ISF 2025
국외출장 결과 보고서

2025. 07.

수요전망팀 차장 박차리(☏8333)

1. 출장목적

□ ISF 2025 전문가 워크숍 및 수요예측 심포지엄 참석을 통한 글로벌 수요전망 동향 파악 및 의견 공유

□ ISF 2025 논문 발표를 통한 국내 수요전망 성과 공유

ㅇ 주제 : Future Electricity Demand of Data Center in South Korea : Based on the Basic Plan for Electricity Supply and Demand

2. 출장개요

□ 출장기간 : ’25.06.28(토) ~ ’25.07.02(수) (4박 5일)

□ 출장자 : 수요전망팀 차장 박ㅇㅇ

□ 출장지 : 중국 베이징

□ 주요일정 및 수행업무

일 정	내 용	비고
6.28(토)	□ 이동(인천 14:50 → 베이징 15:50)	
6.29(일)	□ ISF2025 워크숍 참석(시계열 모형 분석)	
6.30(월)	□ ISF2025 학회 참석 및 논문 발표	
7.1(화)	□ ISF2025 학회 참석	
7.2(수)	□ ISF2025 학회 참석(오전) □ 귀국(베이징 15:30 → 인천 18:30)	

3. 출장결과

가. ISF2025 Workshop 참석(6.29)

No	Contents
1	Forecasting with Temporal Hierarchies
2	Deep Learning & Foundation Models for Forecasting
3	Exploratory Time Series Analysis

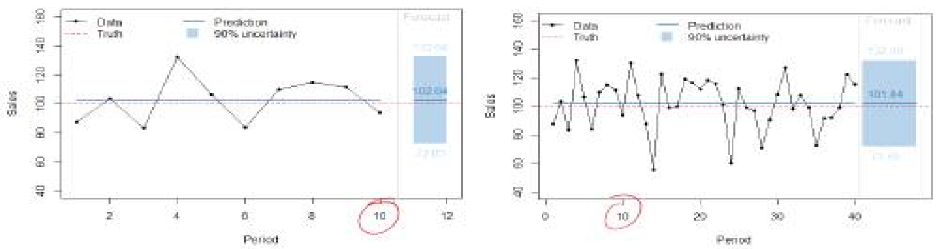
Why bother? The statistical argument

Parameter estimation uncertainty

Let's forecast ice cream sales: as it is well known ice-cream sales ~~are independent~~ of temperature/weather/price, so we have a demand with a constant mean of 100 and some randomness.

This is unknown!

- As they are independent of everything, the mean is the correct model. The only question is to estimate the correct mean (and variance).



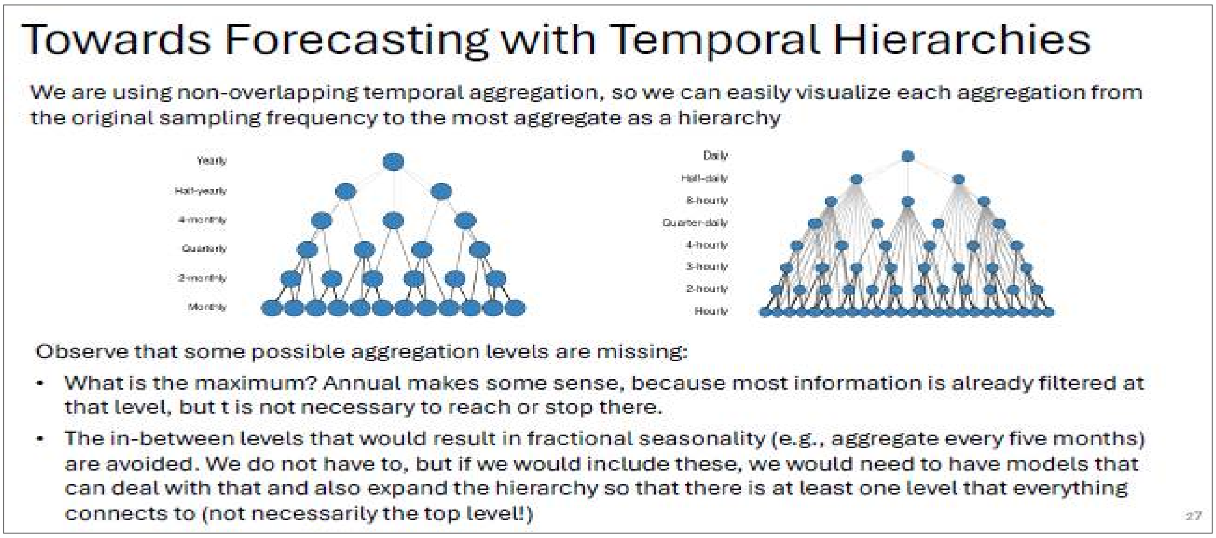
Obviously more data, better estimation,
But at a period t, how good is our estimation?

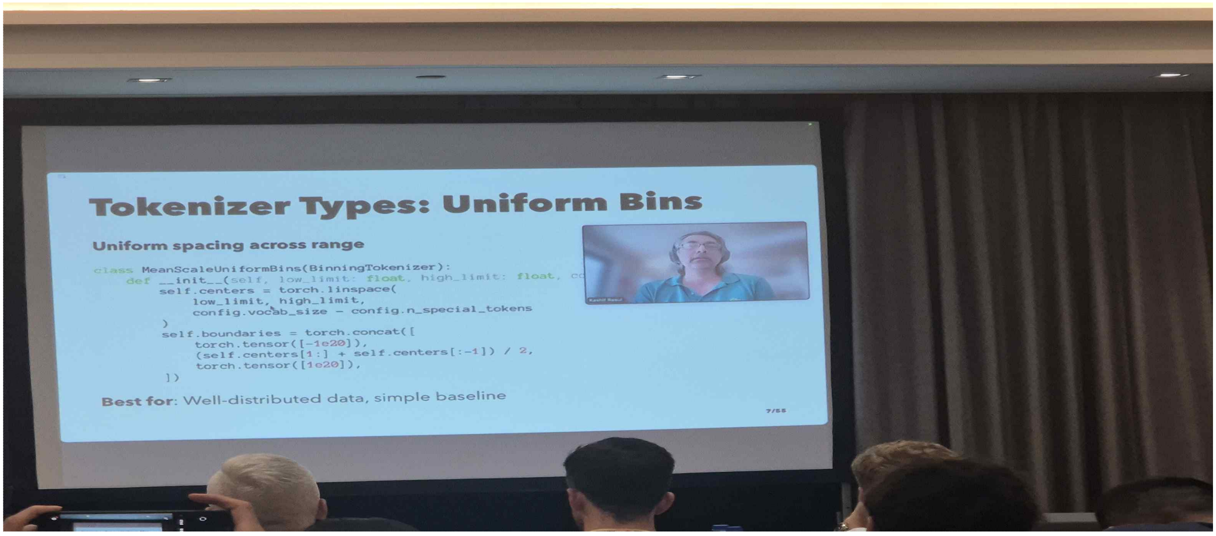
Multiple Aggregation Prediction Algorithm

If we want to go fancy, we would consider linear, spline, or other exotic interpolations. However, we are now imposing a model on our data even before we start modelling. That is not a great idea.

Instead, we take an information argument: The forecasted points in the more aggregate levels contain all the best available information up to that period. When the information is updated, then we get a new forecast. Therefore, to interpolate, we **only replicate the same value**.

(We will return to this and show that this is actually not a random choice and comes out of the equations naturally.)





ㅇ Temporal Hierarchies는 계절성, 잡음(noise)과 같은 고주기 정보를 필터링하고 추세와 같은 저주기 정보를 포착하여 구조적인 추정을 가능하게 함

ㅇ MAPA와 THieF는 Temporal Hierarchy 각각의 예측모형을 적합한 후, 그를 결합함으로써 전망 정확도를 향상시키는 방법론으로, 호주의 관광 수요 예측 사례에서 기존 ARIMA 모델 대비 ThieF 모델에서 더 높은 예측 정확도를 보임

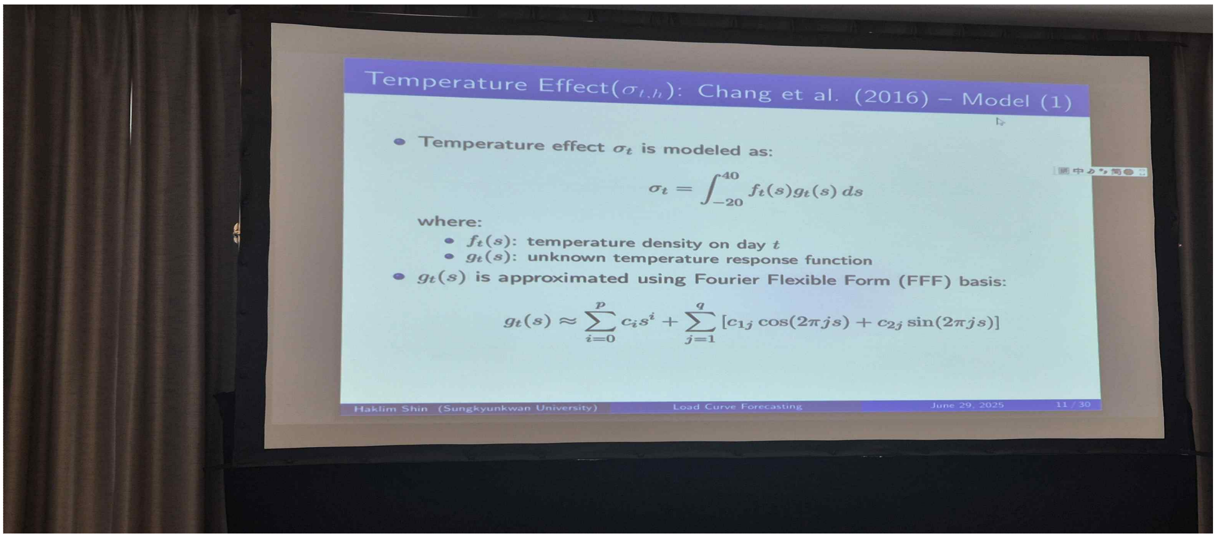
ㅇ THieF 모형은 다양한 베이스 모델과 결합할 수 있어 유연성이 높고, 제품 생애주기 예측 등 복잡한 실제 사례에의 적용, 머신러닝과의 결합 등도 가능

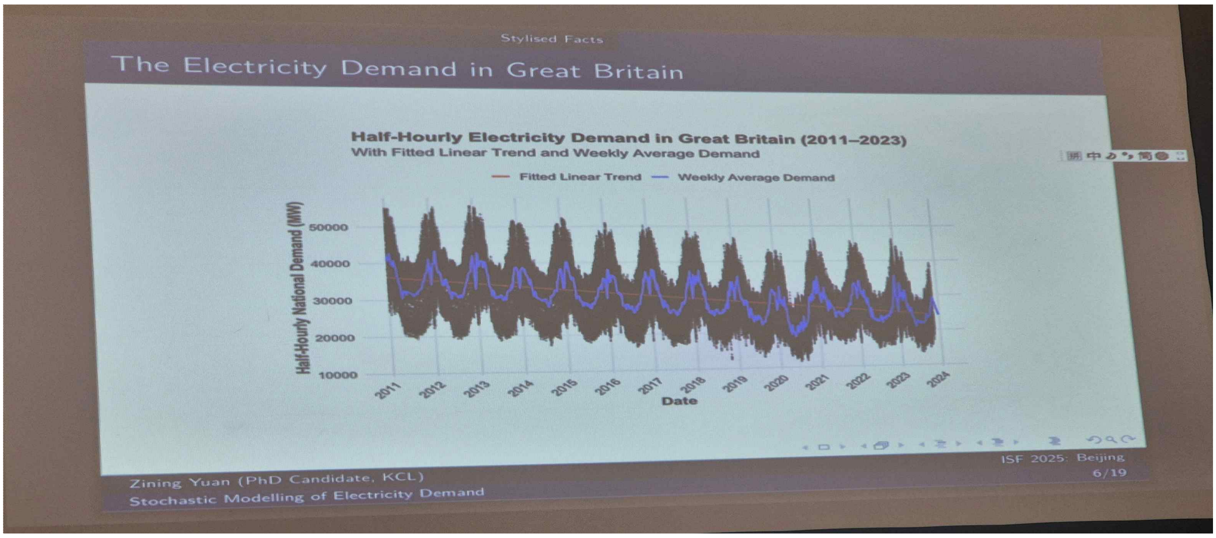
ㅇ 유형별 딥러닝 코드 및 시계열 분석의 기초 이론 학습

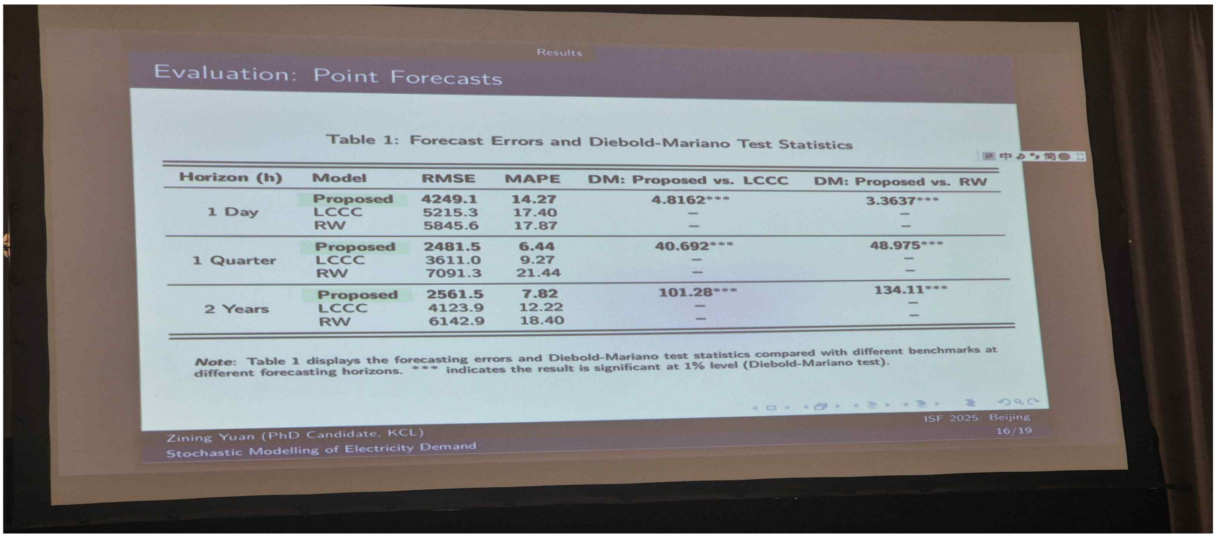
나. ISF2025 학회 참석(6.30~7.2)

□ 6.30(월)

No	Papers
1	(발표 논문) Future Electricity Demand of Data Centers in South Korea : Based on the Basic Plan for Electricity Supply and Demand ☞**[붙임2] 참고**
2	Long-term Total Load Forecasting using a Functional Regression Model
3	Stochastic Modeling of Electricity Demand on Multiple Time Scales
4	Spatiotemporal Solar Forecasting Using a Single Sky Imager and Satellite Data
5	Adaptive Probabilistic Forecasting for Wind Energy Based on Generalised Logit Transformation and Bayesian Method
6	Long-term Forecasting Model for the State of a Zonal Electric Power System

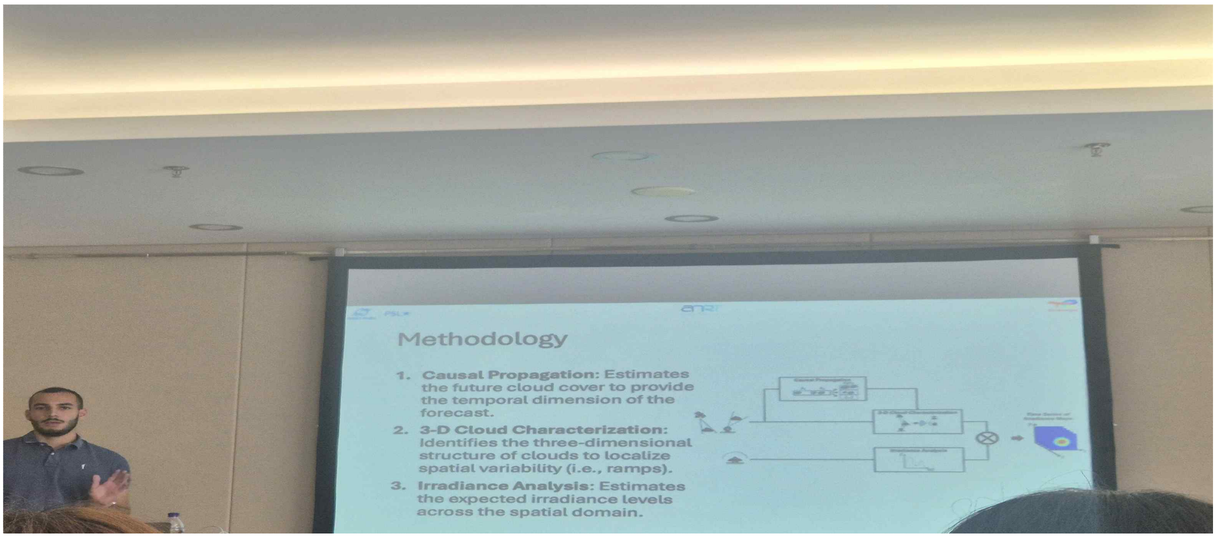


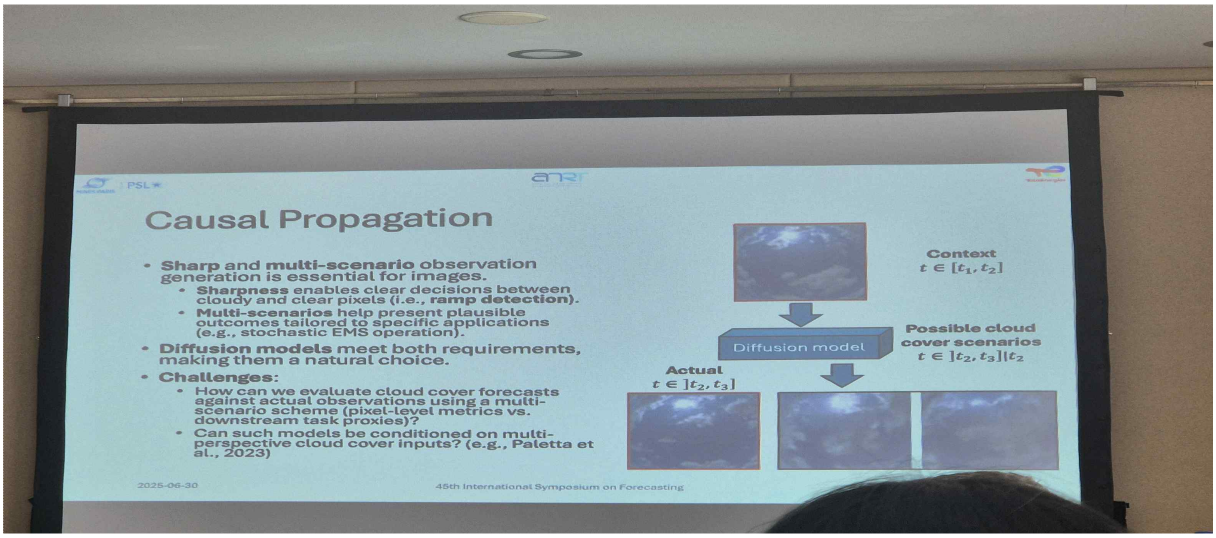

Stylised Facts
The Electricity Demand in Great Britain
Half-Hourly Electricity Demand in Great Britain (2011–2023)
With Fitted Linear Trend and Weekly Average Demand
Fitted Linear Trend
Weekly Average Demand
Half-Hourly National Demand (MW)
50000
40000
30000
20000
10000
2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024
Date
Zining Yuan (PhD Candidate, KCL)
Stochastic Modelling of Electricity Demand
ISF 2025: Beijing
6/19

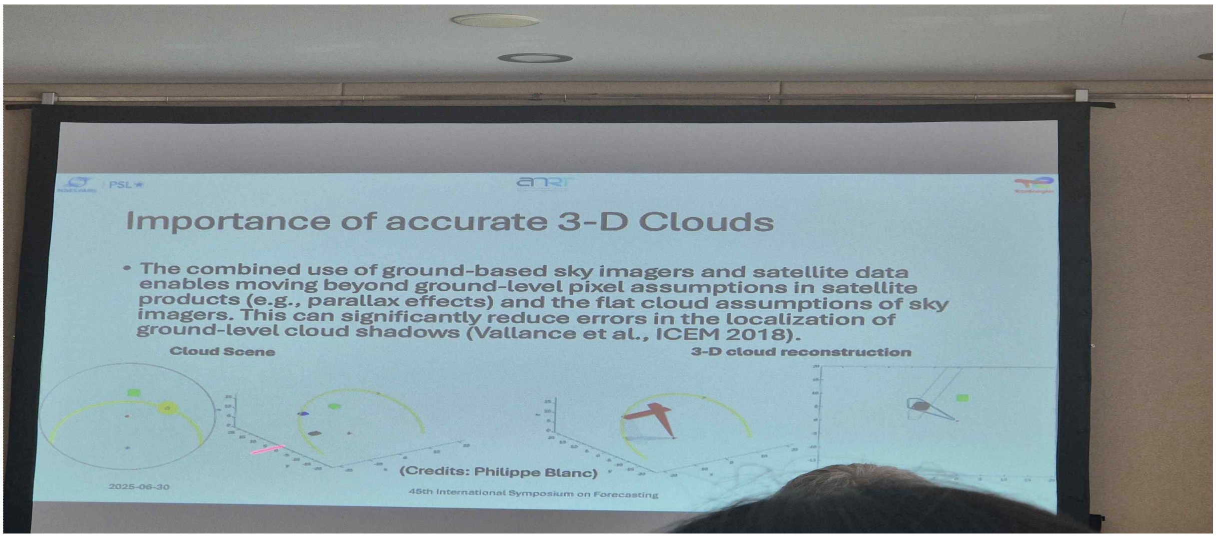

Results
Evaluation: Point Forecasts
Table 1: Forecast Errors and Diebold-Mariano Test Statistics

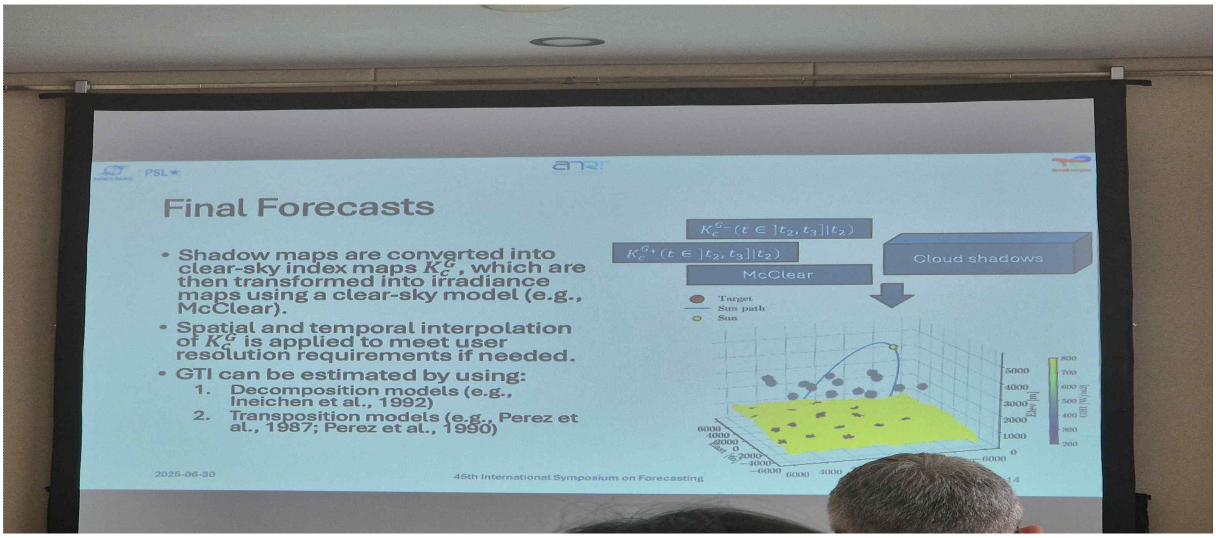
Horizon (h)	Model	RMSE	MAPE	DM: Proposed vs. LCCC	DM: Proposed vs. RW
1 Day	Proposed	4249.1	14.27	4.8162***	3.3637***
	LCCC	5215.3	17.40	–	–
	RW	5845.6	17.87	–	–
1 Quarter	Proposed	2481.5	6.44	40.692***	48.975***
	LCCC	3611.0	9.27	–	–
	RW	7091.3	21.44	–	–
2 Years	Proposed	2561.5	7.82	101.28***	134.11***
	LCCC	4123.9	12.22	–	–
	RW	6142.9	18.40	–	–

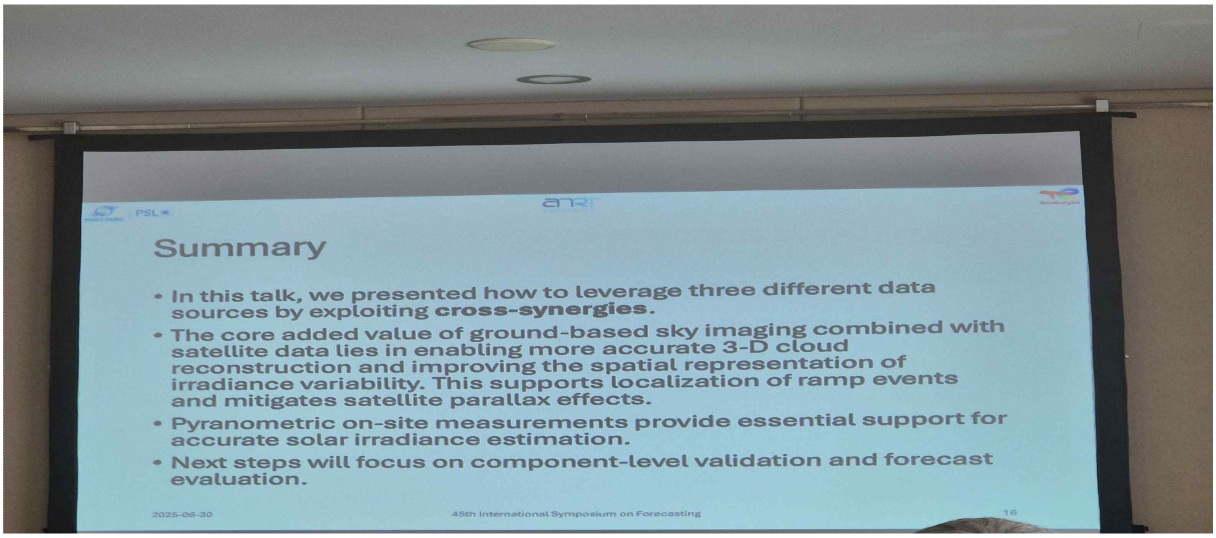
Note: Table 1 displays the forecasting errors and Diebold-Mariano test statistics compared with different benchmarks at different forecasting horizons. *** indicates the result is significant at 1% level (Diebold-Mariano test).
Zining Yuan (PhD Candidate, KCL)
Stochastic Modelling of Electricity Demand
ISF 2025: Beijing
16/19


Methodology
1. Causal Propagation: Estimates the future cloud cover to provide the temporal dimension of the forecast.
2. 3-D Cloud Characterization: Identifies the three-dimensional structure of clouds to localize spatial variability (i.e., ramps).
3. Irradiance Analysis: Estimates the expected irradiance levels across the spatial domain.


PSL
Causal Propagation
• Sharp and multi-scenario observation generation is essential for images.
• Sharpness enables clear decisions between cloudy and clear pixels (i.e., ramp detection).
• Multi-scenarios help present plausible outcomes tailored to specific applications (e.g., stochastic EMS operation).
• Diffusion models meet both requirements, making them a natural choice.
• Challenges:
• How can we evaluate cloud cover forecasts against actual observations using a multi-scenario scheme (pixel-level metrics vs. downstream task proxies)?
• Can such models be conditioned on multi-perspective cloud cover inputs? (e.g., Paletta et al., 2023)
Context
$t \in [t_1, t_2]$
Diffusion model
Possible cloud cover scenarios
$t \in]t_2, t_3] | t_2$
Actual
$t \in]t_2, t_3]$
2025-06-30
45th International Symposium on Forecasting


PSL
Importance of accurate 3-D Clouds
• The combined use of ground-based sky imagers and satellite data enables moving beyond ground-level pixel assumptions in satellite products (e.g., parallax effects) and the flat cloud assumptions of sky imagers. This can significantly reduce errors in the localization of ground-level cloud shadows (Vallance et al., ICEM 2018).
Cloud Scene
3-D cloud reconstruction
(Credits: Philippe Blanc)
2025-06-30
45th International Symposium on Forecasting


PSL
Final Forecasts
• Shadow maps are converted into clear-sky index maps K_c^G, which are then transformed into irradiance maps using a clear-sky model (e.g., McClear).
• Spatial and temporal interpolation of K_c^G is applied to meet user resolution requirements if needed.
• GTI can be estimated by using:
1. Decomposition models (e.g., Ineichen et al., 1992)
2. Transposition models (e.g., Perez et al., 1987; Perez et al., 1990)
$K_c^{G-}(t \in]t_2, t_3] | t_2)$
$K_c^{G+}(t \in]t_2, t_3] | t_2)$
McClear
Cloud shadows
Target
Sun path
Sun
2025-06-30
45th International Symposium on Forecasting


Summary
• In this talk, we presented how to leverage three different data sources by exploiting cross-synergies.
• The core added value of ground-based sky imaging combined with satellite data lies in enabling more accurate 3-D cloud reconstruction and improving the spatial representation of irradiance variability. This supports localization of ramp events and mitigates satellite parallax effects.
• Pyranometric on-site measurements provide essential support for accurate solar irradiance estimation.
• Next steps will focus on component-level validation and forecast evaluation.
2025-06-30
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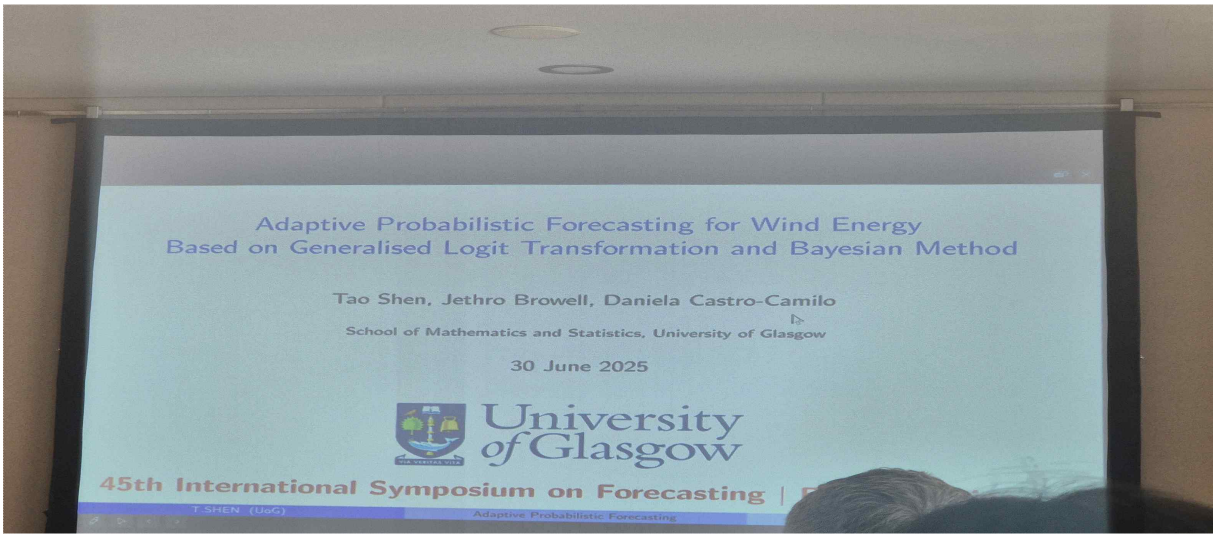
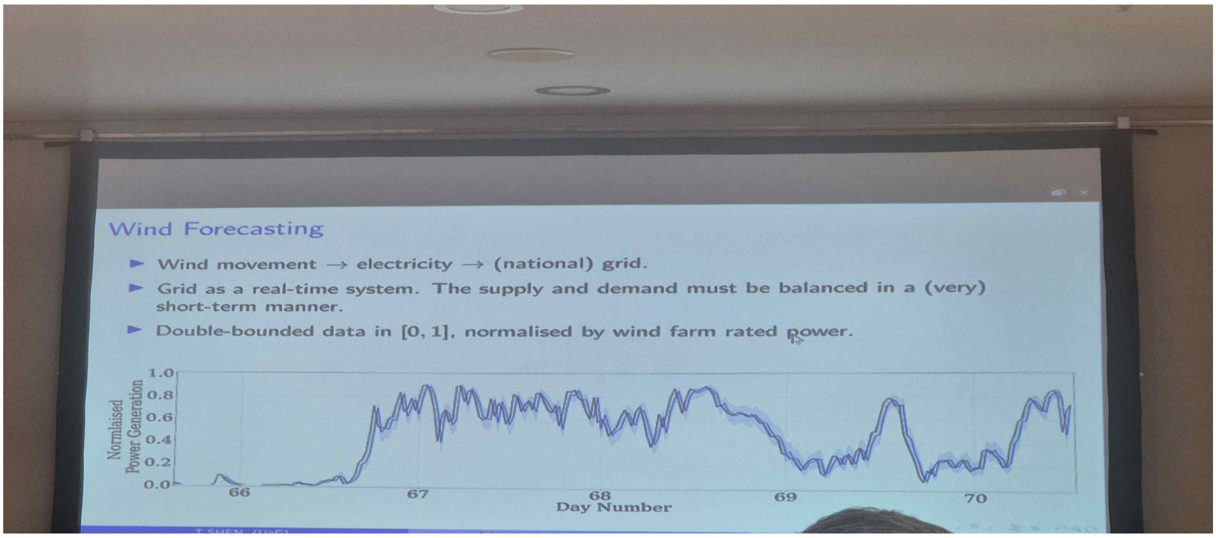
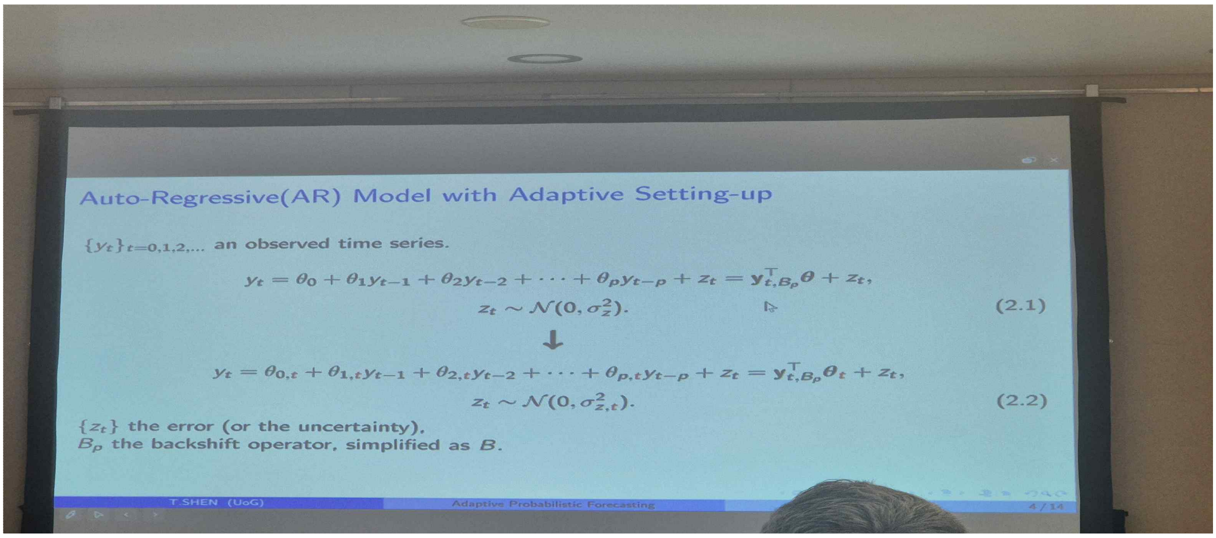

Adaptive Probabilistic Forecasting for Wind Energy
Based on Generalised Logit Transformation and Bayesian Method
Tao Shen, Jethro Browell, Daniela Castro-Camilo
School of Mathematics and Statistics, University of Glasgow
30 June 2025
University of Glasgow
45th International Symposium on Forecasting
T SHEN (UoG)
Adaptive Probabilistic Forecasting


Wind Forecasting
► Wind movement → electricity → (national) grid.
► Grid as a real-time system. The supply and demand must be balanced in a (very) short-term manner.
► Double-bounded data in [0, 1], normalised by wind farm rated power.
1.0
0.8
0.6
0.4
0.2
0.0
Normlaised Power Generation
66
67
68
69
70
Day Number


Auto-Regressive(AR) Model with Adaptive Setting-up
$\{y_t\}_{t=0,1,2,\ldots}$ an observed time series.
$$y_t = \theta_0 + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + z_t = \mathbf{y}_{t,B_p}^{\top}\boldsymbol{\theta} + z_t,$$
$$z_t \sim \mathcal{N}(0, \sigma_z^2). \quad (2.1)$$
$$y_t = \theta_{0,t} + \theta_{1,t} y_{t-1} + \theta_{2,t} y_{t-2} + \cdots + \theta_{p,t} y_{t-p} + z_t = \mathbf{y}_{t,B_p}^{\top}\boldsymbol{\theta}_t + z_t,$$
$$z_t \sim \mathcal{N}(0, \sigma_{z,t}^2). \quad (2.2)$$
$\{z_t\}$ the error (or the uncertainty),
B_p the backshift operator, simplified as B.
T.SHEN (UoG)
Adaptive Probabilistic Forecasting
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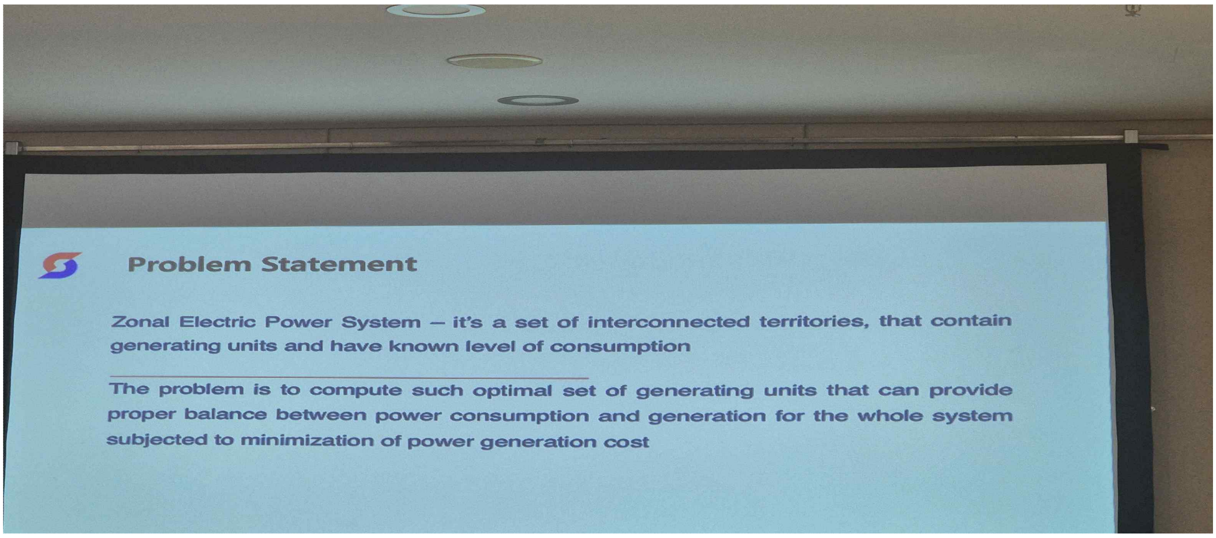
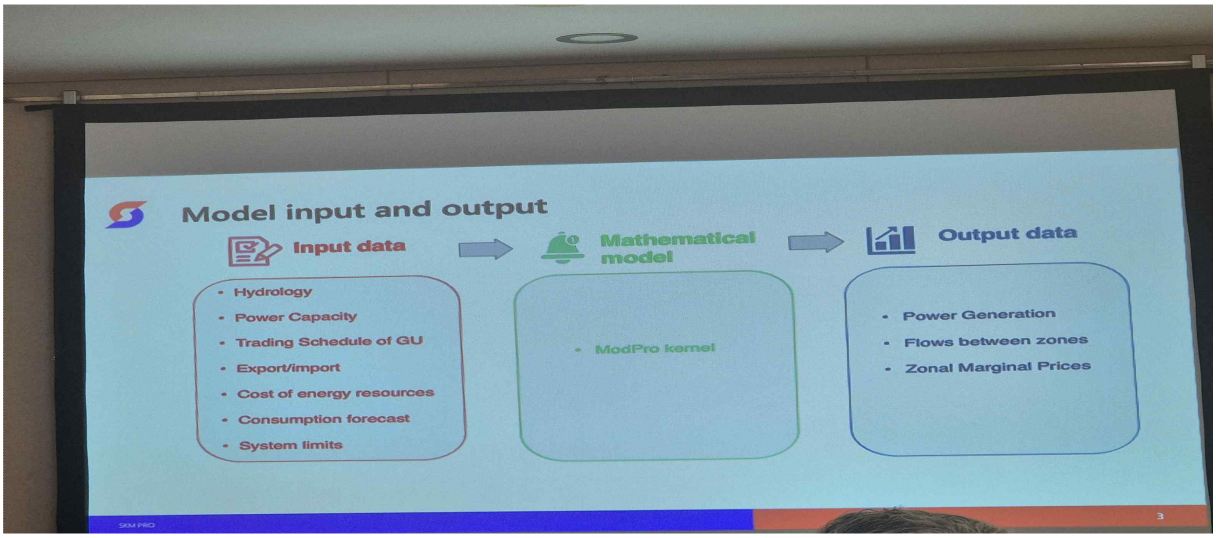
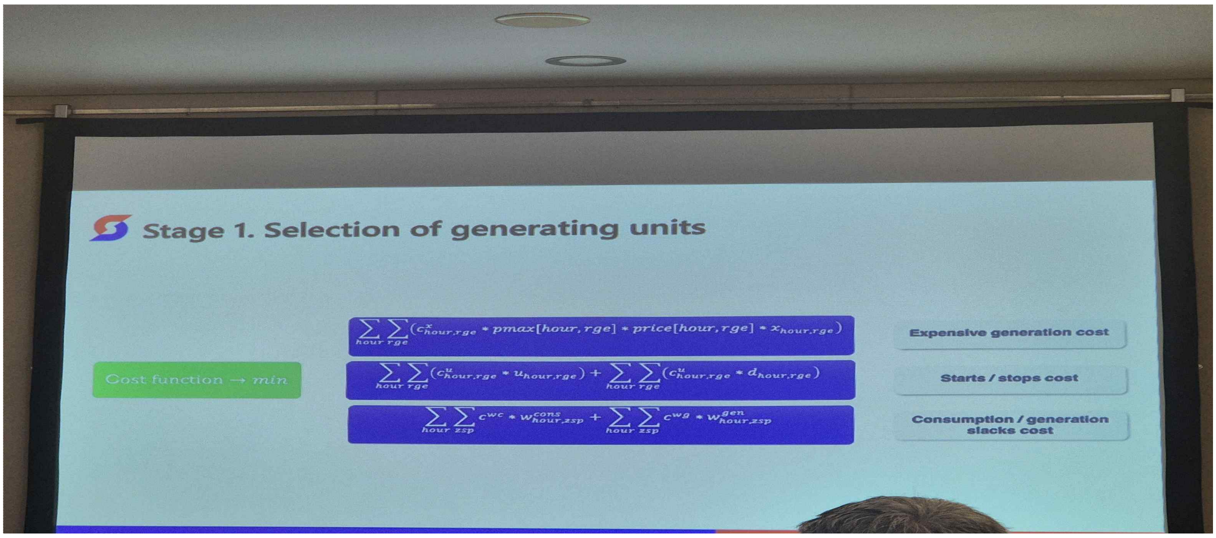
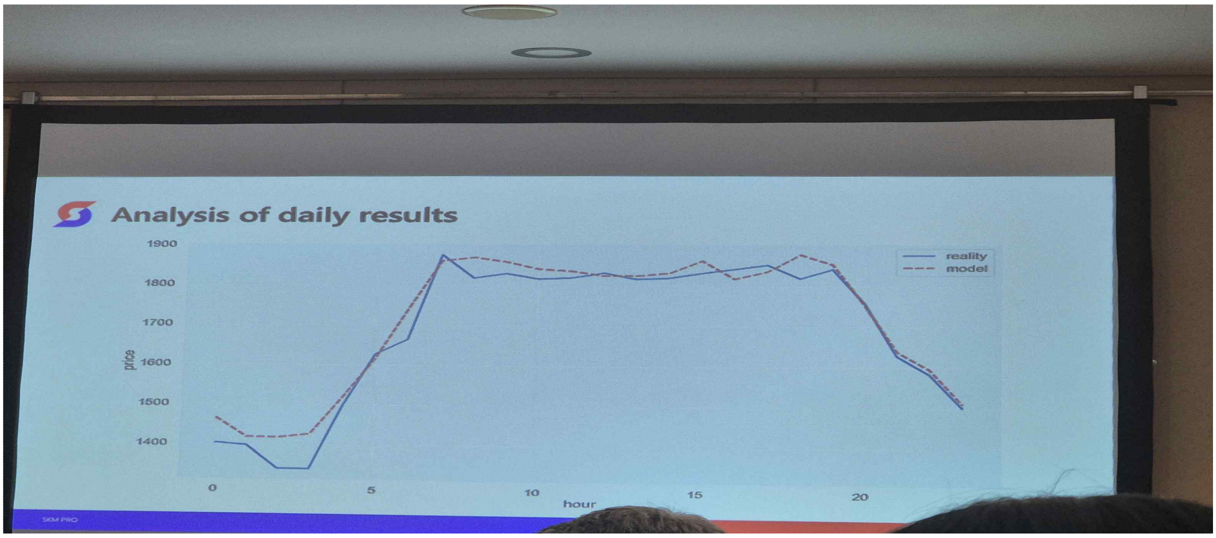

Problem Statement
Zonal Electric Power System – it's a set of interconnected territories, that contain generating units and have known level of consumption
The problem is to compute such optimal set of generating units that can provide proper balance between power consumption and generation for the whole system subjected to minimization of power generation cost


Model input and output
Input data
Mathematical model
Output data
Hydrology
Power Capacity
Trading Schedule of GU
Export/import
Cost of energy resources
Consumption forecast
System limits
ModPro kernel
Power Generation
Flows between zones
Zonal Marginal Prices
SKM PRO
3

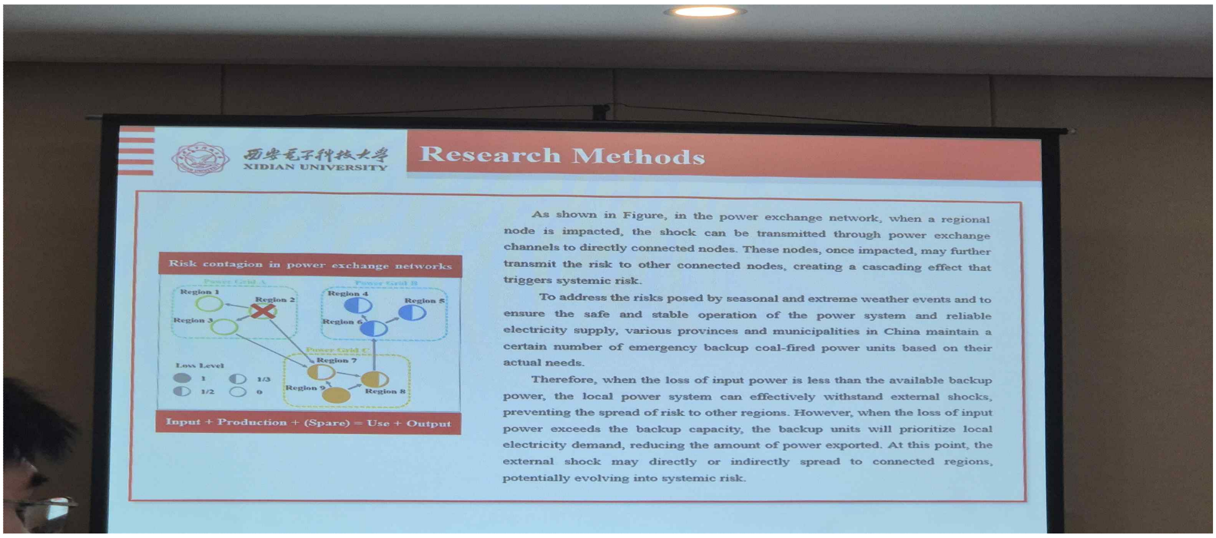


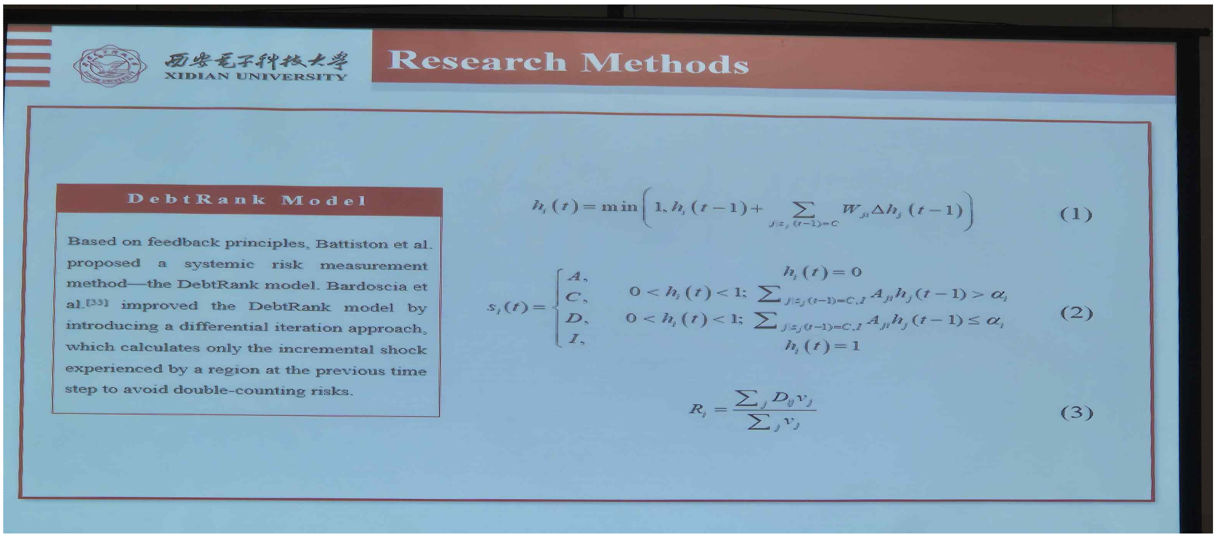


- 전력수요를 추세, 계절성, 주기, 잔차로 분해한 후 다중회귀모형, 특히 함수 계수가 고정된 상수가 아니라 시간에 따라 변한다는 가정을 적용하여 전망 정확도를 제고하는 방안 제시
- 3차원 구름 구조 분석 및 인공지능 기반의 확률적 구름 전이 예측으로 지표면 일사량을 정밀하게 추정하고, 위성 및 지상 관측자료의 결합으로 예측 정확도를 높이는 전략을 제시
- 러시아 casestudy를 통해 지역별(Zonal) 가격제 하 전력계통 운영 최적화 모델링을 제시(수급균형과 전체 시스템의 발전비용 최소화를 동시 달성하는 발전기 운영의 최적점 탐색, 기동비용 등 포함)

☐ 7.1(화)

No	Papers
1	Systemic Risks and Contagion Effects in China's Regional Electricity Exchange Network : A Differential DebtRank Model
2	How do Smart Aging-Friendly Policies Affect Elderly Households' Energy Consumption? Casual Evidence and Policy Scenario Simulations from Intergenerational Technology
3	A Study for Forecasting Solar Energy Power Generation
4	Nationwide Weather Impact on Photovoltaic Generation Forecast
5	Development of Operational PV Generation Forecast Model in Korea Based on CNN and K-means Clustering Method
6	News-driven Load Forecasting : Generative Agents and Large Language Models for Unstructured Data and Event Analysis





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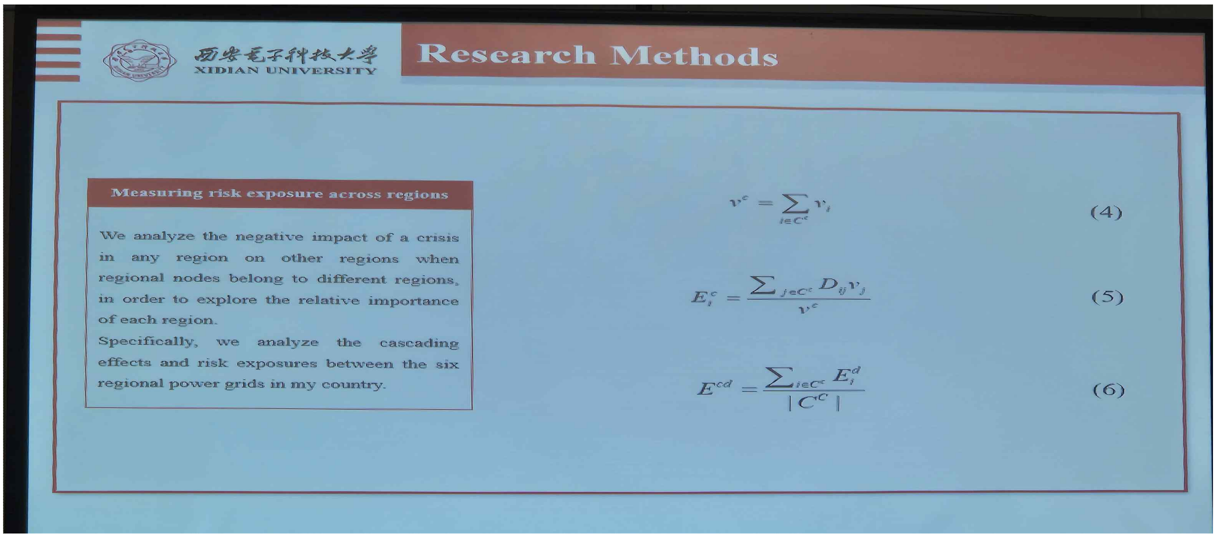
Research Methods
DebtRank Model
Based on feedback principles, Battiston et al. proposed a systemic risk measurement method—the DebtRank model. Bardoscia et al.[33] improved the DebtRank model by introducing a differential iteration approach, which calculates only the incremental shock experienced by a region at the previous time step to avoid double-counting risks.
$$h_i(t) = \min\left(1, h_i(t-1) + \sum_{j:s_j(t-1)=C} W_{ji}\Delta h_j(t-1)\right) \quad (1)$$
$$s_i(t) = \begin{cases} A, & h_i(t) = 0 \\ C, & 0 < h_i(t) < 1;\ \sum_{j:s_j(t-1)=C,I} A_{ji} h_j(t-1) > \alpha_i \\ D, & 0 < h_i(t) < 1;\ \sum_{j:s_j(t-1)=C,I} A_{ji} h_j(t-1) \le \alpha_i \\ I, & h_i(t) = 1 \end{cases} \quad (2)$$
$$R_i = \frac{\sum_j D_{ij} v_j}{\sum_j v_j} \quad (3)$$



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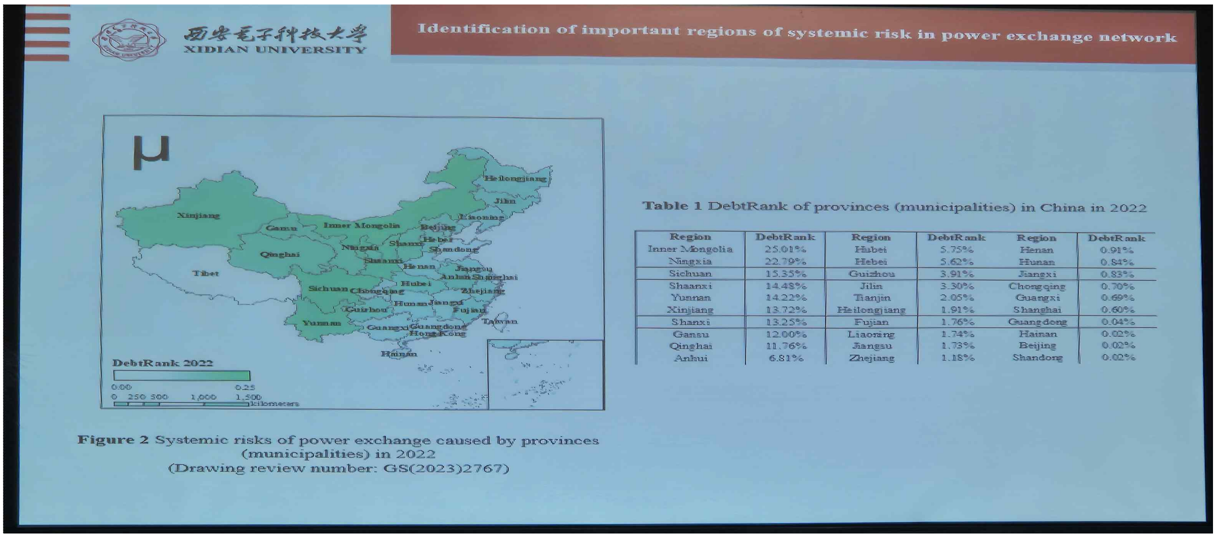
Research Methods
Measuring risk exposure across regions
We analyze the negative impact of a crisis in any region on other regions when regional nodes belong to different regions, in order to explore the relative importance of each region.
Specifically, we analyze the cascading effects and risk exposures between the six regional power grids in my country.
$$v^c = \sum_{i \in C^c} v_i \quad (4)$$
$$E_i^c = \frac{\sum_{j \in C^c} D_{ij} v_j}{v^c} \quad (5)$$
$$E^{cd} = \frac{\sum_{i \in C^c} E_i^d}{|C^c|} \quad (6)$$



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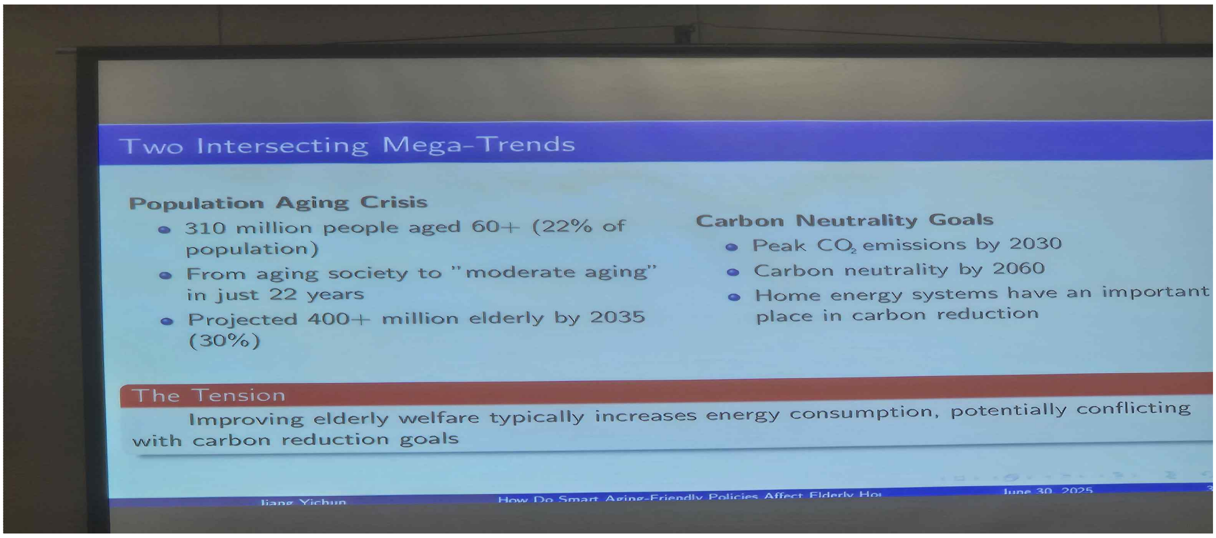
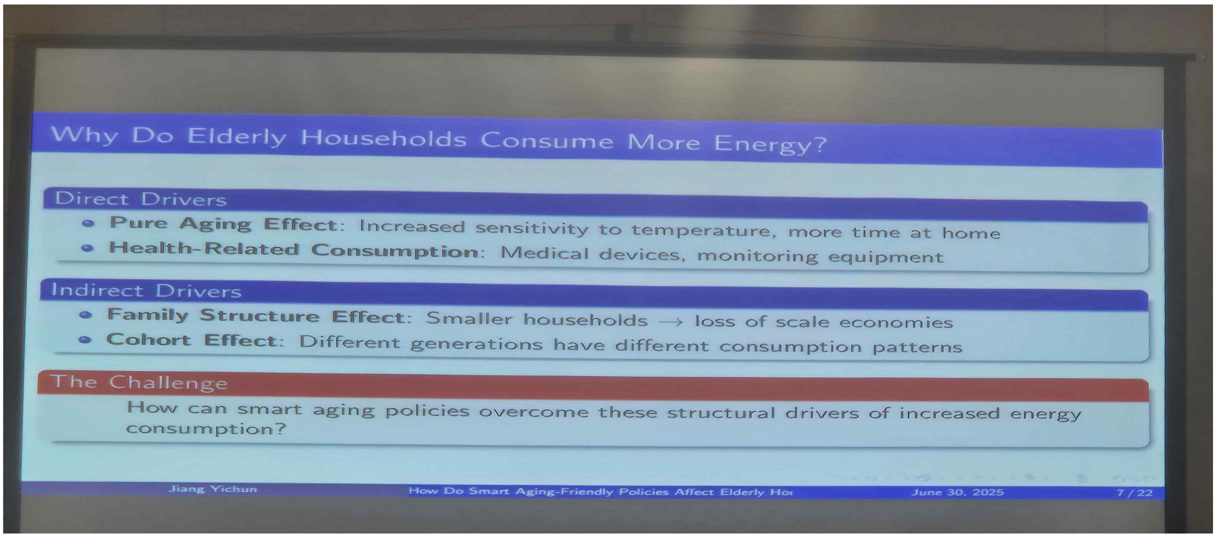
Identification of important regions of systemic risk in power exchange network
Heilongjiang
Jilin
Liaoning
Xinjiang
Gansu
Inner Mongolia
Beijing
Hebei
Shanxi
Shandong
Ningxia
Qinghai
Shaanxi
Tibet
Henan
Jiangsu
Anhui
Shanghai
Hubei
Sichuan
Chongqing
Zhejiang
Hunan
Jiangxi
Guizhou
Fujian
Yunnan
Guangxi
Guangdong
Hong Kong
Taiwan
Hainan
DebtRank 2022
0.00
0.25
0 250 500 1,000 1,500 kilometers
Figure 2 Systemic risks of power exchange caused by provinces (municipalities) in 2022
(Drawing review number: GS(2023)2767)
Table 1 DebtRank of provinces (municipalities) in China in 2022

Region	DebtRank	Region	DebtRank	Region	DebtRank
Inner Mongolia	25.01%	Hubei	5.75%	Henan	0.91%
Ningxia	22.79%	Hebei	5.62%	Hunan	0.84%
Sichuan	15.35%	Guizhou	3.91%	Jiangxi	0.83%
Shaanxi	14.48%	Jilin	3.30%	Chongqing	0.70%
Yunnan	14.22%	Tianjin	2.05%	Guangxi	0.69%
Xinjiang	13.72%	Heilongjiang	1.91%	Shanghai	0.60%
Shanxi	13.25%	Fujian	1.76%	Guangdong	0.04%
Gansu	12.00%	Liaoning	1.74%	Hainan	0.02%
Qinghai	11.76%	Jiangsu	1.73%	Beijing	0.02%
Anhui	6.81%	Zhejiang	1.18%	Shandong	0.02%


Two Intersecting Mega-Trends
Population Aging Crisis
310 million people aged 60+ (22% of population)
From aging society to "moderate aging" in just 22 years
Projected 400+ million elderly by 2035 (30%)
Carbon Neutrality Goals
Peak CO2 emissions by 2030
Carbon neutrality by 2060
Home energy systems have an important place in carbon reduction
The Tension
Improving elderly welfare typically increases energy consumption, potentially conflicting with carbon reduction goals
Jiang Yichun
How Do Smart Aging-Friendly Policies Affect Elderly Ho
June 30, 2025


Why Do Elderly Households Consume More Energy?
Direct Drivers
Pure Aging Effect: Increased sensitivity to temperature, more time at home
Health-Related Consumption: Medical devices, monitoring equipment
Indirect Drivers
Family Structure Effect: Smaller households → loss of scale economies
Cohort Effect: Different generations have different consumption patterns
The Challenge
How can smart aging policies overcome these structural drivers of increased energy consumption?
Jiang Yichun
How Do Smart Aging-Friendly Policies Affect Elderly Ho
June 30, 2025
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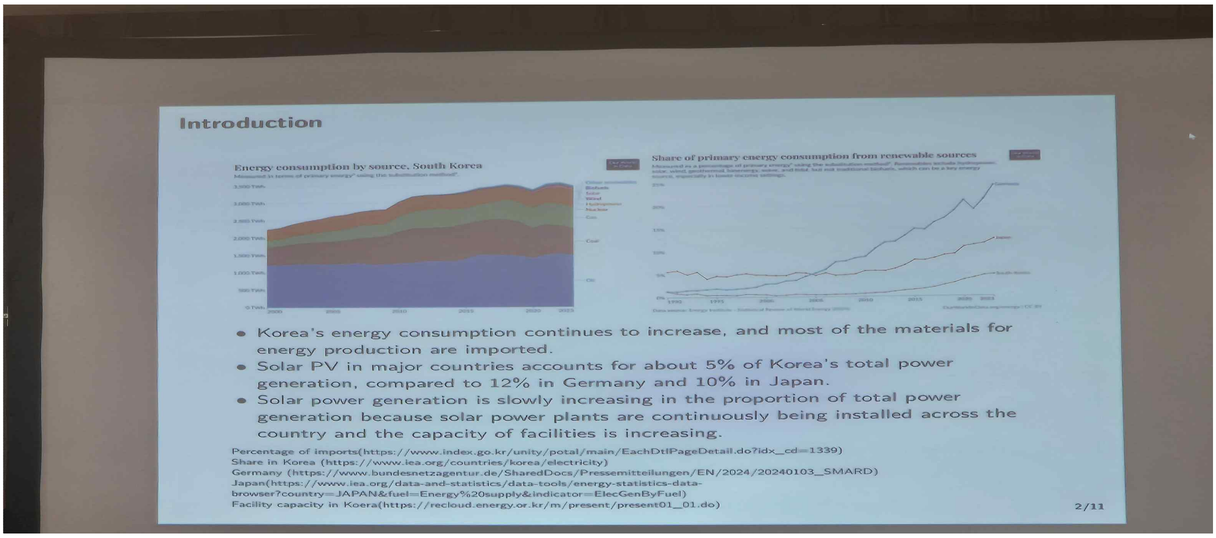
Introduction
Energy consumption by source, South Korea
Share of primary energy consumption from renewable sources
Korea's energy consumption continues to increase, and most of the materials for energy production are imported.
Solar PV in major countries accounts for about 5% of Korea's total power generation, compared to 12% in Germany and 10% in Japan.
Solar power generation is slowly increasing in the proportion of total power generation because solar power plants are continuously being installed across the country and the capacity of facilities is increasing.
Percentage of imports(https://www.index.go.kr/unity/potal/main/EachDtlPageDetail.do?idx_cd=1339)
Share in Korea (https://www.iea.org/countries/korea/electricity)
Germany (https://www.bundesnetzagentur.de/SharedDocs/Pressemitteilungen/EN/2024/20240103_SMARD)
Japan(https://www.iea.org/data-and-statistics/data-tools/energy-statistics-data-browser?country=JAPAN&fuel=Energy%20supply&indicator=ElecGenByFuel)
Facility capacity in Koera(https://recloud.energy.or.kr/m/present/present01_01.do)
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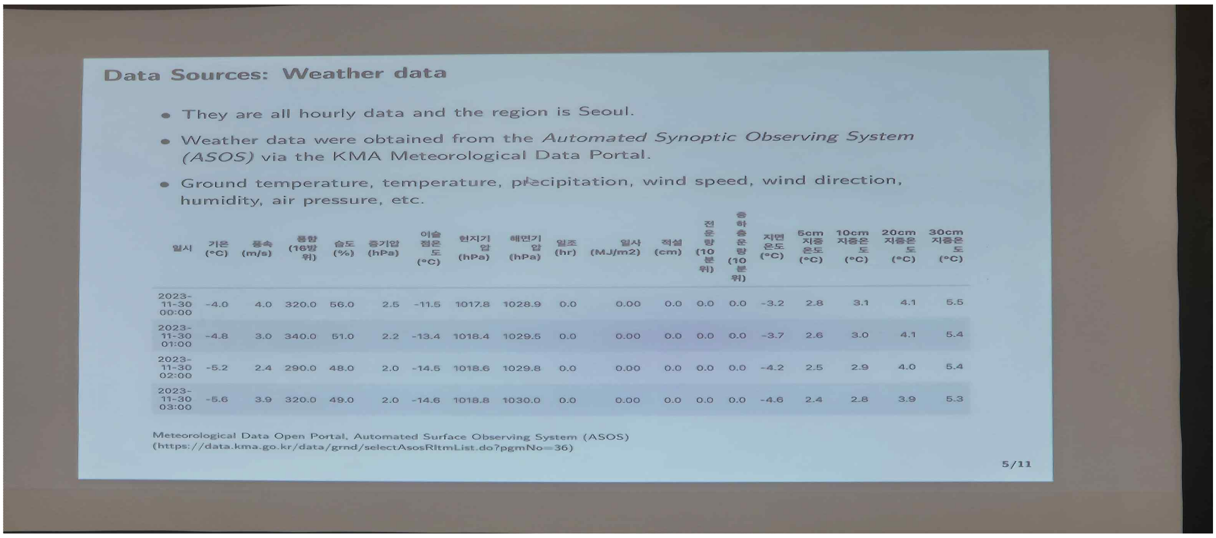
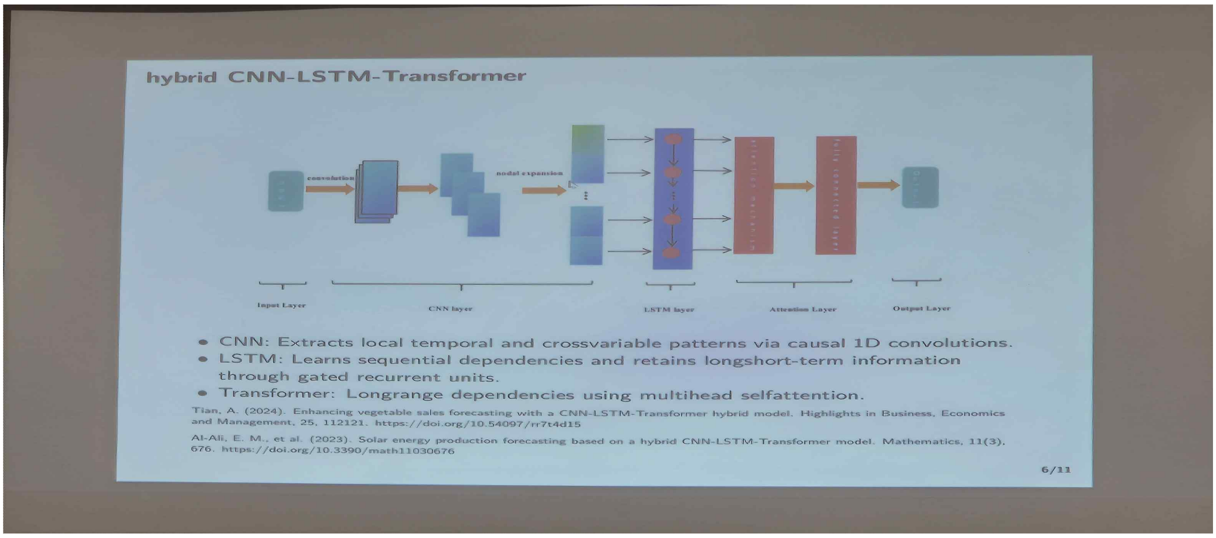
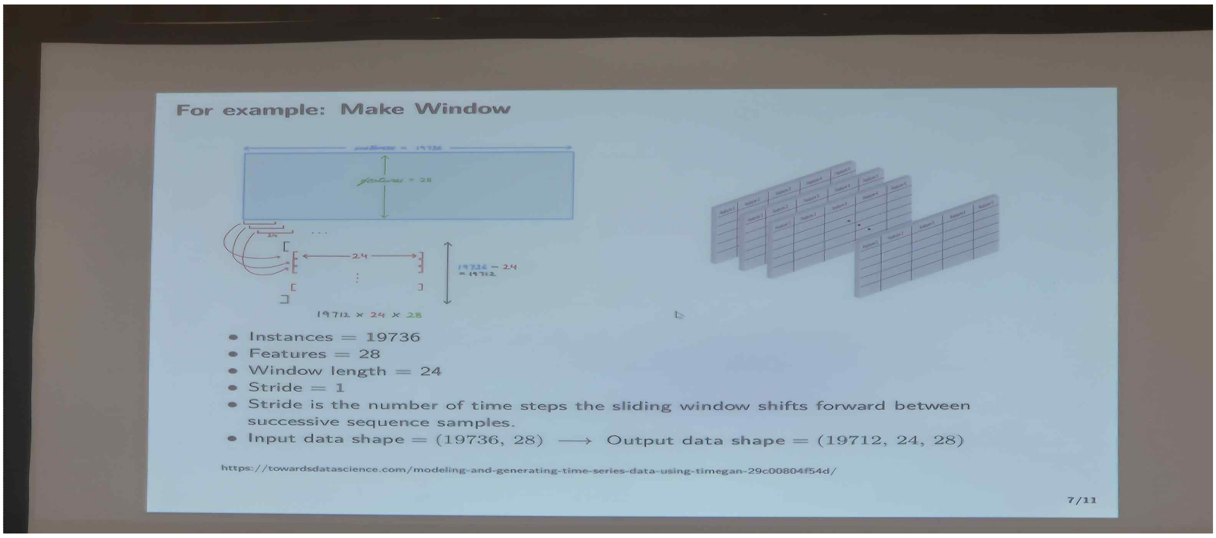
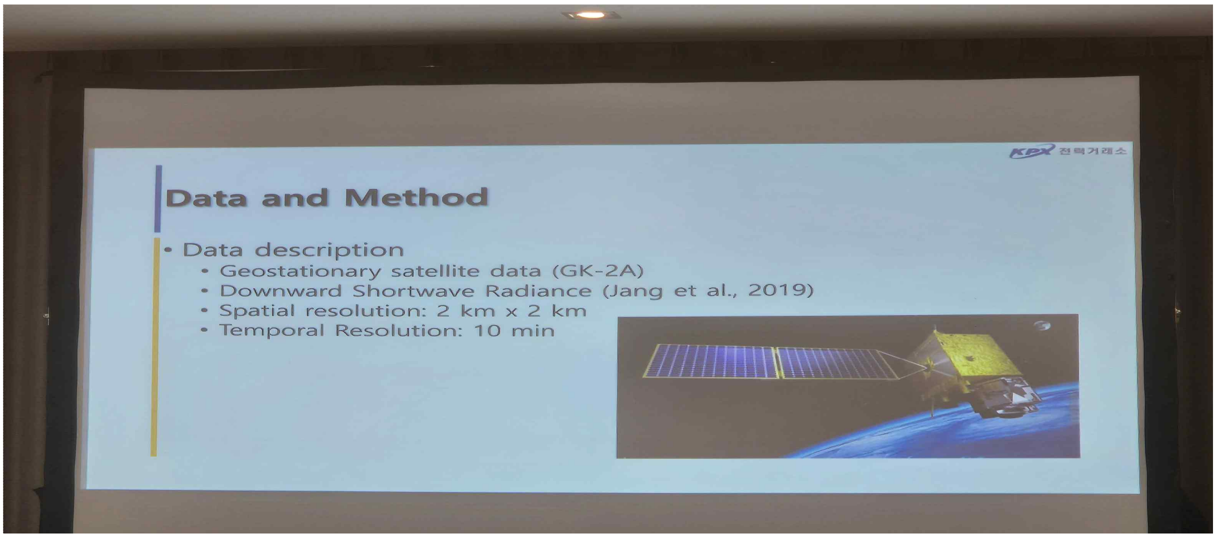
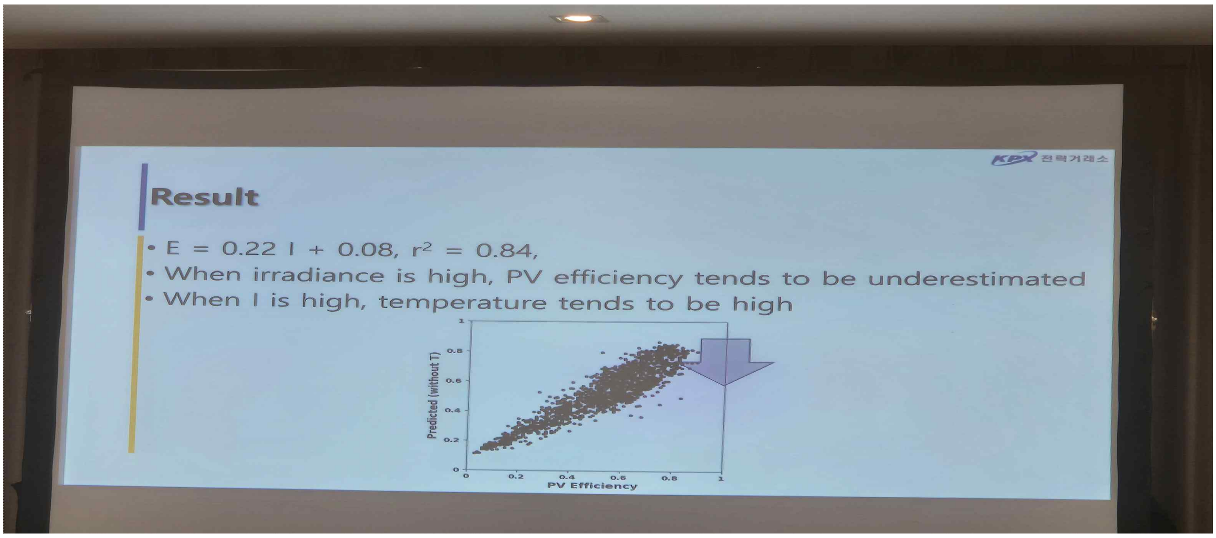


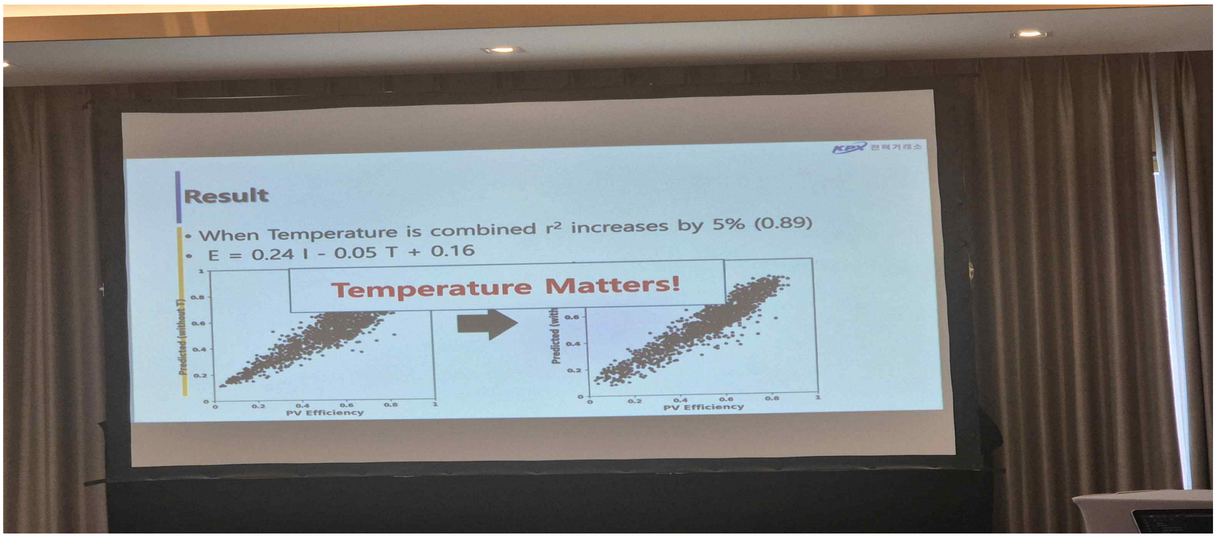
일시	기온 (°C)	풍속 (m/s)	풍향 (16방위)	습도 (%)	증기압 (hPa)	이슬점온도 (°C)	현지기압 (hPa)	해면기압 (hPa)	일조 (hr)	일사 (MJ/m2)	적설 (cm)	전운량 (10분위)	중하층운량 (10분위)	지면온도 (°C)	5cm 지중온도 (°C)	10cm 지중온도 (°C)	20cm 지중온도 (°C)	30cm 지중온도 (°C)
2023-11-30 00:00	-4.0	4.0	320.0	56.0	2.5	-11.5	1017.8	1028.9	0.0	0.00	0.0	0.0	0.0	-3.2	2.8	3.1	4.1	5.5
2023-11-30 01:00	-4.8	3.0	340.0	51.0	2.2	-13.4	1018.4	1029.5	0.0	0.00	0.0	0.0	0.0	-3.7	2.6	3.0	4.1	5.4
2023-11-30 02:00	-5.2	2.4	290.0	48.0	2.0	-14.5	1018.6	1029.8	0.0	0.00	0.0	0.0	0.0	-4.2	2.5	2.9	4.0	5.4
2023-11-30 03:00	-5.6	3.9	320.0	49.0	2.0	-14.6	1018.8	1030.0	0.0	0.00	0.0	0.0	0.0	-4.6	2.4	2.8	3.9	5.3

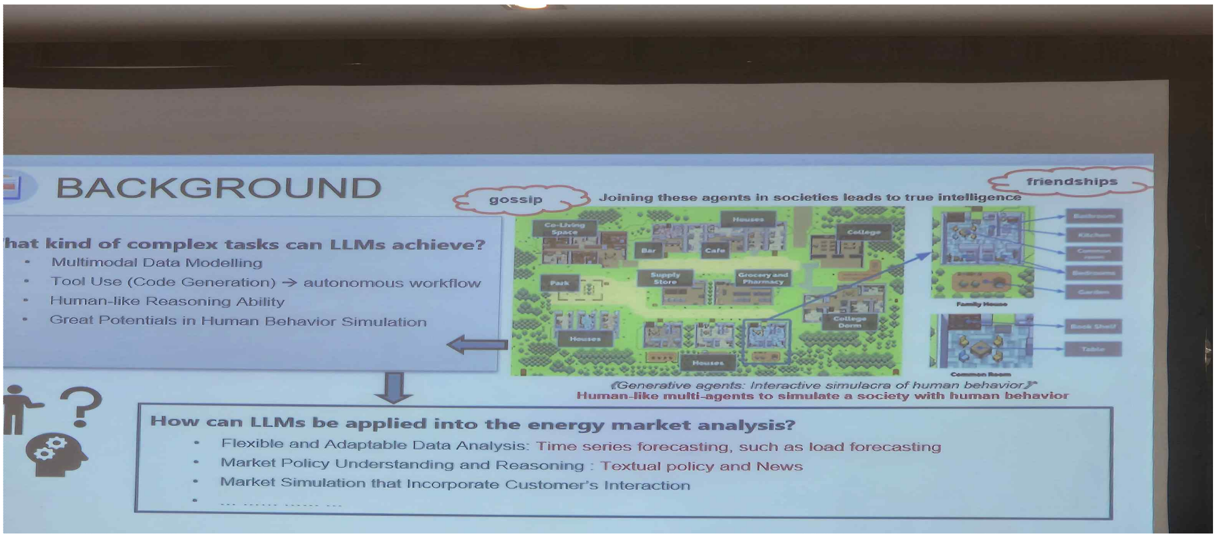


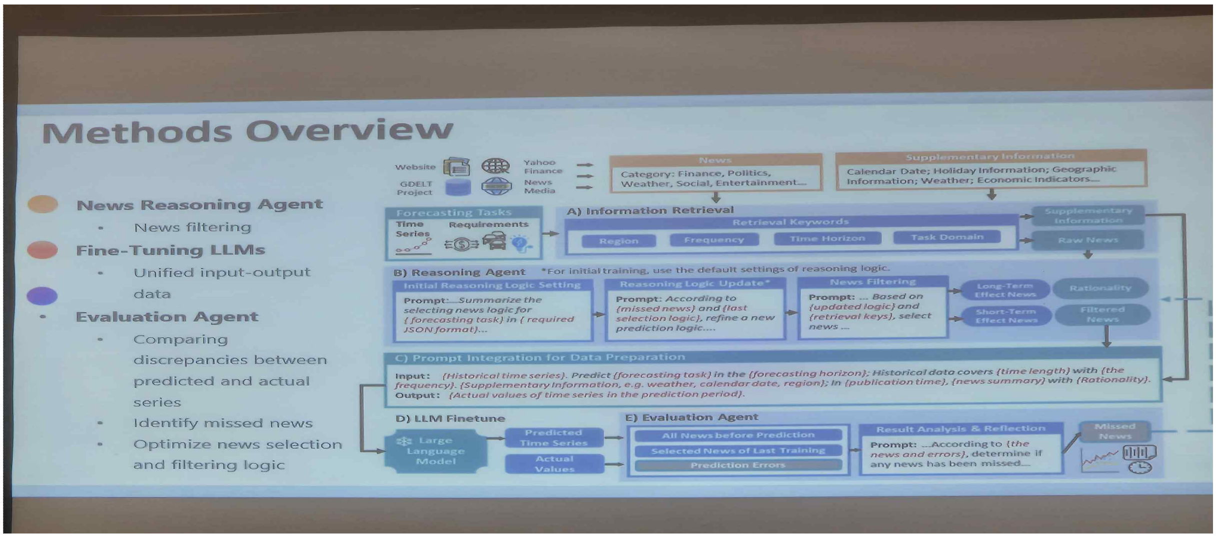



KPX 전력거래소
Data and Method
• Data description
• Geostationary satellite data (GK-2A)
• Downward Shortwave Radiance (Jang et al., 2019)
• Spatial resolution: 2 km x 2 km
• Temporal Resolution: 10 min


KPX 전력거래소
Result
• E = 0.22 I + 0.08, r² = 0.84,
• When irradiance is high, PV efficiency tends to be underestimated
• When I is high, temperature tends to be high
Predicted (without T)
PV Efficiency


KPX 전력거래소
Result
• When Temperature is combined r² increases by 5% (0.89)
• E = 0.24 I - 0.05 T + 0.16
Temperature Matters!
Predicted (without T)
PV Efficiency
PV Efficiency





ㅇ 1인 가구 증가, 노년층 인구 비중의 증가 등 인구(가구) 구조의 변화는 전력수요 패턴의 변화를 초래(중국의 사례 연구에서, 노년층 인구가 증가함에 따라 가정 내 활동시간 증가, 의료기기 활용 증가 등으로 가정용 전력소비량이 증가)

ㅇ 에너지 효율 정책의 성공적인 안착을 위해서는 정부와 민간의 Push&Pull 전략이 동시에 이루어져야 효율적

ㅇ 딥러닝을 위한 "CNN(Convolutional Neural Network)- LSTM (Short and Long Term Memory network)-Transformer 결합 모델"로 태양광의 단기적인 간헐성과 장기적인 추세를 효과적으로 모델링한 한국의 casestudy 사례 발표

□ 7.2(수)

No	Papers
1	Forecasting Japanese Recessions Using Machine Learning and Mixed-Frequency Data

ㅇ 다양한 빈도(frequency) 데이터를 머신러닝으로 결합하여 일본의 경기 침체를 분석하며, 머신러닝을 통해 표준 거시 경제변수 이외에도, 신문에서 추출한 텍스트 변수, 국채 기간 스프레드, DSR과 같은 금융 변수 등 여러 변수의 고려가 용이함을 제시

ㅇ 일본의 여러 경기 침체 사례가 각각 다른 원인에 기인함을 분석(부실 채권과 같은 기업 부실의 신호에 기인한 사례도 있으나, 디플레이션 압력 등 금융적인 신호에 기인한 사례도 존재)하여 머신러닝과의 결합으로 다양한 경제적 동인에 대한 이해가 가능함을 시사

다. 시사점 및 업무 적용방안

ㅇ 재생e 확대에 따라 재생e 발전량 전망 정확도 제고를 위한 여러 실무적 사례들이 논의됨 → 위성/지상 관측자료, 기온 등 여러 데이터의 결합을 통해 예측 정밀도를 향상하고, AI 머신러닝을 적극 활용할 필요

ㅇ 전력수요 전망 역시, 재생e 발전량을 고려한 Net-Load 전망과 AI 머신러닝 도입을 고려할 필요(기온에 의한 수요 변동 효과, 특수일에 대한 달력효과 등의 분석에 유의미)

ㅇ 한국도 고령화가 빠르게 진행 중이므로, 이에 따른 전력소비량, 전력소비 패턴 변화 등을 관찰하고, 수요전망 모형에의 반영을 고민해 볼 필요

ㅇ 중국의 지역별 전력계통 위험성을 평가한 사례, 러시아의 지역별 가격 및 발전량 모의 사례에서 한국도 재생e 확대, 전력계통 여건 등을 고려할 때 장단기적으로 지역별 수요전망이 필요 → 수요전망의 단위가 될 지역 구분, 실제 시장, 계통운영과의 연계 등에 대한 검토 필요

붙임1 **학회 참여 Certificate**

[redacted] Park
Bitgaram-ro 625
Naju-si Jeollanam-do
Korea, Republic of

Dea[redacted] Park,

We would like to thank you for your attendance and participation at the 45th International Symposium on Forecasting, which took place in Beijing, China from June 29-July 2, 2025. Your presentation entitled was a welcome addition to the conference program. We thank you for presenting.

The ISF is hosted by the International Institute of Forecasters, the pre-eminent organization for scholars and practitioners in the field of forecasting. The IIF is dedicated to stimulating the generation, distribution, and use of knowledge on forecasting in a wide range of fields.

We hope you enjoyed the world-renown speakers, stimulating research shared and the many networking opportunities provided at the ISF. We once again thank you for your participation.

Sincerely,

Laurent Ferrara, IIF President

붙임2	논문 발표사진


② Trends in Previous Studies
* Source : LBNL(2024), 2024 United States Data Center Energy Usage Report
Bottom-Up Modeling
- Calculates energy consumption based on detailed data of servers, equipments, and installed base.
- Allows granular analysis but highly dependent on data accuracy and periodic updates.
Top-down Modeling
- Uses aggregated national or regional consumption statistics to infer infrastructure needs.
- Cost-efficient and easy to apply but limited in reflecting technological shifts.
Extrapolation
- Projects future energy use based on growth rates or service demand indicators.