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An aggregator-based resource allocation in the smart grid using an artificial neural network and sliding time window optimization

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Abstract

The success of an efficient and effective aggregator-based residential demand response system in the smart grid relies on the day-ahead customer incentive pricing (CIP) and the load shifting protocols. An artificial neural network model is designed to generate the day-ahead CIP for the aggregator based on historical data. Load scheduling is proposed as a day-ahead optimization problem that is solved using a blocked sliding window technique using parallel computing. With the assumptions made, the proposed algorithm improved the aggregator performance by reducing the overall simulation time from 275 to 45 min and increasing the aggregator forecast profits and customer savings by 11.85% and 35.99% compared to the previous genetic algorithm-based approach.

1 | INTRODUCTION

In 2018, electric utilities in the U.S. had approximately 86.8 million advanced metering infrastructure (AMI) installations, the backbone of demand response (DR) programs [1]. Approximately 88% of these AMI installations were residential customer installations [2, 3]. The challenges of integrating DR programs include the coordination of millions of customer assets while providing profitable DR services [4, 5]. DR can be offered as time-based or incentive-based programs. The former refers to prices set in advance but vary over the day to capture anticipated impacts of changing electricity demands [6]. The latter offers customers incentives in addition to their retail electricity rate, which may be fixed or time-varying for their load reduction [7].

An aggregator is a third party that facilitates the interaction between the bulk electricity market and the distribution level energy consumers [8] to reduce energy usage during periods of peak demand, high electricity rates, system constraints, and/or emergencies. In this study, the customers can examine the tradeoff between savings in electricity bills, by participating in the aggregator-based DR programme, against the inconvenience of adjusting their usage before making decisions to enter into a daily contract with the aggregator; the default option for these customers is the use of electricity from the local utility company billed at the real-time price (RTP).

Aggregators are no longer theoretical entities [9]. As shown in Table 1, there are aggregators in the state of California that provide services to small, commercial or residential users with a valid California Public Utilities.

Commission (CPUC) registration in the business areas of the three major utilities.

The successful implementation of the aggregator-based residential DR approach relies on the customer incentive pricing (CIP) mechanism and the schedule of loads to maximise aggregator profit (AP). The CIP mechanism is

TABLE 1 Residential aggregators in California [10]

Aggregator	Service territory		
	PG&E	SCE	SDG&E
EnergyHub, Inc.	√	√	
OhmConnect, Inc.	√	√	√
Olivine, Inc.	√	√	√
Chai, Inc.		√	
AutoGrid Systems, Inc.	√	√	√
Sunrun, Inc.	√		
Leapfrog Power, Inc.	√	√	√

Abbreviations: PG&E, Pacific Gas and Electric Company; SCE, Southern California Edison; SDG&E, San Diego Gas & Electric.

based on the a priori knowledge of forecast RTP and spot market price (SMP) in the bulk electricity market, information on the customers' schedulable assets, and their willingness to participate.

In our previous study [11], we developed an aggregator-based residential DR approach, named the Smart Grid Resource Allocation (SGRA), using a heuristic optimization technique (i.e. a genetic algorithm [GA]) to maximise the forecast AP and find near-optimal solutions in an acceptable time frame. The results from our prior work demonstrated via simulations that the day-ahead CIP found by the GA was competitive with the utility rates; the customers achieved some savings in their electricity bills by shifting their schedulable loads and the aggregator attained a profit by reducing the peak load in the system by participating in the spot market [11].

Although heuristic methods are applied to these complex problems to find near optimal solutions in polynomial time, computation times may still rapidly increase as the size of the problem grows. To reduce the computational burden and processing time, we solved this SGRA problem using parallel processing in a high-performance computing (HPC) environment [12].

The previous GA-based approach involves dedicated computational platforms, high computational cost, and no guarantee of finding the optimal start time for the smart asset. HPC demonstrates the capability of performing complex calculations, but such specialised and cost-prohibitive assets may not be widely available. There is a need for a better method to reduce the search space, possibly resulting in faster convergence using fewer computational resources and identifying solutions closer to the global optimum.

Artificial neural networks (ANNs) perform nonlinear complex statistical modelling and identify data patterns in a more time-efficient manner [13]. ANNs are used for modelling and prediction in the field of energy and power systems applications, such as renewable energy generation modelling [14–16], load forecasting [17–19], and electricity price forecasting [20–22]. These applications are based on the ANN's ability to implicitly detect complex nonlinear relationships between dependent and independent variables.

The optimization of the residential DR problem has been approached using GAs [23], particle swarm optimization [24], machine learning techniques [25], reinforcement learning [26], ANNs [27], and hybrid algorithms [28]. Given that the area of research in aggregators is nascent, there are limited applications of ANNs to evaluate the aggregator performance. Previously, we designed supervised machine learning models based on historical data to examine the influence of the schedulable loads and the forecasted daily electricity price profiles on AP [9]. The results showed that k-nearest neighbours can identify the set of schedulable loads that yield high AP, and the Gaussian process regression model can give an accurate prediction of the AP based on the day-ahead electricity prices from the utility and the spot market. However, in [9], the supervised machine learning models were developed to directly predict the AP by knowing the customer schedulable loads and the forecasted daily electricity price profile, without evaluating the influences of CIP and the load shifting protocols.

Here, we make the following contributions: (a) design an ANN model that can generate the CIP profile, given the forecast RTP and SMP, in lieu of a heuristic optimization method like the GA; (b) apply the sliding time window (STW) technique to find a new start time for the schedulable asset that yields the highest forecast AP; and (c) compare the efficiency and effectiveness of the ANN-based approach with the GA-based approach. The results presented here are specific to the data, algorithms, and system used and may not yield comparable benefits in all scenarios. Nevertheless, the framework is general and applicable to a wide range of DR environments.

The remainder of this paper is organised as follows. Sections 2 and 3 briefly revisit the SGRA problem and the GA-based approach to solve the SGRA, respectively. The design of the ANN model is described in Section 4. Section 5 explains the blocked sliding window method of finding a new start time for the schedulable assets. In Section 6, the simulation results are presented, and Section 7 concludes.

2 | SGRA PROBLEM

The SGRA problem, described in detail in [11], is designed as an AP maximisation algorithm, subject to smart asset constraints (i.e. availability of smart assets and available time window for shifting) and customer constraints (i.e. customer incentive requirements). By offering a competitive alternative to the utility price for electricity, that is CIP, the peak load is shifted to off-peak hours.

The load of each customer is categorised into two groups: non-schedulable and schedulable loads. Non-schedulable loads cannot be arbitrarily rescheduled and are fixed in time. The loads potentially available for rescheduling each day were generated randomly from 18 predefined types using the data from Table 2 [11].

The SGRA simulation considers 5555 customers with a total of 208,000 loads, of which 56,671 are schedulable (and the remaining 151,329 are not). The penetration level indicates

TABLE 2 Schedulable assets [11]

Penetration (%)	Mean power (kW)	Power std. dev. (kW)	Duration (15-min intervals)	Start mean (hour)	Start std. dev. (hour)
70	0.5	0.05	4	7	1
70	0.5	0.05	4	14	3
70	0.5	0.05	4	17	1
50	0.75	0.1	3	7	1
50	0.75	0.1	3	14	3
50	0.75	0.1	3	17	1
30	1	0.2	2	7	1
30	1	0.2	2	14	3
30	1	0.2	2	17	1
100	0.25	0.01	8	7	1
100	0.25	0.01	8	14	3
100	0.25	0.01	8	17	1
10	1.5	0.3	2	7	1
10	1.5	0.3	2	14	3
10	1.5	0.3	2	17	1
80	0.4	0.05	6	7	1
80	0.4	0.05	6	14	3
80	0.4	0.05	6	17	1

Abbreviation: DR, demand response.

the probability that each asset is present at a customer location. The power and the originally intended start time (i.e. before DR) of the asset is randomly generated from a normal distribution with an associated mean and standard deviation value.

3 | GENETIC ALGORITHM

Because the ANN model relies on the historical input and output data gathered from the SGRA approach in [11], a brief description of the GA from that past work is presented here. To generate the CIP and find a new start time for schedulable assets, a heuristic optimization method processes the inputs received from the customers on the loads available for scheduling, and other pertinent information such as the day-ahead forecast RTP and SMP.

The chromosome structure of the GA contains two portions: the first 96 genes representing the CIP vector with one element for each 15-min interval in the 24-h period; the following 56,671 genes representing the new start times for the same number of schedulable assets.

The initial population of 100 chromosomes is generated randomly, and each chromosome is evaluated and ranked based on the objective value (i.e. the forecast AP). Two parent chromosomes are selected from the population using the linear bias function, with a bias parameter of 1.4, to perform the global search. The linear bias parameter of 1.4 means the best-ranked solution has a 40% higher chance of being chosen than the other solutions. The linear bias parameter is determined based on the size of the populations. After two parent chromosomes are selected, a cross-over operation to form new offspring (children) is performed. Within the child chromosome, each gene has a mutation probability of 0.01. Mutation probabilities normally should be kept low (0.01–0.1), otherwise, convergence may be delayed unnecessarily. The new offspring in the new population are evaluated and ranked in terms of the objective function value again, and the worst two chromosomes are eliminated. The newly generated population is used for subsequent iterations of the algorithm until the stopping criterion of 500,000 total iterations or 10,000 iterations without an increase in the objective function is reached. This GA-based approach presented an example of optimising for economic reasons in the form of AP and enacting an overall reduction on the system peak load.

4 | ARTIFICIAL NEURAL NETWORK

4.1 | Data preparation

The day-ahead forecast pricing information from the utility and spot market used in the simulation was obtained from ComEd® residential RTP and PJM®, respectively [29, 30]. The main dataset used in the ANN model was generated by

simulating the SGRA problem over a time horizon of 365 days on the RMACC Summit HPC [12].

The application of HPC reduces the computation time for this data-intensive resource allocation problem [31]. The dataset consists of 34,944 observations, representing the 96 CIP datapoints for 365 days. The input feature matrix of this model has two elements representing the forecast RTP and SMP, and the target vector has one element representing the CIP. The application randomly divides input vectors and target vectors into three sets as follows: a training dataset (70%), a validation dataset (15%), and a testing dataset (15%).

While the computations for creating the ANN model were performed on the RMACC Summit HPC, the resulting ANN algorithms were executed on a desktop computer with an Intel core i5-4200U 2.30 GHz CPU, and 4 GB of RAM. The MATLAB (version 2019a) neural network toolbox was employed for ANN model development and training.

4.2 | Architecture of ANN

The determination of an optimal CIP was defined as a function approximation problem for which we used a three-layered feed-forward ANN. This ANN model contains an input layer, a hidden layer, and an output layer; each is connected to the other and has two, 10, and one neuron(s), respectively. Inputs for the network are the forecast RTP and SMP, represented by the two neurons in the input layer. The neurons in the hidden layer allow the ANN to detect the pattern in the data and build complicated nonlinear mappings between input and output variables. Here, the number of hidden neurons was set to 10, which was determined empirically. The output layer of the network has one neuron representing the CIP.

The hidden neuron sums its input signals (vectors) after multiplying it by the strengths of the respective connection weights (W) and then adds a bias (b); then, it computes an output (Y) as a function of the sum of all input signals onto a neuron [32]. The activation (transfer) function (f) is necessary to transform the weighted sum of all input signals into a neuron. The activation function can be a threshold, sigmoidal, hyperbolic tangent, radial basis function, or linear function [32]. Here, the activation function (f) is a hyperbolic tangent sigmoid function in the hidden layer, whereas a linear function is used in the output layer, resulting in

$$Y = f\left(\sum (W \times input + b)\right). \tag{1}$$

4.3 | Training algorithms

The Levenberg–Marquardt (LM), Bayesian regularisation (BR), and the Scaled Conjugate Gradient (SCG) are the most widely used training functions for ANNs [33]. LM is the fastest training algorithm for networks of moderate size and is recommended for most problems. BR is a modified version of the LM training method, which is used for small problems that include noisy data. It typically takes longer to converge, but it achieves a better solution. The SCG is usually recommended for large problems [34]. In our work, all three algorithms were applied to train the network. In all cases, the training continued until the validation error failed to decrease for six consecutive iterations.

4.4 | Model evaluation

To evaluate the ANN model performance, it is necessary to identify appropriate performance metrics. The mean squared error (MSE) and the coefficient of determination (regression R value) were used to evaluate the ANN's performance. MSE is the average squared difference between outputs and targets (GA-determined CIPs). Regression R value measures the correlation between outputs and targets. The three input types (the forecast RTP alone, the forecast SMP alone, and the combination of those two) and the three training algorithms (LM, BR, and SCG) were evaluated based on the MSE and R values. The one yielding the highest accuracy was chosen for CIP profile generation for the entire year.

5 | SLIDING WINDOW OPTIMIZATION

Using the predicted day-ahead CIP from the ANN, the resource allocation problem now becomes one of finding a potentially new (rescheduled) start time for each schedulable asset that yields the highest forecast AP and meets the minimum customer savings (CSs) requirement. Each schedulable asset's rescheduling is treated as an independent event.

5.1 | Sliding window approach

An STW approach is applied to compute all the potential forecast APs and CSs, and then determine the maximum forecast AP that meets the CS constraint. To illustrate this process, Figure 1 presents an example of a schedulable asset with 1.5 h as the available window length, 0.75 h as the duration, and 0.25 h as the simulation time step. The available window design consists of the choice of the window length, defined by the available window start and end time. This window indicates the shifting boundary of the asset. Each available time window contains a sub-window (win), representing the schedulable asset, with the length being equal to the schedulable asset duration. The forecast AP and CS are calculated in the sub-window based on the schedulable asset definition and electricity prices. The sub-window is then incremented by 0.25 h, and the process is repeated for the entire time horizon, which is 1.5 h in this case.

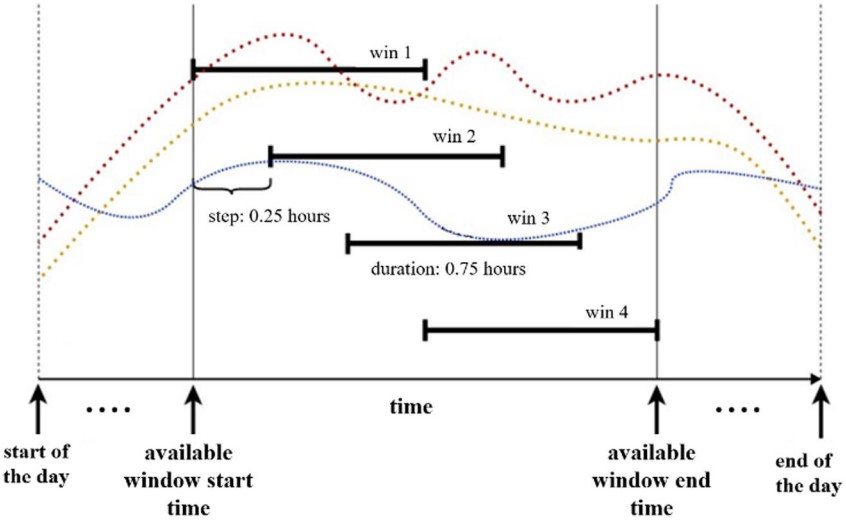

FIGURE 1 Restricted sliding time window. For illustrative purposes, the red, yellow, and blue dashed lines represent the forecast real-time price, forecast spot market price, and customer incentive pricing, respectively

5.2 | Problem formulation

Because each smart asset's rescheduling is an independent event, it can be treated as a sub-problem solved in parallel [35]. All the equations below are indicated for one single asset. All the potential forecast APs are calculated and these values are returned in a vector with 96 elements, denoted $\overrightarrow{AP}$, which represents all the possible forecast AP values (in \$) for every 15-min interval in a 24-h period. Each element is calculated as an argument (window). Elements with smart asset start or end times outside of the restricted window are set to zero.

The determined forecast aggregator profit, AP_{max}, is the maximum value in the vector $\overrightarrow{AP}$, that is,

$$AP_{max} = \max\left(\overrightarrow{AP}\right). \tag{2}$$

and the optimal rescheduled start time t_{resch_opt} is the index of that maximum value, that is,

$$t_{resch\_opt} = index\left(\max\left(\overrightarrow{AP}\right)\right). \tag{3}$$

The t_{start}, t_{resch}, and δ are the normal start time for the asset, the determined (potential) start time for the asset, and the duration of the operation of the asset; P is the rated power of the asset; $cip(t)$ and $rtp(t)$ are the CIP and real-time utility price; and t is the time index (in this case, it is 0.25 h or 15 min).

Each element in the forecast $\overrightarrow{AP}$ comprises the following components [12]: (a) the revenue from the customers willing to reschedule loads and paying the CIP (S); the payment collected from the bulk electricity market for selling a negative load during peak hours (N); the expense for buying electricity from the bulk electricity market for supplying the rescheduled customer loads (B) (see Figure 2); and a binary viable (γ), which indicates whether the customer accepts the aggregator's DR offer and allows the asset to be rescheduled to time t_{resch} (=1) or not (=0), resulting in

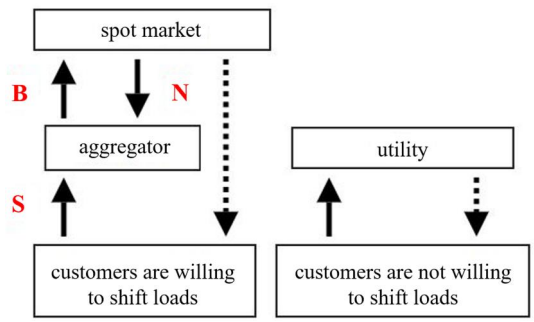

FIGURE 2 Money flow (solid lines) and power flow (dashed lines) apropos the aggregator, customer, spot market, and utility (S: the revenue from customers paying the customer incentive pricing; N: the payment collected from the bulk electricity market; B: the expense for buying electricity from the bulk electricity market) [11]

$$AP = \gamma(S + N - B). \tag{4}$$

See [11] for detailed mathematical definitions of the above-mentioned terms S, N, and B. The binary γ value is determined by the customer original cost C_{orig}, that is,

$$C_{orig} = \sum_{t=t_{start}}^{t_{start}+\delta-1} \frac{rtp(t) * P}{4}, \tag{5}$$

the new cost C_{resch}, that is,

$$C_{resch} = \sum_{t=t_{resch}}^{t_{resch}+\delta-1} \frac{cip(t) * P}{4}, \tag{6}$$

and the threshold metric α. The aggregator can only reschedule an asset if the cost saving satisfies the threshold metric, α,

which is applied to capture the customer inconvenience and flexibility. This variable is private, and the aggregator is assumed to operate without explicitly receiving this information. For example, if the threshold metric value of an asset is 0.85, it indicates that the new cost (C_{resch}) for accepting the CIP offered by the aggregator must be at least 15% lower than the default option (C_{orig}), which is the cost of paying with the RTP. The binary γ is computed as

$$\gamma = \begin{cases} 1, & \text{if } C_{orig} - C_{resch} \geq \alpha * C_{orig} \\ 0, & \text{otherwise} \end{cases}. \tag{7}$$

The CS is computed as

$$CS = C_{orig} - C_{resch}. \tag{8}$$

The determined start time of the asset is subject to the available time window for start, A_{start}, that is,

$$A_{start} \leq t_{resch}, \tag{9}$$

and the duration of this time window, A_{dur}, that is,

$$t_{resch} + \delta \leq A_{start} + A_{dur}. \tag{10}$$

The methodology for generating CIP profile and finding the optimal start time for the smart asset is described in Figure 3.

6 | RESULTS

The input type (the forecast RTP alone, the forecast SMP alone, or the combination of those two) and the training algorithm (LM, BR, or SCG) yielding the best predictions are chosen for the CIP profile generation. After the CIP profile is generated, the STW technique is applied with parallel computing in a search for the new start time of the schedulable assets that yield the maximum AP. The efficiency and effectiveness of the proposed method are evaluated by comparing with the previous method on average daily APs, CS, simulation time, and participation rate. The participation rate is defined as the percentage of the smart assets that accept the CIP. The consistency of different approaches is evaluated.

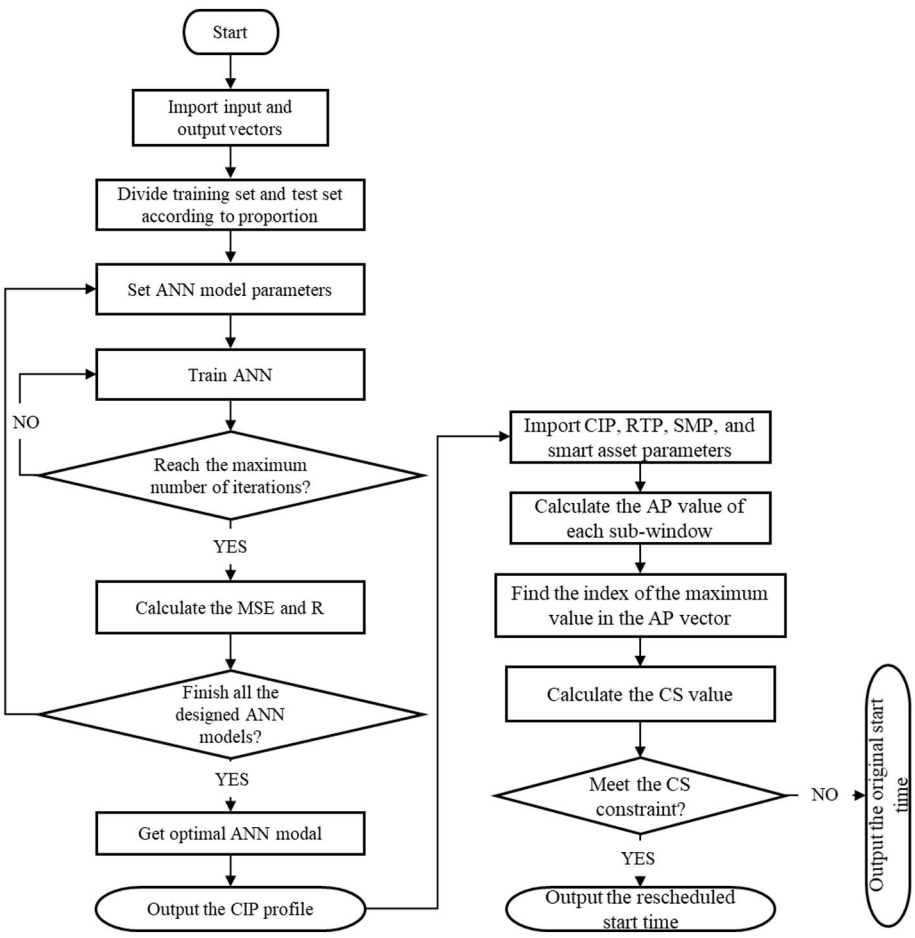

FIGURE 3 Flowchart of ANN training and sliding time optimization. ANN, artificial neural network; AP, aggregator profit; CIP, customer incentive pricing; CS, customer saving; MSE, mean squared error; RTP, real-time price; SMP, spot market price

A sensitivity analysis is performed by changing the scale of the CIP profile.

6.1 | ANN model selection

Table 3 presents the criteria values used to evaluate the performance of the three training functions, and the three input types for the ANN model, which are the day-ahead forecast RTP only, the day-ahead forecast SMP only, and the combination of those two prices.

The smaller the MSE measure, the closer the fit is to the data. An R value of 1 represents a perfect linear correlation, with a value of 0 representing no correlation. According to the MSE and R values, the three training functions result in similar performance. The case with BR as the training function using both forecast RTP and forecast SMP as the input matrix shows slightly better performance than the others. The error histogram of this case shows a peak around 0, meaning that most of the errors are close to 0. No outliers are visible on the error histogram (Figure 4).

6.2 | CIP prediction

As indicated above, the BR algorithm was used to create an ANN with both the forecast RTP and SMP to determine the CIP. Figure 5 shows the CIP profiles from day 203 found by the GA and ANN, compared to forecast RTP and SMP. The CIP profile of day 203 was chosen because it had the highest AP out of the entire year.

The measured CIP (from GA) and the predicted CIP (from ANN) profiles show similar patterns compared to the forecast RTP and SMP. The CIP profiles from both GA and ANN methods are lower than the RTP and SMP profiles, in general. This indicates that the customer receives a competitive electricity rate for choosing to reschedule their loads with the aggregator.

As can be seen in Figure 5, the CIP prediction from the ANN simulation follows the original GA-based CIP closely. However, during some hours of the day, the CIP from the ANN tends to be underestimated. The CIP from the ANN forecast still follows the forecast RTP and SMP profiles more closely when compared to the CIP from GA. It may be because there are input elements—e.g. customers' schedulable assets information and the predefined willingness factors to participate—that are included in the GA-based CIP pricing mechanism that are not included in the ANN's input vectors

TABLE 3 Neural network results

	LM		BR		SCG	
Input (forecast)	**MSE**	**R**	**MSE**	**R**	**MSE**	**R**
RTP + SMP	0.1977	0.9020	0.1880	0.9010	0.1935	0.8968
RTP	0.2001	0.8921	0.2021	0.8991	0.1982	0.8910
SMP	0.2383	0.8744	0.2213	0.8870	0.2545	0.8816

Abbreviations: BR, Bayesian regularization; LM, Levenberg–Marquardt; MSE, mean squared error; R, regression; RTP, real-time price; SCG, Scaled Conjugate Gradient; SMP, spot market price.

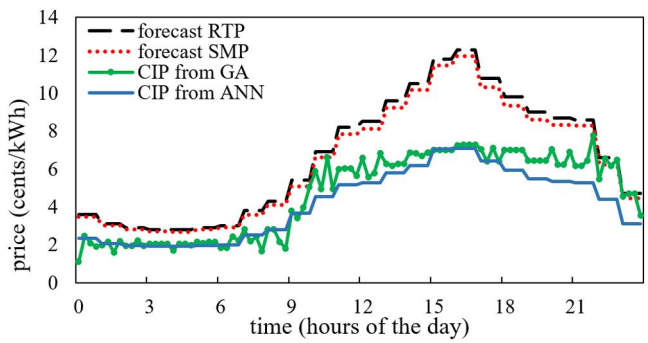

FIGURE 5 Real-time and spot market pricing compared to the CIP found by GA and ANN. ANN, artificial neural network; CIP, customer incentive pricing; GA, genetic algorithm; RTP, real-time price; SMP, spot market price

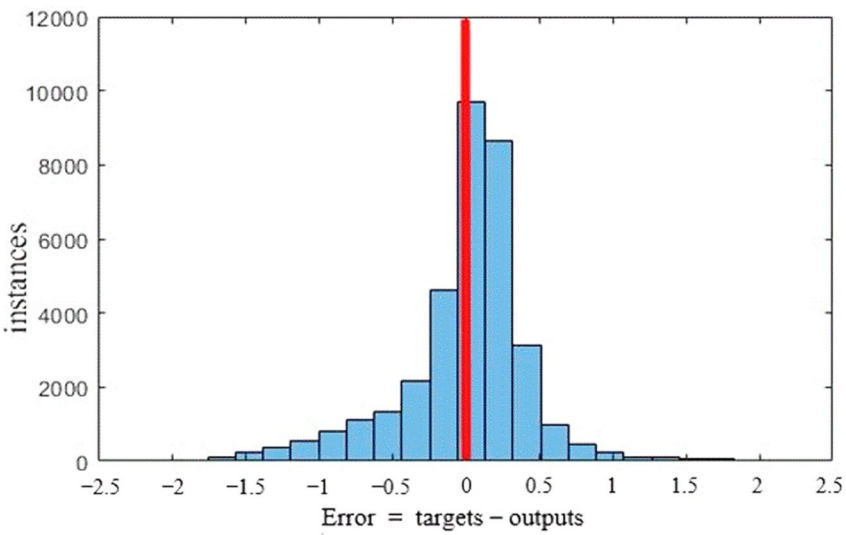

FIGURE 4 The error histogram with simulation data

for the ANN training. The reason for excluding the customer information in the ANN training is that our previous study shows that the AP is highly related to the electricity prices. The training results show that the ANN model has the potential for replacing the GA model for generating the CIP profile.

6.3 | Resource allocation

Four design configuration scenarios were selected to investigate and compare the effectiveness of the two CIP pricing mechanisms and two resource allocation methods (see Table 4). All are based on the same set of a total of 56,671 schedulable loads from the 5555 customers, which were randomly generated using the method from Section 2.

Scenario 1 is the state of art using the GA from [12]. The GA determines both the CIP vector and the new start time for each schedulable asset. Scenario 2 applies the CIP profile from the ANN to the GA-determined resource allocation, that is, the GA in scenario 2 only decides the rescheduled start time, and not the CIP. In scenario 3, the STW-based resource allocation is used with the CIP profile from the previous GA method. In scenario 4, the CIP profile is determined by the ANN model, and the rescheduled start time is decided by the STW optimization.

To demonstrate the efficiency and effectiveness of the proposed ANN and STW approach, the four scenarios are tested and compared on the average daily forecast AP, actual AP, CS, annual simulation time, and the participation rate (see Table 5). Scenario 4, applying the STW method with CIP from the ANN model, achieves the highest AP and CS. Scenario 1, applying the CIP and resource allocation determined by GA, has the third best performance. With mixed ANN and GA methods, scenario 2 results in the lowest AP and CS. For all cases, there is no significant difference in the forecast and actual AP values.

Simulation results show that the proposed algorithm in scenario 4 has managed to increase the average daily forecast AP to $836.02, from a low of $747.44 for scenario 1 (the GA-based method). This occurs due to the lower CIP profile in scenario 4 leading to an increase in the customer participation rate. Moreover, the STW approach in scenario 4 guarantees the reach of a maximum solution once the CIP is fixed.

From a customer's standpoint, scenario 4 achieves the highest CS total over all the 5555 customers for the 24-h period. Scenario 4 is also the best performing algorithm in terms of simulation time and participation rate. Computation time dropped to 45 min for the annual simulation.

For scenario 3, the introduction of STW increases the performance of the resource allocation, ranking the second best for average daily forecast AP, actual AP, and CS; however, the participation rate is the lowest of all scenarios. The simulation time of scenario 3 is an estimated value because the chromosome structure for the GA contains both the genes representing the CIP vector and the genes representing the new start time in resource allocation. The time taken to generate CIP alone in the GA is unknown and is assumed to be equal to the total simulation time minus the time taken for conducting resource allocation alone.

To evaluate consistency, the four algorithms are ranked in terms of the performance on forecast AP, actual AP, and CS for each day. The number of days for each scenario during the year when it achieved the best performance (ranked as first) to the worst performance (ranked as fourth) are counted, with the results shown in Figure 6.

In terms of forecast and actual APs, scenario 2 has over 250 days when it results in the worst performance (ranked as fourth). For scenario 1, the number of best performance (ranked as first) days is less than scenarios 3 and 4; however, this case has the smallest probability of being the worst (less than 10 days), indicating a consistent and stable performance. Scenario 3 is high on both rankings for the "first" and "fourth", indicating large fluctuations day to day. Scenario 4 has consistent performance over the year, displaying many days ranking as "first" and only a few ranking as "fourth."

Scenarios 1 and 3 use the same CIP profiles, and scenario three is expected to perform better due to searching all of the

TABLE 4 Four scenarios

	CIP profile generation		Resource allocation	
Scenario	GA	ANN	GA	STW
1	√		√	
2		√	√	
3	√			√
4		√		√

Abbreviations: ANN, artificial neural networks; CIP, customer incentive pricing; GA, genetic algorithm; STW, sliding time window.

TABLE 5 Simulation results

Scenario	Forecast AP ($)	Actual AP ($)	CS ($)	Simulation time (minutes)	Participation rate (%)
1	747.44	741.63	435.02	275	83.48
2	684.98	683.17	419.05	173	75.44
3	770.62	820.81	452.18	147	73.57
4	836.02	860.62	591.58	45	85.23

Abbreviations: AP, aggregator profit; CS, customer savings.

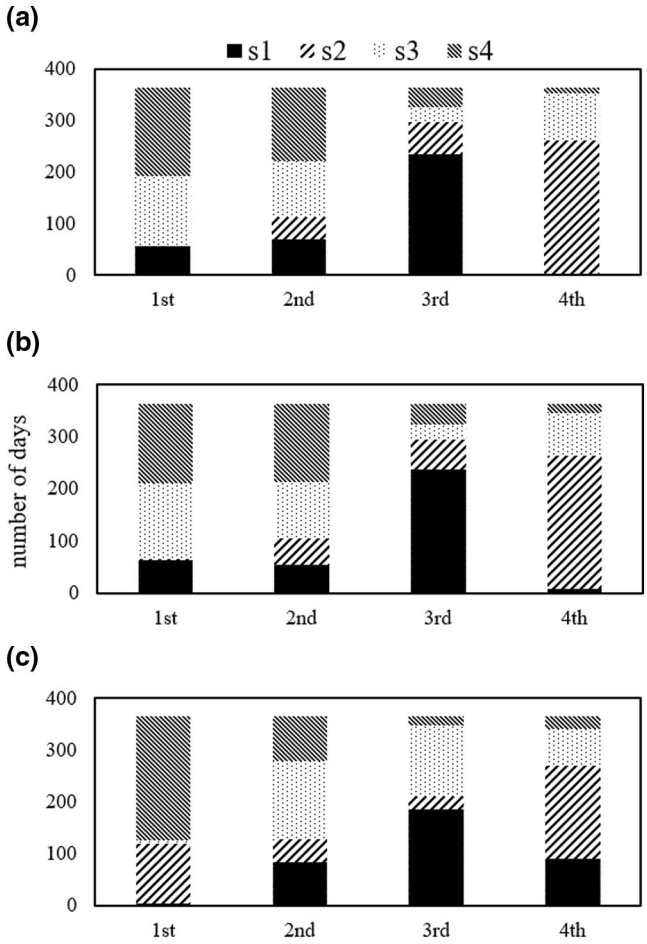

FIGURE 6 Performance consistency evaluated for scenarios 1-4 (s1-4) in terms of (a) forecast AP, (b) actual AP, and (c) CS. AP, aggregator profit; CS, customer saving

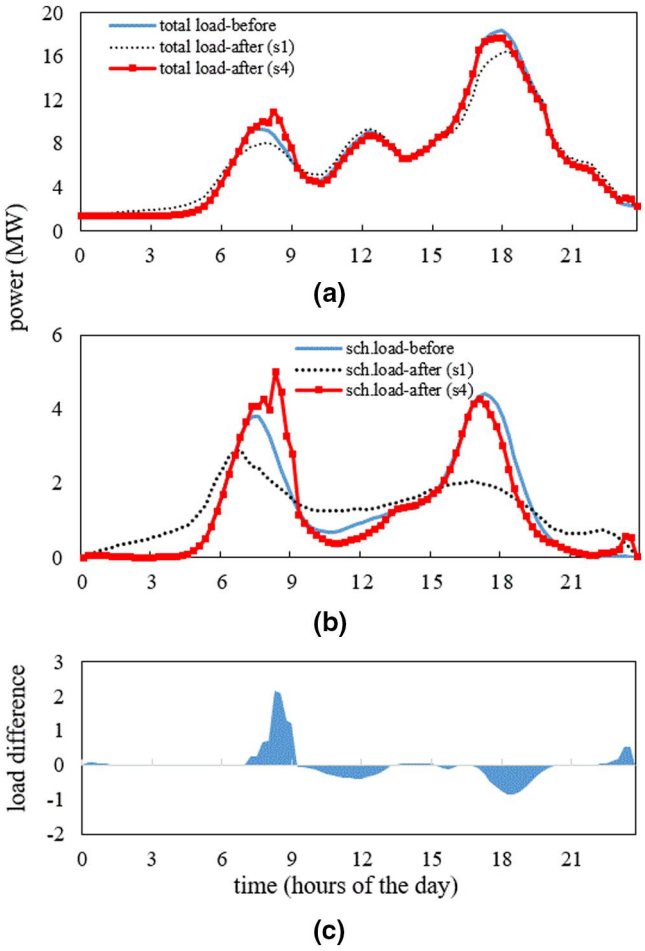

FIGURE 7 The change in load from before and after the aggregator demand response (DR) action. (a) Overall system load. (b) Schedulable load. (c) Difference in load for scenario 4 (i.e. load after DR minus load before DR)

solution space for the given CIP. The reason for scenarios one and three sharing the first place during the year is that scenario one and three can have the same results on some days, and the sorting algorithm applied to rank the four scenarios in terms of the performance on forecast AP gives the first place to scenario 1 instead of scenario three.

In terms of average daily CS, note that scenario 2 has the lowest value of $419.05 CS (see Table 5); however, there are over 100 days of the year where scenario 2 ranks "first" for CS. This is not unexpected as the number of days at the "fourth" section on CS for scenario 2 is also as high as 180 days.

Comparing the results in Table 5 and Figure 6, scenarios 1 and 4 show more consistent performance, and scenarios 2 and 3 demonstrate some inconsistencies. The decision to deploy CIP and the load shifting protocols in the smart grid should consider the odds of obtaining performance below expectations so as to understand the risk.

Figure 7(a) and (b) demonstrate the change in the total and schedulable loads before and after the DR for scenarios 1 and 4. The GA-based DR programme, scenario 1, reduces the peak load (schedulable loads) from 4.4 to 2.9 MW, corresponding to a 34.1% peak reduction from schedulable loads alone. Although scenario 4 is the winning algorithm in terms of AP and CS, the aggregator in scenario 4 moves many schedulable loads to the hours of 7–9 A.M., thus creating a new peak that is higher than the original. A rebound peak, caused by schedulable loads flooding to times with lower energy prices, is not uncommon in DR, and has been observed by others [36, 37].

This DR outcome occurs because the STW-based DR approach depends on the CIP, and the CIP profile learnt from the ANN on that day has a valley around 7 A.M. Figure 7(c) displays the difference in load between the system before and after the DR for scenario 4. The regions with positive values are the areas that the load was increased, corresponding to the increase in the peak. In the other areas, the load was reduced, corresponding to the load moving to off-peak hours.

6.4 | Sensitivity analysis

Figure 8 shows the scenario 4 results obtained by changing the ANN-determined CIP value from 80% below to 80% above the reference value, which is the original CIP generated from the ANN model.

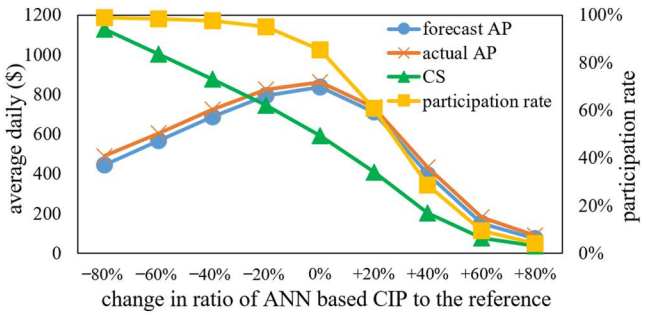

FIGURE 8 Sensitivity analysis of CIP in scenario 4. ANN, artificial neural networks; AP, aggregator profit; CIP, customer incentive pricing; CS, customer saving

The forecast and actual APs show a similar pattern to the CIP value increases, and the forecast AP is slightly lower for all cases. The original and reference CIP from the ANN yields the highest AP. If the CIP value goes higher than the reference (ANN-determined), the profits begin to drop due to the lack of customers' participation. A negative (nearly) linear relationship is found between the CIP value increasing ratio and the CS, which is expected. In general, the aggregator makes less profit and the customer saves more when the CIP value is decreased, and vice-versa. The participation rate is not sensitive to the CIP changing ratio when the CIP is low; the participation rate starts to drop dramatically when the CIP is higher than the reference value.

7 | CONCLUSIONS

Here, we applied an ANN model for determining an aggregator's day-ahead CIP offered to the end users based on historical data. An STW-based load shifting approach using a multicore computer and parallel computing was applied to solve the load shifting problem in DR.

The high prediction accuracy of the ANN, trained using BR, shows that the combination of forecast electricity prices from the utility and the spot market are sufficient inputs to determine CIP. The results can serve as an indicator for the minimum set of input variables in the GA to determine CIP. The proposed STW approach outperforms the previous GA-based method in terms of APs, CSs, simulation time, and participation rate. We attempt to examine the claim that the ANN has the same or even higher effectiveness of finding a (close to) globally optimal solution as the GA approach but with significantly better computational efficiency. Hence, the ANN model combined with the STW approach can compensate for the limitations of the previous GA and reduce the computational burden for aggregators. However, it should be noted that the randomness and uncertainty in machine learning may cause some performance to be below expectations. The results illustrate that a rebound peak is possible.

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