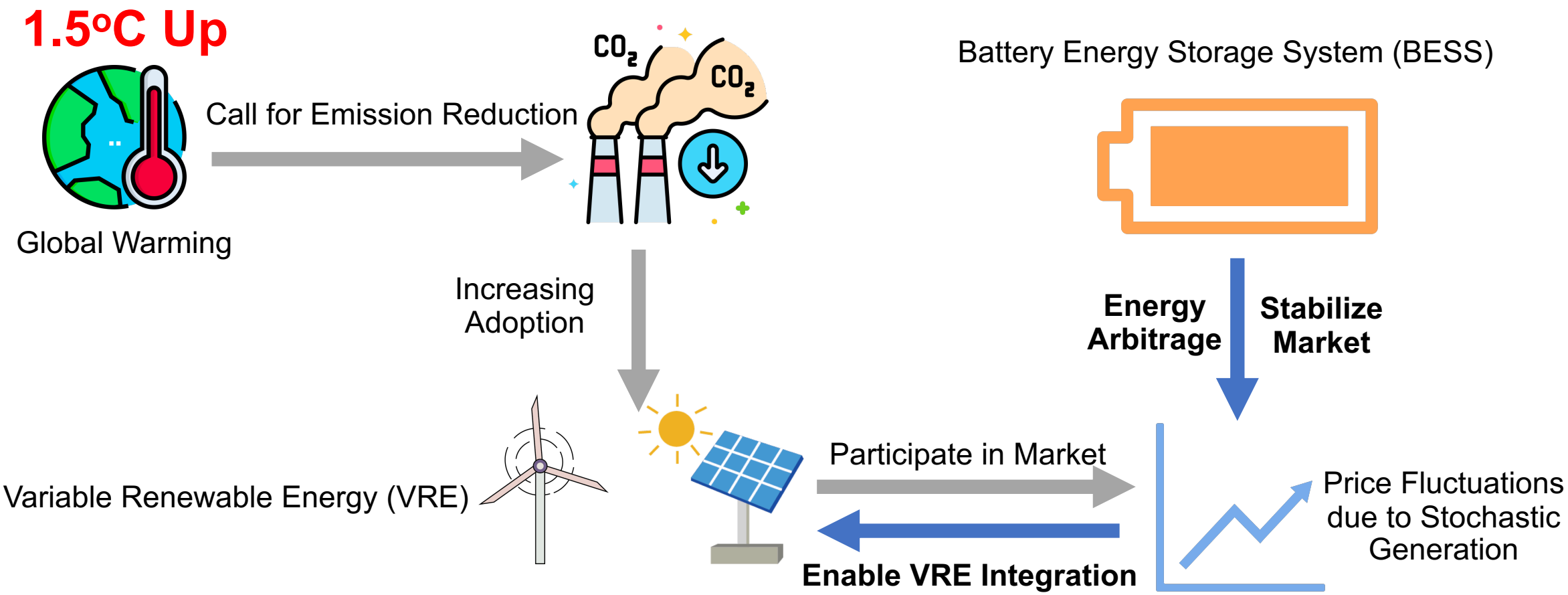
Learn to Bid: Deep Reinforcement Learning with Transformer for Energy Storage in Energy and Contingency Reserve Markets

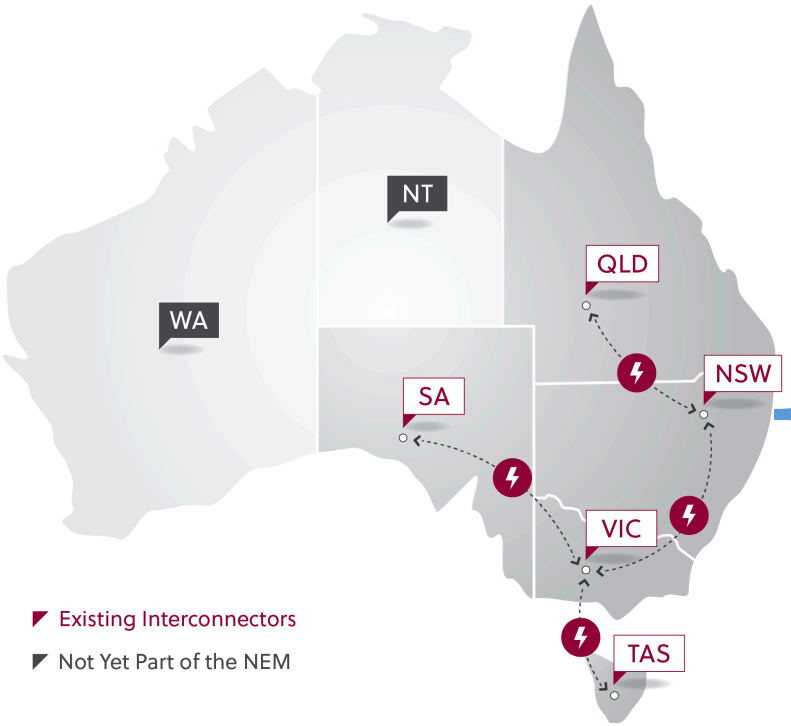
Jinhao Li[1], Changlong Wang[1], Yanru Zhang[2], Hao Wang[1]

[1] Monash University
[2] University of Electronic Science and Technology of China

Background of Battery Storage Adoption in the Electricity Market



Preliminary on the Australian National Electricity Market (NEM)



NEM Illustration

- **Spot Market** — Balance instantaneous power supply-demand mismatches
- **FCAS[1] Market**
  - Maintain frequency within NOB[2]
    - **Regulation FCAS**
      - Reg Raise — Raise frequency
      - Reg Lower — Lower frequency
  - Recover frequency back to NOB[2]
    - **Contingency FCAS**
      - Fast Raise
      - Fast Lower — 6 seconds fast response
      - Slow Raise
      - Slow Lower — 60 seconds slow response
      - Delay Raise
      - Delay Lower — 5 minutes delayed response

1. FCAS: Frequency Control Ancillary Services
2. NOB: Normal Operating Band (49.95 to 50.15 Hz)

Revenue-oriented Bidding Problem in Joint Market

Revenue Maximization

Spot Market

Contingency FCAS Market

Energy Arbitrage—Buy Low and Sell High

Deliver FCAS—Respond to Contingency Event

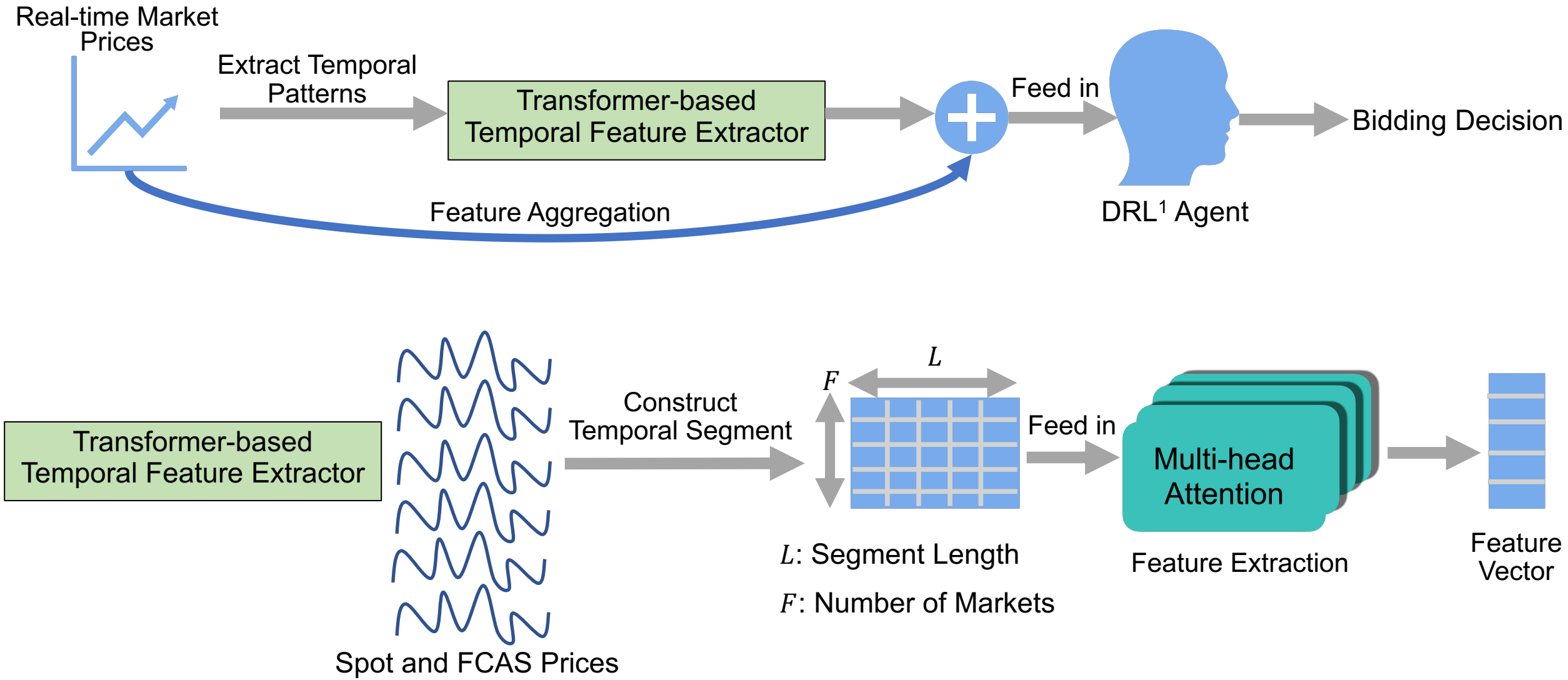
$$R^S = \alpha \sum_{i=1}^{T} \left(b_t^{dch} - b_t^{ch}\right) \rho_t^S p_t^S$$

$$R^{FCAS} = R^{FR} + R^{FL} + R^{\mathrm{SR}} + R^{SL} + R^{DR} + R^{DL}$$

R: Revenue
α: Duration time of one power dispatch interval
b_t^{dch}/b_t^{ch}: Bid to discharge or charge
p_t: Bid power
ρ_t: Market clearing price

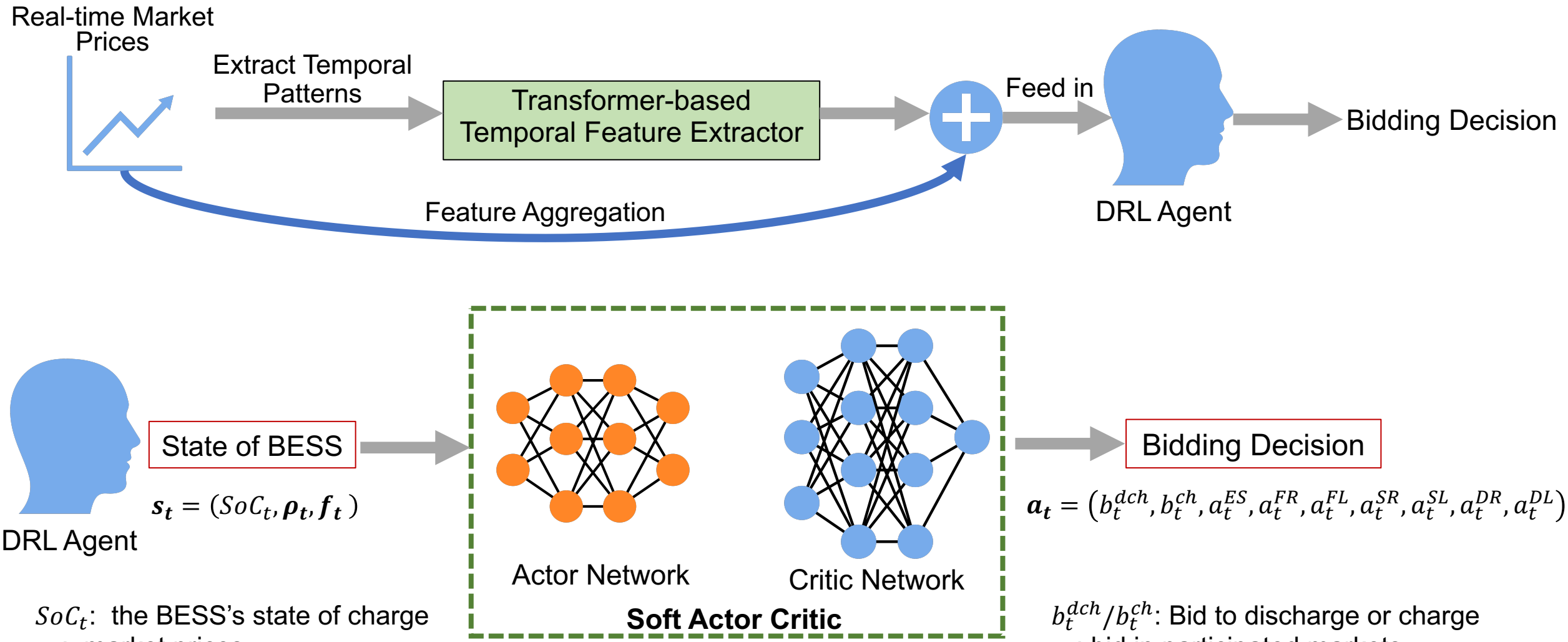
FR: Fast Raise FL: Fast Lower
SR: Slow Raise SL: Slow Lower
DR: Delayed Raise DL: Delayed Lower

Optimal Bidding Strategy via DRL and Transformer



1 DRL: Deep Reinforcement Learning

Optimal Bidding Strategy via DRL and Transformer



SoC_t: the BESS's state of charge
ρ_t: market prices
f_t: extracted feature vector

b_t^{dch}/b_t^{ch}: Bid to discharge or charge
a_t: bid in participated markets.

Experimental Results

MONASH University

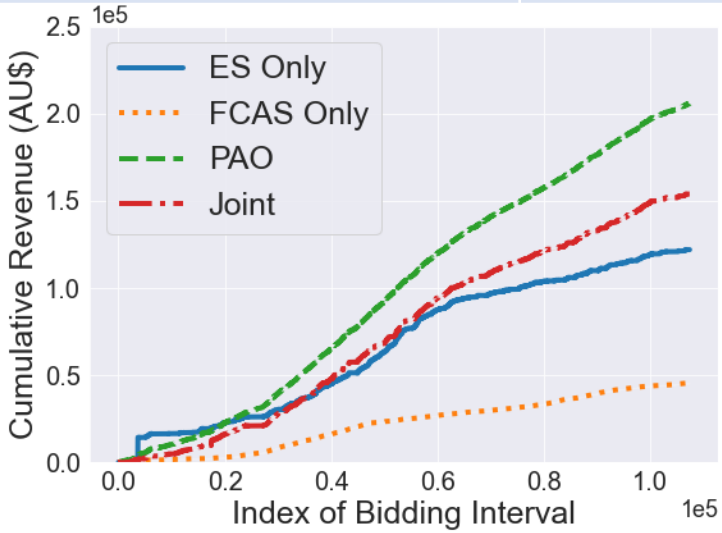
Dataset: Realistic market prices from NEM

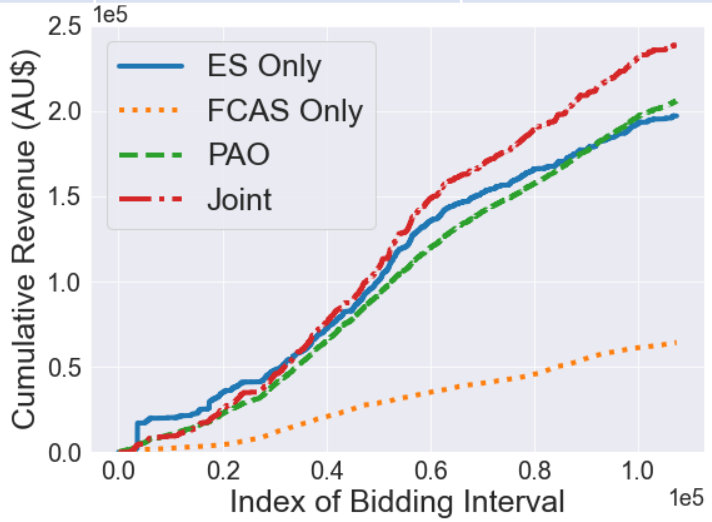
Benchmark: Predict-and-optimize (PAO) — Energy Price Predictor + Optimization Solver → Bidding Decision

Evaluation Results

Bid Scenario	Without TTFE	With TTFE	Boost
Energy Spot Market	$AU\$\ 122{,}005$	$AU\$\ 197{,}157$	**62%**
Contingency FCAS Market	$AU\$\ 45{,}526$	$AU\$\ 64{,}219$	**41%**
Joint Market	$AU\$\ \mathbf{153{,}952}$	$AU\$\ \mathbf{238{,}608}$	**55%**

Without TTFE[1]





With TTFE

1 TTFE: Transformer-based Temporal Feature Extractor

Conclusion

1. We developed a model-free revenue-oriented DRL-based strategy for the BESS to bid in the spot and contingency FCAS markets
2. We proposed a transformer-based temporal feature extractor to exploit temporal patterns of volatile energy prices.
3. Simulations show that bidding in the joint market can dramatically improve the viability of the BESS.
4. The TTFE empowers the BESS to make better decisions, with outcomes significantly outperforming the PAO benchmark.

Contact Information

Jinhao Li (Monash University): stephlee175@gmail.com
Hao Wang (Monash University): hao.wang2@monash.edu
https://research.monash.edu/en/persons/hao-wang