

FLEXIBILITY AGGREGATION OF LOCAL ENERGY SYSTEMS — INTERCONNECTING, FORECASTING, AND SCHEDULING

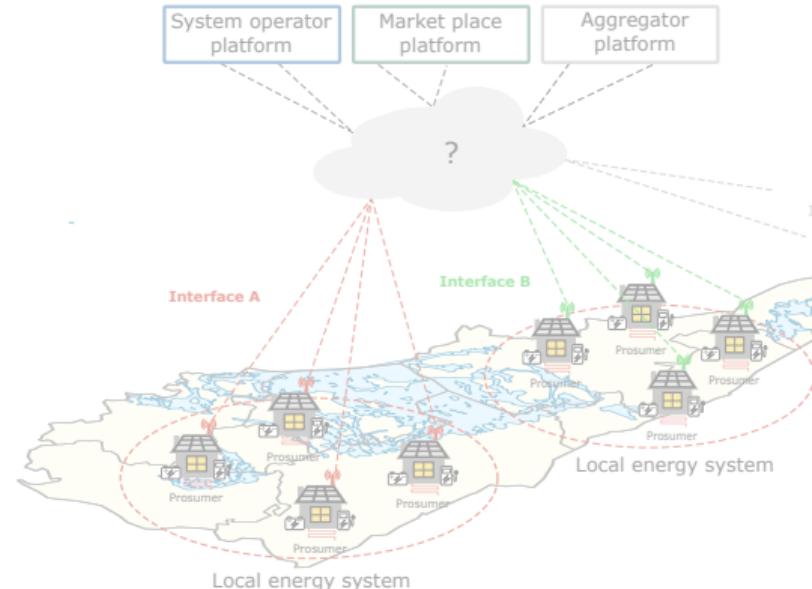
LECTIO PRAECURSORIA

Presented by Aleksei Mashlakov

December 13, 2021

Supervisor: Prof. Samuli Honkapuro, LUT University

Opponent: Prof. Hannu Laaksonen, University of Vaasa



OUTLINE

1 CONTEXT AND MOTIVATION

Supply decarbonization

Demand electrification

Demand democratization

2 RESEARCH AIM, SCOPE, AND QUESTIONS

Research question #1

Research question #2

Research question #3

3 CONTRIBUTIONS

Summary

CONTEXT AND MOTIVATION

Centralization of electric power system

Structure

National objective

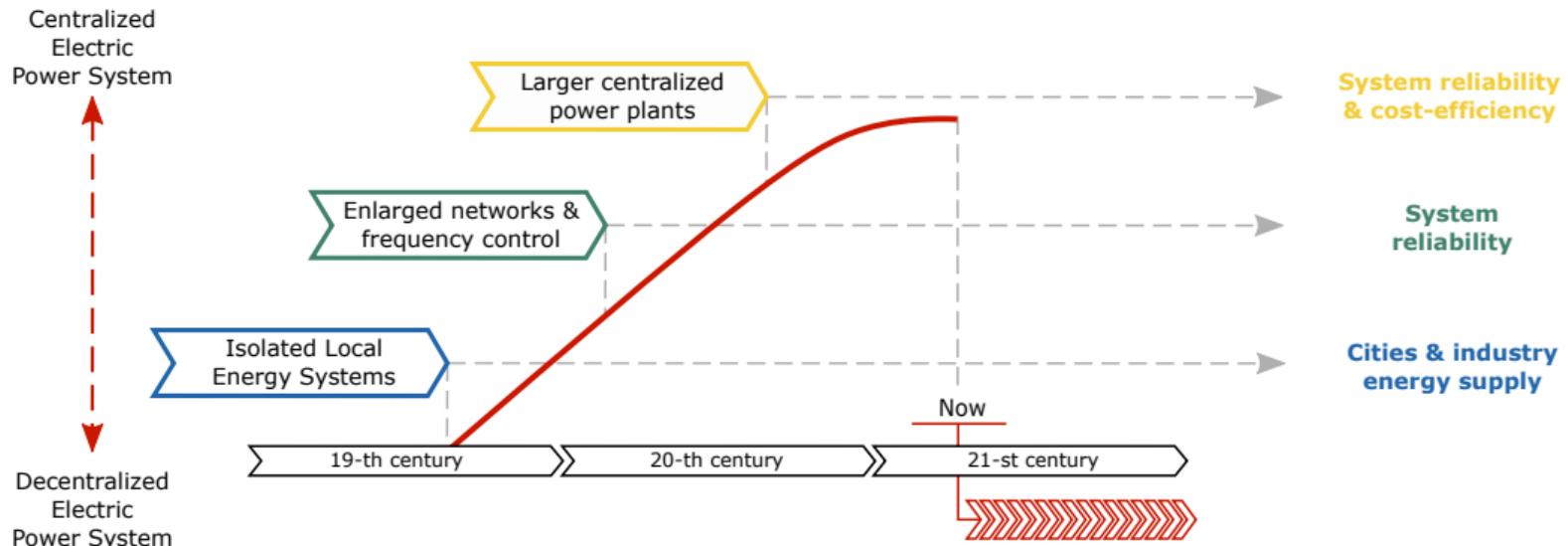
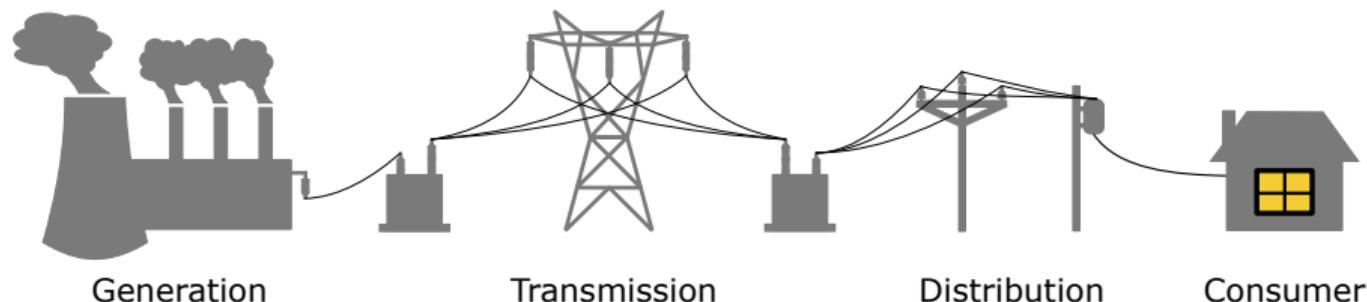


Figure: Evolution of an electric power system. Adapted from Siemens.

CONTEXT AND MOTIVATION

Centralized electric power system



- Unidirectional electricity supply to customers
- Supply is adjusted to follow demand
- System operators guarantee the security of supply
- Large-scale and supply-focused electricity markets
- Customer has no rule or influence over the system

CONTEXT AND MOTIVATION

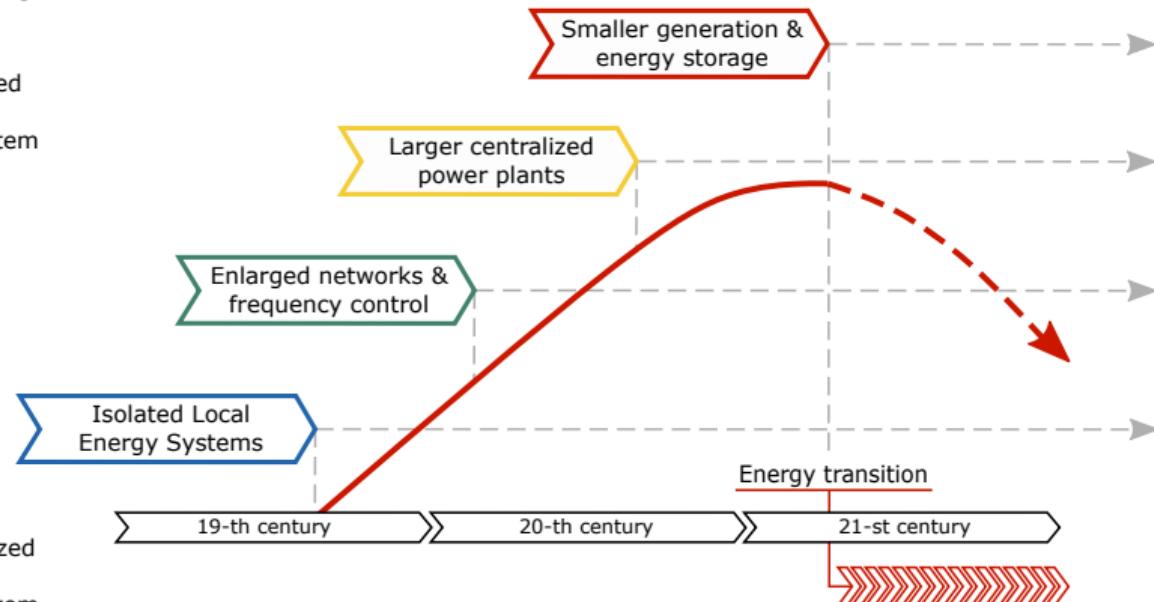
Energy system transition

Structure

Centralized Electric Power System



Decentralized Electric Power System



National objective

Decarbonization & democratization

System reliability & cost-efficiency

System reliability

Cities & industry energy supply

CONTEXT AND MOTIVATION

Supply decarbonization

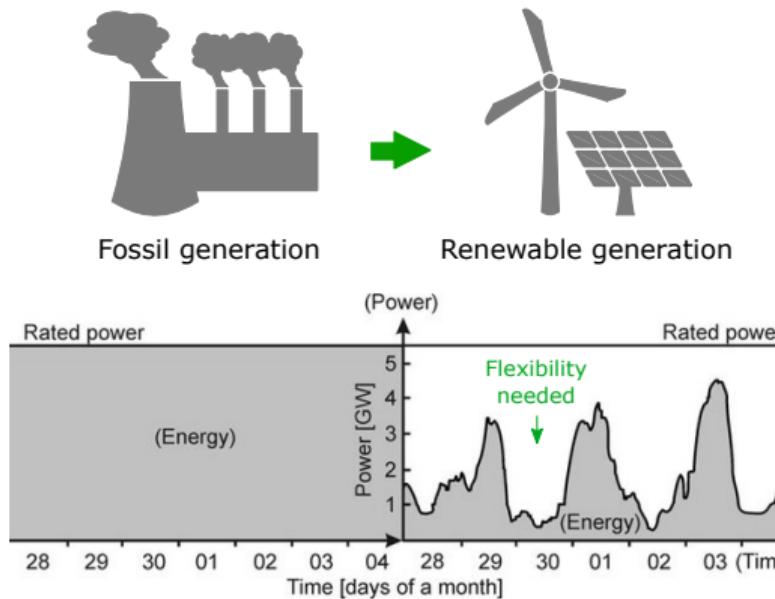
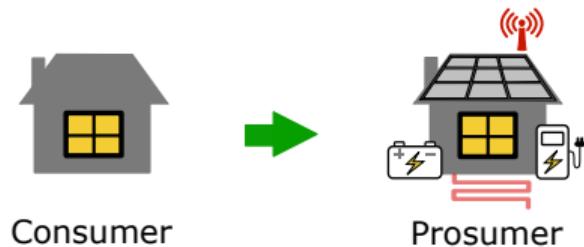


Figure: Dispatchable vs intermittent energy generation [3]

- More supply volatility
 - ▶ Less supply controllability
 - ▶ More forecast uncertainty
- Risks of large redispatch costs for grid stabilisation

CONTEXT AND MOTIVATION

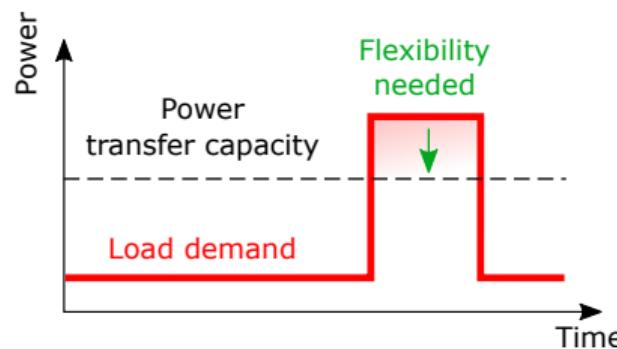
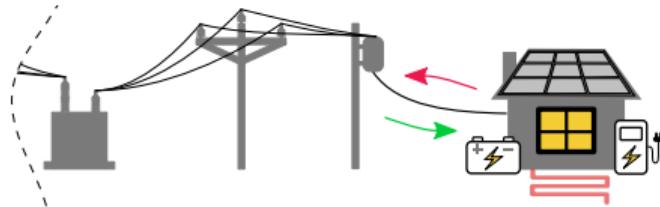
Demand electrification



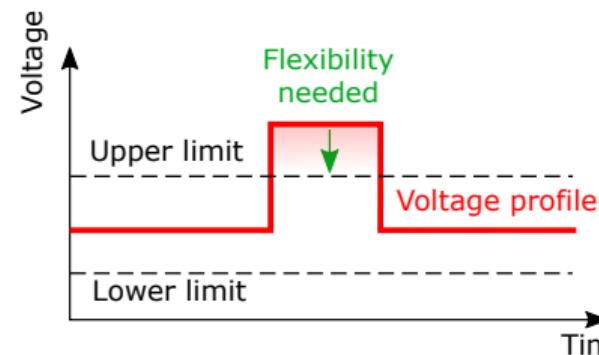
- Growing demand electrification
 - ▶ larger peak demand periods
 - ▶ bi-directional power-flows
- *Risk of worse power quality and reliability of supply in distribution grid*

CONTEXT AND MOTIVATION

Demand electrification

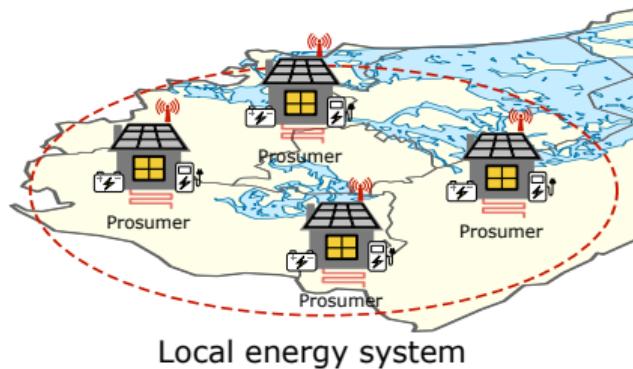


- Growing demand electrification
 - ▶ larger peak demand periods
 - ▶ bi-directional power-flows
- Risk of worse power quality and reliability of supply in distribution grid



CONTEXT AND MOTIVATION

Demand democratization



■ Local energy systems

- ▶ democratization of local energy governance
- ▶ centralized supply as a back-up solution

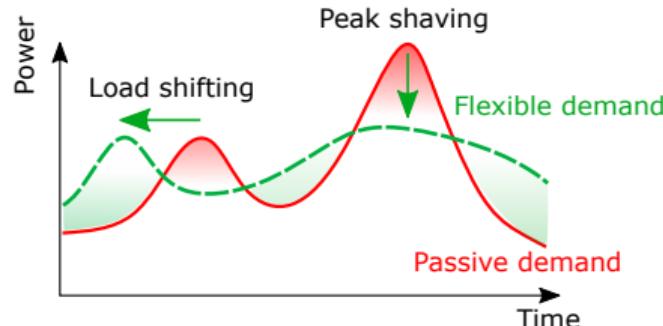
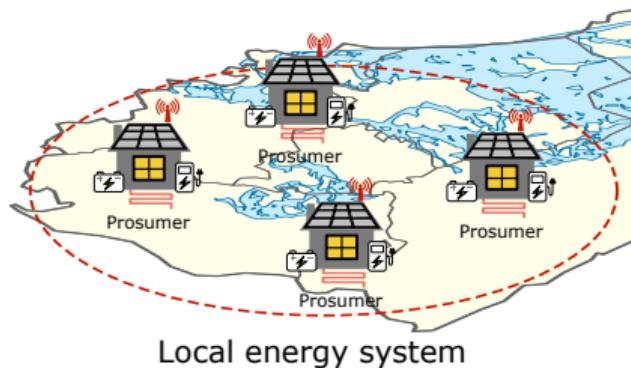
■ Risk of system-wide efficiency loss

■ Joint management of demand flexibility

- ▶ participation of prosumers in grid management
- ▶ cost-efficient to capacity investments

CONTEXT AND MOTIVATION

Demand democratization



Local energy systems

- ▶ democratization of local energy governance
- ▶ centralized supply as a back-up solution

Risk of system-wide efficiency loss

Joint management of demand flexibility

- ▶ participation of prosumers in grid management
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RESEARCH AIM

Flexibility aggregation

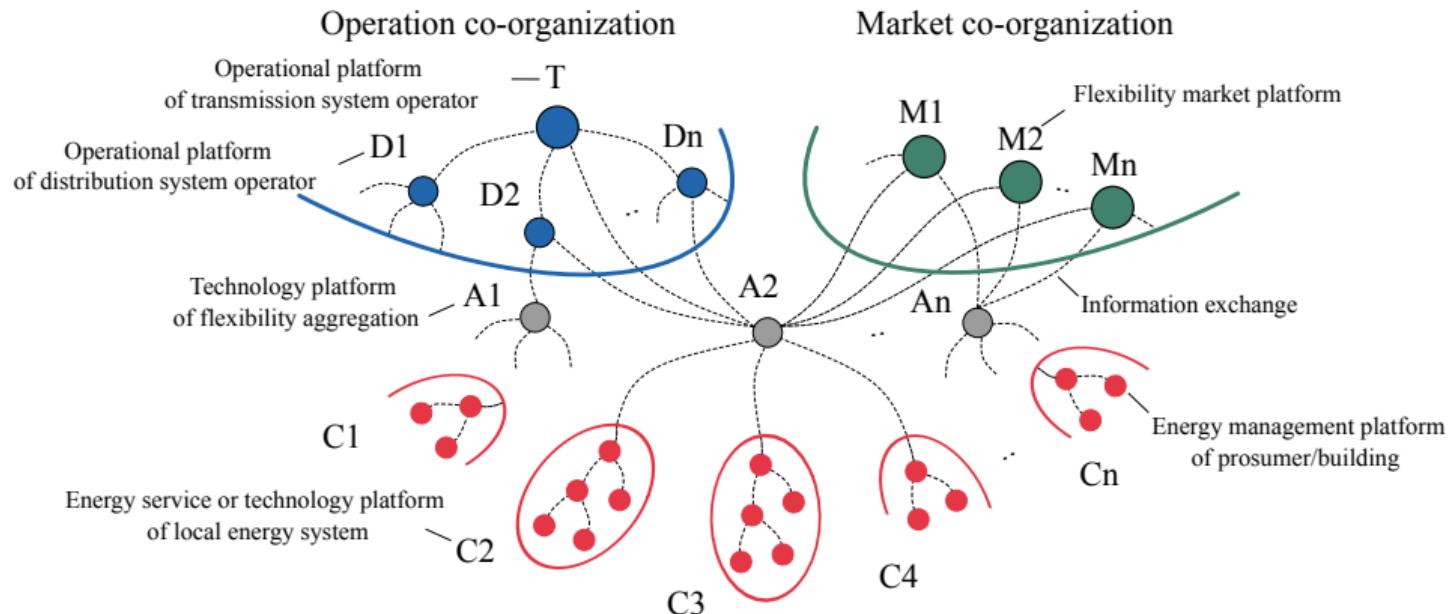


Figure: Conceptual representation of flexibility aggregation in decentralized power grid.

METHODOLOGY

Research areas and fields

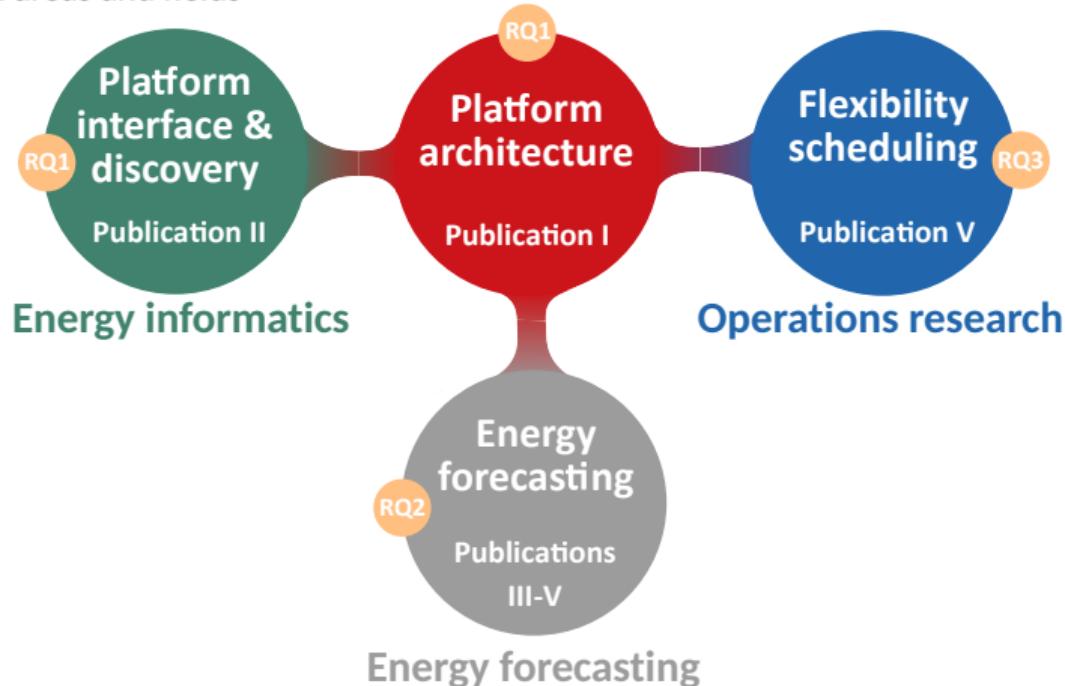
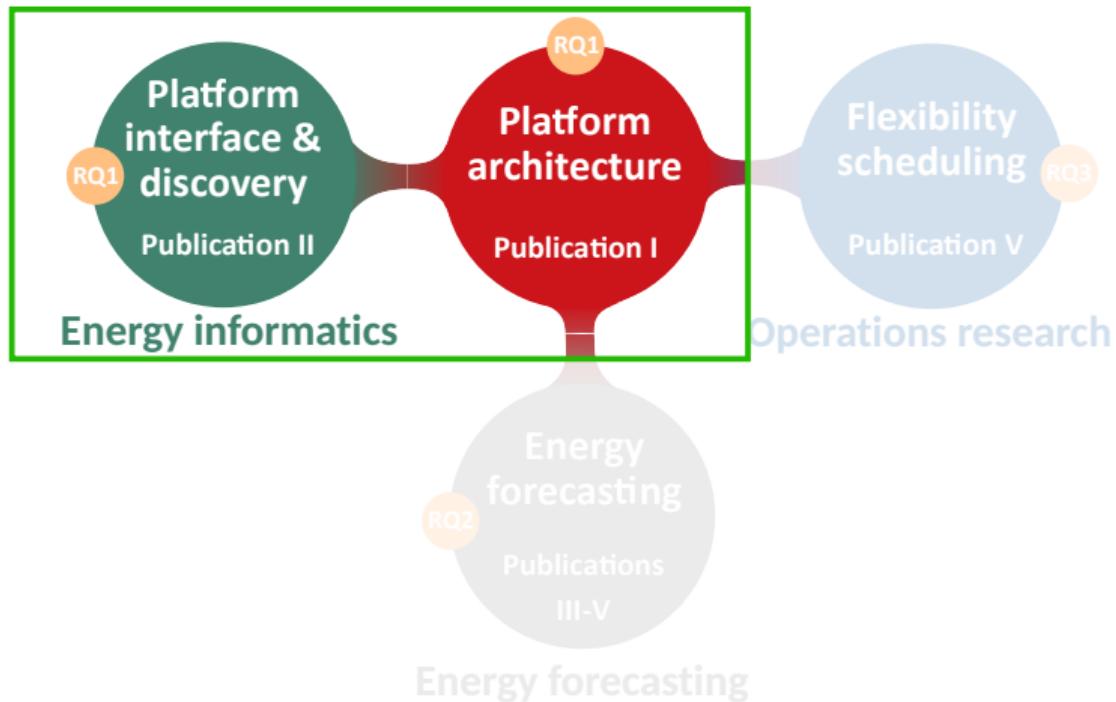


Figure: Overview of the research areas related to the contributions.

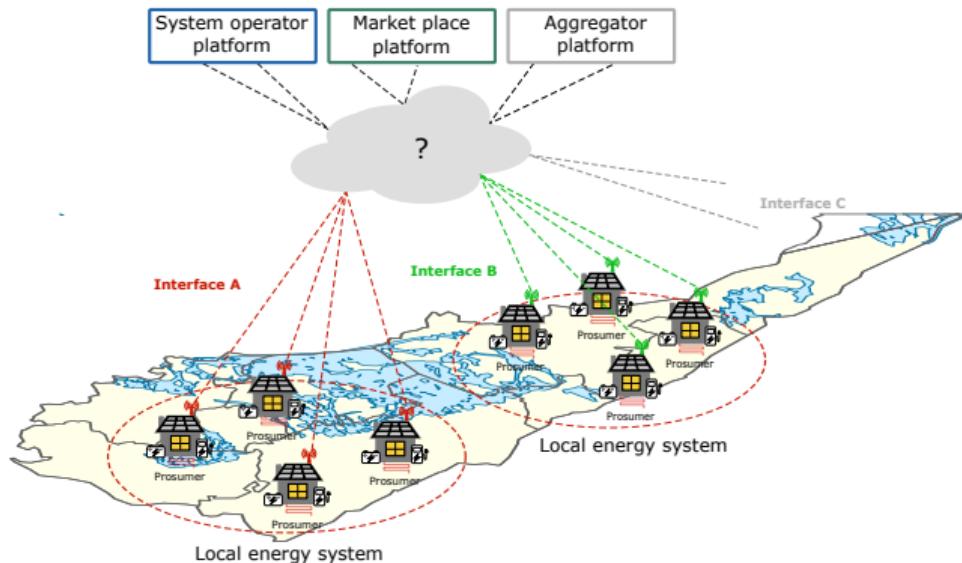
RESEARCH QUESTION #1

Can machines speak the same language?



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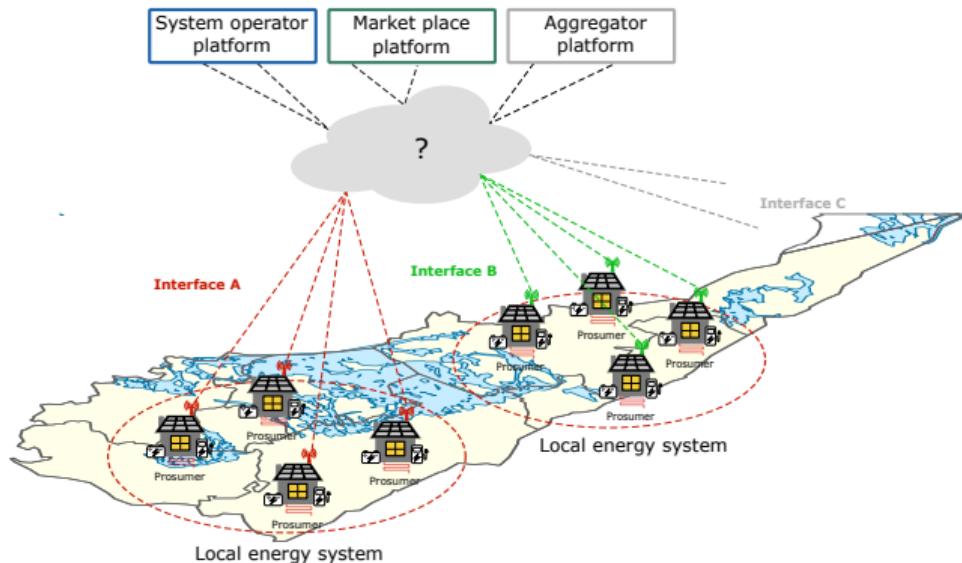


- Lack of interoperability
 - ▶ Automated flexibility procurement is out of system operator toolbox

- Heterogeneity of platforms
 - ▶ costly platform landscape
 - ▶ vendor lock-in

RESEARCH QUESTION #1

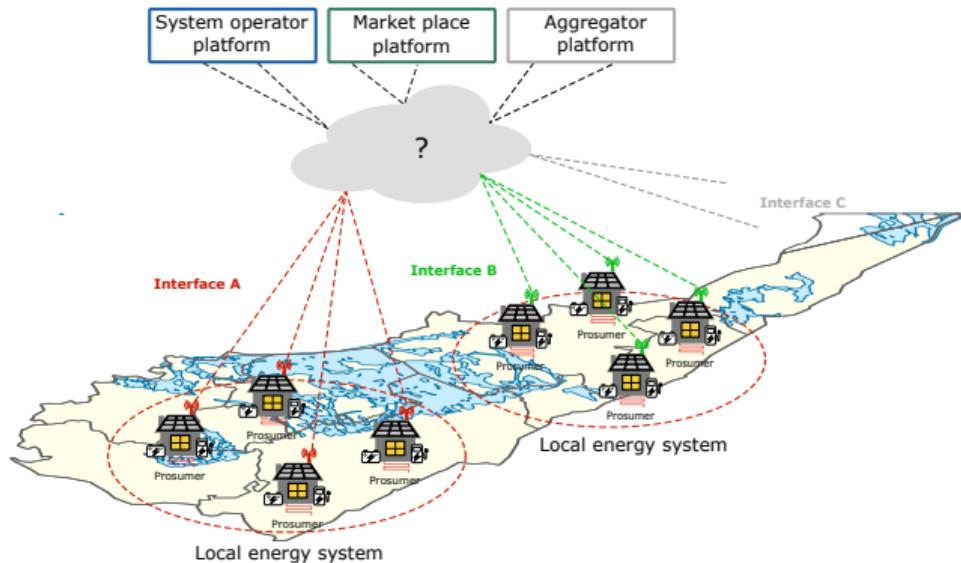
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RESEARCH QUESTION #1

Can machines speak the same language?



- Lack of interoperability
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RQ #1 What are the requirements to enable interoperable technological integration of local energy management platforms into the provision of grid-flexibility services?

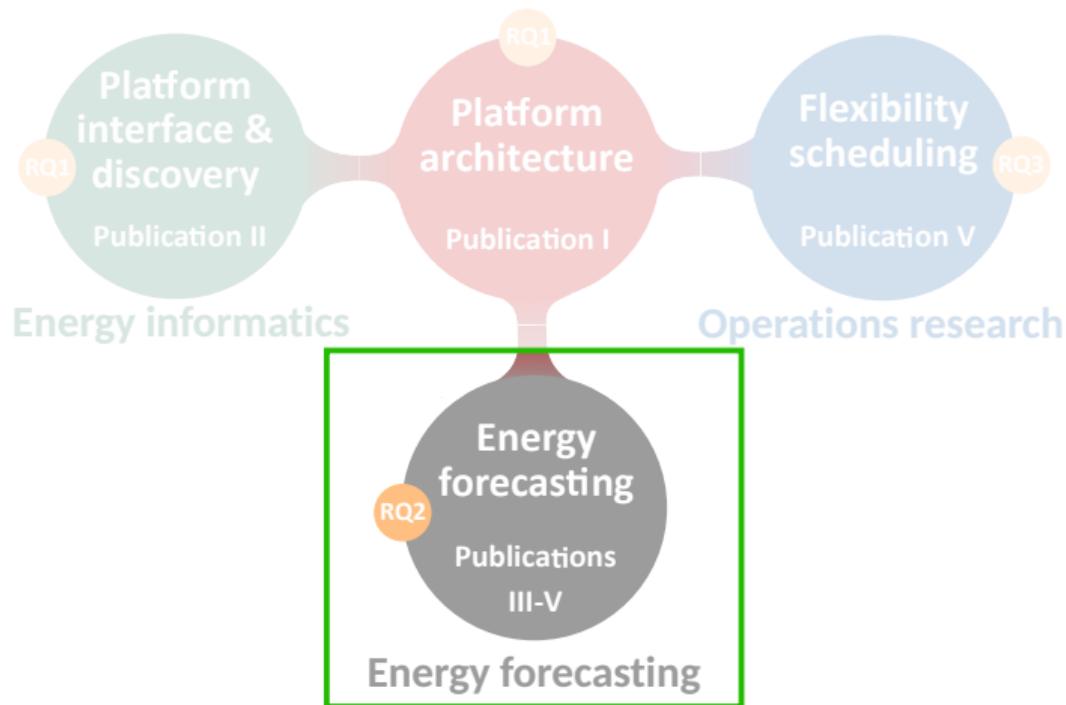
CONTRIBUTIONS

Research question #1

1. Design of a smart grid architecture enabling **interoperable technological integration** of local energy management platforms into the provision of grid-flexibility services (**Publication I**)
 - ▶ summarizes functional, information, and communication requirements;
 - ▶ describes an interoperable information exchange solution.
2. Design and implementation of a high-performance architecture of a **flexibility registry** (**Publication II**)
 - ▶ stores and shares machine-readable information about local energy systems.

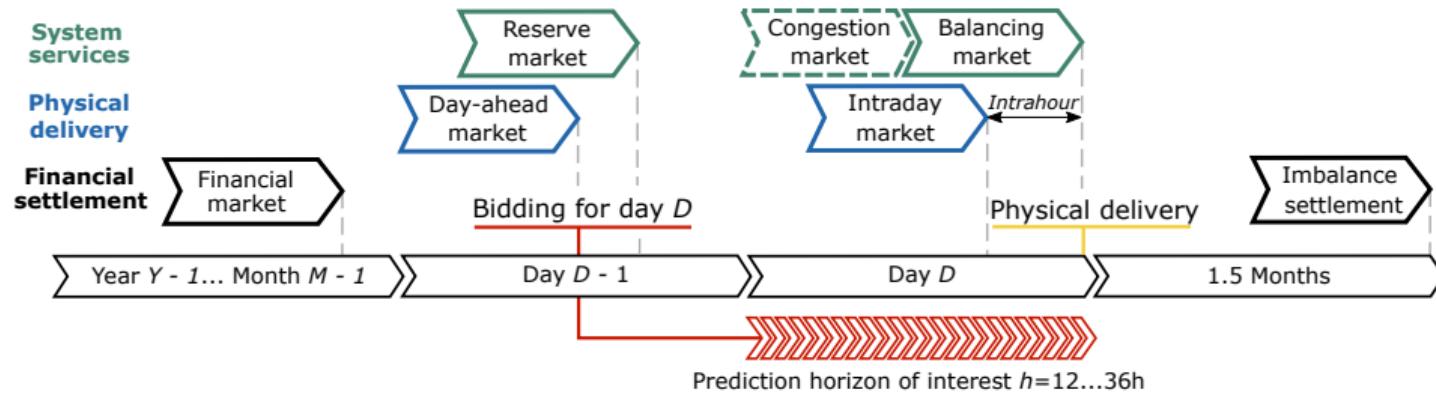
RESEARCH QUESTION #2

How uncertain are deep machine learning models?



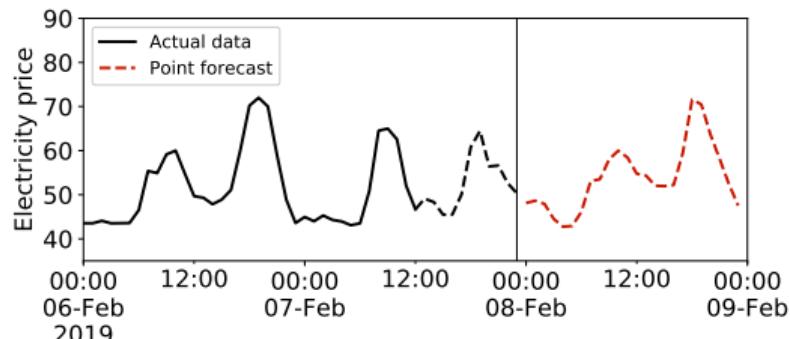
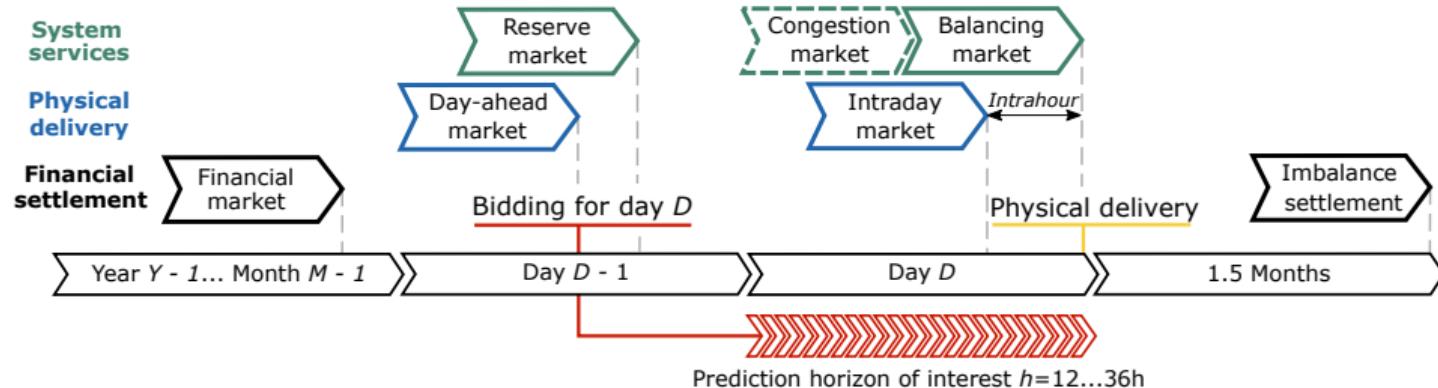
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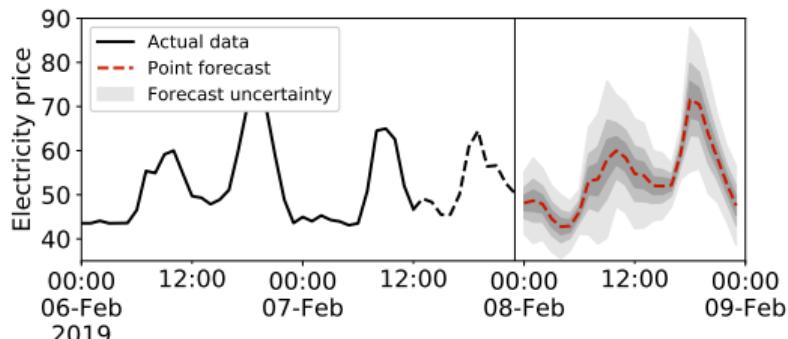
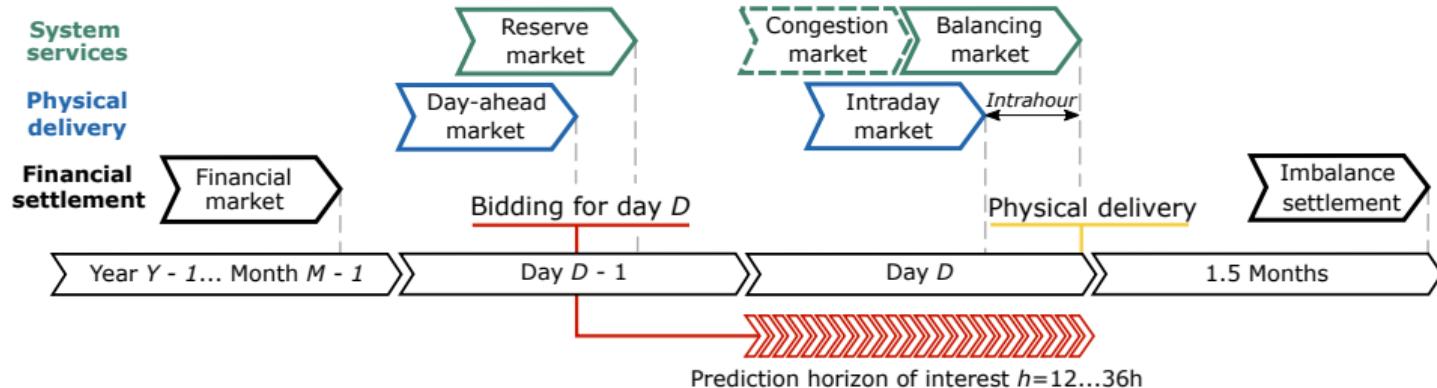
How uncertain are deep machine learning models?



- Vulnerable to forecast errors
- ▶ low risk-awareness

RESEARCH QUESTION #2

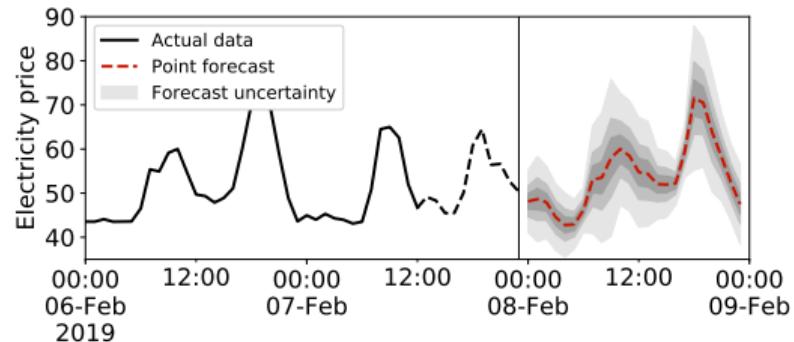
How uncertain are deep machine learning models?



- Predictive region with degree of confidence
 - ▶ Enables risk-aware decision-making

RESEARCH QUESTION #2

How uncertain are deep machine learning models?



RQ #2 *What are the effective criteria in data-driven characterization of the energy forecasting uncertainties arising from the data generating processes associated with flexibility management?*

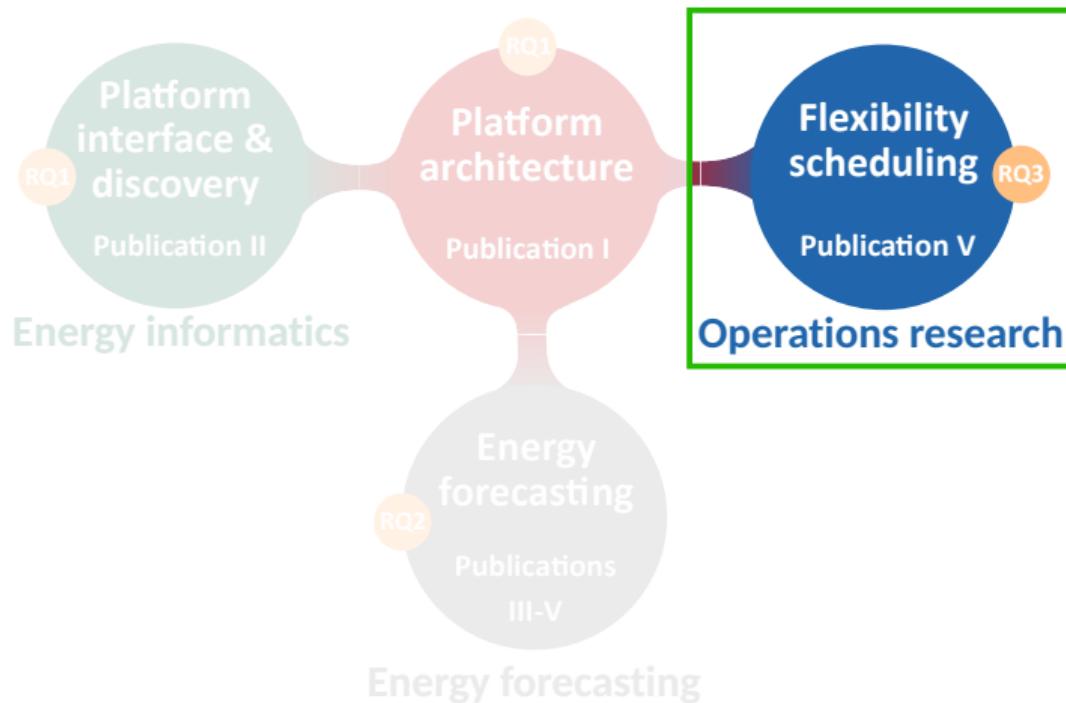
CONTRIBUTIONS

Research question #2

1. Empirical comparison of **uncertainty-aware** deep learning, machine learning, and statistical methods in a **novel application domain** (**Publication III**)
 - ▶ Battery storage energy activation under provision of a frequency control
2. Empirical evaluation of **uncertainty-aware** global deep learning models to **multivariate energy forecasting** problems (**Publication IV**)
 - ▶ individual electricity consumption as well as regional and national electricity consumption, market price, and renewable generation
 - ▶ model sensitivity to dataset transformation
 - ▶ model run-time efficiency
3. Empirical evaluation of **diverse probability distributions** on the predictive capability of global deep learning models
 - ▶ residential prosumer net load, national carbon intensity, and battery storage reserve activation parameters

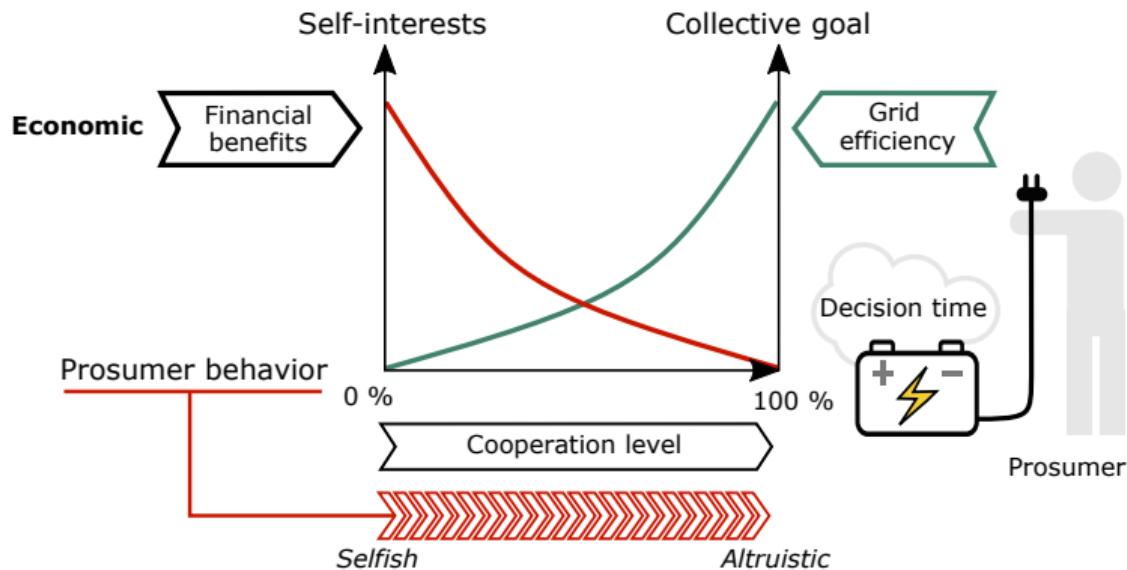
RESEARCH QUESTION #3

Are the prosumers willing to support the grid?



RESEARCH QUESTION #3

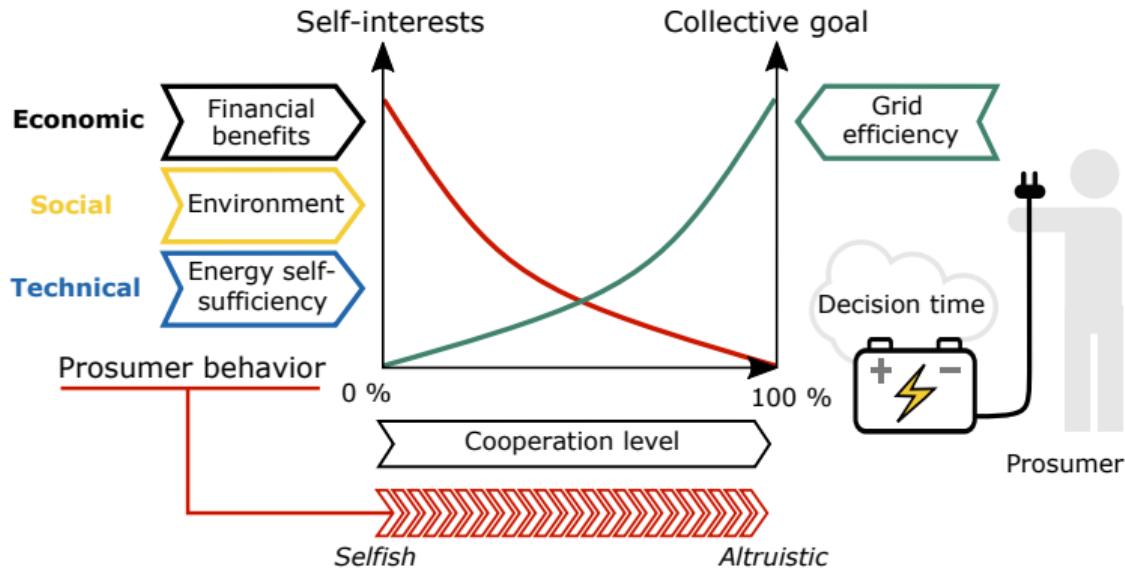
Are the prosumers willing to support the grid?



- Self-oriented decision-making
 - ▶ inefficient or harmful use of a shared grid
 - ▶ need of energy management coordination
- Heterogeneous prosumer motivations
 - ▶ need to fulfill the trade-off

RESEARCH QUESTION #3

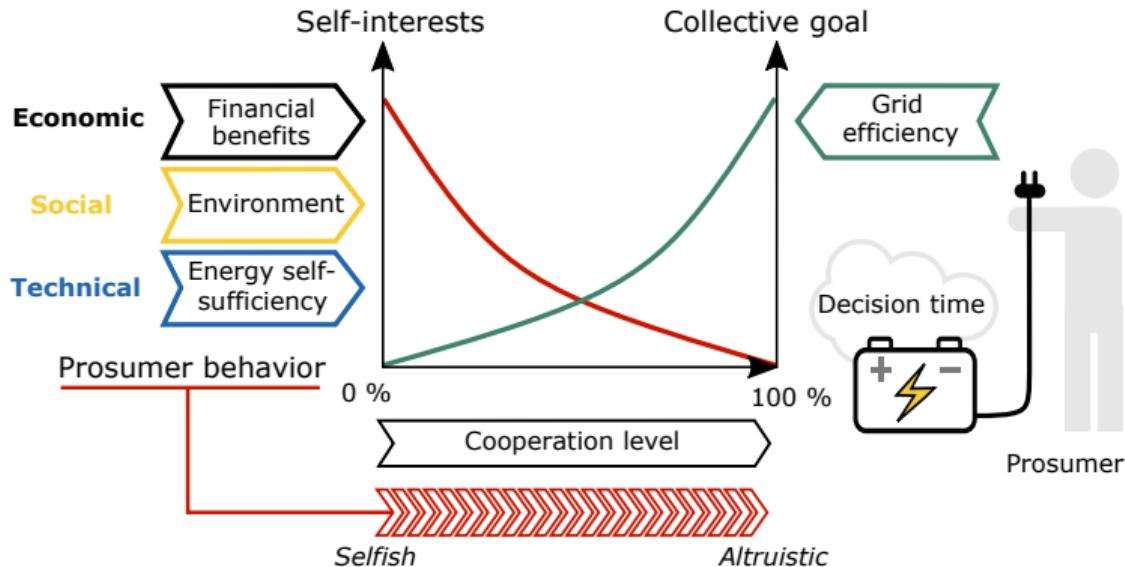
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RQ #3 What are the critical factors of the prosumer operational flexibility allocation fulfilling the system-wide multiobjective objective trade-offs for the preferred flexibility usage?

CONTRIBUTIONS

Research question #3 (Publication V)

1. A household-level **flexibility scheduling framework** for a local energy system that
 - ▶ captures the techno-socio-economic motivations of prosumers
 - ▶ performs cooperative and privacy-preserving coordination for grid efficiency
2. A socio-technical impact and **optimality analysis** of varying prosumer cooperation on
 - ▶ individual vs collective flexibility scheduling objectives
 - ▶ Pareto optimal cooperation level
3. Quantitative analysis of **forecast uncertainty factors** on
 - ▶ realization of a planned net load schedules
 - ▶ battery storage unavailability
4. Quantitative analysis of **techno-economic efficiency** of providing the frequency control service by a population of residential battery storages

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Summary

CONTRIBUTIONS

Summary

- i. Lack of **technological interoperability** between the flexibility aggregation platforms:
 - ▶ Proposed a design of a decentralized smart grid architecture enabling **interoperable integration of local energy management platforms** into the provision of grid-flexibility services;
- ii. **Uncertainty quantification** of energy forecast in the flexibility management:
 - ▶ Empirically evaluated **novel deep learning models** in probabilistic energy forecasting of data generating processes assisting in the decision-making of flexibility management;
- iii. **Flexibility allocation** problem under heterogeneous prosumer interests in its usage:
 - ▶ Formulated and quantitative evaluated decentralized **cooperative flexibility scheduling** of a local energy system under individual **techno-socio-economic trade-offs** of prosumer flexibility allocation.

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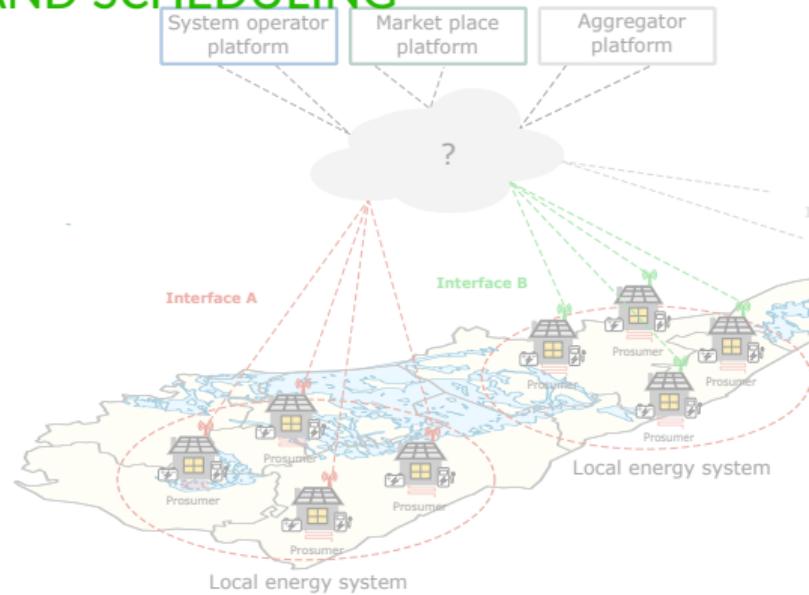
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BACK-UP SLIDES

QUESTION

PUBLICATIONS

- Publication I** Mashlakov, A., Tikka, V., Honkapuro, S., Partanen, J., Repo, S., Kulmala, A., Abdurafikov, R., Keski-Koukkari, A., Aro, M., and Järventausta, P. (2018). Use case description of real-time control of microgrid flexibility. In: *Proceedings of 15th International Conference on the European Energy Market (EEM)*, pp. 1–5, Lodz: IEEE.
- Publication II** Mashlakov, A., Keski-Koukkari, A., Tikka, V., Kulmala, A., Repo, S., Honkapuro, S., Aro, M., and Jafary, P. (2019). Uniform Web of Things based access to distributed energy resources via metadata registry. In: *25th International Conference on Electricity Distribution (CIRED)*, pp. 1–5, Madrid: AIM.
- Publication III** Mashlakov, A., Lensu, L., Kaarna, A., Tikka, V., and Honkapuro, S. (2020). Probabilistic forecasting of battery energy storage state-of-charge under primary frequency control. *IEEE Journal on Selected Areas in Communications*, 38(1), pp. 96–109.
- Publication IV** Mashlakov, A., Kuronen, T., Lensu, L., Kaarna, A., and Honkapuro, S. (2021). Assessing the performance of deep learning models for multivariate probabilistic energy forecasting. *Applied Energy*, 285, pp. 116405.
- Publication V** Mashlakov, A., Pournaras, E., Nardelli, P.H.J., and Honkapuro, S. (2021). Decentralized cooperative scheduling of prosumer flexibility under forecast uncertainties. *Applied Energy*, 290, pp. 116706.

METHODOLOGY

Model-driven architecture development

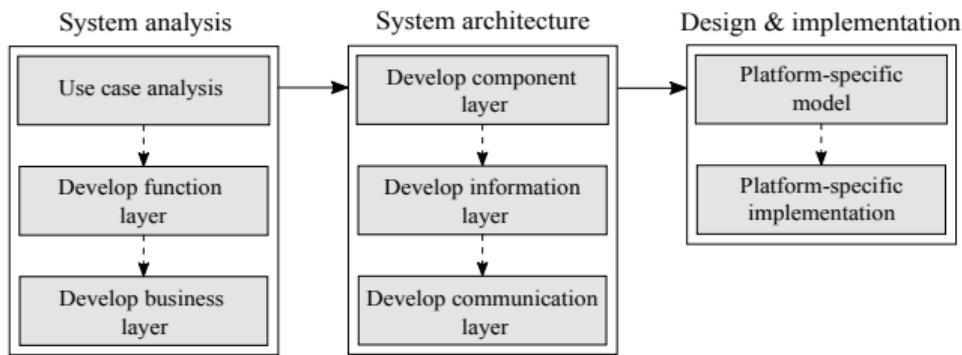


Figure: Model-driven architecture development. Adapted from [2].

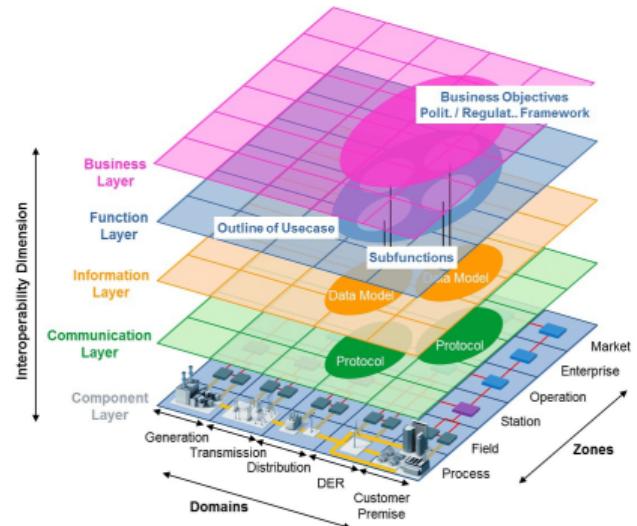
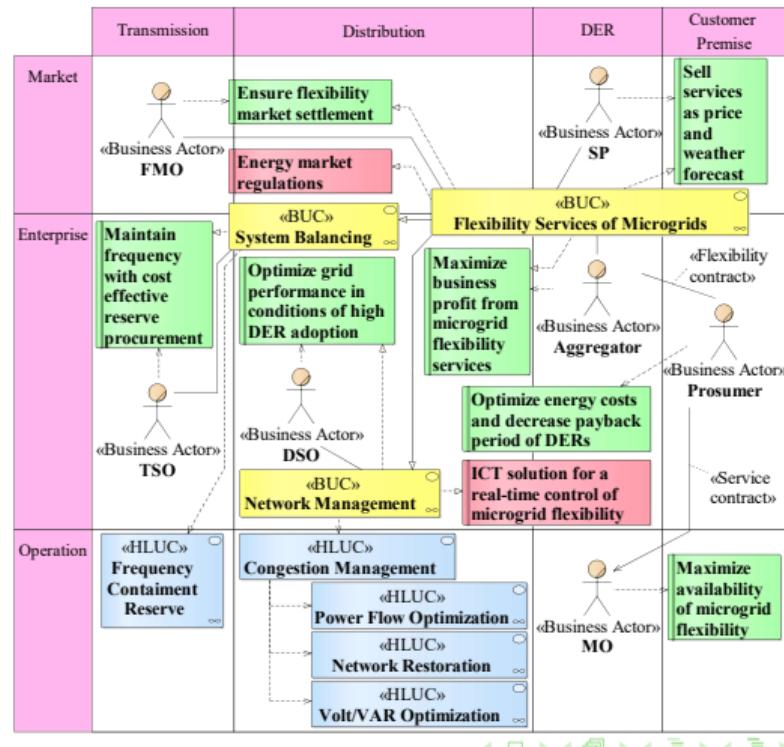
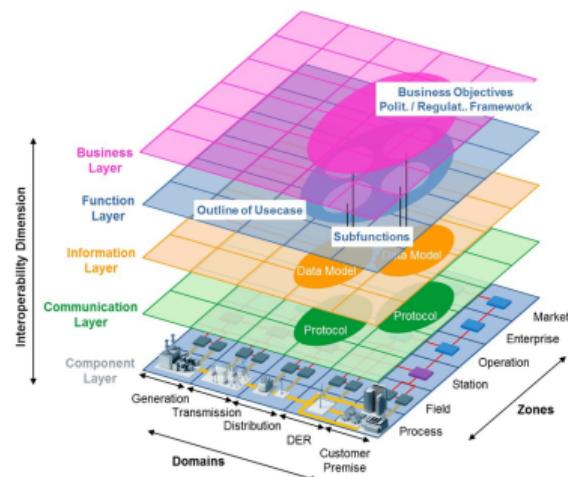


Figure: SGAM representation. Source: [1].

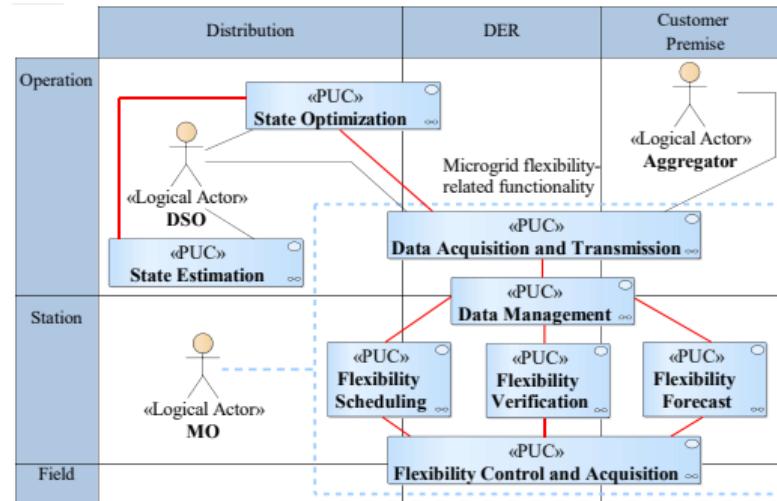
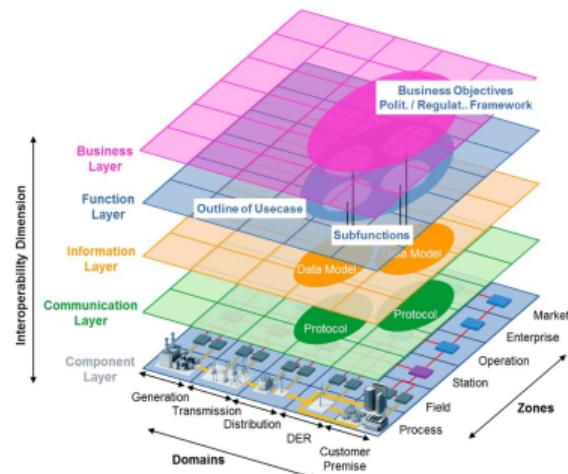
FLEXIBILITY SERVICES OF MICROGRIDS

Business use case



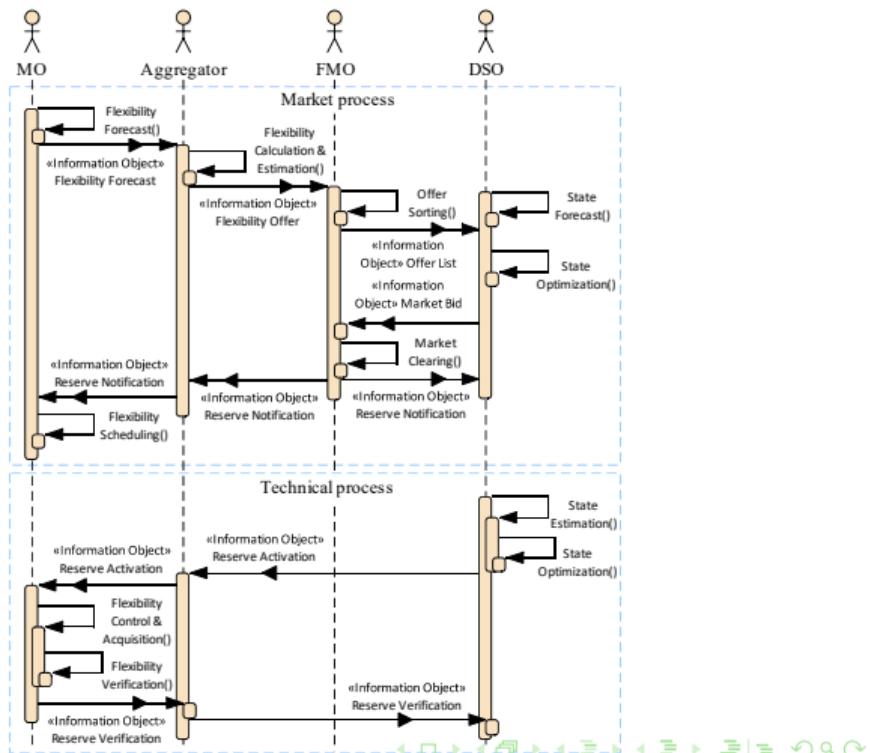
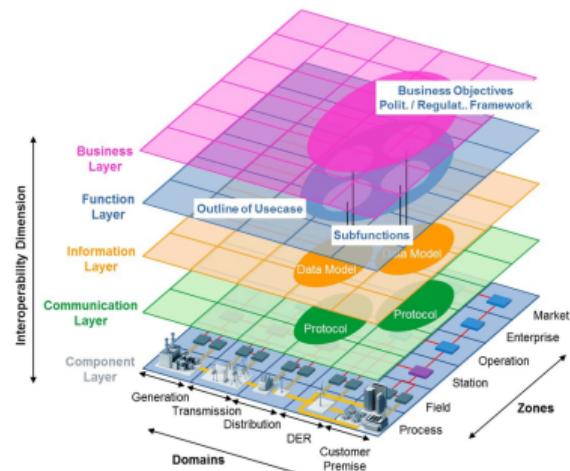
FLEXIBILITY SERVICES OF MICROGRIDS

Functional layer



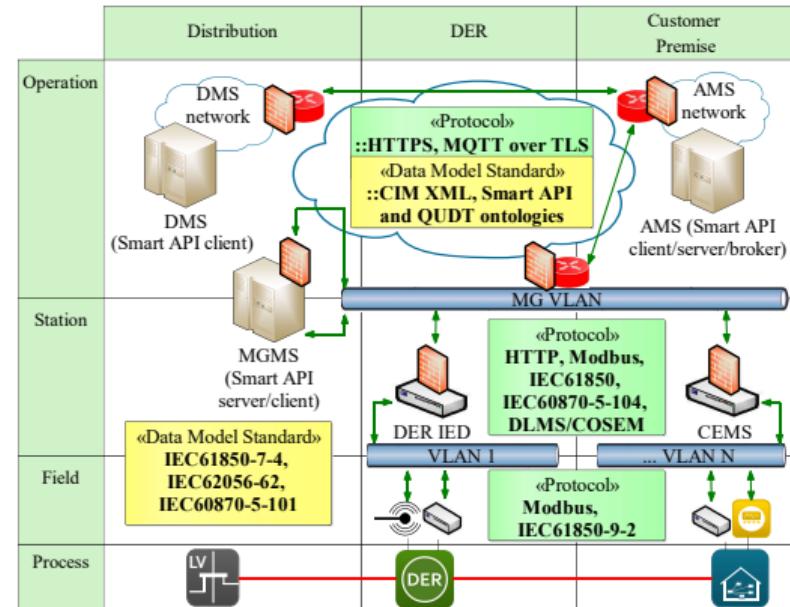
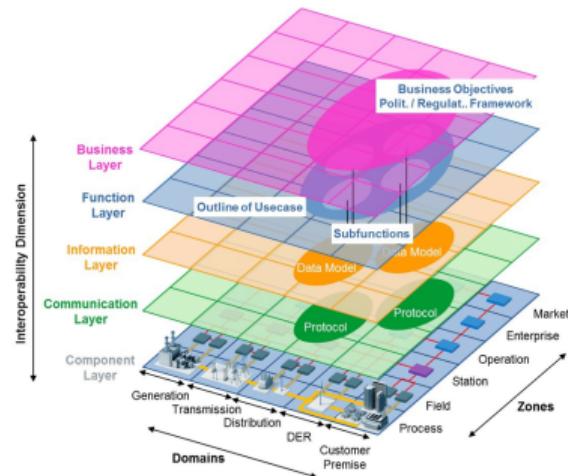
FLEXIBILITY SERVICES OF MICROGRIDS

Exchange messages



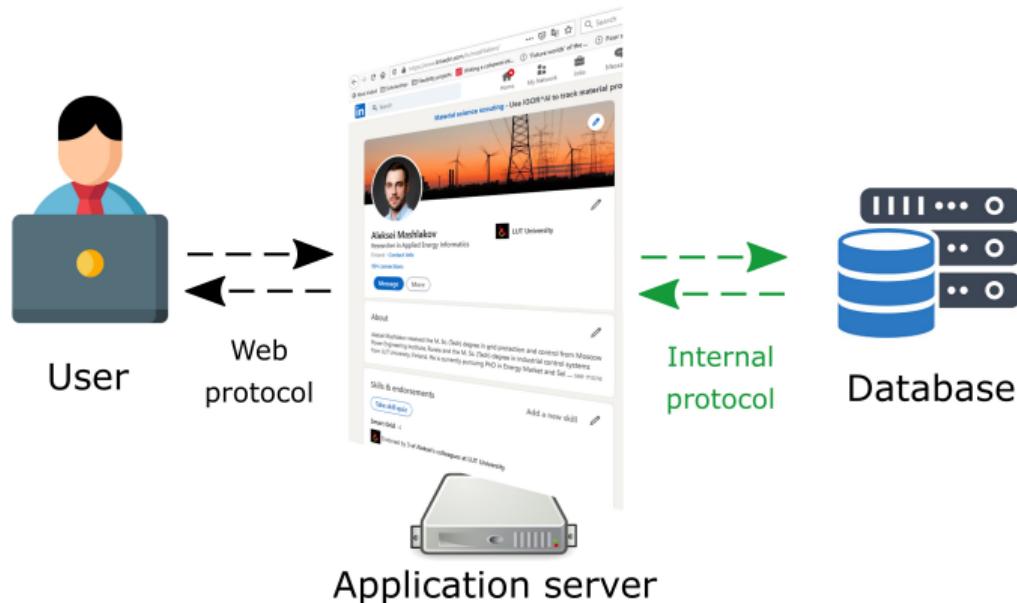
FLEXIBILITY SERVICES OF MICROGRIDS

Information, communication, and component layers



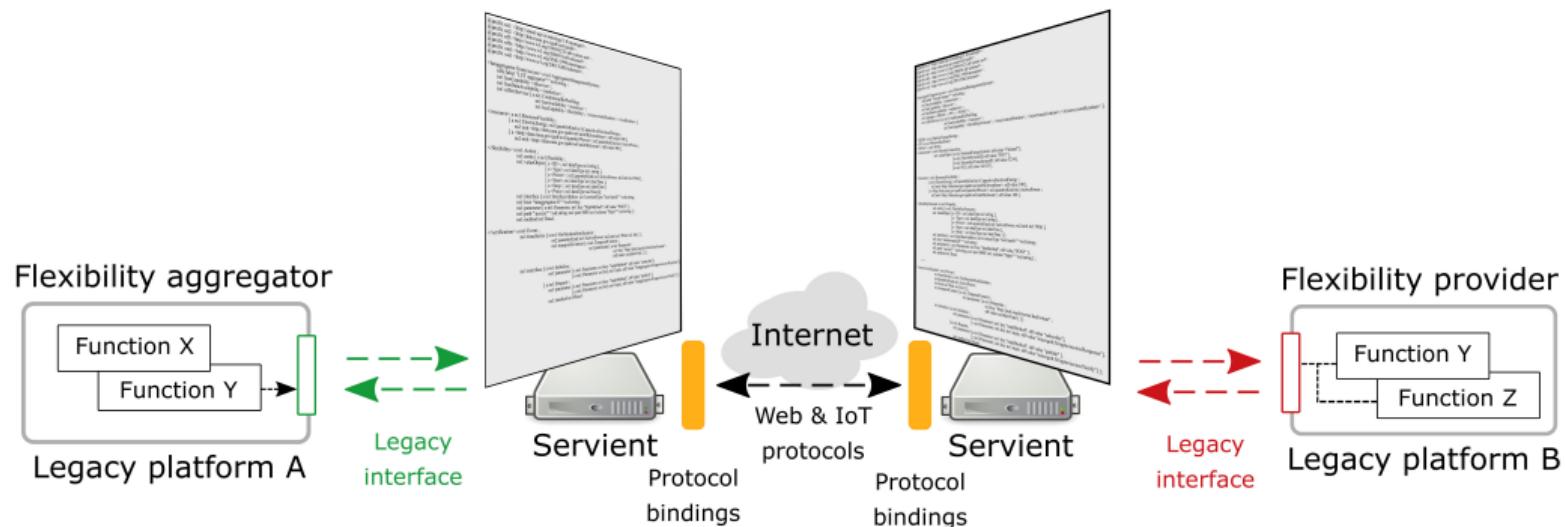
FLEXIBILITY SERVICES OF MICROGRIDS

Web-based information exchange



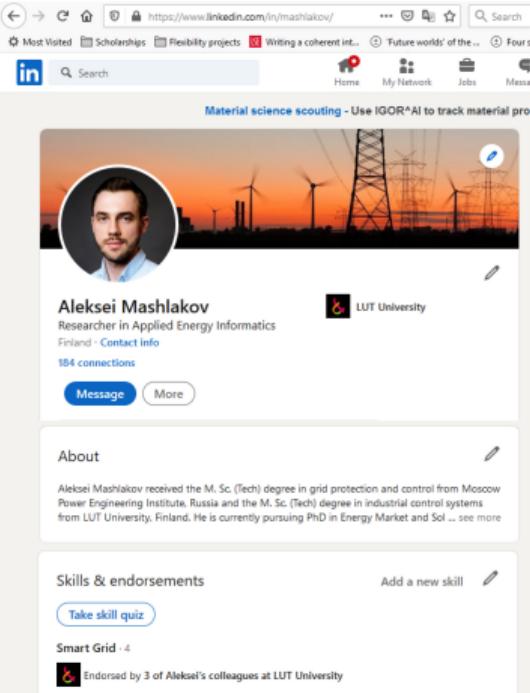
FLEXIBILITY SERVICES OF MICROGRIDS

Web-of-Things-based information exchange



FROM WEB OF PAGES TO WEB OF THINGS

Semantic metadata



A screenshot of Aleksei Mashlakov's LinkedIn profile page. The profile picture shows a man with dark hair and a beard. The background of the profile section features a sunset over wind turbines and power lines. Below the profile picture, the name "Aleksei Mashlakov" is displayed, followed by the title "Researcher in Applied Energy Informatics" and "Finland". It shows "184 connections" and buttons for "Message" and "More". The "About" section contains a brief bio: "Aleksei Mashlakov received the M. Sc. (Tech) degree in grid protection and control from Moscow Power Engineering Institute, Russia and the M. Sc. (Tech) degree in industrial control systems from LUT University, Finland. He is currently pursuing PhD in Energy Market and Sol ... see more". The "Skills & endorsements" section lists "Smart Grid - 4" and "Endorsed by 3 of Aleksei's colleagues at LUT University".

```
@prefix ns1: <http://www.w3.org/2009/08/rif#> .
@prefix ns2: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .
@prefix smil: <http://www.w3.org/XML/1998/namespace#> .
@prefix xsd: <http://www.w3.org/2001/XMLSchema#> .

<#engrid:flexibilityAccess> a ns1:MicroGridManagementSystem ;
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  ns1:hasCapability <discover> ;
  ns1:hasDataAvailability <service> ;
  ns1:manages <BE> ns1:<PV> , ns1:<HVAC> ;
  ns1:offersService <ns1:ConditionalProfileForecast> ;
  ns1:hasAvailability <resource> ;
  ns1:hasCapability <flexibilityForecast> , <reserveNotification> , <reserveActivation> , <reserveVerification> .

<#ERS> a ns1:BatteryEnergyStorage .
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<#HVAC> a ns1:HVAC .
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  ns1:flexibilityArnoldID rdf:value "FIN1" ;
  ns1:secondaryTransfererID rdf:value 3234 ;
  ns1:PCC ; rdf:value 342133 ].

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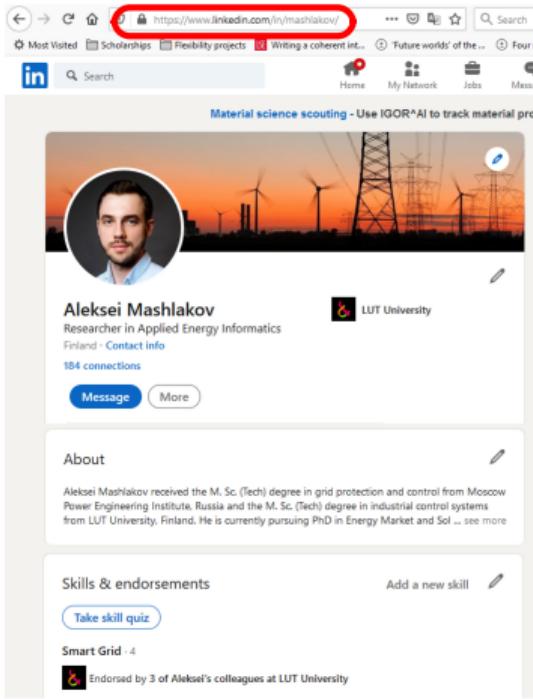
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    a <#Type> ; ns1:dataType ns1:string ] ;
  a <#Power> ; ns2:quantityKind ns1:ActivePower ; ns2:unit ns1:Watt ] ;
  [ a <#Time> ; ns1:datatype ns1:dateTime ] ;
  [ a <#Stop> ; ns1:datatype ns1:dateTime ] ] ;
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  ns1:host "http://minergrid.fi/" ; ns1:string ;
  ns1:parameter [ a ns1:Parameter ; ns1:key "httpMethod" ; ns1:value "POST" ] ;
  ns1:path "/access" ; ns1:value "xsd:string" ;
  ns1:scheme "https" ; ns1:string ] ;
  ns1:method ns1:Read .

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    ns2:unit ns1:Watt ; ns1:list [ ] ] ;
  ns1:temporalContext [ a ns1:TemporalContext ;
    ns1:parameter [ a ns1:Parameter ;
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      ns1:value xsd:dateTime ] ] ] ;
  ns1:interface [ a ns1:Initialize ;
    ns1:parameter [ a ns1:Parameter ; ns1:key "httpMethod" ; ns1:value "subscribe" ] ,
    [ a ns1:Parameter ; ns1:key ns1:topic ; ns1:value "minergid.fi/mgms/access/Response" ] ;
    a ns1:Request ;
    ns1:parameter [ a ns1:Parameter ; ns1:key "httpMethod" ; ns1:value "publish" ] ,
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    ns1:method ns1:Read ] .
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FROM WEB OF PAGES TO WEB OF THINGS

Semantic metadata



The screenshot shows Aleksei Mashlakov's LinkedIn profile. At the top, the URL https://www.linkedin.com/in/mashlakov/ is highlighted with a red box. Below the URL, there are several tabs: Most Visited, Scholarships, Flexibility projects, Writing a coherent int..., Future worlds of the..., Fours. The main content area features a banner for "Material science scouting - Use IGOR^AI to track material pro..." with a circular profile picture of Aleksei. His name, "Aleksei Mashlakov", is displayed with a "LUT University" badge. Below his name, it says "Researcher in Applied Energy Informatics". He has 184 connections and a "Message" button. The "About" section includes a bio: "Aleksei Mashlakov received the M. Sc. (Tech) degree in grid protection and control from Moscow Power Engineering Institute, Russia and the M. Sc. (Tech) degree in industrial control systems from LUT University, Finland. He is currently pursuing PhD in Energy Market and Sol ... see more". The "Skills & endorsements" section lists "Smart Grid" with a value of 4, and it says "Endorsed by 3 of Aleksei's colleagues at LUT University".

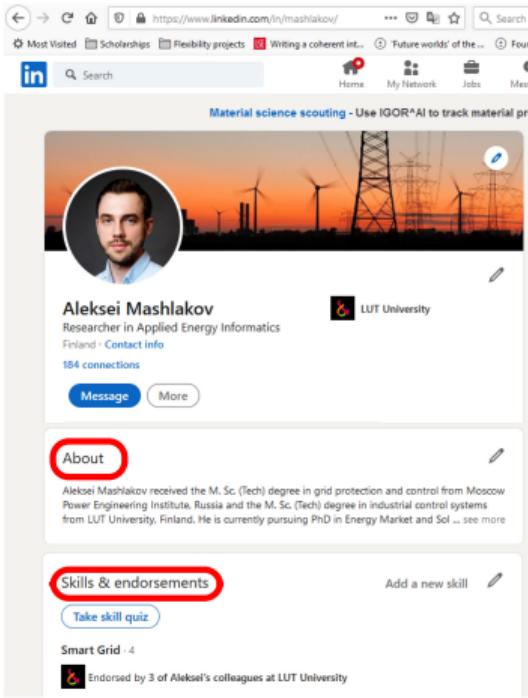
Unique identification

```
@prefix ns1 <http://www.w3.org/2002/07/owl#> .
@prefix ns2 <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix ns3 <http://www.w3.org/2000/01/rdf-schema#> .
@prefix ns4 <http://www.w3.org/1998/03/01-xmlNamespace#> .
@prefix ns5 <http://www.w3.org/2001/XMLSchema#> .
@prefix ns6 <http://www.w3.org/2001/XMLSchema#> .

microgrid:mngs:access a ns1:MicroGridManagementSystem ;
    ns1:hasAvailability <connection> ;
    ns1:hasCapability <discover> ;
    ns1:hasDataAvailability <storage> ;
    ns1:manages <BESS> ;
    ns1:usesService [ a ns1:HasService ;
        ns1:hasAvailability <resource> ;
        ns1:hasCapability <flexibilityForecast>, <reserveactivation>, <reserveverification> ] ;
    <BESS> a ns1:BatteryEnergyStorage ;
    <PV> a ns1:PhotovoltaicPanel ;
    <HVAC> a ns1:HVAC ;
    <connection> a ns1:ElectricConnection ;
        ns1:valueObject [ a ns1:NaturalEnergySystem ; ns1:value "Finland" ;
            a ns1:flexibilityArnID ; ns1:value "FIN1" ;
            a ns1:secondaryTransformerID ; ns1:value 3234 ;
            a ns1:PIC ; ns1:value 342133 ] ;
    <resource> a ns1:ResourceFlexibility ;
        ns1:unit [ a ns1:ElectricQuantityKind ; ns1:quantityKind "Capacitor-ElectricEnergy" ;
            ns2:unit <http://data.nasa.gov/quid/wattKilowattHour> ; ns2:value 100 ] ,
        [ a <http://data.nasa.gov/quid/wattQuantityPower> ; ns2:quantityKind ns1:ActivePower ;
            ns2:unit <http://data.nasa.gov/quid/wattUnitKilowatt> ; ns2:value 100 ] ;
    <flexibilityForecast> a ns1:Property ;
        ns1:unit [ a ns1:flexibilityForecast ;
            ns1:valueObject [ a :ID ; ns1:dataType ns1:string ] ;
            a :Type ; ns1:datatype ns1:string ;
            a :Power ; ns2:quantityKind ns1:ActivePower ; ns2:unit ns1:Watt ] ,
        [ a :start ; ns1:datatype ns1:dateTime ] ;
        ns1:interface [ a ns1:InterfaceAddress ; ns1:socketType "rest/uri" ; ns1:string ;
            ns1:host "microgrid.fi" ; ns1:string ;
            ns1:parameter [ a ns1:Parameter ; ns1:key "httpMethod" ; ns1:value "POST" ] ;
            ns1:path "/access" ; ns1:string ; ns1:port 8080 ; ns1:scheme "https" ; ns1:string ;
            ns1:method ns1:Read ] ;
    ...
</reserveverification> a ns1:From ;
    ns1:toSeries [ a ns1:NotificationNotification ;
        ns2:quantityKind ns1:ActivePower ;
        ns2:unit ns1:Watt ; ns1:unit [ ] ;
        ns1:temporalContext [ a ns1:TemporalContext ;
            ns1:parameter [ a ns1:Parameter ;
                ns1:key "http://purl.org/dc/terms/hasFormat" ;
                ns1:value "sdDate/Time" ] ] ] ;
    ns1:interface [ a ns1:Initialize ;
        ns1:parameter [ a ns1:Parameter ; ns1:key "ingmMethod" ; ns1:value "subscribe" ] ,
        [ a ns1:Parameter ; ns1:key ns1:topic ; ns1:value "microgrid:mngs:access/Response" ] ;
        a ns1:Request ;
        ns1:parameter [ a ns1:Parameter ; ns1:key "ingmMethod" ; ns1:value "publish" ] ,
        [ a ns1:Parameter ; ns1:key ns1:topic ; ns1:value "microgrid:mngs:access/Notify" ] ;
        ns1:method ns1:Read ] .
```

FROM WEB OF PAGES TO WEB OF THINGS

Semantic metadata



Aleksei Mashlakov
Researcher in Applied Energy Informatics
Finland · Contact info
184 connections
Message More

About
Aleksei Mashlakov received the M. Sc. (Tech) degree in grid protection and control from Moscow Power Engineering Institute, Russia and the M. Sc. (Tech) degree in industrial control systems from LUT University, Finland. He is currently pursuing PhD in Energy Market and Sol ... see more

Skills & endorsements
Add a new skill
Take skill quiz
Smart Grid · 4
Endorsed by 3 of Aleksei's colleagues at LUT University

Info &
Properties

```
@prefix ns1 <http://www.w3.org/2005/08/semantics/ns#> .
@prefix ns2 <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix ns3 <http://www.w3.org/2000/01/rdf-schema#> .
@prefix xsd <http://www.w3.org/2001/XMLSchema#> .
@prefix sd <http://www.w3.org/2001/03/XMLSchema#> .

<microgrid/microgridAccess> a ns1:MicroGridManagementSystem ;
  ns1:hasAvailability <connection> ;
  ns1:hasCapability <discover> ;
  ns1:hasDataAvailability <storage> ;
  ns1:manages <BESS> ;
  ns1:offersService <ns1:ConditionalReProfiling> ;
  ns1:hasAvailability <resource> ;
  ns1:hasCapability <flexibilityForecast> ;
  ns1:reservenotification <reservenotification> ;
  ns1:reserveactivation <reserveactivation> ;
  ns1:reserveverification <reserveverification> .

<BESS> a ns1:BatteryEnergyStorage .
<PV> a ns1:PhotovoltaicPanel .
<HVAC> a ns1:HVAC .
<connection> a ns1:ElectricConnection ;
  ns1:valueObject [ a ns1:NationalEnergySystem ; rdf:value "Finland" ] ;
  [ a ns1:FlexibilityAreaID ; rdf:value "FIN1" ] ;
  [ a ns1:SecondaryTransformerID ; rdf:value 3234 ] ;
  [ a ns1:PPCC ; rdf:value 342133 ] .

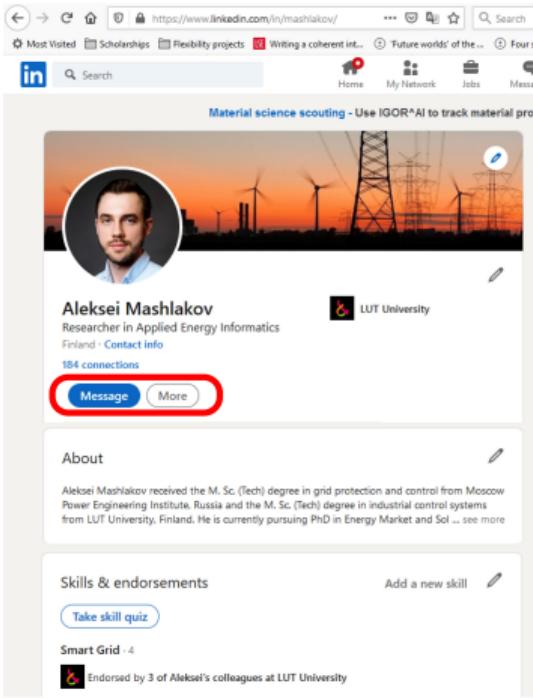
<resource> a ns1:Resourceflexibility ;
  [ a ns1:ElectricQuantityKind ns1:CognitiveElectricEnergy ;
    ns2:unit <http://data.nasa.gov/quantity/unit/KilowattHour> ; ns2:value 100 ] ;
  [ a <http://data.nasa.gov/quantity/power> ;
    ns2:unit ns1:ActivePower ;
    ns2:unit <http://data.nasa.gov/quantity/unit/Kilowatt> ; ns2:value 100 ] .

<flexibilityForecast> a ns1:Property ;
  ns1:entity [ a ns1:FlexibilityForecast ;
    ns1:valueObject [ a <DE> ; ns1:dataType ns1:string ] ,
    [ a <Type> ; ns1:dataType ns1:string ] ,
    a <Power> ;
    ns1:quantityKind ns1:ActivePower ; ns2:unit ns1:Watt ] ;
  [ a <Step> ; ns1:dateTime ns1:dateTime ] ;
  ns1:interface [ a ns1:InterfaceAddress ; ns1:contentType "text/turtle" ; ns1:string ;
    ns1:host "timbergrid.fi" ; ns1:port 8080 ; ns1:scheme "https" ; ns1:method ns1:Read ] ;
  ...

<reserveverification> a ns1:Event ;
  ns1:series [ a ns1:VerificationNotification ;
    ns2:quantityKind ns1:ActivePower ;
    ns2:unit ns1:Watt ; ns1:list [ ] ;
    ns1:temporalContext [ a ns1:TemporalContext ;
      ns1:parameter [ a ns1:Parameter ;
        ns1:key "http://uri.org/terms/hasFormat" ;
        ns1:value nsd:sdTime ] ] ] ;
  ns1:interface [ a ns1:Initialize ;
    ns1:parameter [ a ns1:Parameter ; ns1:key "initMethod" ; rdf:value "subscribe" ] ,
    [ a ns1:Parameter ; ns1:key ns1:topic ; ns1:value "microgrid/microgridAccess/Response" ] ;
    ns1:Request ;
    ns1:parameter [ a ns1:Parameter ; ns1:key "initMethod" ; rdf:value "publish" ] ,
    [ a ns1:Parameter ; ns1:key ns1:topic ; ns1:value "microgrid/microgridAccess/Notify" ] ;
    ns1:method ns1:Read ] .
```

FROM WEB OF PAGES TO WEB OF THINGS

Semantic metadata



```

@prefix ns1 <http://www.w3.org/2005/08/semantics/sparql11-query#> .
@prefix ns2 <http://data.miso.gov/odrl/owl#> .
@prefix rdf <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix rdfs <http://www.w3.org/2000/01/rdf-schema#> .
@prefix xml <http://www.w3.org/XML/1998/namespace#> .
@prefix xsd <http://www.w3.org/2001/XMLSchema#> .

<#mashlakov@lmi.lut.ac.be> a ns1:MicroGridManagementSystem ;
  ns1:label "GreenCampus" ; ns1:odrl:ManagementSystem ;
  ns1:hasAvailability <#connection> ;
  ns1:hasCapability <#discover> ;
  ns1:hasDataAvailability <#service> ;
  ns1:manages <#BESS> ; <#PV> ; <#HVAC> ;
  ns1:servesService [ a ns1:ConditionalOffering ;
    ns1:hasAvailability <#resource> ;
    ns1:hasCapability <#flexibilityForecast> , <#reservenotification> , <#reserveactivation> , <#reserveverification> ] ;
  <#BESS> a ns1:BatteryEnergyStorage ;
  <#PV> a ns1:PhotovoltaicPanel ;
  <#HVAC> a ns1:HVAC ;
  <#connection> a ns1:ElectricConnection ;
    ns1:valueObject [ a ns1:NationalIntergridSystem ; rdf:value "Finland" ] ;
    a ns1:FlexibilityAreaID ; rdf:value "FIN1" ;
    a ns1:SecondaryTransformerID ; rdf:value 3234 ;
    a ns1:PC ; rdf:value 142133 ] ;

<#resources> a ns1:ResourceFlexibility ;
  [ a ns1:flexibleOffer ; ns2:quantityKind ns1:CapacitiveElectricityOffer ;
    ns2:unit <http://data.miso.gov/odrl/owl#Kilowatthour> ; rdf:value 100 ] ,
  [ a <http://data.miso.gov/odrl/owl#quantityOfPower> ; ns2:quantityKind ns1:ActivePower ;
    ns2:unit <http://data.miso.gov/odrl/owl#unit Kilowatt> ; rdf:value 100 ] ;

<#flexibilityForecast> a ns1:Property ;
  ns1:entity [ a ns1:flexibilityForecast ;
    ns1:valueObject [ a <#D> ; ns1:dataType ns1:string ] ,
    a <#Type> ; ns1:dataType ns1:string ] ;
    a <#Power> ; ns2:quantityKind ns1:ActivePower ; ns2:unit ns1:Watt ] ,
  a <#Start> ; ns1:dataType ns1:dateTime ] ;

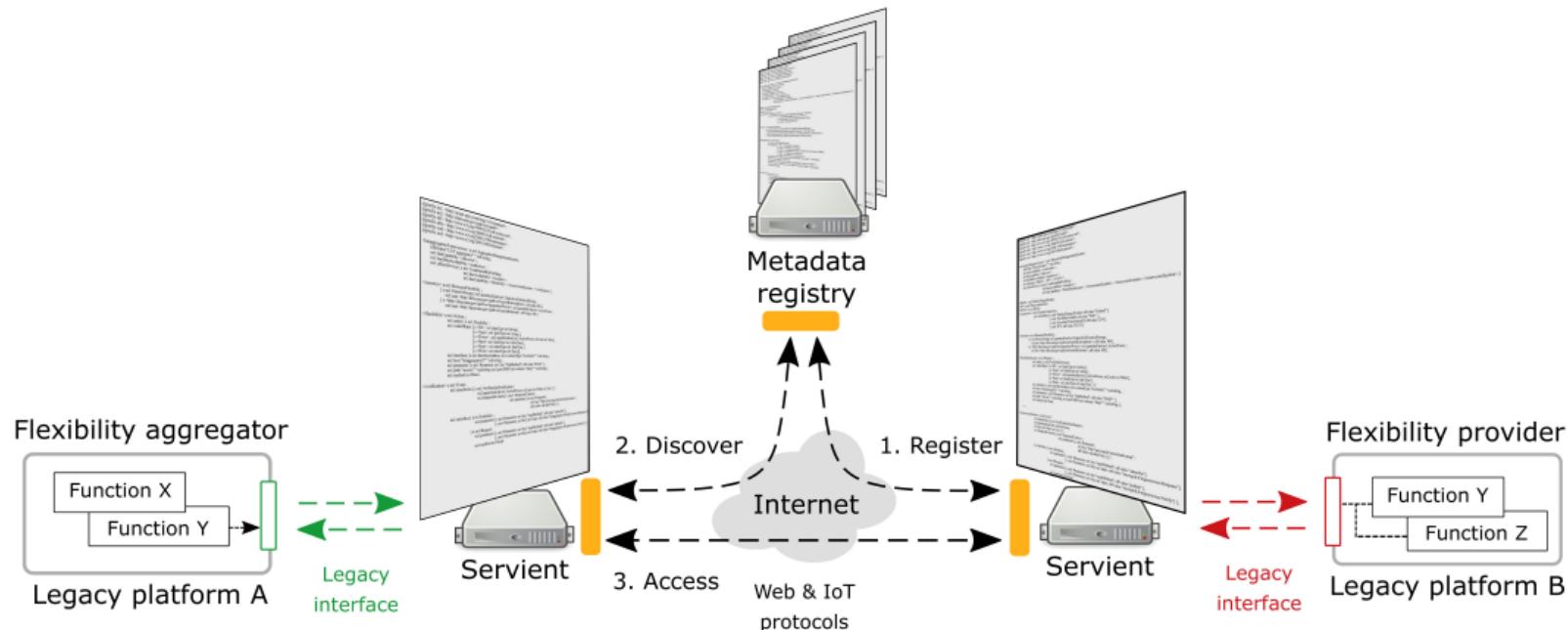
ns1:interface [ a ns1:InterfaceAddress ; ns1:contentType "text/plain" ; ns1:string ;
  ns1:host "lmi-gridif.lmi.lut.ac.be" ; ns1:parameter [ a ns1:Parameter ; ns1:key "httpMethod" ; ns1:value "POST" ] ;
  ns1:path "/access" ; ns1:port 8080 ; ns1:scheme "https" ; ns1:string ] ;
  ***

<#reservenotification> a ns1:Event ;
  ns1:inSeries [ a ns1:VerificationNotification ;
    ns2:quantityKind ns1:ActivePower ;
    ns2:unit ns1:Watt ; ns1:list [] ] ;
    ns1:temporalContext [ a ns1:TemporalContext ;
      ns1:parameter [ a ns1:Parameter ;
        ns1:key "http://uri.org/datetimehasFormat" ;
        ns1:value xsd:dateTime ] ] ] ;
  ns1:interface [ a ns1:Initialize ;
    ns1:parameter [ a ns1:Parameter ; ns1:key "httpMethod" ; ns1:value "subscribe" ] ;
    [ a ns1:Request ; ns1:parameter [ a ns1:Parameter ; ns1:key ns1:topic ; ns1:value "microgrid/lmi-gridif/mgms/access/Response" ] ;
      a ns1:Response ; ns1:parameter [ a ns1:Parameter ; ns1:key ns1:topic ; ns1:value "microgrid/lmi-gridif/mgms/access/Notify" ] ] ;
    ns1:method ns1:Read ] ;
  
```

Access
interfaces

FLEXIBILITY SERVICES OF MICROGRIDS

Web-of-Things-based metadata registry



FLEXIBILITY SERVICES OF MICROGRIDS

Web-of-Things-based metadata registry

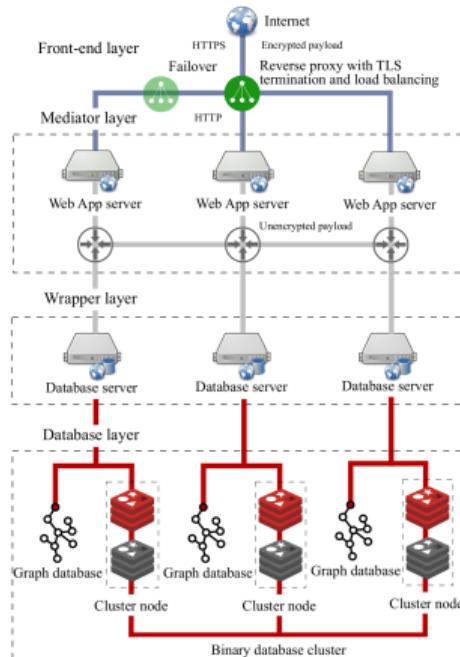


Figure: Flexibility registry architecture.

■ Nonfunctional design principles:

- ▶ multiple flexibility areas
- ▶ system-wide and location-specific flexibility services

■ Functional design principles:

- ▶ security, scalability, and availability even at times of high loads

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Methodology

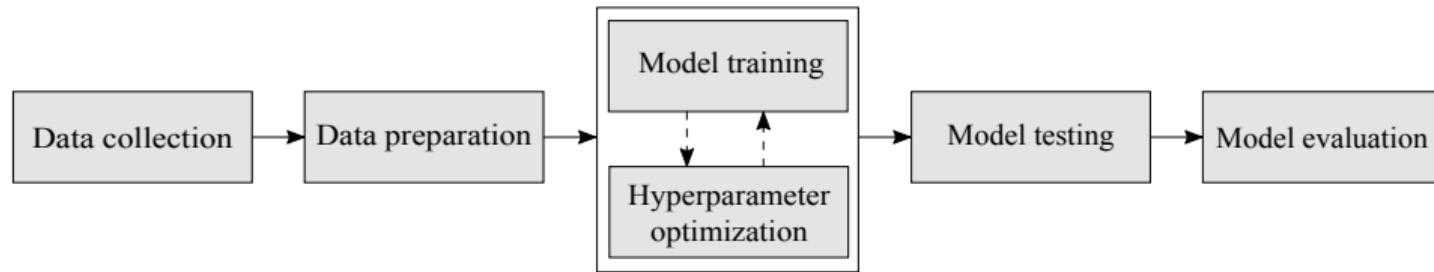


Figure: Research methodology for the performance estimation of probabilistic energy time series forecasting.

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Methodology

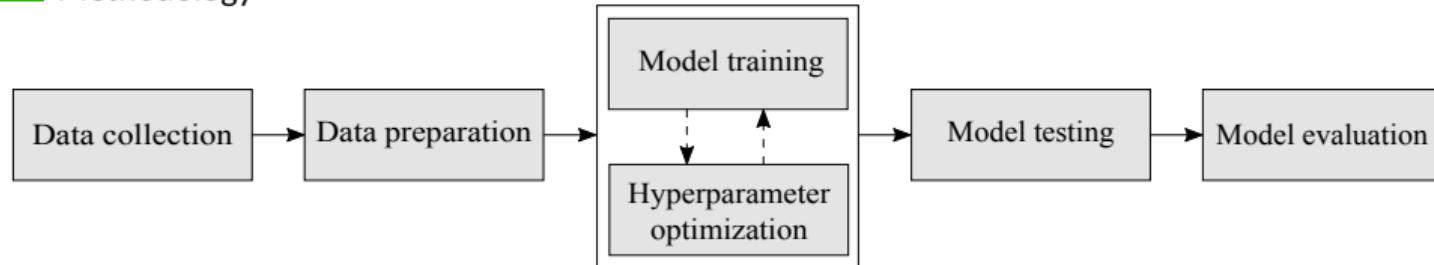


Figure: Research methodology for the performance estimation of probabilistic energy time series forecasting.

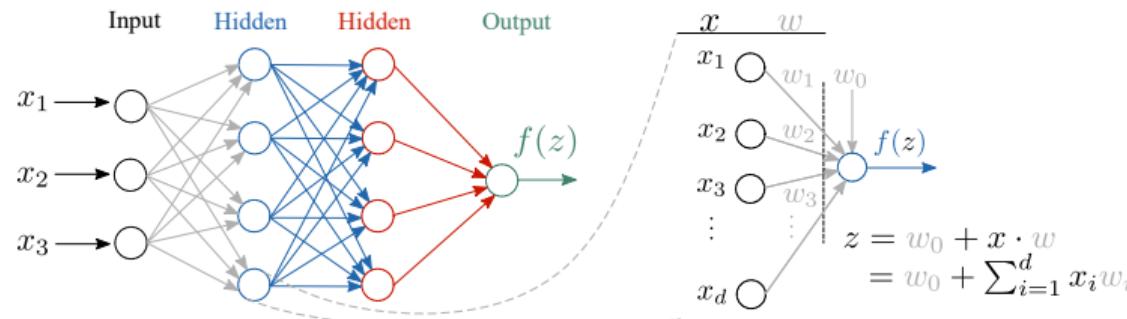


Figure: Deep learning model as a multi-layer artificial neural network.

Neural network training

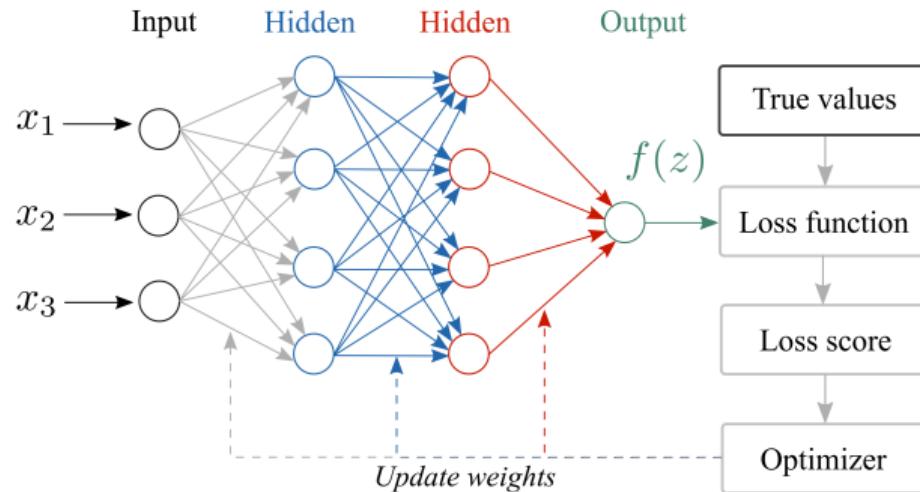


Figure: Neural network training for point forecasting.

DEEP LEARNING

Neural network training

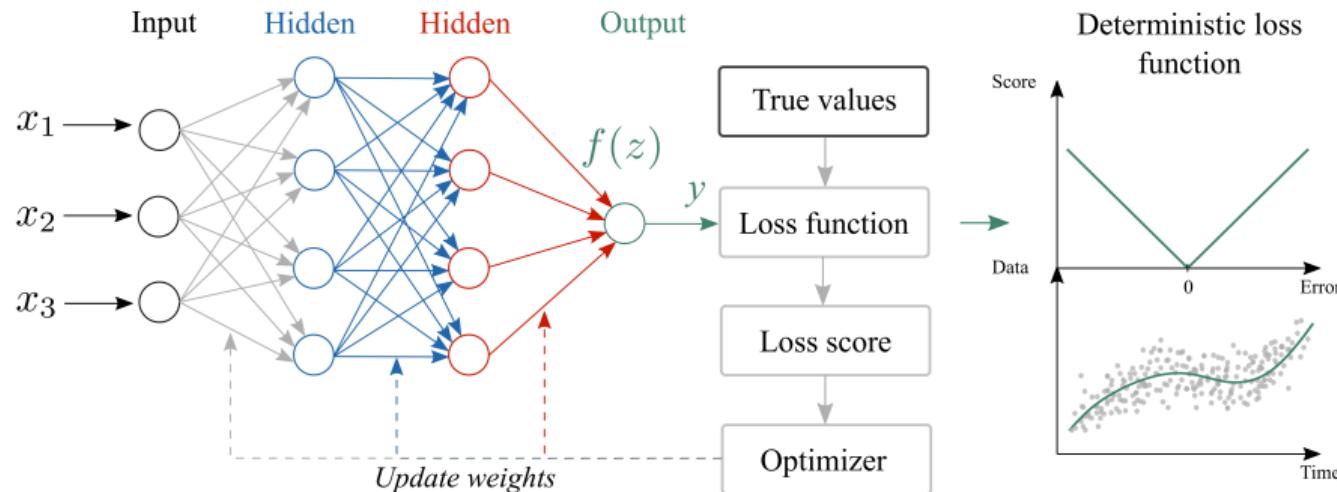


Figure: Neural network training for point forecasting.

Predictive uncertainty methods – Quality-driven loss functions

1. Multi-quantile regression

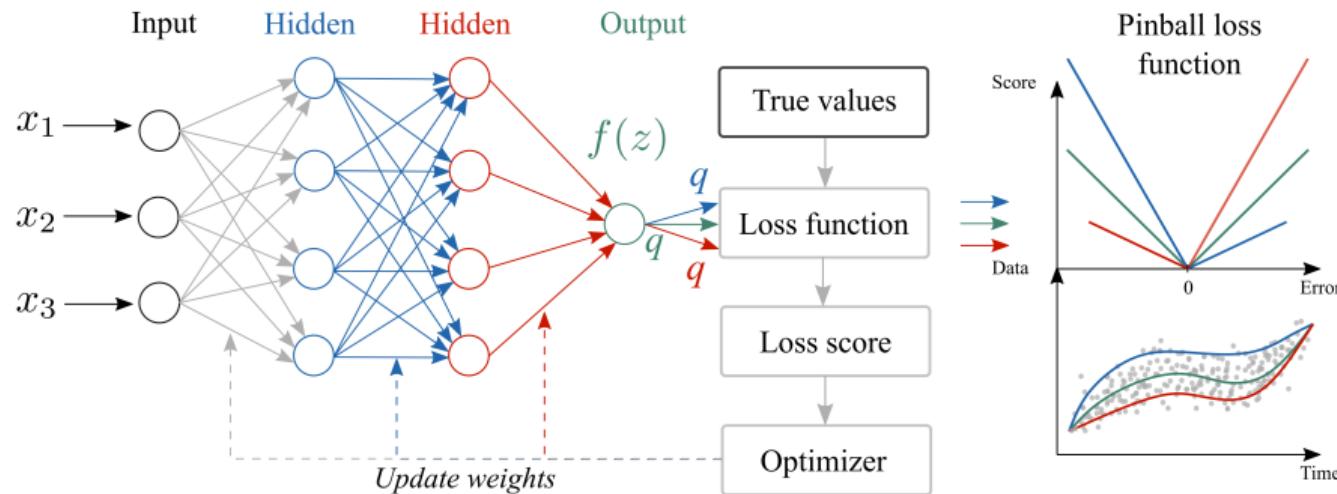


Figure: Neural network training with pinball loss function.

Predictive uncertainty methods – Quality-driven loss functions

2. Regularized maximum likelihood estimation

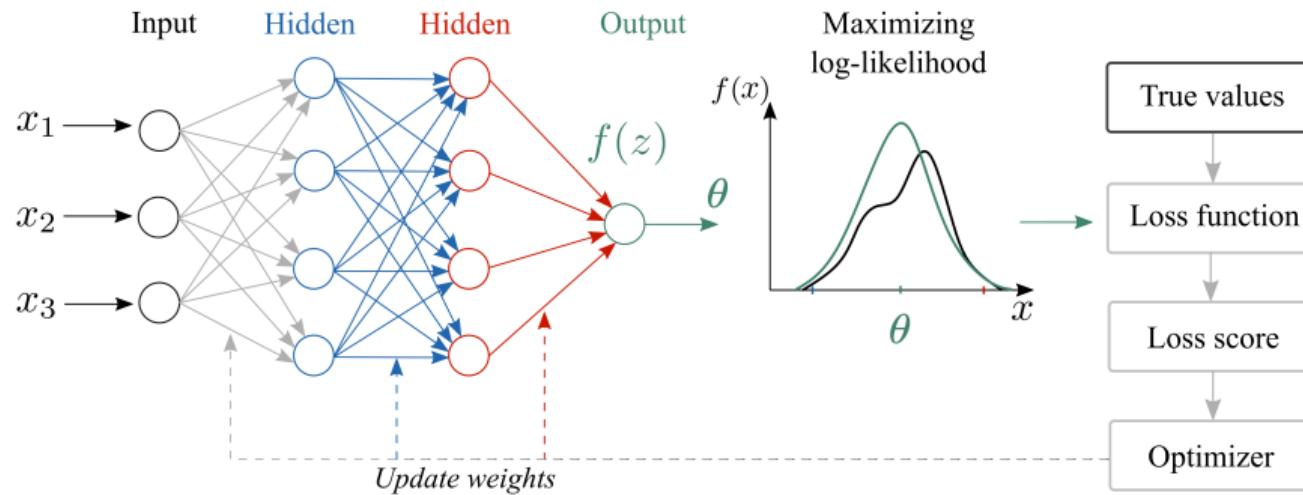


Figure: Neural network training with regularized maximum likelihood estimation.

Predictive uncertainty methods – Quality-driven loss functions

2. Regularized maximum likelihood estimation (cont'd)

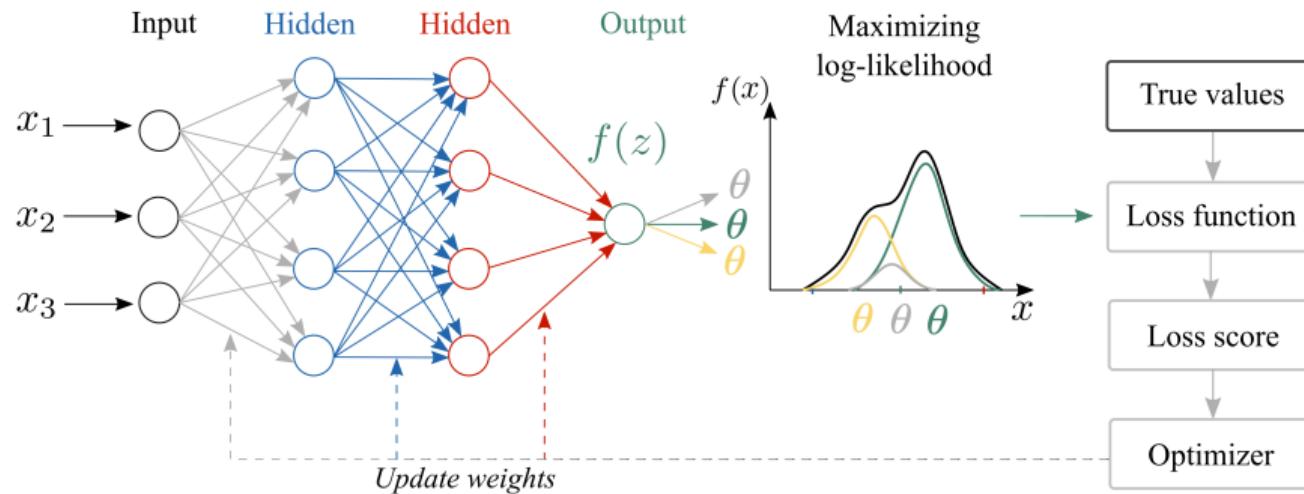


Figure: Neural network training with Mixture density networks.

Predictive uncertainty methods – Bayesian approximation

3. Monte Carlo dropout

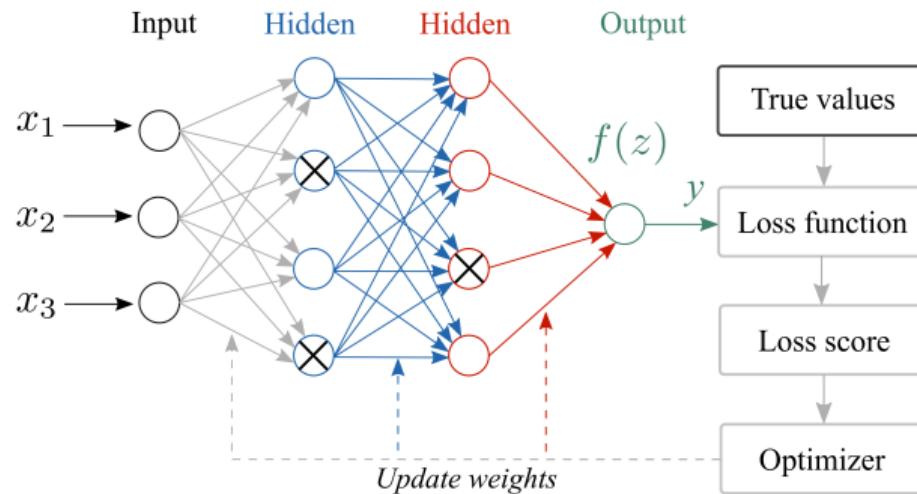


Figure: Neural network training with Monte Carlo dropout.

Predictive uncertainty methods – Bayesian approximation

3. Monte Carlo dropout

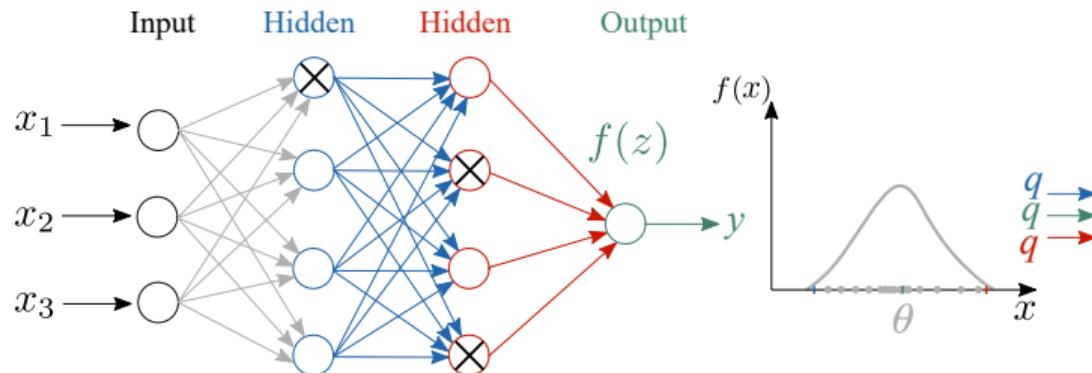


Figure: Random sampling of neural network predictions with Monte Carlo dropout.

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case A – Univariate battery storage energy activation

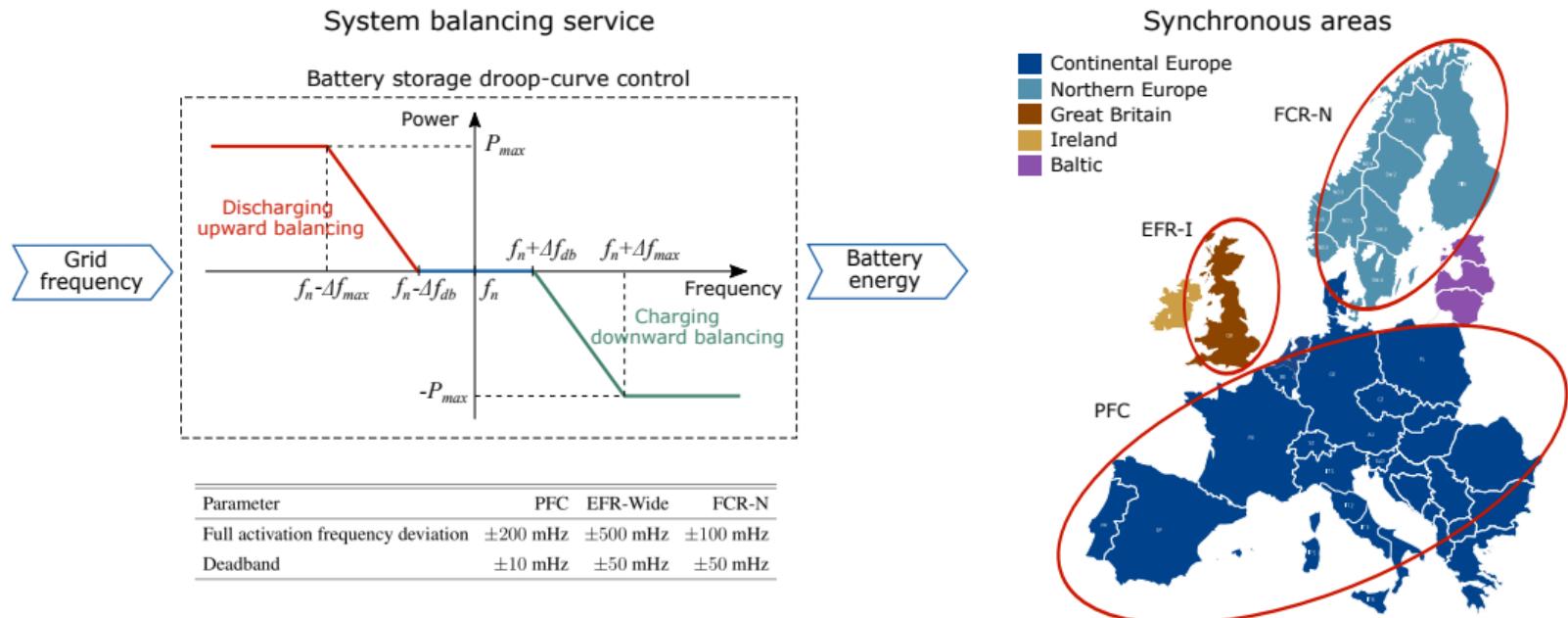


Figure: Characteristics of data generating process.

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case A – Univariate battery storage energy activation – Findings

(a) EFR-I dataset

E_i	LQR			QRF			QGB			QRNN			Variational MARNN		
[%]	ACE	PINAW	CWC	ACE	PINAW	CWC									
10	-0.024	0.021	0.049	-0.019	0.022	0.049	-0.029	0.019	0.045	-0.076	0.003	0.019	0.027	0.033	0.033
20	-0.054	0.042	0.115	-0.033	0.045	0.108	-0.055	0.039	0.106	-0.040	0.043	0.108	0.051	0.068	0.068
30	-0.072	0.065	0.200	-0.040	0.070	0.174	-0.076	0.060	0.189	-0.108	0.052	0.206	0.072	0.104	0.104
40	-0.097	0.090	0.327	-0.050	0.096	0.255	-0.092	0.083	0.292	-0.099	0.082	0.304	0.082	0.141	0.141
50	-0.113	0.118	0.484	-0.060	0.126	0.357	-0.111	0.109	0.437	-0.188	0.085	0.642	0.090	0.181	0.181
60	-0.122	0.150	0.658	-0.065	0.161	0.468	-0.123	0.130	0.612	-0.158	0.127	0.744	0.092	0.226	0.226
70	-0.122	0.188	0.821	-0.066	0.203	0.574	-0.127	0.173	0.791	-0.146	0.168	0.894	0.079	0.279	0.279
80	-0.116	0.238	1.000	-0.053	0.258	0.699	-0.114	0.222	0.916	-0.170	0.198	1.284	0.062	0.344	0.344
90	-0.088	0.320	1.084	-0.043	0.345	0.878	-0.091	0.296	1.033	-0.090	0.298	1.033	0.034	0.442	0.442
95	-0.062	0.397	1.137	-0.033	0.423	1.012	-0.065	0.365	1.068	-0.075	0.356	1.109	0.016	0.527	0.527

(b) PFC dataset

E_i	LQR			QRF			QGB			QRNN			Variational MARNN		
[%]	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC
10	-0.001	0.018	0.036	0.010	0.020	0.020	0.001	0.018	0.018	-0.065	0.007	0.021	0.036	0.024	0.024
20	0.003	0.037	0.037	0.016	0.040	0.040	-0.005	0.035	0.073	-0.073	0.023	0.070	0.062	0.048	0.048
30	0.005	0.056	0.056	0.026	0.060	0.060	-0.006	0.053	0.110	0.027	0.061	0.061	0.076	0.073	0.073
40	0.003	0.078	0.078	0.024	0.083	0.083	-0.010	0.073	0.154	-0.048	0.069	0.181	0.090	0.099	0.099
50	0.003	0.101	0.101	0.031	0.108	0.108	-0.010	0.095	0.199	-0.062	0.085	0.244	0.094	0.127	0.127
60	0.006	0.129	0.129	0.035	0.138	0.138	-0.018	0.119	0.263	0.009	0.130	0.130	0.087	0.158	0.158
70	0.005	0.164	0.164	0.035	0.175	0.175	-0.015	0.151	0.325	0.001	0.163	0.163	0.074	0.194	0.194
80	0.005	0.213	0.213	0.032	0.225	0.225	-0.023	0.191	0.432	0.010	0.218	0.218	0.045	0.241	0.241
90	0.008	0.297	0.297	0.019	0.307	0.307	-0.014	0.259	0.558	0.006	0.291	0.291	0.013	0.309	0.309
95	0.005	0.377	0.377	0.011	0.387	0.387	-0.009	0.332	0.693	0.015	0.408	0.408	-0.002	0.369	0.745

(c) PFC-II dataset

E_i	LQR			QRF			QGB			QRNN			Variational MARNN		
[%]	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC
10	-0.006	0.011	0.022	0.009	0.011	0.011	0.006	0.010	0.010	-0.041	0.006	0.015	0.012	0.017	0.017
20	-0.011	0.022	0.047	0.020	0.024	0.024	0.008	0.021	0.021	0.032	0.025	0.025	0.017	0.034	0.034
30	-0.015	0.037	0.079	0.034	0.039	0.039	0.012	0.034	0.034	-0.094	0.022	0.079	0.021	0.052	0.052
40	-0.015	0.054	0.118	0.039	0.056	0.056	0.007	0.049	0.049	0.053	0.059	0.059	0.010	0.071	0.071
50	-0.019	0.075	0.167	0.035	0.077	0.077	0.005	0.068	0.068	0.016	0.073	0.073	-0.007	0.099	0.188
60	-0.014	0.102	0.219	0.040	0.103	0.103	0.004	0.091	0.091	0.051	0.108	0.108	-0.025	0.113	0.259
70	-0.010	0.136	0.286	0.032	0.136	0.136	0.002	0.121	0.121	0.015	0.129	0.129	-0.046	0.139	0.359
80	-0.011	0.183	0.386	0.027	0.181	0.181	-0.001	0.163	0.328	-0.025	0.157	0.358	-0.077	0.172	0.544
90	-0.001	0.262	0.527	0.012	0.232	0.252	-0.004	0.231	0.472	-0.011	0.227	0.480	-0.087	0.221	0.750
95	-0.000	0.340	0.340	0.003	0.321	0.321	-0.004	0.296	0.604	-0.020	0.279	0.619	-0.087	0.263	0.893

Figure: Coverage metric of prediction interval forecasts.

- Prediction intervals with smaller coverage are easier to quantify

- Low systematic generalization of models to different regulatory environments of balancing services

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case A – Univariate battery storage energy activation – Findings

(a) EFR-I dataset

E _t	LQR			QRF			QGB			QRNN			Variational MARNN		
[%]	ACE	PINAW	CWC	ACE	PINAW	CWC									
10	-0.024	0.021	0.049	-0.019	0.022	0.049	-0.029	0.019	0.045	-0.076	0.003	0.019	0.027	0.033	0.033
20	-0.054	0.042	0.115	-0.033	0.045	0.108	-0.055	0.039	0.106	-0.040	0.043	0.108	0.051	0.068	0.068
30	-0.072	0.065	0.200	-0.040	0.070	0.174	-0.076	0.060	0.189	-0.108	0.052	0.206	0.072	0.104	0.104
40	-0.097	0.090	0.327	-0.050	0.096	0.255	-0.092	0.083	0.292	-0.099	0.082	0.304	0.082	0.141	0.141
50	-0.113	0.118	0.484	-0.060	0.126	0.357	-0.111	0.109	0.437	-0.188	0.085	0.642	0.090	0.181	0.181
60	-0.122	0.150	0.658	-0.065	0.161	0.468	-0.123	0.130	0.612	-0.158	0.127	0.744	0.092	0.226	0.226
70	-0.122	0.188	0.821	-0.069	0.203	0.574	-0.127	0.173	0.791	-0.146	0.168	0.894	0.079	0.279	0.279
80	-0.116	0.238	1.000	-0.053	0.258	0.699	-0.114	0.222	0.916	-0.170	0.198	1.284	0.062	0.344	0.344
90	-0.088	0.320	1.084	-0.043	0.345	0.878	-0.091	0.296	1.033	-0.090	0.298	1.033	0.034	0.442	0.442
95	-0.062	0.397	1.137	-0.033	0.423	1.012	-0.065	0.365	1.068	-0.075	0.356	1.109	0.016	0.527	0.527

(b) PFC dataset

E _t	LQR			QRF			QGB			QRNN			Variational MARNN		
[%]	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC
10	-0.001	0.018	0.036	0.010	0.020	0.020	0.001	0.018	0.018	-0.065	0.007	0.021	0.036	0.024	0.024
20	0.003	0.037	0.037	0.016	0.040	0.040	-0.005	0.035	0.073	-0.073	0.023	0.070	0.062	0.048	0.048
30	0.005	0.056	0.056	0.026	0.060	0.060	-0.006	0.053	0.110	0.027	0.061	0.061	0.076	0.073	0.073
40	0.003	0.078	0.078	0.024	0.083	0.083	-0.010	0.073	0.154	-0.048	0.069	0.181	0.090	0.099	0.099
50	0.003	0.101	0.101	0.031	0.108	0.108	-0.010	0.095	0.199	-0.062	0.085	0.244	0.094	0.127	0.127
60	0.006	0.129	0.129	0.035	0.138	0.138	-0.018	0.119	0.263	0.009	0.130	0.130	0.087	0.158	0.158
70	0.005	0.164	0.164	0.035	0.175	0.175	-0.015	0.151	0.325	0.001	0.163	0.163	0.074	0.194	0.194
80	0.005	0.213	0.213	0.032	0.225	0.225	-0.023	0.191	0.432	0.010	0.218	0.218	0.045	0.241	0.241
90	0.008	0.297	0.297	0.019	0.307	0.307	-0.014	0.259	0.558	0.006	0.291	0.291	0.133	0.309	0.309
95	0.005	0.377	0.377	0.011	0.387	0.387	-0.009	0.332	0.693	0.015	0.408	0.408	-0.002	0.369	0.369

(c) PFC-II dataset

E _t	LQR			QRF			QGB			QRNN			Variational MARNN		
[%]	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC
10	-0.006	0.011	0.022	0.009	0.011	0.011	0.006	0.010	0.010	-0.041	0.006	0.015	0.012	0.017	0.017
20	-0.011	0.022	0.047	0.020	0.024	0.024	0.008	0.021	0.021	0.032	0.025	0.025	0.017	0.034	0.034
30	-0.015	0.037	0.037	0.014	0.039	0.039	0.012	0.034	0.034	-0.094	0.022	0.079	0.021	0.052	0.052
40	-0.015	0.054	0.118	0.039	0.056	0.056	0.007	0.049	0.049	0.053	0.059	0.059	0.010	0.071	0.071
50	-0.019	0.075	0.167	0.035	0.077	0.077	0.005	0.068	0.068	0.016	0.073	0.073	-0.007	0.099	0.188
60	-0.014	0.102	0.219	0.040	0.103	0.103	0.004	0.091	0.091	0.051	0.108	0.108	-0.025	0.113	0.259
70	-0.010	0.136	0.286	0.032	0.136	0.136	0.002	0.121	0.121	0.015	0.129	0.129	-0.046	0.139	0.359
80	-0.011	0.183	0.386	0.027	0.181	0.181	-0.001	0.163	0.328	-0.025	0.157	0.358	-0.077	0.172	0.544
90	-0.001	0.262	0.527	0.012	0.232	0.252	-0.004	0.231	0.472	-0.011	0.227	0.480	-0.087	0.221	0.750
95	-0.000	0.340	0.340	0.003	0.321	0.321	-0.004	0.296	0.604	-0.020	0.279	0.619	-0.087	0.263	0.893

Figure: Coverage metric of prediction interval forecasts.

- Prediction intervals with smaller coverage are easier to quantify
- Low systematic generalization of models to different regulatory environments of balancing services

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case A – Univariate battery storage energy activation – Findings

(a) EFR-I dataset															
E.	LQR			QRF			QGB			QRNN			Variational MARNN		
[%]	ACE	PINAW	CWC	ACE	PINAW	CWC									
10	-0.024	0.021	0.049	-0.019	0.022	0.049	-0.029	0.019	0.045	-0.076	0.003	0.001	0.027	0.033	0.033
20	-0.054	0.042	0.115	-0.033	0.045	0.108	-0.055	0.039	0.106	-0.040	0.043	0.10	0.051	0.066	0.068
30	-0.072	0.065	0.200	-0.040	0.070	0.174	-0.076	0.060	0.189	-0.108	0.052	0.20	0.072	0.104	0.104
40	-0.097	0.090	0.327	-0.050	0.096	0.255	-0.092	0.083	0.292	-0.099	0.082	0.30	0.082	0.141	0.141
50	-0.113	0.118	0.484	-0.060	0.126	0.357	-0.111	0.109	0.437	-0.188	0.085	0.6	0.090	0.181	0.181
60	-0.122	0.150	0.658	-0.065	0.161	0.468	-0.123	0.130	0.612	-0.158	0.127	0.7	0.092	0.226	0.226
70	-0.122	0.188	0.821	-0.066	0.203	0.574	-0.127	0.173	0.791	-0.146	0.168	0.8	0.079	0.279	0.279
80	-0.116	0.238	1.000	-0.053	0.258	0.699	-0.114	0.222	0.916	-0.170	0.198	1.2	0.062	0.344	0.344
90	-0.088	0.320	1.084	-0.043	0.345	0.878	-0.091	0.296	1.033	-0.090	0.298	1.0	0.034	0.442	0.442
95	-0.062	0.397	1.137	-0.033	0.423	1.012	-0.065	0.365	1.068	-0.075	0.356	1.10	0.016	0.527	0.527

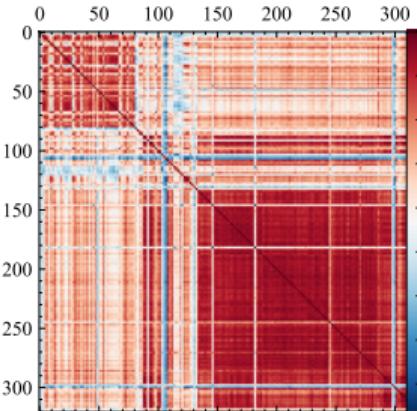
(b) PFC dataset															
E.	LQR			QRF			QGB			QRNN			Variational MARNN		
[%]	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC
10	-0.001	0.018	0.036	0.010	0.020	0.020	0.001	0.018	0.018	-0.065	0.007	0.021	0.036	0.024	0.024
20	0.003	0.037	0.037	0.016	0.040	0.040	-0.005	0.035	0.073	-0.073	0.023	0.070	0.062	0.048	0.048
30	0.005	0.056	0.056	0.026	0.060	0.060	-0.006	0.053	0.110	0.027	0.061	0.061	0.076	0.073	0.073
40	0.003	0.078	0.078	0.024	0.083	0.083	-0.010	0.073	0.154	-0.048	0.069	0.181	0.090	0.099	0.099
50	0.003	0.101	0.101	0.031	0.108	0.108	-0.010	0.095	0.199	-0.062	0.085	0.244	0.094	0.127	0.127
60	0.006	0.129	0.129	0.035	0.138	0.138	-0.018	0.119	0.263	0.009	0.130	0.130	0.087	0.158	0.158
70	0.005	0.164	0.164	0.035	0.175	0.175	-0.015	0.151	0.325	0.001	0.163	0.163	0.074	0.194	0.194
80	0.005	0.213	0.213	0.032	0.225	0.225	-0.023	0.191	0.432	0.010	0.218	0.218	0.045	0.241	0.241
90	0.008	0.297	0.297	0.019	0.307	0.307	-0.014	0.259	0.558	0.006	0.291	0.291	0.13	0.309	0.309
95	0.005	0.377	0.377	0.011	0.387	0.387	-0.009	0.332	0.693	0.015	0.408	0.408	-0.002	0.369	0.369

(c) PFC-II dataset															
E.	LQR			QRF			QGB			QRNN			Variational MARNN		
[%]	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC	ACE	PINAW	CWC
10	-0.006	0.011	0.022	0.009	0.011	0.017	0.006	0.010	0.010	-0.041	0.006	0.015	0.012	0.017	0.017
20	-0.011	0.022	0.047	0.020	0.024	0.024	0.008	0.021	0.021	0.032	0.025	0.025	0.017	0.034	0.034
30	-0.015	0.037	0.039	0.034	0.039	0.039	0.012	0.034	0.034	-0.094	0.022	0.079	0.021	0.052	0.052
40	-0.015	0.054	0.118	0.039	0.056	0.056	0.007	0.049	0.049	0.053	0.059	0.059	0.010	0.071	0.071
50	-0.019	0.075	0.167	0.035	0.077	0.077	0.005	0.068	0.068	0.016	0.073	0.073	-0.007	0.09	0.188
60	-0.014	0.102	0.219	0.040	0.103	0.103	0.004	0.091	0.091	0.051	0.108	0.108	-0.025	0.113	0.259
70	-0.010	0.136	0.286	0.032	0.136	0.136	0.002	0.121	0.121	0.015	0.129	0.129	-0.046	0.139	0.359
80	-0.011	0.183	0.386	0.027	0.181	0.181	-0.001	0.163	0.328	0.025	0.157	0.358	-0.077	0.172	0.544
90	-0.001	0.262	0.527	0.012	0.232	0.252	-0.004	0.231	0.472	-0.011	0.227	0.480	-0.087	0.221	0.750
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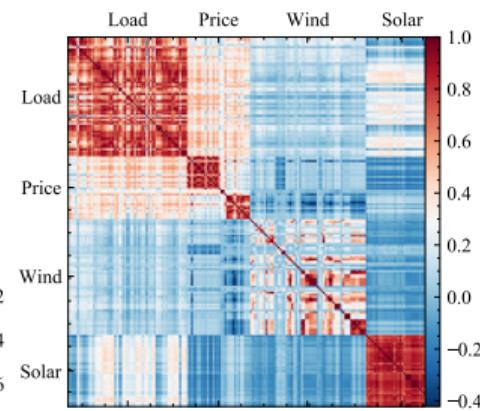
Figure: Coverage metric of prediction interval forecasts.

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case B – Multivariate forecasts of high-dimensional datasets



(a) Customer electricity consumption



(b) Europe power system data

Figure: Correlation matrix of time series in the datasets.

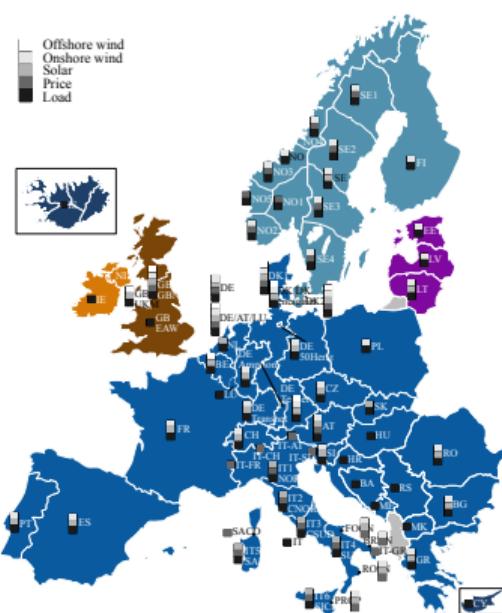


Figure: Geolocations of the variables in the power system dataset.

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case B - Multivariate forecasts of high-dimensional datasets - Findings

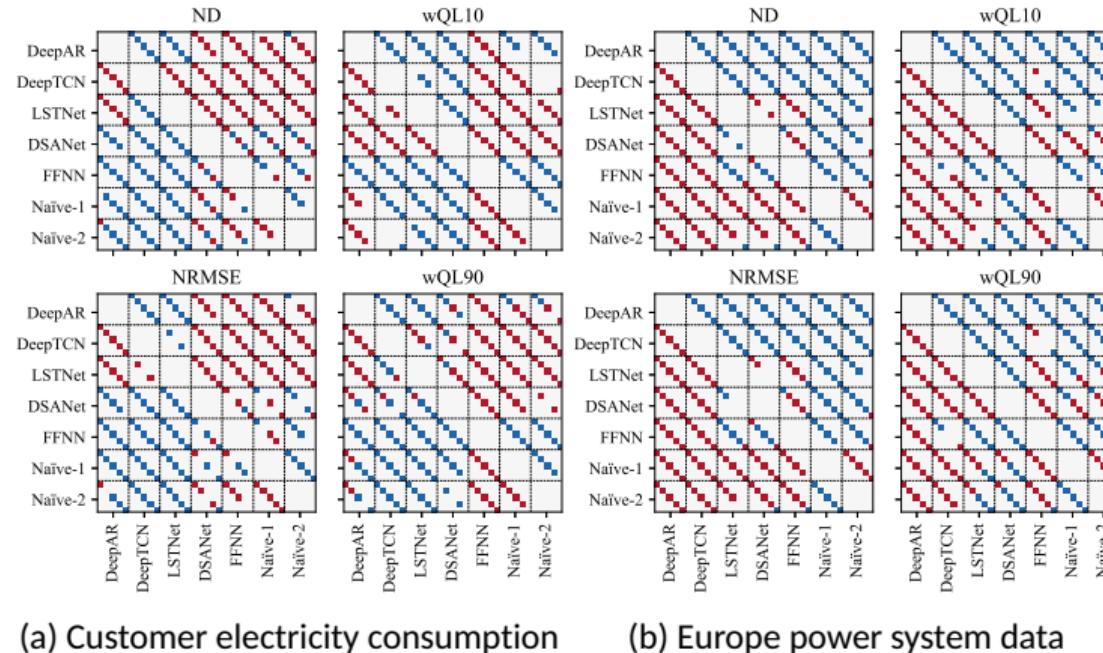
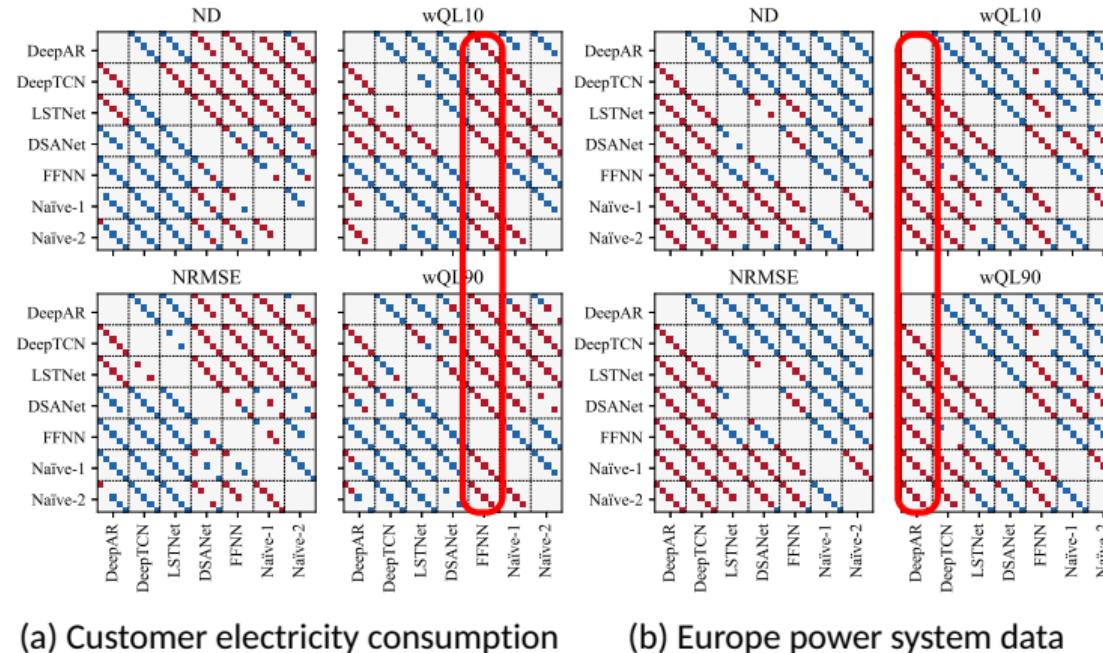


Figure: One-sided Diebold–Mariano tests at the 5% significance levels on the predictive accuracy (ND and NRMSE) and predictive uncertainty (wQL) of the 0.1 and 0.9 quantiles.

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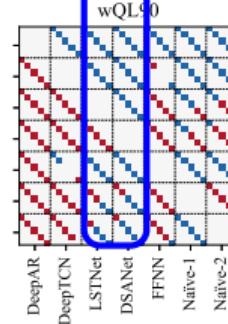
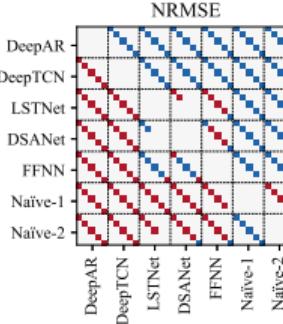
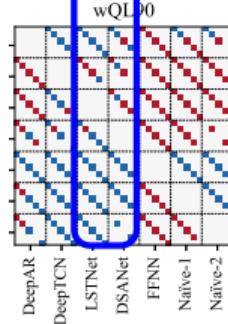
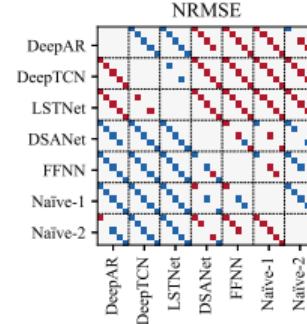
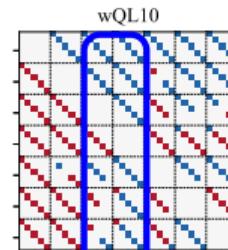
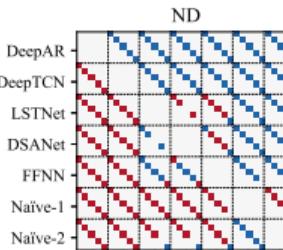
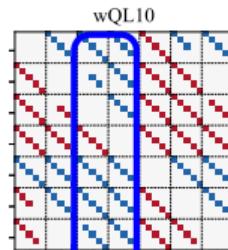
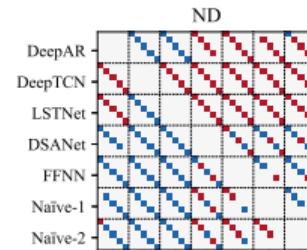
Case B - Multivariate forecasts of high-dimensional datasets - Findings



- Deep learning models trained with the cross-learning technique and regularized likelihood estimation show the best sharpness

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case B - Multivariate forecasts of high-dimensional datasets - Findings



(c) Customer electricity consumption

(d) Europe power system data

- Deep learning models with Monte Carlo dropout poorly estimate the predictive uncertainty region

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case C - Multidistribution testing of half-hourly datasets

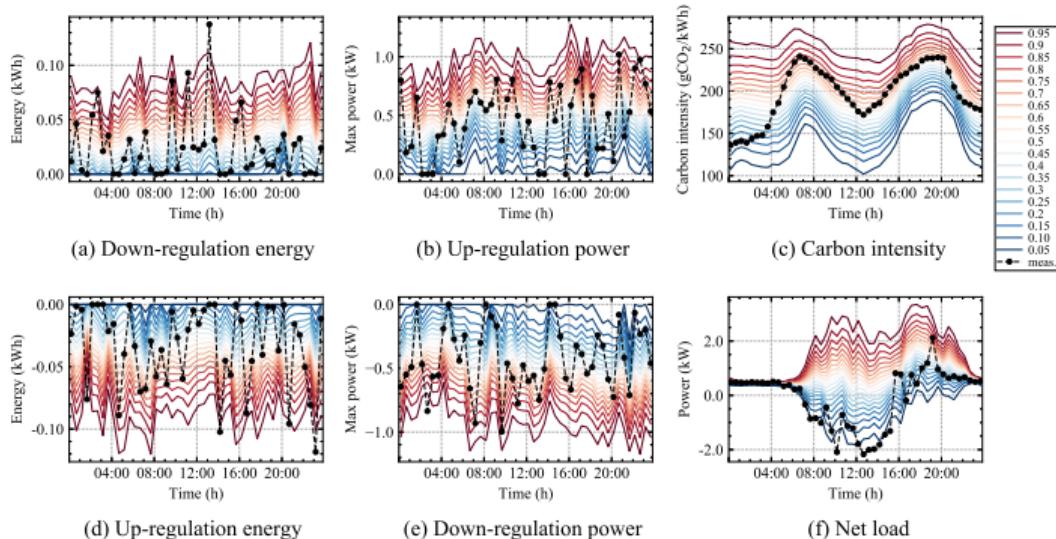


Figure: Example of the data generating processes.

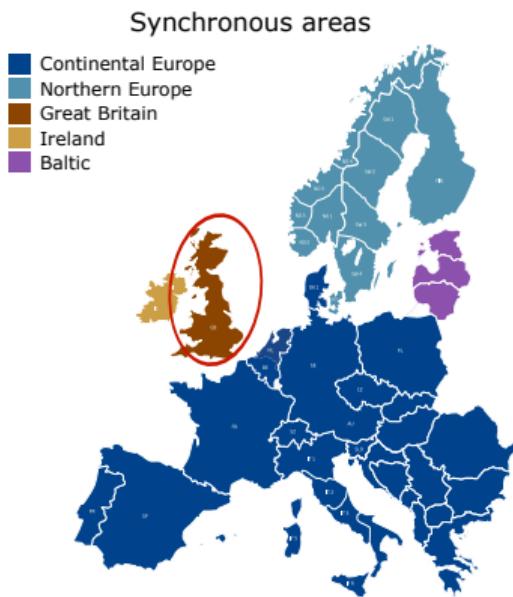


Figure: Geolocations of the data generating processes.

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case C - Multidistribution testing of half-hourly datasets – Findings

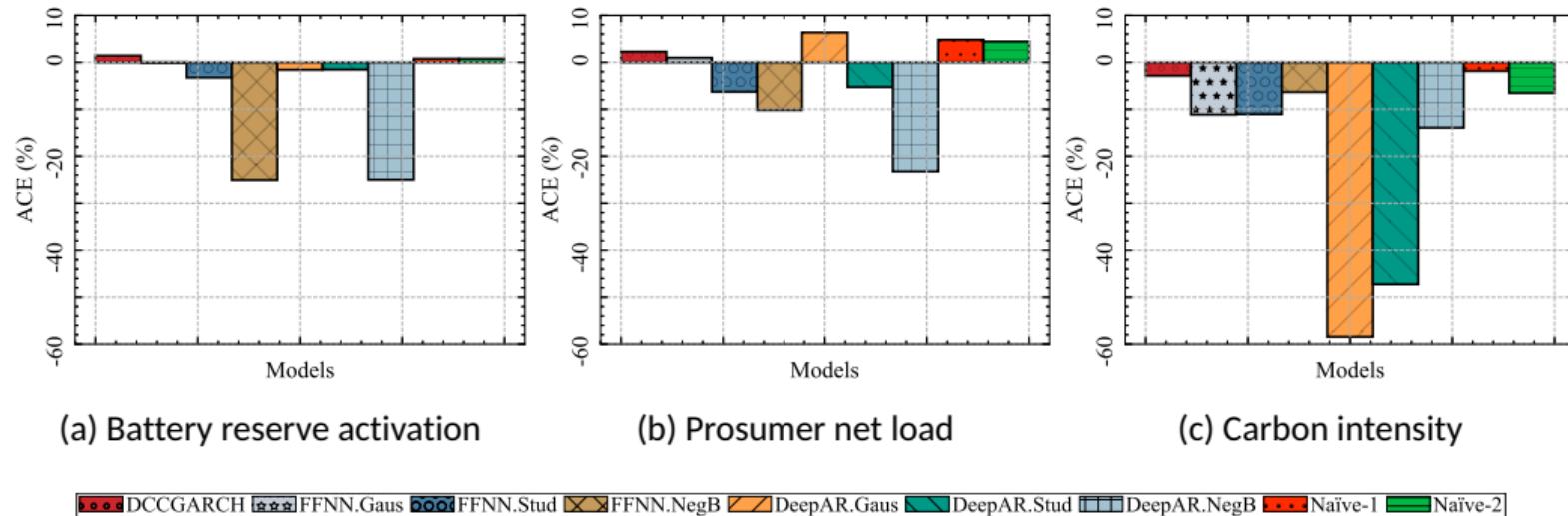
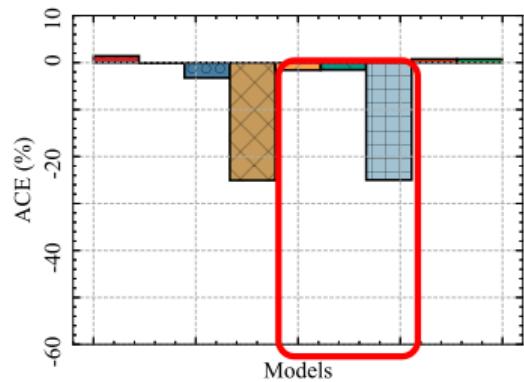


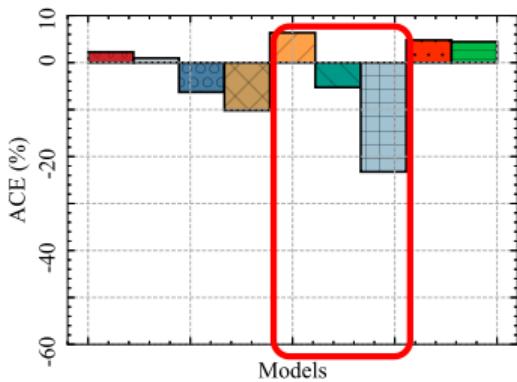
Figure: Average coverage error for 80% prediction interval of the 24 h ahead forecasts.

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

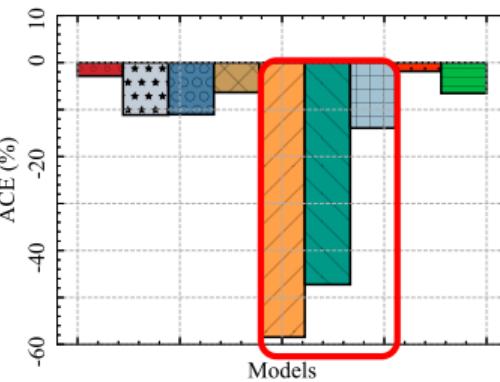
Case C - Multidistribution testing of half-hourly datasets – Findings



(a) Battery reserve activation



(b) Prosumer net load



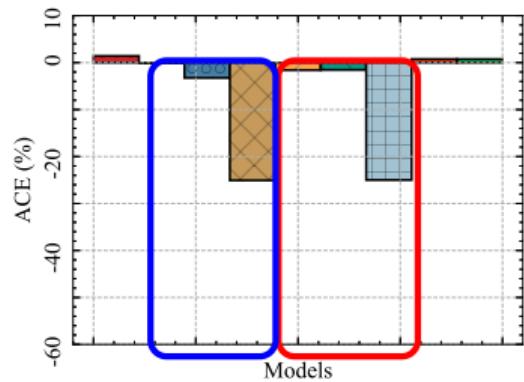
Models

(c) Carbon intensity

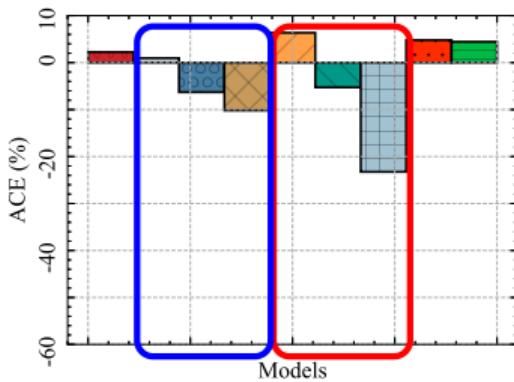
DCCGARCH FFNN.Gaus FFNN.Stud FFNN.NegB DeepAR.Gaus DeepAR.Stud DeepAR.NegB Naïve-1 Naïve-2

UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

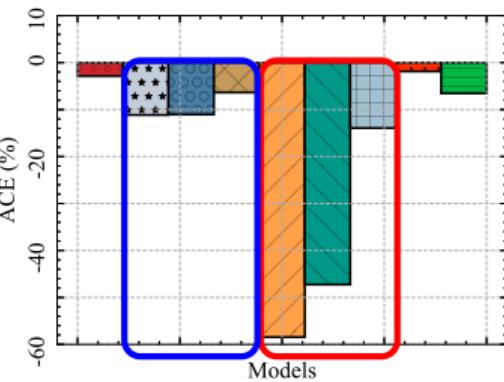
Case C - Multidistribution testing of half-hourly datasets – Findings



(d) Battery reserve activation



(e) Prosumer net load

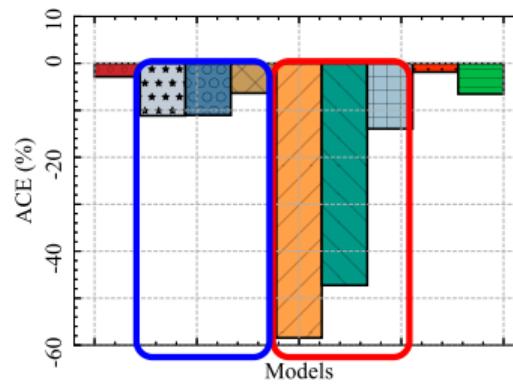
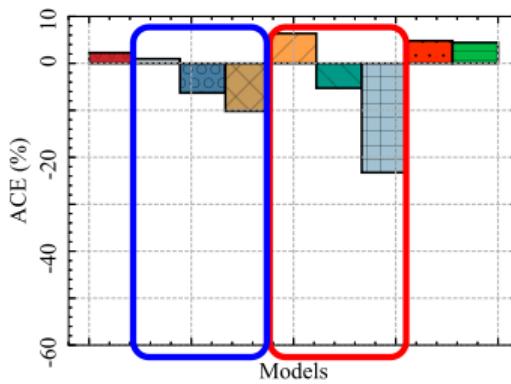
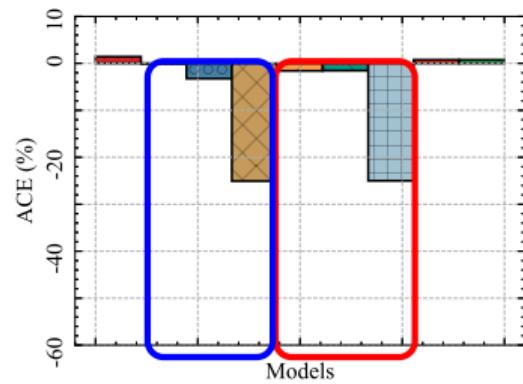


(f) Carbon intensity



UNCERTAINTY QUANTIFICATION IN ENERGY FORECASTING

Case C - Multidistribution testing of half-hourly datasets – Findings



- Predictive uncertainty of deep learning models with maximum likelihood estimation highly depends on the appropriate distribution of a specific dataset

PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Methodology

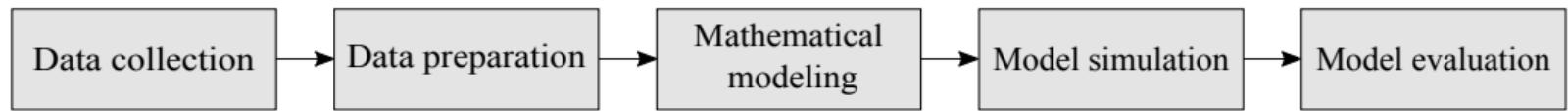


Figure: Research methodology for prosumer flexibility scheduling and coordination in a community microgrid.

PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Methodology

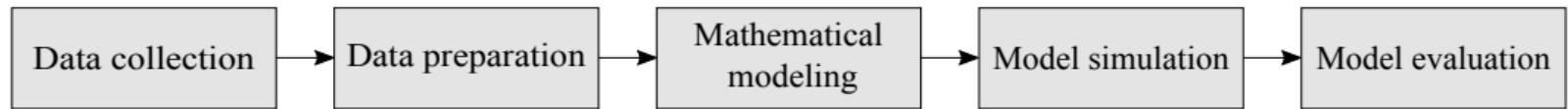


Figure: Research methodology for prosumer flexibility scheduling and coordination in a community microgrid.

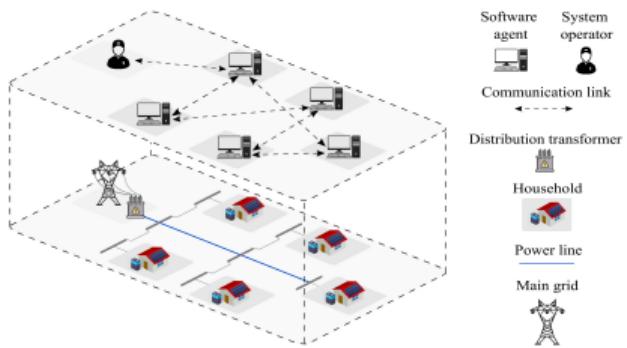


Figure: Community microgrid as a cyber-physical system.

PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Methodology

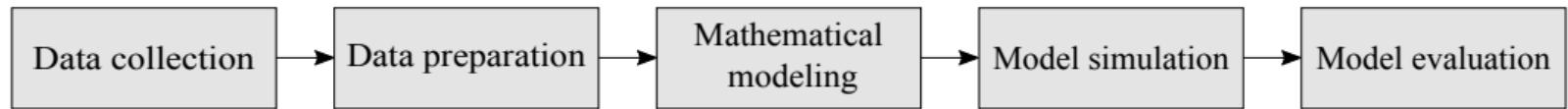


Figure: Research methodology for prosumer flexibility scheduling and coordination in a community microgrid.

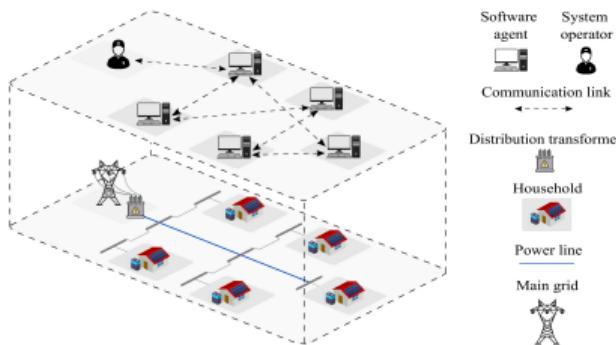


Figure: Community microgrid as a cyber-physical system.

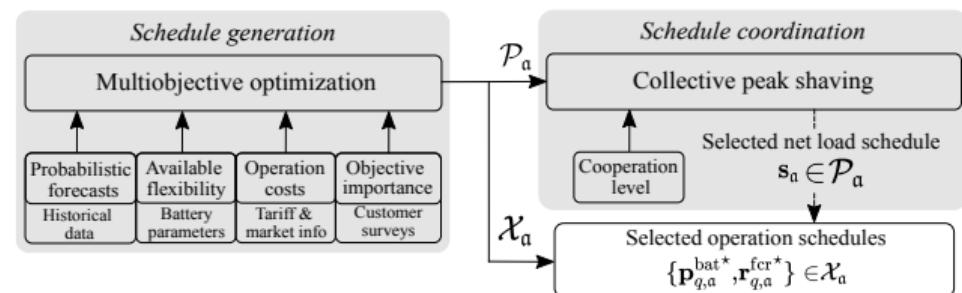
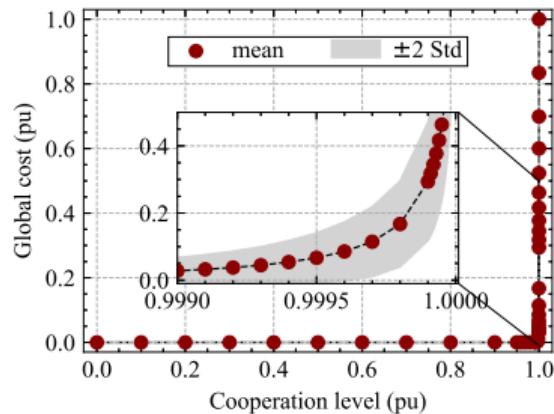


Figure: Prosumer decision-making framework.

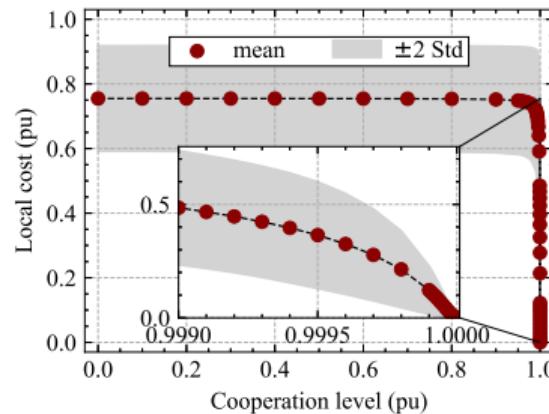
PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Findings

1. Socio-technical impact and optimality of varying prosumer cooperation



(a) Global cost



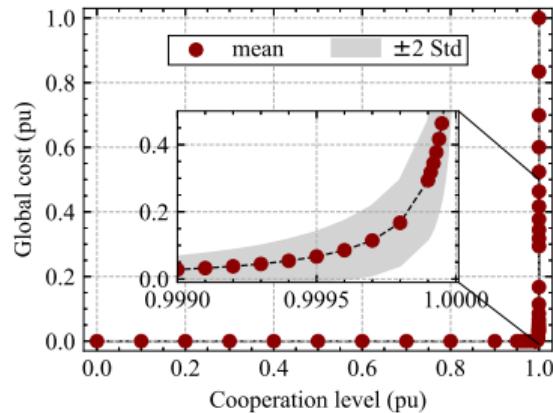
(b) Local cost

Figure: Impact of the agents' cooperation level $\lambda \in [0, 1]$.

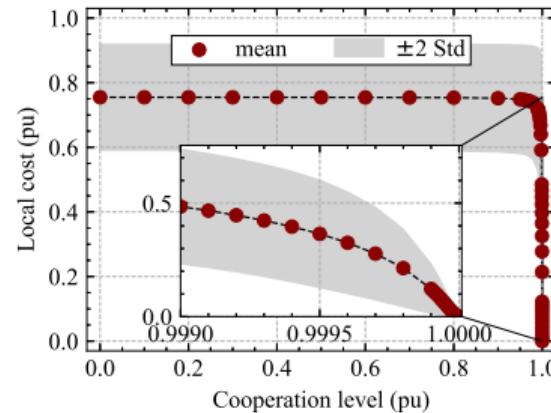
PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Findings

1. Socio-technical impact and optimality of varying prosumer cooperation



(a) Global cost



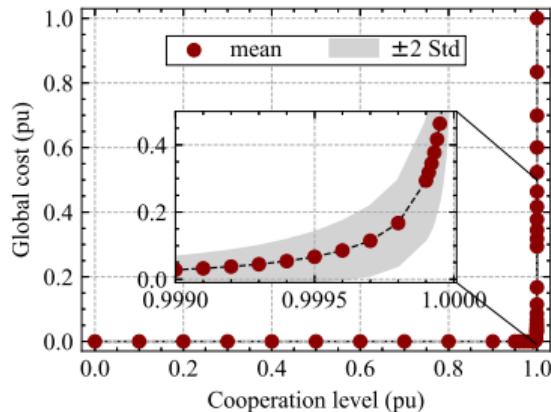
(b) Local cost

- Noncooperative behavior of individuals (high λ values) sacrifices the system-wide efficiency of the shared power grid infrastructure

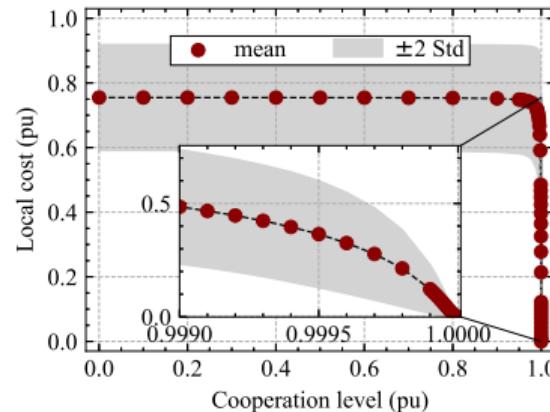
PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Findings

1. Socio-technical impact and optimality of varying prosumer cooperation



(a) Global cost



(b) Local cost

With Pareto-optimal prosumer cooperation level:

- ▶ peak shaving costs \downarrow by 83%
- ▶ prosumer dissatisfaction $\sim 28\%$

PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Findings (cont'd)

1. Socio-technical impact and optimality of varying prosumer cooperation

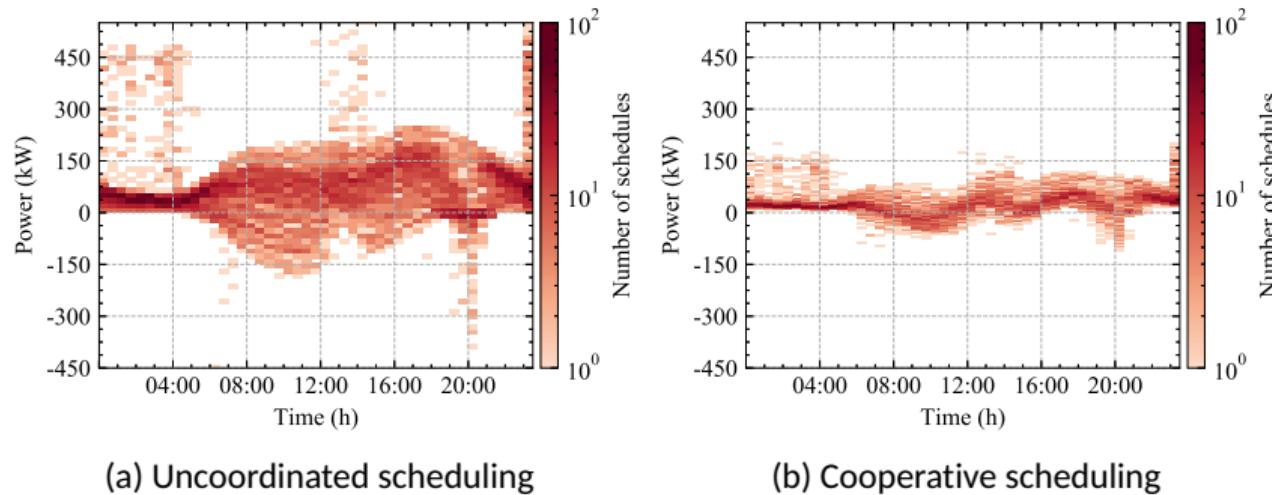
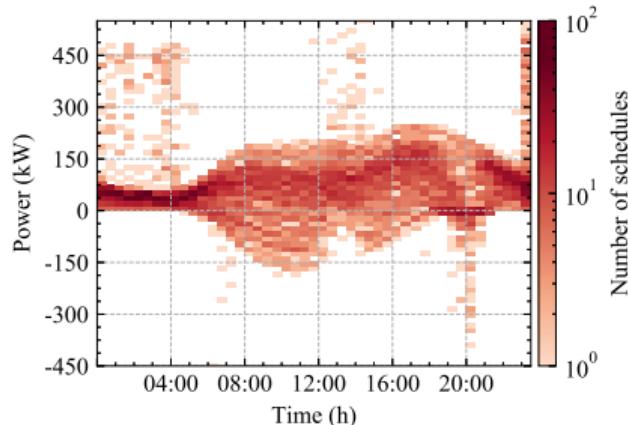


Figure: Net load profile of the community microgrid.

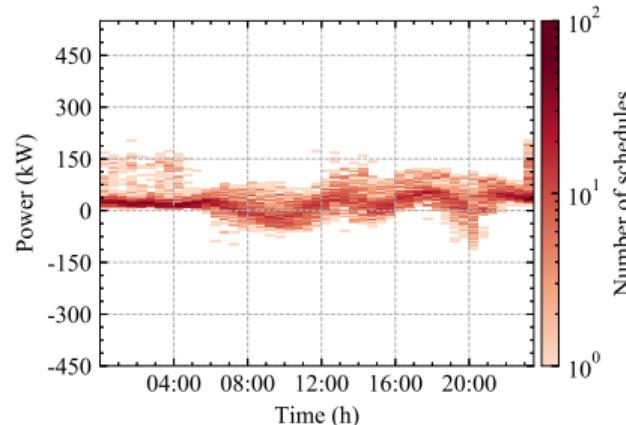
PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Findings (cont'd)

1. Socio-technical impact and optimality of varying prosumer cooperation



(a) Uncoordinated scheduling



(b) Cooperative scheduling

Finding #1 *Grid-oriented cooperative scheduling improves the local energy system efficiency through reduced stress for the grid equipment*

PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Findings (cont'd)

2. Effect of forecast uncertainty factors

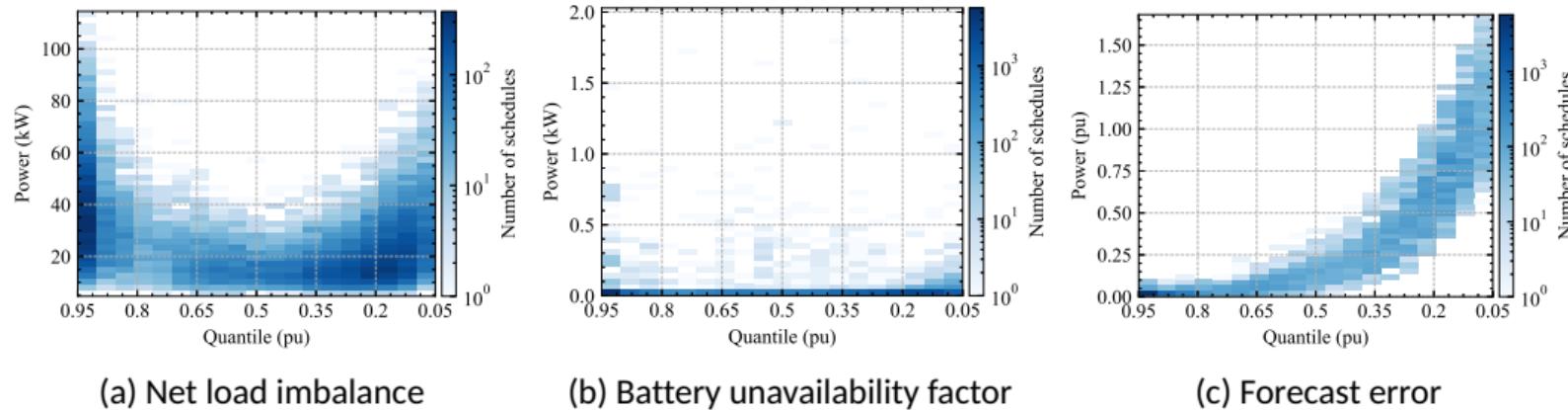
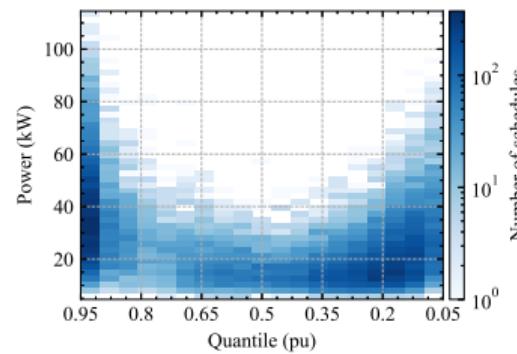


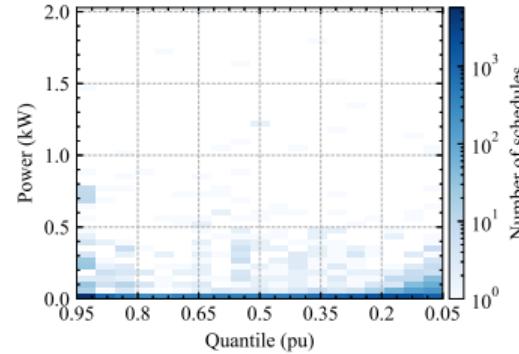
Figure: Effect of the forecast uncertainty (as a function of quantile levels).

Findings (cont'd)

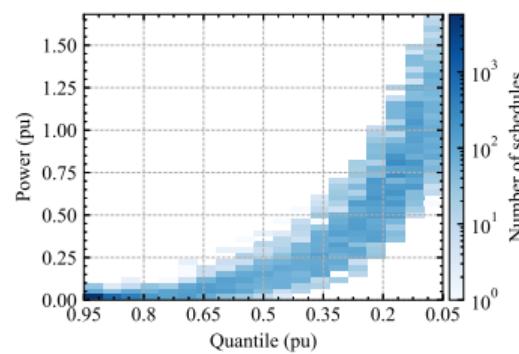
2. Effect of forecast uncertainty factors



(a) Net load imbalance



(b) Battery unavailability factor



(c) Forecast error

Finding #2 The realization of the flexibility scheduling is heavily affected by the forecast uncertainty and requires *uncertainty-aware planning*

PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Findings (cont'd)

3. Techno-economic efficiency

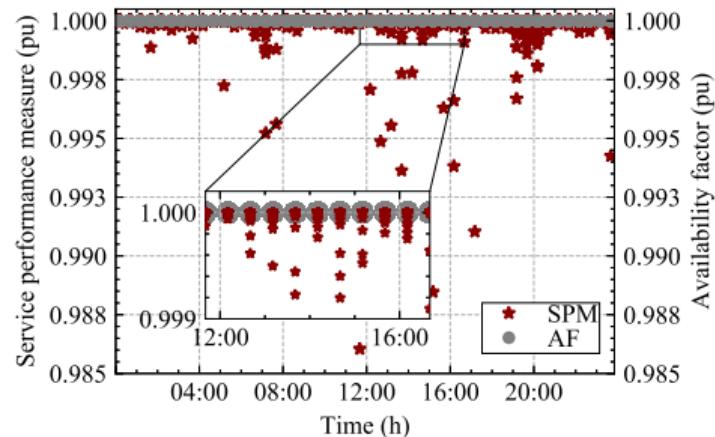
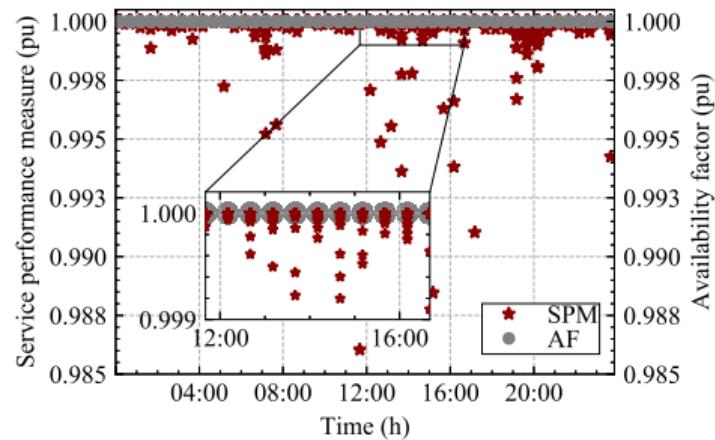


Figure: Technical (SPM) and economic (AF) indicators of the provided frequency control service.

PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Findings (cont'd)

3. Techno-economic efficiency

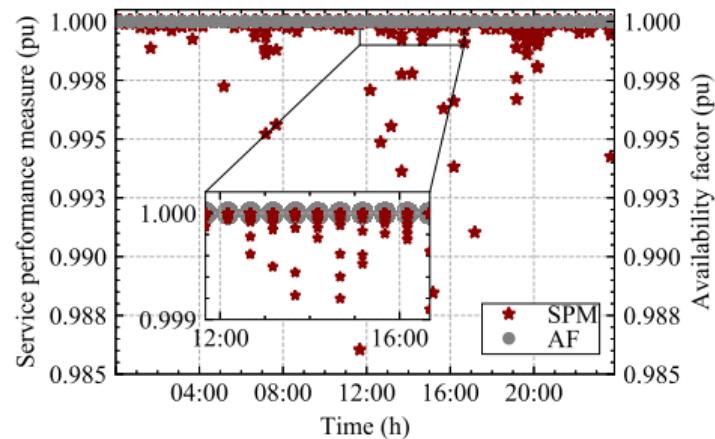


- Population of residential battery storages provide the highest quality level of the service performance above 98.5% and 100% availability

PROSUMER FLEXIBILITY SCHEDULING AND COORDINATION

Findings (cont'd)

3. Techno-economic efficiency



Finding #3 The use of residential solar battery systems for the frequency control demonstrates low risks of resource unavailability

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- [2] Christian Neureiter. "Introduction to the SGAM Toolbox". In: *Josef Ressel Center for User-Centric Smart Grid Privacy, Security and Control, Salzburg University of Applied Sciences*, Tech. Rep (2013).
- [3] Rafael Waters. "Energy from ocean waves: full scale experimental verification of a wave energy converter". PhD thesis. Uppsala University, 2008.