AI for Energy Informatics

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Professor

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University of Oslo

UiO : University of Oslo

5th ANAIS Annual Nepal AI School

Jan. 5 2025

UNIVERSITY OF OSLO, NORWAY

TOP-100 UNIVERSITY IN THE WORLD

73#

Academic Ranking of World Universities

ACADEMIC RANKING OF WORLD UNIVERSITIES
SINCE 2003

104#

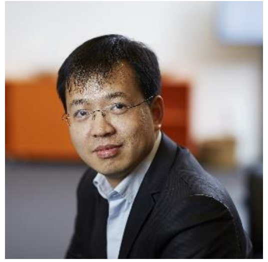
US.NEWS Best Global Universities Ranking

BEST
GLOBAL UNIVERSITIES
U.S.News & WORLD REPORT
RANKINGS

Energy Informatics group at IFI, UiO

Professors

Prof. Sabita Maharjan



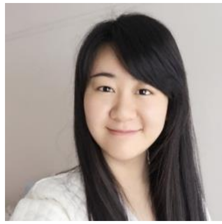
Prof. Yan Zhang

Prof. Frank Eliassen

Master Students + Visiting researchers

Postdoc and PhD students

Dr. Shiliang Zhang



Min Zhang

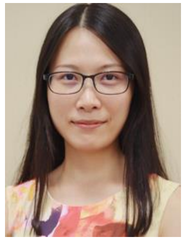
Awadelrahman M. Ali Ahmed

Mehdi Foroughi

Poushali Sengupta

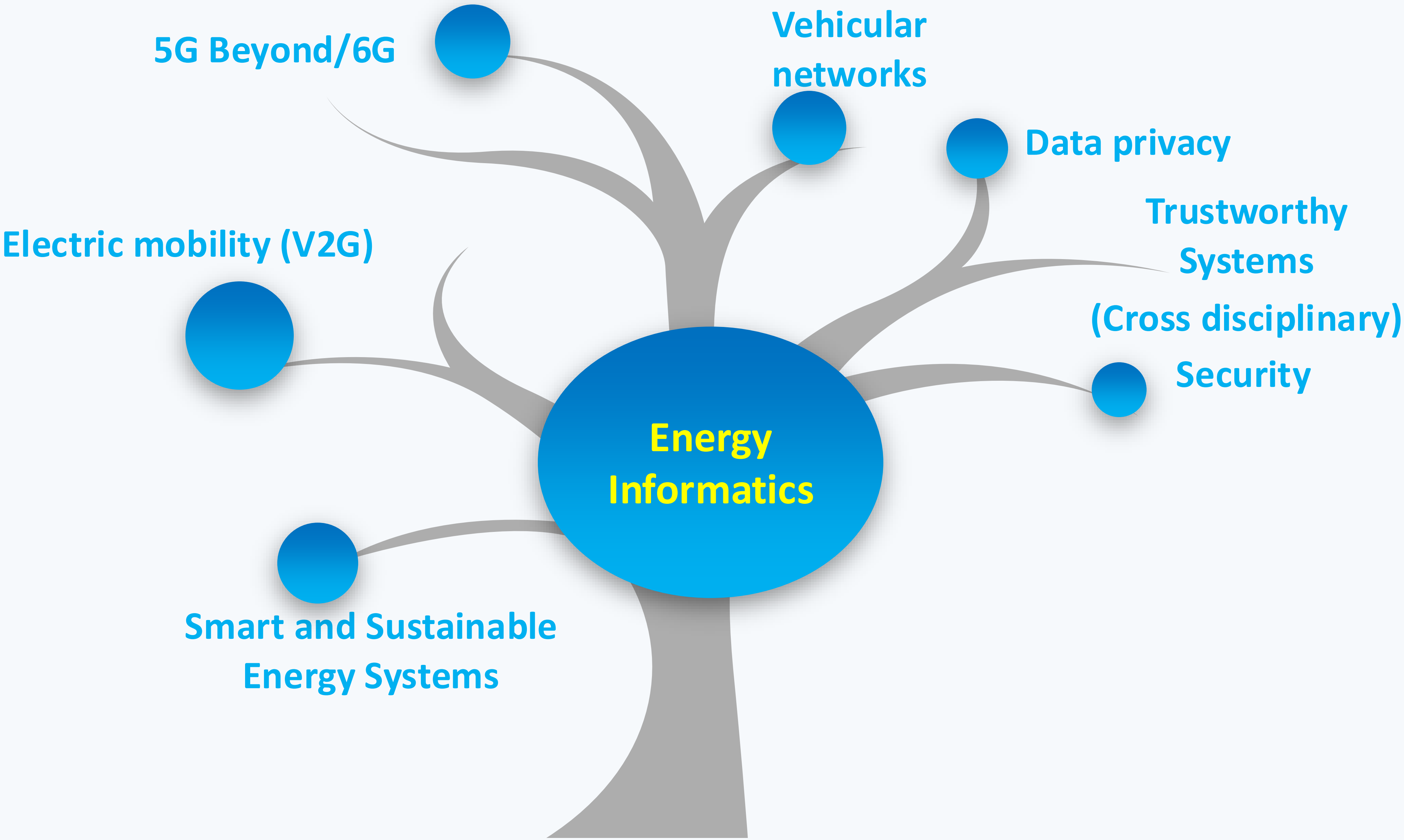
Zhengyu Shan

Daniel Gerbi



Hui Zhang

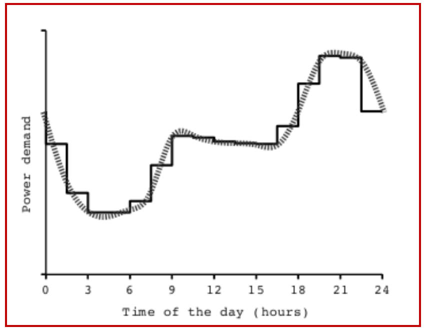
Energy Informatics: Research Activities



Outline

Energy Informatics: Overview

Demand Response Management



Introduction to the PriTEM Project

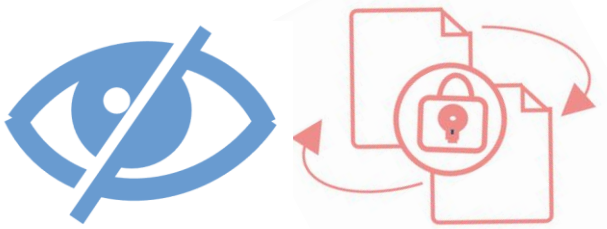


Figure source: https://www.einfochips.com/blog/edge-intelligence-enabling-intelligence-beyond-cloud/

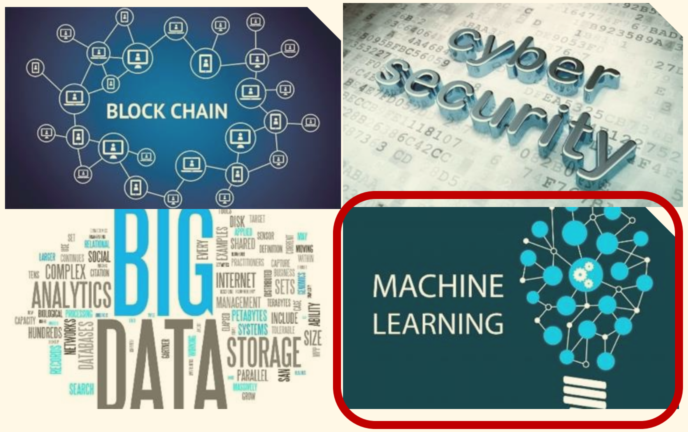
Energy Informatics: Part 1

Energy system

Information, Communication, Networking and Control technologies

Smart grid

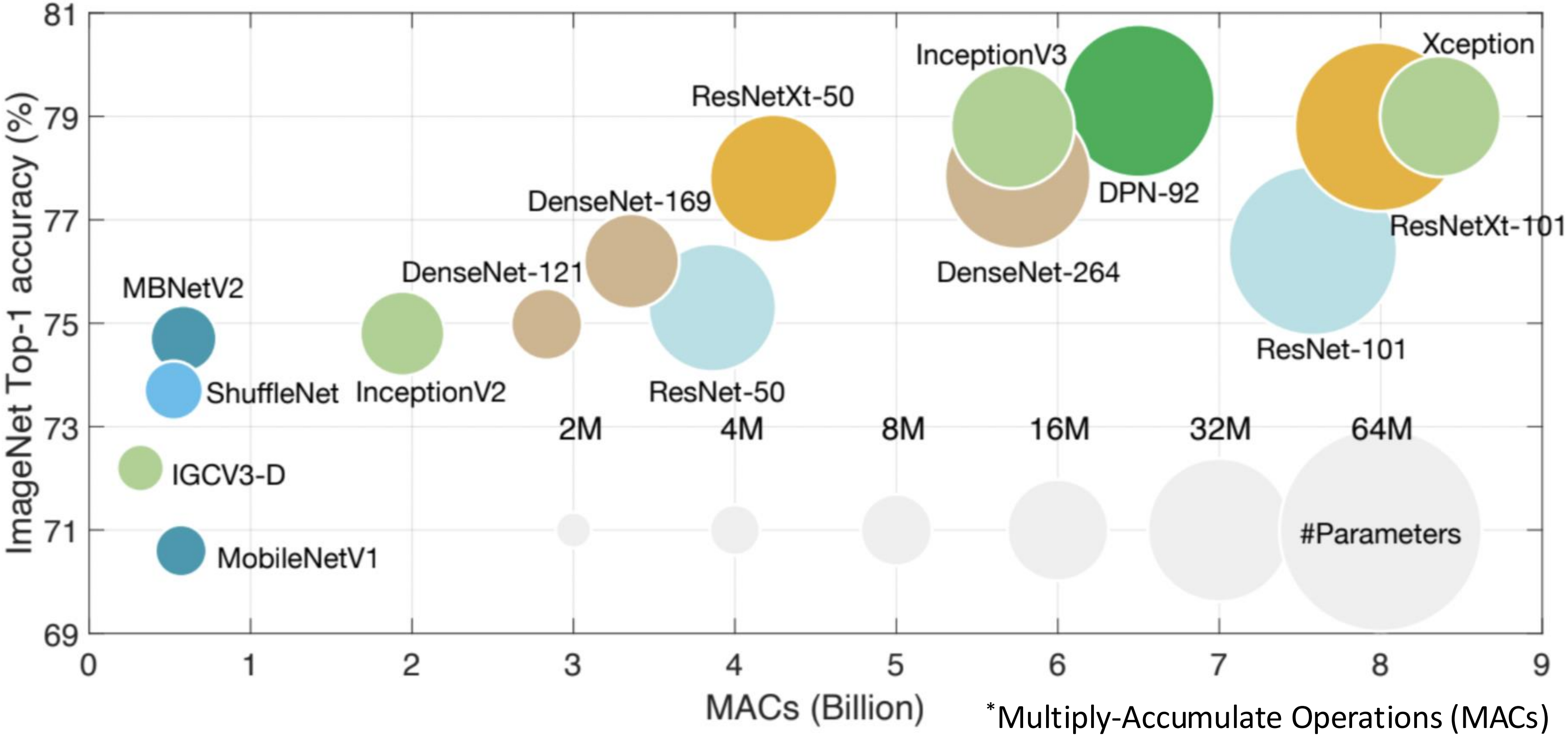
Informatics



Energy Informatics

Artificial Intelligence techniques

Today's Deep Networks are MASSIVE



*Multiply-Accumulate Operations (MACs)

Deng, Lei & Li, Guoqi & Han, Song & Shi, L.P. & Xie, Yuan. (2020). Model Compression and Hardware Acceleration for Neural Networks: A Comprehensive Survey. Proceedings of the IEEE. PP. 1-48. 10.1109/JPROC.2020.2976475.

Carbon Footprint

Training a deep neural network (DNN) can emit as much carbon as five cars in their lifetimes

Transformer network, which presented in 2019 with 213M of parameters, consumes 656,347 kWh only for one time training

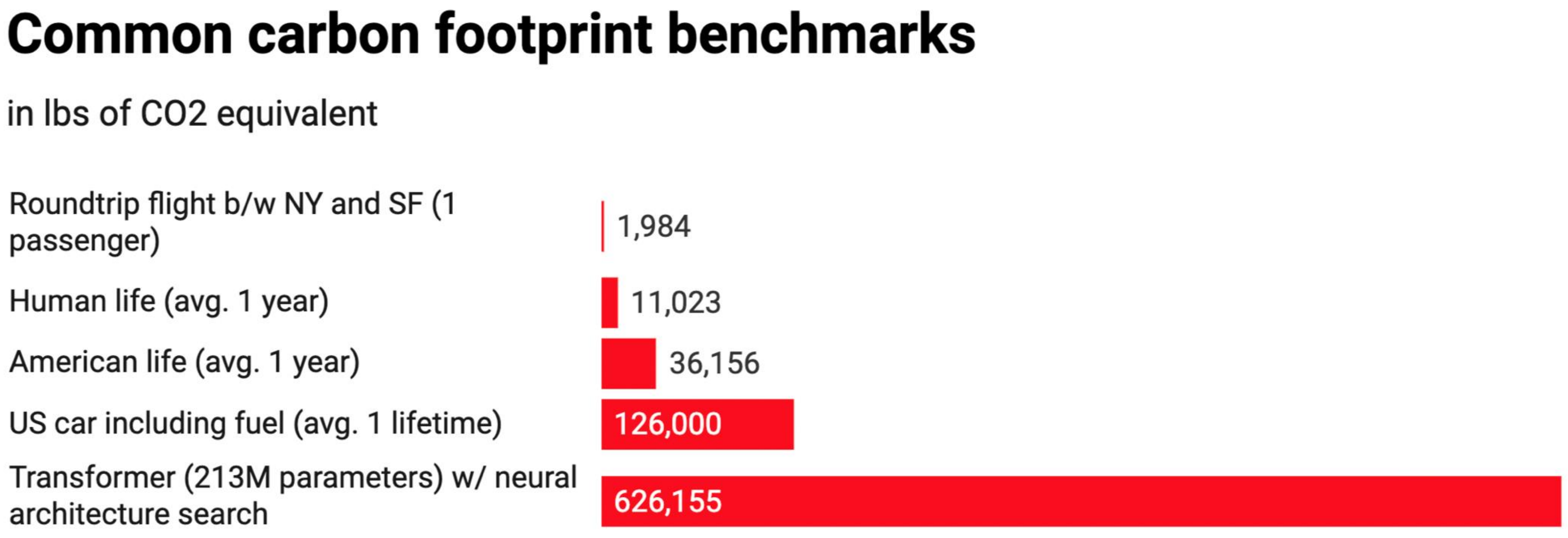


Image: https://www.technologyreview.com/2019/06/06/239031/training-a-single-ai-model-can-emit-as-much-carbon-as-five-cars-in-their-lifetimes/

Slide from H. Darshivi, June 2023

Energy Informatics: Part 2

Communication/Computation networks + Green/Sustainable energy resources

Green, energy-efficient, sustainable networks

- Renewable power supply to networks
- Power consumption minimization
- Energy harvesting
- ……..

Examples

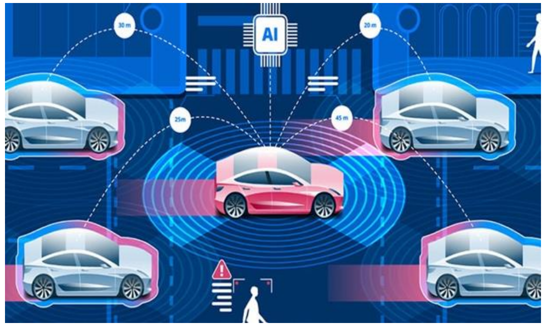
- Green data centers
- Demand response management for data centers
- Solar powered base stations
- 5G Beyond/6G: Energy efficient communication
- Vehicular networks

Energy efficiency will be an overarching theme for many emerging applications

Smart grid

Electrification of Transport

5G Beyond/6G

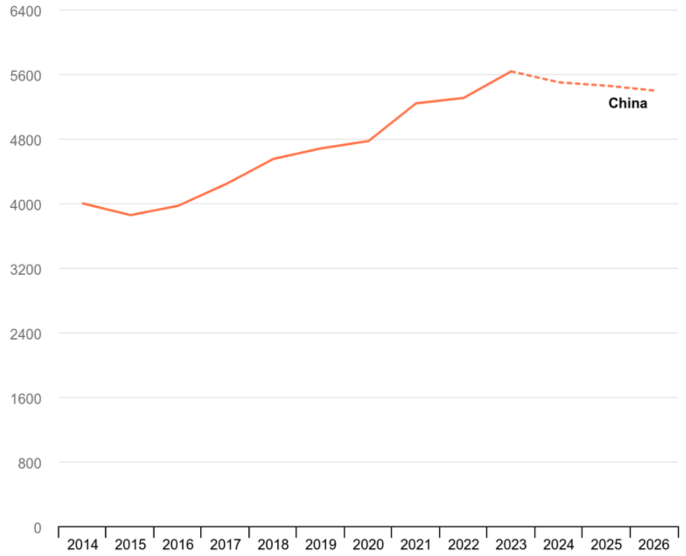


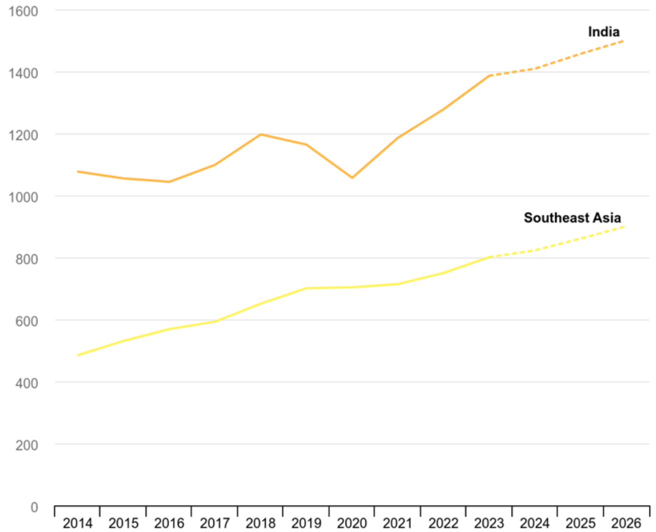
Vehicular networks

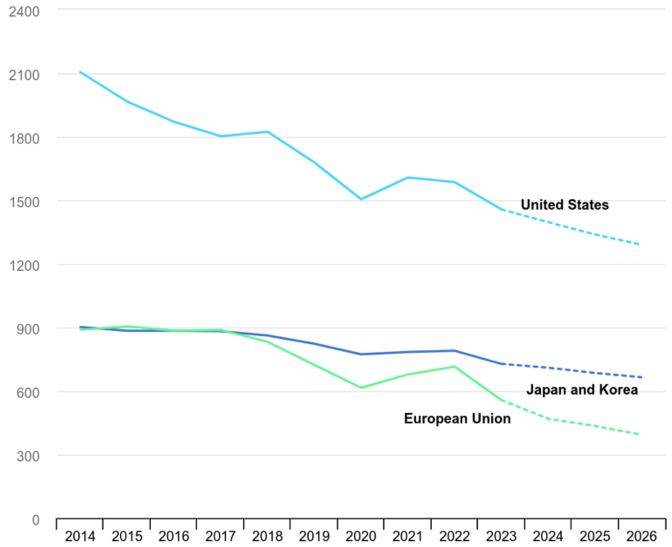
Autonomous driving

Artificial Intelligence .....

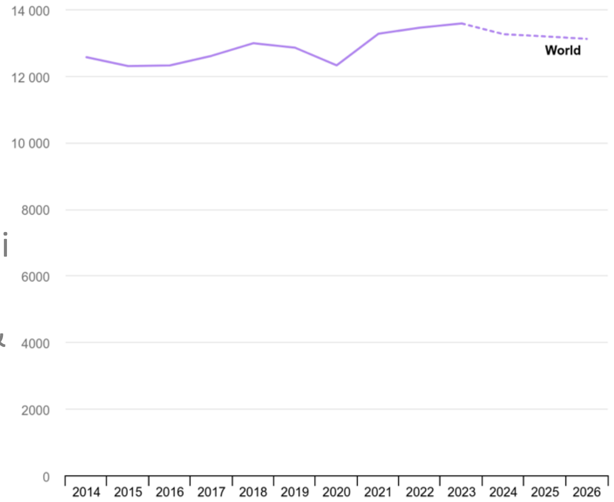
Global Electricity Demand and CO2 Emmission

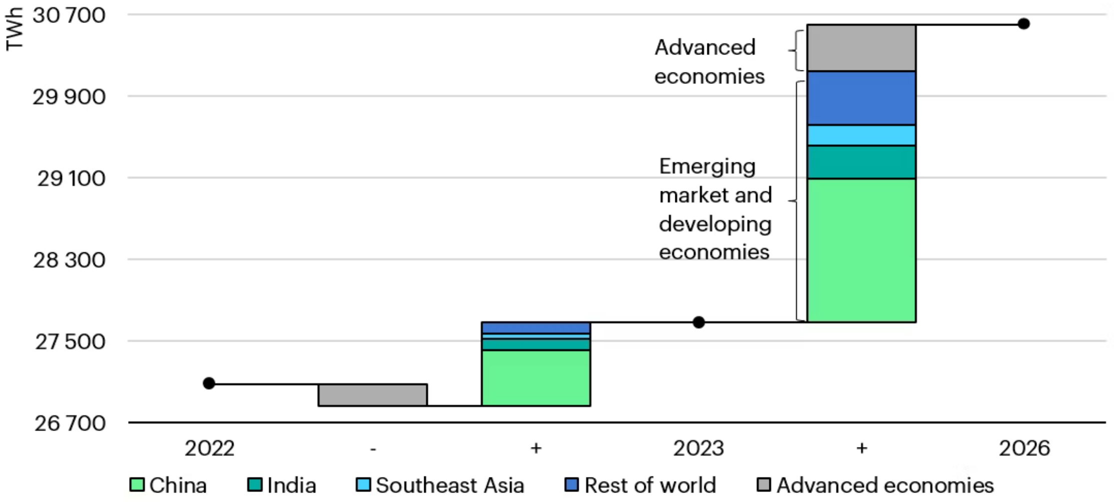




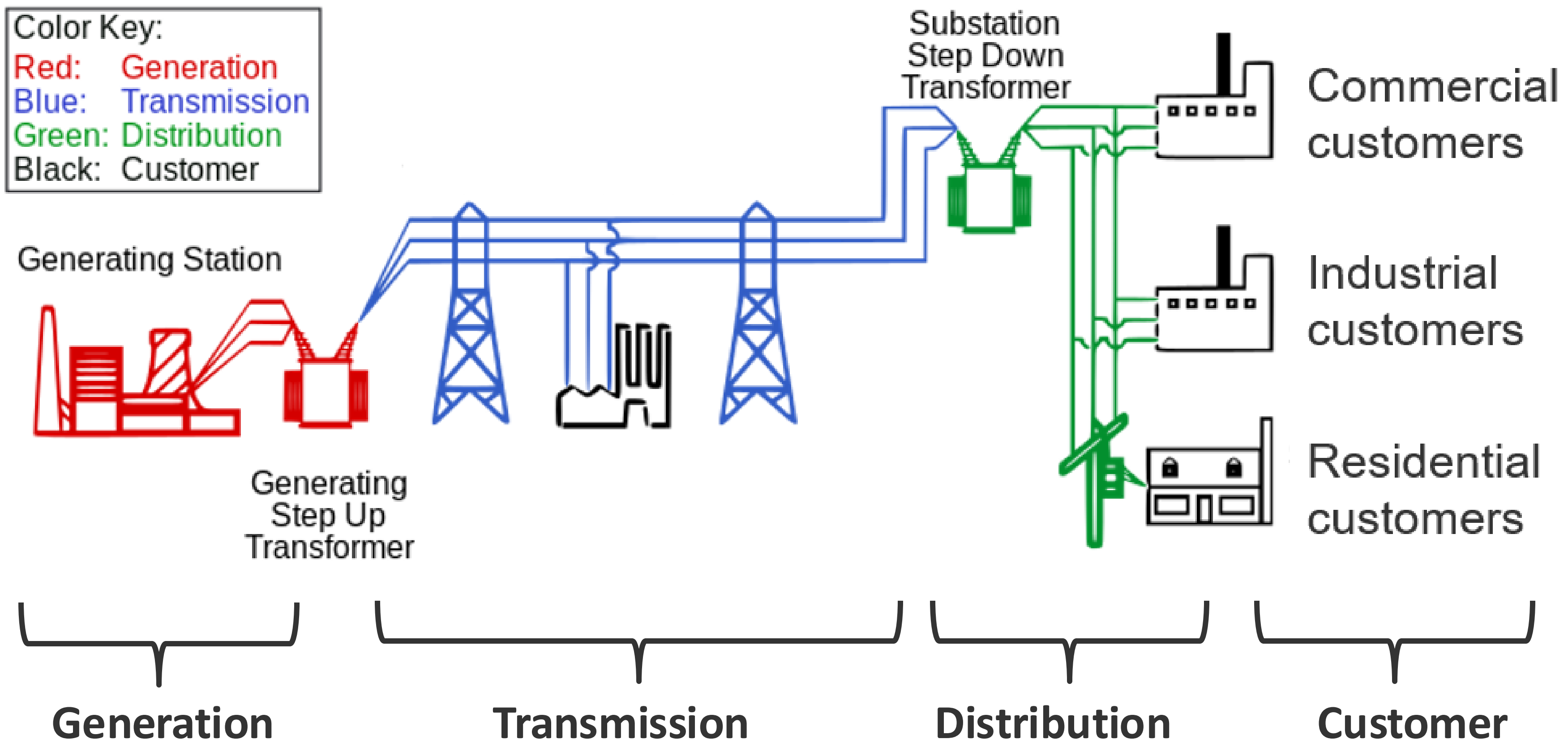


https://iea.imgix.net/0d61ae1c-c181-4219-b2dd-fcaaf51d298b/Changesinglobalelectricitygeneration%2C2022-2026.png?auto=compress%2Cformat&fit=min&q=80&rect=%2C%2C%2C





The Power Grid Abstract Model



Smart Grid

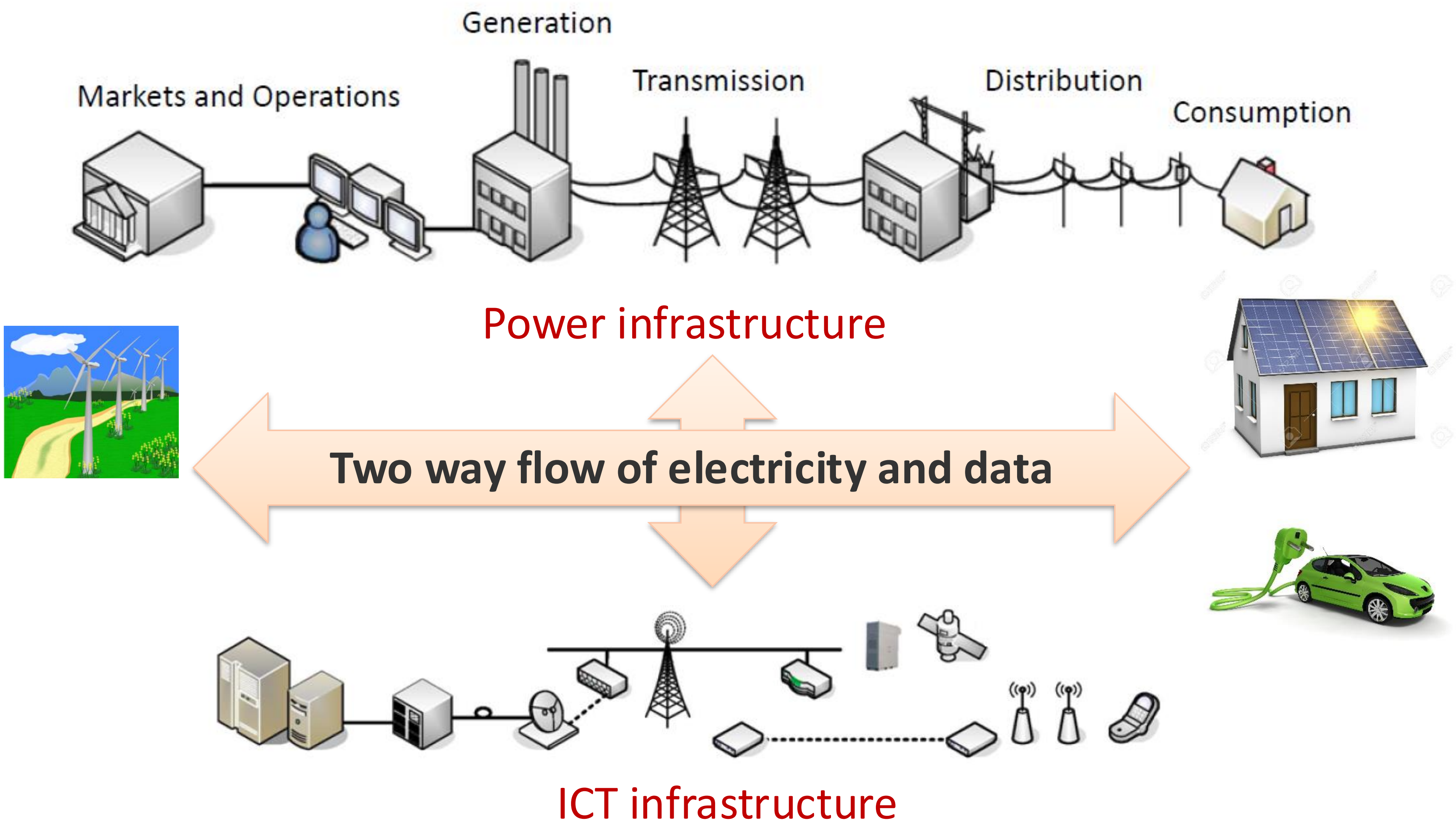


Fig.: *Raconteur*

NIST Smart Grid Conceptual Model

Interaction between the 7 fundamental units through communication flow (information) and electrical flow

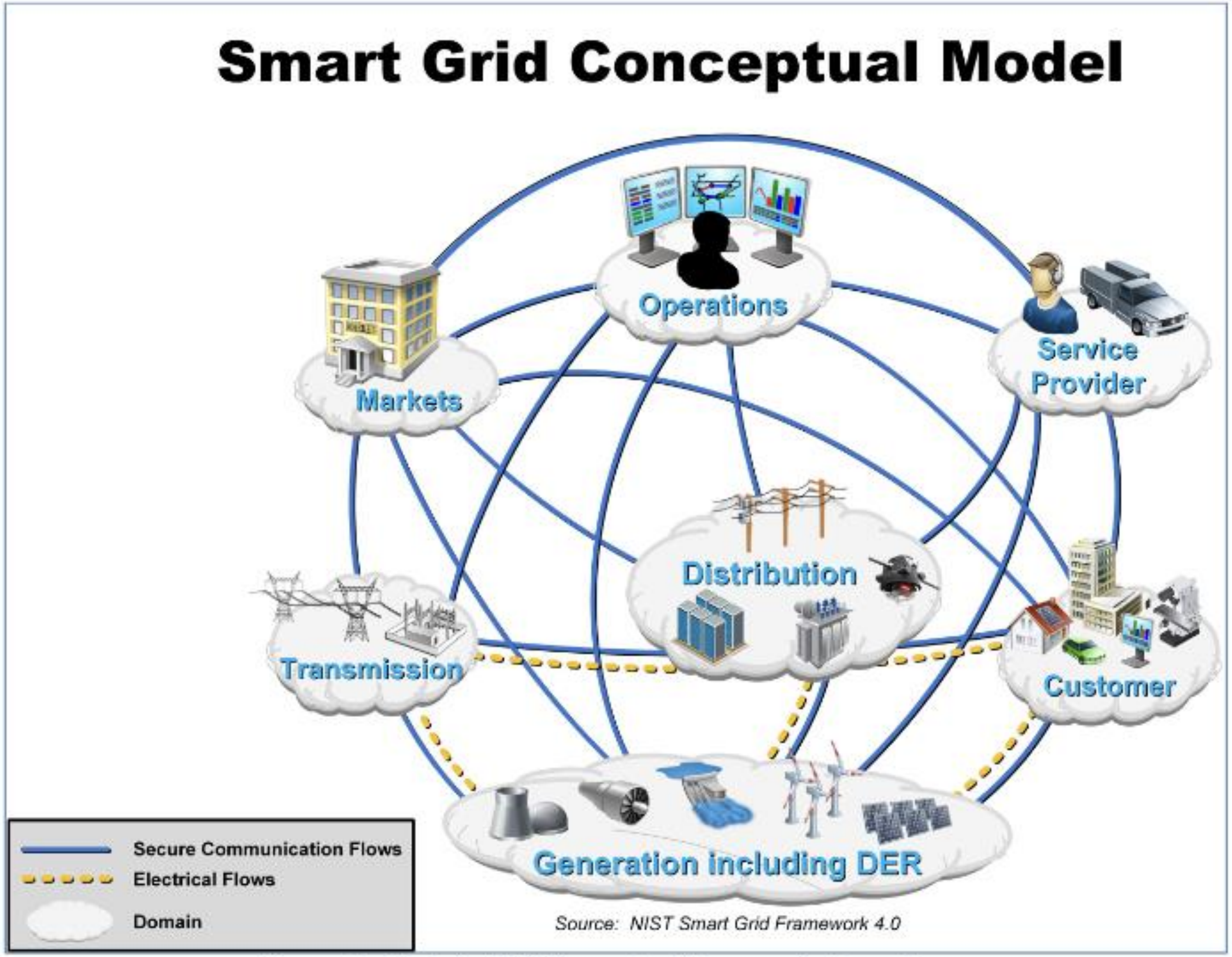


Figure 4 – Updated NIST smart grid conceptual model

Avi Gopstein, Cuong Nguyen, Cheyney O'Fallon, David Wollman and Nelson Hasting, ***NIST Framework and Roadmap for Smart Grid Interoperability Standards***, *Release 4.0, Feb. 2021,* https://doi.org/10.6028/NIST.SP.1108r4

https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1108r4.pdf

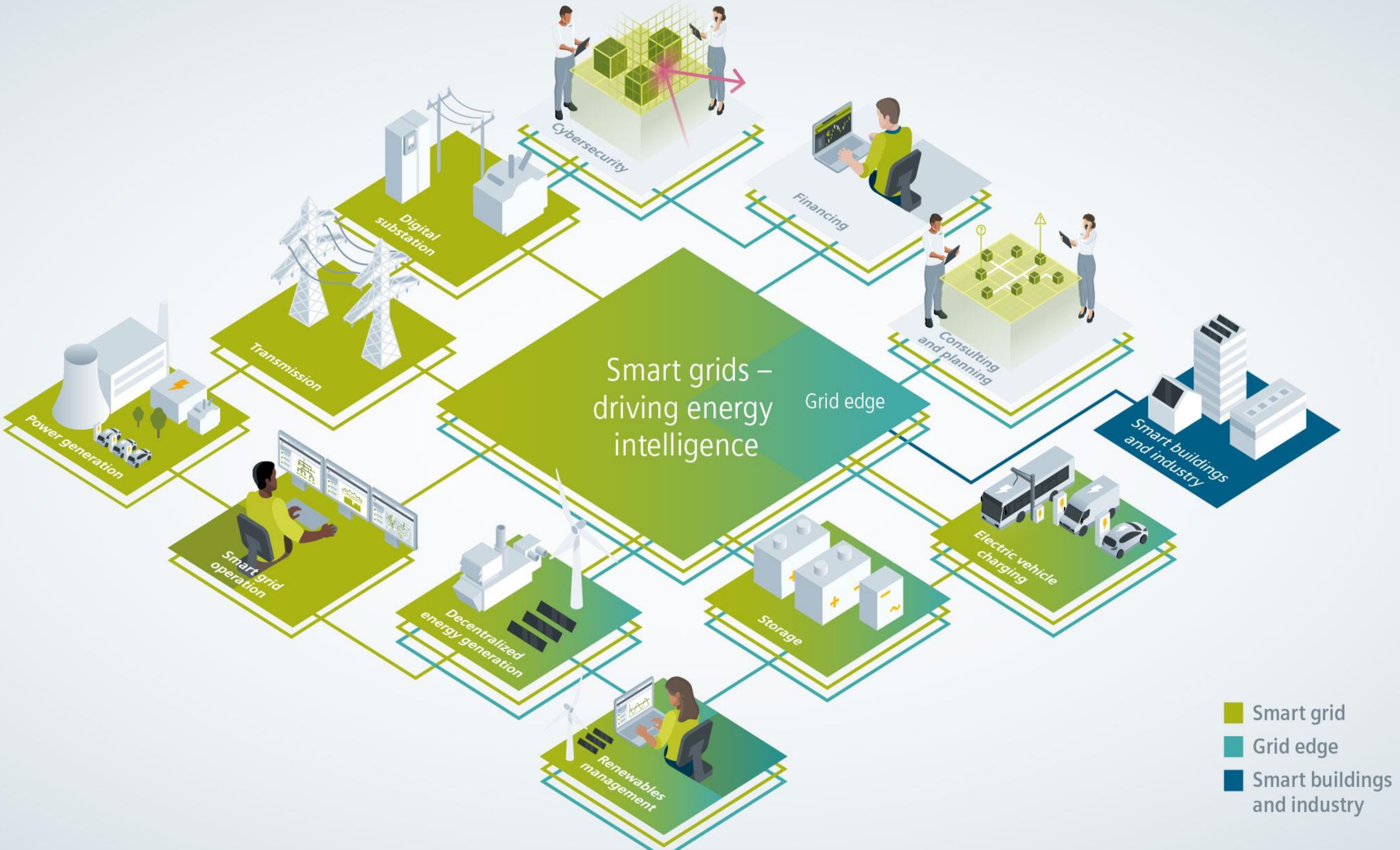


Figure source: https://new.siemens.com/global/en/products/energy/topics/smart-grid.html

Artificial Intelligence in the Energy Industry

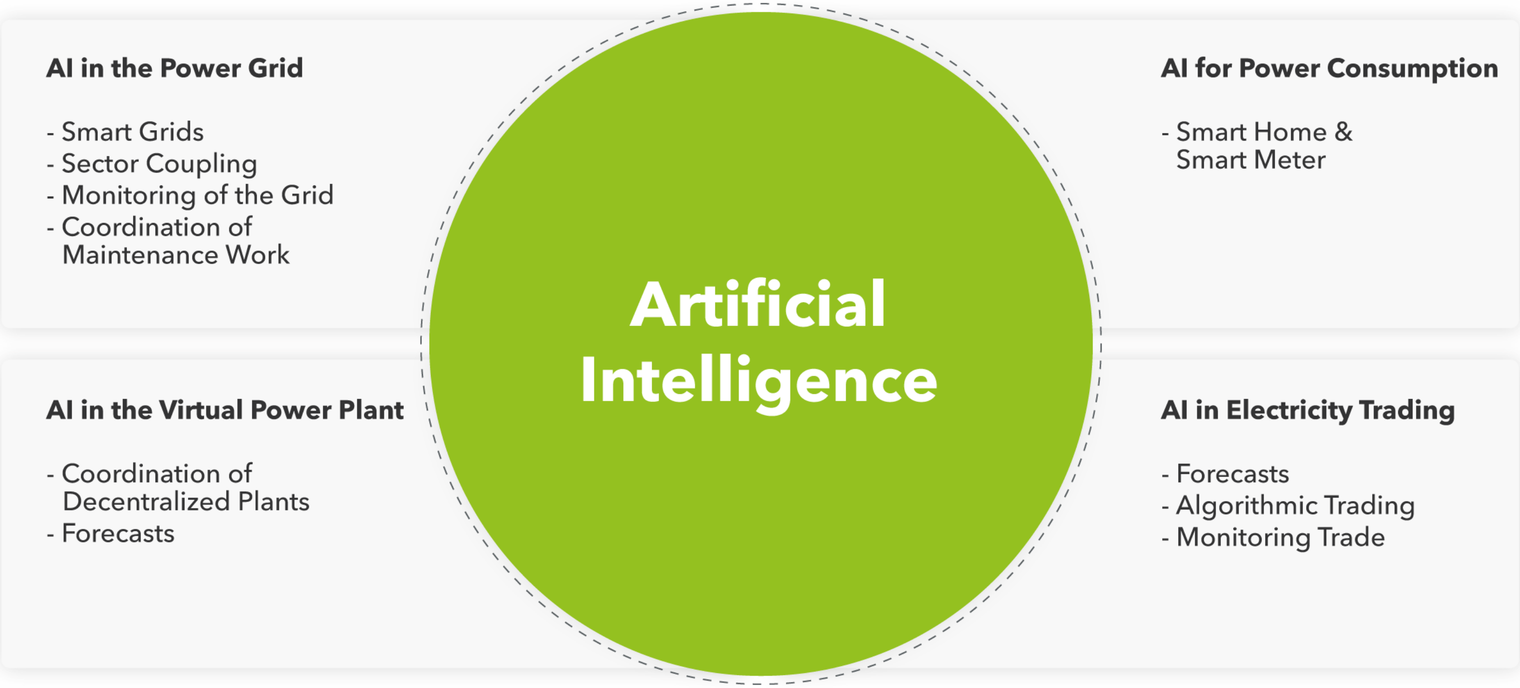


Figure source: https://www.next-kraftwerke.com/knowledge/artificial-intelligence

Smart grid: The Energy Information Network

Decarbonization

Decentralization

Digitalization

Incorporation of distributed renewable energy resources

Advanced metering infrastructure

Distributed electricity trade

Demand response management

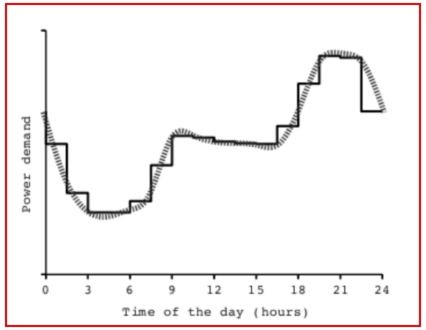
Distribution system automation

Enhanced user responsiveness and grid automation

Outline

Energy Informatics: Overview

Demand Response Management



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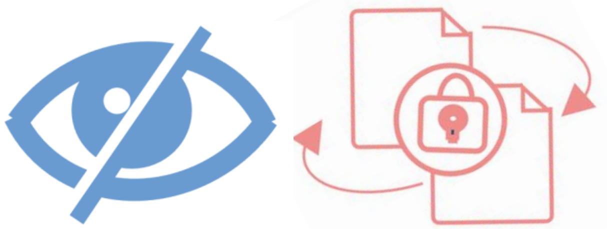
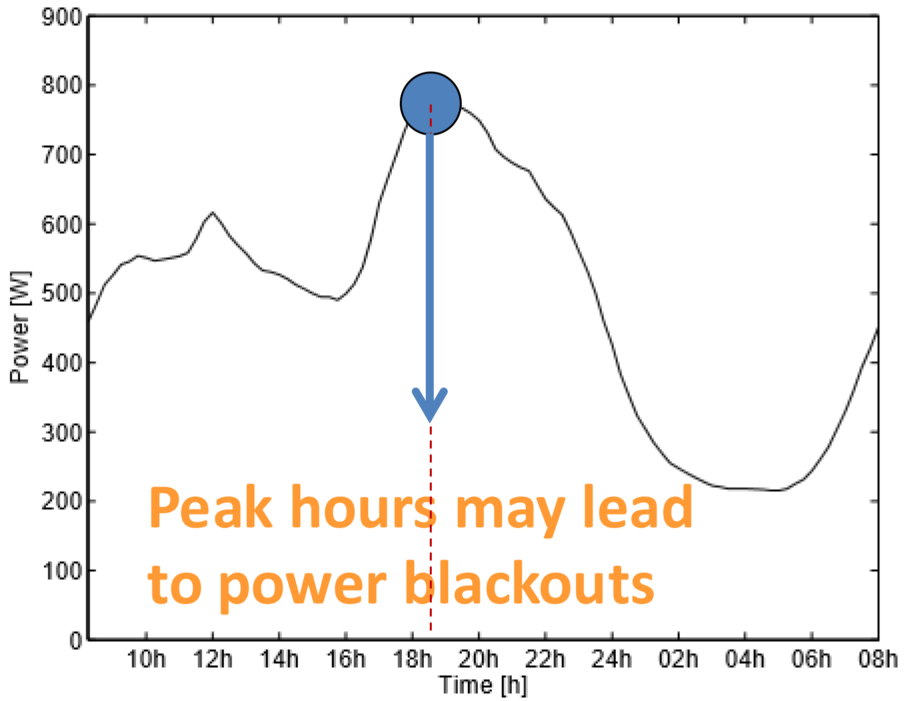


Figure source: https://www.einfochips.com/blog/edge-intelligence-enabling-intelligence-beyond-cloud/

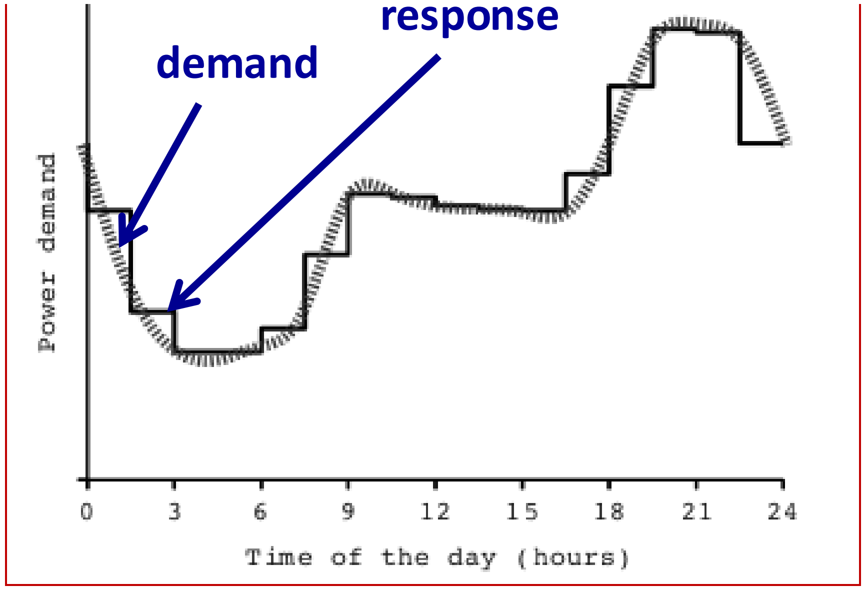
Demand Response Management

Demand response management

The response system of the end-users to changes in price of electricity at different times or from different providers



DRM can help reduce peak load points, power generation costs and user bills

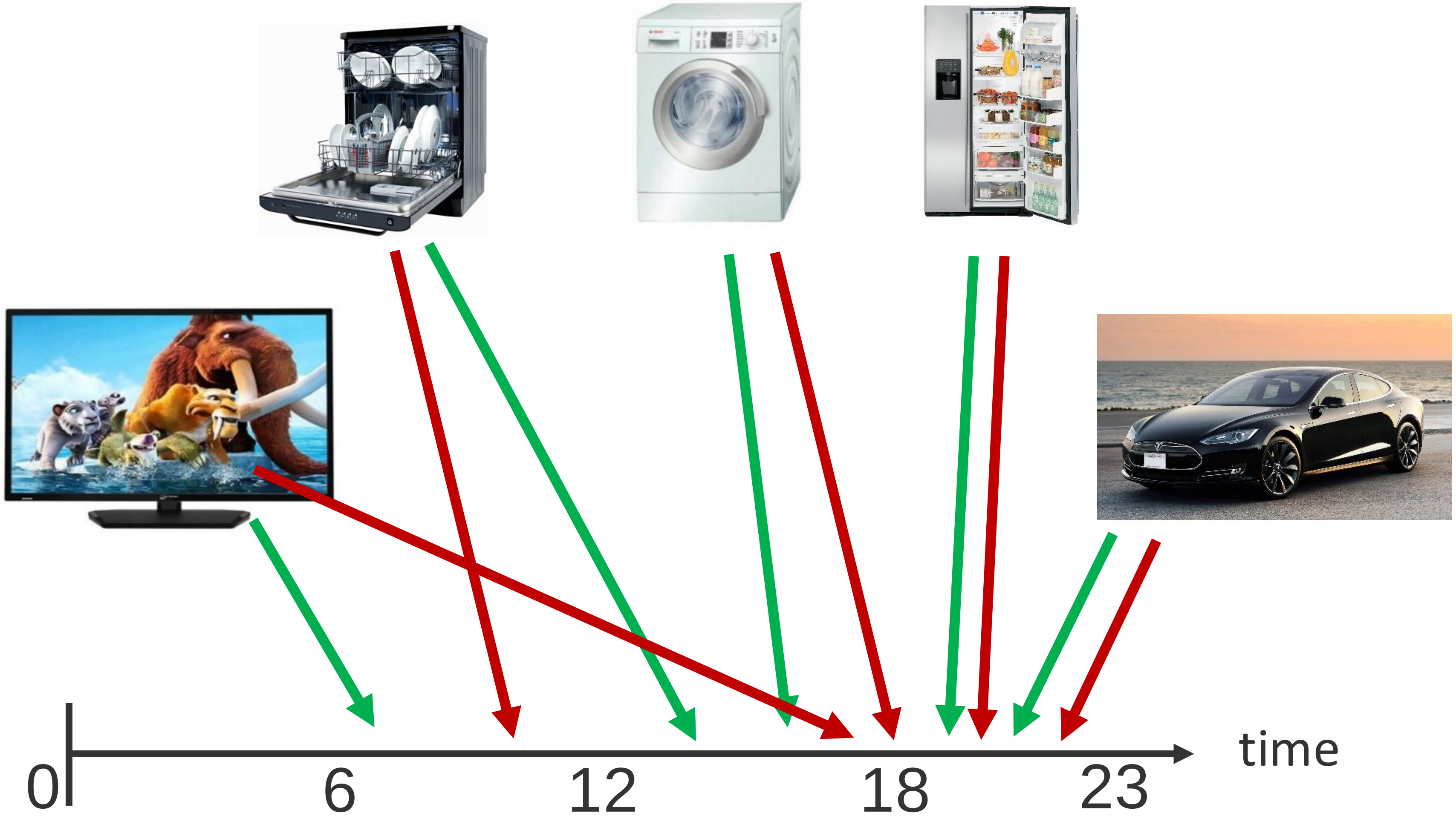


Moreover, DRM can contribute in improving grid reliability

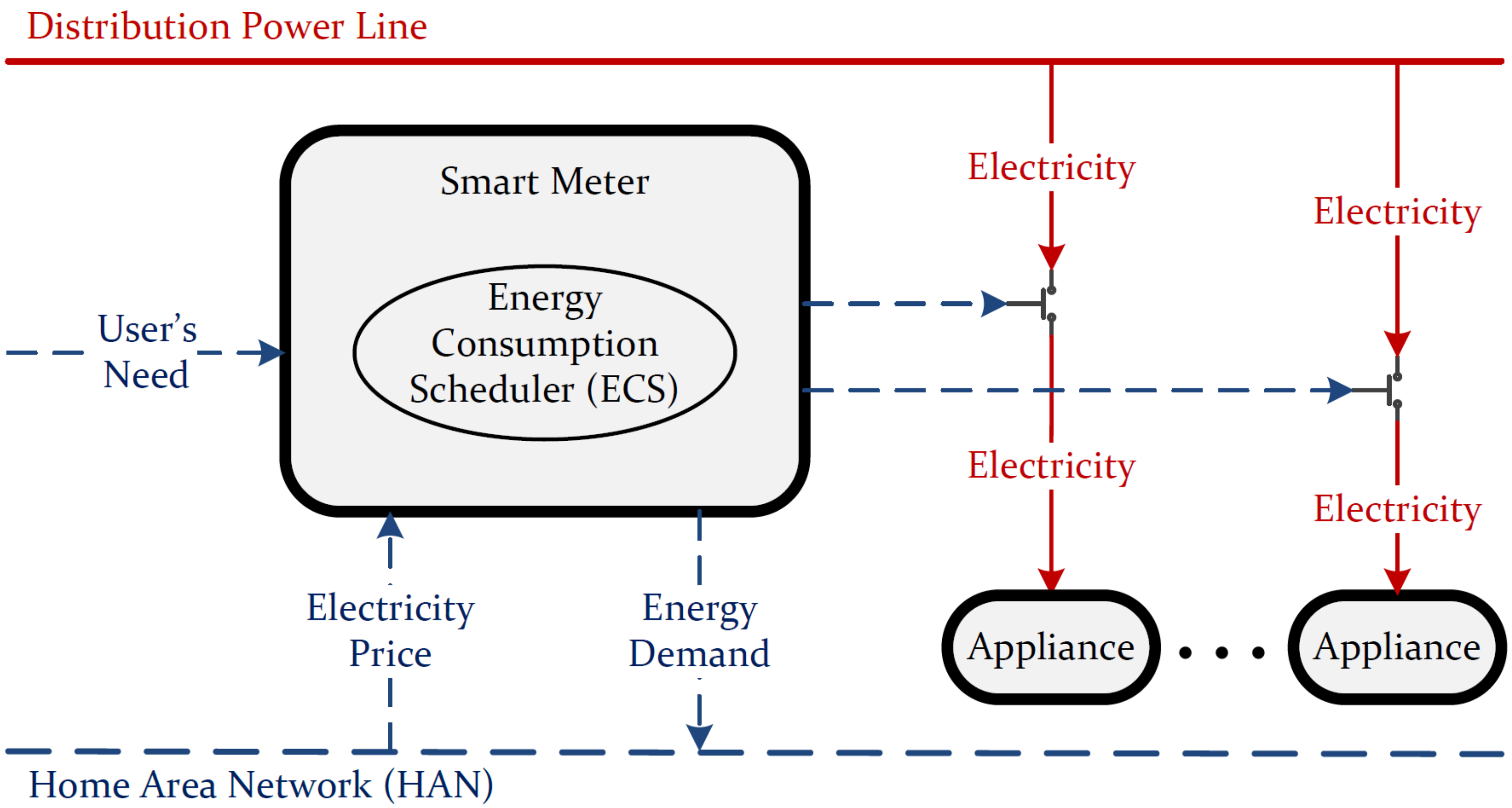
DRM Example: Home Energy Management

Home Energy Management Systems (HEMS): Energy Consumption Scheduling

When shall one use appliances/devices at home for minimizing electricity bill?



Demand Response Management (DRM Examples Problems: Home Energy Management Systems (HEMS)



Residential Load Scheduling: Cost Minimization Problem

$$\min_{\boldsymbol{x}} \sum_{h=1}^{H} p^h \times \left(\boxed{\sum_{a \in A} x_a^h} \right)$$

Consumption of all appliances in hour *h*

Subject to

$$\boxed{\sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a, \qquad \forall a \in A,}$$

Total consumption of the appliance (within the operational period)

$$\boxed{\begin{array}{ll} \gamma_n^{\min} \le x_a^h \le \gamma_n^{\max}, & \forall a \in A, h \in [\alpha_a, \beta_a] \\ x_a^h = 0, & \forall a \in A, h \notin [\alpha_a, \beta_a] \end{array}}$$

Power level constraint

p^h: unit price of electricity in hour *h*.
Could be ToU or RTP model

Smart Energy Neighborhood

Brooklyn microgrid

Discussion

How do we formulate the cost minimization problem for a smart energy neighborhood?

EMPOWER: Hvaler microgrid

Intelligent Residential Load Scheduling

Intelligent load scheduling is challenging due to the stochasticity in consumption behavior (appliance use) and also in electricity prices.

Key contributions

- **The interactions between households and the power grid are modelled as a noncooperative stochastic game**
- **We adopt distributed deep reinforcement learning also preserving privacy of the households**

2752 IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, VOL. 17, NO. 4, APRIL 2021

Distributed Deep Reinforcement Learning for Intelligent Load Scheduling in Residential Smart Grids

Hwei-Ming Chung, *Graduate Student Member, IEEE*, Sabita Maharjan, *Senior Member, IEEE*, Yan Zhang, *Fellow, IEEE*, and Frank Eliassen, *Member, IEEE*

***Abstract*—The power consumption of households has been constantly growing over the years. To cope with this growth, intelligent management of the consumption profile of the households is necessary, such that the households can save the electricity bills, and the stress to the power grid during peak hours can be reduced. However, implementing such a method is challenging due to the existence of randomness in the electricity price and the consumption of the appliances. To address this challenge, in this article, we employ a model-free method for the households, which works with limited information about the uncertain factors. More specifically, the interactions between households and the power grid can be modeled as a noncooperative stochastic game, where the electricity price is viewed as a stochastic variable. To search for the Nash equilibrium (NE) of the game, we adopt a method based on distributed deep reinforcement learning. Also, the proposed method can preserve the privacy of the households. We then utilize real-world data from Pecan Street Inc., which contains the power consumption profile of more than 1000 households, to evaluate the performance of the proposed method. In average, the results reveal that we can achieve around 12% reduction on peak-to-average ratio and 11% reduction on load variance. With this approach, the operation cost of the power grid and the electricity cost of the households can be reduced.**

in households, the energy consumption in residential households has increased considerably in the recent years, and is anticipated to grow even further [1]. Improvements in energy efficiency have not been significant enough to counteract the increasing demand [2]. To overcome this situation, the deployment of intelligent devices and communication infrastructure in smart grids becomes an important initiative. By doing so, the demand side is able to play an active role in energy management to balance demand and supply. More specifically, the demand side can change the consumption profile based on information (such as electricity price and generation capacity) provided by the supply side. For example, the authors in [3] proposed several concepts for scheduling the consumption of appliances in households to reduce the electricity cost.

Subsequently, many research papers [4]–[11] have suggested several mechanisms to schedule the consumption of the appliances. The authors in [4] and [5] applied game theory to model the interaction between the utility companies and the customers to reduce the power consumption. A real-time pricing (RTP) scheme was adopted in [6], and a genetic algorithm was utilized to minimize the electricity cost. Instead of scheduling the appliances in the residential area, the scheduling of industrial

H. M. Chung, S. Maharjan, Y. Zhang and F. Eliassen, "Distributed Deep Reinforcement Learning for Intelligent Load Scheduling in Residential Smart Grids," in *IEEE Trans. on Industrial Informatics,* vol. 17, no. 4, pp. 2752-2763, April. 2021

System Model: Pricing Model

$$\lambda_t = \alpha_1 L_t^2 + \alpha_2 L_t + \alpha_3, \qquad (1)$$

Generation cost

$$L_t = \sum_{i \in \mathcal{N}} P_{i,t} + \sum_{i \in \mathcal{N}} \sum_{j \in \mathrm{NSA}_i} E_{i,j,t}. \qquad (2)$$

Total load in the grid

$$\mathrm{RTP}_t = \begin{cases} \lambda_t, & 0 \leq L_t \leq \delta_1, \\ \sigma_1 \lambda_t, & \delta_1 \leq L_t \leq \delta_2, \\ \sigma_2 \lambda_t, & L_t > \delta_2, \end{cases} \qquad (3)$$

Real-time pricing (Inclining Block Rate (ICB) + (1)

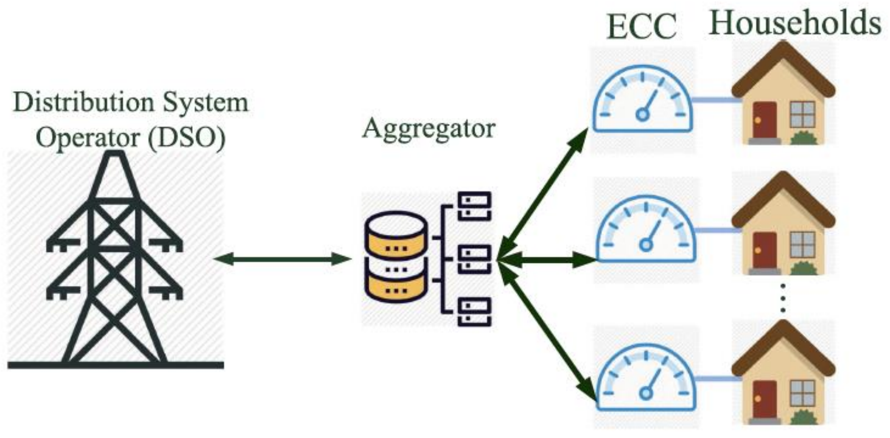


Fig. 1. System model used in this article.

Consumption Scheduling Game: Game Formulation and Nash Equilibrium

$$\boxed{r_{i,t}^1 = \mathrm{RTP}_t \times P_{i,t}.}$$

Electricity cost- i,t

$$\begin{aligned} J_i(\pi_{\theta_i^\mu}) &= \mathbb{E}\left[R(o_{i,1}, P_{i,1}) | \pi_{\theta_i^\mu}\right], \\ &= \int_{\mathcal{O}_i} \rho^{\pi_{\theta_i}^\mu}(o_{i,1}) R\left(o_{i,1}, \pi_{\theta_i^\mu}(o_{i,1})\right) do_{i,t}, \\ &= \mathbb{E}_{o_{i,t} \sim \rho^{\pi_{\theta_i}^\mu}}\left[R\left(o_{i,1}, \pi_{\theta_i^\mu}(o_{i,1})\right)\right], \end{aligned}$$

Expected accumulative reward

$$r_{i,t}^2 = \begin{cases} 0, & t \neq T, \\ \epsilon_1, & t = T, E_{i,j,t} > 0, \\ \epsilon_2, & t = T, E_{i,j,t} = 0, \end{cases}$$

Power requirement coefficient

$$J_i\left(\pi_{\theta_i^\mu}^* | \pi_{\theta_{-i}^\mu}^*\right) \geq J_i\left(\pi_{\theta_i^\mu} | \pi_{\theta_{-i}^\mu}^*\right)$$

Nash equilibrium : Best Response

$$R(o_{i,k}, \pi_{\theta_i^\mu}(o_{i,k})) = \sum_{t=k}^{T} \gamma_i^{t-k} r_{i,t},$$

Accumulative reward for the ith household

$$P_{i,k} = \pi_{\theta_i}(o_{i,k}).$$

$$\max_{\theta_i^\mu} J_i\left(\pi_{\theta_i^\mu} | \pi_{\theta_{-i}^\mu}\right).$$

Optimization problem for each ECC to find the NE

System Model and Numerical Results

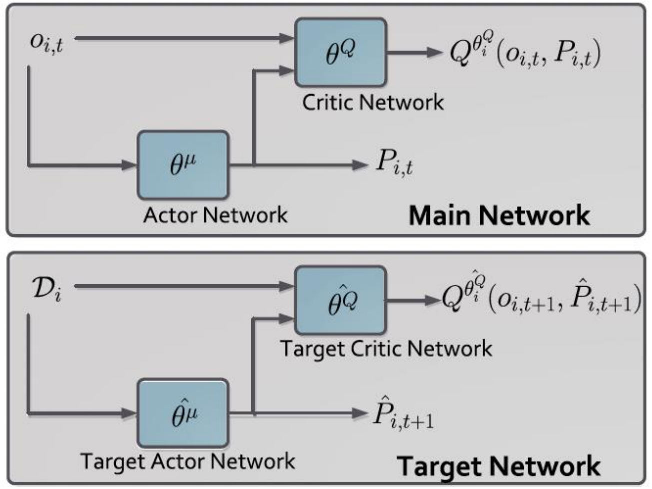


Fig. 2. Actor–critic architecture.

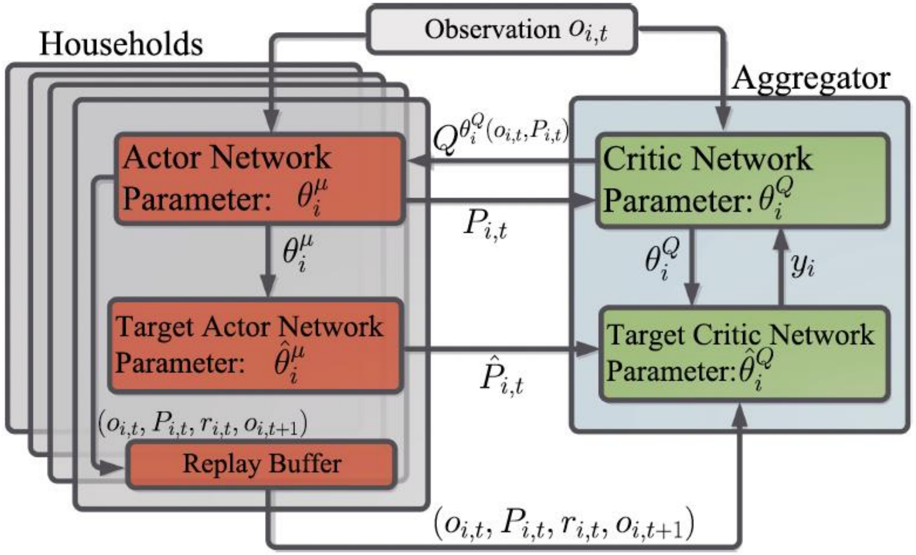


Fig. 3. Architecture of centralized critic distributed action.

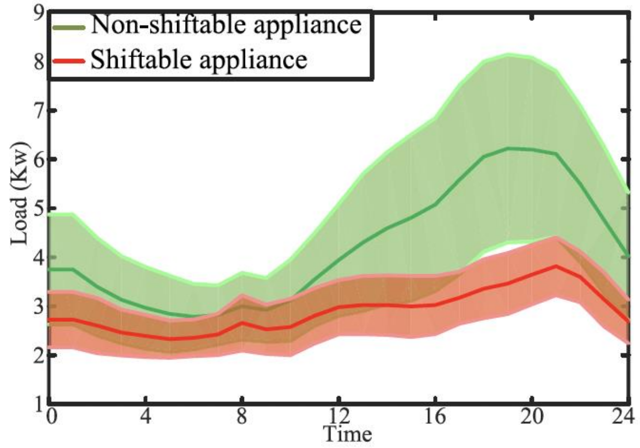


Fig. 4. Load profile of four appliances.

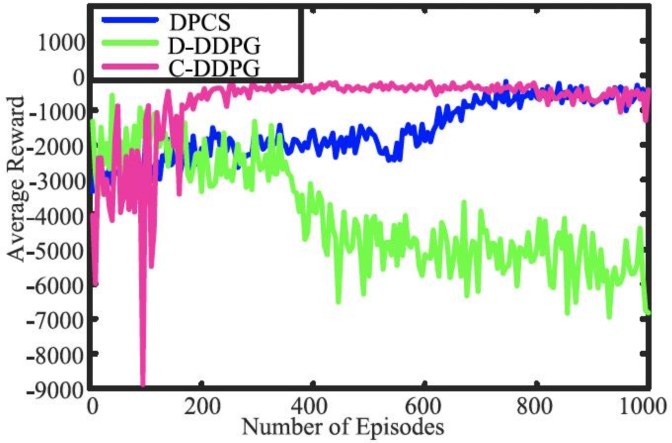


Fig. 5. Average reward for the algorithms.

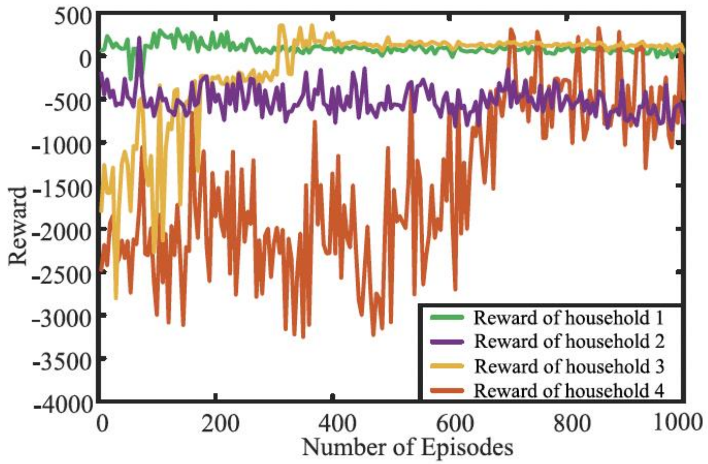
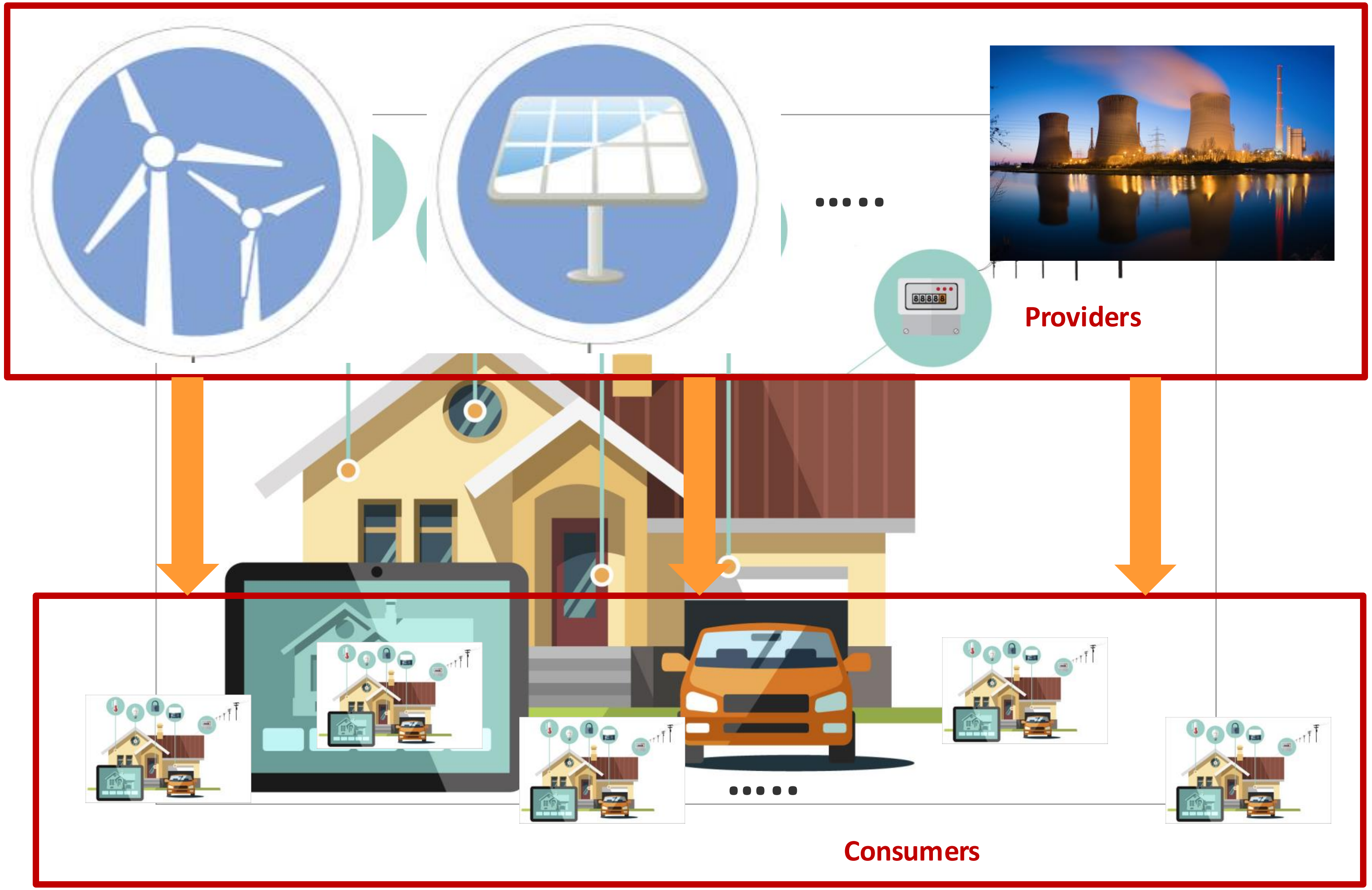


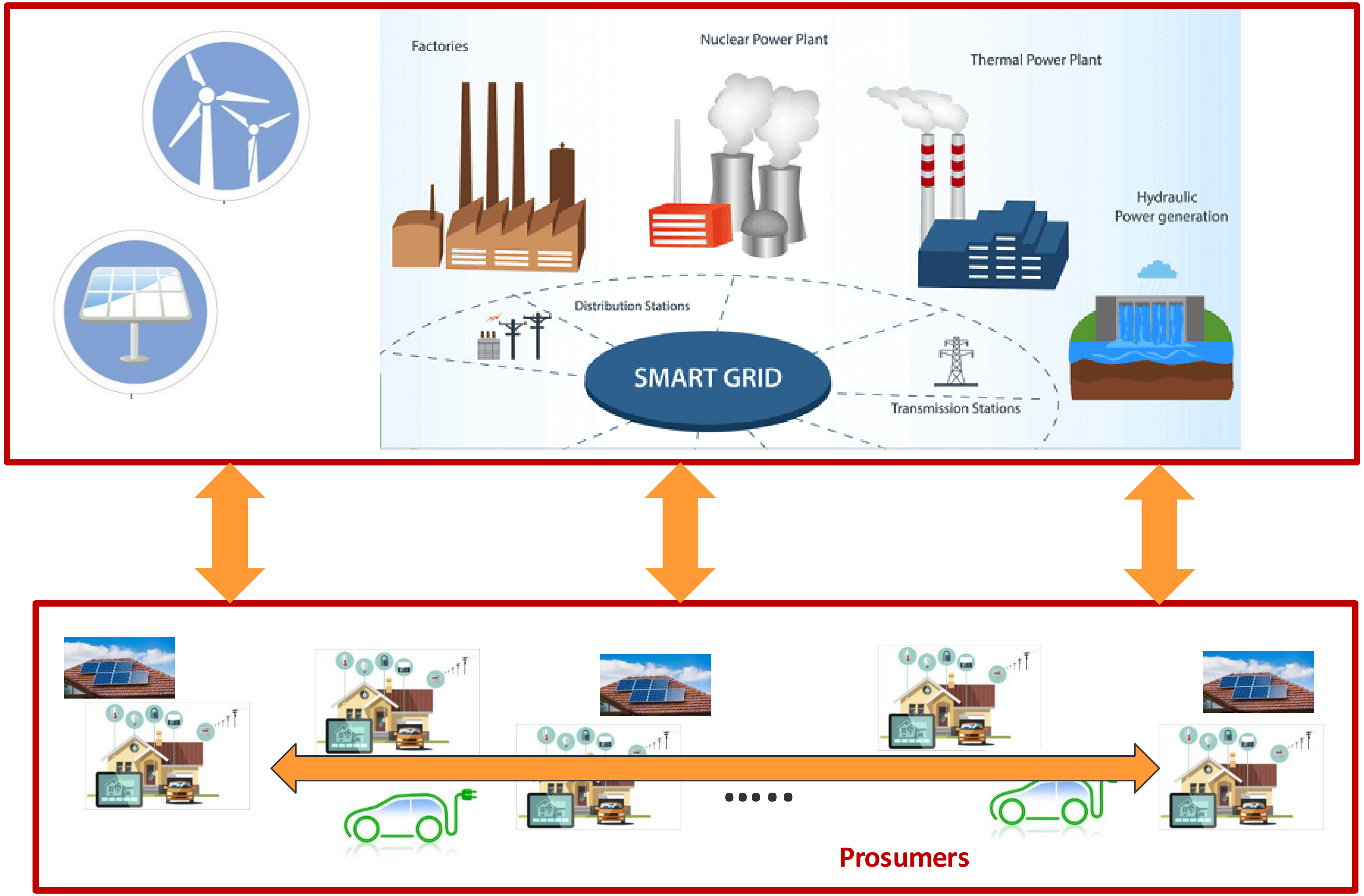
Fig. 6. Individual reward of the households during the training phase.

DRM Examples: The broader view

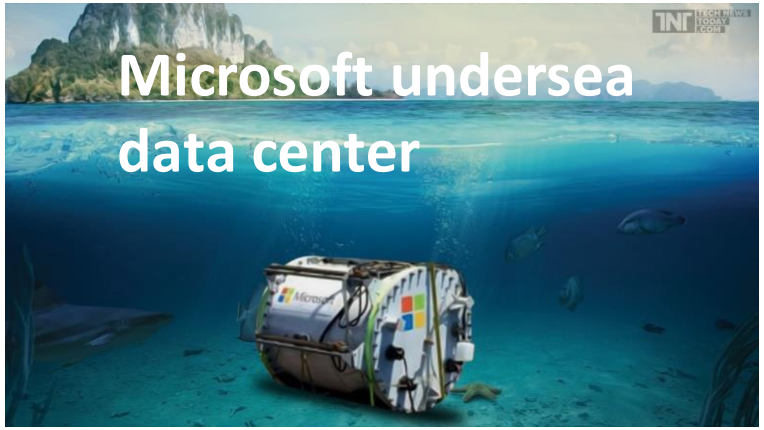
DRM involving multiple providers: Selection of providers or amount?



DRM involving multiple prosumers



Demand response applications: Data Centers

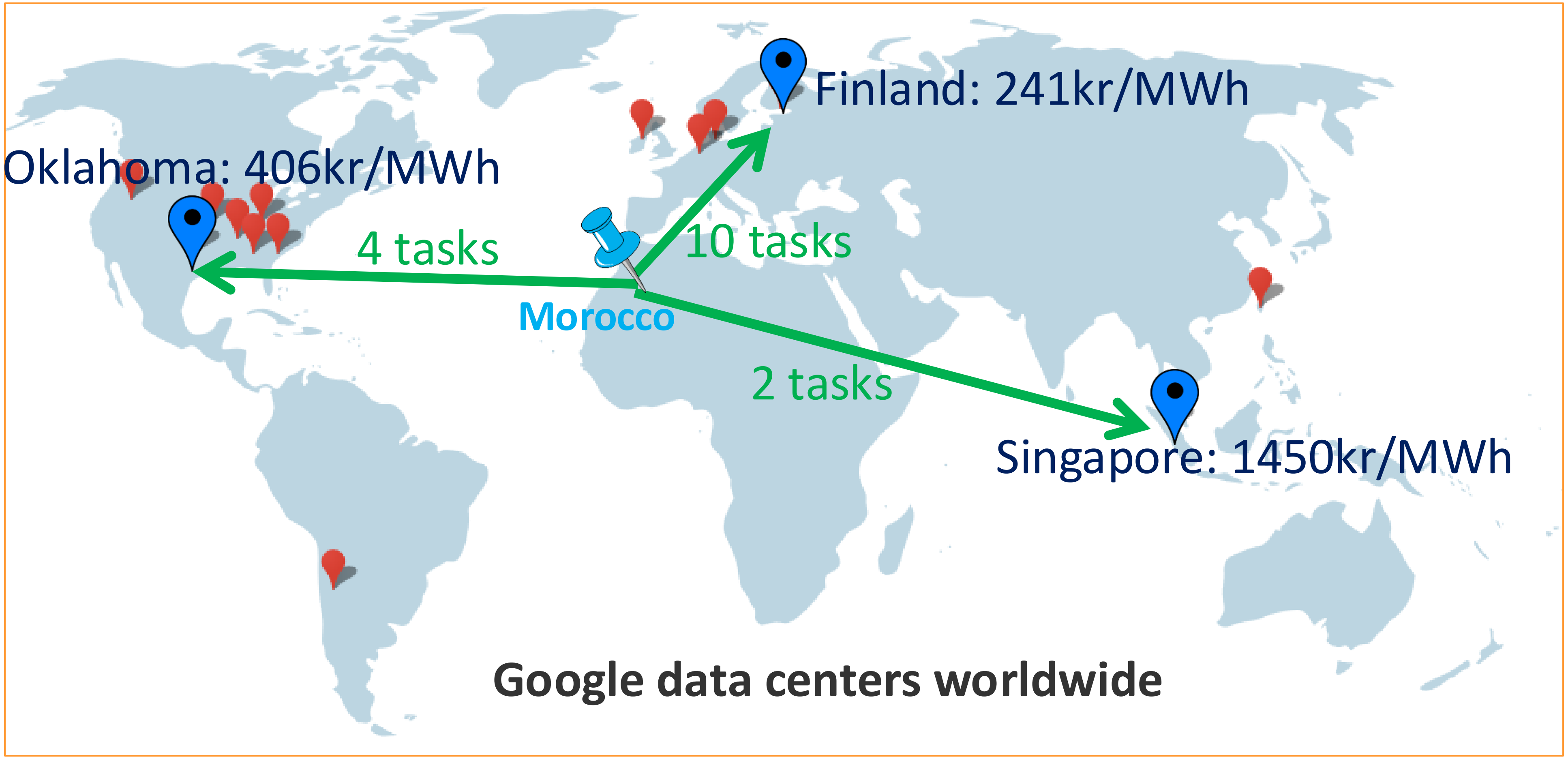


Data centers are huge energy consumers, in particular cooling systems,

- electricity bill
- power grid stability during peak hours

Cooling system uses sea water from the Bay of Finland and reduces energy use

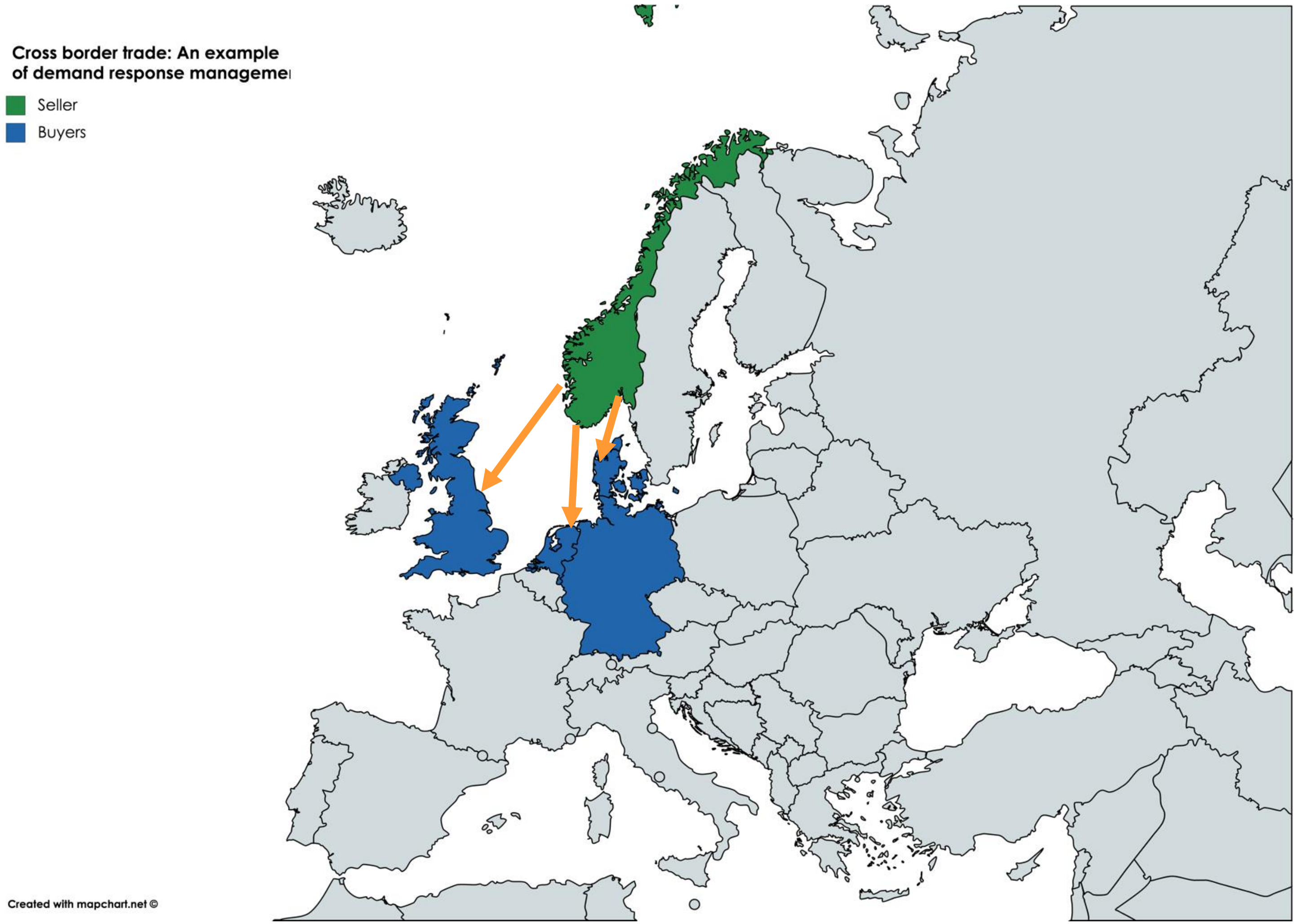
Demand response applications: Data Centers



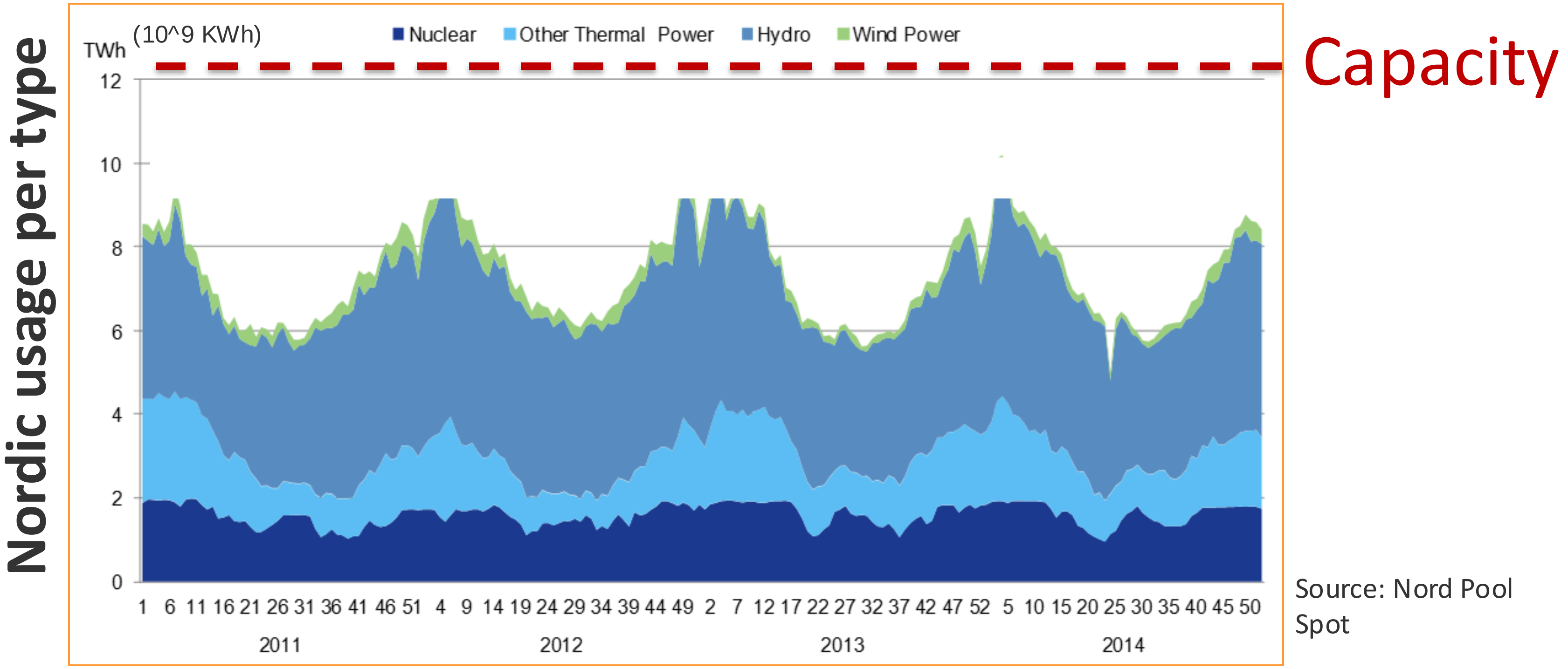
Can DRM help data centers to reduce energy cost?

Allocate computation tasks to locations with cheaper prices

Cross border electricity trade: An example of DRM



The Peak Load Issue and DRM:
Capacity Planning and Infrastructure Investment Perspective



Source: Nord Pool Spot

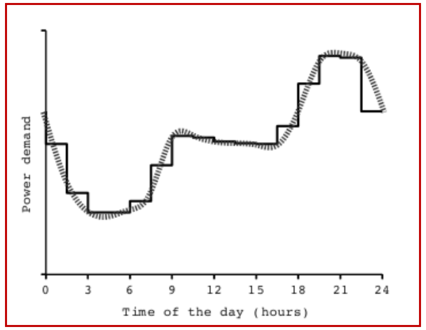
Power infrastructure is designed for peak loads.

Peaks have less than 1% of the time. Reducing peaks can then reduce power generation and save considerable costs and also save investments in the long run.

Outline

Energy Informatics: Overview

Demand Response Management



Introduction to the PriTEM Project

Figure source: https://www.einfochips.com/blog/edge-intelligence-enabling-intelligence-beyond-cloud/

Related Projects and ongoing initiatives

Brooklyn microgrid

EMPOWER: Hvaler microgrid

Transactive ENERGY Colombia

RESO LV D

LCE-01-2016-2017
European Union's Horizon 2020
Under grant agreement No 773715

Renewable penetration levered by Efficient Low Voltage Distribution grids

solshare®

Create a network. Share electricity.
Brighten the future

INVADE

FLEXGRID

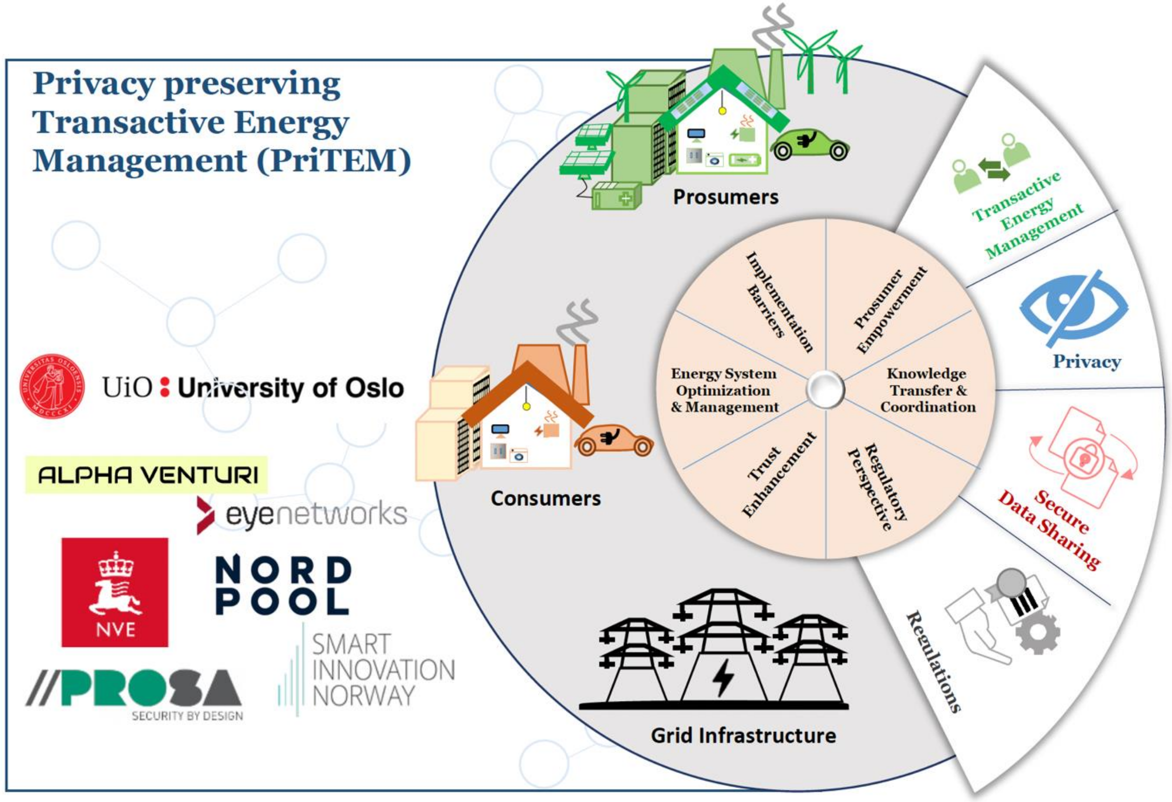
GREEN CHARGE

piclo®

ENCHANT

Energy Efficiency through behaviour Change Transition Strategies

E-LAND



Psychological factors

Privacy issues

Regulatory aspects

Energy Informatics

System Optimization

PriTEM will develop and deliver a holistic framework that will generate new knowledge, novel research and high impact results for the future sustainable energy system.

PriTEM

PROJECT TEAM

PSI

Assoc. Prof. Cato Bjørkli

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IFI

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Prof. Frank Eliassen

Prof. Yan Zhang

Prof. Roman Vitenberg

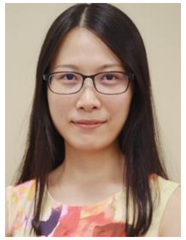
Prof. Olaf Owe

Prof. Lars Bocker

Dr. Geir Horn

Shiliang Zhang (Postdoc)

Daniel Gerbi (PhD student)



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Assoc. Prof. Matin Bagherpour

Jonathan Muringani (Postdoc)

Meysam Aboutalebi (PhD student)

ALPHA VENTURI

eyenetworks

NORD POOL

NVE

//PROSA SECURITY BY DESIGN

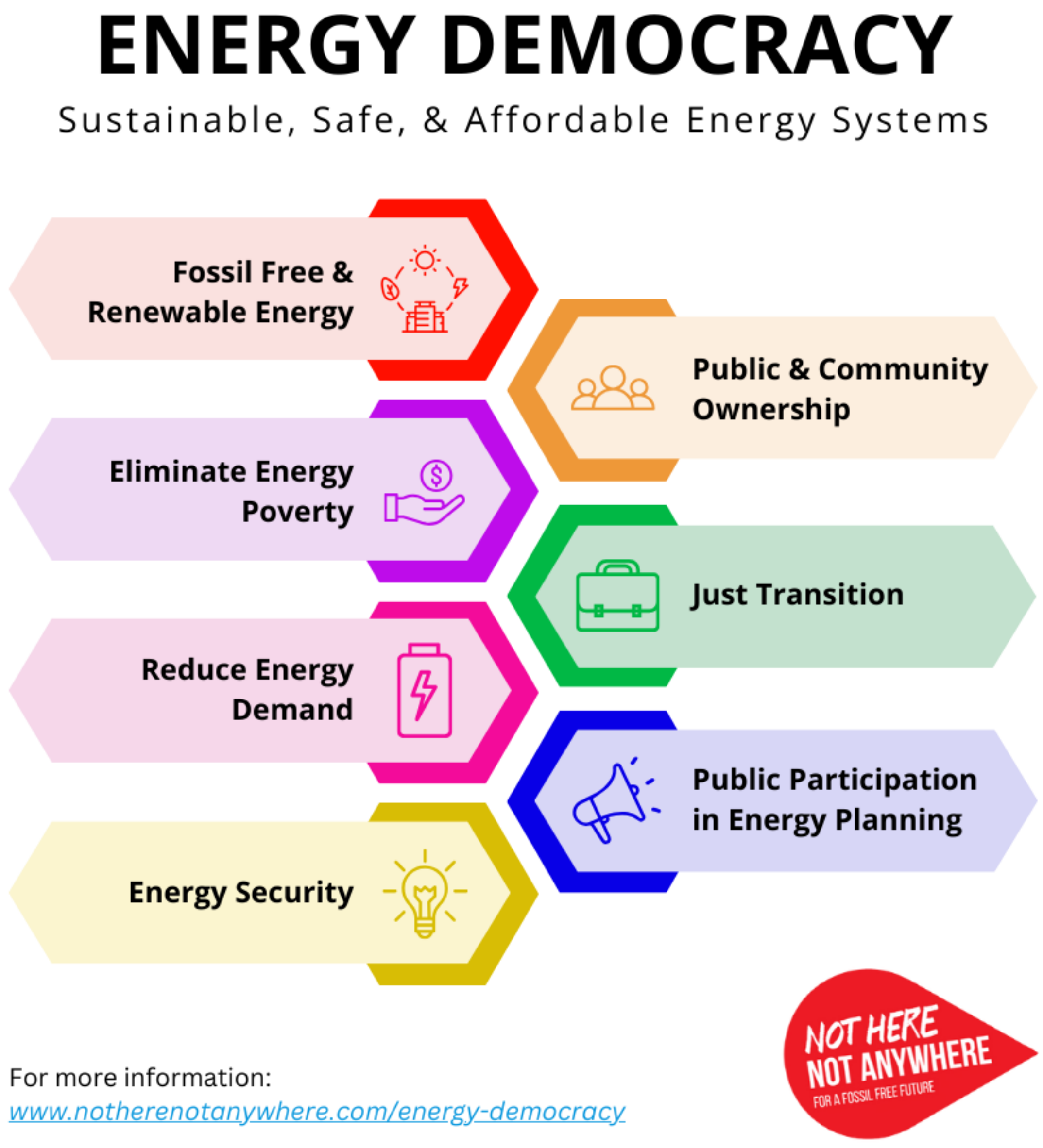
SMART INNOVATION NORWAY

Energy Edge

Edge: Closer to and including the prosumers

Brings production and consumption together

Integration beyond utilizing the roof



Energy Edge Landscape

Decentralized energy production and massive uptake of renewable energy from the edge

Optimally exploiting flexibility while mitigating the impact of uncertainty at various levels

Optimal energy management and control incorporating stochastic prosumer behavior and local energy flow at the edge

Flexibility market (local/Distribution level), Demand response, VPPs,...

Prosumer Empowerment: Participatory Approach

Citizen/Stakeholder considerations

- Technical barriers
- Socio-psychological aspects
- Flexibility market models/barriers

Prosumer empowerment

- Privacy concerns
- Secure data storage/sharing
- Generative models?
- Notions of Trust, Transparency and measurable privacy

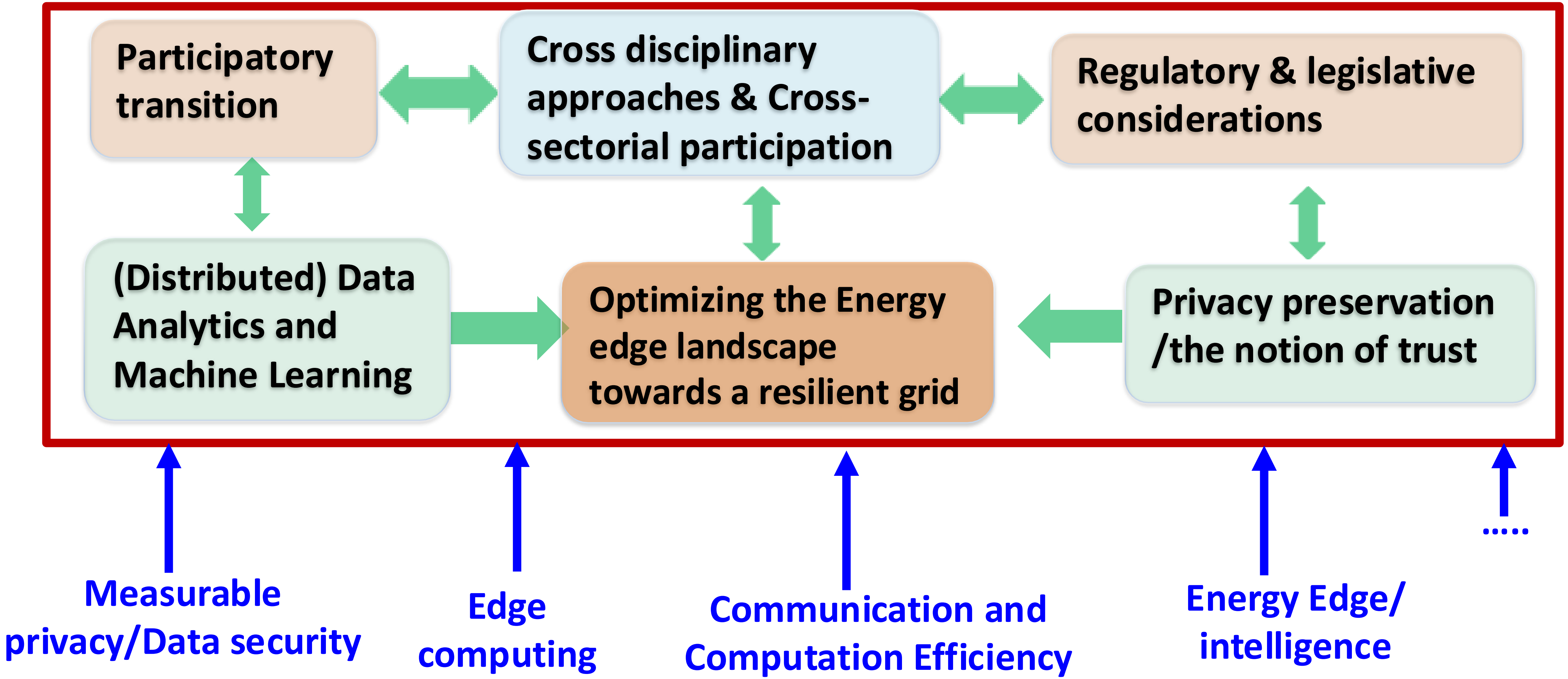
Legislative considerations

Stakeholder coordination enforcement

- Data law
- Energy law

Digitally aided prosumers (+ other relevant edge stakeholders') engagement

Trust enhancement and prosumer empowerment: The PriTEM Project



Objectives

- Trust enhancement
- User empowerment

- User-specific privacy
- Measurable privacy
- Privacy pricing

- Privacy issues
- Energy pricing

2024 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)

P^4S: Privacy-Preserving Personalized Pricing Scheme for Smart Grid

Hui Zhang, Shiliang Zhang, *Member, IEEE*, Sabita Maharjan, *Senior Member, IEEE*, Yan Zhang, *Fellow, IEEE*

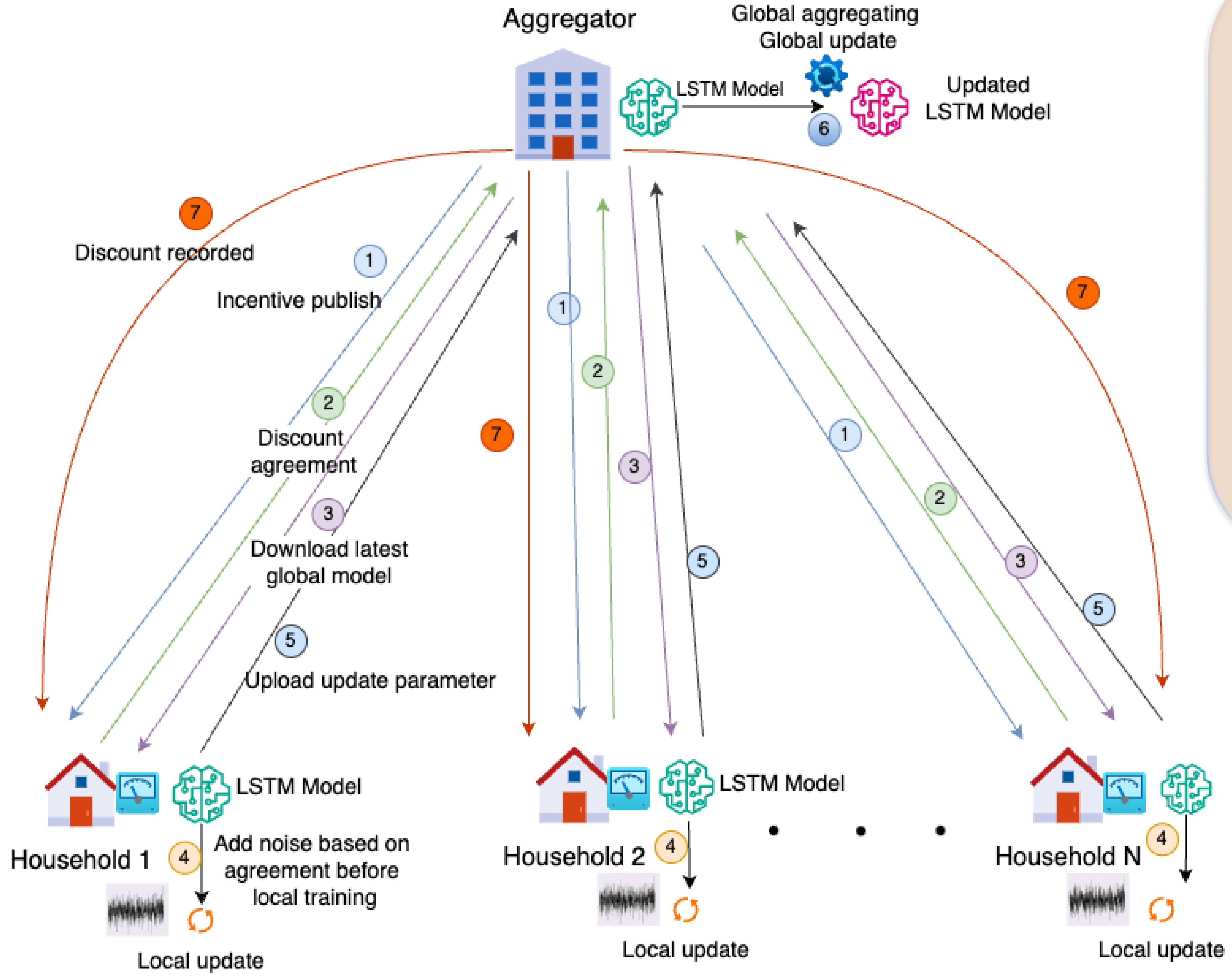
***Abstract*—Smart grids are evolving towards a more decentralized, distributed, prosumer-centric, and autonomous energy exchange framework. Data-driven models are key for informed decision-making in such frameworks, yet bring significant privacy concerns on the prosumer part. End-users in the smart grid are becoming increasingly vigilant about unauthorized usage of their personal information, necessitating the demand for enhanced control over the processing of their data. In this paper, we introduce a pricing framework that can incorporate our proposed user-specific privacy levels for consumers, and based on that, propose a Privacy-Preserving Personalized Pricing Scheme (P^4S) tailored for smart grids. In particular, we integrate the concept of differential privacy into the federated learning framework to facilitate and enable pricing discounts on electricity bills for customers based on their privacy budgets and preferences. In this way, end-users are empowered with the freedom to customize their privacy choices, while guaranteeing transparency in the form of the cost associated with privacy. We conduct simulations, and the results show that our scheme ensures robust convergence performance across diverse privacy settings. We anticipate that P^4S will promote trust enhancement and user empowerment, encouraging consumers to actively participate in the emerging distributed energy market.**

development [8], [9]. The economic benefits of RTP over MEP and ToU were highlighted in a study of a home energy management system (HEMS) [10]. A decentralized transactive energy market strategy was proposed in [11], utilizing LMP and Distribution LMP (DLMP) to enhance market operations efficiency. Various pricing mechanisms for peer-to-peer energy sharing and trading within smart communities were explored in [12], [13]. These studies emphasize the importance of grid-friendly pricing strategies in facilitating market diffusion, improving decision-making, and supporting effective financial compensation schemes for participants.

User concerns about personal data privacy are significant in the development of smart grids. Privacy issues primarily revolve around data collected by smart meters, which can reveal detailed household energy consumption patterns and device usage, posing privacy risks if mishandled [14]. Once aggregators obtain user consent, they analyze the data to optimize energy usage and improve service quality. This analysis helps in offering tailored energy solutions and enhances

H. Zhang, S. Zhang, S. Maharjan and Y. Zhang, ”P⁴S: Privacy-preserving Personalized Privacy Scheme for Smart Grid," in *IEEE SmartGridComm 2024, Oslo Norway, Sept. 2024.*

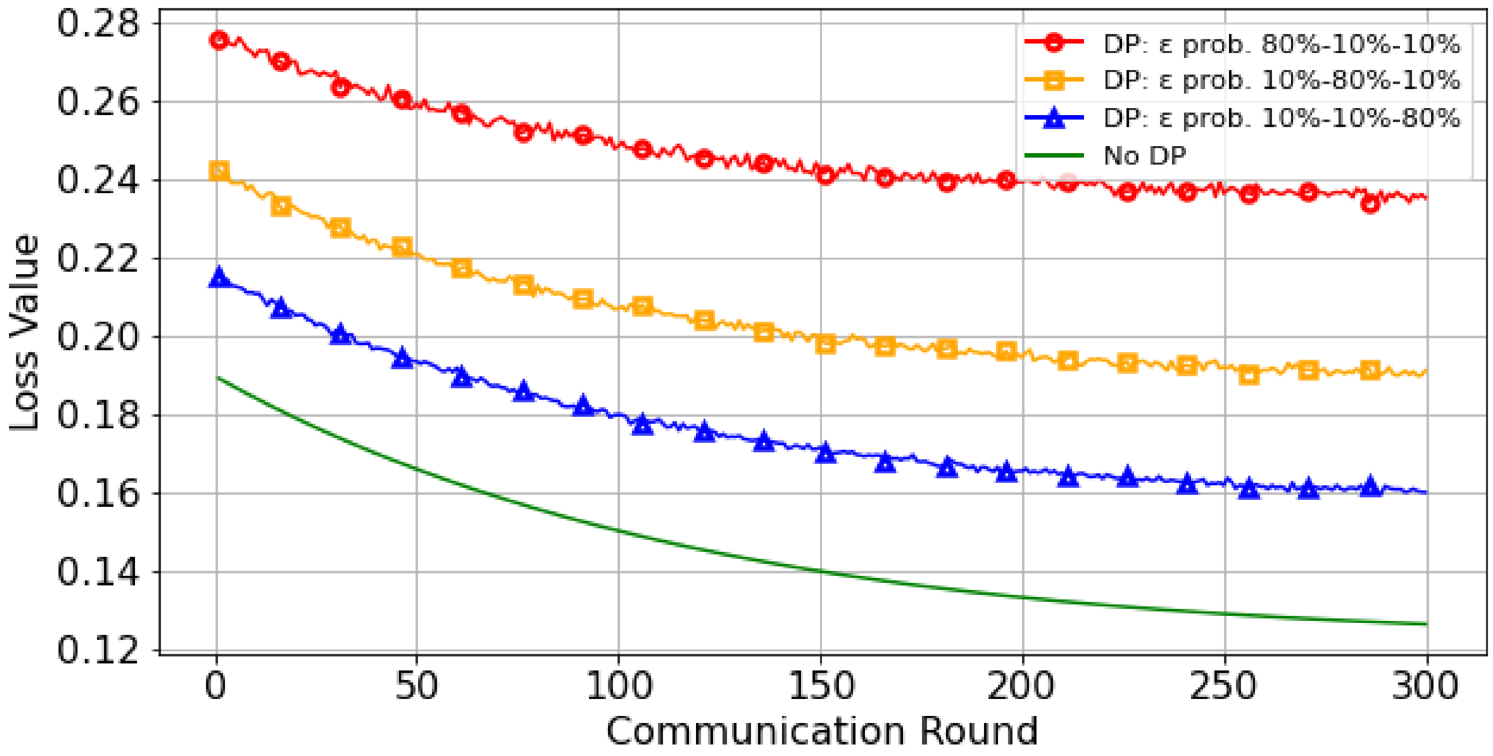
Our Proposed System Model of Federated Learning with Differential Privacy



1. The aggregator offers personalized discount agreements.
2. Each household selects a privacy level and enters into an agreement with the aggregator.
3. Households download the latest global model from the aggregator.
4. Households add noise to their data, train locally.
5. Households upload the parameters to the aggregator.
6. The aggregator updates the global model.
7. The aggregator records the discount for each household.

Our model empowers users to control their privacy levels, giving them the freedom to select the degree of privacy they are comfortable with through incentive mechanism.

Our Experimental Results: User-Specific Privacy Levels

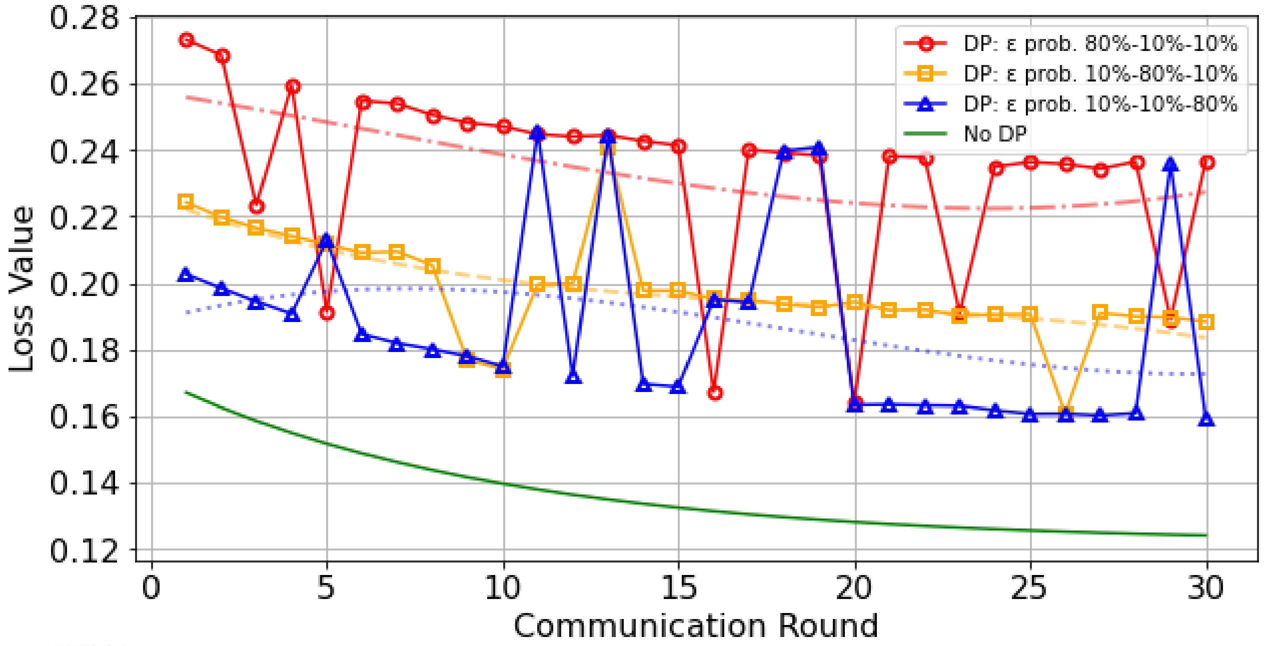


We evaluate the impact of clients choosing their privacy levels ϵ randomly based on predefined distribution ratios.

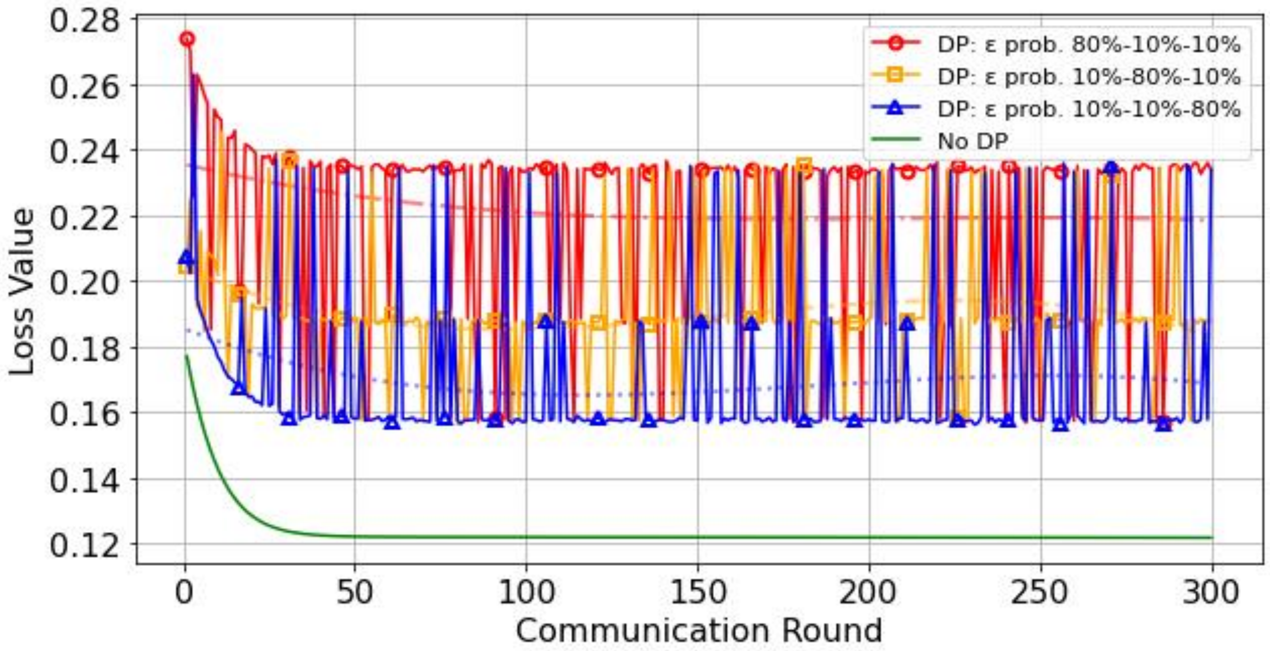
Results with ϵ values (5, 7, 10) allocated across three different distribution ratios:

1) 80% -10% - 10% for ϵ = 5, 7, 10 respectively
2) 10% - 80% -10% for ϵ = 5, 7, 10 respectively
3) 10% - 10% - 80% for ϵ = 5, 7, 10 respectively

Our Experimental Results: Dynamic Adjustment of Privacy Levels



We then allow the households to dynamically change their ϵ values in each communication round, assigning these values randomly according to previously specified proportions among the 50 households.



- Dynamic and flexible privacy settings lead to faster convergence in just 30 rounds.
- Early stabilization underscores the effectiveness of dynamic adjustment of privacy levels.
- Better performance in lower computation overhead and shorter time constraint.

Edge-grid: Interactions and Integration

Grid

- Integration of renewable energy resources of various kinds and at various levels (VPPs):
- Generation uncertainty, market volatility, ...

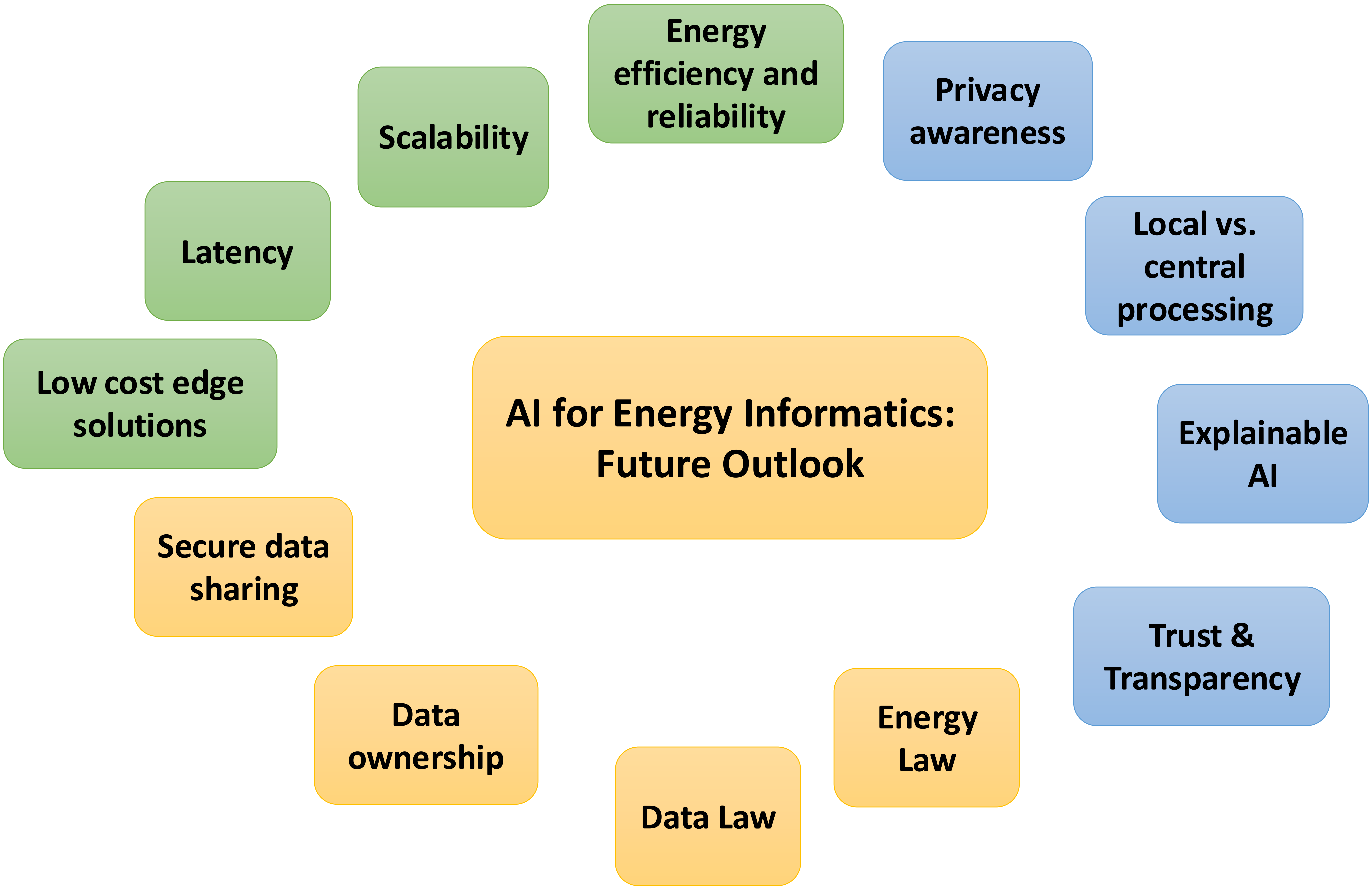
Modeling Interactions for seamless Integration

More Dynamic and more complex interactions at all levels for the edge-grid value-chain with massive uptake of renewable energy

Energy Edge

- Higher Intermittency in energy production
- Stochastic prosumer behavior (demand, supply and interactions)
- VPPs

Energy edge-grid Integration towards resilience, graceful degradation and stability


AI for Energy Informatics: Future Outlook
Energy efficiency and reliability
Privacy awareness
Local vs. central processing
Explainable AI
Trust & Transparency
Energy Law
Data Law
Data ownership
Secure data sharing
Low cost edge solutions
Latency
Scalability

References

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- Section 1. Purpose and Scope: pages 17-26 (1-10)
- Section 2.1 Models of the Smart Grid: pages 26-30 (10-14)

[2] Cali et. al., "Digitalization of Power Markets and Systems using Energy Informatics," Springer, 2021 https://link.springer.com/book/10.1007/978-3-030-83301-5

- Chapter 1, Pgs. 1-14
- Chapter 2: Section 2.3, Pgs. 26-37
- Chapter 3: Section 3.2.3, 3.2.4, 3.2.6
- Chapter 7: pgs. 139-162
- Chapter 10: Pgs. 217-230

[3] H. M. Chung, S. Maharjan, Y. Zhang and F. Eliassen, "Distributed Deep Reinforcement Learning for Intelligent Load Scheduling in Residential Smart Grids," in *IEEE Trans. on Industrial Informatics,* vol. 17, no. 4, pp. 2752-2763, April. 2021

[4] H. Zhang, S. Zhang, S. Maharjan and Y. Zhang, "P^4S: Privacy-preserving Personalized Privacy Scheme for Smart Grid," in *IEEE SmartGridComm 2024, Oslo Norway, Sept. 2024.*

Thank you for your attention!

Questions?

- *ESI Highly Cited Researcher, 2024*
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- *ESI Highly Cited Researcher, 2022*
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