ANALYSIS OF THE EFFECT OF PARAMETER VARIATION ON A DYNAMIC COST FUNCTION FOR DISTRIBUTED ENERGY RESOURCES: A DER-CAM CASE STUDY

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ABSTRACT

This paper investigates the effect of selected strategies of distributed energy resources (DER) on an energy cost function, which optimizes the allocation of distributed energy resources for a mid-rise apartment building. This is achieved by comparison of parameter optimization results for both a high- and low-level optimizer respectively. The optimization process is carried out using the following approach: (1) a two-objective function is constructed with one objective function similar to that of the high-level optimizer (DER-CAM); (2) an evolutionary algorithm (EA) with modified selection capability is used to optimize the two-objective function problem in (1) for 4 selected cases of DER utilization previously optimized in DER-CAM. (3) the optimization results of the low-level optimizer are compared with the outcome of DER-CAM optimization for the 4 selected cases. This is done to establish the capability of DER-CAM as an effective tool for optimal distributed energy resource allocation. Results obtained demonstrate the effect of load shifting and solar photovoltaic (PV) panels with power exporting capability on the optimization of the cost function. The Pareto-based MOEA approach has also proved to be effective in observing the interactions between objective function parameters. Mean inverted generational distance (MIGD) values obtained over 10 runs for each of the 4 cases considered show that a DER combination of PV panel, battery storage, heat pump and load shifting outperforms the other strategies in 70% of the total simulation runs.

Keywords: Evolutionary algorithm; pareto front; distributed energy resource

1 INTRODUCTION

Distributed energy resources (DER) is the collective term given to alternative sources of electricity that operate separately from the conventional power grid, but can be incorporated into the existing grid. An optimized combination of these sources results in strategies which make energy usage more efficient, accessible and environmentally sustainable [1]. When these energy sources operate apart from the grid, they are said to be in 'islanding' mode (commonly called distributed generation); and when they are connected to the grid, they are in grid mode.

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Acronyms

PV Photovoltaic
DER-CAM Distributed Energy Resource Customer Adoption Model
DER Distributed energy resources
MOEA Multi-objective evolutionary algorithm
MIGD Mean inverted generational distance
SCADA Supervisory control and data acquisition
OF Objective function
DSM Demand-side management
ToU Time-of-use
HOMER Hybrid Optimisation Model for Electric Renewables
MILP Mixed-integer linear programming
OSR Optimal stopping rule
MFCFS Modified first come first serve
PEEDF Priority enable early deadline first
PEM Point estimate method
DE Differential evolution
PSV Pareto set variation
PS Pareto set
PF Pareto front
IGD Inverted generational distance
NSGA-III Non-dominated Sorting Genetic Algorithm-III
NBI Normal boundary intersection
FE Feature evaluation

Parameters

t=1 hr
d=1 - 365
For $f_1(x,t)$:
$\theta_{1,h}$, $\theta_{k,24}$ battery charging constraint
f_c cost coefficient for DER
$gen_{max,der}$ maximum energy generation coefficient for DER
$c_{cap,der}$ capital cost coefficient for DER
c_{fix} fixed investment capital cost coefficient for DER
$P_{gen,pv}$ power generation coefficient for PV module
$P_{max,pv}$ maximum power generation coefficient for PV module
$P_{cap,pv}$ power generation capacity coefficient for PV module
μ_{pv} energy conversion coefficient for PV module
I_{pv} current generation coefficient for PV module
$t_{op,der}$ time-of-use operating constraint for DER
$l_{max,der}$ maximum power generated by heat pump
$P_{sup,der}$ power supplied by heat pump in DER mix
COP_{der} heat pump operating coefficient in DER mix
For $f_2(x,t)$:
S_{min} minimum operating power for battery state-of-charge
S_{max} maximum operating power for battery state-of-charge
$S_{op,h,24}$ daily battery operating power wrt state-of -charge
$e_{d,h,24}$ hourly energy discharge rate of battery
$e_{c,h,24}$ hourly energy charging rate of battery
P_{conv} maximum power delivered by battery converter
V_{pv} output voltage of PV module
V_{occ} open-circuit voltage of PV module
$V_{m,T}$ maximum voltage at temperature T
$P_{pv,t}$ power supplied by PV module at time t
$P_{pv,T}$ power delivered at temperature T
$P_{pump,t}$ power supplied by heat pump at time t
$\vartheta_{comp,t}$ pump voltage coefficient at time t
$T_{comp,t}$ pump temperature coefficient at time t
P_{ref} pump reference power
$H_{pump,t}$ heat delivered by pump at time t
$c_{heat,t}$ pump heating coefficient at time t
T_{diff} temprature differential for heat pump at time t

There are generally two categories of DER, namely discrete and continuous DER. Discrete forms of DER are those sources that can be switched on and off instantaneously, such as diesel and petrol generators, micro turbines, reciprocating engines and fuel cells [2]. The second category consists of energy sources that are renewed on a frequent basis (for, instance daily) such as wind turbines, solar photovoltaic (PV) panels, and stationary battery banks. The present increase of small-scale urban PV in buildings [3] and urban wind generators [4] can help home electricity consumers also become producers using the smart grid (SG) concept [5][6][7] and the micro-grids approach [8][9]. Over the years, efficient energy dispatch management has become an important priority for distribution network operators. This is because they seek to minimize distribution system losses and cost of maintenance of energy distribution equipment, while maximizing profits and customer satisfaction. This has been made possible through the evolution in distribution network architecture by the application of advancements made in computer science and engineering, and also supervisory control and data acquisition (SCADA) systems [10]. These advancements have led to the development of the concept of smart power grids which are capable of adjusting relevant power supply parameters based on changing demand patterns. A review of the key concepts of smart grids can be found in [5][6][7]. Specifically, [5] explores the optimization of distribution smart grids with distributed renewable generation using a novel approach based on complex networks concepts [11] with evolutionary algorithms. The use of evolutionary algorithms and other computational intelligence techniques in energy can be found in [12][13][14]. Also, with the recent passage of laws in countries like Spain, Germany and the United Kingdom banning restrictions on private energy sourcing [15][16], the demand is rising for specialized software to meet the consumer's energy needs. Since the distribution side of a power supply system represents the downstream sector of the system which links the generation sector with the final consumer, efficient and reliable power supply can only be guaranteed when the distribution system is optimally modelled. Also, the development of alternative energy sources has transformed energy consumers to 'prosumers', which means that they can now play a more active role in the utilization of electricity. Therefore, having a distribution network that is able to accommodate these changes would result in enormous benefits for both the supply and demand side of the energy distribution network.

Optimization is the process of achieving a set objective with the least possible resources. This is important when it is difficult to determine by simple observation, which combination of variables yields the most viable outcome. In such cases, it would be impossible to make a decision based on simply observing the given data because the data points are likely to be as diverse as they are similar, based on the given objective and predefined parameters. The optimization process involves the development of a mathematical model of the problem which represents the problem's variables, constraints and features [17]. This mathematical model of the problem being optimized is commonly referred to as the objective function (OF). When a suitable OF has been obtained, the next step involves selecting a suitable optimization strategy to find the best possible extreme trade-off among the variables (and, in the case of multiple objectives, among the objectives) that best solves the problem. Popular search strategies include stochastic, deterministic and evolutionary algorithms [17]. The fundamental concepts of evolutionary algorithms (EAs) are inspired by two biological phenomena [13][18]: (1) the characteristics of living beings are encoded (represented) using genetic information; and (2) evolution is the result of the interaction between the random creation of new genetic information and the selection of those individuals that are best adapted to the ecosystem [5]. In an EA, candidate solutions ("individuals") for the OF are encoded in a way that simplifies the search for the optimal solution. A set of individuals ("population") is evolved by applying operators (mutation, crossover, selection) in each iteration ("generation"). When fulfilling a stop criterion, the EA ends in providing the solution that optimizes the OF (the individual that is best adapted to the ecosystem, in the biological analogy). More details of EAs applied to DER can be found in [5]. With respect to evolutionary algorithms, they are classified as single-objective, multi-objective or many-objective. The advantage of multi-objective evolutionary algorithms is that they are capable of finding a set of non-dominated solutions rather than a single optimal solution.

The process of optimizing a combination of alternative energy sources with respect to cost minimization and efficient energy supply from the demand side involves developing an OF representing the various sources in the DER mix, subject to specified constraints. The result of the optimization process is a combination of DER technologies that could benefit the consumer from both a cost and demand perspective. This ensures that both sides of the distribution network benefit mutually. A typical optimization process is shown in Fig. 1. The process of parameter selection and optimization has been investigated in [19][20][21]. Reinforcement learning has been applied to the training and validation of network parameters for wireless communications systems. This paper adopts a similar approach, and involves the optimization of a cost function for selected combinations of DER technologies in a mid-rise apartment building. Using a low-level Pareto-based evolutionary algorithm, the optimal mix of energy sources is obtained for four scenarios: a base case with no DER, and 3 other cases involving varied combinations of PV solar panel, battery storage, air source heat pump and load shifting. The rest of the paper is organized as follows: Section 2 discusses the impact of optimization in determination of DER dispatch strategies. Section 3 discusses the DER-CAM and two-objective cost function for the 4 selected cases of DER strategies, as well as the parameter specification for the two-objective cost function. Section 4 discusses the outcome of the optimization using the multi-objective evolutionary algorithm and compares results with DER-CAM optimization. Section 5 concludes the paper.

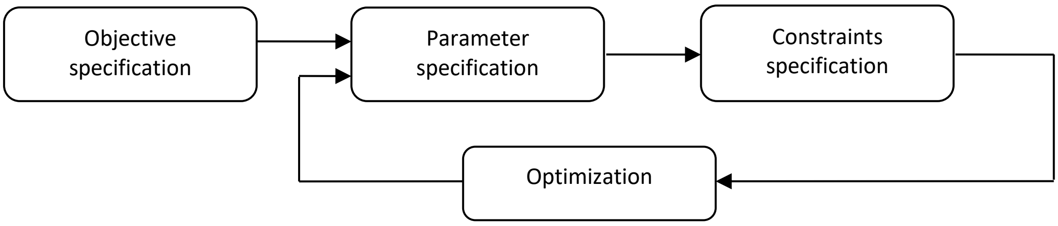

Fig. 1 Steps involved in the process of Optimization

2 THE ROLE OF OPTIMIZATION IN DEMAND SIDE MANAGEMENT (DSM) OF DER

Smart power grids are the result of a system of technologies, which are able to anticipate the needs of consumers based on an accurate prediction of their energy usage profiles over a specified period of time. With regard to buildings and microgrids, the optimization of parameters related to energy demand, energy pricing for time-of-use (ToU) patterns and weather information (with regard to renewable sources) can allow consumers to minimize both the amount paid for electricity and the effect of distributed generation on the environment. There is therefore the need for reliable algorithms which are capable of ensuring that these smart grids balance usability with cost-effectiveness.

A lot of research has focused on the application of optimization techniques to distributed generation of electricity. However, not much work has analysed the results of these optimizers in order to determine whether or not they are likely to translate to cost-effective physical implementations. This real-life scenario implementation problem has been highlighted in [1] and [16].The following are some approaches that have been adopted to issues relating to load scheduling, optimal DER combination and scheduling and capacity expansion.

In [22], the effect of capacity expansion strategies on long-term economic performance for a rural mini-grid operator was investigated. The research proposed a linear bottom-up model, and used DER-CAM to implement the capacity investment model. The results of the research revealed that a cost-optimized model alone is likely not the best long-term investment solution. In [23], another optimal DER combination for rural areas in Nigeria was considered. Hybrid Optimisation Model for Electric Renewables (HOMER) was used to analyse various combinations of renewable energy sources for six randomly selected rural communities across the country. It was found that for a sensitivity of $1.1 and $1.3/l of diesel, the PV/diesel/battery combination was the most cost-effective solution. This model was the most effective in terms of fuel consumption and CO_2 reduction.

A trade-off between grid expansion and stand-alone electricity generation from renewable sources was considered in [24]. An off-grid, remote village in the state of Chhattisgarh in India was used as a case study; and the electricity demand profile included domestic consumption, as well as industrial, commercial and agricultural utilization. The research outcome proposed a least-cost combination of small hydropower, solar PV, bio-diesel and batteries. However, it was concluded that the reliability of the proposed system was likely to reduce in the winter season with less availability of hydropower. A mixed integer linear programming (MILP) model was adopted in [25] for DSM with renewable sources including optimally scheduled injection from electric vehicles (while they were parked). The aim of this work was to reduce reliance on the main electricity grid by scheduling consumer demand. The DSM schedule included time- and power-shiftable appliances, and also the contribution of EVs in V2G mode while parked. Compared to a base case with no EV injection and no home DSM, the proposed model provided the best energy and cost savings model for the consumer.

A scheduling algorithm based on the optimal stopping rule (OSR) technique was proposed in [26]. OSR uses a sequence of reward functions to select an optimal time slot in the search process, which either minimizes total cost or maximizes expected return. This approach was used to efficiently manage limited grid supply using modified first come first serve (MFCFS) and priority enable early deadline first (PEEDF) algorithms for the load scheduling process. Also, in [27], a demand response algorithm was proposed using a cost minimization function consisting of maintenance and power loss costs, as well as the cost of energy not supplied. The ant colony optimization approach was used to realize the point estimate method (PEM). The proposed approach was applied to a 69-bus distribution system consisting of 4 wind turbines, 3 PV panels and 3 battery storage systems. The simulations resulted in a flattened load profile based on optimal load shifting from high price periods to other cost-saving periods.

Many of the above mentioned research for optimal DER mixing and scheduling (especially those based on specialized platforms like HOMER and DER-CAM) typically adopt a 'blackbox' approach to the simulation/optimization of energy usage data, and they adopt more of an optimization approach than a simulated one. Furthermore, since proposed results are based on simulation, there is need for a means of verifying that the optimized output of these platforms is indeed the best possible, cost-effective outcome for real-life implementation.

3 MODELLING OF THE COST FUNCTION: A DER-CAM CASE STUDY

Several tools and methods of optimizing various aspects of a smart grid have been used in the literature, as discussed in the previous section of this paper. However DER-CAM has gained attention in recent years due to the following reasons:

- Its input and output can be easily interfaced with common software platforms like MATLAB and Vensim
- Due to its optimization-based mathematical model, it can be reliably applied to situations involving a large number of decision variables to make accurate DER investment and dispatch decisions
- Its customer-based model makes it suitable for DSM and time-of-use (ToU)-based DER scheduling

This paper is based on the idea of ‘optimizing the optimizer’ in which the performance of DER-CAM as an optimization model is analyzed using a Pareto-based multi-objective evolutionary algorithm (MOEA). The main contributions of this paper are:

- To analyse the performance of DER-CAM using a Pareto-based MOEA with differential evolution (DE)-inspired candidate selection strategy.
- To test the capability of the Pareto-based optimization approach to provide a cost-effective balance among selected parameters of the DER strategies being considered

Performance metrics of mean inverted generational distance (MIGD), Pareto solution spread and Pareto set variation (PSV) will be used to compare the performance of the selected DER cases optimized by DER-CAM [29]. The flowchart representing the proposed optimization approach is shown in Fig. 2.

(a) DER-CAM Cost Function

DER-CAM is an optimization platform that provides information regarding the viability of various DER configurations from both an economic and environmental perspective. The latter is achieved by providing information on the DER mix that yields the least CO_2 emissions, while the former is done by obtaining the most cost-effective mix of generation and storage installations [29]. Therefore, DER-CAM is useful for both investment and planning decisions. DER-CAM does not perform simulations or power flow analyses, and can be utilized for both buildings and microgrids. The data being used in this paper is for a mid-rise building, and data points have been adapted from [28]. This is as a result of the fact that DER-CAM is a physically-based optimization model [29]. The microgrid to which the apartment is connected is shown in Fig. 3, and the information about microgrid cable impedances and transformer specifications can also be obtained from [28].

The cost function for DER-CAM is formulated as a mixed integer linear programming (MILP) problem in which objective functions and constraints are linear, while decision variables can be either integer or continuous [29]. The objective cost function to be minimized consists of:

- Retail electricity charges (by the distribution network operator on a monthly basis)
- Energy charges per unit load/hour/day/month (for peak, week, and weekend days)
- Maximum power charges (for peak days)/hour/day/month
- Total generation cost/DER/hour/day/month (for each DER utilized)
- Total depreciation cost for each DER (over a 20-year period)
- Excluding the total energy exported to the grid by each DER

The high-level mathematical representation of the cost function can be found in [29].

(b) Proposed two-objective Pareto-based Optimization

The Pareto-based dynamic evolutionary algorithm attempts to optimize the Pareto front for two objective functions $f_1(x,t)$ and $f_2(x,t)$. The first objective is similar to the cost function for DER-CAM while the second is an energy consumption minimization function with regard to the DER utilized with a resulting decrease in CO_2 emissions. The mathematical forms of the objective functions are given in equations (2) and (3).

$$f_1(x,t) = \min \alpha_c(t) \tag{1}$$

$$\alpha_c(t) = \sum_1^m r_e + \sum_1^m \sum_1^t \sum_1^n \mu_l \cdot r_e + \sum_1^p \sum_1^m r_{e,p} \cdot \mu_{l,p} + \sum_1^s \sum_1^m \sum_1^t P_{gen,der} \cdot c_{gen,kwh} + \sum_1^s P_{max,der} \cdot C_{c,der} \cdot F_a - \sum_1^s \sum_1^m \sum_1^t P_{gen,der} \cdot r_{exp,der} \tag{2}$$

where:
r_e = electricity rate (peak, week, weekend)
s = no. of DER technologies
$P_{gen,der}$ = power generated by DER
$c_{gen,kwh}$ = cost of generation/KWh
$P_{max,der}$ = max. power gen. by DER over 20 year period
$C_{c,der}$ = cap. cost of DER over 20 year period (maintenance, etc.)
F_a = annuity factor
$r_{exp,der}$ = electricity export rate/DER/day/month
m = number of months
t = 1hr (interval between data points)
n = denotes peak, week or weekend day
μ_l = normalization factor
$\mu_{l,p}$ = normalization factor for electricity rates on peak days
p = denotes rates that relate to peak days

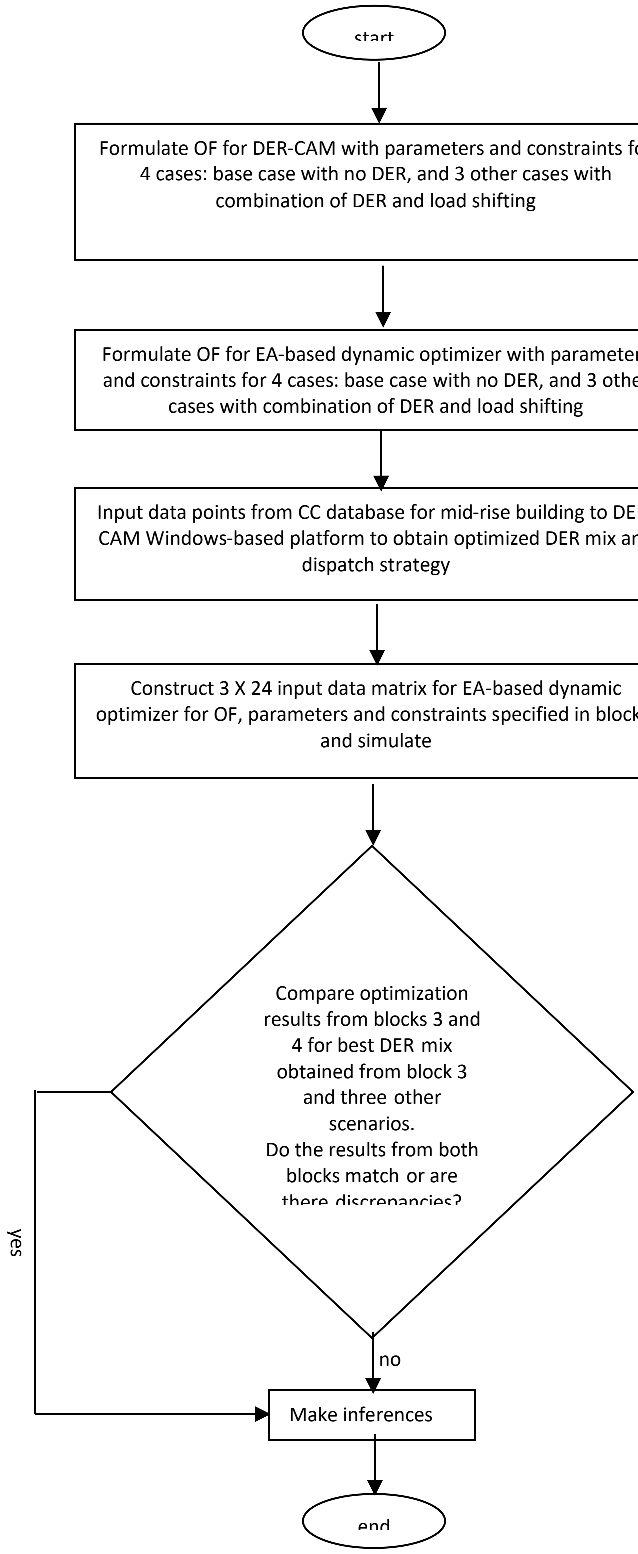

Fig. 2 Proposed optimization approach for comparison with DER-CAM optimization

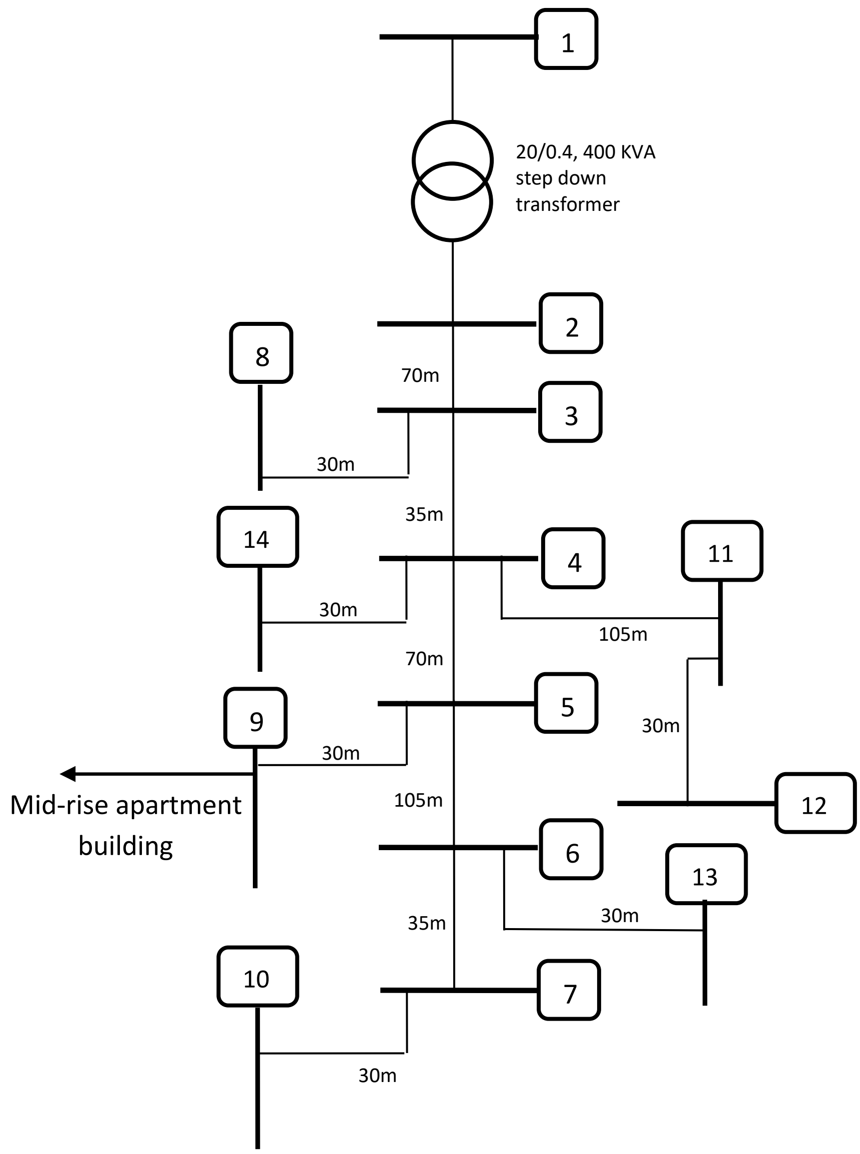

Fig. 3 14-bus microgrid connecting mid-rise apartment (all bus connection cable lengths are in metres) [28]

$$f_2(x,t) = \sum_1^d \sum_1^t \left(e_b + e_{pv} + e_{hp}\right) + \sum_1^d \sum_1^t \sum_1^n \eta_s \tag{3}$$

where:

e_b= battery energy coefficient, e_{pv}= solar PV panel energy coefficient, e_{hp}= air source heat pump energy coefficient, η_s= model for load shifting strategy, d=day (week, weekend, peak), n=number of shiftable loads (it is assumed that for all d, n=3).

Parameters in Equation (3) are defined as follows:

$$e_b = S(t-1) + \begin{cases} e_c \cdot t \cdot \mu_b \\ -e_d \cdot (t/\mu_b) \\ 0 \end{cases} \tag{4}$$

where:

S= State-of-charge of battery, t= charging time, μ_b= battery efficiency, e_c= charging power, e_d= discharging power.

$$e_{pv} = k\beta_a - (0.01\beta_{op}) \tag{5}$$

where:
k= Boltzmann constant, β_a= adjusted power of PV module due to temperature changes across the module, β_{op}= output power of PV module under standard operating conditions.

$$e_{hp} = \frac{\alpha_{he}}{P_c} \tag{6}$$

where:
α_{he}= power generated through heat exchange process, P_c = thermal power of compressor

$$\eta_s = \begin{cases} \gamma_1\delta_t(d-1) + \gamma_2\delta_t[d-2] + \gamma_7\delta_t[d-7] \\ \gamma_1\rho_t[d-1] + \gamma_2\rho_t[d-2] + \gamma_7\rho_t[d-7] \end{cases} \tag{7}$$

where:
$\gamma_1, \gamma_2, \gamma_7$= shifting constants, d= day of the week, δ_t, ρ_t= shifting parameters

Constraints for $f_1(x,t)$ include:

$\theta_{1,h} = \theta_{k,24}$ (battery constraint) (8)
$f_c \leq gen_{max,der} \cdot c_{cap,der} \cdot F_a + c_{fix}$ (DER investment constraint) (9)
$P_{gen,pv} + P_{max,pv} \leq P_{cap,pv} \cdot \mu_{pv} \cdot I_{pv}$(PV module generation capacity constraint) (10)
$P_{gen,der} + P_{max,der} \leq c_{inv,der} \cdot P_{maxgen,der}$(DER max. power gen. constraint) (11)
$P_{gen,der} + P_{max,der} \leq c_{inv,der} \cdot P_{maxgen,der} \cdot t_{op,der}$(ToU constraint) (12)
$l_{max,der} = P_{gen,der} + P_{sup,der} \cdot COP_{der}$(heat pump operating constraint) (13)

Constraints for $f_2(x,t)$ include:

$S_{min} \leq S_{op,h,24} \leq S_{max}$(battery constraint) (14)
$e_{d,h,24} \leq P_{conv}$(battery constraint) (15)
$e_{c,h,24} \leq P_{conv}$(battery constraint) (16)
$V_{pv} = V_{occ} + V_{m,T}$(PV module operating constraint) (17)
$P_{max,PV} = P_{pv,t} + P_{pv,T}$(PV module operating constraint) (18)
$P_{pump,t} = \vartheta_{comp,t} \cdot T_{comp,t} \cdot P_{ref}$(heat pump constraint) (19)
$H_{pump,t} = c_{heat,t} \cdot T_{diff}$(heat pump constraint) (20)

f_1 represents the constructed cost function based on distributed energy resources (similar to that used in DER-CAM optimization model). f_2 specifies the variables for the considered energy sources (PV, battery and air source heat pump).The two-objective optimization space has been used in order to validate the optimization capability of DER-CAM. Three test cases are considered which have been selected from the DER-CAM optimization in [28] for the following cases:

Case 1: Investment is made in solar PV panels with capability to export excess energy, and battery, air source heat pump, and load shifting are also utilized

Case 2: Investment is made in solar PV panels for self-consumption only, and battery and air source heat pump, with load shifting are also utilized

Case 3: Investment is made in solar PV panels with capability to export excess energy, and battery and air source heat pump are utilized

Case 4: This is base case without DER strategy, and all supply and demand are met by distribution utility

The three test cases (Case 1 – Case 3) have been considered in this paper because they are the optimal cases selected by DER-CAM based on the analysis in [28]. Parameter variation for the above investment scenarios are compared with the base case in which no investment is made in DER with all supply and demand being made by the energy distribution utility. For the above mentioned cases, the effect of the utilization of PV panels on the Pareto set for both self-consumption and energy export will also be considered. The Pareto-based Genetic algorithm used to optimize the dynamic bi-objective problem specified in equations (1) and (2) is detailed in Algorithm 1. All simulations are done using PlatEMO open source MATLAB-based platform [30].

Algorithm 1 Steps in optimizing $f_1(x,t)$ and $f_2(x,t)$

Input: OF parameters, optimization parameters
Output: Pareto optimal set, MIGD
Start
Specify $f_2(x,t)$ based on case (n)
Activate input matrices for $f_2(x,t)$
Perform genetic mutation, crossover and selection based on specified crossover rate. Adjust mutation and crossover rate for optimal Pareto front (PF)
Use DE/rand-to-best/ for final selection of Pareto set (PS)
End

The mean inverted generational distance (MIGD) is the metric that is being used in this paper to evaluate the Pareto front for each of the 4 cases optimized by DER-CAM. The smaller the numerical value of the MIGD, the better the PF is likely to be. The mathematical form of the MIGD is given in Equation (21).

$$MIGD = \frac{1}{|\tau|}\sum_{t\in\tau} IGD(\hat{\rho}_t, \hat{\beta}_t) \quad (21)$$

where
$\hat{\rho}_t$ and $\hat{\beta}_t$ are the directional vectors for $f_1(x,t)$ and $f_2(x,t)$ respectively

With regard to Algorithm 1, crossover is uniform and real-valued. Randomized mutation has been used based on vector change. Selection is done using the DE/rand-to-best/ strategy which allows the selection of the best-performing candidates for the Pareto set. Therefore, this strategy also helps in mutation of candidates towards final selection. The algorithm is based on the Non-dominated Sorting Genetic Algorithm (NSGA-III) [31][32]. Reference points and Euclidean distance are used to control crowding of candidates. Mutation and crossover rates are adaptively adjusted using the orientation of reference points and normal boundary intersection (NBI) discussed in [33].

The behaviour of the particles in the OF space is also observed using the Pareto set variation, as well as the spread of the particles along the PF. The simulation parameters are specified in Table 1. The crossover rate is adaptive based on the use of both reference points and the NBI technique to balance both convergence and diversity. The number of feature evaluations (FEs) is selected as 10,000 to allow for the settling of non-dominated solutions to constitute the final Pareto set. The differential evolution (DE) selection strategy aids both mutation and final selection of the Pareto set by controlling selection pressure.

Table 1 Parameter Settings for two-objective Pareto-based Evolutionary Algorithm

Parameter	Setting
Number of dimensions	100
Number of Feature Evaluations (FEs)	10,000
Number of simulation runs per case	10
Mutation rate	1/n
Crossover rate (adaptive)	0.5 – 1.0
Population size	50
Selection strategy	DE/rand-to-best/1
Number of generations	500

4 RESULTS AND DISCUSSION

Fig. 5 shows the approximation of the true Pareto front (shown in Fig. 4) for each of the specified cases. The approximation is done by using the normal boundary intersection (NBI) method [32] to guide the candidates towards the final non-dominated Pareto front. It can be seen that the scenario in which there is no adoption of DER (Case 4) has the worst approximation of the PF, while Case 1 has the best approximation. This demonstrates that in this case study, DER-CAM gave the most economically viable solution based on the adopted DER mix. For the Cases 2 and 3, it can be seen that the use of the load-shifting strategy marginally improves the cost and energy consumption optimization functions for the consumer. This results in a comparatively more stable and cost-effective energy profile. It can also be seen that cases 1 and 2 take less time to explore and exploit the search space (observed from the axial calibrations of $f_1(x,t)$ and $f_2(x,t)$) compared to the Cases 3 and 4. This means that the parameter selection for the cases involving load shifting as an economically viable strategy results in a more optimized PF. For each case (particularly Case

3 and 4), it is observed that some of the points on the Pareto front are dominated. This is likely due to the interaction of selected parameters in the OF space on selection pressure of candidates.

The manner in which the particles in the search space settle on the final Pareto set is observed by the variation of the Pareto set over the selected number of dimensions (Fig. 6). Each particle in the search space explores the best possible solution in 100 different directions before finally converging to the final optimal candidate. For Case 1, it is observed that the particles settle much more quickly compared to the other three cases. In the Cases 3 and 4, the particles are in a state of almost constant oscillation, which makes it difficult for them to settle on the final PF. This is evidenced by the disoriented PF in both cases.

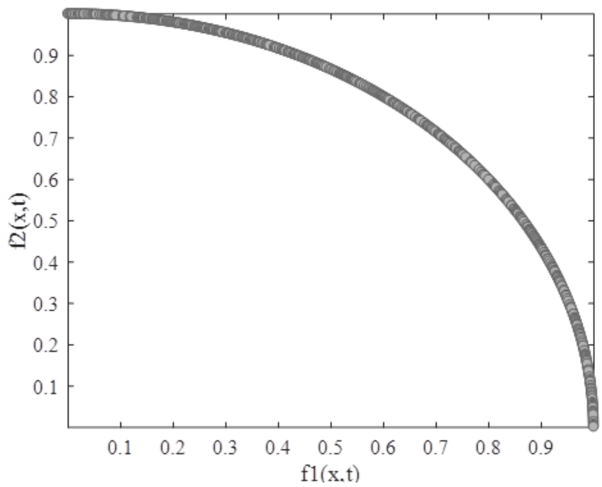

Fig. 4 True PF for $f_1(x,t)$ and $f_2(x,t)$

Table 2 MIGD values over 10 runs for each case of DER mix

	Case 1	**Case 2**	**Case 3**	**Case 4**
Run 1	**1.5672e-02**	2.0148e-02	3.7531e-02	4.4972e-01
Run 2	**2.2234e-01**	3.5951e+00	2.1093e+00	1.7693e+01
Run 3	**2.0087e-03**	3.8502e-02	1.1096e-01	3.0875e+02
Run 4	2.5073e-01	**1.9617e-01**	1.0462e+00	2.9839e+02
Run 5	**2.3394e-01**	3.5183e+00	5.1907e-01	4.4097e+00
Run 6	**1.9431e-03**	2.6783e-02	4.4219e-01	3.8519e+01
Run 7	2.1104e-02	**1.5072e-03**	6.0173e-02	6.3184e-01
Run 8	**1.8257e-01**	2.3725e+00	3.2038e+00	5.0318e+01
Run 9	**1.9736e-03**	4.5932e-02	1.2563e-01	2.3058e+00
Run 10	2.8847e-01	2.7931e-01	**3.5072e-02**	1.9417e+01

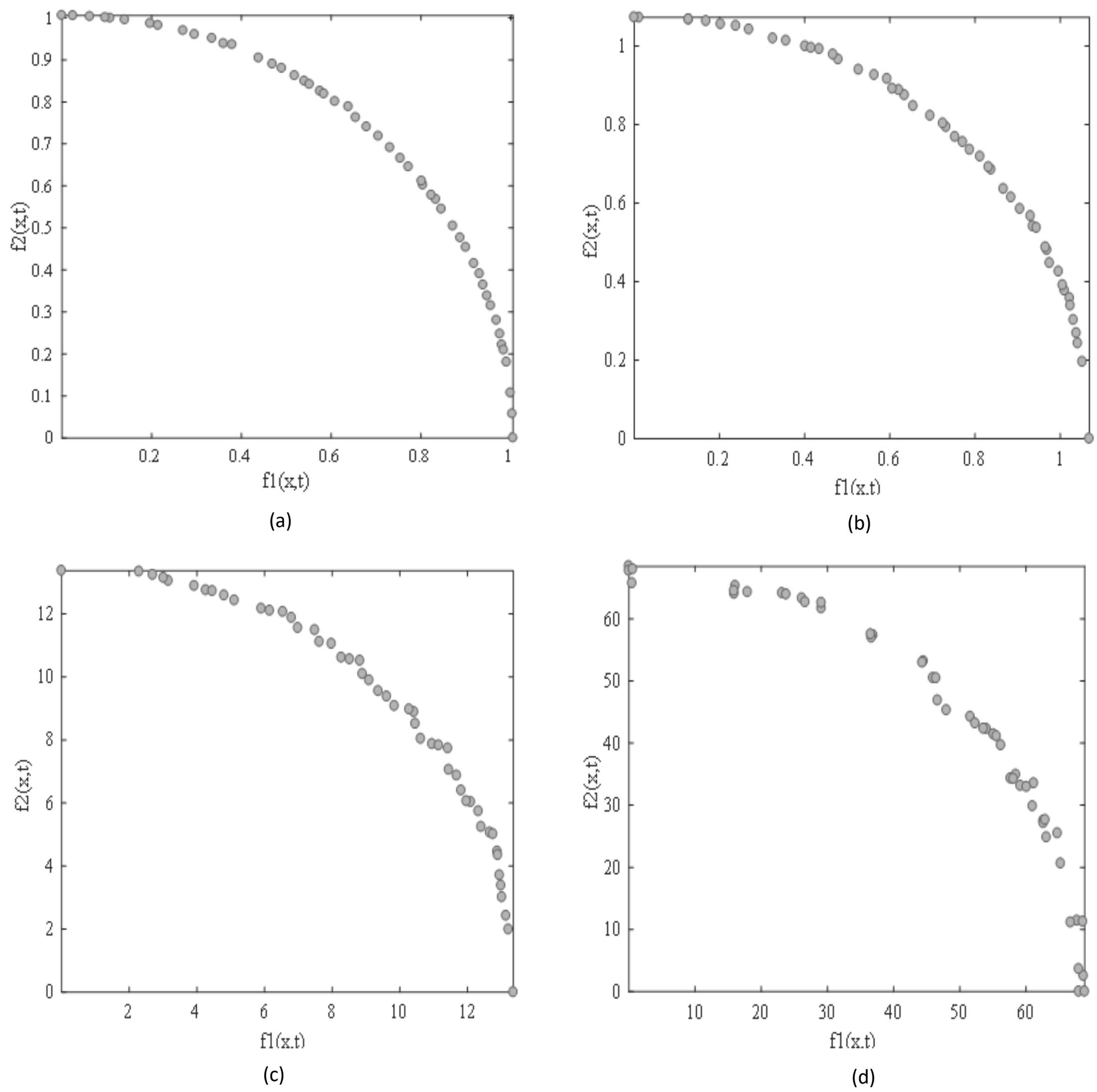

Fig. 5 Two-objective PF for (a) Case 1 (b) Case 2 (c) Case 3 (d) Case 4

The diversity of the particles that constitute the final Pareto set has also been considered by observing the behaviour of the Pareto set over 10,000 feature evaluations (FEs). The ability of the particles to efficiently explore the search space for potential solutions ensures a uniform spread of solutions over the PF. In Case 4 (Fig. 6), evidence of premature convergence, and consequently poor solution spread over the PF is observed over 5,000 FEs (between 2,000 and 7,000 FEs). Therefore, the OF parameters cannot be fully explored, thus leading to the poor PF observed in Fig. 5d. Since parameter selection is made based on the DER mix, it is to be expected that there would be a poor performance over the two-objective space since $f_2(x,t)$ is almost non-existent for Case 4.

By contrast, the spread for Case 1 can be seen to be steady over 7,000 FEs (between 2,000 and 9,000 FEs). The outlier around 7,000 FEs is likely a case of premature converge which is handled by the DE/rand-to-best/ selection strategy in such situations. Cases 2 and 3 are also quite impressive in terms of maintaining diversity of the Pareto front due to a utilization of elements of the DER mix such as PV panels and load shifting. For Case 2 in particular, the spread over the PF appears to be more stable compared to Case 3 which has no load shifting strategy.

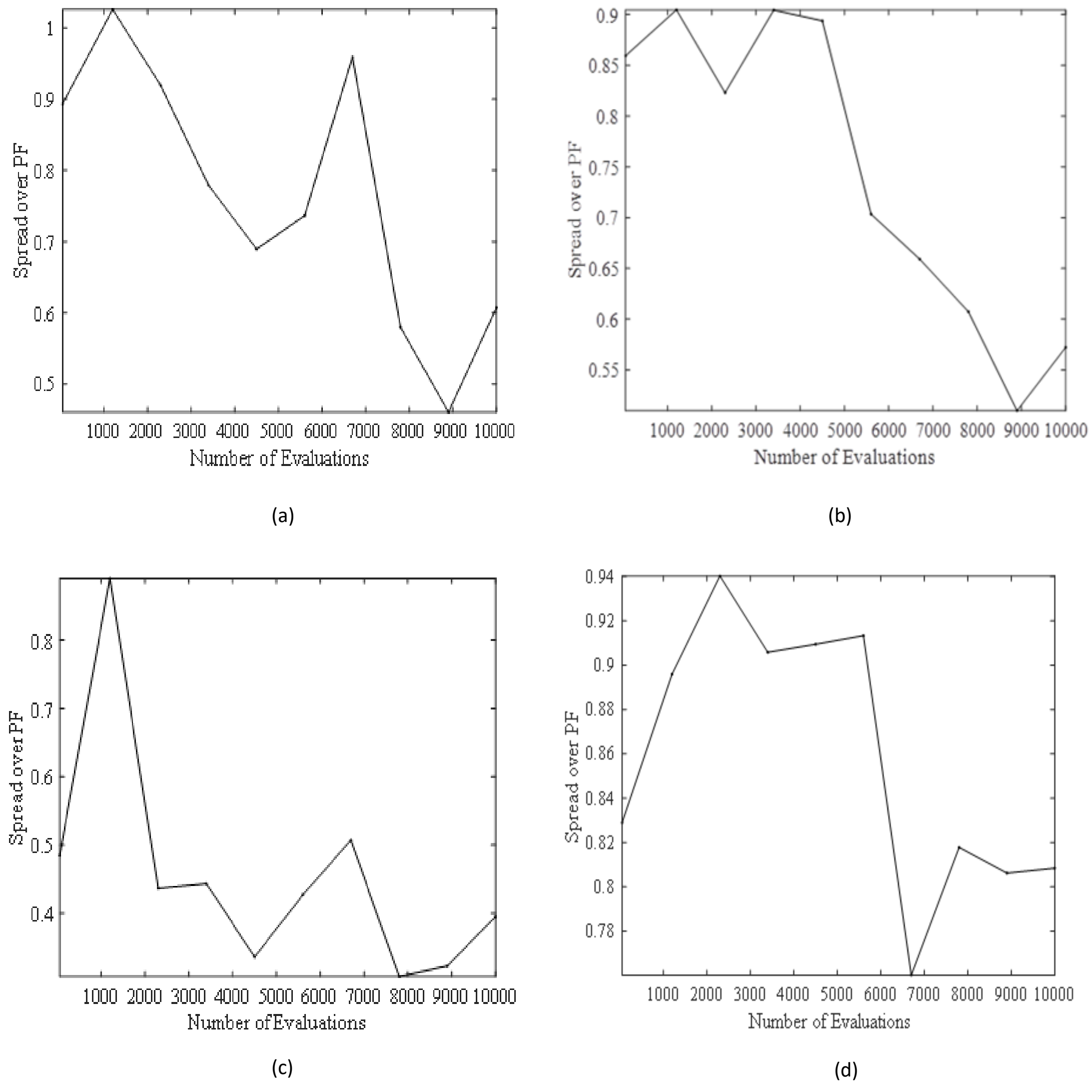

Fig. 6 Solution spread over the PF for (a) Case 1 (b) Case 2 (c) Case 3 (d) Case 4

The Pareto set variation is a measure of the ability of particles in the objective search space to settle on the final optimal Pareto front. This was simulated over 100 dimensions for each case with results shown in Fig. 7. As predicted by DER-CAM, Case 1 had the best Pareto set variation over the specified number of dimensions, with case 4 having the worst variation. Case 2 outperformed Case 3 in being able to settle on the final PF (as seen in Fig. 5). The extremely erratic response observed in Fig. 7d for Case 4 is as a result of the fact that the parameter matrices for $f_2(x,t)$ have all been set to zero since no DER strategy is adopted. Therefore, there is no attempt to balance the tradeoff between the two objectives.

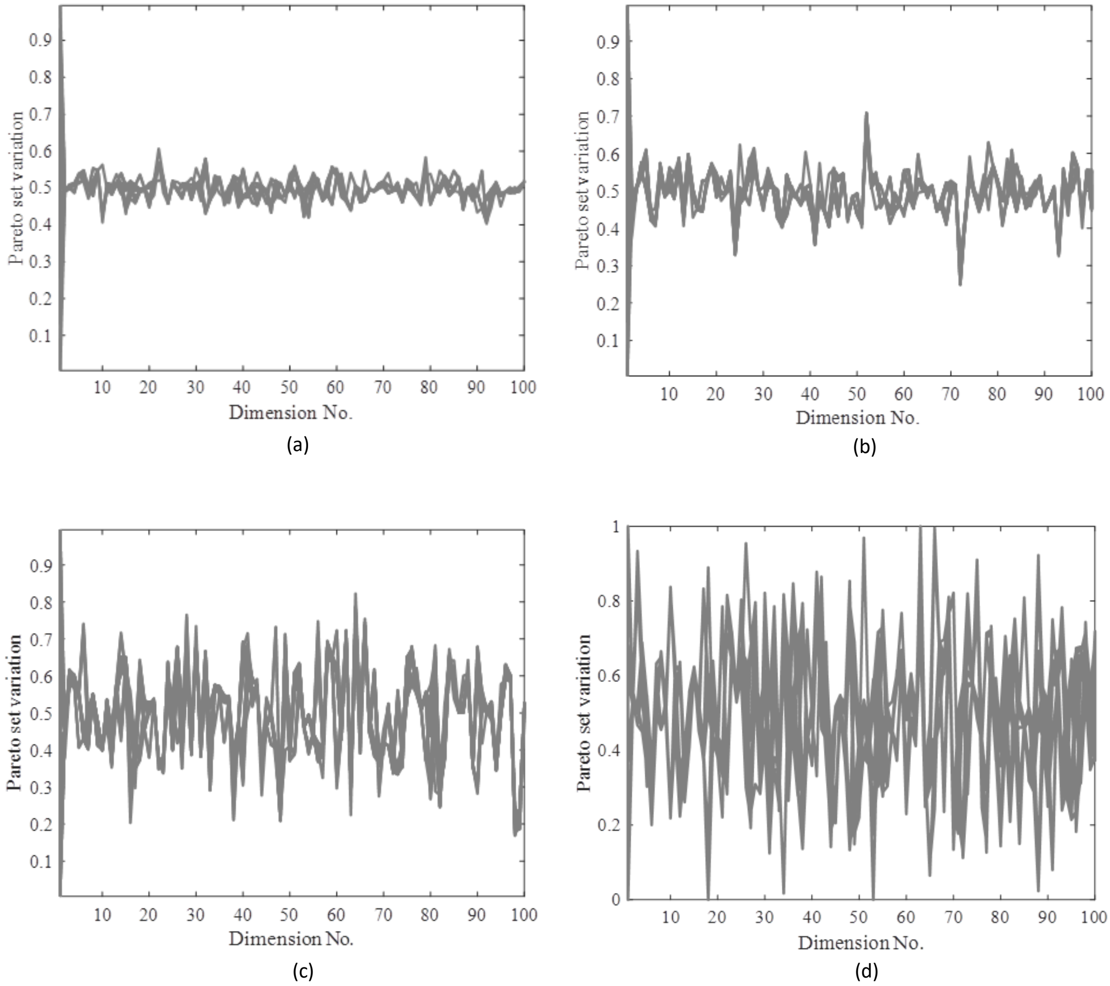

Fig. 7 Pareto set variation over the PF for (a) Case 1 (b) Case 2 (c) Case 3 (d) Case 4

For the analysis carried out in Figs. 5, 6 and 7, the best results over 10 simulation runs were selected for each case. In order to ascertain the results obtained, MIGD values were obtained over 10 runs for each of the four cases considered. Results are shown in Table 2. Each test case has 10 simulation runs because it is observed that the MIGD values do not vary significantly beyond this number of runs. It is observed from the results that Case 1 had the best MIGD values (shown in boldface) for 7 out of 10 runs for all cases over the two objective functions while it was outperformed by Case 2 in 2 runs (run 4 and run 7) and by Case 3 in 1 run (run 10). With exception of run 1, Case 4 had the highest MIGD value for all other simulation runs, which means that it had the worst performance for 90% of the simulation runs.

From the results obtained, it has been established that the combination of both solar PV panels with capability to export excess energy and load shifting strategy has the best tradeoff between the two objectives. This result also confirms the optimized output from DER-CAM for the mid-rise building, thereby confirming the capability of DER-CAM to give accurate optimization results regarding the most cost-effective DER strategies for a particular energy usage profile and location. The results obtained also raised questions regarding the economic viability of combining PV panels with and without energy export capability, and load shifting strategies for particular scenarios. While energy export to the grid may have its merits, the results obtained for the Cases

2 and 3 suggest that combination of energy export and load shifting may not always be the best economic strategy given specific energy usage profiles (particularly situations in which there are generally few peak energy usage periods).

5 CONCLUSIONS

This paper has examined the effect of parameter variation for 4 cases of DER mix using a dynamic two-objective Pareto-based evolutionary optimization. The objective function has been designed such that the first cost function is similar to the MILP objective function used by DER-CAM for finding the optimal mix of distributed energy resources from an economic and environmental perspective. The microgrid under consideration supplies a mid-rise apartment building and the energy usage profiles used in the optimization, and results obtained are to efficiently manage energy usage for the specific building and microgrid.

The paper has made the following research contributions based on the results obtained:

1. A Pareto-based modelling approach has been used to investigate the ability of DER-CAM to optimize distributed energy resources for real-life applications
2. The Pareto-based approach has been used to examine the effect of parameter variation on the optimization of an energy cost function. This has been achieved by observing the effect of parameter variation of selected cases of DER mix on the approximation of a 2-objective Pareto front
3. The Pareto-based approach has the capability to allocate DER in a sustainable and cost-effective manner

Further research will examine the relationship between energy usage profiles with and without considerable peak energy usage profiles, and the economic viability of combining load shifting with energy export to the grid. Also, the effect of parameter selection and interaction in the objective function space will be investigated. The aim of this will be to improve the integrity of the non-dominated candidate solutions. Overall, it has been established that DER-CAM is indeed an effective tool for optimization of distributed energy resources for specific energy usage profiles. Also, the Pareto-based EA optimization approach provides an effective means of examining the effect of parameter variation on the behaviour of the energy cost function.

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REFERENCES

[1] D. Steen, M. Stadler, G. Cardoso, M. Groissböck, N. DeForest and C. Marnay, “Modeling of thermal storage systems in MILP distributed energy resource models,” *Applied Energy,* vol. 137, pp. 782-792, 2015.

[2] X. Feng, J. Stoupis, S. Mohagheghi and M. Larsson, “Introduction to Smart Grid Applications,” in *Smart Grid: Applications, communications, and security*, New Jersey, John Wiley & Sons, 2012, pp. 25-26.

[3] J. Salpakari and P. Lund, “Optimal and rule-based control strategies for energy flexibility in buildings with PV,” *Applied Energy,* vol. 161, pp. 425-436, 2016.

[4] A. Yang, Y. Su, C. Wen, Y. Yuan, W. Wang and C. Cheng, “Estimation of wind power generation in dense urban area,” *Applied Energy,* vol. 171, pp. 213-230, 2016.

[5] L. Cuadra, M. Pino, J. Nieto-Borge and S. Salcedo-Sanz, “Optimizing the structure of distribution smart grids with renewable generation against abnormal conditions: A complex networks approach with evolutionary algorithms,” *Energies,* vol. 10, no. 8, p. 1097, 2017.

[6] I. Colak, S. Sagiroglu, G. Fulli, M. Yesilbudak and C. Covrig, “A survey on the critical issues in smart grid technologies,” *Renew. Sustain. Energy Rev,* vol. 54, pp. 396-405, 2016.

[7] M. Tuballa and M. Abundo, “A review of the development of Smart Grid technologies,” *Renew. Sustain. Energy Rev.,* vol. 59, pp. 710-725, 2016.

[8] Y. Yoldas, A. Onen, S. Muyeen, A. Vasilakos and I. Alan, “Enhancing smart grid with microgrids: Challenges and opportunities,” *Renew. Sustain. Energy Rev,* vol. 72, pp. 205-214, 2017.

[9] R. Mallol-Poyato, S. Salcedo-Sanz and P. Diaz-Villar, “Optimal discharge scheduling of energy storage systems in MicroGrids based on hyperheuristics,” *Renewable Energy,* vol. 83, pp. 13-24, 2015.

[10] X. Feng, J. Stoupis, S. Mohagheghi and M. Larsson, “Introduction to Smart Grid Applications,” in *Smart Grid: Applications, communications, and security*, New Jersey, John Wiley & Sons, 2012, pp. 29-32.

[11] L. Cuadra, S. Salcedo-Sanz, J. Del Ser, S. Jimenez-Fernandez and Z. Geem, “A critical review of robustness in power grids using complex networks concepts,” *Energies,* vol. 8, no. 9, pp. 9211-9265, 2015.

[12] S. Faizollahzadeh Ardabili, B. Najafi, S. M. B. B. Shamshirband, R. Deo and K. Chau, “Computational intelligence approach for modeling hydrogen production: a review,” *Engineering Applications of Computational Fluid Mechanics,* vol. 12, no. 1, pp. 438-458, 2018.

[13] L. Cuadra, S. Salcedo-Sanz, J. Nieto-Borge, E. Alexandra and G. Rodriguez, “Computational intelligence in wave energy: Comprehensive review and case study,” *Renewable and Sustainable Energy Reviews,* vol. 58, pp. 1223-1246, 2016.

[14] L. Jiang, R. Srivatsan and D. Maskell, "Computational intelligence techniques for maximum power point tracking in PV systems: A review," *Renewable and Sustainable Energy Reviews,* vol. 85, pp. 14-45, 2018.

[15] J. Tant, F. Geth, D. Six, P. Tant and J. Driesen, "Multiobjective battery storage to improve PV integration in residential distribution grids," *IEEE Transactions on Sustainable Energy,* vol. 4, pp. 182-191, 2013.

[16] A. S. Hassan, L. Cipcigan and N. Jenkins, "Optimal battery storage operation for PV systems with tariff incentives," *Applied Energy,* vol. 203, pp. 422-441, 2017.

[17] S. Kiranyaz, T. Ince and M. Gabbouj, Multidimensional Particle Swarm Optimization for Machine Learning and Pattern Recognition, Berlin: Springer-Verlag, 2014.

[18] A. Eiben and J. Smith, "What is an evolutionary algorithm?," in *Introduction to Evolutionary Computing,* Berlin, Springer, 2015, pp. 25-48.

[19] "Interest-aware Energy Collection & Resource Management in Machine to Machine Commnications," *Ad Hoc Networks,* vol. 68, pp. 48-57, 2018.

[20] S. J. Gershman, "Reinforcement learning and causal models," *The Oxford Handbook of Causal Reasoning,* p. 295, 2017.

[21] L. P. Kaelbling, M. L. Littman and A. W. Moore, "Reinforcement learning: A Survey," *Journal of artificial intelligence research,* vol. 4, pp. 237-285, 1996.

[22] E. Hartvigsson, M. Stadler and G. Cardoso, "Rural electrification and capacity expansion with an integrated modeling approach," *Renewable Energy,* vol. 115, pp. 509-520, 2018.

[23] L. Olatomiwa, S. Mekhilef, A. Huda and O. S. Ohunakin, "Economic evaluation of hybrid energy systems for rural electrification in six geo-political zones of Nigeria," *Renewable Energy,* vol. 83, pp. 435-446, 2015.

[24] R. Sen and S. C. Bhattacharyya, "Off-grid electricity generation with renewable energy technologies in India: An application of HOMER," *Renewable Energy,* vol. 62, pp. 388-398, 2014.

[25] P. Mesaric and S. Krajcar, "Home demand side management integrated with electric vehicles and renewable energy sources," *Energy & Buildings,* vol. 108, pp. 1-9, 2015.

[26] M. B. Rasheed, N. Javaid, A. Ahmad and M. Awais, "Priority and delay constrained demand side management in real-time price environment with renewable energy source," *Int. J. Energy Res.,* vol. 40, pp. 2002-2021, 2016.

[27] F. S. Gazijahani, H. Hosseinzadeh, N. Tagizadeghan and J. Salehi, "A new point estimate method for stochastic optimal operation of smart distribution systems considering demand response programs," in *22nd Electrical Power Distribution Conference,* Semnan, 2017.

[28] A. S. Hassan, L. Cipcigan and N. Jenkins, “Impact of optimised distributed energy resources on local grid constraints,” *Energy,* vol. 142, pp. 878-895, 2018.

[29] F. Ewald, G. Cardoso, M. Heleno, M. Stadler, N. DeForest and S. Mashayekh, “DER-CAM: Decision support tool for decentralized energy systems,” Berkley Labs, California, 2016.

[30] Y. Tian, R. Cheng, X. Zhang and Y. Jin, “PlatEMO: A MATLAB platform for evolutionary multi-objective optimization,” *IEEE Computational Intelligence Magazine,* 2017.

[31] K. Deb and H. Jain, "An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part i: solving problems with box constraints", *IEEE Transactions on Evolutionary Computation,* Vol. 18, no. 4, pp. 577-601, 2014

[32] K. Deb and H. Jain, "An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part ii: handling constraints and extending to an adaptive approach", *IEEE Transactions on Evolutionary Computation,* Vol. 18, no. 4, pp. 602-622, 2014.

[33] I. Das and J.E. Dennis, "Normal Boundary Intersection: A new method for generating the Pareto Surface in nonlinear multicriteria optimization problems," *Siam J. Optim.,* vol. 8, no. 3, pp. 631-657, 1998.