based MPPT performance. Specifically, a comparative analysis of hybrid Model Predictive Control (MPC) and (P&O (Duty Cycle) MPPT methods is reported under Standard Test Conditions (STC) for PV and irradiance step change conditions, using accurate Matlab/Simulink simulations. Under STC conditions, MPC demonstrated a significantly faster tracking speed and reduced steady-state oscillations; during step change analysis, MPC maintained a increased mean efficiency. The MPC framework also adds complexity to the design; if implemented correctly, it has promise for next-generation solar PV applications where real-time adaptability is crucial.**

Keywords: Model Predictive Control (MPC), Maximum Power Point Tracking (MPPT), Perturb & Observe (P&O), Solar Photovoltaics (PV).

I. Introduction

The global energy demand continues to rise, necessitating the shift towards sustainable and renewable energy sources. Among various renewable energy technologies, solar photovoltaic (PV) systems have gained significant attention due to their environmental benefits and scalability. However, the efficiency of PV systems is highly dependent on environmental conditions such as irradiance and temperature, which cause fluctuations in output power [1]. To address these variations, Maximum Power Point Tracking (MPPT) techniques are employed to ensure that the PV system operates at its Maximum Power Point (MPP), thereby optimising energy extraction.

Traditional MPPT methods, such as the Perturb & Observe (P&O) algorithm, are widely used due to their simplicity and ease of implementation. P&O MPPT operates

speed by considering future behaviour, leading to improved stability and higher efficiency. Furthermore, MPC reduces oscillations and improves transient response, particularly under step change conditions, making it a promising alternative to conventional MPPT techniques.

II. Literature Review

Maximum Power Point Tracking (MPPT) is an essential technique used in solar photovoltaic (PV) systems to optimize energy extraction despite environmental variations. Since its introduction by Stuart Watkinson in 1985, MPPT technology has become a fundamental component in grid-connected solar inverters and solar charge controllers [4]. Over the years, research in MPPT strategies has intensified, with IEEE publishing over 1000 papers annually, highlighting the growing significance of enhancing MPPT techniques to improve PV system efficiency.

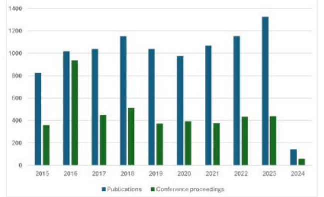


Figure 1 - Graph of IEEE Publications and Conference Proceedings per Annum

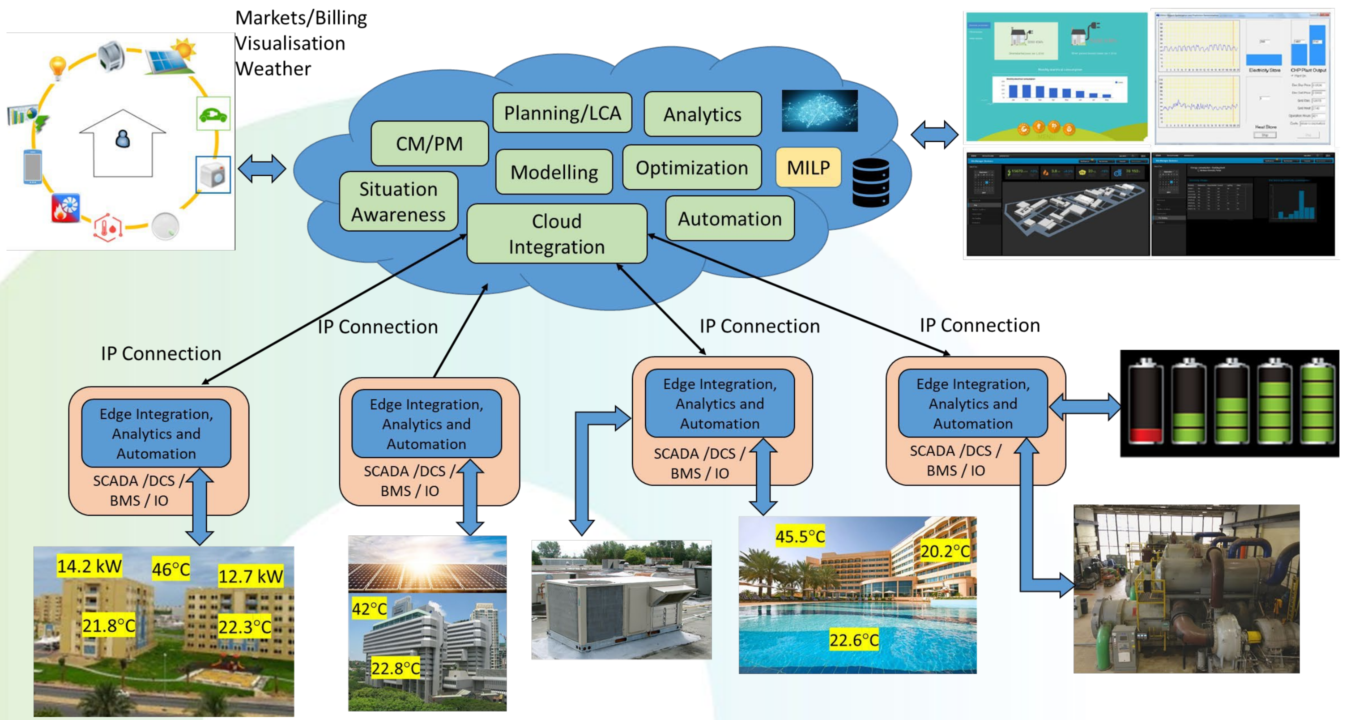
A. Conventional MPPT Methods

Among the conventional MPPT techniques, Perturb & Observe (P&O) and Incremental Conductance (INC) remain widely used due to their simplicity and cost-effectiveness [5]. P&O MPPT operates by iteratively adjusting the duty cycle of the DC-DC converter and observing changes in

BELIEVE IN THE POSSIBILITIES

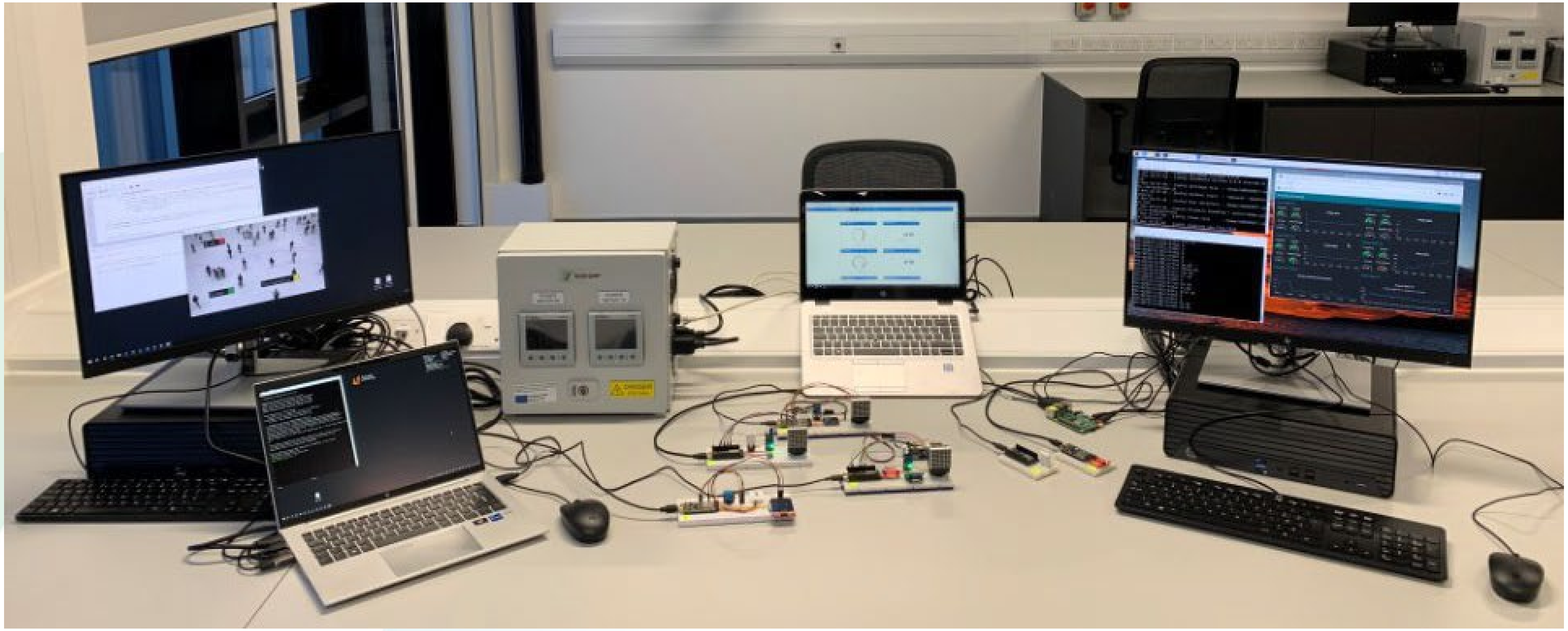
Smart HCVAC in Buildings

- Energy efficiency solutions for buildings - Electrical Energy Efficiency/District Cooling Efficiency and Renewables Integration



- The purpose of the project is to develop (increase TRL), configure and demonstrate an IoT-based energy management system in large-scale pilots involving multiple buildings, renewable technologies and District Cooling Plant (DCP) in Abu Dhabi, Singapore and Saudi.
- The principal goal is to improve energy and asset efficiency and leverage direct and indirect cost reductions, and to enable better integration of local renewable resources (Solar, Wind) in real-world practical situations.

Smart HCVAC in Buildings



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CNN-Based Smart Cooling in Buildings

أدنوك
ADNOC

مكتب أبوظبي للاستثمار
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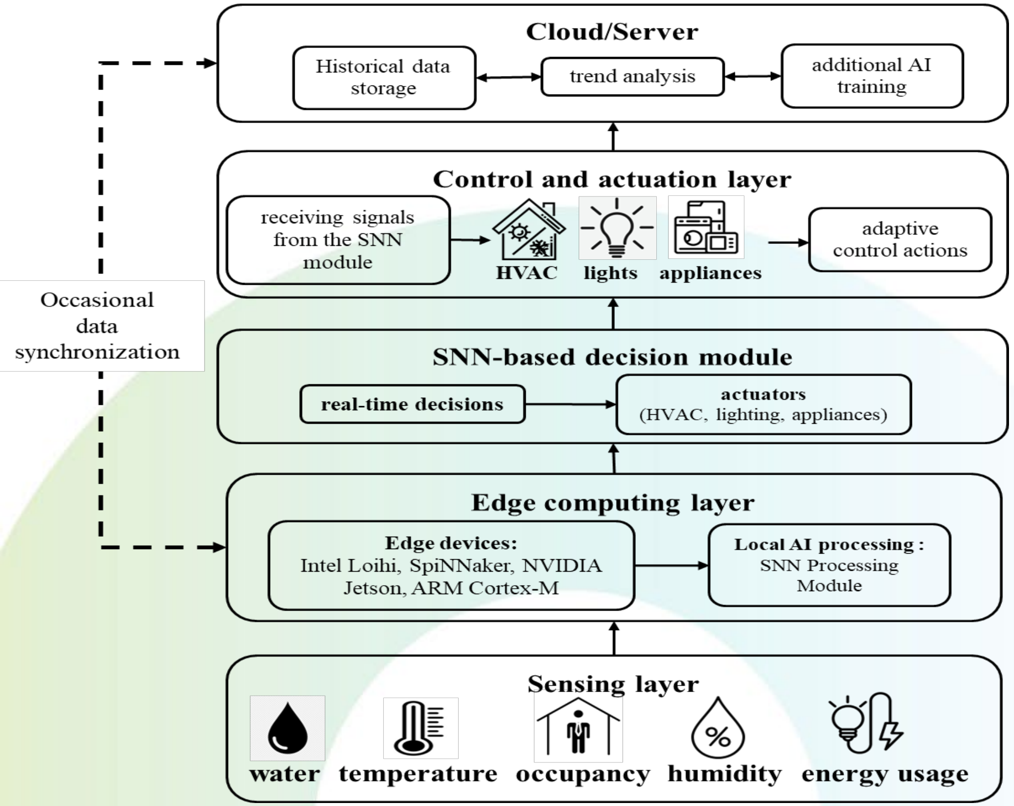
SNN-Based Automation in Buildings



energies MDPI

Article

Energy and water management in smart buildings using spiking neural networks: A low-power, event-driven approach for adaptive control and anomaly detection

Malek Alrashidi [1], Sami Mnasri [2,1,*], Maha Algibly [1], Mansoor Alghamdi [1], Michael Short [3], Sean Williams [3], Nashwan Dawood [3], Ibrahim S. Alkhazi [4], Majed Abdullah Alrowaily [5]

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Abstract: The growing demand for energy efficiency and sustainability in smart buildings necessitates advanced AI-driven methods for adaptive control and predictive maintenance. This study explores the application of Spiking Neural Networks (SNNs) to event-driven processing, real-time anomaly detection, and edge computing-based optimization

Event	Rule-based	CNN	LSTM	RNN	GRU	SNN	BO-STDP-SNN (our proposed model)
Occupant enters room	800	250	180	190	170	60	50
Temperature exceeds threshold	900	280	200	210	190	70	60
Appliance left ON	850	300	210	220	200	65	45

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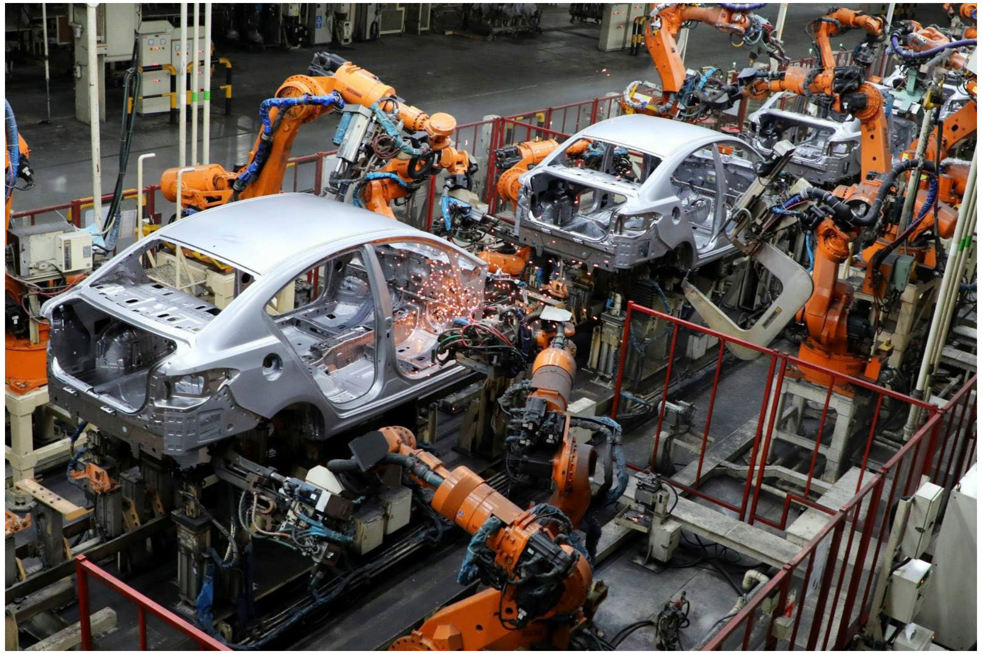
Smart Manufacturing



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Predictive Analytics and LLMs for Manufacturing Efficiency

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European Union
European Regional Development Fund

TASCOMP 40 Est 1981

$$E_n(k) = a_1 E_n(k-1) + b_1 U_1(k-1) + \cdots$$

Cell n Predictive Model

Cell n Utilities Forecasts

Machine Learning Utilities Use and Efficiency Model

Cell n real-time utilities readings

Utilities Timeseries Data

SCADA/Asset Operations Data

SCADA Utilities/ Plant Metering IoT Platform

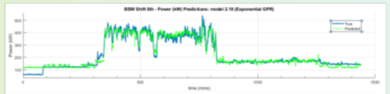
Cell Operation Classifier

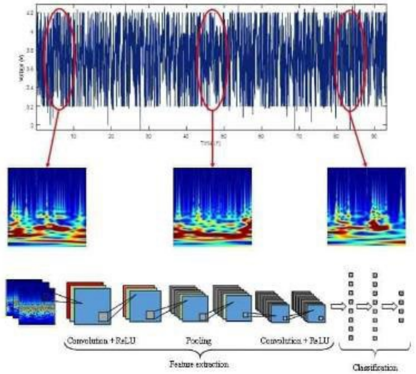
Cell n real-time production status

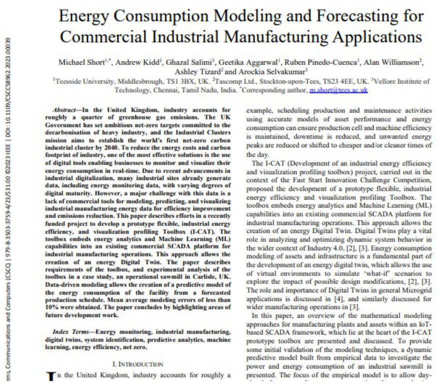
Ancillary Configuration

Efficiency Gen AI Model Actionalable Insights

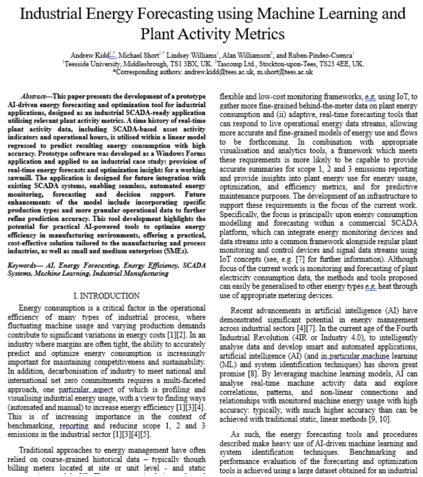
Insights / Reporting



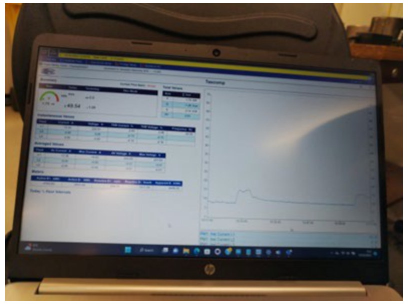




Energy Consumption Modeling and Forecasting for Commercial Industrial Manufacturing Applications



Industrial Energy Forecasting using Machine Learning and Plant Activity Metrics



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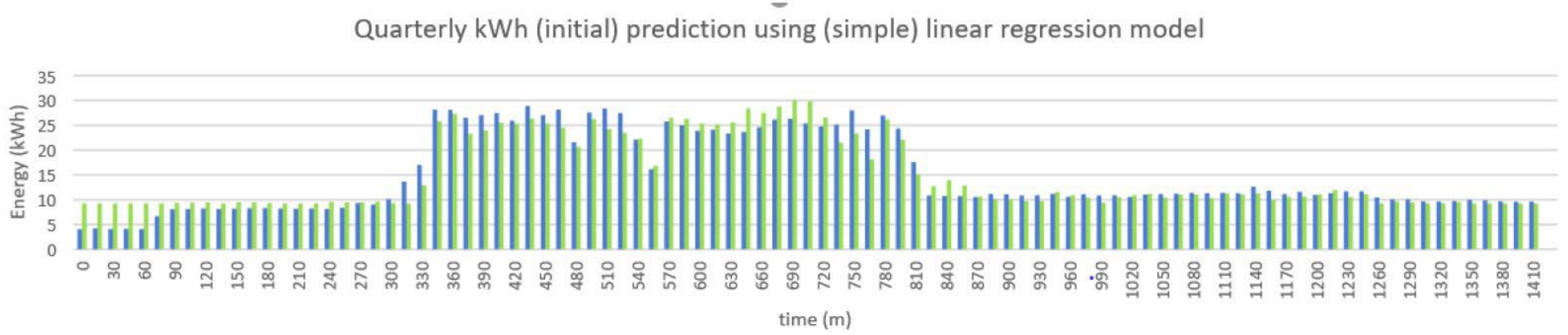
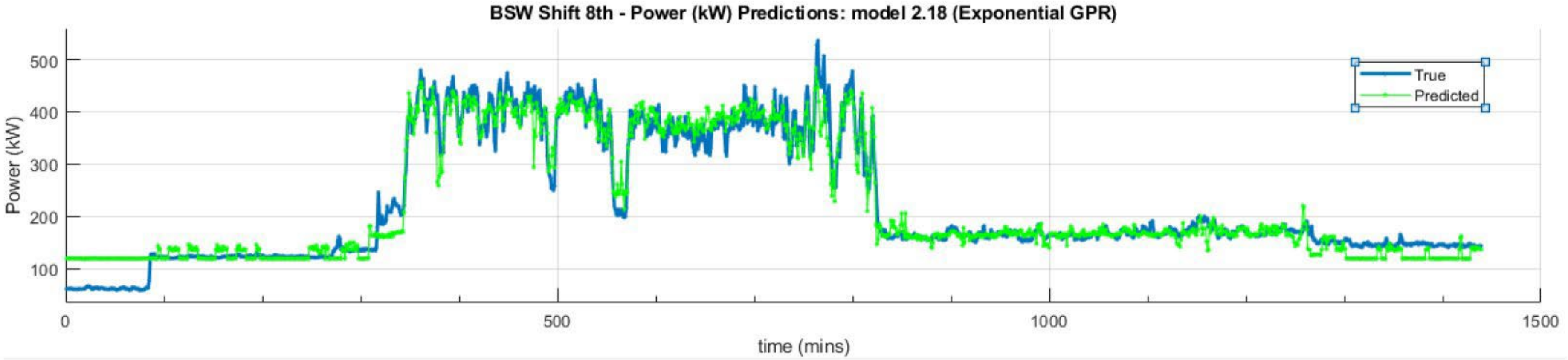
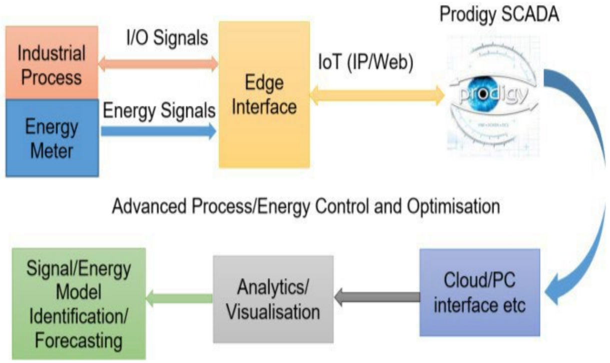
Industrial Application (BSW, Carlisle)

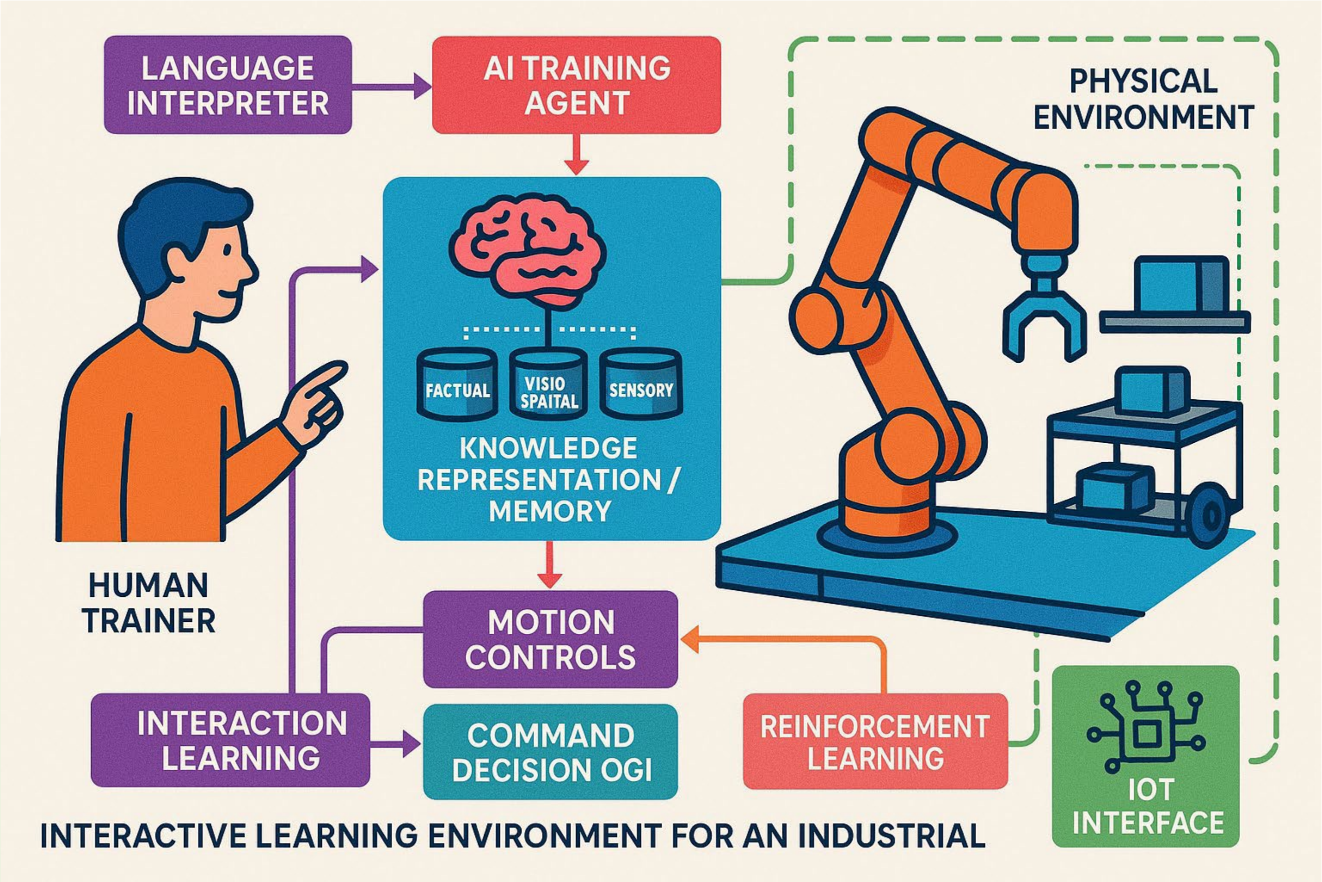




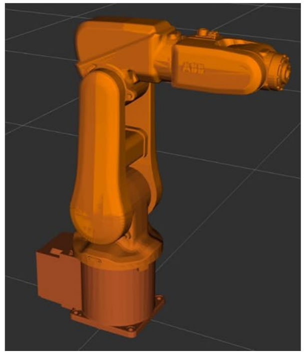


Smart Recycling

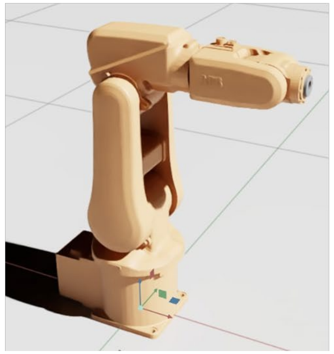
Interactive Learning Environment for Cobots (JARVIS)



ROS Rviz Multibody Model



Nvidia Isaac Digital Twin



Real ABB IRB120 in IDTC

LMM & AI Agent
- Plans steps
- Generates tool calls
- Document actions

Supervisory System
- Torque limits
- Collision checks
- Reject invalid calls

Context and Governance Layer
- SQL/RAG data pools
- Human-in-the-loop

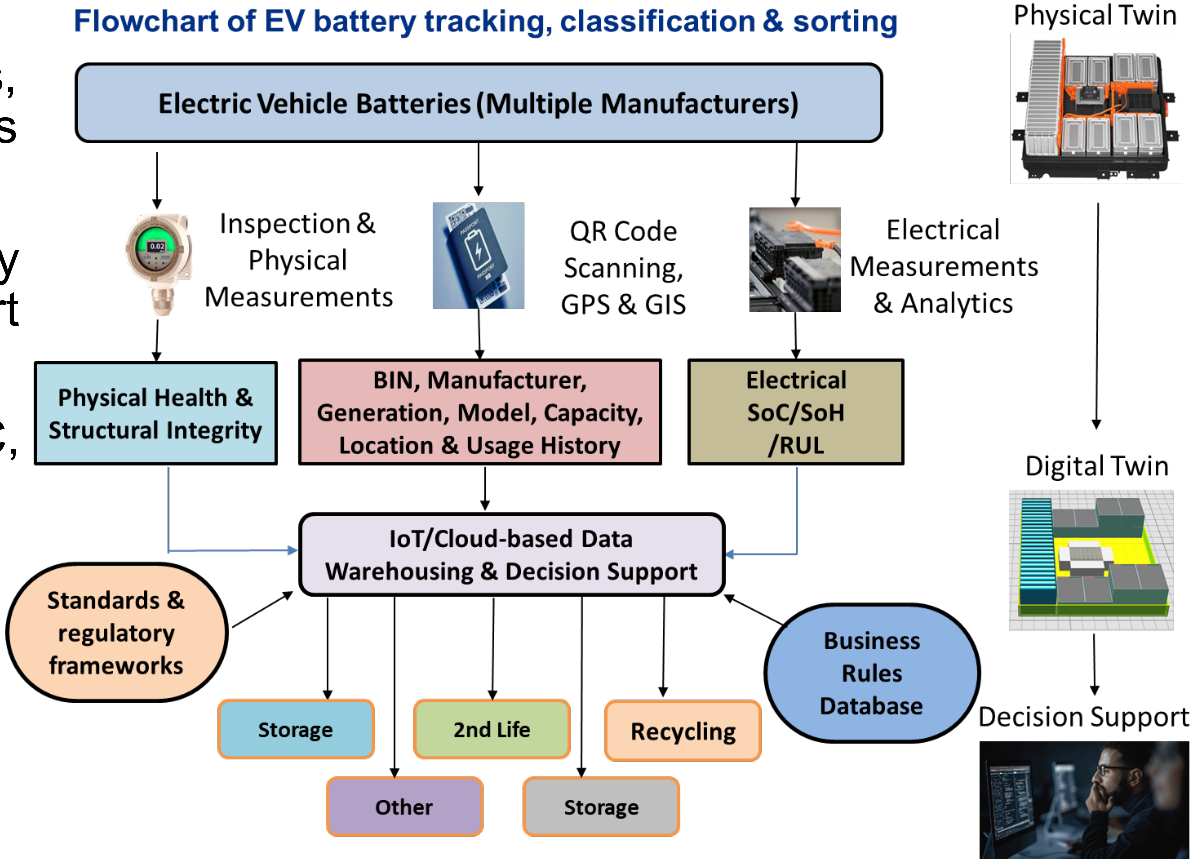
Robot Execution:
- ROS2
- Isaac Sim digital twin
- Data bridge to Robot

Telemetry Logging
- Run Report (JSON)
- Performance Metrics
- Return Data to LMM

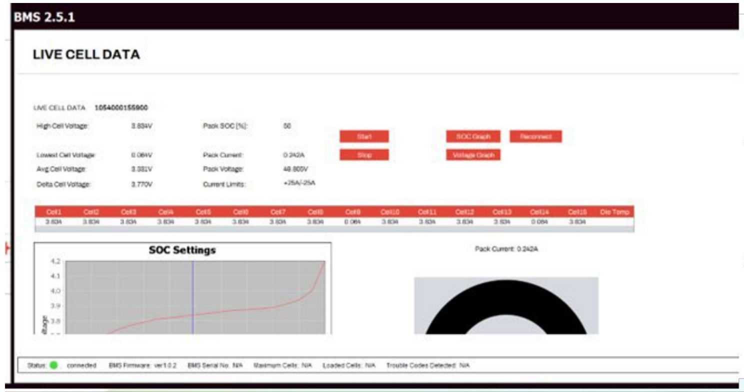
Smart EV Battery Recycling

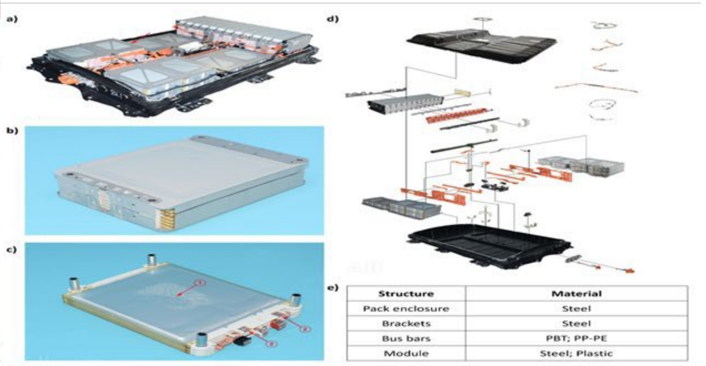
- Deployment of advanced IoT technologies, standardized cloud-based tracking and analytics framework for batteries;
- Provision of vendor-independent upstream battery health assessment and recycling decision support framework for handling EoL EV (and other) batteries.
- Upstream tech platform prototyping in NZIIC, downstream processing in Devon.

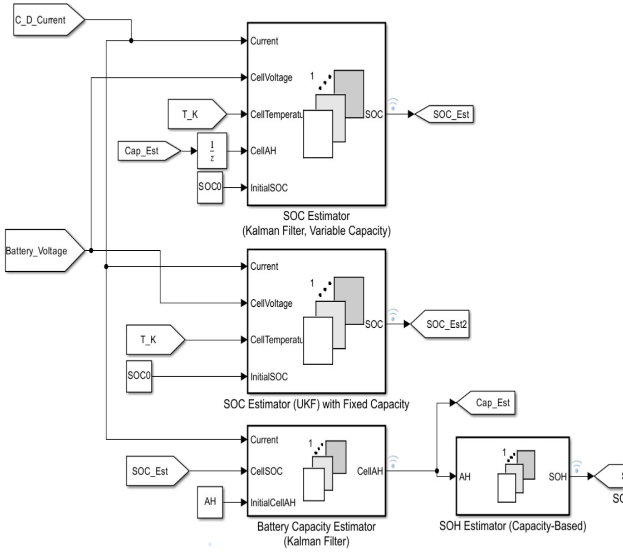
Flowchart of EV battery tracking, classification & sorting

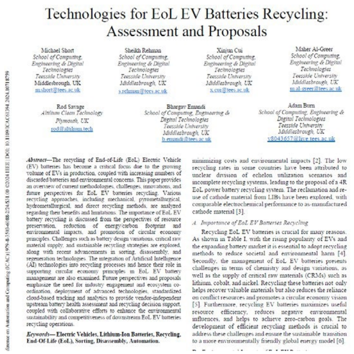


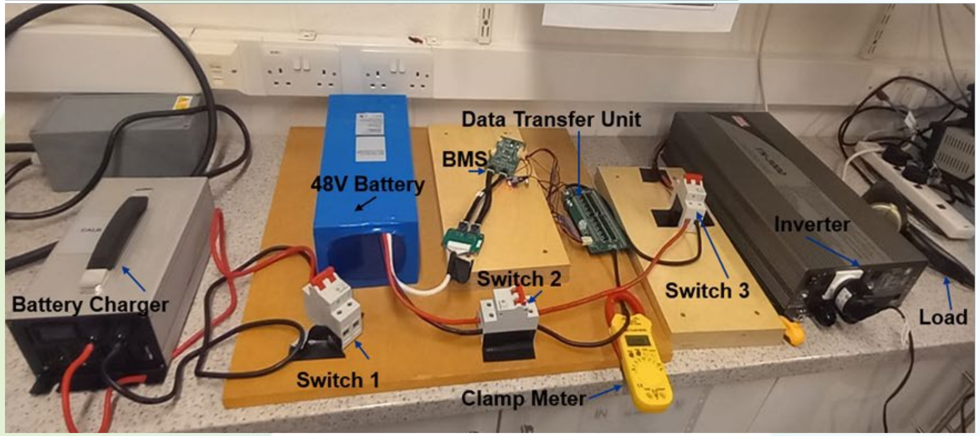
Disassembly and Thermally-Aware Fast/Safe Deep Discharge

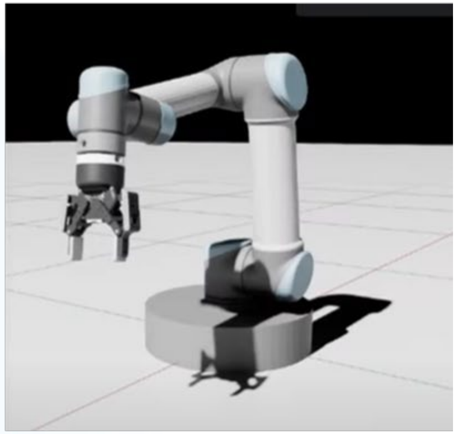


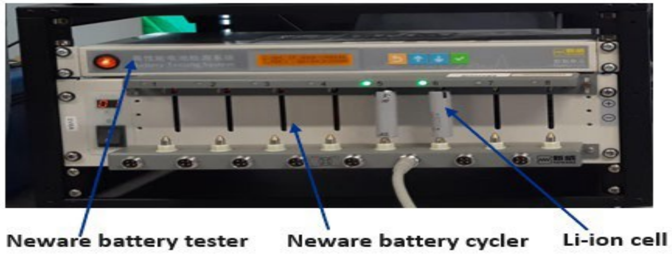





Technologies for EoL EV Batteries Recycling: Assessment and Proposals







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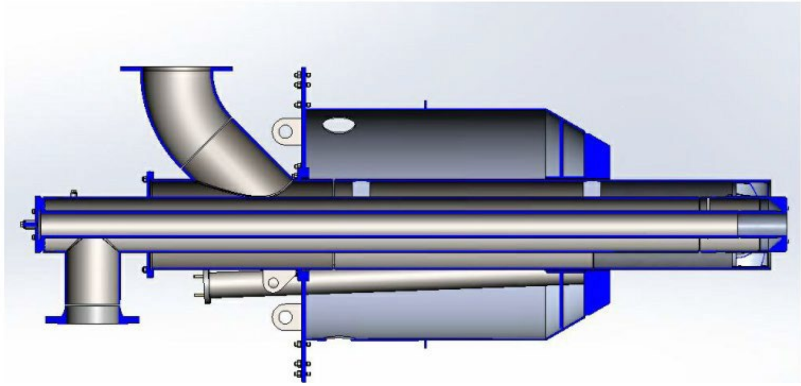
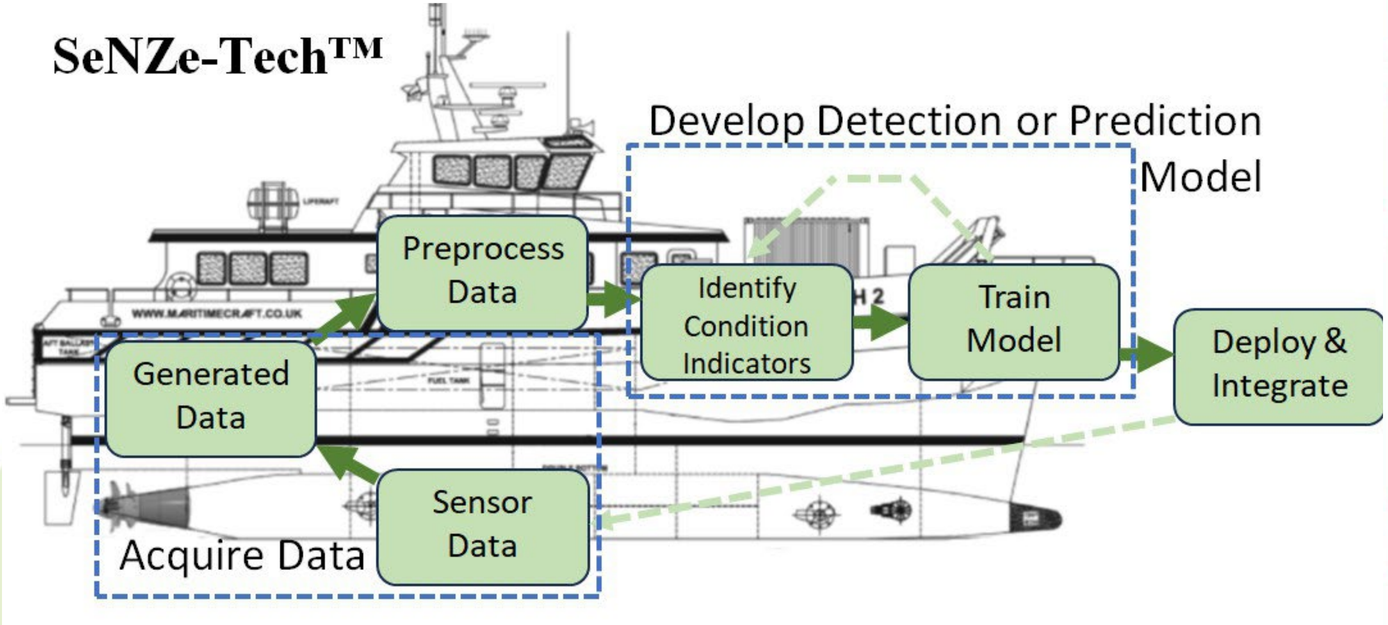
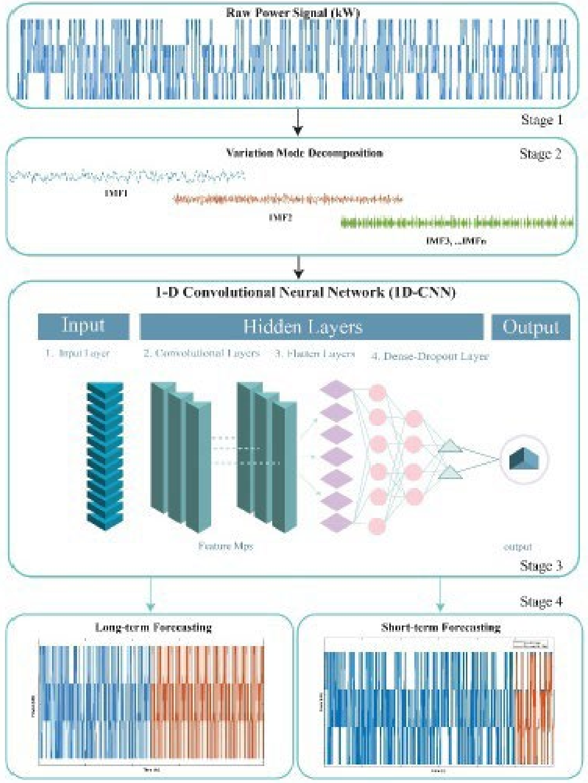
Smart Refuelling



Smart Controls for Electrified Marine Propulsion





Vessel Propulsion Power Forecasting Using Variational Mode Decomposition and Convolutional Neural Networks

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Abstract—**Vessel digitalisation can provide vital insights to support efficient deployment and optimisation of alternative/clean fuel propulsion systems to support marine vessel decarbonisation. In this context, this paper explores the effectiveness of a data-driven hybrid prognostic approach using Variational Mode Decomposition (VMD) and Convolutional Neural Networks (CNN) to forecast vessel thrust/propulsion power for a small to medium sized crewed vessel. The VMD method decomposes propulsion power data from a 27-meter Crew Transfer Vessel (CTV) into Intrinsic Mode Functions (IMFs) during typical maritime operational scenarios such as maneuvering, push on operations, transit, and loitering phases. The IMFs are reconstructed to create a refined signal representation that enables the effective training of the CNN model on a ratio of 70% training and 30% testing. The CNN model architecture is optimised for time series forecasting and is trained on the first 10 hours of data and validated on the subsequent 2-hour interval (10 to 12 hours) with a Root Mean square Error (RMSE) of 0.3. The validated model is then applied for extended prognostic forecasting over the subsequent 12-hour horizon (12 to 24 hours). It is reported that the VMD/CNN approach accurately captures dynamic short-term patterns and provides insightful trend predictions, and concludes it is a promising approach for prognostic maritime energy management and operational planning applications.**

Keywords—Convolutional Neural Network (CNN), Crew

mechanical propulsion systems are deployed, and often requires expensive instrumentation to even provide low-accuracy results. Crew Transfer Vessels (CTVs) which operate in offshore dynamic conditions, create demanding challenges for power forecasting because of their non-linear power responses together with data variability [4]. Traditional power estimation methods, based on empirical formulas and physical simulations, have shown effectiveness under static or calm sea conditions; however, their ability to adapt to rough weather and transient operational regimes remains limited[5]. Hence, current research employs data-driven approaches like machine learning (ML) and deep learning (DL) techniques to model non-linear dynamics while avoiding explicit physical formulations [6, 7]. The evaluation of different ML models for marine applications has focused on support vector machines (SVMs), random forests (RF), artificial neural networks (ANNs), and ensemble learners including XGBoost [8, 9]. In [8], the authors investigate nine supervised learning models which include ridge regression, kernel ridge, elastic net, ANN, XGBoost and deep neural networks (DNNs) for predicting main engine shaft power and fuel consumption in container vessels. Real voyage data was used to train these models which proved the significance of proper algorithm selection and hyperparameter tuning according to the results. The study in [9], presents research on electric propulsion ships by

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Smart Controls for Industrial Dual-Fuel Combustion

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Home › Net Zero › News releases › Helping make more sustainable snacks

Helping make more sustainable snacks

23 October 2024 @TeessideUni

Experts from Teesside University are helping make one of the UK's most popular snack brands become more environmentally sustainable.

members of the KP Snacks Ltd. IETF project team at Teesside University's Net Zero Industry Innovation Centre

The academics are working alongside KP Snacks Ltd. to investigate ways in which hydrogen can be incorporated into its production processes.

KP Snacks Ltd., which has a production facility in Billingham, manufactures some of the UK's most recognisable snack brands including Hula Hoops, McCoy's and Skips.

To meet its net zero ambitions, KP Snacks Ltd. is looking at ways in which hydrogen can be substituted for natural gas within its production lines.

Teesside University, through its Net Zero Industry Innovation Centre (NZIIC), is working with the company to investigate the best way it can reduce its emissions by switching to the alternative fuel.

29th IEEE International Conference on Circuits, Systems, Communications and Computers (CSCC) 2025

Modelling, Control Design and Validation for an Industrial Dual-Fuel Combustion Unit

Michael Short[1,*], Edgar Segovia[1], Faik Hamad[1], Craig Tether[2], Philipp Schönberger[3] and Katerina Nika[3]
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Abstract—**Industry accounts for roughly a quarter of total United Kingdom greenhouse gas emissions. The UK Government has set ambitious net zero targets, committed to the decarbonisation of heavy industry. The regional Industrial Clusters mission aims to establish the world's first net-zero carbon industrial cluster by 2040. Key to the decarbonisation of heavy industry will be the deployment of technologies such as carbon capture and storage, alongside the use of alternative, low-emission fuels such as Hydrogen. This work is focused upon the potential use of Hydrogen as a replacement for natural gas in an industrial food manufacturing unit requiring very high temperatures for cooking potatoes at high production volumes. Specifically, aspects of a proposed dual-fuel approach to combustion are considered from a dynamic modelling and control perspective. For small perturbations around key steady-state equilibria, linear dynamics models are experimentally obtained and used to formulate a gain-scheduled cascade, regulatory control strategy for various dual-fuel and air-fuel ratios. Simulation results show effective behavior under the developed control approaches, with good potential for further gain-scheduling performance enhancements. Practical implementation aspects are discussed along with future work.**

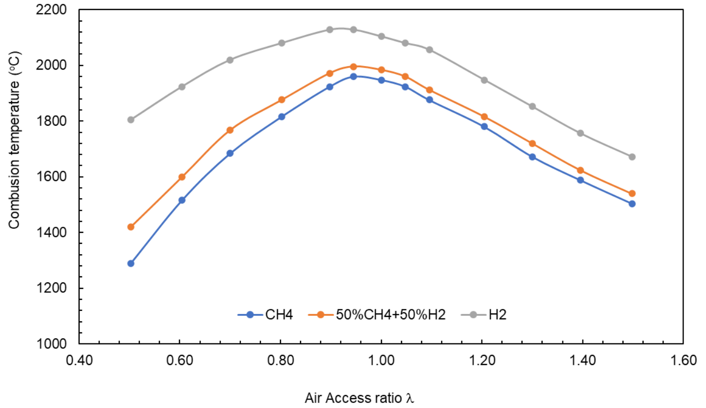
Index Terms—**Industrial decarbonisation, alternative fuels, system identification, regulatory controls, net zero.**

I. INTRODUCTION

considered from a dynamic modelling and control perspective. Following a study of existing (natural gas fueled) process technology and equipment, an energy balance model is obtained and then modified to consider co-firing using a secondary (hydrogen) fuel source using an experimental burner. Experimental data is used to explore small perturbations around various key steady-state equilibria to obtain accurate linear dynamic models. These models are then used to formulate a regulatory control strategy robust for various dual-fuel and air-fuel ratios, along with oil and product mass flow rates. Simulation results show effective behavior under standard feedback (PID) control approaches, with good potential for gain-scheduling performance enhancement using DCS. Practical implementation aspects are discussed along with future work.

Section II presents a review of recent literature related to energy modelling for dual fuel deployment in industry, with focus on combustion and thermal engineering. Section III reviews modelling and system identification of main thermodynamic elements. The new control philosophy is described in Section IV, while control design and initial validation testing using simulation is described in Section V. Section VI presents conclusions and outlines areas for future work.

HEAT AND CONTROL
SAACKE
UKRI
KP Snacks



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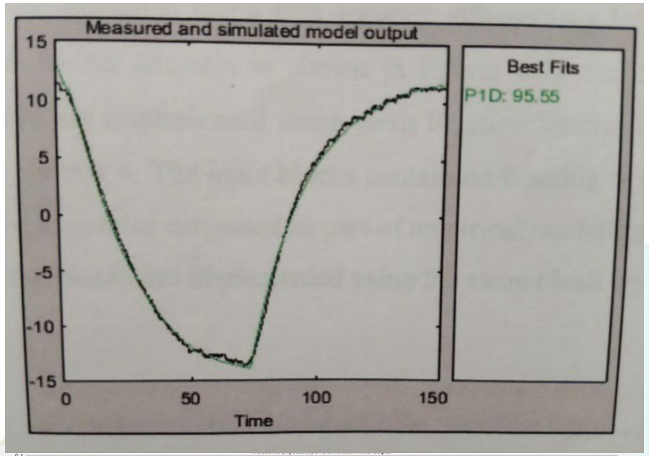
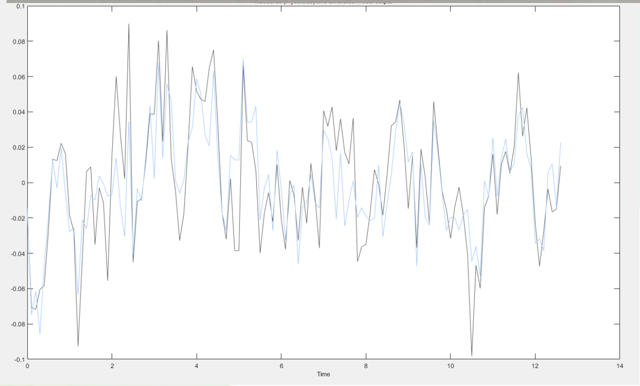
BELIEVE IN THE POSSIBILITIES

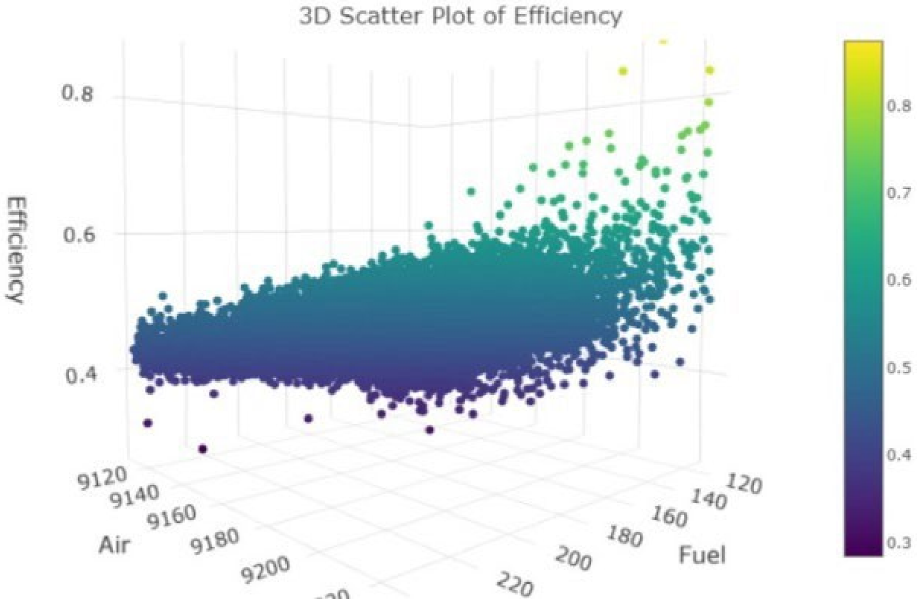
Automated Analytics for Non-Linear Plant Modeling





$$G(s) = \frac{K(1 + zs)e^{-sd}}{(1 + ps)}$$

Combustor, heat exchanger, and fryer HT dynamics are non-linear – but can be locally linearized



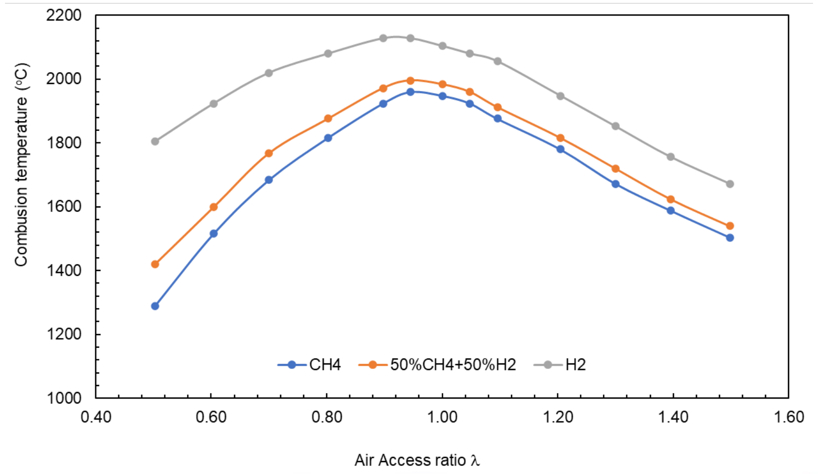
K, *p*, *d* and *z* vary with local operating point: the global system model has averaged nearer the lower efficiency end during the measurement period.

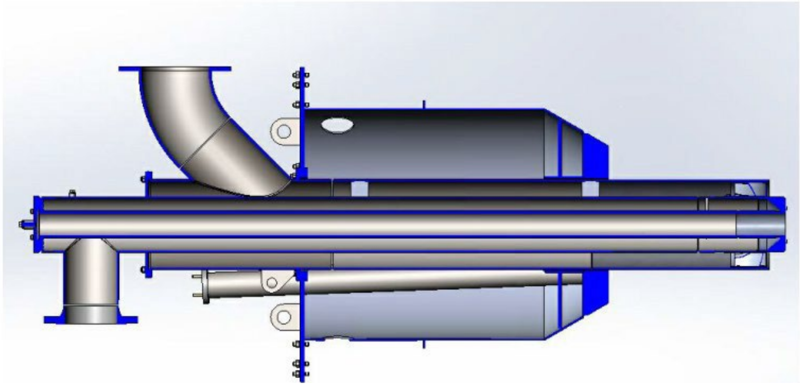
Automated Digital Control Design for Non-Linear Plant

- Efficiency and HT lags (local linear model properties) are now a function of the CH4 / H2 blend δ, with $0 \leq \delta \leq 1$, as well as fuel flow and air/fuel ratio.

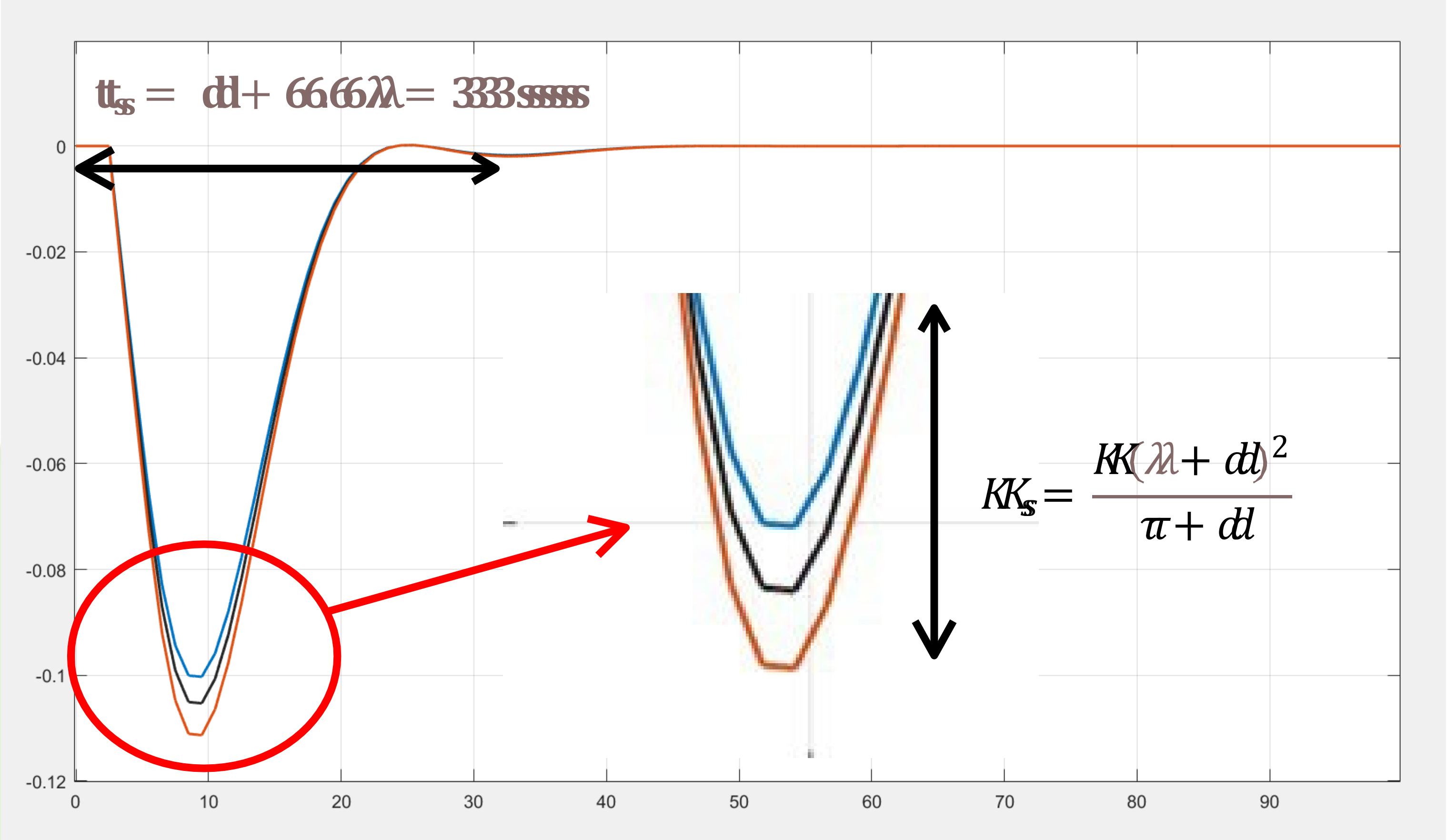
- Maximal fuel/air efficiency points automatically mapped as convex surface dependent upon commanded combustion mixture temp and fuel blend, and partitioned using clustering techniques.

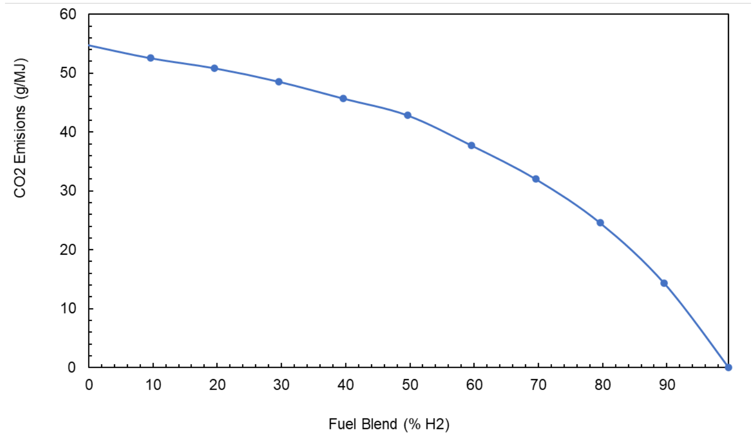
- Gain-scheduled PI regulators synthesis for primary/secondary air flow, H2 and CH4 flow.





Regulatory Responses (δ = {0.0; 0.5; 1.0})





- Type 1 Carbon emissions drop to effectively zero for 100% Hydrogen
- In terms of SOx and NOx emissions, the introduction of H2 has no impact on the former as there is no increase in sulfur content in the combustor; negligible increase in the latter.

NET ZERO INDUSTRY INNOVATION CENTRE

Teesside University

Everyone here today can strive towards positive change, embrace science and education, and help to innovate a clean, sustainable digital future!

- Digitalization, informatics and decarbonisation are redefining industry and society and delivering impactful change.

- We are on the verge of transformative technology use becoming standard in intelligent buildings, which can make significant gains in supporting decarbonisation, recycling and improved sustainability across facilities.

- The technology on its own will not do much – planning is key, and people, skills, and education are all important factors too!

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Thank you

For further details, please contact:

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