Planning the location and rating of distributed energy storage in LV networks using a genetic algorithm with simulated annealing

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Abstract
In light of the expansion of domestic photovoltaic (PV) systems in the UK, there are concerns of voltage rise within LV networks. Consequently, network operators are interested in the costs and benefits of different technologies to manage their assets. This paper examines the particular case for distributed energy storage.
A heuristic planning tool is developed using a genetic algorithm with simulated annealing to investigate the problem of locating and sizing energy storage within LV networks. This is applied to investigate the configuration and topologies of storage to solve voltage rise problems as a result of increased penetration of PV. Under a threshold PV penetration, it is shown that distributed storage offers a financially viable alternative to reconductoring the LV network. Further, it is shown that a configuration of single phase storage located within the customer home can solve the voltage problem using less energy than a three phase system located on the street.

Keywords
Distributed storage and generation, power distribution planning, genetic algorithms, simulated annealing

Nomenclature

a	Random number in the interval zero to one, applied in simulated annealing
$CAPEX_i$	Capital cost of storage unit i [£]
C_I	Installation cost of each storage unit [£]
C_{kW}	Power cost of particular energy storage technology [£/kW]
C_{kWh}	Energy cost of particular energy storage technology [£/kWh]
C_r	Cost of reconductoring the network [V]
D	Permissible depth of discharge [%]
$\mathbb{E}_i$	Capacity of energy storage unit i [kWh]
f_i^r	Roulette wheel fitness of solution i during algorithm round r
p_i^r	Probability that solution i is selected during algorithm round r
$\mathbb{P}_i$	Rating of energy storage unit i [kW]
t	Length of time that storage operates at full power [h]
$\mathbb{T}$	Temperature, applied in simulated annealing
V_i^{max}	Highest voltage in LV network when storage solution i is implemented [V]
η	Round trip efficiency of particular energy storage technology [%]

1. Introduction

As of January 2014, more than 482,000 solar photovoltaic (PV) systems of capacity 1-4 kW have been registered under the UK feed-in-tariff scheme and the installation rate remains high despite the subsidy being reduced in 2012 [1], [2]. Installation of such distributed generation introduces fundamental changes to the electrical power network and within the low-voltage (LV) network, particular issues for distribution network operators (DNOs) are reverse power flow, thermal constraints and voltage rise [3].

Reverse power flow and voltage rise are related events which are most extreme when generation is highest and demand is lowest [4]. These both become more problematic as the penetration of rooftop PV increases, and can limit the amount of distributed generation that should be installed in a network area [5]. Consumers connected to the LV network may have no direct problems as a consequence of reverse power flow, but this can affect voltage regulation on the medium voltage network including additional cycling of tap changing transformers [4]. Reverse power flow is currently evident on the UK distribution network, as metered data from an LV transformer shows (Figure 1-1). In terms of voltage, the voltage must not exceed 10% above or 6% below 230 V under UK regulation [6] and failure to do so can have negative impacts on electrical equipment.

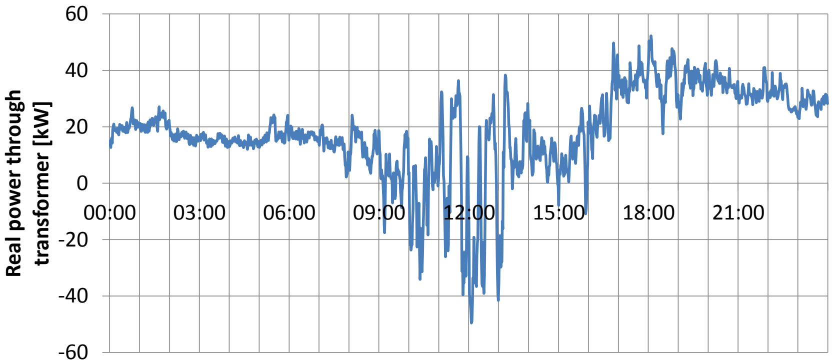

Figure 1-1: Real power through an LV transformer located in Stockport, UK on 21st April 2012

It is estimated £32 billion of investment is needed to mitigate the effects of distributed generation on the UK electrical network. To manage the network without directly interfering with generation or customer demand, network operators can either reduce network impedance (reconductor), add discretionary loads, demand side management or energy storage [4]. Indeed, under the new price control scheme (RIIO) there is a financial incentive for DNOs to invest in new technologies and techniques such as energy storage [7]. In a competitive industry, there is a need to assess the cost implications of these innovative technologies relative to traditional mitigation methods. Energy storage is widely considered to be a technically viable solution to the problems expected in the distribution network, for example in [8], however there are few industrial distributed storage projects, costs are high and DNOs do not necessarily have the experience to plan for new technologies. This paper examines the particular case of energy storage.

Electrical energy storage technologies can generally be split into three broad categories. Utility or bulk scale energy storage, such as pumped hydro and compress air, are capable of delivering several megawatts of power over one to eight hours and due to cost and geological restrictions are suitable for transmission applications [9]. Distributed storage systems typically deliver smaller amounts of power for a similar period to utility storage but can be scaled in terms of rating, location and capacity [10]. Short term storage, typically capable of delivering large amounts of power for short periods, includes flywheels and supercapacitors. The flexibility, capacity and rating of distributed storage makes it most relevant for this application.

This paper presents a heuristic planning tool that can inform DNOs about the deployment of storage projects in their networks. Firstly energy storage for distribution networks is discussed in general terms including benefits to the network, a discussion of suitable technologies and relevant approaches taken by others in designing storage projects. Secondly, a review of relevant heuristic algorithms for locating distributed energy sources are discussed, followed by a discussion of the heuristic approach developed for this paper. This heuristic is subsequently applied to give relevant results for network operators which are discussed before conclusions are drawn.

2. Electrical energy storage in distribution networks

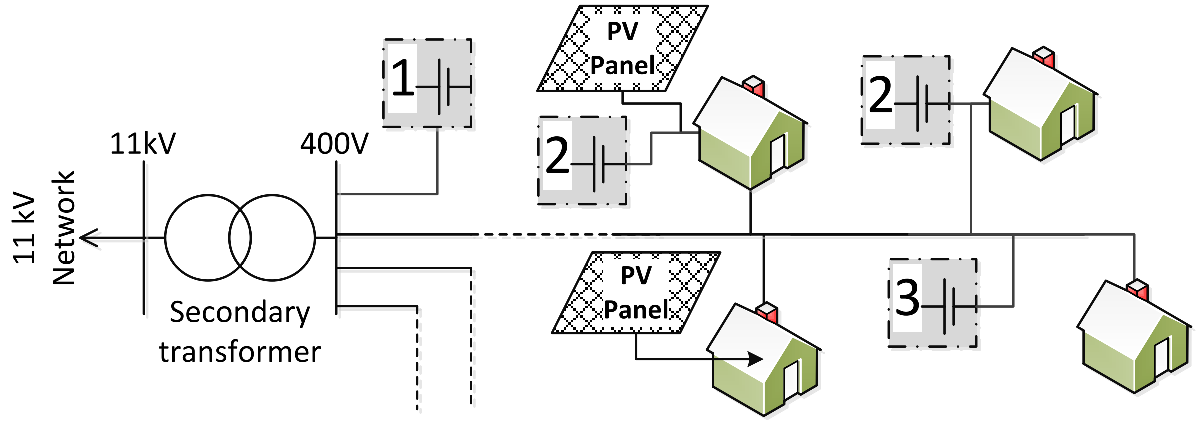

Figure 2-1: Locating energy storage in an LV network: 1- at the secondary transformer, 2- connected at the property beyond the meter and 3- on the street

As shown in Figure 2-1, there are a number of configurations for installation of distributed energy storage in LV networks. Systems connected on the customer side of the meter, frequently called solar home systems, generate wide academic interest. In [11], such systems are described as offering benefits to the consumer though supporting local critical loads in the event of a system failure. Benefits to the utility include peak shaving, supporting other customers and the ability to load shed customers with autonomous power capabilities in the event of a power shortage [12], something which may be relevant given recent predictions of power problems in the UK [13]. Combining PV and storage is shown in [14] to be cheaper than alternatives for emergency backup and has greater value than PV alone. Storage can also enable a grid to operate as a micro-grid with islanding in the event of grid failure [15]. In [9], it is shown that as the penetration of PV increases, energy storage (and load shifting) may be required to avoid energy spilling. In this case, real time pricing signals are proposed to enable demand side response. In [16], a combination of demand side response and energy storage are used in a smart home to increase self-consumption of energy. Demand side response alone provides a 26% increase in self-consumption for the home, which the addition of storage further improves. In [17], the authors propose a technique for using a single battery and distributed generator to inject real power into an 11kV network to prevent voltage drop. By reducing customer demand from the grid, storage can be used to reduce thermal losses in the transmission and distribution network [16], [17]. In the UK distribution network it is difficult to measure the effect on loss reduction throughout the entire network and the value in loss reduction for an small distributed unit is small [18]. However, the benefits from upgrade deferral are important and provide predictable revenues for network operators [17], [18].

As summarised in [8], storage can offer a number of benefits to DNOs including voltage support, power flow management, restoration, network management and compliance with regulatory requirements. Reverse power flow and voltage rise can be managed using storage to absorb power from the generators. Peak shaving requires discharge of stored energy into the network to reduce the loading on transformers and cables. To reduce reverse power flow or to peak shave requires a specific amount of energy to be supplied or absorbed. Assuming thermal limits are not exceeded, power/energy specifications of the storage are unaffected by its location in the network.

However, the power required to manage a voltage problem is directly affected by the location of the storage unit [17], [19]. As such, to reduce the capacity and power required to solve a voltage problem, storage should be distributed at many nodes within the network. This paper proposes that locating the storage within the network (in properties or on the street) will allow the greatest ability to reduce the power needed to solve the voltage problem. In real networks however, there may be hundreds of nodes (busbars, customer connection points) where an energy storage unit could be connected. If multiple storage units are proposed, the number of feasible combinations of energy storage increases rapidly; for example, there are 2.25×10^{16} ways of locating ten storage units among two hundred feasible locations. Due to the complexity of this problem, this study applies a heuristic approach for locating distributed storage.

2.1 Applications of heuristic algorithms in distribution networks

There are a number of examples of the application of heuristic algorithms in network planning. Early applications include the “capacitor placement problem”, which attempts to determine the location, type, number and size of capacitors in a radial distribution network to minimize costs, voltage problems and/or losses. A number of established heuristics are used such as Tabu search [20] and genetic algorithm [21]. Evolutionary [22] and particle swarm [23] algorithms are also considered for the problem of determining the location and capacity of distributed generation.

A number of papers consider heuristic approaches in the location, sizing or operation of energy storage in power networks. In [24] a Tabu search approach is used for sizing energy storage by considering unit commitment. In [25], the authors use a genetic algorithm to locate superconducting magnetic energy storage to maximise the voltage stability index. In [19], three cost based heuristics are shown for managing voltage rise in LV networks and shows that deterministic approaches are not as good as stochastic methods because they are unable to search the entire problem space. In [26] a genetic algorithm is used to locate and size a single energy storage unit to achieve benefits in reducing loss, voltage deviation and costs. In [27] a genetic algorithm is combined with a sequential quadratic programming approach to locate capacitors and energy storage in an MV smart grid. In [10], a multi-objective algorithm is used to locate and size storage units in a 34 bus, 24 kV network. Objectives include reduction of storage power and capacity, minimising the probability of voltage deviations, maximisation of arbitrage revenue and minimisation of lost ancillary service opportunities. The heuristic used in [10] builds on work in [28] where wind, PV and CHP units are located in a network in a distribution network using a genetic algorithm. The authors in [10] use the multi-objective SPEA2 algorithm [29] to locate multiple storage units in a distribution network to provide voltage support, arbitrage and ancillary services. Genetic algorithms are also used to determine control strategies such as in [30] where the heuristic is used to determine controlled gain factors for a hybrid generation system. Further, in [31], a genetic algorithm is used to size and determine the operation of energy storage to participate in electricity price arbitrage, defer investment and reduce transmission access costs. In [32], a simulated annealing is used for locating energy storage in micro-grids and power networks for emergency backup. As discussed in [33], the simulated annealing approach allows non-improving moves to be selected and therefore allows the algorithm to escape from local optima. In [34], the genetic algorithm and simulated annealing approaches are combined to locate distributed generation for loss reduction. The combination of these approaches is shown to produce more effective results than the genetic algorithm on its own.

Although global and local search methods have been applied to distribution networks in literature, further consideration is needed into how their application can provide relevant results to DNOs in relation to distributed energy storage. This particularly applies in the area of planning given uncertainty and a lack of control of the location of distributed generation. Therefore, this paper firstly presents a suitable cost based method for finding the optimal location of energy storage in LV networks. Secondly, this algorithm is used to compare different storage configurations in economic terms as the penetration of distributed generation increases.

3. Heuristic

3.1 Heuristic design and implementation

As discussed, a variety of global and local search heuristics are applied in network planning studies. Two particular approaches (genetic algorithm and simulated annealing) are combined in this paper in contrast to other work.

A genetic algorithm is an iterative heuristic optimisation method which is inspired by the theory of evolution. A population of candidate solutions to a problem are initially generated across the entire problem space with chromosomes which represent the characteristics of the solution. For example, a chromosome of a particular population member could describe the location of energy storage units within a LV network. The fitness of each population member is then evaluated against an objective function. Population members are subsequently combined to produce a new generation of solutions. The selection of population members to carry to the next generation is stochastic, but typically weighted towards solutions with a higher fitness. The process is repeated for either a fixed number of generations, or until a convergence criteria is met. Through successive rounds, the genetic algorithm will converge to a population of fitter solutions. The genetic algorithm allows a wide exploration of the search space.

Simulated annealing is inspired by the heating and cooling of metals to change their properties. Random changes are applied to a population member for a fixed number of rounds. These changes are accepted if they improve the fitness of the solution. However, crucially, if these do not improve the fitness, they are accepted with a probability which decreases every round. As such, non-improving moves can be accepted which take the current solution away from a local maxima. This could be, for example, the moving of an energy storage unit to a node with a higher impact on the solution. The addition of the simulated annealing to the genetic algorithm is designed to allow local search to improve each solution.

Both heuristics are implemented in a customised Matlab script which interfaces with a detailed, 4-wire Open-DSS [35] model of the network. The LV network is constructed along with a higher voltage network. A fixed load is applied on the 11 kV feeder to represent other LV networks as shown in Figure 3-1. The networks contain only domestic properties, with a selection of these having rooftop PV systems. A single load flow is performed under a worst case scenario to evaluate solutions. Storage is added at feasible nodes by the heuristic at a charging power determined by the heuristic.

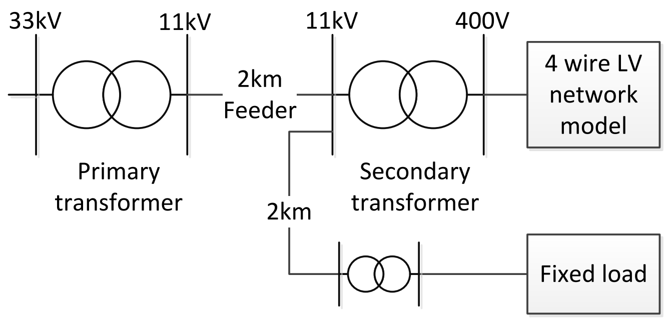

Figure 3-1: Network model used in heuristic

3.2 Heuristic structure

The heuristic structure is outlined in Figure 3-2. At the start of the algorithm an initial population is generated and evaluated. Simulated annealing is performed on the best population members and the fitness of the new population is evaluated. Genetic algorithm mating and crossover routines are then completed to generate a new population. At the end of each round, the most expensive population members are replaced with a new population. Under an elitist approach, the solution with the highest fitness is carried through the algorithm, and is only replaced when a fitter solution is found. The algorithm is repeated over a fixed number of rounds/generations.

It is important to add diversity to each population generation to allow the genetic algorithm to escape local minima. This is commonly achieved through mutation, which is a random change to population members. However, in this algorithm, diversity is achieved through both the inclusion of new, stochastically determined population members to each generation and also through local search within the simulated annealing. This was found to generate sufficient diversity in the population.

3.2.1 Fitness function

The objective of the heuristic is to minimise the capital cost of the storage, which is evaluated for a single system as the sum of installation (C_I) and system costs. According to [36], the cost of storage is the sum of power and capacity costs. The power costs is the product of the cost per kW (C_{kW}) and the storage rating ($\mathbb{P}_i$) and the capacity cost is the product of the cost per kWh (C_{kWh}) and the storage capacity ($\mathbb{E}_i$). The total capital cost of each storage unit is calculated according to (1).

$$CAPEX_i = C_I + C_{kW}\mathbb{P}_i + C_{kWh}\mathbb{E}_i \quad (1)$$

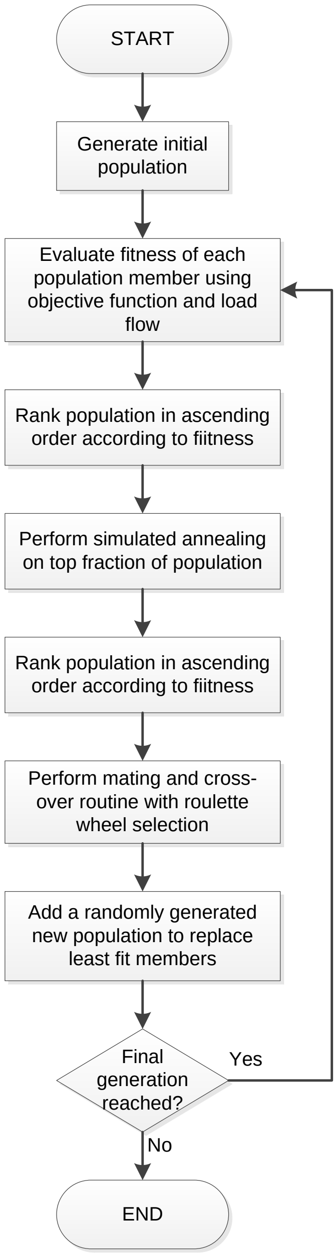

Figure 3-2: Heuristic structure

This equation has been adapted for this study (2). The capacity is calculated as the time t over which the storage delivers full power. The maximum depth of discharge D of the storage is included to reflect realistic battery parameters. The charging efficiency (which reduces the amount of energy that is stored [37]) is estimated as the root of the round trip efficiency.

$$CAPEX_i = C_I + C_{kW}\mathbb{P}_i + \frac{C_{kWh}\mathbb{P}_i t\sqrt{\eta}}{D} \tag{2}$$

The optimisation problem can therefore be reduced to a single cost-based objective function (3).

$$\text{minimise} \quad \sum_{i=1}^{N} CAPEX_i + \begin{cases} 0 & if\ voltage\ is\ within\ limits \\ C_r & if\ the\ voltage\ is\ outside\ the\ limits \end{cases} \tag{3}$$

If the voltage problem cannot be solved a penalty function of the cost of reconductoring (C_r) is applied. Costs and performance parameters applied in this paper are discussed in section 3.4.

3.2.2 Initial population generation

The original population is generated through application of the voltage sensitivity factor algorithm used in [19]. Storage is incrementally added at nodes with the highest voltage sensitivity factor until voltage is brought within limits. This produces a population of identical solutions to which simulated annealing is applied, without a probability acceptance function, to produce a varied population.

3.2.3 Simulated annealing

As discussed in [38], simulated annealing should understand and make use of properties of the problem to be effective. Accordingly, the following simulated annealing moves are defined, with an equal probability of being applied during each annealing round:

1. Turn off a randomly selected system;
2. Turn off a randomly selected system and divide the power between the remaining systems;
3. Turn on a randomly selected system with a randomly assigned power;
4. Select a random active storage unit and decrease its power by a random amount;
5. Select a random active storage unit and increase its power by a random amount.

This resulting solution is selected either if it has a lower cost (evaluated using the fitness function) than the previous best solution, or randomly according to the probability acceptance function (4). Here, the temperature $\mathbb{T}$ increments for each annealing round.

$$a < \min(0.2, \frac{1}{\mathbb{T}}) \tag{4}$$

3.2.4 Mating and crossover

Mating and crossover probabilistically combines the properties of two different parent solutions to generate a new population. Roulette wheel selection is used to determine which two parents are combined for child as opposed to the tournament based selection used in [10]. As discussed in [39], tournament selection can become susceptible to premature convergence as the problem size increases. This can be mitigated through adjusting the tournament size, but the authors wished to avoid additional parameter selection

A cost based proportional based roulette wheel would give unnecessary bias to outstanding individuals in this heuristic due to the penalty (reconductoring cost) used in fitness function. Accordingly, a voltage based proportional based fitness evaluation is applied, using the deviation from the voltage limit (f_i^r). This more evenly distributes the probability that an individual is selected and is found to be a good compromise between rank and proportional selection. Under the crossover routine, for each valid storage location, the new child takes the storage assignment from either parent with probability relative to the parents' fitness according to (5). The probability (p_i^r) that any individual solution (i) is selected to be a parent can therefore be calculated (6):

$$f_i^r = \frac{1}{\left|253 - V_i^{max}\right|} \tag{5}$$

$$p_i^r = \frac{f_i^r}{\sum_{i=1}^{N} f_i^r} \tag{6}$$

3.3 Heuristic Performance

The performance of the genetic algorithm with simulated annealing heuristic is shown in Figure 3-3 (left) in comparison to heuristics employing just simulated annealing or a genetic algorithm. Performance is measured relative to the fitness of the initial population, which is kept constant. It can be seen that all heuristics produce a similarly large initial improvement after round one. The genetic algorithm quickly stabilises to a solution because, without simulated annealing, it is unable to cause significant changes to the population. The simulated annealing approach is generally slower to converge, and the nature of the algorithm means that the fittest solution may not be the one at the end of the final algorithm round. The genetic algorithm with simulated annealing generally produces the lowest cost solutions with greater stability as shown in Figure 3-3.

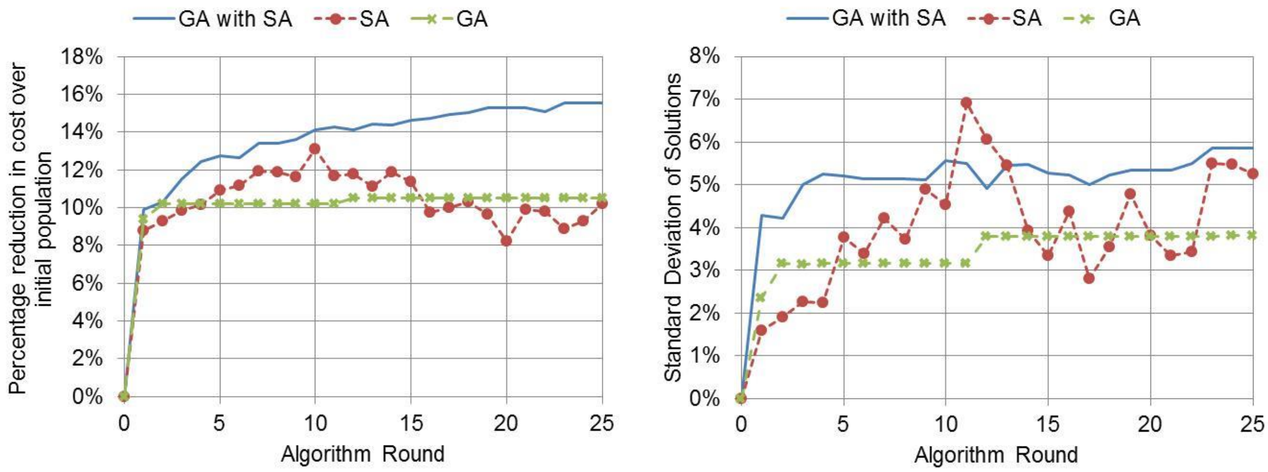

Figure 3-3: Average performance of different heuristics where heuristics are performed ten times. (left) and standard deviation of solutions for different heuristics (right). GA denotes genetic algorithm and SA denotes simulated annealing

3.4 Problem formulation

To demonstrate the heuristic, it is used to investigate which storage installation strategies that a DNO should support to prevent voltage problems in LV networks. The feasibility of two storage topologies are investigated: single phase storage located within the customer property and larger three phase storage units at customer connection points, the transformer or junctions in the radial network. Storage cost and technical parameters are summarised in Table 3-1, which taken from [36] or from discussion with the sponsoring DNO (costs are converted with exchange rate of $1.6 to £1).

The parameters used in the heuristic (Table 3-2) were selected based upon experience using the heuristic to produce relevant results within a reasonable computation time. For example, the number of rounds was selected based upon the number of rounds to produce a near optimal solution (Figure 3-3). The algorithm is performed over a 10 rounds with a population size of 500. The fittest 400 population members have a simulated annealing routine applied with a maximum temperature of 5 and mating and crossover replaces all population members 250 to 450 when ranked in order of fitness. 50 new population members are added each round using the method described in section 3.2.2. The fittest population member is always carried forward through each generation under an elitist approach.

Table 3-1: Simulation parameters

Parameter and symbol	Single phase storage	Three phase storage
Install cost, C_I	£400	£8,000
Maximum unit power, $P_{i,max}$	1.5 kW	15 kW
Power cost, C_{kW}	£206/kW	
Capacity cost, C_{kWh}	£250/kWh	
Storage time, t	5 hours	
Round trip efficiency, η	75%	
Depth of discharge, D	80%	
Cost of reconductoring, C_r	£70,000 (calculated at £80/m [19])	

Table 3-2: Genetic algorithm parameters

Parameter	Value
Population size	500
Number of generations	10
Crossover probability	0.4
Number of elite population members	1
New population members added per round	50
Simulated annealing maximum temperature	5

3.5 Network model

In order to compare these two topologies, the genetic algorithm with simulated annealing heuristic is applied to a real UK LV network. This network, which was used in [18], has 406 loads applied to 281 buses and 53 PV systems installed. There is a potential for a total of 247 domestic PV systems. Within the heuristic, PV systems in the network have fixed outputs of 2.25 kW and each domestic property draws 290 W. This represents a realistic high PV penetration scenario according to known specifications of the panels and measured network power flows on the LV side of the secondary transformer taken from a low carbon network fund project [40].

To understand the effect of these potential PV systems on the voltage, a Monte Carlo method is used to randomly site PV systems at full power at feasible locations and the highest LV network voltage recorded (Figure 3-4). A load flow is used to obtain the highest voltage in the network and it can be seen that the magnitude of the voltage is sensitive to the exact locations of the PV systems. Voltage rise (magnitude greater than 1.1 p.u.) can occur with as little as 98 systems installed, and certainly occurs with more than 155 systems. Due to voltage drop under high demand, it is not possible to change the tap position on the transformer to alleviate this.

3.6 Results of heuristic application

The Monte Carlo method used in 3.4 is used to randomly locate PV at storage within the network. Then, the heuristic is applied to determine the storage needed to solve the associated voltage problem. The costs of the optimal solutions are shown in Figure 3-5 and Figure 3-6 and are labelled according to the following regions:

A) If there is a voltage problem then storage provides an alternative to reconductoring;
B) Depending on the PV configuration, storage may provide an alternative to reconductoring;
C) Reconductoring is always more financially viable than using energy storage.

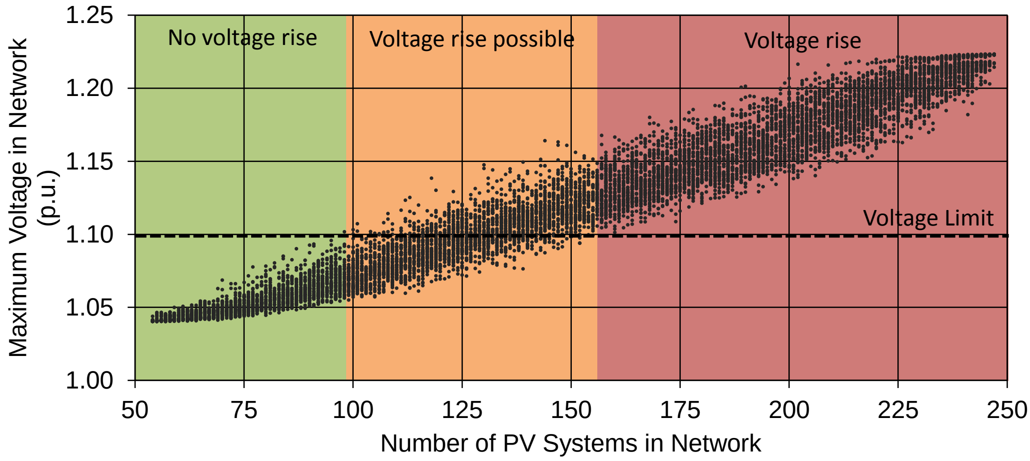

Figure 3-4: Highest voltage in network given 50,000 randomly selected PV configurations

As can be seen by comparing Figure 3-5 to Figure 3-6, the single phase storage is cheaper than the three phase storage under this model and, importantly for DNOs, as single phase storage it is feasible for accommodating a higher PV penetration before reinforcement. When the data is further analysed, single phase storage also has the advantage of using less power to solve the voltage problem (Figure 3-7). The single phase storage is more effective for each unit of power due to the fact it is naturally located by the heuristic on phases relative to the severity of the voltage problem. Accordingly, the power requirement for the three-phase storage may be reduced if it is allowed to act in an unbalanced mode. However, as shown in Figure 3-7 approximately 60% more single phase storage units are required due to the lower rating. This has the benefit of adding more redundancy in the network if a single unit fails but has the disadvantage of requiring more customers to allow the DNO to situate the storage within their home.

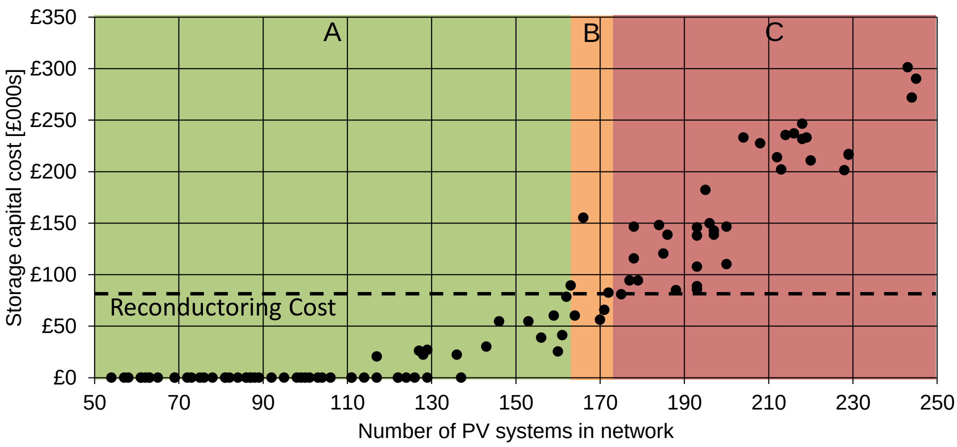

Figure 3-5: Cost of three-phase energy storage compared to traditional re-conductoring

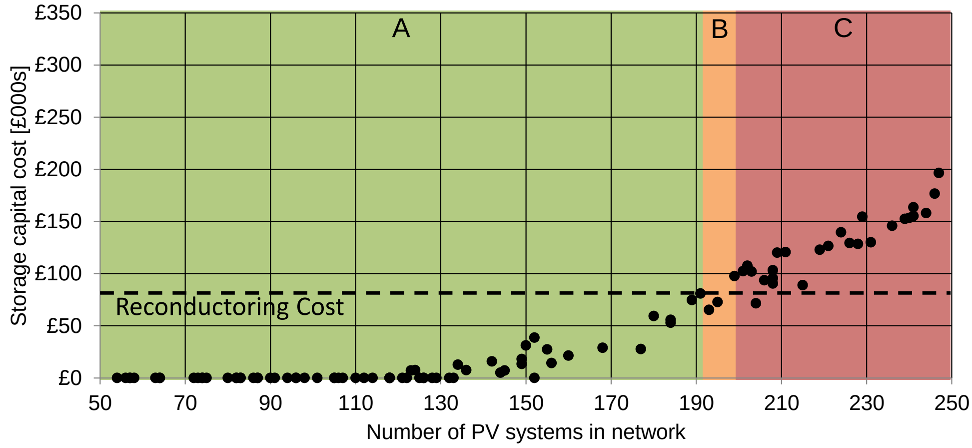

Figure 3-6: Cost of single-phase energy storage compared to traditional re-conductoring

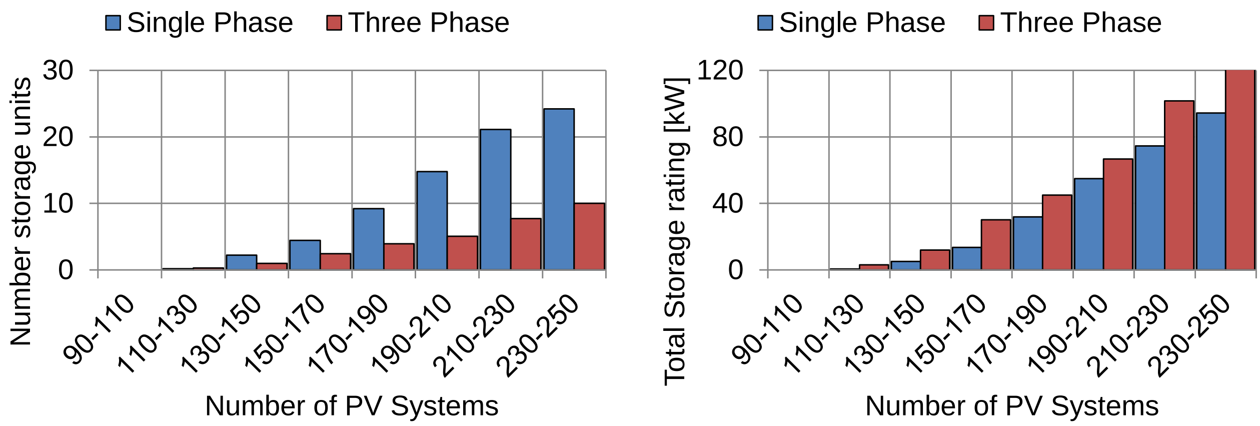

Figure 3-7: Average number of storage units installed for different PV penetrations (left) and average total storage power installed for different PV penetrations (right)

4. Discussion

The new heuristic presented in this paper uses a combination of a genetic algorithm and simulated annealing. This is more stable and produces solutions that require less storage capacity than genetic or simulated annealing algorithms applied on their own. The chosen heuristic is feasible within reasonable computation time because the fitness evaluation has been reduced in complexity to a single time step. This is opposed to other approaches reported in the literature which use time series analysis to assess the storage benefits and specifications. Such detailed time series analysis could subsequently be applied to investigate whether storage configurations found in this paper can be reduced, particularly if the worst case scenario is not a common occurrence in a given network.

Reducing the computational time allows for a number of solutions to be easily calculated. Because of this, it has been possible to evaluate the different storage solutions as the penetration of PV changes in a given network. Such an approach is particularly beneficial in network planning because it allows DNOs to assess the amount of PV that they can allow in a network and when storage is a financially viable alternative to reconductoring. For example, within this paper PV penetrations are found where either storage or reconductoring are financially viable alternatives.

Application of this new heuristic and planning approach shows that single phase storage is potentially more viable than three phase storage for DNOs. This is because it can solve the voltage problem for lower power and energy ratings and lower assumed install costs (primarily because of lower civil costs). However, locating storage in customer property is in practice unattractive for DNOs for a number of reasons, including the possibility of public concerns around battery safety and space requirements. Furthermore, since DNOs do not currently install or manage equipment beyond the cut-out fuse, there are issues surrounding ownership, control, maintenance and access.

This work does not include revenue from thermal protection of network assets under load growth, reducing reverse power or providing backup power which have benefits to DNOs and could improve the business case. Ownership structures need to be considered if the storage is to participate in electricity price arbitrage. This is not permissible by DNOs in the UK regulatory system. Alternative selection methods may also be applied in the heuristic such as tournament or stochastic uniform selection. However, the roulette wheel approach was found to be suitable in this paper for the reasons given in 3.2.4

The heuristic has applications beyond energy storage as it can be adapted to measure the benefits of demand side response or network reconfiguration. Future studies may want to consider the cost of energy storage against other technologies to provide better decision making tools for DNOs as they look for innovative ways to plan and operate their networks. The method could also be applied to inform control algorithms for distributed energy storage or demand side response systems by determining which units to use as the generation and demand changes.

5. Conclusions

This paper presents a heuristic planning tool for locating distributed electrical energy storage in LV networks. Below a particular penetration of PV, distributed storage is shown to offer a lower capital cost method of resolving a voltage rise problem when compared with network reconductoring. Single phase storage at customer premises provides solutions that require overall lower power and energy ratings than three phase storage located on the street. Locating storage in homes can offer benefits to customers by storing self-generated energy and reducing the consumer bill, owing to the structure of the Feed-in-Tariff. This provides additional revenue to offset the cost storage.

The work aligns with the UK Government's Electricity Market Reform process/ by looking at the extent to which energy storage can contribute to addressing problems in the electricity network [41]. To take such a configuration for storage forward would require regulatory support and incentives to instigate demonstration projects in customer homes. Further work is also needed to evaluate operational/maintenance requirements and alternative revenue streams to fully understand the long term costs and benefits to storage owners.

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