NATIONAL RESEARCH FOUNDATION

SYSTEMIC RISK AND RESILIENCE INITIATIVE PLANNING GRANT

FINAL REPORT

SECTION I: DETAILS OF PROJECT

a)	**Award No.**	NRF2018-SR2001-018
b)	**Project Title**	Grid-customer integrated resilience assessment and enhancement for modern power systems
c)	**Salutation of Lead PI**	Prof.
d)	**Name of Lead PI**	Jimmy Chih-Hsien Peng
e)	**Host Institution**	National University of Singapore
f)	**Department**	Electrical and Computer Engineering
g)	**Approved Budget (inclusive of Indirect costs – if any)**	S$150,000
h)	**Duration of Project**	12 months
i)	**Project Start Date**	01 October 2018
j)	**Project End Date**	30 September 2019
k)	**Reporting Period**	

SECTION III: PROJECT APPRAISAL

Project Objectives

There were two broad objectives that were studied in this planning grant:

1. Studying the vulnerability of the power grid to a society-targeted disinformation attack.
2. Assessing the role of consumer behaviour in reinforcing the resilience of the power grid under emergency conditions such as blackouts.

Both objectives have been achieved fully during the course of the project. There were no deviations from the original proposal.

Results

1. <u>Vulnerability of the power grid to society-targeted disinformation attacks</u>

We analysed the possibility of an external adversary attacking a city's power grid using disinformation, and not using other physical or cyber intrusions. In particular, we developed an attack scenario in which fake discount notifications are sent to residential consumers in the city. These notifications encourage the recipients to shift their energy consumption into the peak-demand period, which can potentially overload and trip the distribution lines. A schematic of such an attack is shown in Fig. 1.

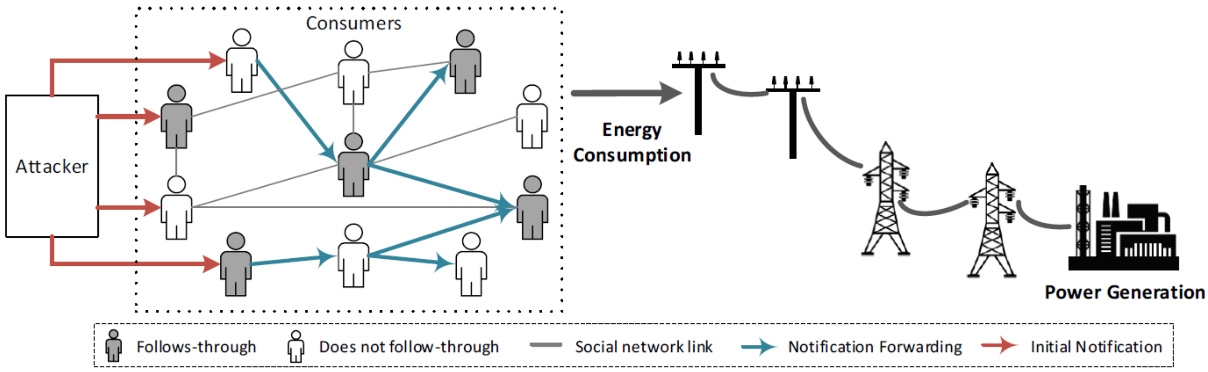

Fig. 1. A disinformation attack on the power system.

We further considered the possibility that such an attack can be amplified by unwitting consumers who forward such disinformation to their friends, who in turn forward it to their own friends, and so on. This required the modelling of information propagation or diffusion through social networks. For this, two standard models of influence propagation were chosen, namely, independent cascade, and linear threshold. In the former, every exposure to the notification has an independent probability to persuade the recipient to modify their behaviour. In contrast, in the linear threshold model, each person has a threshold specifying the number of exposures required for them to modify their behaviour. These probabilities and thresholds constitute the parameters of the two models.

To ensure that the probabilities of following-through and forwarding the notification in our simulation are realistic, we surveyed over 18,000 participants on the Amazon Mechanical Turk online crowdsourcing platform. Each participant was shown a message notifying them of a discount of 50% in their electricity rate during a specific time period and was then asked to specify the likelihood of them changing their electricity-use patterns to take advantage of this discount. They were also asked to specify the likelihood that they would forward such messages to their friends. We tested two factors that may influence the behaviour of the participants: (i) the notification sender, and (ii) the notification content. As for the first factor, while such notifications are typically received from the power utility, we analysed the cases when they are instead received from either a stranger or a friend. We considered these two possibilities since some people may receive the spoofed message directly from the attacker (who is a stranger to them), while others may receive it indirectly through friends who forward it to them. As for the second factor---the notification content---we analysed two variants: one where the discount can only be availed by clicking on an external link, and another where the discount is unconditional. This manipulation allows us to understand the differences, if any, between the context of phishing and spam attacks---which require the recipients to click on an external link embedded in the message---and the context of our disinformation attack---where no such link is necessary. Accordingly, the participants were randomly assigned to one of four conditions: (i) receive a notification with a link from a stranger; (ii) receive a notification without a link from a stranger; (iii) receive a notification with a link from a friend; (iv) receive a notification without a link from a friend. The participants were further split into two groups depending on the influence model being studied (independent cascade or linear threshold), since the parameters of each model require the questions to be framed differently.

We were cognizant of the possibility that the survey respondents may report higher probabilities of following-through or forwarding the disinformation notification when compared to their actual behaviour in reality. To mitigate this effect, we used three mapping functions: linear, squared, and cubic as shown in Fig. 2(a) to translate the reported propensities in the survey to the actual probabilities of the social network members in our simulations. To make simulations even more realistic, we modified the traditional diffusion process by capping the number of friends (*k*) a given person could forward the message to. The diffusion results are summarized in Fig. 2(b) and (c), which illustrate the different follow-through levels achieved as the value of *k* varies from 1 to 3. Referring to Fig. 2(c), we found that the absence of a link in the message results in consistently higher follow-through rates when compared to those achieved by a message with an external link. For instance, up to 10.9% increase in the follow-through rate can be achieved by the attacker just by avoiding framing of the disinformation using external links.

We then analysed the impact caused by such behaviour manipulation on the power grid. To this end, we modelled the power grid of Greater London using map data (available online) and simulated the behaviour of residential energy consumers. Importantly, we consider the impact of residential electric vehicle (EV) charging, which adds a significant flexible load to the power system. The results of our analysis are shown in Fig. 3(a). This figure illustrates the size of the blackout that is caused by a disinformation attack for varying follow-through rate and EV adoption by the consumers. Note that in our analysis, EV adoption serves a synecdoche as well as a factor for the flexibility in the system demand.

Our analysis provides insight into the impact of grid capacity upgrades on the vulnerability of the power grid to the attack under consideration here. The simulations in Fig. 3(a) assume that for each EV penetration level, the grid has already been upgraded to support the resultant increase in peak demand under normal conditions (i.e., no attack). In other words, the grid has been upgraded to support the increased peak demand that results from the adoption of the EVs. Clearly, the heat map illustrates that beyond a certain EV penetration level, increasing the capacity of the grid adds to the resilience of the power grid. This is because the increase in the grid resilience due to the increased line capacity more than compensates for the increased peak demand resulting from the attack. Fig. 3(b) and (c) show two snapshots of the grid, indicating the extent and spread of the blackout resulting from the attack. We find that these blackouts are spread city-wide due to the failure of local distribution lines due to overloading.

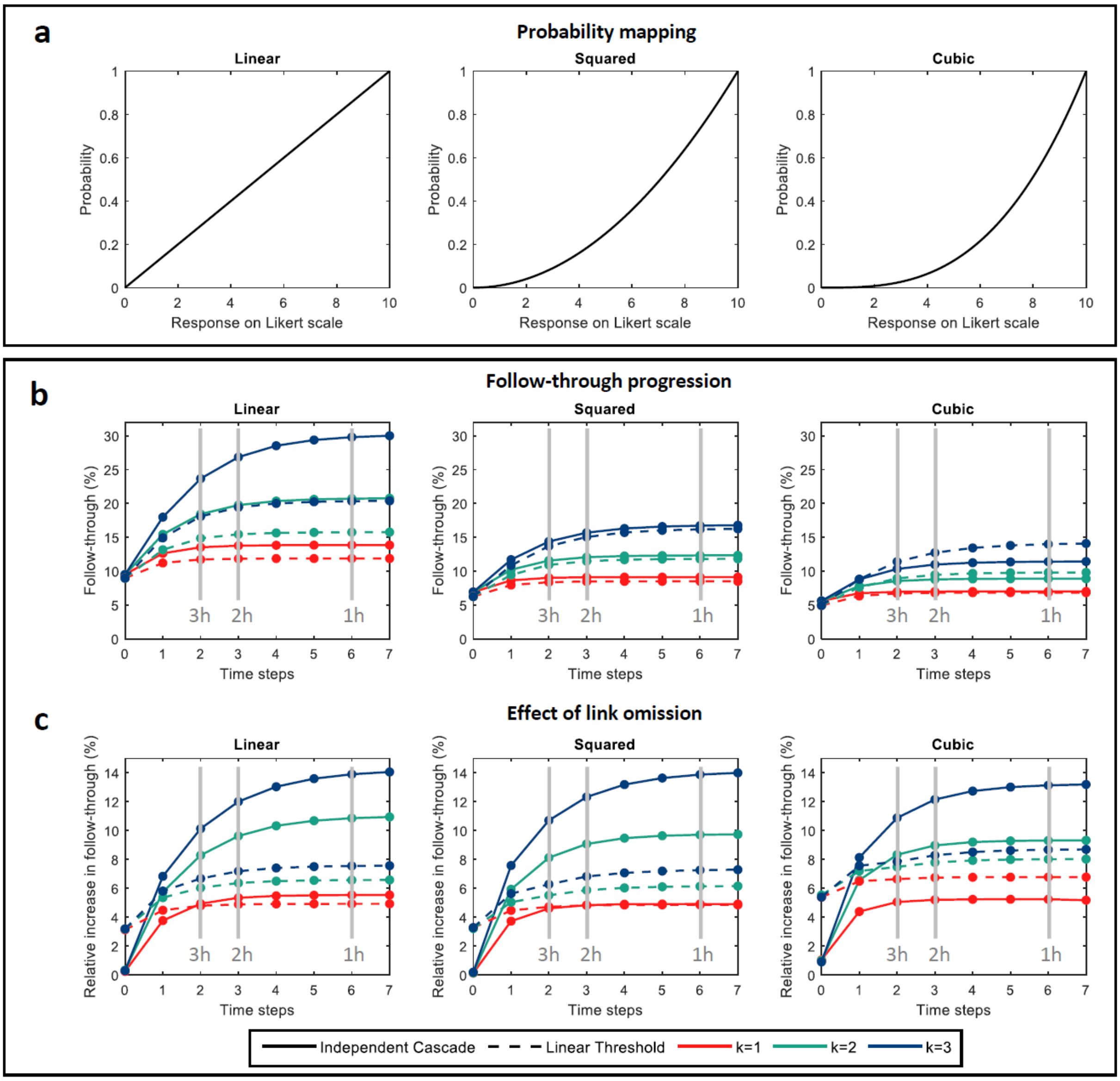

Fig. 2. Diffusion of the disinformation message through social networks. (a) Different mappings of the respondents' reported probabilities to actual probabilities, (b) percentage of residents following-through on the disinformation notification, and (c) increased follow-through due to the absence of external links in the notification.

Overall, our simulations indicate that the need for future grid upgrades must not only be dictated by the technical aspects governed by physical laws, but also need to consider the behavioural aspects of the consumers who may act unpredictably and irrationally, especially when subject to disinformation.

Further, note that after the fake notifications are sent out and before a blackout happens, the law enforcement and other governmental agencies have a window of opportunity to act, e.g., by broadcasting notices on local TV stations to warn the general public of the attack. In our scenario, to allow for the fake notification to propagate in the social network, the attacker was assumed to send the notification a few hours before the peak demand period, which is the time available for the authorities to act. However, if the fake notifications are sent out to a sufficiently large number of people to begin with, then the attacker need not rely on propagation at all. This, in turn, allows the attacker to send the notifications only a few minutes before the peak demand period, thereby reducing the authorities' window of opportunity even further. As such, it is critical that any such attacks are detected as soon as possible, and any proposed mitigation strategy can be implemented at a short notice.

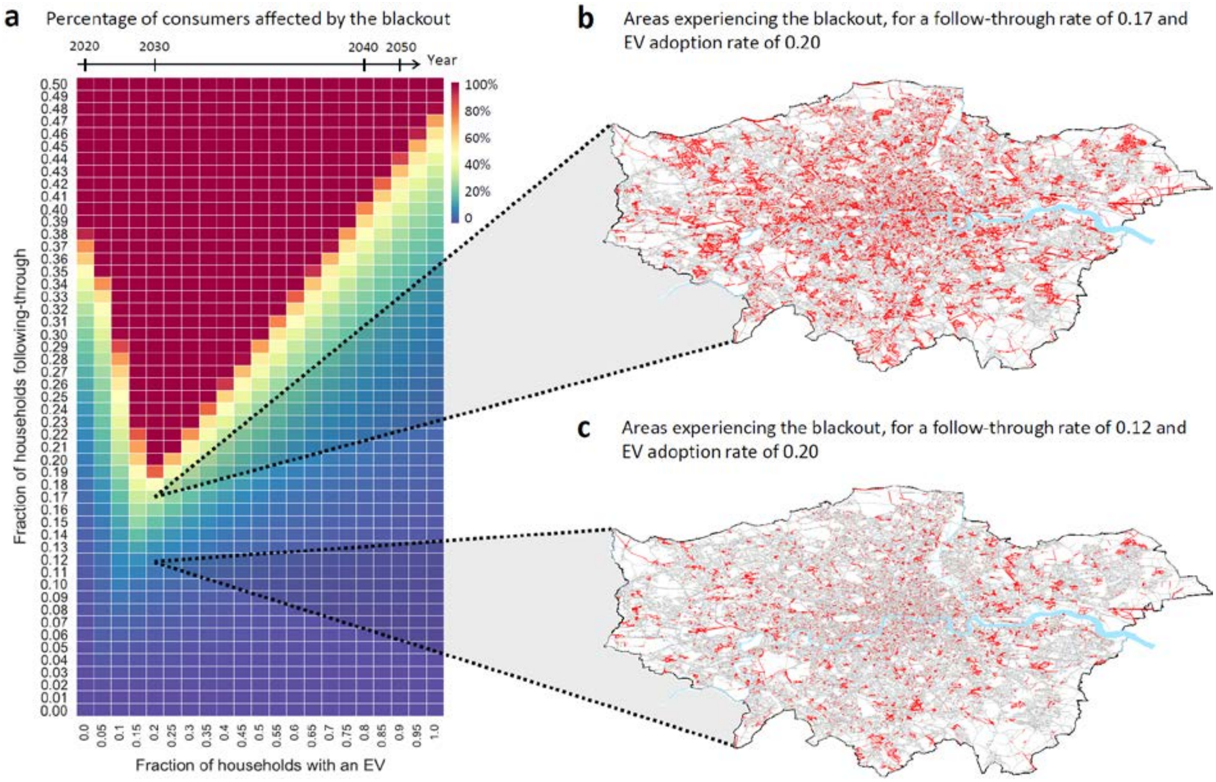

Fig. 3. Impact of the disinformation attack on the power grid of Greater London.

2. <u>Grid-resilience assessment and reinforcement using consumer behaviour</u>

Firstly, we propose a comprehensive consumer behavioural model predicting load profiles under demand response implementations (considering both price-based demand response (PBDR) programs and incentive-based demand response (IBDR) programs).

In PBDR programs, a customer will adjust their power consumption according to a pre-received (e.g., day-ahead) price signal from the utility company. The load model of a PBDR program can be expressed as

$$d(i) = d_0(i) + E(i)\frac{d_0(i)}{\rho_0(i)}[\rho(j) - \rho_0(i)] + \sum_{j=1, j\neq i}^{24} E(i,j)\frac{d_0(i)}{\rho_0(j)}[\rho(j) - \rho_0(j)], i = 1, 2, ..., 24$$

where ρ_0 and ρ are the electricity price with PBDR and nominal electricity price, while d and d_0 are the load with PBDR and initial load value, respectively. $E(i,j)$ is the cross elasticity between hours i and j.

In IBDR programs, customers will adjust their power consumption according to a pre-received (e.g., hourly-ahead) incentive for direct load control (DLC) or interruptible/curtailable (I/C services) from the utility company.

For DLC, the load demand will be directly reduced by the utility. Thus, it is assumed that the required reducing load value is equal to the actual reducing load value, which can be expressed as follows:

$$\Delta D_{DLC,a} = \Delta D_{DLC,n}$$

where $\Delta D_{DLC,a}$ and $\Delta D_{DLC,n}$ denote the actual load reducing value and the required load reducing value in DLC program, respectively.

For I/C services, customers adjust their demands to maximize their benefits (S), which includes economics losses of the customers due to load curtailment (C_1), electricity tariff (C_2), incentive received from the utility company (R), as well as punishment for not accomplishing the load reducing task (F).

$$\max S = R - C_1 - C_2 - F$$

$$C_1 = (K_1 \Delta D_{IC,a}{}^2 + K_2 \Delta D_{IC,a} - K_2 \Delta D_{IC,a} u_I)$$

$$C_2 = \eta \rho_i (d_0 - \Delta D_{IC,a})$$

$$\eta = \begin{cases} \eta, & \Delta D_{IC,a} \geq \Delta D_{IC,n} \\ 1, & \Delta D_{IC,a} \leq \Delta D_{IC,n} \end{cases}$$

$$R = \begin{cases} \Delta D_{IC,a} A, & \Delta D_{IC,a} \geq \Delta D_{\mathrm{IC,n}} \\ \Delta D_{IC,a} A, & \Delta D_{IC,a} \leq \Delta D_{\mathrm{IC,n}} \end{cases}$$

$$F = \begin{cases} 0, & \Delta D_{IC,a} \geq \Delta D_{IC,n} \\ (\Delta D_{IC,n} - \Delta D_{IC,a}) P_f, & \Delta D_{IC,a} \leq \Delta D_{IC,n} \end{cases}$$

Here, $\Delta D_{IC,a}$ and $\Delta D_{IC,n}$ are the actual load reducing value and the required reducing load value through I/C services, respectively.

Thus, the end-use customer behaviour model in system resilience evolution can be expressed as:

$$d(t) = \boxed{d_0(t)} \rightarrow \text{Base load}$$

$$\boxed{+\mu_I (\Delta D_{IC,a} + \Delta D_{DL(}} \rightarrow \text{Load change due to IBDR}$$

$$\boxed{\begin{aligned} &+\mu_P \cdot E(t) \frac{d_0(t)}{\rho_0(t)} [\rho \\ &+\mu_P \cdot \sum_{t'=1,t' \neq i}^{24} E(t,t') \frac{d_0(t)}{\rho_0(t')} [\rho(t') - \rho_0(t')] \end{aligned}} \rightarrow \text{Load change due to PBDR}$$

where μ_P denotes the customers' participation rate in PBDR during a large disturbance and μ_I denotes the customers' participation rate in IBDR during the same.

The proposed customer responsive model comprises of three components: base load, the load change due to IBDR, as well as the load change due to PBDR. In order to get the specific model (mathematical expression) of $\boldsymbol{\mu_I}$ and $\boldsymbol{\mu_P}$, we designed a questionnaire survey to determine the relationship between customers' classification and their acceptance rate of PBDR and IBDR when large disturbance or blackouts occurs.

The general customers' survey results are shown below in Fig. 4. Note that other parameters were obtained from research papers and reports. After data collection and analysis, μ_P and μ_I can be calculated as follows:

$$\mu_P = 0.531 - 0.054C_A - 0.0147C_B - 0.0462C_C + 0.0393C_D$$

$$\mu_I = 0.531 - 0.045C_A + 0.0634C_B - 0.0656C_C - 0.0038C_D$$

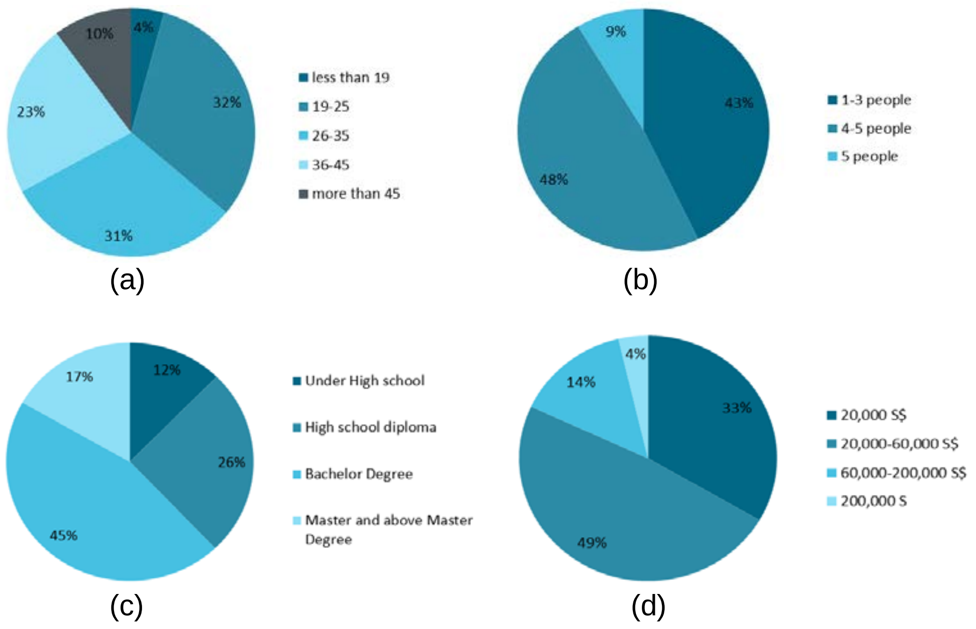

Fig. 4. Customer survey data collection: (a) Family size. (b) Age. (c) Annual income. (d) Education level.

Subsequently, the proposed end-use customer behaviour model is integrated into the multi-timescale coordinated self-healing strategy for the power system.

Our second work package aims to fully utilize the customers' response and involvement to reinforce the power grid's resilience. The approach covers the entire resilience evolution timeframe and is multi-timescale coordinated via multiple controllable resources.

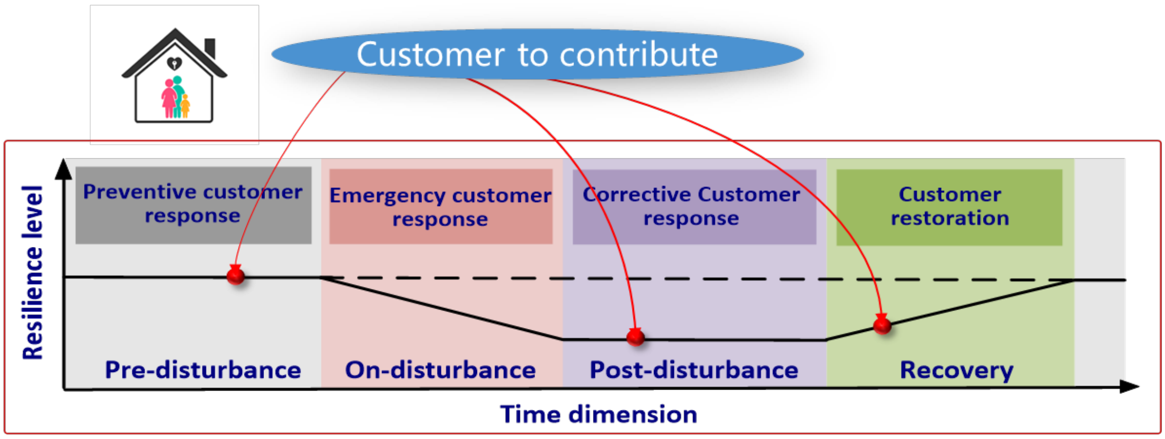

Fig. 5. The power grid's resilience evolution trajectory.

Fig. 5 shows a conceptual resilience trapezoid with customers' participation, which clearly demonstrates the states (phases) of a power system subjected to an external disturbance Breaking the event into different stages (namely pre-disturbance, on-disturbance, post-disturbance, and recovery stages) enables the dynamic multi-timescale resilience assessment. Demand response management (customers' behaviour) will contribute to improve the system stability and resilience through the pre-disturbance stage, post-disturbance stage and the recovery stage. Thus, in this work package, a multi-timescale self-healing strategy is firstly developed to optimally coordinate preventive, emergency, and corrective control means towards economic and resilience objectives. Preliminary simulations are conducted based on the IEEE 33-bus distribution network.

In this work package, we propose a multi-timescale self-healing strategy for the power system: at the pre-disturbance stage, the objective is to optimally operate the system (e.g., minimizing operation costs, maximizing utilization rate of renewable energies, etc.) while providing sufficient reserve (e.g., emergency power support capacity). A PBDR strategy will be employed for load reduction. At the post-disturbance stage, the primary objective is to maintain the system's static and dynamic security, and an integrated demand response support (including both IBDR and PBDR) are supplied. At the recovery stage, the objective is to rapidly restore the power supply, and a combination of corrective control actions such as generation restoration, and load recovery are investigated. The control actions among the three stages are integrated and coordinated.

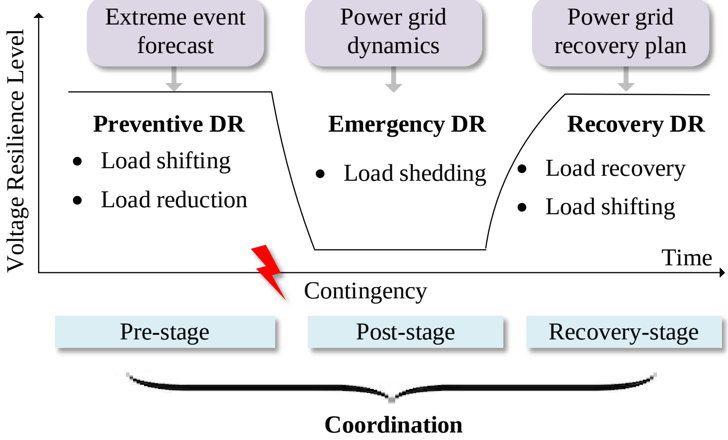

Fig. 6. Multi-timescale self-healing strategy.

The proposed model is verified on a benchmark system, the IEEE 33-bus distribution radial system. To verify the advantages of the proposed self-healing strategy, two cases are compared here:

Case 1: Base case. Here, no customers' participation is considered. The 33-bus distribution system is operating without any DR strategy.

Case 2: The proposed approach. DR strategies are employed to guide customers to contribute to the load shifting/reduction and so on.

The simulation results for the three stages are shown below in Figs. 7-9.

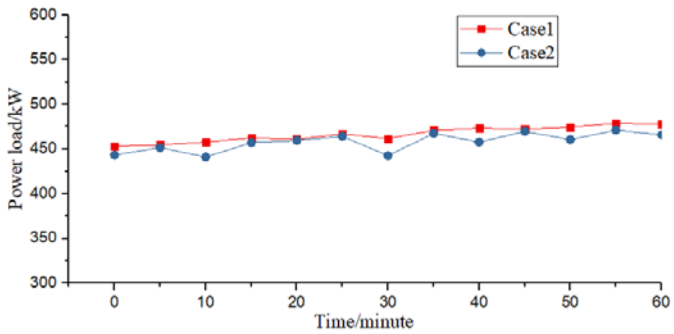

Fig. 7. Power loads under two cases in the Pre-Disturbance Stage.

It can be seen from Fig. 7 that power loads are slightly reduced after considering the demand response strategy, which means that the DR program can help modify the power loads profile so that the peak load can be shifted or reduced. Besides, it helps the power system to provide more reserve for the upcoming contingency.

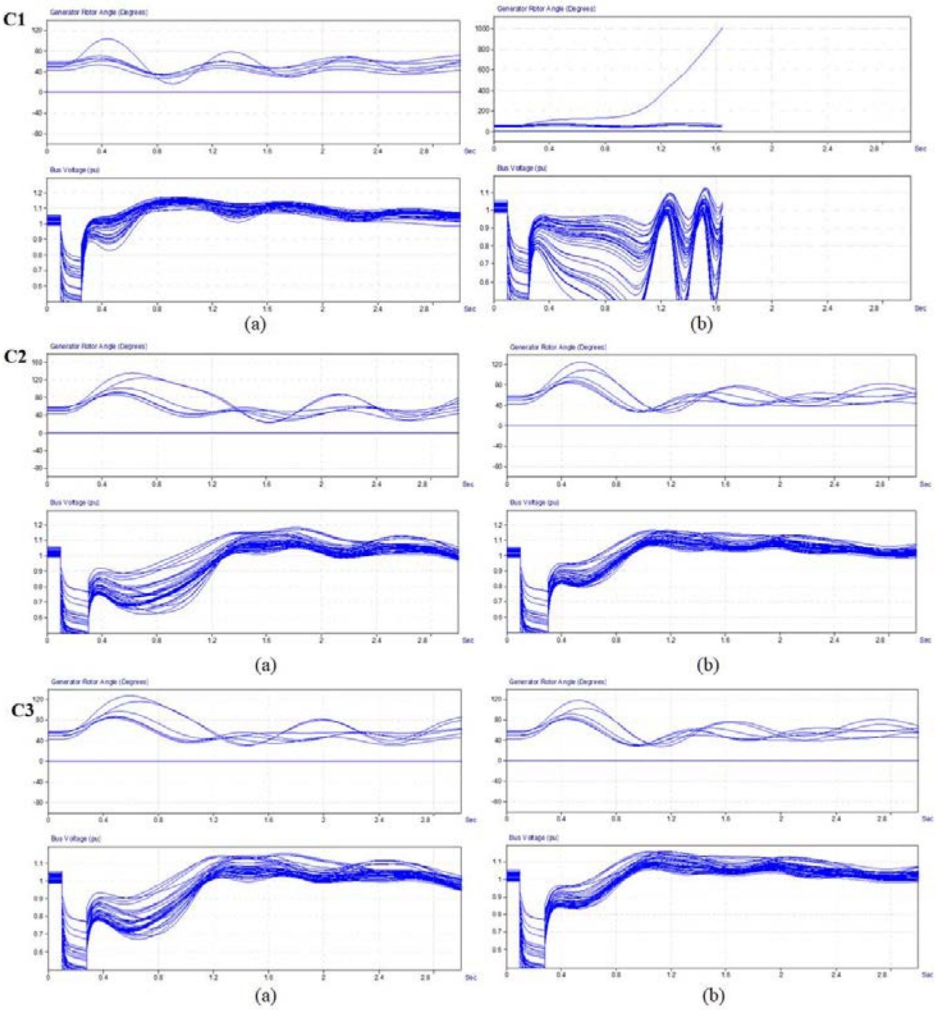

Fig. 8. Illustration of stable trajectories in the Post-disturbance Stage. (a) Case 1 without DR. (b) Case 2 with DR.

In order to verify the validity of the proposed approach in the post-disturbance stage, we consider three different contingencies (C1, C2 and C3). The simulation results are shown in Fig. 8. For this dispatch solution, the stability margins under C1-C3 are given in Table 1. It can be concluded that after integrating the customers' responsive model of the power system physical disturbance, the system becomes more stable.

TSI	Case 1	Case 2
C1	-9.63	40.41
C2	7.86	50.08
C3	0.57	66.54

Table 1. Transient stability margin under C1-C3.

It can be seen from Fig. 9 that Case 2 takes lesser time to restore the load power to the original level. In Case 1, the restoration time is 9 minutes. Whereas in Case 2, it is only 7 minutes, almost 22% faster than Case 1. This is mainly because after supplying incentives at an attractive price, customers are more willing to turn on electric appliances, and thus they actively participate in the load restoration procedure, which is beneficial for the power system resilience.

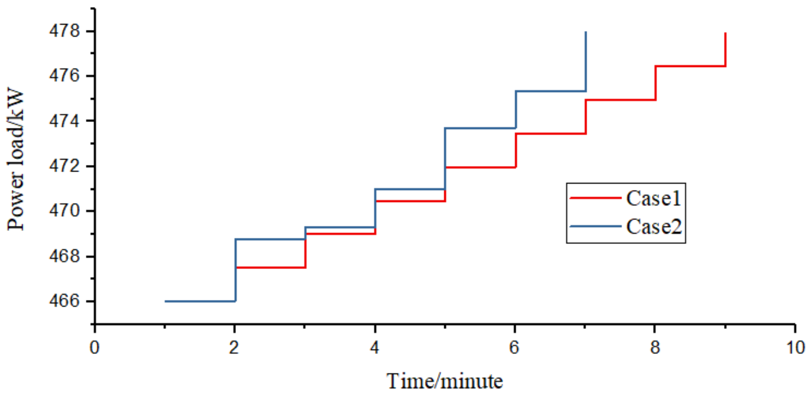

Fig. 9. Load restoration process in the Recovery Stage.

In conclusion, a preliminary test has been conducted to validate the effectiveness of the proposed multi-timescale coordinated self-healing strategy for resilience reinforcement in power systems. Simulation results show that considering customers participation can indeed greatly enhance the power system resilience and stability.

Challenges experienced in our research

1. Assessing how consumers respond to disinformation in reality

It was a challenge to ensure that our study modelled the behaviour of energy consumers in a realistic manner. Ideally, the methodology would be to identify a large group of residential households, install real-time power monitoring equipment in each, and subject a part of this group to disinformation messages in a controlled experiment. However, given the limitation of the project's timeframe and practical considerations, we had to rely on a survey instrument to obtain data regarding consumer behaviour for our preliminary study. Though this survey-based technique is not ideal, we took precautions to correct for the possibility that survey respondents over-reported the extent to which their behaviour would change in response to a notification related to energy usage. In particular, we considered several mapping functions between the participants' reported probabilities to the actual probabilities used in our influence propagation simulations. As such, performing a controlled field experiment that verifies our findings in this planning grant is an important part of our Full Proposal.

2. Assessing how customers' response and involvement can be fully utilized to reinforce the power grid's resilience

A second challenge was to bridge the end-user social behaviour (customer level), critical electric assets (component level), and the system operation (grid level). There is very less existing research on integrated resilience reinforcement, especially on modelling the impact of customer behaviour and interaction with the grid. Further, most of the methods are model-based, which require detailed and accurate knowledge of the equipment and the system. As such, we have proposed a multi-timescale (pre-disturbance stage, post-disturbance stage and recovery stage) self-healing strategy for the power system. A combination of corrective control actions such as generation restoration, and load recovering were investigated in this planning grant. The control actions among the three stages were integrated and coordinated. Although this technique may not be the best way to combine customers' behaviour and system operation, we conducted preliminary simulations to test its effectiveness.