

Centralised control of Distributed Energy Resources for participation in electricity markets in presence of uncertainties

Gayan Chaminda Lankeshwara

Advisors : Dr. Rahul Sharma Prof. Tapan Saha Dr. Ruifeng Yan

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School of Information Technology and Electrical Engineering (ITEE) The University of Queensland, Brisbane, Australia



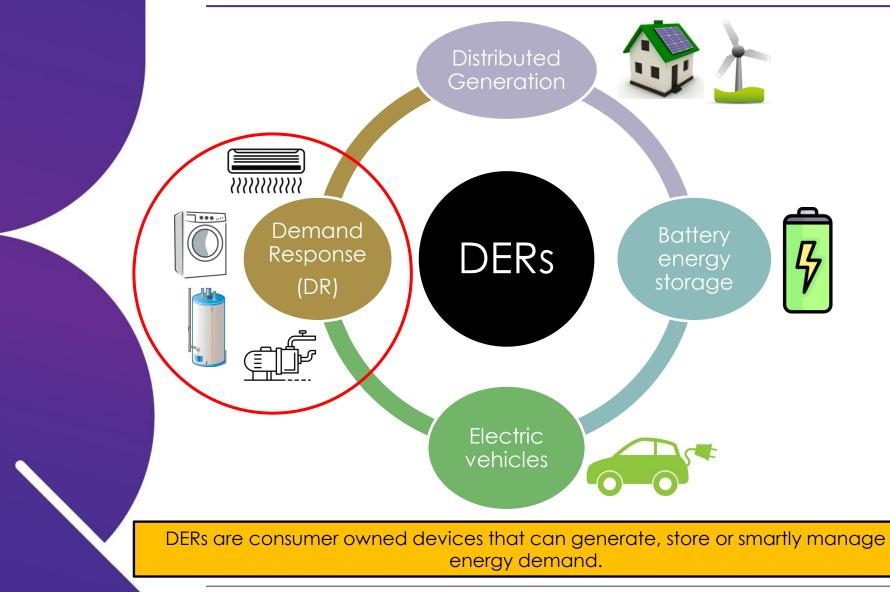
- Introduction
- Research Objectives
- Motivation
- Literature Review and Gaps
- Proposed Methodology
- Progress up to date
- Timeline



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What are Distributed Energy Resources (DERs) ?

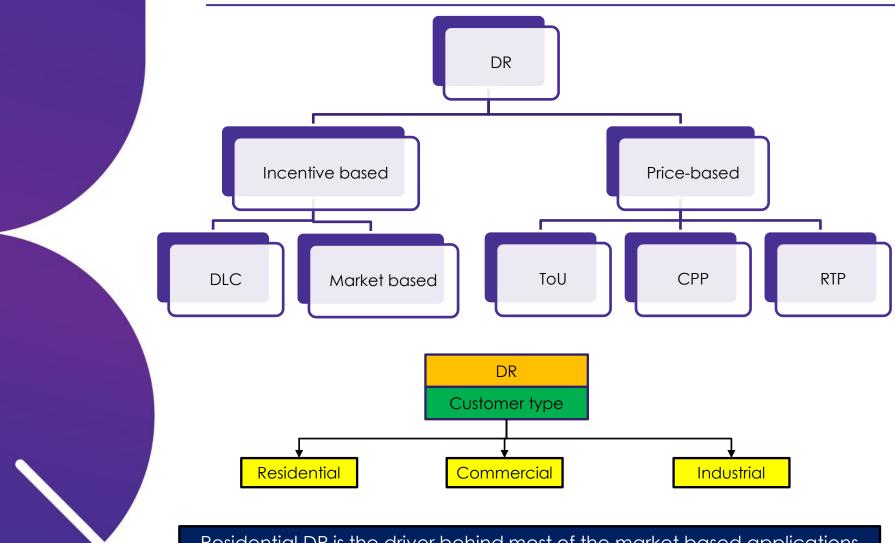


. https://aemo.com.au/en/initiatives/major-programs/nem-distributed-energy-resources-der-program

https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Feb/IRENA_Market_integration_distributed_system_2019.pdf?la=en&hash=2A67D3A224F1443D529935DF471D5EA1E23C774A



Classification of DR

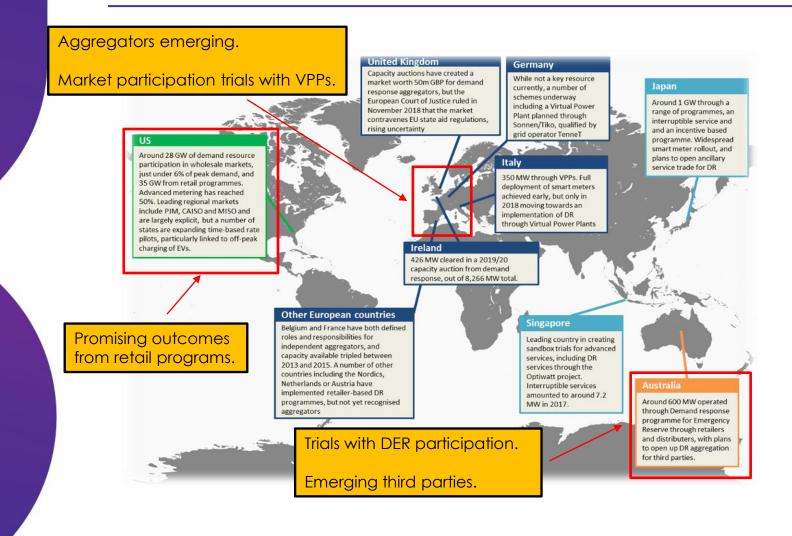


Residential DR is the driver behind most of the market based applications in the future.

Albadi, M.H. and El-Saadany, E.F., 2008. A summary of demand response in electricity markets. Electric power systems research, 78(11), pp.1989-1996.



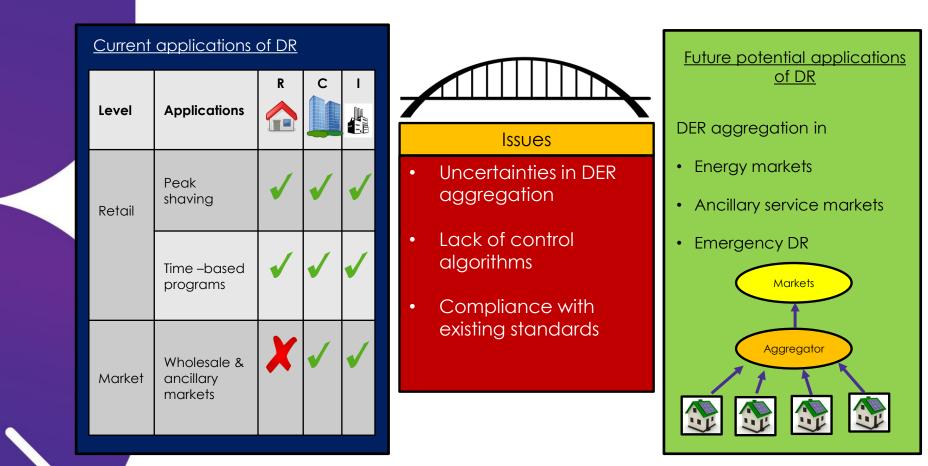
A glimpse of DR initiatives around the world



Trials have not been able to capture the residential DER aggregation.



Existing vs. Future prospects



Under-utilising the capacity of DER possessed by residential customers is a missed opportunity in electricity markets.



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Research Objectives

- 1. To develop a <u>control mechanism</u> for the aggregator to <u>accurately track</u> <u>the set-point power load reduction</u> assigned by the system operator through aggregation of DERs.
- 2. To <u>model the system uncertainties</u> which could arise in the process of aggregator tracking the set-point power load reduction assigned by the system operator.
- 3. To develop a <u>fully automated model-based control scheme</u> that is <u>robust enough to handle system uncertainties</u> and successfully achieve provision of bids with <u>precise load reductions in real-time</u> under aggregated participation of DERs.
- 4. To <u>analyse the performance</u> of developed control schemes <u>under</u> <u>different market scenarios</u> and <u>comparison</u> with existing aggregator based DER management approaches.



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Outcomes of DR trials

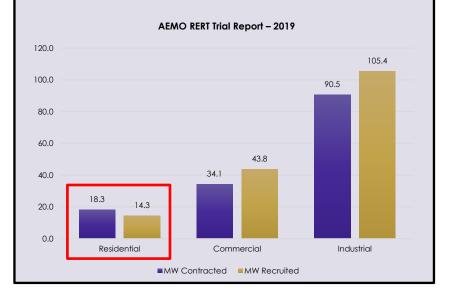


Learnings from existing Load Control Trials





- Low customer participation due to 'loss of perceived control'.
- Allowing flexibility at the consumer end, resulted in frequent overriding in trials.



Market participation trials

Significant mismatch in residential contribution.

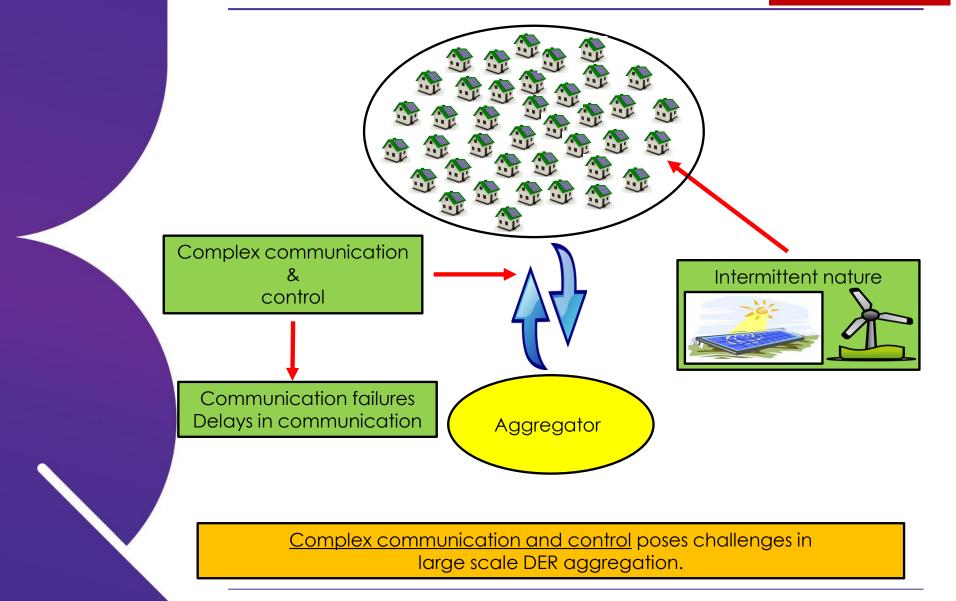
<u>Customer overriding</u> poses challenges in the successful aggregation of DERs to participate in market events.

SDG&E "Smart Thermostat Pilot", ConEd Cool NYC program, Ausgrid CoolSaver program, ZEN ECOSYSTEMS ARENA/AEMO DR Trial https://arena.gov.au/assets/2019/03/demand-response-rert-trial-year-1-report.pdf



Large scale aggregation of DERs

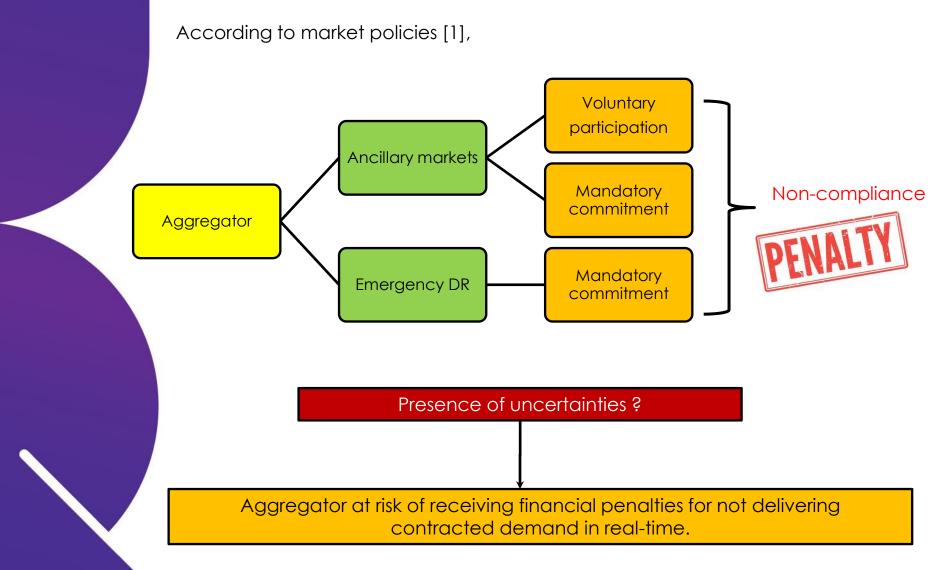






Why uncertainties need to be addressed?

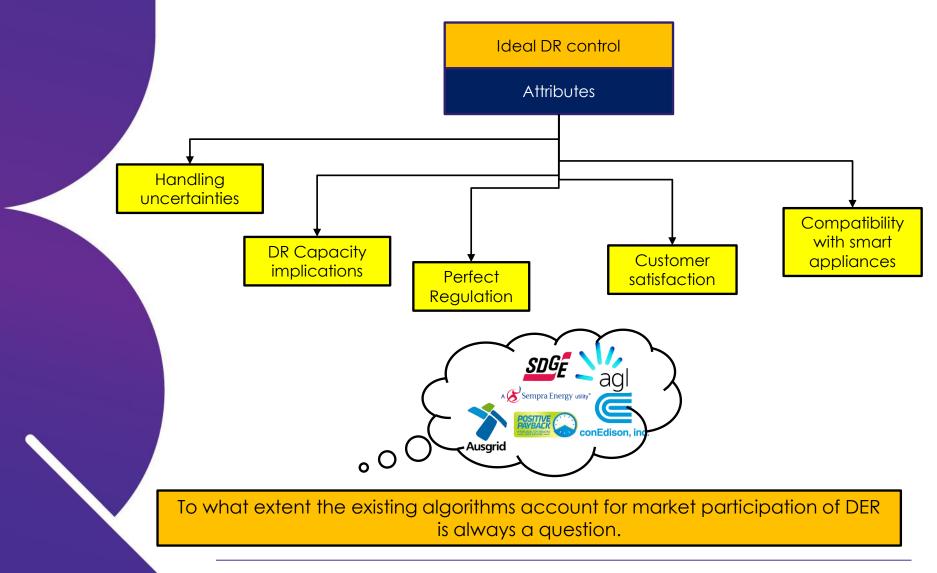






Drawbacks of existing load control programs

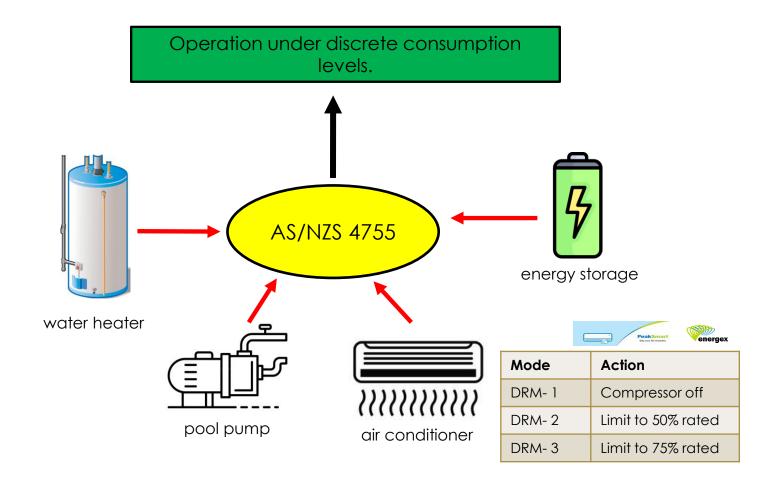






Demand Response Standards





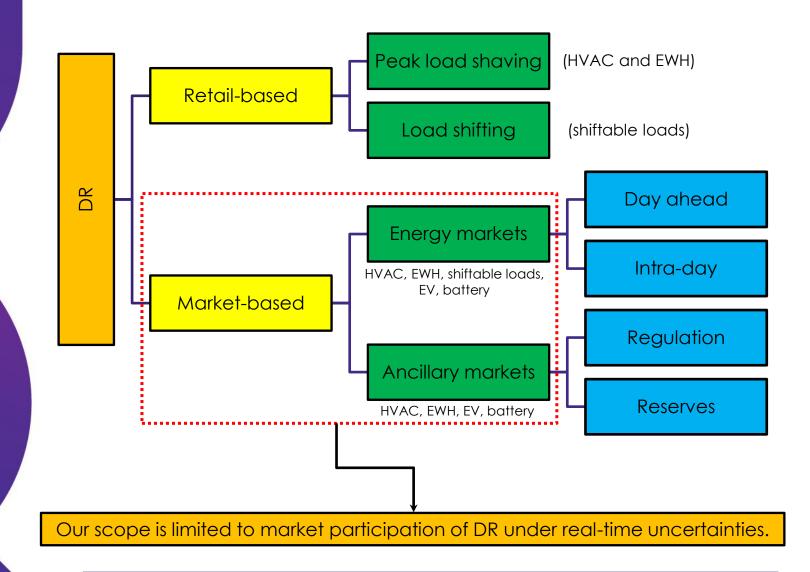
Load control algorithms in existing literature hardly take account of existing DR standards.



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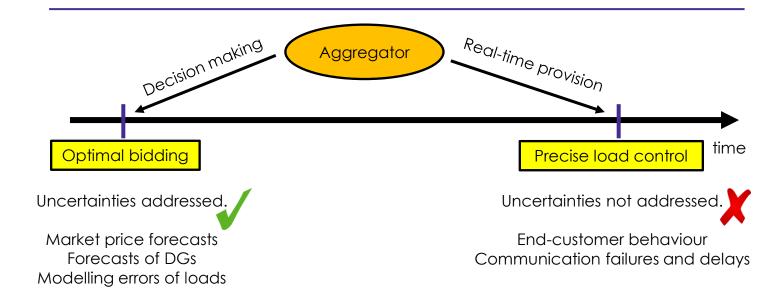


Literature Review





Gaps in Literature



Uncertainties are taken into account to determine the optimal bidding strategy, but not in developing control algorithms in real-time provision of bids.

Uncertainty modelling at bidding stage does not capture the dynamics in real-time operation.

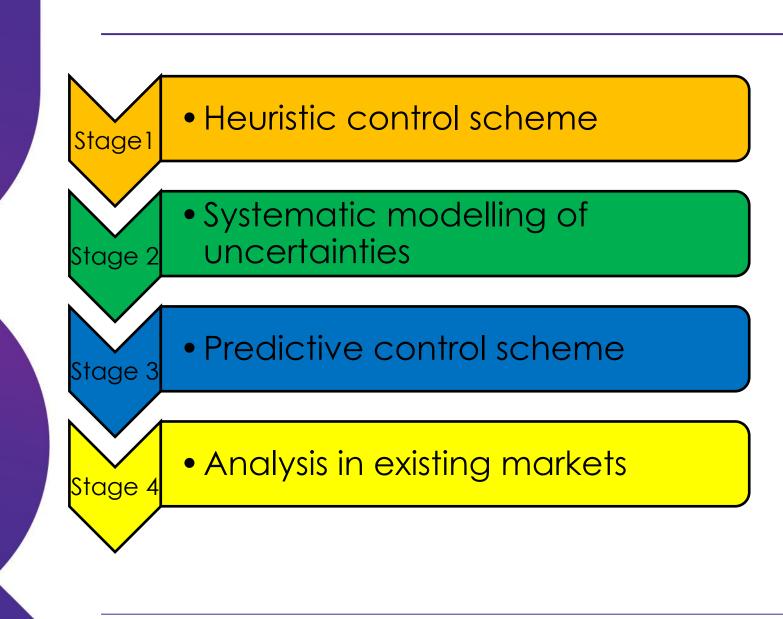
Inadequacy of existing algorithms in resembling real-implementation under existing standards and policy related to DR.



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Proposed Methodology

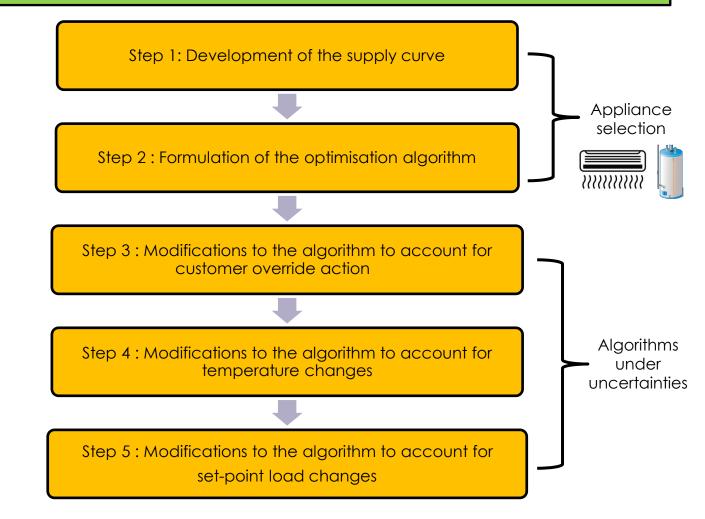




Stage 1: Heuristic control scheme



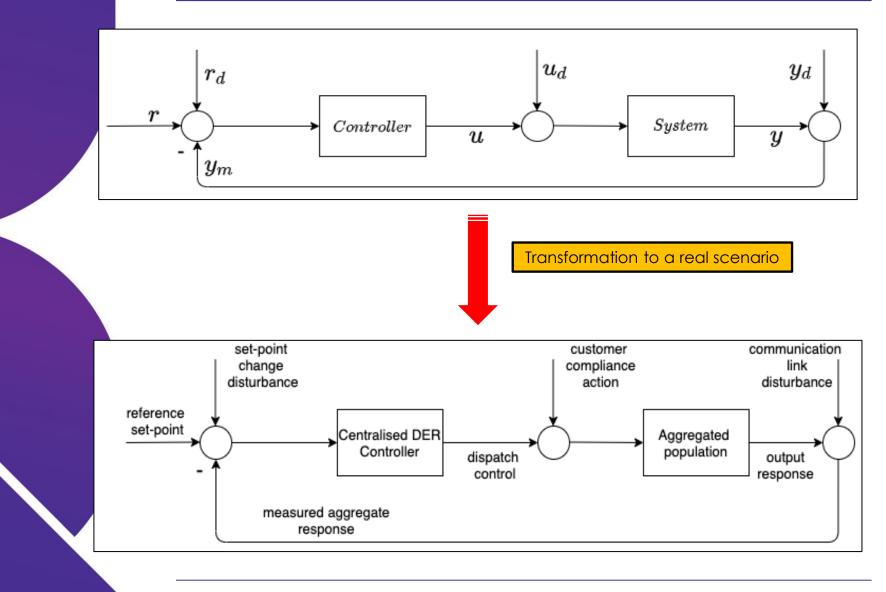
Developing control algorithms for thermostatically controllable loads to deliver a certain set-point reduction under uncertainties





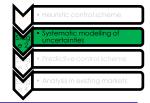
Stage 2: Uncertainty modelling

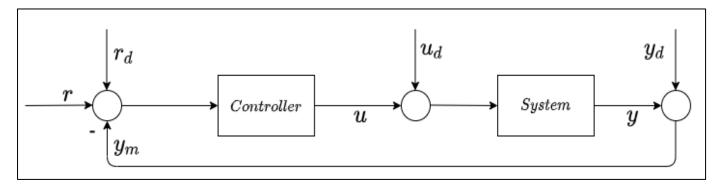






Stage 2: Uncertainty modelling





Mathematical modelling of uncertainties

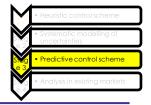
If
$$\mathbf{u} = \{u_1, u_2 \dots u_N\}^T$$
 where $u_i = \{0, 1\} \quad \forall i \in \{1, 2 \dots N\}$
 $u_i = \begin{cases} 1 & \text{if dispatch instructions sent} \\ 0 & \text{if not sent} \end{cases}$

If $\mathbf{y} = \{y_1, y_2 \dots y_N\}^T$ where $y_i = \{0, 1\} \quad \forall i \in \{1, 2 \dots N\}$

Customer overriding	Communication failure
$u_{d,i} = \left\{egin{array}{ccc} 0 & ext{if} & y_i = u_i \ 1 & ext{if} & y_i eq u_i \end{array} ight.$	$y_{d,i} = \left\{egin{array}{ccc} 0 & ext{if} & y_{m,i} = u_i \ 1 & ext{if} & y_{m,i} eq u_i \end{array} ight.$

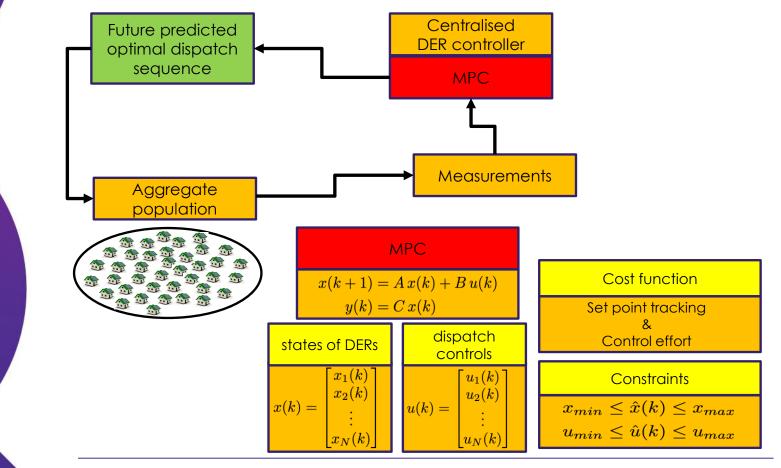


Stage 3: Predictive control scheme for aggregators



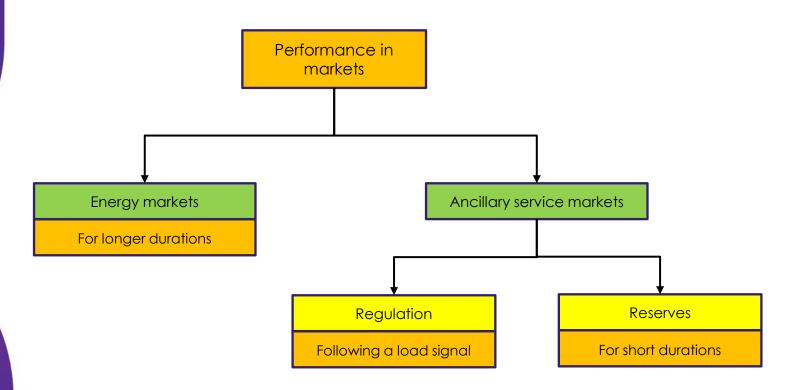
Model Predictive Control (MPC):

Solving a finite horizon optimal dispatch problem (subject to constraints of DERs) based on the current state of the aggregated population.





Stage 4: Analysis in existing markets



Performance criteria								
Robustness to uncertainties	Comparison with existing schemes	Practical commercial implementation						

Analysis in existing market



Data & Software tools

Data

Appliance specific consumption, generation data



Sensor measurements

Weather data : UQ weather stations

Market related data : from AEMO website, PJM and NordPool

Software

Data pre-processing



Control algorithm development



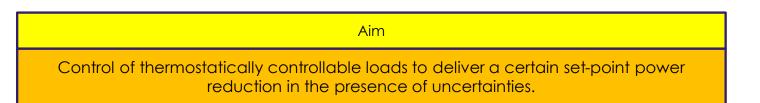


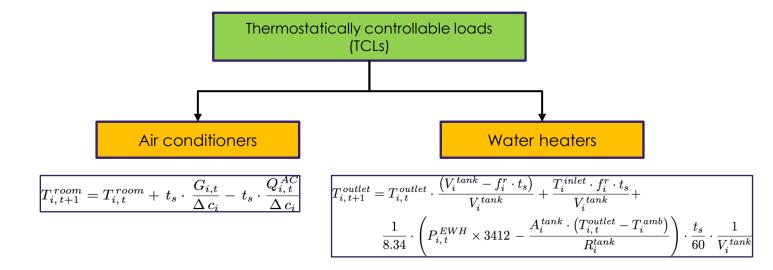
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Progress up to date

Work under stage 1 is almost completed.



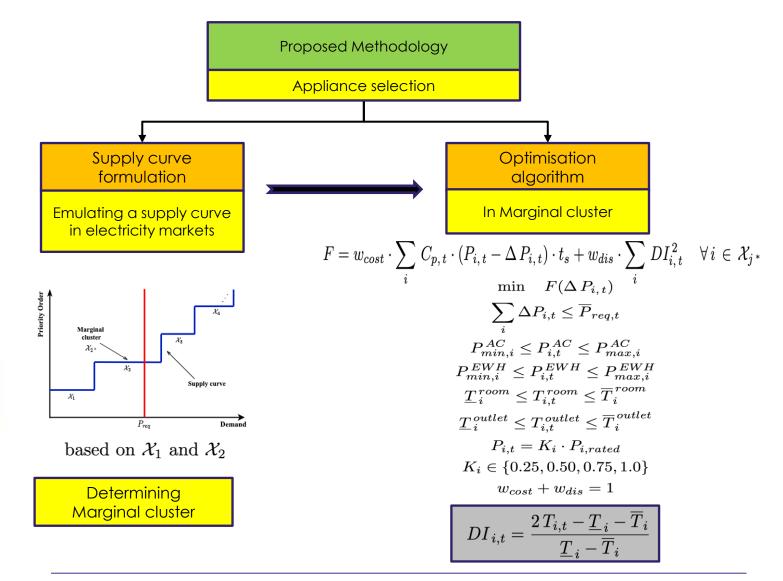


Realistic consumption data for air conditioners and water heaters used in modelling.

100 appliances for the study

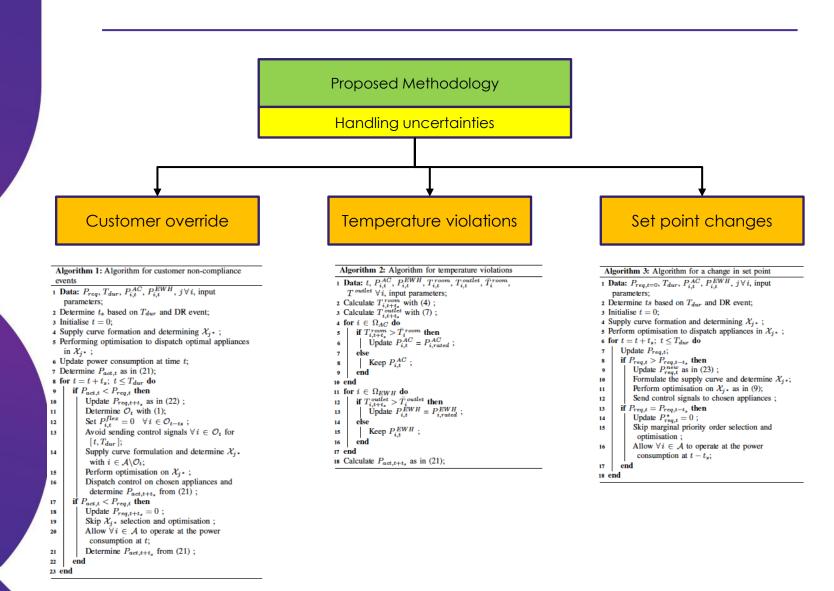


Methodology



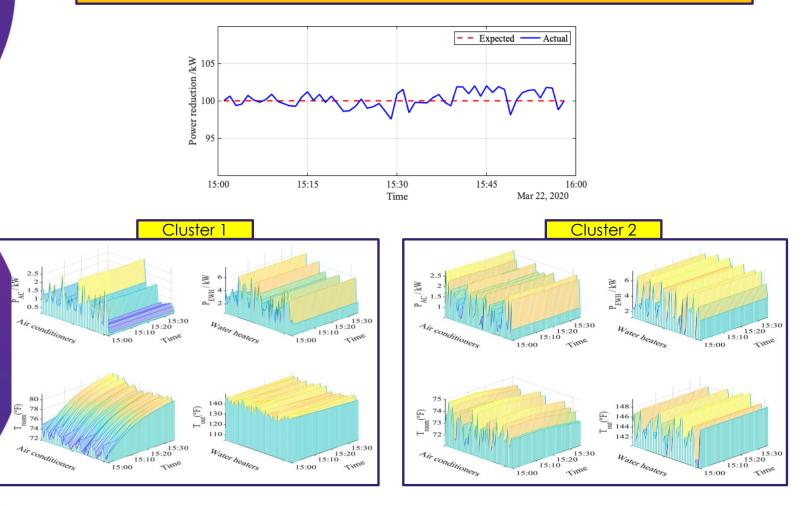


Methodology



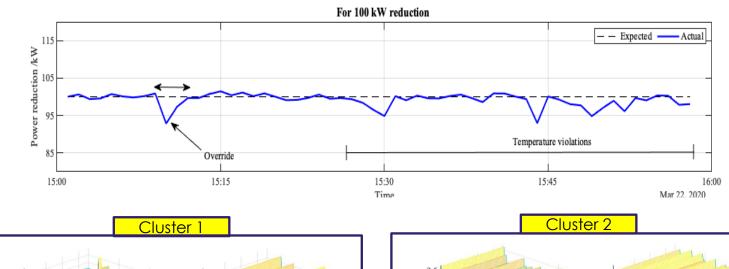


Objective : To obtain 100 kW load reduction from the TCLs in cluster 1 and cluster 2 in the absence of uncertainties in the system





Objective : To obtain 100 kW load reduction from the TCLs in cluster 1 and cluster 2 in the presence of uncertainties due to customer override action and temperature violations



AC KW

Air conditioners

74

Air conditioners

(H.)

T room

15:20 15:10

15:20 15:10

Time

15:00

15:00

Time

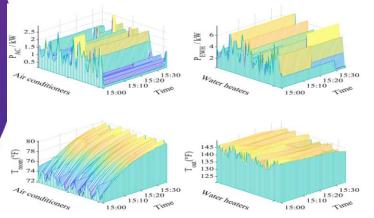
Water heaters

Water heaters

148

144 142

(eF) 146



15:10 15:10

15:20 15:10

Time

15:00

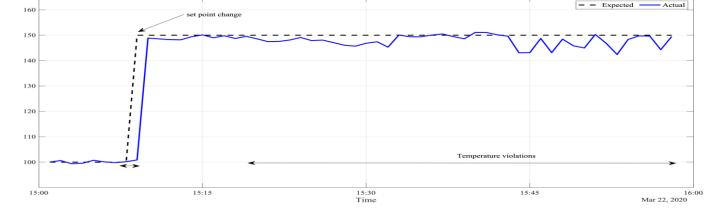
15:00

Time



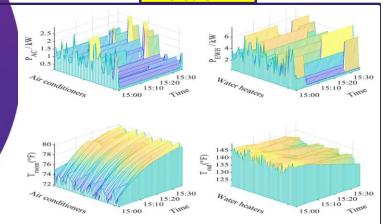
Objective : To follow the load reduction signal when the set–point changes from 100 kW to 150 kW at a certain time step, while taking into account the uncertainties arising from temperature violations.

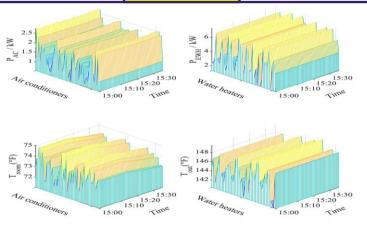






Cluster 2







This work is nearly ready for submission in IEEE Transactions on Sustainable Energy.

Centralised control of thermostatically controllable loads for participation in electricity markets in presence of real-time uncertainties

Gayan Lankeshwara, Student Member, IEEE, Rahul Sharma, Senior Member, IEEE, Ruifeng Yan, Member, IEEE, and Tapan Saha, Fellow, IEEE

Absect-Bashing aggregated participation of behindures the statistic control in prok load uburging the due particulates of the value of the gargestare due to the value of the statistic sector of the statistic secto the uncertainties occurring from customer non-compliance vents and change in set point events. Further, the developed heuristic control scheme is compared with an existing industry approach. The results yield that the proposed control scheme is robust to uncertainties and applicable for practical implementations.

Index Terms-Demand Response, direct load control, un-ertainties, electricity markets, customer override, aggregator,

I. INTRODUCTION

N the presence of two-way communication and advanced metering infrastructure (AMI), demand side management approaches are a promising alternative for the grid operators manage the network when it is stressed [1]. One such alternative which is widely used in the industry is demand

alternative which is widely used in the industry is demand response (DH). According to FERC demand response report. [2], the annual peak demand awings from retail demand response corresponds to more than 31 GW. Direct load control (DLC) [3], is one of the most com-mon strategies used in practice. In this approach, the end cantomers allow the utility or a third party to control their household applicance (gi FUAC, sume fraker, FU and good pamp) when the grid is in need of additional support. With improved accuraty and neilability, DLC is most preferred by the erid operator [4]. Extensive work is available in the ture based on the inertial capabilities of thermostatically vollable appliances to participate in DLC [5], [6]. HVAC

Gayan Laskoshwara, Rahai Sharma, Ruifeng Yan and Tapan Saha are with the School of Information Technology and Electrical Engineering, Uwiernity of Queenland, Brishnae, QLD 4072, Australia (email: glankethwara@queetchuan, rahai.sharma@uqedn.au, rahin@g@tecu.queu.au.au.ai.shab@tec.au.gcd.au.u

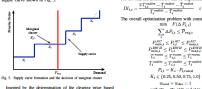
trials suggest that residential customers are more-likely to participate in price-based approaches (eg. ToU, CPPRTP [11]) compared to DLC. The root cause for this issue is end susers "losing the perceived control" when an aggregator control their appliances at households [12]. Furthermore, it is suggested that customers are likely to have an override or external control customers are integy to nave an overrise or external control option to opt-out during a DR event. However, only a handful of studies are published on the feasibility of DLC in the presence of customer voluntary compliance during a DR event. Atthough modelling of voluntary compliance is done in [13], Autorogin incomension of volumary comparative is order in [12], the authors have only generalised compliance at household level, but not appliance level. At the same time, although overriding has been highlighted in [14], [15], [16], no explicit modelling has been done to determine its consequences. Meantime, enabling voluntary compliance creates com because the canonic ca

bid amounts, which leads to penalties for non-compliance. The DR trial conducted by the Australian Energy Market Operate (AEMO) in 2019 [18], gives evidence of volatile behaviour of residential customers compared to their counterparts during an emergency DR event. To add more, DLC programs conducted across the world [19], [20] have recorded significant custom override events during the operation. Considering all these scenarios, it can be claimed that a systematic approach is essential if residential aggregators are to participate in markets and maximise social welfare under real-time uncertainties. Fig. 1 illustrates the effect customer override can have on the performance of a DR event. The figure is based on Redback data [add ref] and illustrates successive the divergence of Consider n number of controllable appliances are present

in each house $h \in \{1,...,N\}$. For each appliance $i \in detrmine the marginal <math>A$, a customer is required to define a priority index j s.t. clusters to be controlled to $j \in \{1,...,n\}$. The priority index j is used as a quantitative B. Optimisation problem asure of the importance of one appliance over the others. measure of the importance of one approache over the others. For example, if the customer in house h assigns priority index j = 1 to the water heater and priority index j = 2 to the air conditioner, it implies that the operation of the air conditioner is more critical than the water heater for that customer during a DLC event. To put it in a simple way, as the priority index j increases, the importance of the appliance for the customer

or deplinence with the lowest j and then sequentially control higher proving regulators. It is a signed for V is $(\mathcal{A}, \mathcal{A})$ by the c automers in V is $(\mathcal{A}_1, \dots, \mathcal{A}_k)$ as not of priority orders. In defined as 1, Control travel by non-sequences with priority index j. In practice, most of the existing approaches in DLC do not allow an appliance to be fully controlled, instead allow a minimum consumption level which is usually a fraction of the netd power [23]. Addrening to this, the factility power of an appliance is at onic c can be expressed as $\mathcal{A}_{interval}^{(M)}$ (1) $\mathcal{A}_{interval} \mathcal{K}$ is the minimum fraction of power that power of chieder \mathcal{K} at times I can be corrected as $\mathcal{A}_{interval}^{(M)}$. power of cluster X_j at time t can be expressed as,

 $P_{X_j, t}^{flex} = \sum_{i} P_{i,t}^{flex}$ $\forall i \in X_j$ Likewise for $\forall X_j$, the aggregated flexible power at time t can be cascaded in an increasing priority order to form an e supply curve shown in Fig. 5.



Inspired by the determination of the clearing price based on the interaction between the supply carve and the demand rarve in electricity match, a similar graph is followed to determine the marginal cluster X_{μ} , and the lower priority to determine the marginal cluster X_{μ} and the lower priority corresponds to the minimum demand reduction required from classes X_{μ} for $j \in [1, ..., 3^{-1}]$ that tenses to be controlled the marginal priority corresponds to the minimum demand reduction required from cluster X_{μ} for $j \in [1, ..., 3^{-1}]$ that tenses to be controlled the marginal priority corresponds to the minimum demand reduction required from during a certain time step in a DR event. For example, when and (15) describes the power limits for ACs and EWHs in the P_{reg} is required by the system operator as shown in Fig.

A. Conceptual priority based ranking mechanism and emu-lated supply curve formation 5 (represented with a red solid line), the appliances in χ_1 and χ_2 only needs to be controlled, where χ_3 will be the marginal cluster. Likewise, the emulated supply curve is used to determine the marginal cluster X_{j*} and the lower priority clusters to be controlled to achieve P_{reg} at a certain time.

One marginal cluster X_j is determined from the supply curve as in section III-A, a step-ahead optimisation problem is solved to determine the optimal selection of appliances to be controlled in X_j , for the next time step. From the point of view of the aggregator, the objectives are to minimise the cost of buying electricity from wholesale markets or contracts, and to majorities the discustories of the nonzented ta advancement. increases, the importance of the appliance for the consomer also increases. Hence, the aggregator aways guarantees to initiate the demand response by controlling the consumption of appliances with the lowest *j* and then sequentially control of the lowest *j* and then sequentially controlling the *consumption* of total costs for the aggregator and the total discontion. to minimise the discomfort for the contracted end customer Therefore the problem is formulated as a multi-objectiv end customers. Considering the marginal priority cluster X_j at time t, it can be expressed as,

$F = w_{cost} \cdot \sum C_{p,t} \cdot (P_{i,t} - \Delta P_{i,t}) \cdot t_s$

$$+ w_{dis} \cdot \sum_{i} DI_{i,t}^2 \quad \forall i \in X_j$$
. (9)

where $C_{p,t}$ is the market price of electricity at time t, $\Delta P_{i,t}$ is the power reduction of appliance i at time t and $CI_{i,t}$ is the discomfort index for appliance i at time t. In addition to that

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(8)
```

The overall optimisation problem with constraints are, min $F(\Delta P_{i,t})$ (12) $\sum \Delta P_{i,t} \leq \overline{P}_{req,t}$ (13) $\begin{array}{l} & i \\ P_{min,i}^{AC} \leq P_{i,t}^{AC} \leq P_{max,i}^{AC} \\ P_{min,i}^{EWH} \leq P_{i,t}^{EWH} \leq P_{max,i}^{EWH} \\ T_i^{room} \leq T_i^{room} \leq T_i^{room} \end{array}$ (14) (15) ദര $T_i^{outlet} < T_i^{outlet} < T_i^{outlet}$

much power (cauchy at set point) (f) at i = 0 for keep one into water temperature at set point. This assumption is reasonable for short DR events (max, upto 1 hour) where the water heating occurs to restore a fully empty tank with heated water. However, due to TOU tariff schemes introduced [36], EWHs will not usually operate during peak demand hours, hence DR action cannot be performed. A demand reduction event is considered for $T_{dur} = 1$ hour, starting from 15:00 and ending at 16:00 on 22-03-2020.

s followed to avoid any over-sizing or under-sizing in AC

ooling capacity decision making. For the EWH subsystem, it is assumed that T_{inlet} and

are constant as in [35]. Furthermore, it is assumed that

the f^{*} is uniformly distributed and remains constant during the DR horizon. Hence, all the EWHs are operating at their

rated power (calculated from (7) at t = 0) to keep the hot

statume from 15.00 and enhang as 100.0 on 22.03-2020. The market price of electricity $G_{\rm pk}$ to assume constant based on contracts and obtained from (37). Depending on the value of $P_{\rm rego}$ demand reductions can be obtained from either X_i or X_i and X_2 . Hence a monte carlo simulation (MCS) is performed in X_i to determine $P_{\rm reg}$ to be obtained. The results of the MCS are given in Figure ??.

The total power consumption of the population at time t = 0is 609.45 kW. It is distributed between X_1 and X_2 as 295.67 kW and 313.77 kW respectively. The MCS is performed by kw and 515.77 kw respectively. The wices is periodiced by assigning $\alpha_i = \{0, 0.25, 0.50, 0.75\}$ for each *i* with equally likely occurrences. The results provide a narrow approximation that achieving 100 - 120 kW reduction is possible in X_1 . Hence the rest of the simulation results are based on the

following scenarios. • 100 kW (around 16% from the total) demand reduction (within the range of MCS) • 150 kW (around 24% from the total) demand reduction

(not within the range of MCS)

In addition to that, for each of the scenarios discussed In automotion to make the each of the section of use Section the section of the

A. Ideal system scenario

At t = 1 min, the aggregator requests for $P_{reg} = 100$ kW, and the algorithm is executed to obtain the desired reduction. Once the demand reduction is achieved in the next time step, i.e. at t = 2 min, for the rest of the event, the ACs and EWHs In both χ_1 and χ_2 operate within permissible power limits defined by the aggregator. According to Fig. 6, the actual reduction follows the expected reduction within the threshold δ (described in section III-D) which is assumed to be 0.05.

Performance under the influence of uncertainties Simulations are performed mainly for two scenarios: 1) a ertain group of customers override the control signals sent by contain group of custometers that contains groups are to y in a group of custometers that the argengator custometers are being the OR were it. The argengator custometers to increase the target reduction during a DR event. Recovering and following the targeted reduction under the aforementioned scenarios are considered while Algorithm 2 takes care of $\delta = 0.05$. Hence an optimisation is solved at t = tncertainties arising due to temperature violations.

Fig. 8. The v the ACs in X_1 min and additional units dispatched to compensate for t

variation of powe

- Expected

1) Customer non-compliance event: In actual implement

tions, the non-compliance action is only realisable with air conditioners. Once the customer overrides the DR event, the control action will be released and the AC continues to operate

under the normal consumption for the rest of the DR ever while the aggregator delivering 100 kW and 150 kW demand reduction, it is simulated that 10% of the ACs in λ engage in non-compliance event at t = 10 mins.

- - Expected -

- Expected

15:30 Time

eduction under override for two cas

Fig. 6 Demand reduction under the ideal system sc

15:45 Mar 22, 2020

Actual

15:45 I Mar 22, 2020

15:45 16 Mar 22, 2020

Actual

Given into time to or approximate r in time t, in advantion to use discontrol to use the cost and discontrol to use the cost and discontrol to use the cost and discontrol time trapper individual to the cost and discontrol time advantage to the discontrol time adv For EWHs, the discomfort can be expressed as, $DI_{i,t} = \frac{2 T_{i,t}^{outlet} - T_{i}^{outlet} - T_{i}^{outlet}}{T_{i}^{outlet} - T_{i}^{outlet}} \quad i \in \Omega_{EWH} \quad (11)$ each step.

(17) (18) (19) (20)



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Timeline

	Activity/Milestone 2019 2020				2021				2022					
	rectively/milestone		RQ4	ROI	RQ2		RQ4	RQ1		RQ3	RQ4	RQ1	RQ2	RQ3
		1020	1.24	I QI	1.2-	1020	1.24	I.VI	1.2-	Inq.	1.24	nqı	1.2-	1025
1	Literature Review													
	Modelling of													
	Thermostatically													
2	controllable loads for													
	direct load control													
	Developing the													
3	heuristic control													
	algorithm													
4	Journal publication													
	Confirmation													
5														
-	Systematic modelling													
6	of uncertainties													
	Conference													
7	publication													
	Modelling of shiftable													
8	appliances													
9	Developing the predictive control													
9	algorithm													
	algorithm													
10	Journal publication													
11	Mid-candidature													
	Modelling distributed													
12	energy resources													
	Conference													
13	publication													
	-													
	Extending the predictive control													
14	algorithm to DERs													
	_													
15	Journal publication													
16	Thesis writing													
	Thesis Review													
17														
	-	•				-		•	•	•				

Thank You !

