An optimisation model to determine the capacity of a distributed energy resource to contract with a balancing services aggregator

Ussama Rai [a,*], Gbemi Oluleye [b], Adam Hawkes [c]

a, ⁎ Corresponding author, Department of Chemical Engineering, Imperial College London, South Kensington Campus, SW7 2AZ, London, UK, u.rai17@imperial.ac.uk

b Centre for Environmental Policy, Imperial College London, South Kensington Campus, SW7 2AZ, London, UK, o.oluleye@imperial.ac.uk

c Centre for Process Systems Engineering, Imperial College London, South Kensington Campus, SW7 2AZ, London, UK, a.hawkes@imperial.ac.uk

Abstract

Electricity systems require a real-time balance between generation and demand for electricity. In the past, changing the output of larger generators has been the primary means of achieving this balance, but more recently, smaller distributed energy resources (DERs) are becoming a contributor. As electricity generation becomes more intermittent due to the uptake of renewables, the task of balancing the electricity system is becoming more challenging. As such, there will be a greater need for DERs for grid balancing in future. DERs may be delivered via aggregators for this purpose, where several individual resources are grouped to be traded in contracts with a System Operator (SO). This paper presents a novel framework for DERs aggregators to determine by optimisation the capacity of a generating unit to contract with the SO, using mixed integer non-linear programming (MINLP). Results show the site revenue increases between 6.2% to 29.8% compared to the heuristic approach previously employed. Sensitivity analysis is performed to assess the impact of temporal resolution of demand characterisation on results, showing that increased resolution improves accuracy significantly, and reduces the estimate of capacity that the site should contract with the aggregator.

Keywords: Short term operating reserve (STOR), Demand side response (DSR), Distributed energy resources (DERs), System operator (SO), Balancing mechanism (BM), Optimisation.

Nomenclature

Sets

$I \in I$ Set of site demand bins (This represents the annual half-hourly electricity site demand divided into various sections. Demand bin is the distribution of STOR year site electricity demand data into 5, 25 & 50 divisions using histogram i.e., dividing the entire range of yearly HH demand data into a series of intervals and then counting how many values fall into each interval.

Parameters

$d_{(i)}$ *site demand in each demand bin*

$Ks_{(i)}$ *Total number of STOR calls in each demand bin*

$ah_{(i)}$ *Availability hours in each demand bin*

$G_{(Max)}$ *Maximum generation capacity of a site in MW* *guc* *Generator utilisation cost in £/MWh*

gac *Generator availability cost in £/MWh*

fc *Fuel cost in £/MWh*

Ls *Duration of STOR call in hours*

gahm *Generator availability hours/ month*

Variables

$Z_{(Total)}$ *Total Annual Profit*

X *Optimal contractual generation capacity to offer in STOR market in kW*

$XACT_{(i)}$ *Actual Generation capacity delivered per demand bin during STOR call*

$P_{(i)}$ *Penalty cost for under or no delivery for a single STOR call per demand bin*

$Ps_{(i)}$ *Penalty cost for under or no delivery for all STOR calls per demand bin*

Positive Variables

$AR_{(i)}$ *Availability revenue per demand bin*

$UR_{(i)}$ *Utilisation revenue for a single STOR call per demand bin*

$GFC_{(i)}$ *Generator fuel cost for a single STOR call per demand bin*

$AR_{(Total)}$ *Total availability revenue per year from STOR contract*

$UR_{(Total)}$ *Total utilisation revenue per year from STOR contract*

$GFC_{(Total)}$ *Total generator fuel cost per year from STOR contract*

$PS_{(Total)}$ *Total penalty cost per year from under or no delivery during STOR event*

Binary Variables

$YP_{(i)}$ *Indicates if there is a STOR penalty or not*

1. Introduction

The challenge of mitigating climate change and increasing energy independence results in significant uptake of low carbon generation, and distributed energy resources (DERs) in electricity systems worldwide and this trend is likely to increase substantially in the future [1]. Many of these energy resources like wind and solar due to their unreliable nature and intermittency and nuclear due to their inflexibility cause system adequacy (capacity balancing) [2] problems resulting in system instability[3], [4].

To strengthen system stability, backup capacity is available to a System Operator (SO) in the form of conventional thermal units, gas and diesel generators for system balancing when intermittent and inflexible generation is present. In the past, these services were often provided by large centralised generators[5], [6], but more recently smaller generators are playing a huge part, driven by a market where sustainability, scalability, carbon footprint reduction and market competition are key priorities [7], [8], [9]. Manipulation of demand itself is also gaining interest in this regard, where flexible demand resources may be aggregated and used to adjust demand to match supply, rather than vice-versa [10], [11], [12].

Aggregating these small resources and trading them in single contracts with a SO has emerged as a way to contribute towards achieving system balance [13], [14], where the flexibility provided by DERs can counter fluctuations caused by renewables compared to relying on conventional generation alone [15], [16]. Whilst the benefits of the flexibility provided has been investigated; there is a need to determine the optimal contractual generation capacity of a grid-connected generating unit on a site level to participate in the Balancing Mechanism (BM) from a DER investor perspective. Previous works apply risk eversion and heuristic approaches to determine the generation capacity of a grid-connected generator to offer in BM; hence there is scope to improve approaches to increase the efficiency and profitability from DERs in the electricity system.

A systematic approach to determine the contractual generation capacity has the potential to increase the cost-effectiveness of future electricity systems, and enable aggregators to dispatch the most economical and reliable assets. The novelty of this research is a systematic framework for determining the optimal level of contractual generation capacity of a grid-connected generating unit to participate in the Short Term Operating Reserve (STOR) service of BM whilst fulfilling the site electricity demand and maximizing site revenue. Another novelty is determining the optimal number of site demand bins to represent the annual half-hourly (HH) demand of the site. Additionally, the use of real case studies adds value to the research carried out in this paper.

1.1 Background

The power sector is experiencing a global transformation to decarbonisation [17], [18], [19], [20] and power system flexibility and stability have become a priority [21]. The development towards the digitalisation of the grid [22], cost reductions, security and low carbon aspirations have increased interest in DERs [23]. A grid with a large penetration of intermittent renewables requires reliable resources, possibly in the form of small generators or ESS, that can ramp up or down to maintain the overall balance of supply and demand [24]. These DERs offer the potential to improve power system stability. However, there is still a gap in determining the optimal capacity to offer from these DERs to the SO in the BM.

SOs and regulatory bodies have a mandate to ensure a timely and cost-effective investment to achieve grid balancing [25]. These policies bring about generation projects directed at grid balancing, including those controlled by aggregators, which may, for example, include the expansion of Combined Heat and Power (CHP) capacity resulting in a greater number of small generators [26] and ESS connected with the grid. To achieve system balancing cost-effectively, regulatory bodies have the option of incentivising network operators and aggregators in providing support using ancillary services.

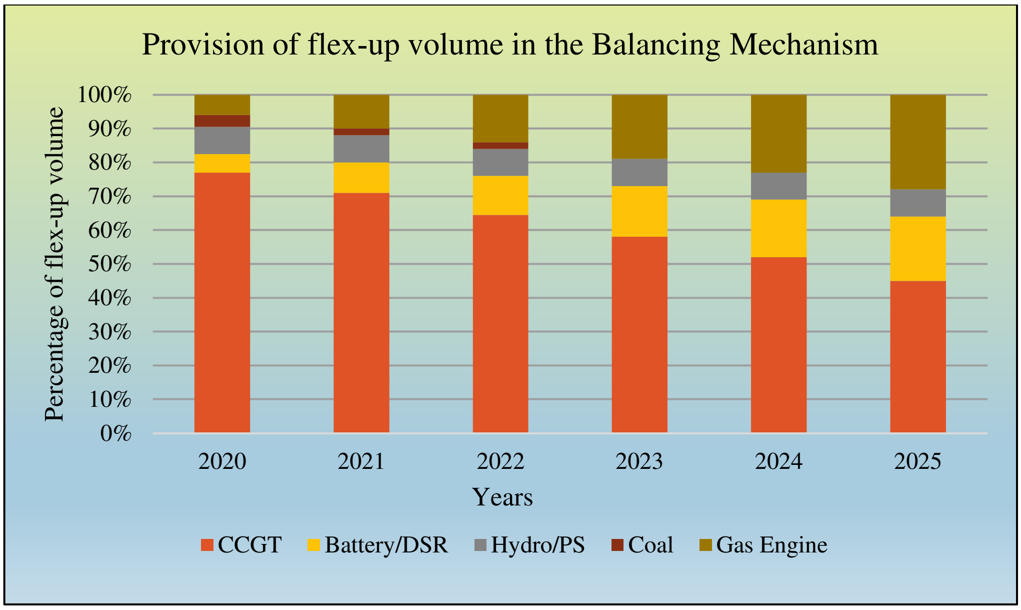


Fig. 1. Provision of flex-up volume in the Balancing Mechanism [27]

In the UK, combined cycle gas turbines (CCGTs) are currently dominating the flex-up volume, as shown in Fig. 1. By 2025, it is estimated that almost 50% of the flex-up volume will be provided by DERs and ESS, while gas engines will cover more market share for BM than they do now. Most small scale renewables and ESS in future will be connected to the distribution system networks rather than transmission networks [26]. On the other hand, coal-fired power stations which once were the largest source of electricity in the UK are, at the time of writing, limited to only four with a phase-out plan by 2025 since the UK has legislated for net-zero emissions by 2050 via an amendment to the Climate Change Act 2008[28], [29].

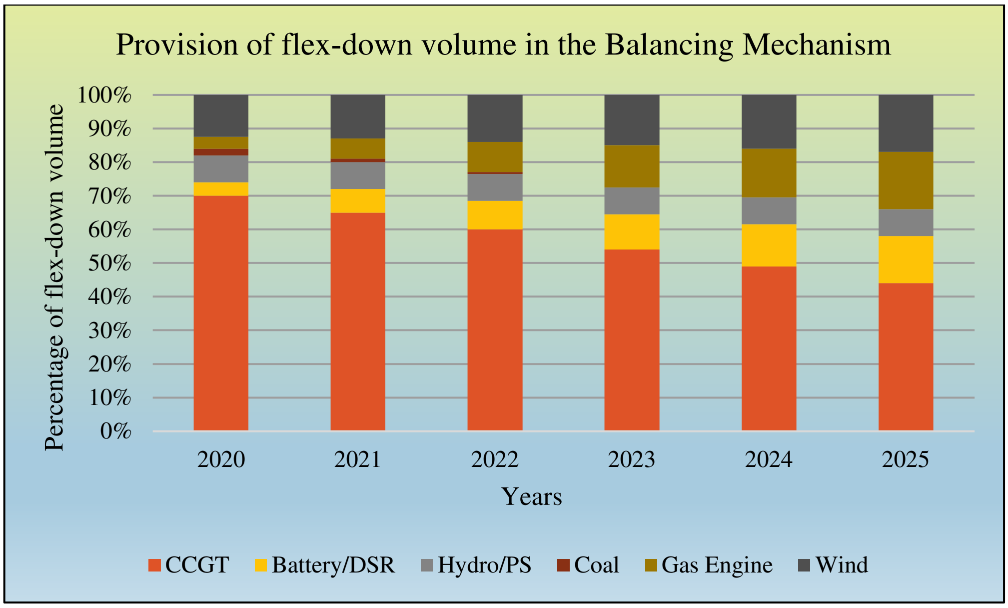


Fig. 2. Provision of flex-down volume in the Balancing Mechanism [27]

An illustration of the evolution of various technology sources participating in BM in flex-down volumes across 2020- 2025 is shown in Fig. 2. Even for flex-down volume, batteries and renewables are considered to occupy an increased share due to their instant curtailment capabilities.

One key objective of a SO has always been to balance the supply and demand of electricity [30] in real-time, though historically, this has been with limited recourse to ESSs and DERs [31]. However, given that such resources may play a greater role in future, a systematic approach to account for the trade-offs in the economic impacts is required. To achieve system balance, a SO predicts if there will be a discrepancy between the amount of electricity produced and consumed during each HH trading period of the day [32]. Based on that prediction, bids are accepted from contractors, and SOs utilise several reserve resources to mitigate uncertainties either through generation or demand reduction [33].

DERs play a significant role in power system balancing in many electricity grids worldwide. Substantial work has been done on the unit commitment problem to increase site revenue by computing the production schedule of the electricity generating units to meet their technical, operational and system-wide constraints [34] using fuel costs, the maximum number of starts, modulation & stability, line flow limits, voltage limits, ramp up/downtime, the capacity of generation, number of generating units, generation in first & last hour [35] geographical location, reliability, regulatory & financial limitations, power balancing and much more to balance the equilibrium of electricity demand and generation [36]. There is no existing published research to determine the optimal additional capacity of a grid-connected generating unit on a site level to offer in a STOR market to maximise site revenue whilst fulfilling site electricity demand, using a systematic site demand bin characterisation. The novel optimisation based approach proposed in this paper increases site revenue by reducing non-delivery penalties from offering an optimal capacity of a generating unit given the uncertainty in the timing of STOR calls and site demand. The use of real case studies adds value to the research carried out in this paper. Primary novelties in the approach are;

(a) The dissection and mathematical characterisation of the site perspective on the aggregator contract.

(b) Insights on the impact of STOR call and demand timing uncertainty on the optimal capacity that a site should offer to contract for grid balancing purposes.

(c) Clarification of the impact of site temporal demand representation on optimal contracting.

1.2 Overview of the UK balancing mechanism

Balancing Mechanism (BM) is the primary tool used by the National grid (NG) to ensure efficient management of the supply and demand of electricity in the UK. NG uses BM to purchase changes in consumption and generation to correct the mismatch between demand and generation. BM is the period between gate closure (One hour prior to real-time) until the end of the settlement period (30 min window) [37]. For each HH period, NG works out what the difference would be between the amount of electricity generated and its demand. It may then accept a bid or offer to either increase or decrease the generation of electricity or demand to close any gaps and keeping the system in balance. The process of contracting electricity happens in advance of the actual usage and is agreed upon for every HH period. At the end of each HH period, the settlement process begins and once the HH period is over, actual metered volumes are available that can be compared with contracted volumes to determine imbalance volume and imbalance price.

The inevitable potential system imbalance that leads up to the BM helps NG to minimise this in advance of the BM by procuring balancing or ancillary services [27]. Various ancillary services can be called upon to deal with unforeseen increases in electricity demand or generation unavailability ahead of the relevant settlement period. NG chooses the most suitable and cost-effective source based on the nature of imbalance and the time taken for its activation after the instruction from the NG. These services include STOR [38], which is called at certain times of the day when electricity demand exceeds generation and when it is economic to do so for NG. This service is met either by providing additional generation or demand reduction by the STOR provider. Fast reserve (FR) [39] involves the rapid delivery of power injection in the grid on receipt of dispatch call from the NG which is two minutes. FR is procured via monthly tender and requires prequalification of generating units in advance of tendering. NG calls fast reserve providers when there is a major trip of generating unit on the grid and a high delivery rate in excess of 25MW/min with a minimum of 50MW is required for at least 15 minutes. Another service BM startup is used on the day-ahead basis by the NG to ensure that enough generating capacity is available and in a state of readiness to meet anticipated demand plus an adequate operating margin [40]. This service is procured through bilateral agreements between the NG and the service provider and involves those generating units which require longer lead times to start up and can deliver electricity within 89 minutes from dispatch instruction from the NG. Payments are made for making units available and sustaining a state of readiness for the required time period. In the current UK BM, various ancillary services are categorised under four basic product categories; voltage control services, system security services, reserve services and frequency response services [41].

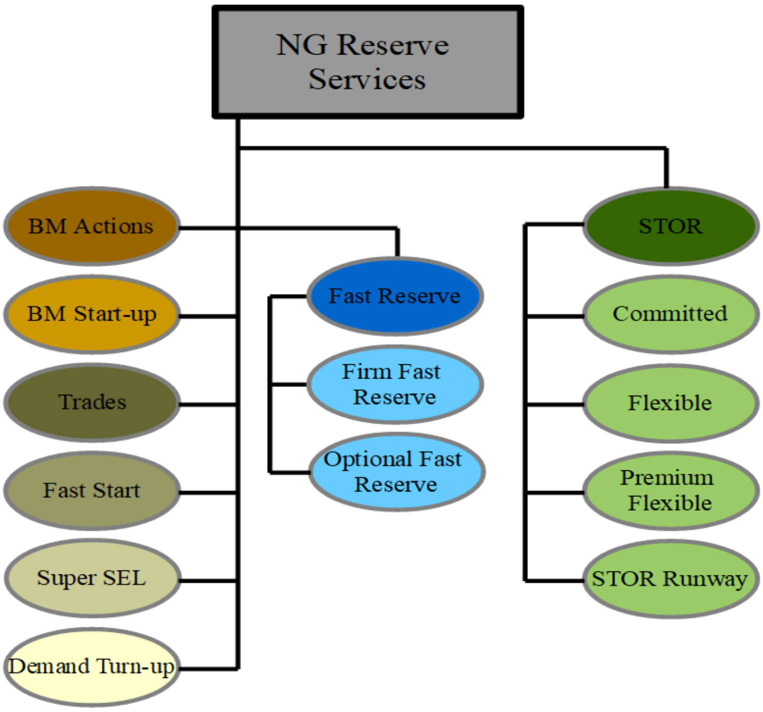


Fig. 3. Reserve services offered by the NG [42]

The reserve services offered by the NG help to facilitate and support the continuous balancing of electricity is shown in Fig. 3. These services have proved to be extremely effective to deliver carbon commitments efficiently while providing a reliable, safe and secure supply of electricity at a competitive cost beyond generation and transmission of electricity [41]. The impact of climate change, government regulations, technological innovations, reliance on renewable energies, cost of fossil fuel and dwindling revenue margins in ancillary services can be hypothesised to play a significant role in the future value of aggregation and BM [43].

STOR is chosen as one of the ancillary services to be focused on in this research as there are hundreds of grid-connected small and medium-size diesel and gas generators participating in this service which also fulfil site demand and are dispatched by the SO on regular basis during STOR calls. To determine the optimal generation capacity to offer in STOR contracts for these generators would generate extra revenue for the sites these generators are installed on. Another factor that influenced the selection of STOR service at the time of the literature and market review of this article was the utilisation and availability prices which were substantially higher than the other ancillary services offered hence increasing the profit margin for the sites.

1.3 The STOR market context and site capacity selection (aggregator perspective)

In energy markets, full integration of DERs is performed by aggregation of small consumers and producers connected to distribution networks [44], and sophisticated communication architecture, automation concepts and control approaches are required [45]. Aggregators use specialised hardware and software to allow clients to participate in a broad portfolio of revenue-generating programmes. A STOR dispatch routine followed by an aggregator during the STOR event is shown in Fig. 4.

STOR is still a part of the SO's arsenal of tools used to achieve the balance of supply and demand of electricity and the requirements depend on the time of the year, and the system demand profile [32]. The STOR programme allows the SO to balance power generation and consumption during peak power demand [32], [46]. The capacity an aggregator offers in BM is below the maximum generation capacity of the site minus the demand of the site, to ensure that onsite demand can always be met. There is a possibility of contracting more than this, i.e., by taking a calculated risk that a STOR event will not occur at the time of maximum demand. A systematic framework is required to determine the optimal capacity of a grid-connected generating unit participating in BM not only to meet site demand but also to increase site revenue or reducing penalty costs, and that is the focus and novelty of this article.

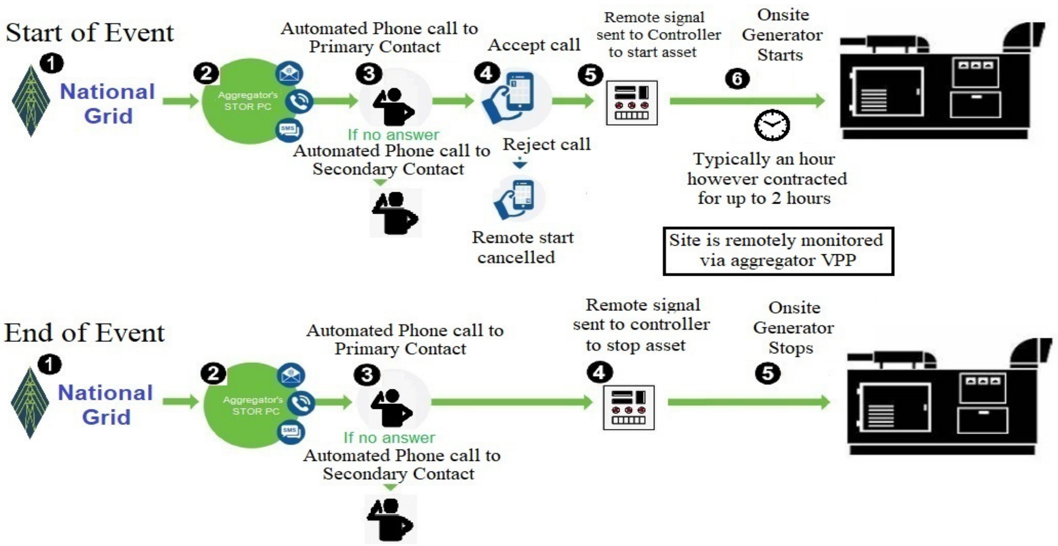


Fig. 4. Aggregator methodology to dispatch & end STOR event

In the current STOR market, the evidence available suggests that aggregators follow a trial-and-error approach to select the capacity to contract, as there is no accepted published methodology available. Usually, the aggregator considers the full range of site demand levels seen over an analysis period and determines the level of capacity to offer based on the site being able to serve a STOR call 95% of the time, a performance measure set by the SO [47]. The analysis done by previous authors [48-50] does not rely on assuming a particular statistical distribution of demand, but rather simply considers observed data over a defined analysis window. There is a need to consider data in multiple demand windows and the frequency of STOR calls during each demand window. The state-of-art in determining the capacity to offer using heuristics is shown in Fig. 5 based on Kiwi Power Ltd demand data analysis tool.

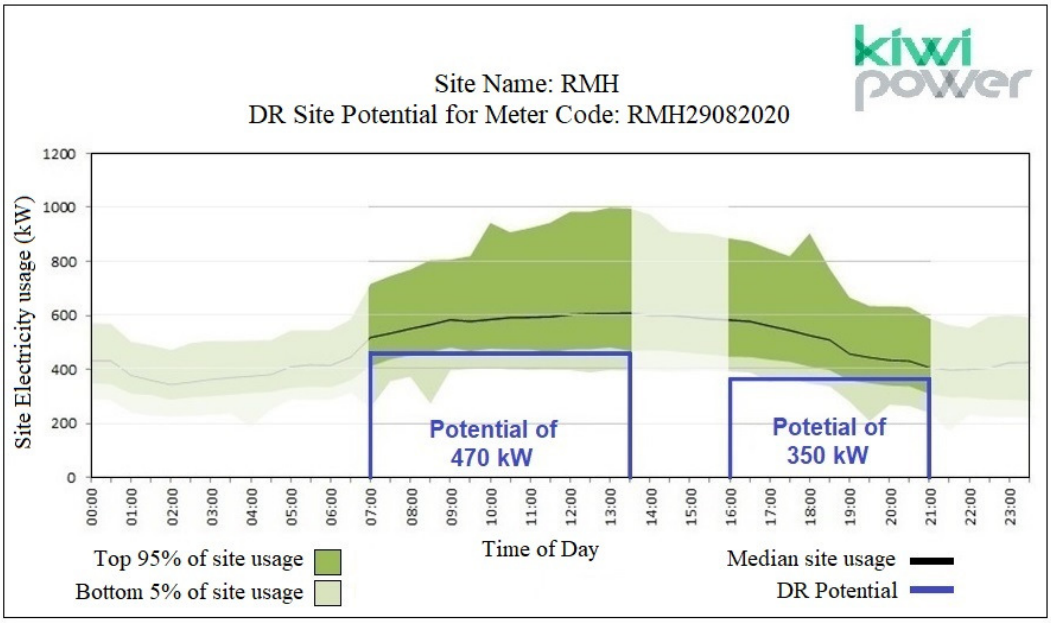


Fig. 5. DR potential analysis via Kiwi Power's analysis tool [51]

The dark green shaded area represents the upper 95% of the site's electricity usage for the period of data selected is shown in Fig. 5. The top value is the maximum value recorded for each HH timeslot, and the bottom value is at the top of the bottom 5% of values for each HH timeslot. The light green shaded area shows the bottom 5% of the site electricity. The top value for this is the 5% percentile value for each HH timeslot, and the bottom value is the minimum value recorded for each HH timeslot. The black line through the green shaded area shows the median electricity usage for each HH time slot for the period of data selected. The blue box shows the demand response (DR) potential for the programme, in this case, the STOR programme with windows of 7:00 AM - 1.30 PM and 4.00 PM - 9.00 PM. The DR potential value is calculated based on the top of the bottom 5% values (i.e., bottom of the dark green area) for each HH timeslot within the STOR window period with a 5% error. The green shaded areas that are not in the programme window are faded lightly [51].

This is a conservative approach to gain sufficient revenue and to avoid penalties that can be incurred due to under or no delivery during the STOR event. However, it does not consider the likelihood of a STOR call occurring at the same time as peak site demand, and therefore may reduce revenue relative to a case where this uncertainty is considered, hence limiting the potential to provide grid stability.

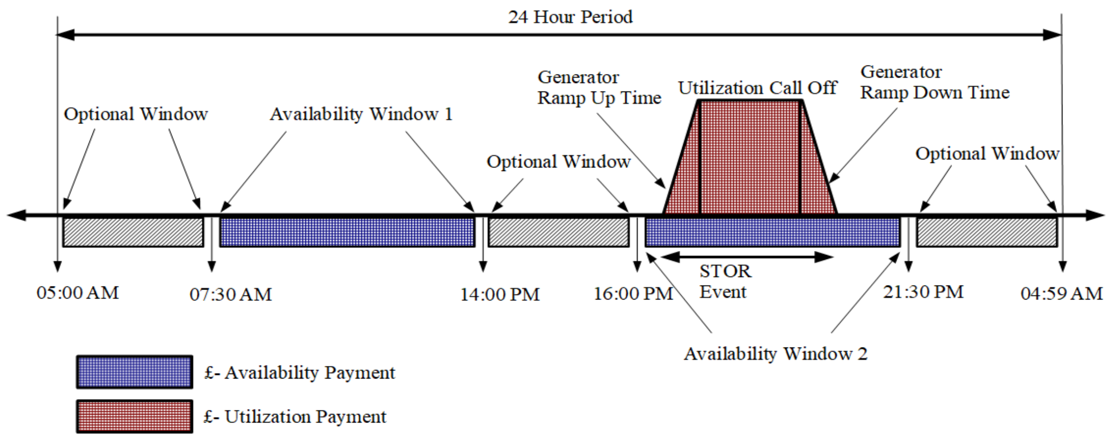


Fig. 6. A Typical Working Day in STOR Format [32]

A typical working day in STOR format is shown in Fig. 6. Blue shaded areas represent availability windows, whereas the red shaded area represents a STOR event during the availability window when the resource is utilised. There can be two or three availability windows in a day. Aggregator gets paid for both availability and utilisation of an asset.

1.4 Literature review

There are several studies focused on unit commitment optimisation problems of power generating units with varying parameters and constraints to minimise operating costs, maximise revenues, number of starts, voltage limits, ramp up/down time, number of generating units, regulatory or financial implications and power balancing. This research adds to the body of literature by being the first to determine for aggregators the optimal capacity of a grid-connected generator participating in BM using demand bin characterisation. The unique methodology increases availability and utilisation revenue and reduces penalty costs whilst fulfilling the site demand even during peak demand periods.

Several mathematical models exist to determine the optimal operational schedule of a generation unit: Chang, Tsai, Lai & Chung [52] formulated a mixed-integer linear programming (MILP) unit commitment (UC) model to obtain power schedule and marginal price information associated with system constraints such as load demand requirements, spinning reserve (SR) [53], generation and reserve capacity to assist strategic bidding in a flexibility market. The demand data was represented using 24 time periods from a single data, and results could improve by selecting a whole year of plant generation and dual price data. Selvakumar et al. [54] formulated a UC problem using Cat Swarm optimisation (CSO) to maximise the revenue of a power generation company and DR aggregator, the load was reduced during peak hours of the day. The profit of the consumer also increased by reduction of fuel usage during peak hours. Though peak shaving or load shifting is an excellent technique to increase revenues, it differs from the framework of the STOR market being considered in this research which focuses on the optimal capacity of a grid-connected generating unit to offer to the SO to increase revenue.

Ortega & Kirschen [3] proposed a technique using Monte Carlo simulation to calculate the optimal amount of Spinning reserve (SR) that a SO should provide to respond not only to generation outages but also to mitigate forecast errors for load and wind power generation. The technique determined the amount of SR that minimises the total operating cost of the system.

There is need to also determine the optimal capacity a site can offer to the BM. Another approach by Chaoyue, Jianhui, Watson & Yongpei [55] involves the use of a multi-stage robust UC mixed integer programming (MIP) considering wind and DR uncertainties. An exact solution approach leveraging Benders' decomposition is applied to solve the wind power output uncertainty through DR by lowering the unit load cost. Whilst the approach can be applied to other system uncertainties like inelastic demand, it cannot be applied to determine the capacity to offer to STOR whilst maximising revenue and minimize penalties for a site. A genetic algorithm approach to UC was formulated by Swarup & Yamashiro [56] by satisfying generation load balance and generation up and down time constraints. Their proposed schedule minimises the system operating cost over a planning horizon of one day to a week while respecting physical, operational and contractual constraints. The method is focused on generation, neglecting the need for small end-users aggregated as part of STOR. Simon, Padhy & Anand [57] formulated an ant colony system approach for the UC problem for a generating unit to minimise total generation cost, but the proposed model cannot guarantee a better solution at each and every hour as compare to dynamic programming (DP) and branch and bound integer programming that was also analysed in the model. Again, their method was focused on generating assets. Qianfan, Jianhui & Yongpei [50] proposed a two-stage stochastic UC problem with uncertain DR with UC decision at the first stage and real-time generation and load amount decisions in the second stage with an objective to maximise generating profit. The aforementioned research ensures generation is flexible; however, there is an increased need for backup capacity available to a SO in the form of conventional thermal units, gas and diesel generators for system balancing. There is no systematic method to determine the optimal capacity of these grid-connected generating units to offer in a STOR market for system balancing. Furthermore, in previous works the site demand for electricity has been overly simplified.

Parvania, Fotuhi-Firuzabad & Shahidehpour [58] proposed a MILP model for optimal DR aggregation in the wholesale market; however, their method is focused on using load reduction strategies, i.e. load curtailment, load shifting, utilising onsite generation and ESS. Even though a price-based self-scheduling model is proposed for DR aggregator to maximise the revenue in the day ahead wholesale market, no consideration is given to penalties as load reduction is the focus.

Two-stage adjustable robust optimisation for UC under uncertainty is formulated by Xiong & Jirutitijaroen [59]. The two uncertainties modelled in the UC problem are generator unavailability and demand variability where site demand is variable and generating units may or may not be available due to a failed start. Again, the optimal capacity to offer is not determined. Zendehdel, Karimpour & Oloomi [60] formulated an MINLP UC problem with the linear objective function of minimising the energy dispatch cost, binary decision variables and non-linear minimum up and downtime constraints. Even though the model avoids diverging the optimisation program due to limitations in power generation and transmission line capacity, the focus is not on determining the optimal capacity to offer whilst satisfy a site electricity demand. Another model to formulate the UC problem for flexible generating units is proposed by Bo & Shahidehpour [61]. Lagrangian relaxation was used for modelling various types of generating units under fuel type, minimum up/down, ramping, generating capacity and start-up constraints. However, this model cannot be used in STOR contracts because STOR contracts do not allow switching between assets without notifying the SO in advance.

Additionally, in the research mentioned above, demand data sets either consist of only 24-hourly values or a maximum of one week of data, and none of them is focused on the procedure for determining optimal contract capacity for any DR service, let alone the STOR market which is the focus of this paper.

1.5 Comparison between heuristic and the proposed approach

The main focus of this paper is the optimal determination and selection of the capacity of a grid-connected power generating unit participating in the STOR market that can be offered to the SO to increase the availability and utilisation revenue both for the aggregator and the site by reducing or mitigating penalty costs incurred either by reduced or no delivery of electricity during a STOR event. The key advantages and comparison of the proposed approach over the heuristic approach are given below in Table. 1.

Table. 1. Comparison between heuristic and the proposed approach

Heuristic/Conservative approach	Proposed approach
Aggregators use risk aversion, conservative and heuristic approaches to determine the contractual capacity of a grid-connected generating unit to participate in balancing services that are also fulfilling site electricity demand and miss out on extra revenue they can generate by taking a calculated risk that a dispatch event may not occur at the time of maximum site demand.	The principle difference proposed in this novel optimisation based approach is that it increases both availability & utilization revenue by reducing or mitigating non-delivery penalties during STOR dispatch calls by offering an optimal capacity of a generating unit given the uncertainty in the timing of STOR calls and site demand.
revious analysis oversimplified the site demand data to improve model tractability. The proposed approach is not catered for in the heuristic and more conservative approaches by DR aggregators due to the risk of higher penalties and the generation capacity chosen to offer in STOR contract is normally less than the maximum demand of the site.	The maximised revenue approach proposed in this article where calculated risks are taken has an advantage over the heuristic approach by using an annual half hourly site demand data and finding the optimal number of demand bins the site demand data should be divided into to analyse the impact of coincidence of STOR calls with various site demand levels. The proposed approach has better results both in annual site revenue generation and in reducing penalty costs incurred by under or no delivery.
Previous models in this area are not applicable in STOR contracts because aggregators must state the actual generation capacity to offer at the start of the STOR contract, and switching between assets is not allowed during a live contract if they want to increase the contractual capacity limit.	Another advantage of the proposed approach is there is a trade-off between the likelihood of a STOR call when site demand is high, and the availability and utilisation revenue obtained for contracting a higher capacity with the SO. Hence there is a need to represent the demand more accurately without over-complicating the model.

In this present study, site demand for the whole STOR year is considered and divided into several demand windows to get more realistic results by looking into the chance of having STOR calls in each demand window without disturbing the requirement of fulfilling the site demand by the grid-connected generating unit. Results of this research show the site revenue increases between 6.2% to 29.8% compared to the heuristic approach previously employed. The proposed model is better than the heuristic approach as it captures the essence of the problem and uncertainties in STOR calls. The work in progress for future article considers stochastic elements in the model to represent this problem.

The aspect is also supported by real case studies to provide robust insight into the systematic methodology that can balance revenue and penalties. The methodology can be applied to multiple sites. Furthermore, these perspectives have not been discussed in earlier literature for any of the ancillary services, let alone the STOR service offered by the SO.

2. Methodology

A MINLP model is proposed in this study to determine the capacity of a grid-connected generator to offer in STOR service to mitigate penalty costs and increase site revenue. The MINLP model considers the trade-off between the frequency/likelihood of STOR calls during periods of high site demand (i.e., if site demand is high when a STOR call occurs, it is possible that the generator will not have enough capacity left to serve the STOR contract volume, thus attracting a penalty), against the increased revenue obtained from a higher STOR contracted capacity due to higher availability and utilisation revenues.

2.1 Problem statement

A more specific definition of the design problem is;

- Given:
  - Generator capacity: Maximum generation capacity of the generator at a site participating in STOR.
  - The energy demand of the site: A HH site demand data for the whole year
  - Utilisation revenue: The contracted revenue obtained for electricity generated by the site and exported to the grid during grid STOR utilisation calls by the SO.
  - Availability cost: The contracted revenue for the availability of the site generator during potential STOR call periods.
  - Fuel cost: The cost of fuel for electricity generation during utilisation calls.
  - The total number of availability hours in a STOR year.
  - The average duration of STOR dispatch call by the SO.
  - Penalty cost for under or no delivery of electricity by the site during utilisation call. (i.e., the penalty when a call cannot be served because site demand is too high to enable sufficient export of electricity to the grid to meet the contracted STOR capacity).
  - The total number of grid dispatch calls in a year.
- Determine:
  - Optimal capacity of the generating unit at a site that can be offered for STOR to the SO by an aggregator.
  - Demand bin characterisation: Optimal number of site demand bins in which site annual HH demand should be divided into to get optimal results to increase revenue

and decrease penalties that can be incurred either by reduced or no delivery at all by the site generator.

- Subject to:
  - Maximum electricity generation capacity of the site generator constraint.
  - Site STOR generation capacity limits due to uncertain site demand.
  - Actual electricity generation capacity delivered by the generator constraint.
- In order to:
  - Maximise site revenue (comprising of both availability and utilisation revenue of site generator)
  - Minimise penalty costs incurred either by no or under-delivery of electricity during grid dispatch call.

2.2 Modelling data acquisition

The site demand data from the STOR year starting 01/04/2018 to 31/03/2019 is acquired for analysis from a DSR aggregator. The data is the real HH site electricity usage from three different sites participating in the UK STOR market. The data is first divided into several bins using a histogram, i.e., dividing the entire range of yearly HH demand data into a series of intervals and then counting how many values fall into each interval. The sensitivity of the results to temporal resolution is tested in section 5 below.

2.3 Solution strategy for MINLP

A deterministic MINLP approach is applied to the model to calculate the optimal generation capacity a site should offer for a STOR contract by using the same number of STOR calls, that site was called for in STOR Year. The results are then compared with the aggregator approach of selecting the capacity of a site, as described in section 1.3.

2.4 Mathematical formulation

The fourth stage in this framework is the mathematical modelling formulation. The objective function in Equation (15) can be stated as $Z_{(Total)}$, which is the annual profit. The optimal design is obtained by maximising the annualised profit, defined as the sum of annual availability revenue, utilisation revenue, minus the sum of the total annual fuel cost incurred by the operation of the generator and any penalty costs incurred either by non or reduced capacity delivered in comparison to the contractual capacity during STOR event. The average duration of STOR call is taken as one and a half hours.

The generator supplies electricity to the site as a primary function to fulfil site electricity demand; hence some operational constraints need to be followed, as shown in Fig. 7a. – Fig. 7c. A no-penalty scenario when the generating unit delivers the contractual capacity X is given in Fig. 7a. A penalty scenario when the delivered capacity $XACT$ is less than the contractual capacity X is given in Fig. 7b. A special case scenario when the generating unit fails to start during STOR dispatch call or there is no delivery at all is given by Fig. 7c.

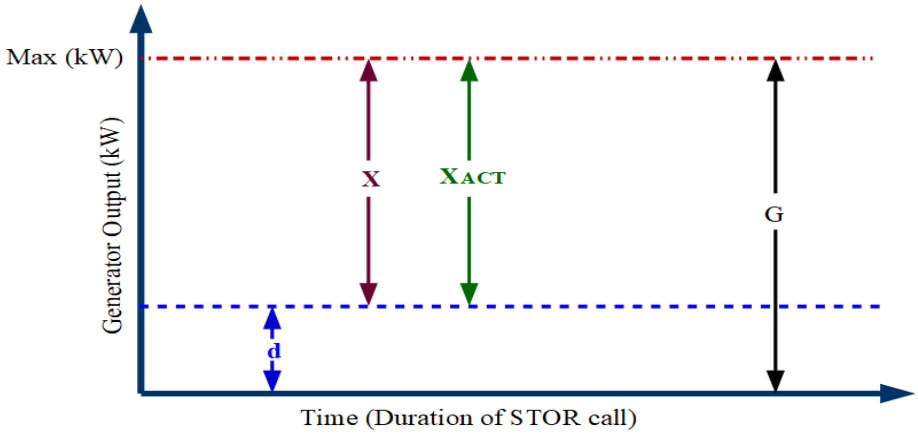


Fig. 7a. Single STOR call without Penalty XACT = X (Full Delivery)

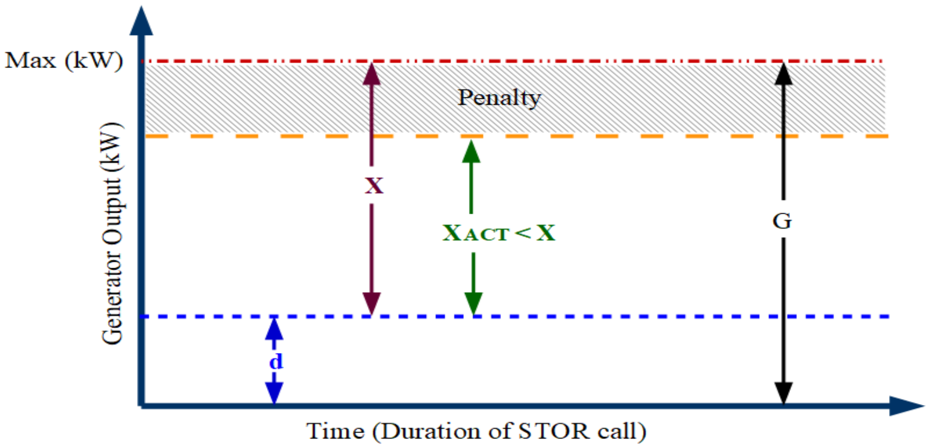


Fig. 7b. Single STOR call with Penalty XACT < X (Under Delivery)

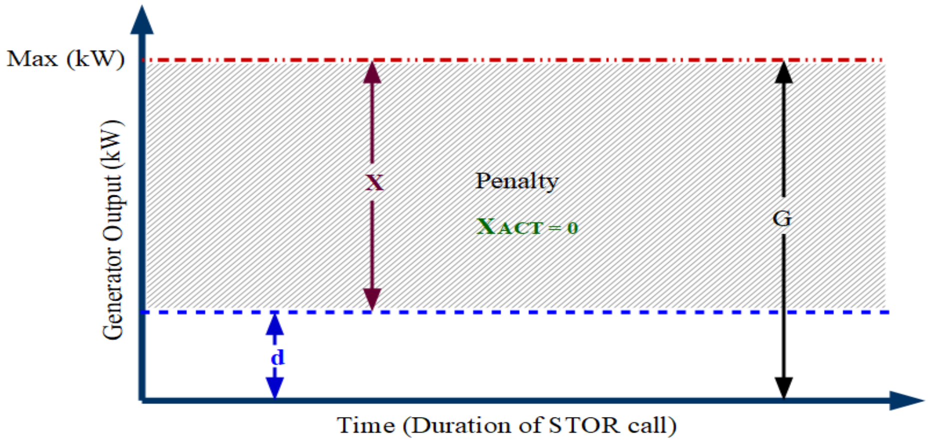


Fig. 7c. Single STOR call with Penalty XACT = 0 (No Delivery)

G: Maximum generation capacity of the generator in kW
d: Yearly Variable site electricity demand
X: Amount of generator capacity to offer in the STOR market
XACT: Actual Generator capacity delivered during STOR call
(XACT can be equal to X or less than X)
Penalty due to under delivery XACT < X
Penalty due to No delivery XACT = 0

The optimal capacity of a generator that can be offered in a STOR contract represented by X cannot exceed the maximum generation capacity of the generator $G_{(Max)}$ as shown in Fig. 7a. and this condition is only valid when there is no site demand but the generator is running 24 hours a day behind the meter and fulfilling site electricity demand. The generation capacity constraint applied in the models is;

$$X \leq G_{(Max)} \tag{1}$$

The actual generation capacity delivered by the generator during each STOR call cannot exceed the total generation capacity of the site minus site demand at any time;

$$XACT_{(i)} \leq G_{(Max)} - d_{(i)} \tag{2}$$

Where $XACT_{(i)}$ is the generation capacity delivered in each demand bin and $d_{(i)}$ is the site demand in each bin. Furthermore, the third constrain is the capacity delivered by the generator can either be less than or equal to that of the maximum generation capacity to offer in the STOR contract. The only condition when $XACT_{\ (i)}$ can be equal to X is when there is no site demand.

$$XACT_{\ (i)} \leq X \tag{3}$$

Availability window is the time period during which the reserve provider (site generator) is required to be available to operate at contracted MW [32]. Availability revenue represented by Equation (4) in the STOR contract is the number of availability hours $ah_{(i)}$ for each time period that the generating unit was available times the generator availability cost per hour gac represented by £/MW/hr times the optimal contractual generation capacity to offer in STOR market *X*. It is calculated by this Equation for each demand bin;

$$AR_{(i)} = ah_{(i)} \times gac \times X \tag{4}$$

Total availability revenue $AR_{(Total)}$ for *n* number of demand bins is the sum of all availability payments in the STOR year when the generator was available for STOR event and is given by;

$$AR_{(Total)} = (ah_{(1)} \times gac \times X) + (ah_{(2)} \times gac \times X) + \cdots + (ah_{(n)} \times gac \times X) \tag{5}$$

$$AR_{(Total)} = \sum_{i=1}^{n} [AR_{(i)}] \tag{6}$$

The utilisation window is the time period during which the reserve provider actually delivers the contracted MW to Grid during the STOR event. Utilisation revenue is the payment for the energy delivered on a £/MWh basis. This also includes the energy delivered in ramping up and ramping down from the contracted MW level [32]. In this model, the utilisation revenue earned during each STOR call per demand bin is calculated by Equation (7) and utilisation revenue $UR_{(i)}$ per demand bin is given by;

$$UR_{(i)} = XACT_{(i)} \times guc \times Ls \times Ks_{(i)} \tag{7}$$

Where Ls is the duration of STOR call in hours, $Ks_{(i)}$ is the no of STOR calls in that demand bin and guc is the generator utilisation cost which is constant for the STOR contract.

Total utilisation revenue $UR_{(Total)}$ for n number of demand bins are the sum of all utilisation payments in the STOR year when the generator was operational and utilised to generate electricity during STOR event and is given by;

$$\begin{aligned} UR_{(Total)} = {} & \left(XACT_{(1)} \times guc \times Ls \times Ks_{(1)}\right) \\ & + \left(XACT_{(2)} \times guc \times Ls \times Ks_{(2)}\right) \\ & + \cdots \left(XACT_{(n)} \times guc \times Ls \times Ks_{(n)}\right) \end{aligned} \tag{8}$$

$$UR_{(Total)} = \sum_{i=1}^{n} [UR_{(i)}] \tag{9}$$

Fuel cost is the expense of running the generator during the STOR event. Fuel cost per demand bin and total fuel cost for n number of demand bins is given by the equations (10), (11) and (12) respectively, where fc is a fuel cost in £/MWh.

$$GFC_{(i)} = XACT_{(i)} \times fc \times Ls \times Ks_{(i)} \tag{10}$$

$$\begin{aligned} GFC_{(Total)} = {} & (XACT_{(1)} \times fc \times Ls \times Ks_{(1)}) \\ & + (XACT_{(2)} \times fc \times Ls \times Ks_{(2)}) \\ & + \cdots (XACT_{(n)} \times fc \times Ls \times Ks_{(n)}) \end{aligned} \tag{11}$$

$$GFC_{(Total)} = \sum_{i=1}^{n} [GFC_{(i)}] \tag{12}$$

STOR clients are paid in full for utilisation by the aggregator. If they fail to deliver due to late or no response, 20% of monthly availability revenue will be deducted by the aggregator as per their contract with the client [32]. In the case of under-delivery, the site is penalised by 0.5% of its monthly availability revenue for every 1% of under-delivery plus 20% of monthly availability revenue by the aggregator. Only the site in a contract that has failed to deliver would be penalised. Aggregator penalty contracts are standard with all sites. The methodology developed in this paper accounts for these penalties and try to reduce or mitigate them by offering an optimal capacity of a grid-connected generating unit.

Based on the contract performance, the SO penalises the aggregator quarterly/ yearly, including a reconciliation where if the contract delivers at least 95% of its contractual capacity in a STOR year it will not be penalised. Yearly each contract needs to be available 85% during its availability windows. The availability is calculated at the end of each STOR year. Different aggregators could have different arrangements of penalty contracts with their sites/ clients, but the arrangement of penalty contracts with the SO remains unchanged for the STOR market. Based on the above-mentioned parameters, STOR penalty cost for a single failure is given by;

$$P_{(i)} = \begin{bmatrix} 0.005 \times gahm \times gac \times X \times \dfrac{\left(X - X_{ACT(i)}\right)}{X} \times 100 + \\ 0.2 \times gahm \times gac \times X \end{bmatrix} \tag{13}$$

Where $gahm$ and gac are generator availability hours per month and generator availability cost in £/ MWh respectively. Further solving the Equation by assigning average $gahm$ to 320 as the total no of availability hours in STOR year-12 were 3832.5 gives;

$$P_{(i)} = \begin{bmatrix} 0.005 \times 320 \times gac \times (X - X_{ACT(i)}) \times 100 + \\ 0.2 \times 320 \times gac \times X \end{bmatrix} \tag{14}$$

$$P_{(i)} = \begin{bmatrix} (0.005 \times 320 \times gac \times X \times 100) - \\ \left(0.005 \times 320 \times gac \times XACT_{(i)} \times 100\right) + \\ (0.2 \times 320 \times gac \times X) \end{bmatrix} \tag{15}$$

$$P_{(i)} = \begin{bmatrix} (160 \times gac \times X) - \\ \left(160 \times gac \times XACT_{(i)}\right) + \\ (64 \times gac \times X) \end{bmatrix} \tag{16}$$

$$P_{(i)} = \left[(224 \times gac \times X) - (160 \times gac \times X_{ACT(i)})\right] \tag{17}$$

Where $P_{(i)}$ is the penalty cost for under or no delivery for a single STOR call per demand bin. A binary variable $YP_{(i)}$ is introduced in the model to indicate if there is a STOR penalty or not in each scenario due to under or no delivery. Solving the above Equation (17) for aggregation of penalties for all STOR calls per scenario gives us;

$$Ps_{(i)} = YP_{(i)} * \left[224 \times gac \times X - 160 \times gac \times X_{ACT(s)}\right] \times Ks_{(i)} \tag{18}$$

In the above equation (18) $Ps_{(i)}$ is the total penalty cost per year from under or no delivery during STOR event and $Ks_{(i)}$ is the total number of STOR calls in each demand bin. Further solving equation (18) gives;

$$Ps_{(i)} = YP_{(i)} \times P_{(i)} \times Ks_{(i)} \tag{19}$$

Total penalties per STOR year due to under or no delivery would be given as;

$$Ps_{(Total)} = (YP_{(1)} \times P_{(1)} \times Ks_{(1)}) + (YP_{(2)} \times P_{(2)} \times Ks_{(2)}) + \cdots + (YP_{(n)} \times P_{(n)} \times Ks_{(n)}) \tag{20}$$

$$PS_{(Total)} = \sum_{i=1}^{n} [Ps_{(i)}] \tag{21}$$

The objective function can also be written as;

$$Z_{(Total)} = \sum_{i=1}^{n} [AR_{(i)}] + \sum_{i=1}^{n} [UR_{(i)}] - \sum_{i=1}^{n} [FC_{(i)}] - \sum_{i=1}^{n} [Ps_{(i)}] \tag{22}$$

The objective function is formulated to maximise the economic potential of a STOR site. The economic incentive in terms of site profit also depends on the availability and utilisation cost bids offered by an aggregator during the bidding process of NG. If the site is in a STOR contract with medium or low availability and utilisation prices, NG would likely call that site quite often during a STOR event. Hence the selection of the optimal capacity of a STOR site is of utmost importance as the annual revenue, and the risk factor of penalties depends on it. The proposed optimisation framework is solved using the MINLP solver CONOPT3 version 3.17K

3. Case study

The case study presented is for real sites participating in STOR BS with an objective to apply the methodology presented in this research and analyse the results against the heuristic approach followed by an aggregator to offer the generation capacity of the same site in the STOR market. The chosen sites are from STOR contracts with relatively medium utilisation and availability prices.

3.1 Case study input

Total generation capacities of the sites, generation capacities offered by the aggregator in STOR using heuristic approach, utilisation, and availability costs are shown in Table. 2. The methodology developed in Section 3 is applied to provide an optimal capacity to offer. The results of the optimal STOR generation capacity determine in this work would be compared with the aggregator STOR offering capacity. An improvement in results shows the method presented in this work advances state of the art in this area.

Table. 2. Site total generation capacities, STOR offering, utilisation & availability price data

Site No	Total Generation Capacity	STOR Capacity Offering	Utilisation Cost	Availability Cost
Site-1	1500 kW	800 kW	£170/ MWh	£4.50/ MW/Hr
Site-2	1600 kW	1000 kW	£170/ MWh	£4.50/ MW/Hr
Site-3	2000 kW	1280 kW	£180/ MWh	£5.20/ MW/Hr

The annual HH demand data of the three sites are shown in Figs. 8-10. Demand is indicating the shifts in the consumption of electricity on all three sites. Peak demand at site-1 is around 1300 kW, at site-2, it is around 1100 kW and about 800 kW at site-3.

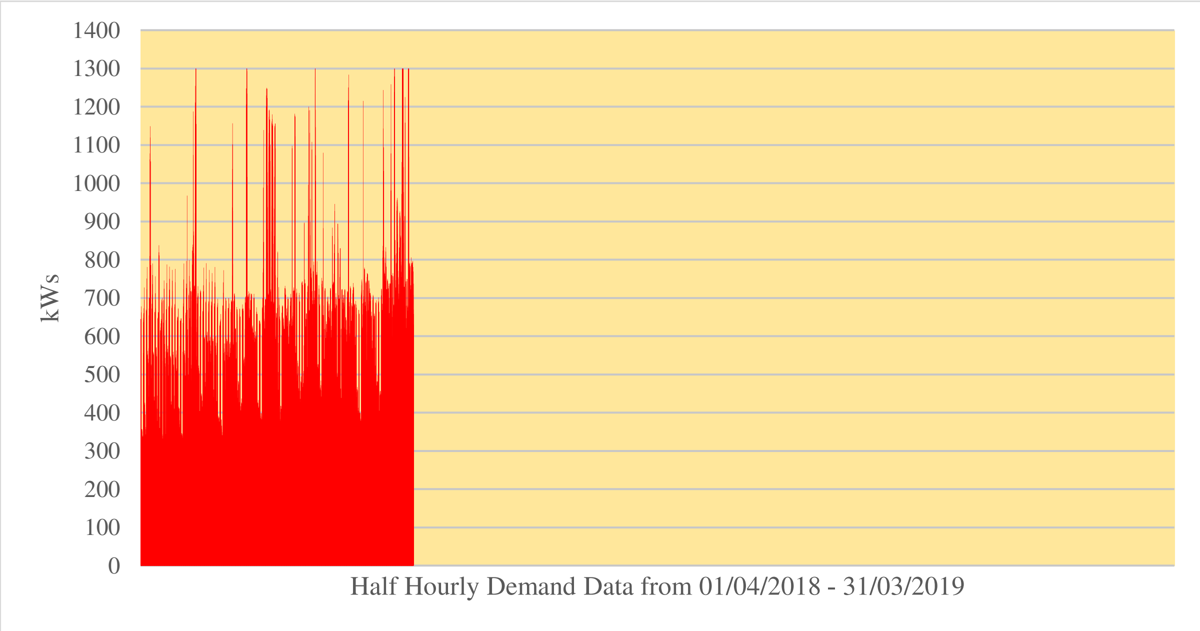


Fig. 8. Annual Half Hourly site-1 demand data

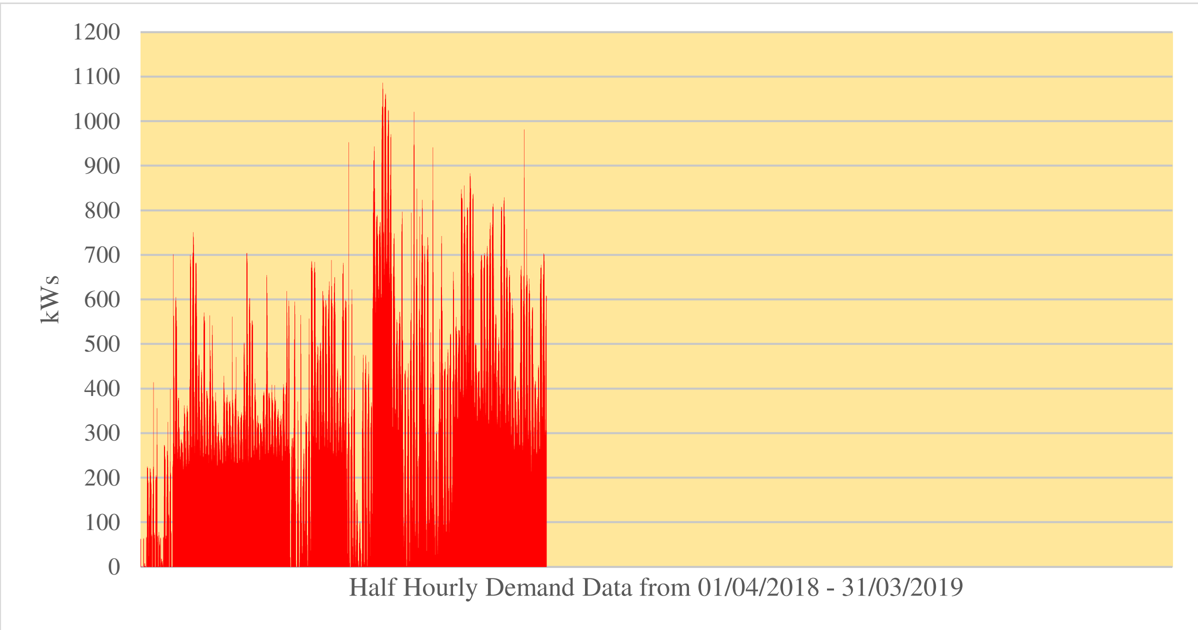


Fig. 9. Annual Half Hourly site-2 demand data

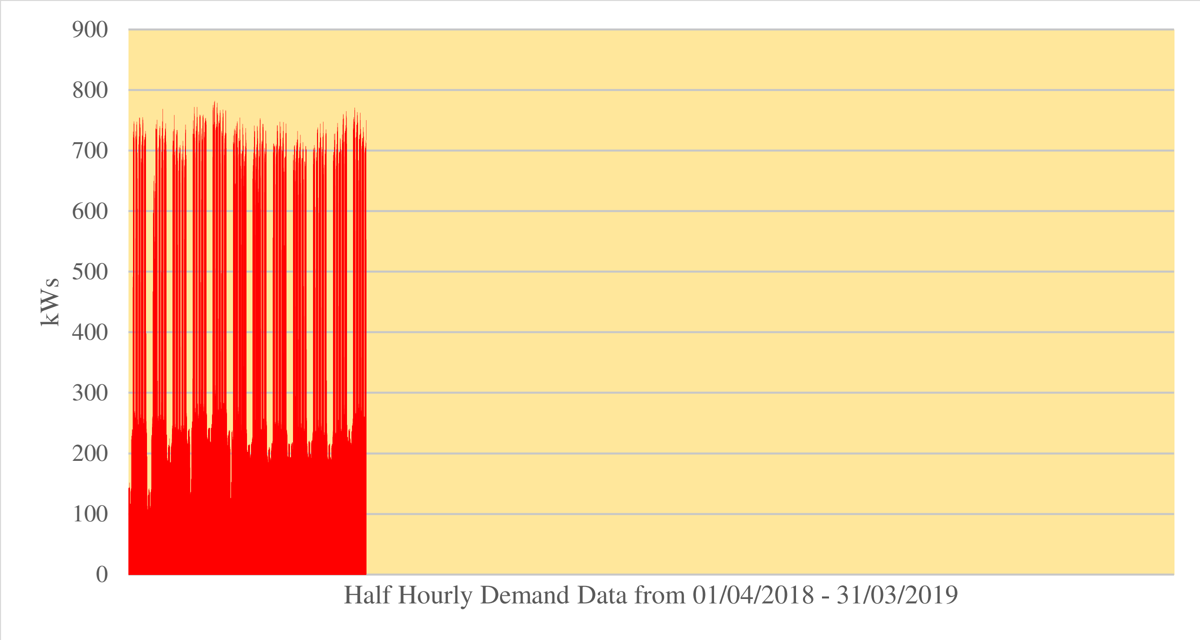


Fig. 10. Annual Half Hourly site-3 demand data

The total number of availability hours are calculated using STOR Calendar season-12 released by the NG. STOR windows in each season during weekdays and weekends are given in Table. C1 - Appendix C. Availability hours in each demand window were then extracted from this data. Table. 3 shows the number of availability hours in each month of the STOR year-12 from April 2018 to March 2019.

Table. 3. Total availability hours in Season-12 of STOR (April 2018-March 2019)

Month	Availability hours	Month	Availability hours
April - 2018	270	October-2018	306.5
May - 2018	346	Nov-2018	325
June-2018	334	December-2018	331.5
July-2018	339.5	January- 2019	334.5
August-2018	339	February- 2019	288
September-2018	302.5	March- 2019	316
Total		**3832.5**	

3.2 Demand bin characterisation

The optimisation methodology defined in section-3 has been implemented in the General Algebraic Modelling System (GAMS) using MINLP with three approaches. Using the histogram, the annual site demand was first divided into five, then twenty-five and finally fifty demand bins to analyse the impact of demand bins on the results. Fig. A1-A3 in Appendix A shows the approximate representation of the distribution of annual HH demand data of Site-1 in 5, 25 and 50 demand bins.

The total number of STOR calls in each demand bin is calculated by the actual number of STOR events called in by the SO in the STOR year for these particular STOR contracts and the site demand during the STOR events. The results of generation to offer in STOR by the

MINLP model using 5, 25 and 50 demand bins are shown in (Table. 4). The results indicate that dividing the annual HH demand data into 25 demand bins gives us the maximum generation to offer capacity for a STOR contract.

Table. 4. Generation capacity to offer for 5, 25 & 50 demand bins

Site No	Total Gen Capacity of site	Generation to offer (5 demand bins)	Generation to offer (25 demand bins)	Generation to offer (50 demand bins)
Site-1	1500 kW	821 kW	987 kW	966 kW

The results of the MINLP model of site-1 in GAMS are shown in Figs. 11-16 indicate that the revenue generation and optimal capacity to offer depend on the number of demand bins. Therefore, previous research using a day demand missed an opportunity to maximise revenue and improve grid stability. Fig. 11 shows the results of generation to offer in the BS by the model using 5, 25 and 50 demand bins. The capacity to offer is sensitive to how demand is represented. A more accurate representation supports improved capacity to offer in the STOR market. Total annual availability revenues from demand bins are shown in Fig. 12. Higher the generation to offer, higher will be the availability revenue unless the generator is off-line due to maintenance.

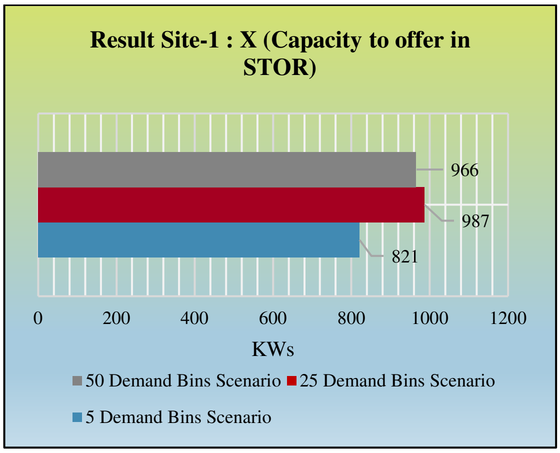


Fig. 11. Case study result: X (Capacity to offer in STOR)

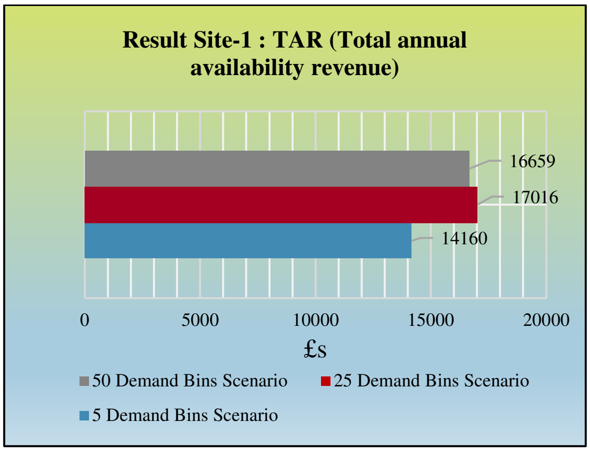
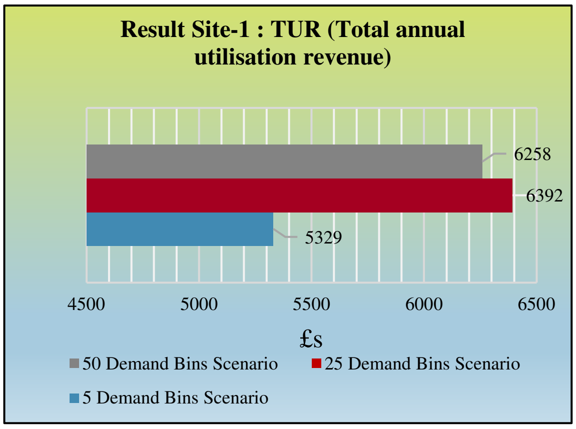


Fig. 12. Case study result: TAR (Total annual availability revenue)

Total utilisation revenue and fuel cost for three capacities to offer based on demand bins characterization are shown in Fig. 13 and Fig. 14. It is noticeable that there is a significant difference in utilisation revenue between 5 demand bins to 25 or 50 demand bin scenarios because most of the STOR calls occurred when the site demand was low. The model offered a low capacity to offer in the case of the 5 demand bins scenario, resulting in low utilisation revenue.



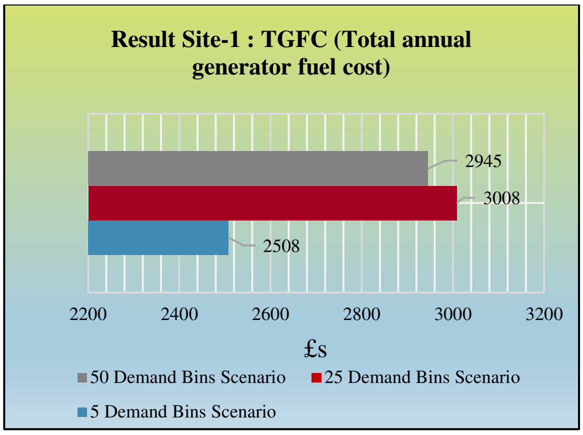
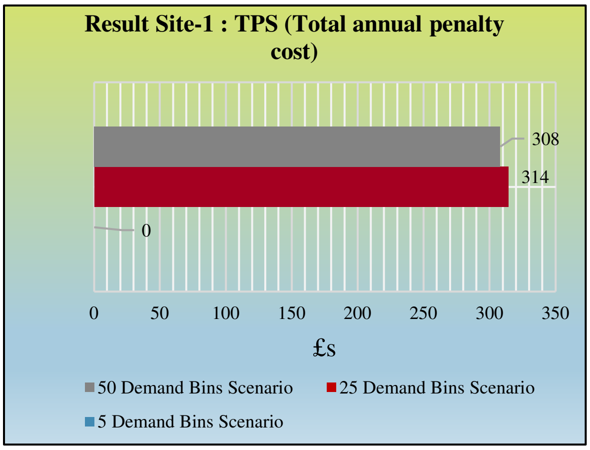


Fig. 13. Case study result: TUR (Total annual utilisation revenue)

Fig. 14. Case study result: TGFC (Total annual generator fuel cost)

Total penalty costs against each demand bin scenario to offer in the STOR market are shown in Fig. 15. In the case of the 5 demand bin scenario, there is no penalty as the site successfully delivered contracted capacity during each STOR event resulting in the lowest profit as shown in Fig. 16.



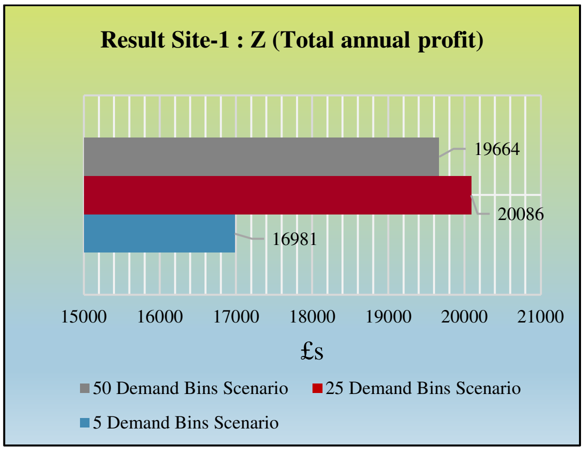


Fig. 15. Case study result: TPS (Total annual penalty cost)

Fig. 16. Case study result: Z (Total annual profit)

The reason for choosing 5, 25 and 50 bins is that below 5 demand bins the results were not accurate and above 50 bins there is no substantial change in the results. The results in terms of lower penalty costs were obtained by dividing the demand data into 50 bins as the contractual capacity X in Fig. 11. obtained by dividing the site demand data into 50 bins is slightly less than by dividing the demand data into 25 bins and hence the risk of missing out on STOR call is less if STOR call comes at a time of higher site demand level which results in lower penalty costs as shown in Fig. 15.

However, the estimate of optimal capacity 'X' to offer in STOR contract using 25 bin resolution was reasonable to aid computational tractability for the mathematical modelling. The total annual profit $Z_{(Total)}$ in Fig. 16. generated by dividing site demand into 25 bins is higher though the penalty and fuel consumption costs were also higher in comparison with 50 demand bins. Higher contractual capacity would result in higher availability and utilization revenues which in turn compensates for the fuel and penalty costs and results in higher total annual profit. This resolution has been applied to two other STOR sites. The sites data is given in Table. 2.

3.3 Application of the methodology to multiple sites

The DR potential of site-1 used in the case study using the aggregator analysis tool is shown in Fig. 17. The generation capacity to offer in the STOR market for site-1 by the aggregator is 800 kW, which is slightly higher than what the analysis tool recommended but significantly lower than the optimal value as presented in Fig. 11 (966 KW for 50 bins). The difference between the optimal value of capacity to offer derived from the model and the value of capacity offered by the aggregator is 166 kW, which confirms that dividing the site demand data into a higher number of bins, intuitively must increase the accuracy of the result, also leads to more revenue in terms of availability and utilisation costs.

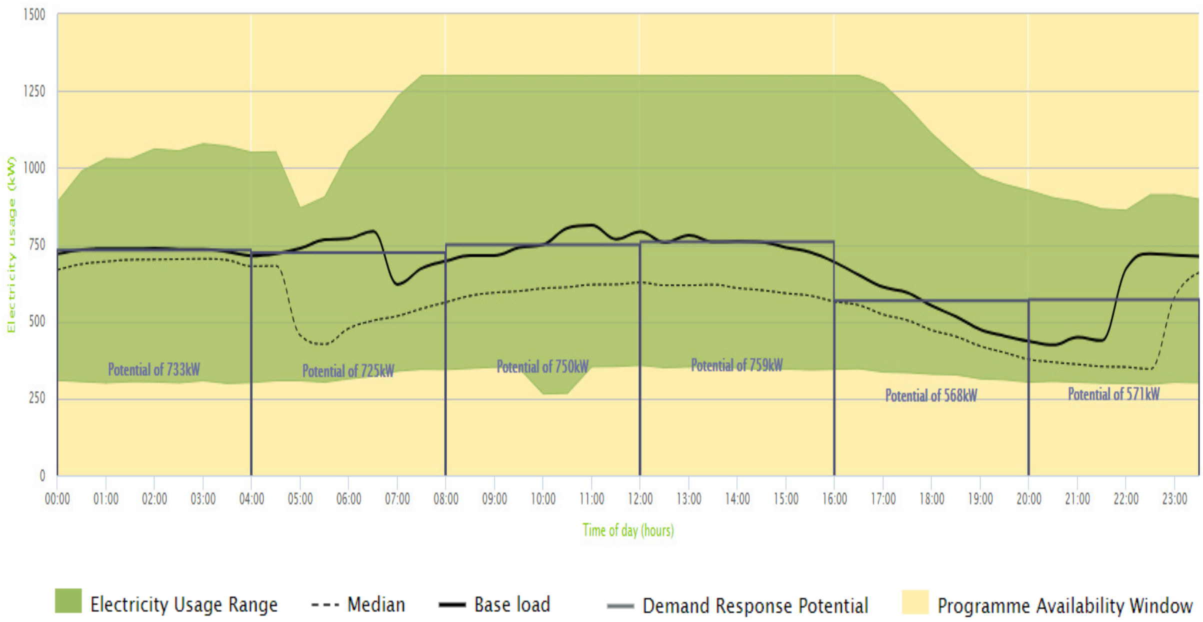


Fig. 17. Site-1 Aggregator Analysis tool results [51]

The total annual profits shown in Fig. 16 using model results indicate scope for improvement in revenue generation compared with the heuristic approach followed by the aggregator of choosing the capacity of the site to offer in the STOR market as explained in section 3.2. Comparing the results derived from the mathematical model shown in Fig. 11 with the aggregator results derived from the data analysis tool shown in Fig. 17 shows a significant difference in the generation capacity to offer in the STOR market as shown in Fig. 18.

The safe approach used by the aggregator can result in mitigating penalties shown in Fig. 22 during utilisation calls by the SO but at the expense of generous revenue that can be earned if the approach is less conservative as shown in Fig. 23. Results of 25 demand bins characterisation of site-1 compared with the heuristic approach are shown below.

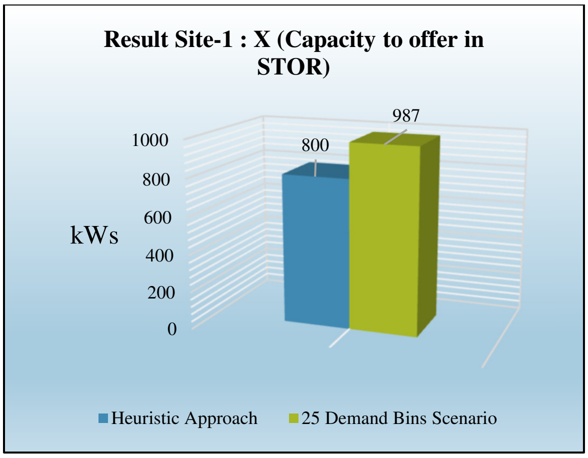


Fig. 18 Case study result: X (Capacity to offer in STOR)

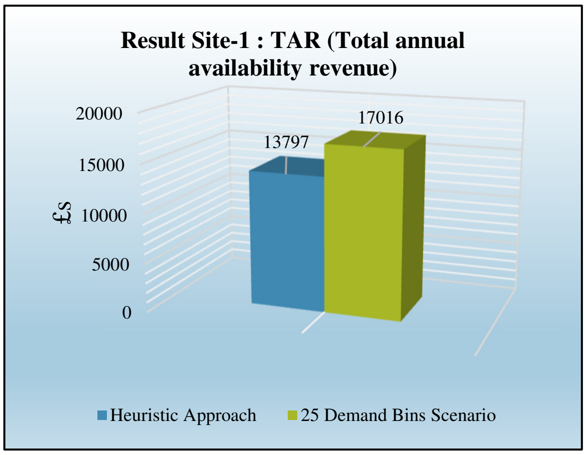


Fig. 19. Case study result: TAR (Total annual availability revenue)

The difference in annual availability and utilisation revenues of site-1 by using the heuristic approach and MINLP model is shown in Fig. 19 and Fig. 20. The total annual generator fuel cost is shown in Fig. 21.

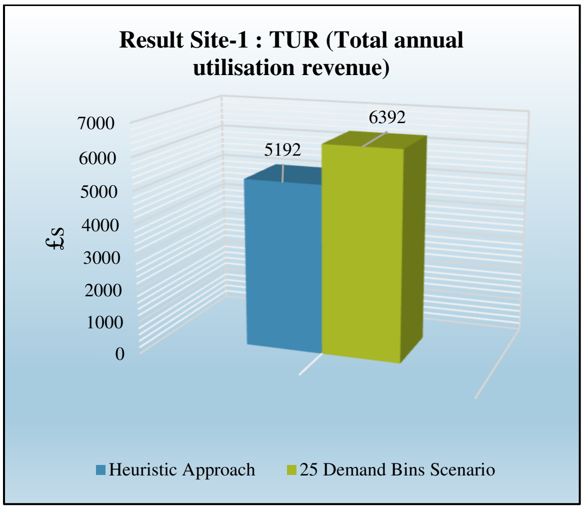


Fig 20. Case study result: TUR (Total annual utilisation revenue)

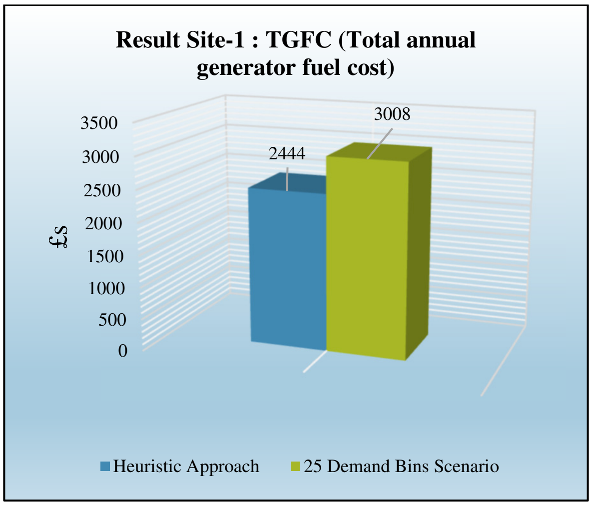


Fig 21. Case study result: TGFC (Total annual generator fuel cost)

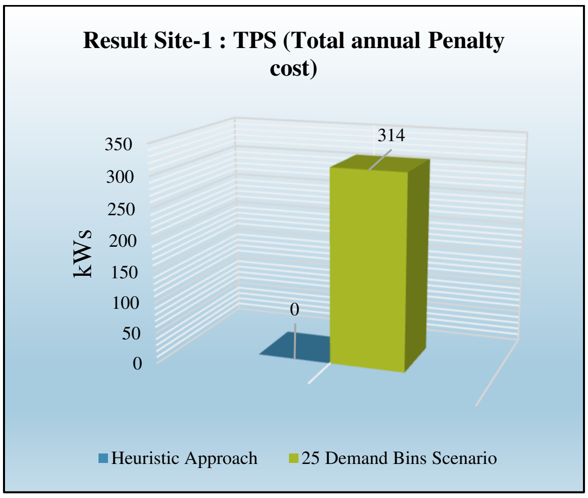


Fig. 22. Case study result: TPS (Total annual penalty cost)

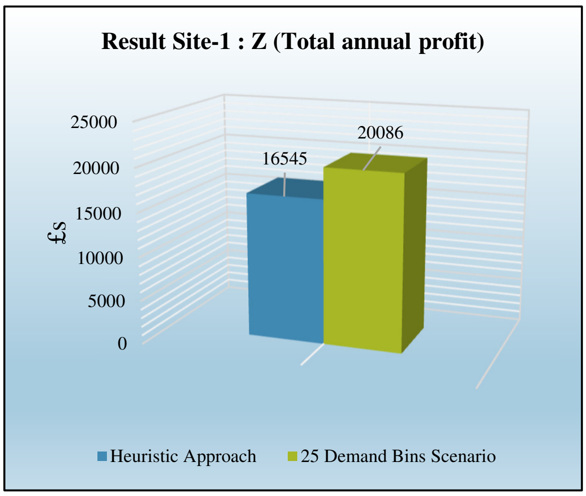


Fig. 23. Case study result: Z (Total annual profit)

The analysis of the annual HH demand data of site-2 using the aggregator analysis tool is shown in Fig. 24. The result shows the maximum potential to offer in BS is 862 kW. The generation capacity to offer in the STOR market by the aggregator is 1000 kW, which is higher than what the analysis tool recommended but significantly lower than the optimal value presented in Fig. 26 (1470 kW for 25 demand bins). The maximum site demand did go up to 1100 kW a few times in a year as shown in Fig. 9, but the aggregator followed a conservative approach by not offering more than 1000 kW as flexibility offering to reduce any chance of getting penalised.

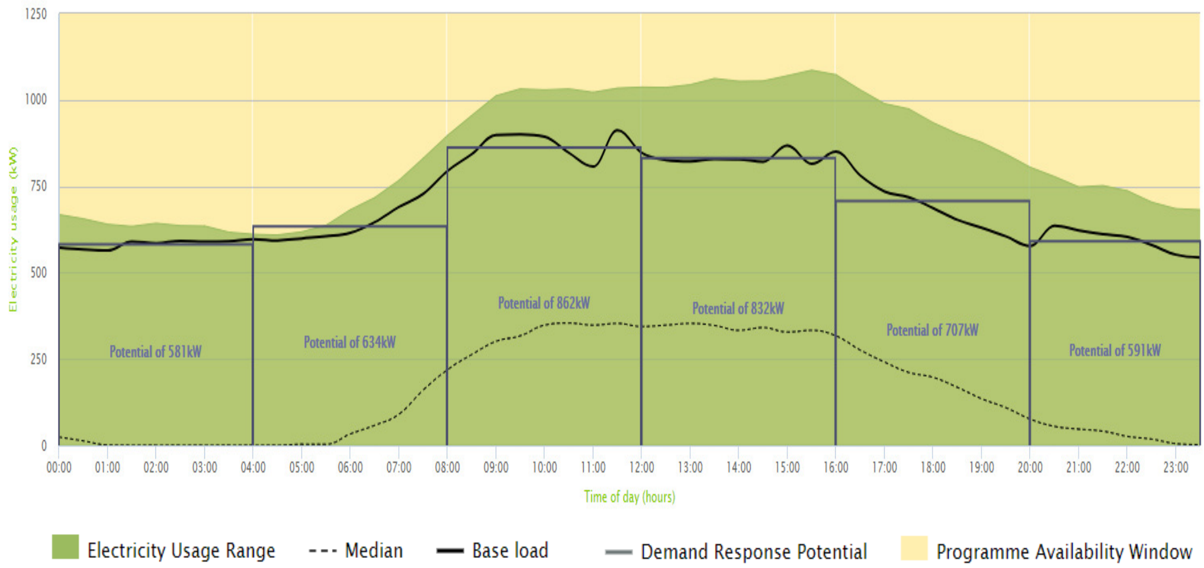


Fig. 24. Site-2 Aggregator Analysis tool results [51]

Similarly, the analysis of the annual HH demand data of site-3 using aggregator analysis tool as shown in Fig. 25 indicates the maximum potential to offer in flexibility service as 778 kW which is again a very conservative result when comparing it with the site annual HH demand data in Fig. 10 which shows that the maximum site demand is around 800 kW. The analysis tool offering though is on the very safe side but at the expense of losing a high availability and utilisation revenue as the total generation capacity of the site-3 is 2000 kW. The generation capacity to offer in the STOR market chosen by the aggregator for this site is 1280 kW, which is significantly higher than what the analysis tool recommended but again comparatively lower than the optimal value calculated by the model presented in Fig. 32 (1568 kW for 25 demand bins).

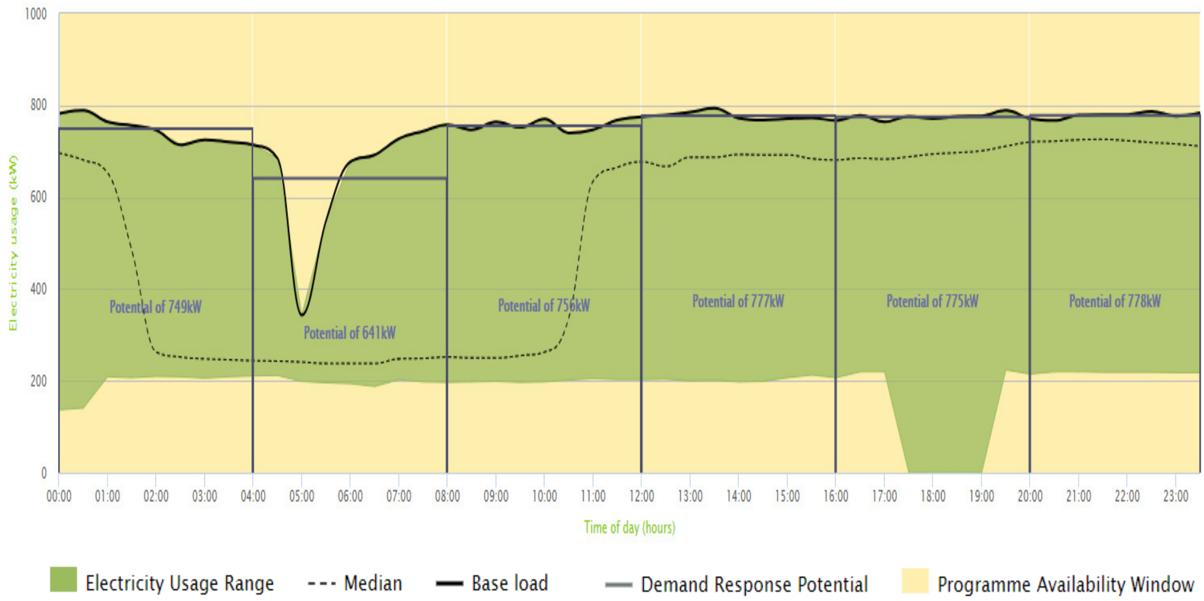
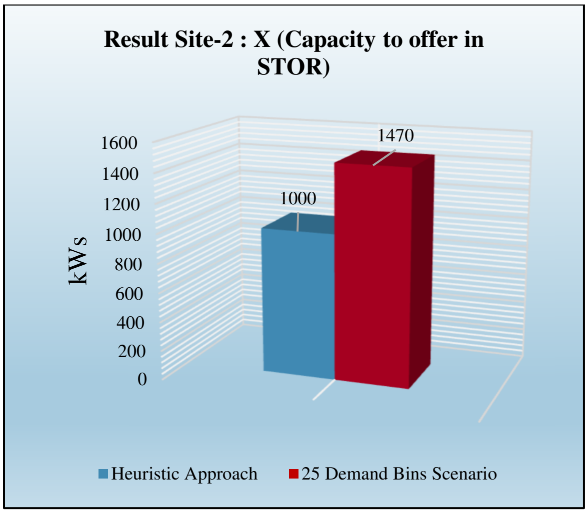


Fig. 25. Site-3 Aggregator Analysis tool results [51]

Using the data from site-2 and site-3 and programming in GAMS gives us the following results for 25 demand bins compared to the heuristic approach followed by the aggregator. Fig. 26 shows the capacity to offer in STOR contract for site-2 by aggregator compared to the MINLP model result.



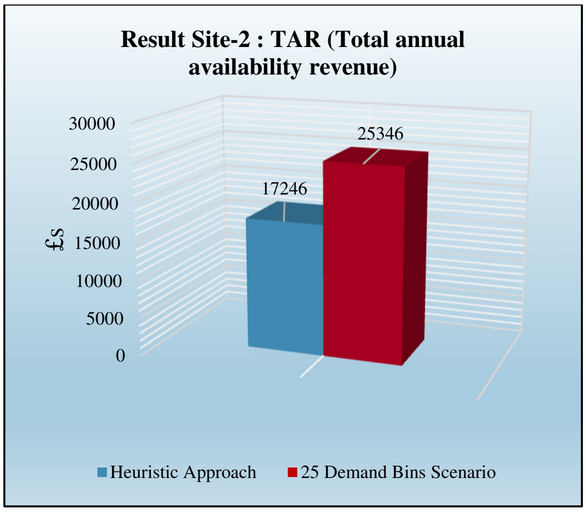
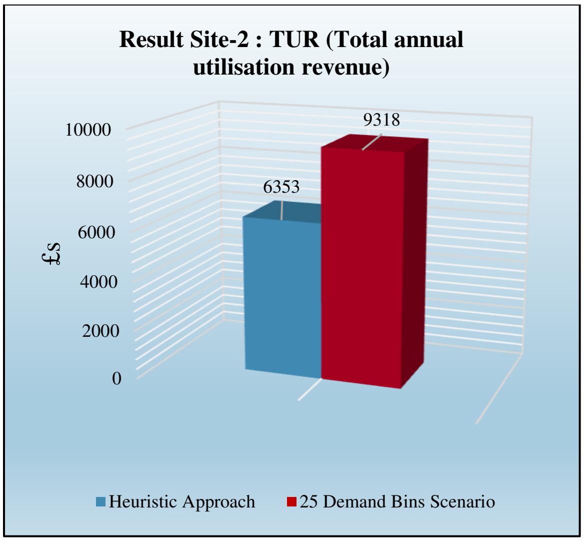


Fig. 26. Case study result: X (Capacity to offer in STOR)

Fig. 27. Case study result: TAR (Total annual availability revenue)

The difference in annual availability and utilisation revenues of the site by using the heuristic approach and MINLP model is shown in Fig. 27 and Fig. 28. The total annual generator fuel cost is shown in Fig. 29.



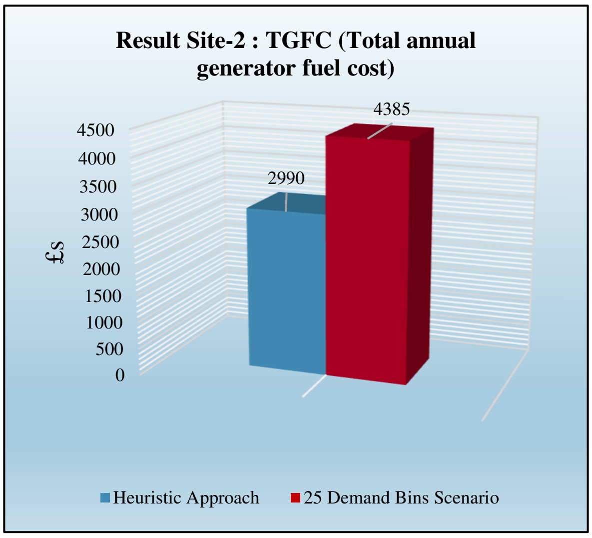
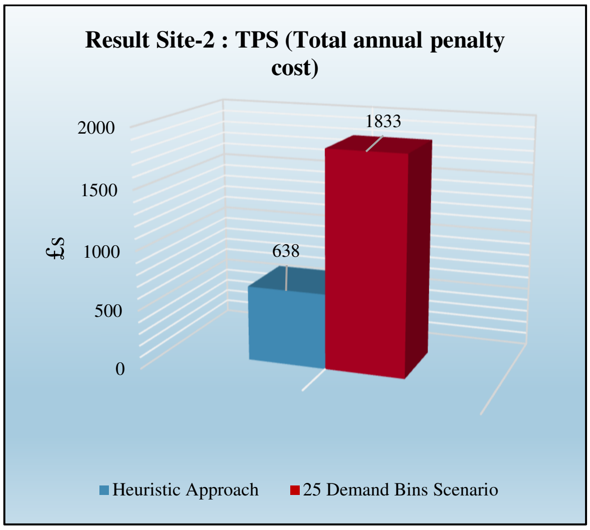


Fig 28. Case study result: TUR (Total annual utilisation revenue)

Fig 29. Case study result: TGFC (Total annual generator fuel cost)

Total penalty cost and total annual profit of site-2 are shown in Fig. 30 and Fig. 31. Results show a significant difference in the generation capacity to offer in the STOR market. The safe approach used by the aggregator can result in mitigating penalties incurred due to no or under-delivery during utilisation calls by the SO but at the expense of generous revenue that can be earned if the approach is less conservative.



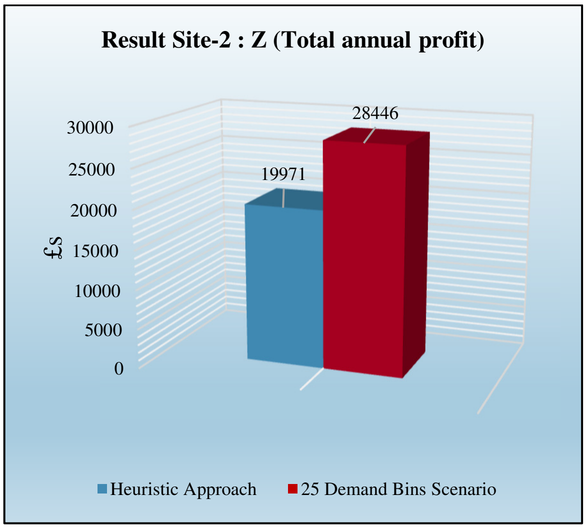


Fig 30. Case study result: TPS (Total annual penalty cost)

Fig 31. Case study result: Z (Total annual profit)

Results in Figs. 32-37 show that the existing generation capacity selection in site-3 to offer in STOR service is optimised to increase the revenue margin by mitigating any penalties incurred due to under or no delivery.

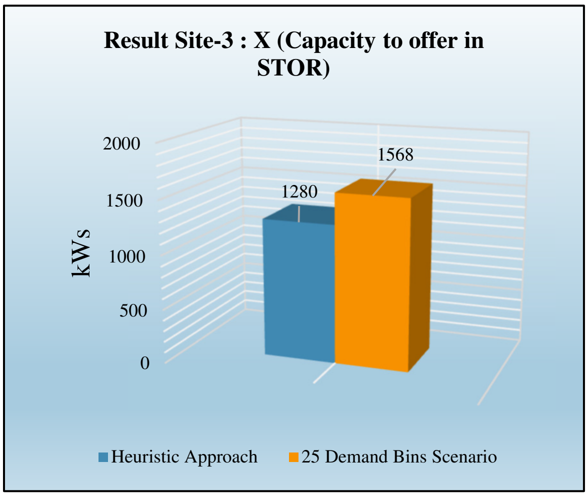


Fig 32. Case study result: X (Capacity to offer in STOR)

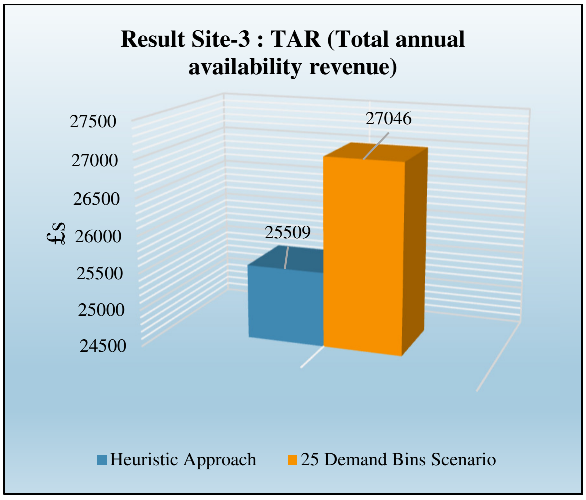


Fig 33. Case study result: TAR (Total annual availability revenue)

In this case, the site was importing electricity from the grid, and the generator was not running during any of the STOR events; hence the total capacity of the generator which is 2000 kW was available, but the model chose 1568 kW when the annual demand data was divided into 25 demand bins as shown in Fig. 32. The difference in annual availability and utilisation revenues of the site by using the heuristic approach and the MINLP model is shown in Fig. 33 and Fig. 34. The total annual generator fuel cost is shown in Fig. 35.

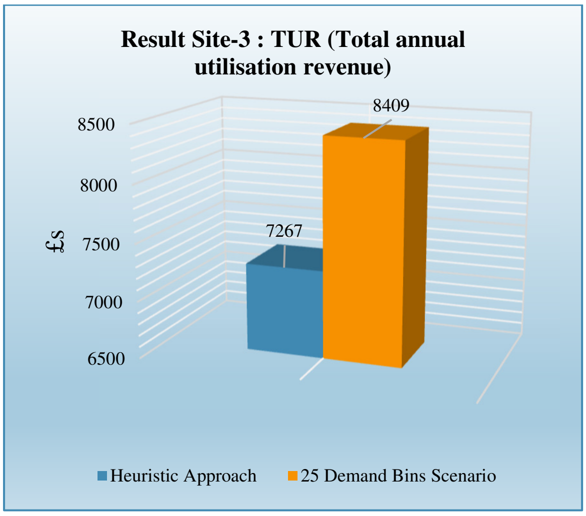


Fig 34. Case study result: TUR (Total annual utilisation revenue)

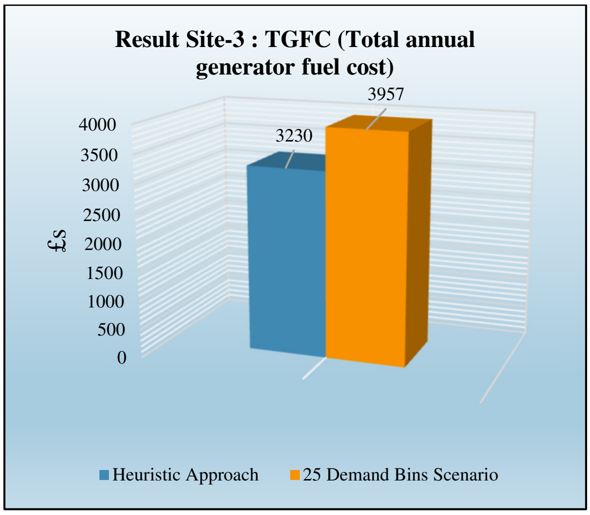


Fig 35. Case study result: TGFC (Total annual generator fuel cost)

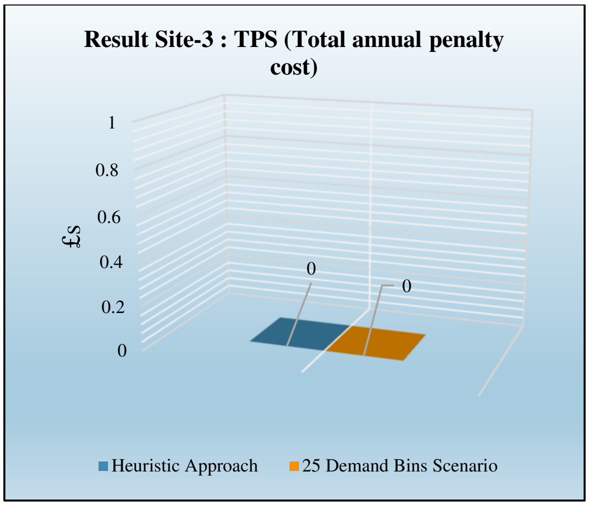


Fig 36. Case study result: TPS (Total annual penalty cost)

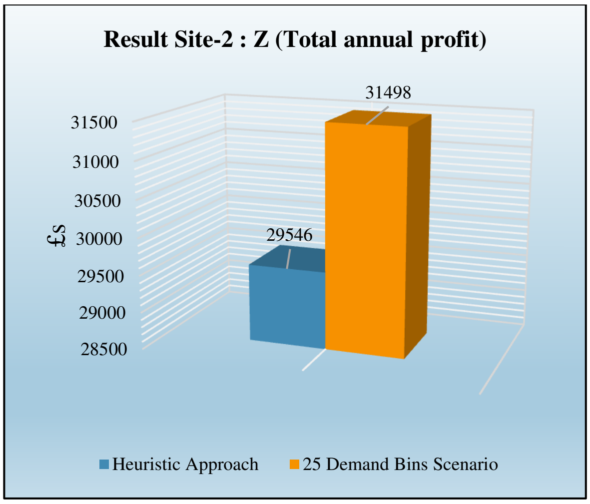


Fig 37. Case study result: Z (Total annual profit)

There is no penalty in both cases, as shown in Fig. 36. Site-3 is different from the first two sites where during STOR events, generators were also satisfying the site demands. In this case, the site was importing electricity from the grid during the STOR call. There is a risk that if the site chooses to give full 2 MW capacity for STOR, it can incur a penalty for under-delivery if the generator is fulfilling site demand when the STOR event is called. The total annual profit is shown in Fig. 37. The safe approach used by the aggregator can result in mitigating penalties during utilisation calls but at the expense of generous revenue.

3.4 Summary

Results of the case studies indicate the difference between the heuristic approach followed by the aggregator and the MINLP model approach discussed in this article. Results show the generation capacity to offer in the STOR market, availability and utilisation revenues, annual fuel cost and penalties incurred during STOR events and total annual profits of the sites by first dividing the annual demand into 5, 25 and 50 demand bins as shown in Appendix A – Figs. A1-A3 and then selecting 25 demand bins data as the most tractable approach to identify the optimal generation capacity for the grid-connected generators to offer in STOR, as shown in Appendix B – Figs. B1-B2.

The results obtained after optimisation show that there is scope for improving the current conservative approach followed by the aggregator to avoid penalties that can be incurred by reduced or no delivery during STOR events. Using the current heuristic approach aggregators miss a substantial opportunity to generate extra revenue. By following the approach presented in this article using demand bin characterisation of the site annual HH demand data, the optimal capacity of the generating unit to offer in STOR service can be determined, and the risk of getting penalised by the SO for under or no delivery minimised.

4. Conclusions and further developments

This paper presents a novel framework for DER aggregators to determine by optimisation the capacity of a grid-connected generating unit to contract with the SO using mixed integer non-linear programming (MINLP). Results show the site revenue increases between 6.2% to 29.8% compared to the heuristic approach previously employed. MINLP model captures everything. In fact, it captures the changes by performing a sensitivity analysis based on the number of STOR calls in each site demand bin. Sensitivity analysis is performed to assess the impact of temporal resolution of demand characterisation on results, showing that increased resolution improves accuracy significantly, and reduces the estimate of capacity that the site should contract with the aggregator.

The potential of the model is studied by MINLP formulated in GAMS. Three real-life case studies have been used to illustrate the optimal capacity selection of the generator, which shows that revenue can be substantially increased compared to the aggregators capacity selection approach currently in use. This result was consistent across all three sites studied. Thus, it is asserted that the proposed generation capacity selection model can be applied to real STOR sites to enhance revenue streams.

From the application point of view, it is simple to implement and doing an analysis of the demand data of the real sites. With regards to its industry adoption, aggregators mostly used heuristic and conservative approaches but this model is more pragmatic and is being used in industry to do demand data analysis of real sites for contractual capacity selection.

Future work would extend the model using 2-stage stochastic optimisation by choosing the capacity of a generator to offer in the STOR market as a first stage variable. There will be a random variable in the second stage for the probability that there will be a STOR event. The objective function will trade-off revenue from the utilisation and availability against costs of penalties for under or no delivery by choosing the capacity to offer in the STOR market.

This research will contribute towards adding valuable information in the capacity selection of DERs for grid BS and its applicability as an extension to knowledge in academia will enable future researchers to build the corpus of knowledge discussed in this article.

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Appendices

Appendix A.

Probability distribution of annual site demand data of site-1 in 5, 25 and 50 demand bins

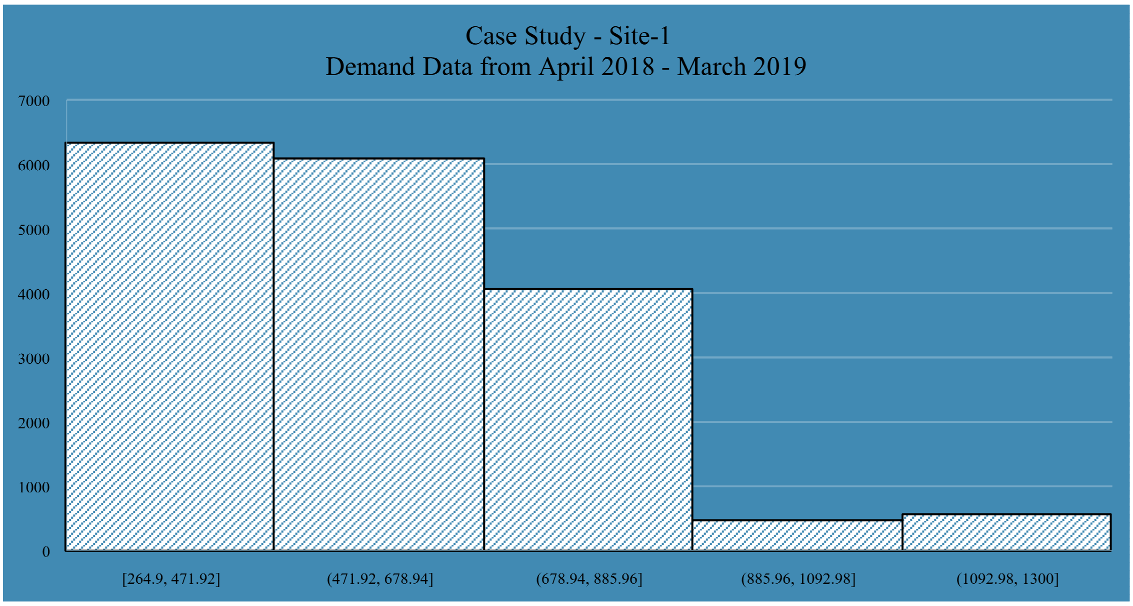

Fig. A1. Site-1 Probability distribution of annual demand data in 5 demand bins

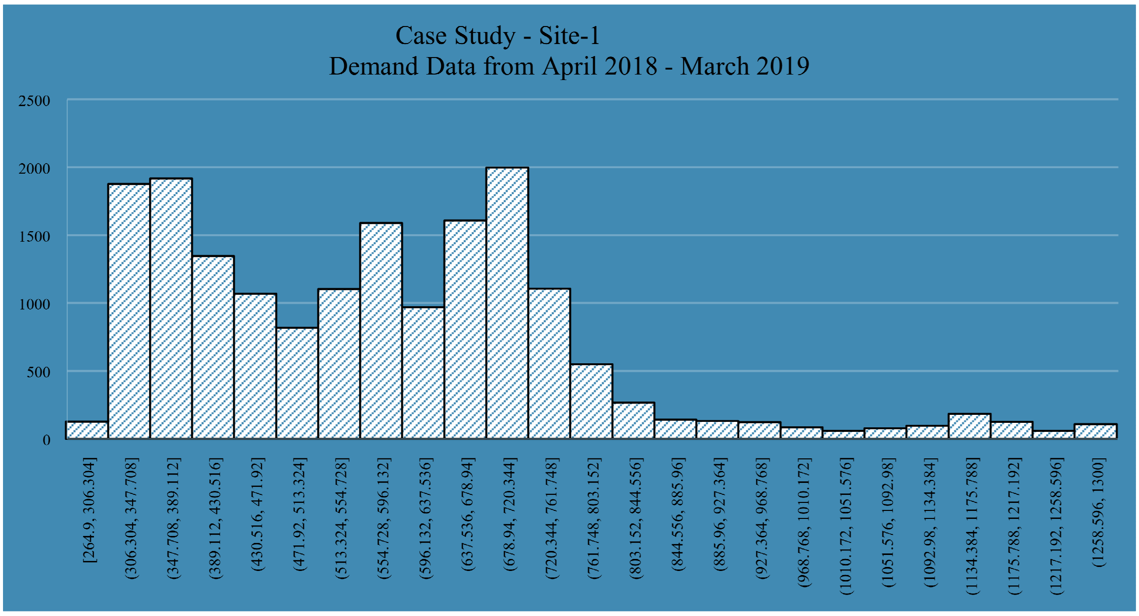

Fig. A2. Site-1 Probability distribution of annual demand data in 25 demand bins

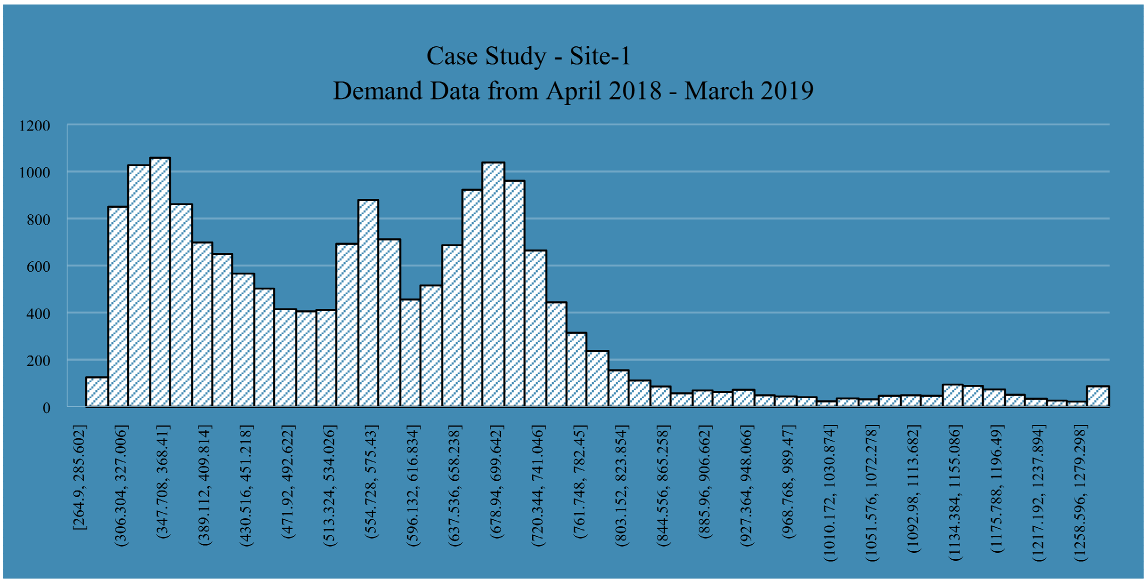

Fig. A3. Site-1 Probability distribution of annual demand data in 50 demand bins

Appendix B.

Probability distribution of annual site demand data of site-2 and site-3 in 25 demand bins

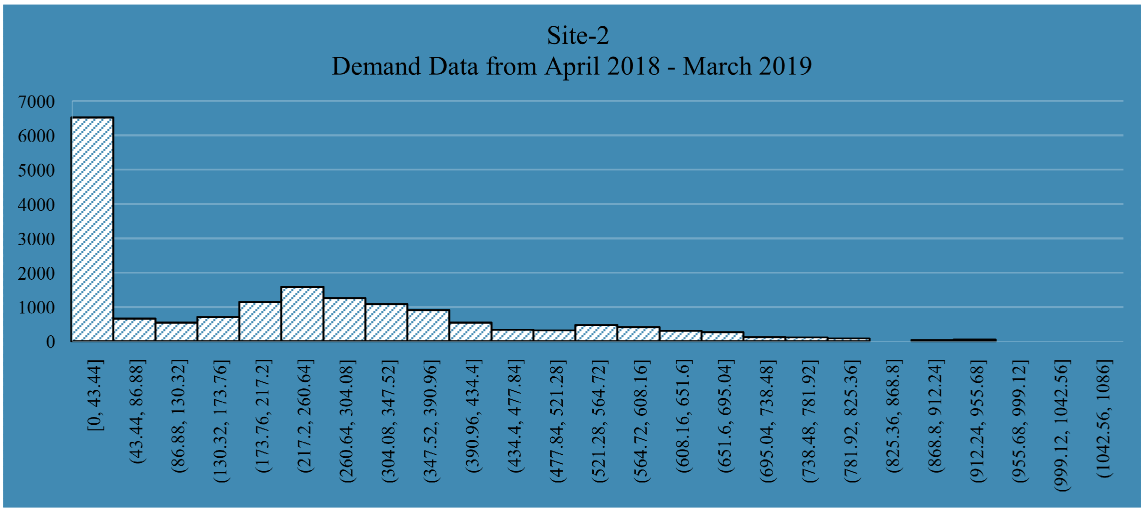

Fig. B1. Site-2 Probability distribution of annual demand data in 25 demand bins

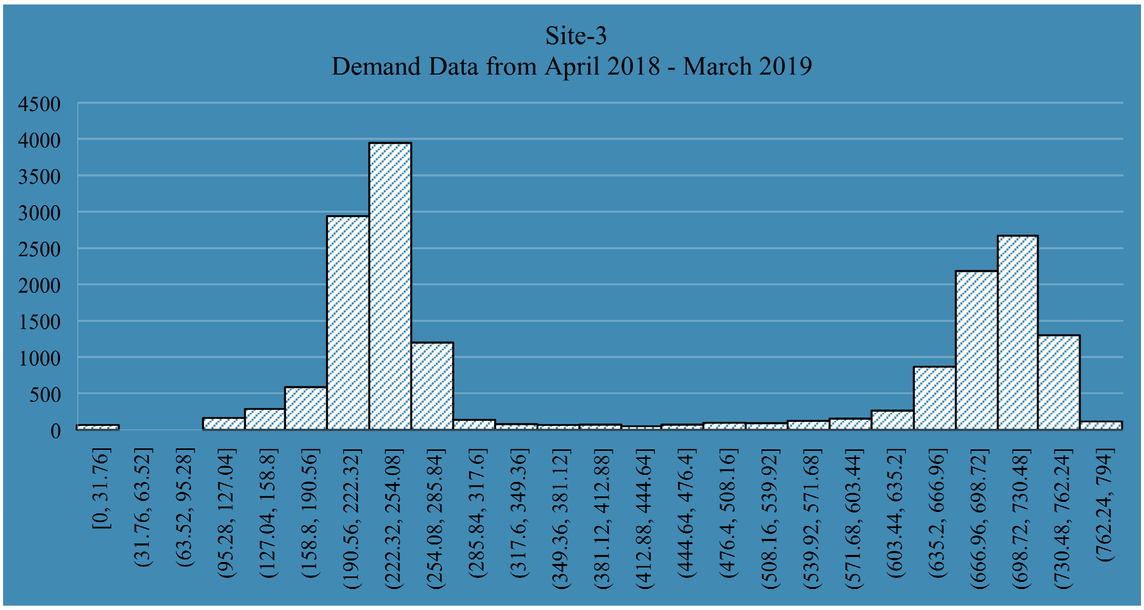

Fig. B2. Site-3 Probability distribution of annual demand data in 25 demand bins

Appendix C.

STOR Seasonal data from STOR Year-12

Season	Dates		Mon- Sat			Sun- Holidays		
	Start	End	Start time	End Time	Duration	Start time	End Time	Duration
12.1	01-Apr-18	29-Apr-18	06:00	13:00	07:00	10:00	14:00	04:00
			19:00	21:30	02:30	19:30	21:30	02:00
12.2	30-Apr-18	19-Aug-18	06:30	14:00	07:30	10:30	13:30	03:00
			16:00	18:00	02:00	19:30	22:00	02:30
			19:30	22:00	02:30	-	-	-
12.3	20-Aug-18	23-Sep-18	06:30	13:00	06:30	10:30	12:30	02:00
			16:00	21:00	05:00	19:30	21:30	02:00
12.4	24-Sep-18	28-Oct-18	06:00	13:00	07:00	10:30	13:00	02:30
			17:00	20:30	03:30	17:30	20:00	02:30
12.5	29-Oct-18	27-Jan-19	06:00	13:00	07:00	10:30	13:30	03:00
			16:00	20:30	04:30	16:00	19:30	03:30
12.6	28-Jan-19	31-Mar-19	06:00	13:00	07:00	10:30	13:00	02:30
			16:30	20:30	04:00	16:30	20:00	03:30

Table. C1. STOR daily windows in Season-12 (01/04/2018 to 31/03/2019)

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