Real-Time Energy Storage Simulators for the Electricity Grid

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***Abstract*—In this paper, a novel Distributed Real-Time Simulation Environment (DRTSE) which enables the coordinated control of multiple Real-Time Simulators (RTSs) positioned across the UK is introduced and demonstrated for an energy storage application. Using RTSs instead of physical energy storage assets enables the testing of different communication and control strategies, thereby reducing the risk of failure when the physical storage assets are deployed. In addition, the testing of different storage types (e.g. batteries, compressed air, flywheels, etc.) and storage locations can be conducted without expensive hardware modifications. In this paper, technical details of the RTSs are given, including the hardware and electrical storage models. The Central Controller (CC) and communication are also described, and results from the DRTSE presented.**

***Index Terms*—Battery management, Electricity grids, Energy storage, Hardware-in-the-loop, Real-time systems**

I. Introduction

Increasing the quantity of renewable electricity in the United Kingdom reduces the reliance on imported energy, reduces global greenhouse gas emissions, and reduces local pollution. The intermittency of renewable generation is a challenge and energy storage is one of the most cost effective methods of incorporating more renewable electricity generation [1].

Significant research has been conducted into optimising the planning [2], [3] and operation [4], [5] of energy storage on the electricity grid, as well as the forecasts required for these optimisations [6], [7]. After such studies are completed and the specifications and operating approach are known, the energy storage could be installed. Alternatively, an intermediate step of real-time simulation can be used before committing to an investment in physical energy storage hardware.

A. Real-Time Energy Storage Simulation

Real-time simulation involves running a model at the same speed as it would be run if it were a physical system, i.e. one second in the model takes one second in reality. In [8], real-time simulation was used to develop an algorithm to estimate the state of charge of a lithium-ion battery pack. A physical battery module is connected to an electrical load and a real-time model estimating the state of charge is run on a computer. The real-time simulation validates the correctness and effectiveness of the algorithm and evaluates the accuracy, robustness, and real-time computing ability in practice.

In [9], a physical battery is used and connected to a controller and a real-time model of a distribution grid. An optimisation algorithm is developed and the algorithm is demonstrated using a grid peak shaving application, with the objective of minimising the net peak load of a building. The use of real-time simulation enables detailed monitoring of battery energy storage systems under different design scenarios.

B. Geographically Distributed Real-Time Simulation Benefits

Fig. 1 compares methods to develop energy storage control algorithms, ranging from developing the algorithm on a single computer using historical data, to physically installing hardware costing millions of dollars. This paper is focused on method c), developing the DRTSE with multiple RTSs at geographically distributed locations on the electricity grid.

Often methods b), c) and d) from Fig. 1 may be skipped and the energy storage hardware installed and operated after an algorithm has been developed using historical data (method a)). However, these methods cannot fully account for phenomena observed in real-time operation such as communication latencies, real hardware constraints, and measurement errors. These can have a significant effect, particularly in the delivery of services aimed to compensate for fast transients and where a high number of storage assets might be required to respond in a coordinated way. Using the DRTSE developed in this paper can inform and increase confidence in modelling approaches, as such effects can be recorded, analysed, and ultimately accounted for before the expensive hardware is installed.

Increasing representation of reality, cost

a) Single computer using historical data	b) Single computer real time simulation	c) Computers geographically distributed real time	d) Lab scale installed energy storage hardware	e) Physically installed energy storage hardware
1-5 k$	1-5 k$	10-50 k$	50-200 k$	>1 M$

Fig. 1. Methods to develop energy storage control algorithms

The DRTSE developed is more expensive than using a single computer, with the total cost being roughly 40 k$. However, this cost is small compared to the likely cost of physically installing hardware. The geographically distributed aspect of the DRTSE has the benefits over a single computer of ensuring control algorithms are developed with realistic communication commands and delays and are subject to unexpected communication failures, which will undoubtedly occur in a real system. These benefits of the DRTSE may counter the increased costs as there will be less risk of integration problems when the energy storage assets are physically installed.

A further benefit of the DRTSE is that different types of energy storage system can be tested, simply by changing the model running on the RTSs, without changing any hardware. For example, a battery could be replaced with a flywheel simply by changing the model running on the RTS.

An overview of the DRTSE is given in Section II. Section III describes the RTSs, including the hardware and the model running on the RTSs. Section IV describes the CC, which controls the RTSs, and the communication method. An experiment using the DRTSE is shown in Section V.

II. Distributed Real-Time Simulation Environment

The DRTSE is developed to represent multiple energy storage systems across the United Kingdom being controlled from a central location by an aggregator. To represent this scenario, five RTSs are installed and each RTS runs a model of an energy storage system in real-time. The five RTSs are placed at five locations around the UK where energy storage systems may be deployed in the future (see Fig. 2).

The RTSs are controlled by a CC, which continually runs a model to determine the commands to send to each of the RTSs. The commands include the power that the RTS should charge or discharge at. The commands can also request the status of the RTS, for example the grid power, the state of charge, or the local measurements of frequency and voltage, all of which are calculated locally by the RTS.

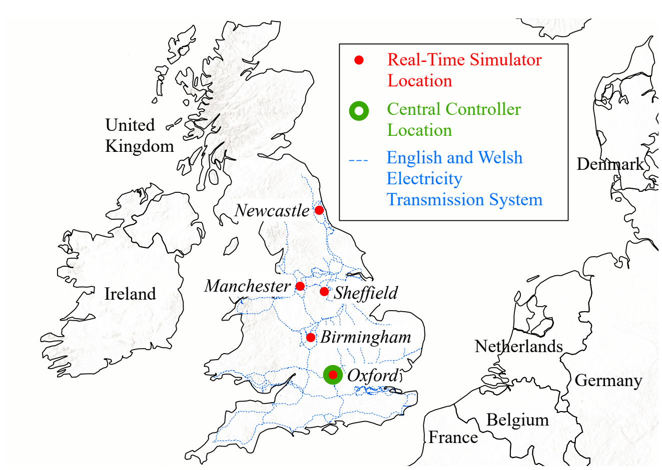


Fig. 2. Locations of the RTSs and CC [10], [11]

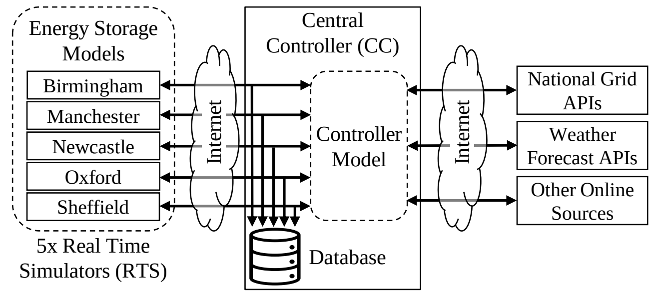


Fig. 3. The Distributed Real-Time Simulation Environment (DRTSE)

This creates a DRTSE as illustrated in Fig. 2 which is a close facsimile of an aggregator controlling five energy storage systems, the only difference being that no power is physically transferred to or from the grid at each location.

This lack of power transfer is a limitation of the DRTSE, for if the RTSs were real energy storage systems the grid would be impacted by the energy storages charging and discharging. Local changes in grid voltage can be incorporated by including a local grid model on the RTS, but it is not possible to impact the global grid frequency. If the energy storage power is relatively small, the global impact of the energy storage on the grid frequency would not be significant and the DRTSE can be considered a close representation of a real system.

III. Real-Time Storage Simulators

A. *Electronics Hardware*

An overview of the electronics hardware can be seen in Fig. 4. The main component of the RTSs is the real-time simulation machine, which continually runs the model of the storage asset and obtains real-time voltage measurements. For this work, a Speedgoat Unit Real-Time Target Machine is used [13]. The machine has an Intel Atom x5-E3940 1.6 GHz quad-core CPU and 4 GB DDR3 of memory. To measure voltage, the IO191

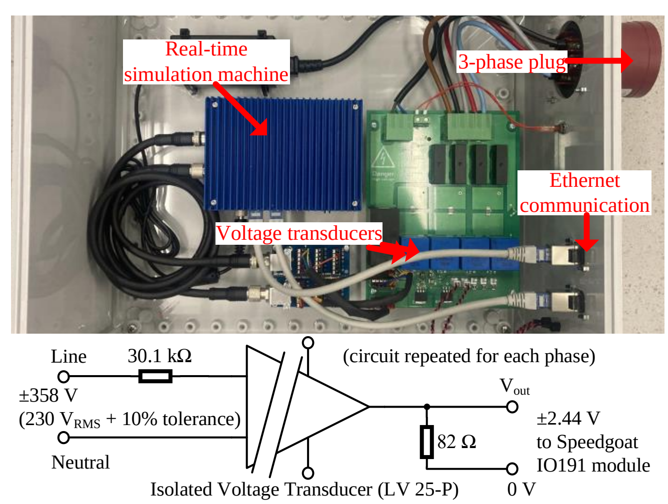


Fig. 4. RTS electronics hardware, including voltage transducer [12]

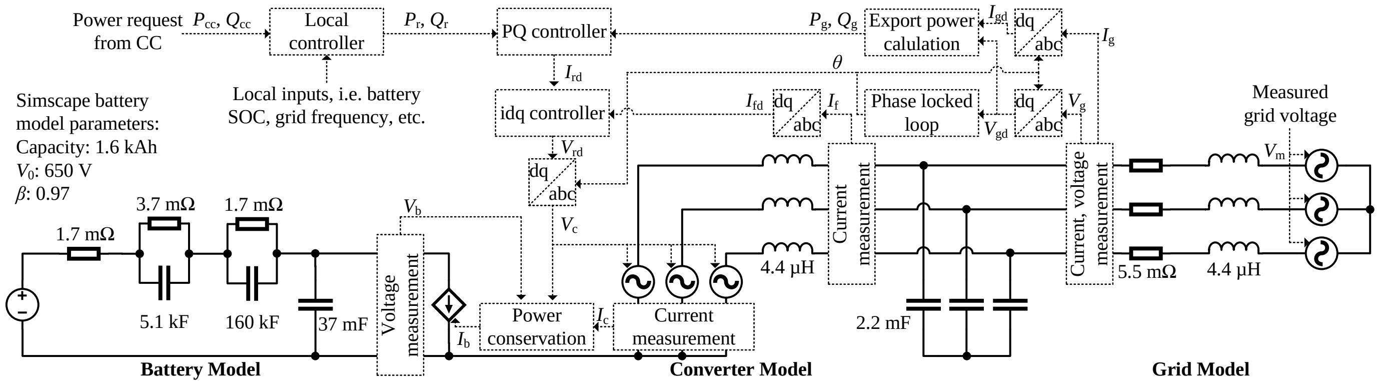


Fig. 5. Overview of the model running on each RTS

module is added, which includes analogue inputs of 16-bit resolution and sampling up to 250 kSPS.

To ensure the RTSs are representative of real energy storage assets, grid voltage measurements are obtained at each RTS location. The voltage measurements are used to calculate the grid frequency and RMS voltage, and are used as inputs for the power converter model.

B. Energy Storage Model

In the future, different energy storage models can be run on the RTSs. At present, each RTS runs the same model, which includes an averaged model for a bi-directional power converter and the Simscape behavioral battery model [14], an overview of the model is given in Fig. 5. The converter model uses the measured grid voltages to obtain phase and frequency information using a phase locked loop. It includes an inner current controller and an outer real and reactive power controller, implemented in the d-q domain. The battery model is an electrical 2RC (Resistor Capacitor) model, which is commonly used for battery modelling [15]. The RC values are averaged across all states of charge and based on the University of Sheffield Willenhall battery [16].

The electrical values used in the model are seen on Fig. 5. Key considerations for the model are the timestep and the control loop gains. Higher control loop gains mean the converter reaches the requested powers in a shorter time, however higher gains also mean a smaller timestep is required. The smaller the timestep, the more computational power is required and so a tradeoff must be made when selecting the gains. With the Speedgoat machine running the model in Fig. 5, the smallest timestep possible was 200 µs (5 kHz). Below this value the Speedgoat machine could not complete the model calculations for each step in real-time. With a timestep less than 500 µs (2 kHz), missed ticks did occur occasionally (1-2 times per minute). The largest timestep possible was 1000 µs (1 kHz), above this value the control loops did not converge to the requested powers even with very low gains. At 1000 µs, power settling time for a step change from 0 to 1 MW is approximately 120 ms (6 line cycles).

The real-time simulation machines use the Backward Euler method [17] as part of the real-time solver. The Backward Euler method exhibits numerical damping which improves stability for long timesteps. However, it also introduces small errors in time-varying signals which become noticeable when the errors are integrated over time. This means that, for example, the state of charge of a battery (which is a result of the integral of battery current over time) tends to drift even when zero real power flows through the converter. Over the course of a day, this drift can be significant, depending on the capacity of the storage and the rating of the converter (e.g. 32% SoC/day for a 1 MW, 1 MWh battery, with a 1.5 kHz timestep). Reducing the timestep reduces the drift error in rough proportion to the timestep, but this requires more powerful real-time simulation machines to run a model of a given complexity. Other integration methods can be used that do not suffer from similar drift (such as a Trapezoidal method), however these tend to require shorter timesteps to ensure stability (4 kHz minimum for the model here). In practice, given the computational limits of the Speedgoats, Backwards Euler at 1.5 kHz was found to be a good compromise.

IV. Central Controller and Communication

A. Hardware and Controller Model

The CC is run on a Linux PC in Oxford with 16 GB System memory and an Intel Core i7-10700 2.90 GHz CPU.

The CC model is a python script run in a loop. An overview of the steps that may be taken on the CC can be seen in Fig. 6. To make decisions, the CC model can obtain data from 1) the RTSs, which respond with locally calculated data, such as local voltage and frequency, real and reactive power, state

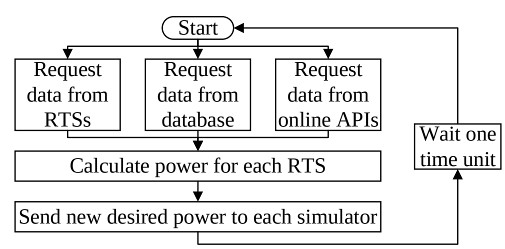
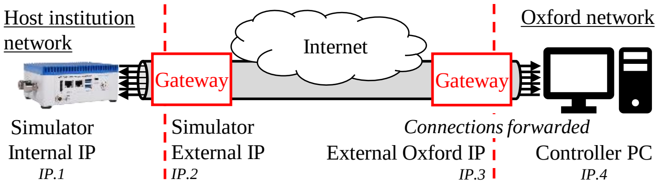


Fig. 6. Example of an algorithm running on the CC




```
ssh -N user@IP.3 -R 30002:localhost:22 -R 51002: localhost:51000
-R 52002:localhost:52000 -L 41000:localhost:41002 -L 42000:localhost:42002
-L 31000:localhost:31002 &
```

Fig. 7. Overview of the SSH tunnels created

of charge, etc., 2) the database, which is continually storing historical data from the DRTSE, or 3) online data sources, such as National Grid APIs, weather forecasts, etc. Once the CC has the data, the CC then decides what powers are required from each RTS, and then sends these power requests to the RTSs. In this example, the loop is a time loop and executes at regular time intervals. Some control algorithms may be event driven, whereby the loop executes when triggered by external events occurring at the RTSs or elsewhere (e.g. a dispatch command from the grid system operator).

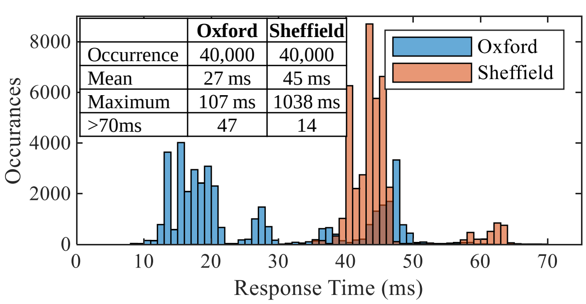
B. Communication

To establish communication between the RTSs around the country and the CC in Oxford, Secure Shell (SSH) tunnelling is used. The SSH tunnel creates links between ports on the RTSs and ports on the CC. The location and host network of each RTS is different and so may have different network protections, therefore each RTS is programmed to automatically create an SSH tunnel to the Oxford CC on startup. Once this SSH tunnel is created, the CC can reverse-tunnel back to the RTS to communicate with the RTS, as shown in Fig. 7.

The SSH tunnel cannot be made directly to the CC as the CC sits behind the Oxford network gateway. Instead, each RTS connects to an external facing IP address and the gateway forwards connections to the CC PC on the local network. In total, six ports are opened, three from the CC to the RTS, for 1) transfer of files, 2) sending power commands, and 3) sending a request for data. Three connections are made from the RTS to the CC, to 4) send data to the database, 5) send data when requested, and 6) check if the tunnel is still open.

Once the SSH tunnel is created, requests from the RTSs and CC are sent to local ports. For example, when the CC sends a power request to the Sheffield RTS, the relevant SSH argument for sending power commands is -R $51002{:}\mathrm{localhost}{:}51000$. Port 51002 is the port on the CC assigned for sending powers to Sheffield. The CC therefore sends the power to IP $\mathrm{localhost}$, port 51002 and the RTS is programmed to listen for power requests from IP $\mathrm{localhost}$, port 51000.

In the above case the RTS then responds to the request and the data is received by the CC. A histogram showing the time between sending the request and receiving the data can be seen in Fig. 8. The average response time of Sheffield, 45ms, is likely to be acceptable for grid applications.



	Oxford	Sheffield
Occurrence	40,000	40,000
Mean	27 ms	45 ms
Maximum	107 ms	1038 ms
>70ms	47	14

Fig. 8. Response times from the RTSs

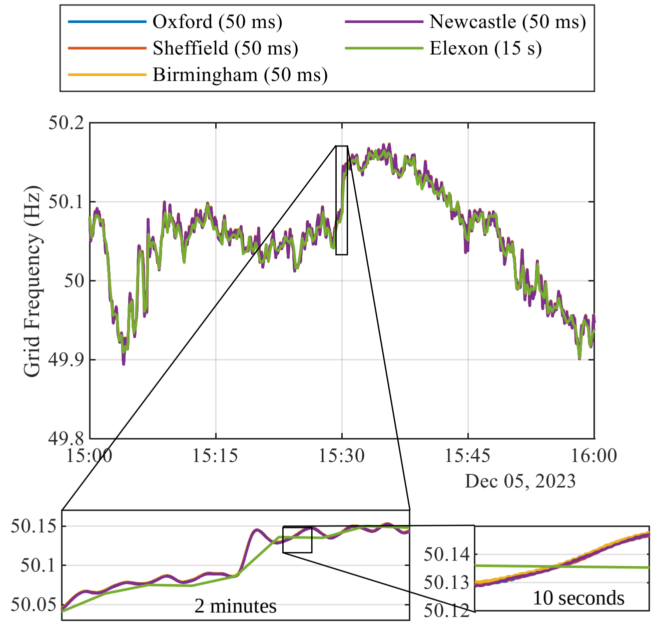


Fig. 9. Data from RTSs and Elexon [18]

C. Timing

To obtain accurate data from across the UK, each measurement from each RTS is timestamped when it is collected. The RTS clocks are set using the Network Time Protocol (NTP). A snapshot of grid frequency data from Oxford, Sheffield, Birmingham, Newcastle and data recorded by Elexon for National Grid [18] can be seen in Fig. 9. From this figure it can be seen that the frequencies recorded in all locations are very similar (± 0.001 Hz or 20 ppm) and match well to the National Grid recorded frequency.

V. Discussion

The purpose of this paper is to introduce the technical details of the DRTSE. In future work detailed algorithms will be developed to test on the DRTSE. Therefore, only a simple scenario is used for demonstration of the DRTSE in this paper. In this scenario, an aggregator is controlling four batteries located in Oxford, Sheffield, Birmingham and Newcastle. Initially, all the batteries are providing the frequency response service, with the exception of the Oxford battery, which is idle. The frequency response service provided is the National Grid

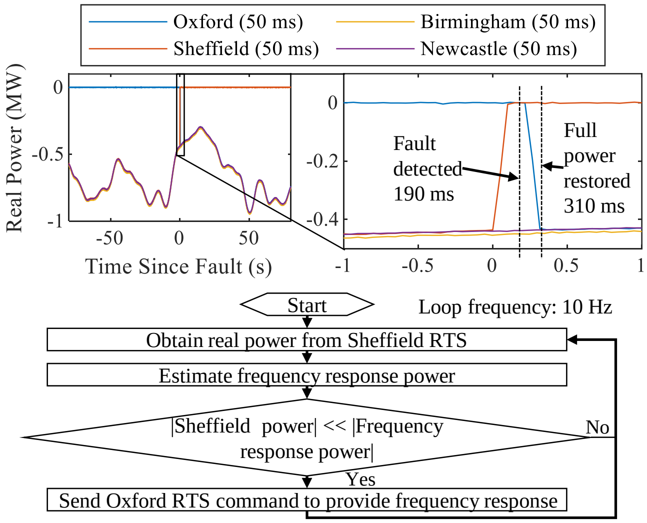


Fig. 10. Experiment demonstrating the DRTSE, data extracted database

service, Dynamic Containment [19], which uses a lookup table to set the battery power depending on the grid frequency. For frequency response, fast response times (<0.5 s) are required. The lookup table is therefore stored locally on the RTS and the only signal from the CC is to start and stop providing frequency response.

In the scenario, after some time, the Sheffield battery experiences a fault and its real power delivery drops to zero. The aggregator is contracted to provide frequency response service to the grid and so the aggregator then instructs the Oxford battery to provide frequency response to the grid, the results and decision flow chart can be seen in Fig. 10. Although the model is being run with a timestep of 1 ms, the data is only recorded to the database every 50 ms and the CC polls the RTSs every 100 ms. In this example, the 1 MW lost from Sheffield was delivered by Oxford within 310 ms. This 310 ms includes 1) the CC polling time, 2) two network delays and 3) the controller settling time.

VI. Conclusion

A novel DRTSE that enables the coordinated control of five Real-time Storage RTSs across the UK has been created. Compared to simulating coordinated control of energy storage devices on one computer, the DRTSE has the advantages of forcing the control algorithm to deal with realistic uncertain grid and communication behaviour. During longer term studies, simulating in real-time is also likely to highlight issues which are not easily predicted, for example local controller response to unexpected abnormal grid events.

The main limitation of the DRTSE is that power is not transferred to or from the grid. The impact of the power transfer on the local grid voltage can be modelled on the RTS, however the impact on the global grid frequency cannot be included without physical power transfer. Physical power transfer with the grid would require physical storage hardware, which would significantly increase the cost and time of experiments.

The main benefits of the DRTSE are that coordinated control algorithms can be developed and rapidly tested before being deployed in real assets. Different storage technologies can also be tested without expensive hardware modifications. Future work will involve developing more storage technology models to run on the RTSs and developing and testing new CC control strategies.

Acknowledgment

This research is sponsored by the Engineering and Physical Sciences Research Council (EPSRC), EP/W02764X/1.

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