VARIABLE WEIGHTED MULTI-OBJECTIVE MULTI-DIMENSIONAL GENETIC ALGORITHM FOR DEMAND RESPONSE SCHEDULING IN A SMART GRID

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ABSTRACT

This research presents the optimized scheduling of demand response loads of a residential community of 30 houses using a multi-objective multi-dimensional genetic algorithm (MOMD-GA) with a variable weighted objective function. Incorporating day ahead hourly real time pricing (RTP), the MOMD-GA attempts to present possible optimized dispatch patterns with their associated penalties and constraints (environmental, consumers and suppliers) thus providing system operators (SOs) and distribution network operators (DNOs) sufficient data for real time decision making. The variable weights for each considered component of the cost function is chosen to force the MOMD-GA towards exploring optimum solutions with lower environmental cost. Further shown are the trade-offs in selecting particular dispatch bias (consumer, supplier, environmental and optimized) and the impact of the various dispatch scenarios on the cost of overall electricity bill of the community.

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KEYWORDS: MOMD-GA, scheduling, demand response, environmental, penalties, system operators

1 INTRODUCTION

Traditionally, capacity has always been increased from the generation side to match anticipated increase in electricity demand. Anticipatory activities have included constructing bigger generation plants and increasing reserve capacity (redundancy) (Zhao et al, 2013) that seamlessly compensate for any sudden load increase. The associated costs and environmental issues have however altered significantly this perspective as demand is being forced to match supply via emerging policy and innovative technology measures. In constraining demand to match supply, attention has been shifted from the supply end to the demand side. Demand Side Management (DSM) are activities designed to influence customer use of electricity and could be incentive based (Wang et al, 2012; Chavali et al 2014) or price based (Wu et al, 2014; Wang et al 2015). When DSM activities are price based they are generally referred to as Demand Side Response (DSR) or Demand Response (DR). The shift in focus to the consumer side is based on the fact that they are the highest consumers of electricity and thus offer the best opportunity for the application of DSM techniques.

Furthermore, additional impetus to the application of DSM techniques in the United Kingdom (UK) is derived from successes gained from the application of government energy efficiency programs. According to (Warren, 2014), the Energy Efficiency Commitment Phases 1 and 2 (EEC1) and (EEC2) programs which ran from 2002 – 2005 and 2005 – 2008 achieved energy savings of 86.8 TWh and 187 TWh. Similarly, a carbon reduction of about 293MtCO2 was achieved via the Carbon Emissions Reduction Target (CERT) and Community Energy Saving Program (CESP) between 2008 – 2012.

Utility companies in applying DSM techniques aim at introducing some form of flexibility to consumption (load). Hence, load could either be clipped for peak-to-average reduction (PAR) in demand, reduced via conservation, increased to meet excess generation, shifted/deferred based on prevailing grid constraints etc. With the planned roll out of smart meters in the United Kingdom, the need therefore arises for a decision support system that is capable of creating a platform for the aligning of participating interests from both consumers and suppliers. Furthermore, the constraints associated with the regulators (environmental) can also play a significant role in this proposed field. A multi-objective multi-dimensional genetic algorithm (MOMD-GA) is thus proposed to optimize the various participating constraints and evolve solutions that could aid in decision making by system operators.

2 REVIEW OF RELEVANT LITERATURE

The application of DR mechanism to specific loads was investigated by (Chavali et al, 2012). Here, real time scheduling (RTS) of electric water heater (EWH), air conditioner (AC), clothes dryer (CD), electric vehicles (EVs), photovoltaic (PV) cell and battery was carried out to obtain reduced electricity costs and optimized operation for the appliances. In industrial applications, a DR energy management scheme was proposed by (Ding et al, 2014) for industrial facilities based on the state task network (STN) and mixed integer linear programming (MILP). The proposed scheme which aimed at maximizing the participation of distributed energy resources (DERs) also shifted demand from peak to off peak periods.

A cooperative demand response (CDR) scheme was further proposed by (Ma et al, 2014) for industrial refrigerated warehouses. The proposed scheme formulated as a constrained optimization problem reduced electricity costs. Aside residential homes and industrial complexes like warehouses and factories, DSM schemes are also being exploited in internet data centres (IDCs) with positive results. In (Li et al, 2015), an electric demand management solution was proposed for minimizing the electricity costs of IDCs while (Yao et al, 2014) proposed a novel approach to enable the buffering of electrical energy in batteries in order to predictively minimize IDCs electricity cost.

An agent based intelligent energy management system (IEMS) was presented by (Nunna and Doolla, 2012) for easy facilitation of electricity between the micro grids while supporting the participation of customers in demand response. The proposed IEMS was developed using a Java Agent Development Framework (JADE). In improving the flexibility of retail consumers participating voluntarily and equipped with smart meters, a coupon incentive-based demand response (CIDR) was developed by (Zhong et al, 2013). The proposed CIDR program in achieving flexibility anticipated future intermittent generation and price spikes.

The possibility of synergizing demand response bids with smart grid constraints in real time was modeled by (Vlachos and Biskas, 2013) while (Arteconi et al, 2014) analyzed the influence of demand side control strategies on the performance of a thermally activated building system (TABS). A novel method utilizing the probabilistic approach was developed and used for the generation of residential energy consumption profile based on the energy demand contribution of each participating household appliance in (Gruber et al, 2014). In reviewing the potential of demand response for Europe, an assessment was carried out by (Gils 2014). It was reviewed that system stability and renewable energy share could be enhanced through the use of demand side load management.

While preceding works have focused solely on the consumer side via QoL and costs, this work takes existing research a step further by incorporating the needs/constraints of the supplier into the demand response mix and optimizing allocation within allowed environmental and economic constraints. A strong reason for this is the fact that flexibility being offered consumers could further be enhanced if suppliers could optimize their supply mix. Rather than having to anticipate consumer bids, a platform is envisaged that allows the user specify within a time zone the duration for the demand response appliances and the supplier the maximum generation for each time slot. The proposed multi-objective, multi-dimensional genetic algorithm (MOMD-GA) then optimizes generation and dispatch taking into consideration the costs incurred by the consumer and supplier, carbon emission limits etc. This work thus contributes to existing scholarship on demand response optimization by incorporating supply constraints into the dispatch optimization and concurrently optimizing dispatch by seeking an optimal balance between consumer satisfaction (met through maximum time dispatch of participating loads), environmental constraints (carbon emissions reduction and maximization of dispatched generator) and costs (maximizing dispatch during low prices and overall lower electricity price) in a dynamic pricing (DP) scenario.

The rest of the paper is described as follows: section 3 presents a brief description of the case study, section 4 presents the problem statement, and section 5 describes the proposed MOMD-GA and presents the cost component evaluation. The results are presented in section 6 with conclusions made in section 7.

3 DESCRIPTION OF CASE STUDY

Thirty (30) typical middle class British homes located within the same locality in the Yorkshire region are modeled and used for this research. A typical house is assumed to have 3 bedrooms (with their toilet facilities), 1 living room, a kitchen, a dining room and a hall way. The electrical equipment and power (kW) rating for each equipment is taken into consideration. In establishing the Table 1, a manual inspection of each considered electrical equipment was carried out. The Table 1 highlights the list of the basic electrical equipment considered and their equivalent power rating. Further provided in the Table 1 is the status of the load with respect to deferment (dispatchable – D or non dispatchable – ND).

Table 1: Electrical equipment and power rating

S/N	Equipment	Abbreviation	Power (kW)	Status
1	Dish washer	DW	1.20	D
2	Cloth washer	CW	0.50	D
3	Cloth dryer	CD	1.00	D
4	Pumping machine	PM	0.40	D
5	Microwave	MW	1.15	ND
6	Cooker	CK	2.15	ND
7	Heater	HT	2.00	ND
8	Pressing iron	PI	1.00	ND
9	Fridge	FRI	0.15	ND
10	Freezer	FRE	0.40	ND
11	Air conditioning	AC	1.00	ND
12	Vacuum cleaner	VC	0.20	ND
13	Lighting	LGH	0.06	ND
14	Electric jug	EJ	2.00	ND
15	Toaster	TST	0.75	ND
16	Ceiling fan	CF	0.075	ND
17	Television	TV	0.10	ND
18	Personal computer	PC	0.15	ND

19	Laptop	LT	0.075	ND
20	Phone chargers	PCH	0.025	ND
21	Satellite decoders	SDC	0.025	ND
22	Luxury lighting	LLGH	0.15	ND

A generic and detailed load profile that captures the possible dispatch period (1 represents dispatch possible while 0 means no dispatch possible for that hour) common to all of the households under consideration is presented in the Fig. 1. It should be pointed out that the occupants of the houses are assumed to be majorly working class and thus have similar pattern of consumption. However, to create some real scenario, variability in electricity usage and duration is introduced.

The classification of all the load in a household is done into the following classifications namely; Kitchen (DW, MW, CK, EJ and TST), others (CW, CD, PM, PI, VC and CF), entertainment (TV, DC, LT, PCH, SDC and LLGH), Heating, Ventilation and Cooling, HVAC (HT, FRI, FRE and AC) and lighting (LGH). The Fig. 2 shows the contribution of each load classification to the overall energy composition.

Load	Rating (W)	00:00-05:00	05:00-06:00	06:00-07:00	07:00-08:00	08:00-09:00	09:00-10:00	10:00-11:00	11:00-13:00	13:00-14:00	14:00-16:00	16:00-17:00	17:00-20:00	20:00-21:00	21:00-22:00	22:00-23:00	23:00-00:00
DW	1200	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
CW	500	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
CD	1000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PM	400	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MW	1150	0	0	1	1	1	0	0	1	1	0	0	1	1	0	0	0
CK	2150	0	1	1	1	1	0	0	1	1	0	1	1	1	1	0	0
HT	2000	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1
PI	1000	0	1	1	1	0	0	1	1	1	0	0	0	1	1	0	0
FRI	150	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
FRE	400	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
AC	1000	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0
VC	200	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0
LGH	60	1	1	1	0	0	0	0	0	0	0	1	1	1	1	1	1
EJ	2000	0	1	1	1	0	0	0	0	0	0	0	1	1	1	0	0
TST	750	0	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0
CF	75	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
TV	100	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
DC	150	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
LT	75	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PCH	25	0	1	1	1	1	0	0	0	0	0	0	1	1	1	0	0
SDC	25	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
LLGH	150	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0

Figure 1: The generic load profile showing possible dispatch period

The problem presented by the case study under consideration is quite complex and multi-dimensional as it incorporates economics, environment and satisfaction (QoL). From the economics perspective, there is a divergence as the following are to be considered in the optimization process.

- Reducing to the barest minimum the cost of allocating participating DR loads to the benefit of the consumer.
- Reducing/limiting the capacity of participating generator to the benefit of the supplier. This is achieved by penalizing allocations that do not utilize up to 70% of the activated generators capacity.
- Minimizing carbon emissions by penalizing emissions from the diesel generators. This ensures that the renewable sources are completely utilized.

From the environment point of view, the proposed algorithm in optimally allocating load, strives at reducing the carbon emissions from the diesel generators by employing a standard carbon factor as used in (Lau et al, 2014) and applying a cost on every kilogram of CO_2 emitted. The satisfaction criterion is met by ensuring that all demand is met and that the cloth washer is always dispatched before the cloth dryer. This is ensured to create a level “field” that allows for comparison between allocation employing DR and allocation using the fixed price.

Monetization is applied on all considered constraints (for unit sake) and normalized (after summing costs up) to determine the overall penalty for that particular allocation. The aim of the optimization is thus to provide options for dispatch decisions. In policy making this becomes even more important since dispatch could be altered in real time to either satisfy customers maximally (in order to encourage/stimulate higher electricity usage by reducing their electricity cost and following their pre-defined dispatch order), or satisfy suppliers (to guarantee a return on their investments within a time frame by increasing electricity price beyond the suppliers spot price) or the environment (for emissions control). Furthermore, the preceding reasons could also be weighted appropriately based on the system operator or overall goal and applied in the dispatch. This variableness and flexibility in dispatch is a major novelty of the proposed MOMD-GA.

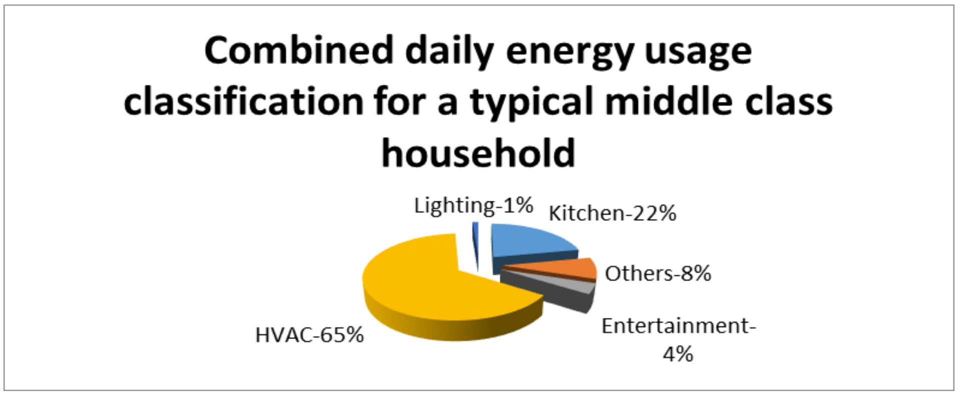

Figure 2: The generic load profile showing possible dispatch period

The fig. 3 presents the description of the case study showing the interconnections between the demand response loads and their source of electricity supply.

4 PROBLEM STATEMENT

The aim of the proposed MOMD-GA is to optimize the monthly residential cost $e_{DR}^{cost,DP}$ to meet pre-defined objectives. The objective function Z is thus defined in (1) as

$$Z = AP_{diff}^{DP} + BE_{cost} + CS_{cost}^{FP} \qquad (1)$$

Where,

$$A, B, C \in \mathbb{R} \text{ and } 0 \le \sum (A, B, C) \le 1$$

P_{diff}^{DP} is the consumer bias variable that guarantees lowered reduction of the consumers' monthly electricity bill. For maximized consumer bias, $A=1, B=C=0$. E_{cost} is the environmental bias variable that guarantees reduced emissions. This could come however at a higher electricity cost to the consumers. For maximized environmental bias $A=C=0, B=1$. S_{cost}^{FP} is the supplier bias variable that guarantees higher per unit price for electricity beyond the suppliers' spot price. This could be used in ensuring a quick return on investment (ROI) by suppliers on electricity projects. For maximized supplier bias $A=B=0, C=1$

However, aside the bias methods described above, it is possible to vary the weights (A, B and C) and obtain solutions that meet several constraints.

In dispatching the participating demand response loads therefore, we seek to vary intelligently the start position of each demand response load within the day to achieve full dispatch and pre-determined dispatch bias. In doing this, the following assumptions are made:

1. The demand response loads are only constrained by the day limits. This means that the consumer **ONLY** specifies the length of operation and not the time of dispatch.
2. Dispatched demand response loads operate in discrete numbers of 15 minutes' cycle.

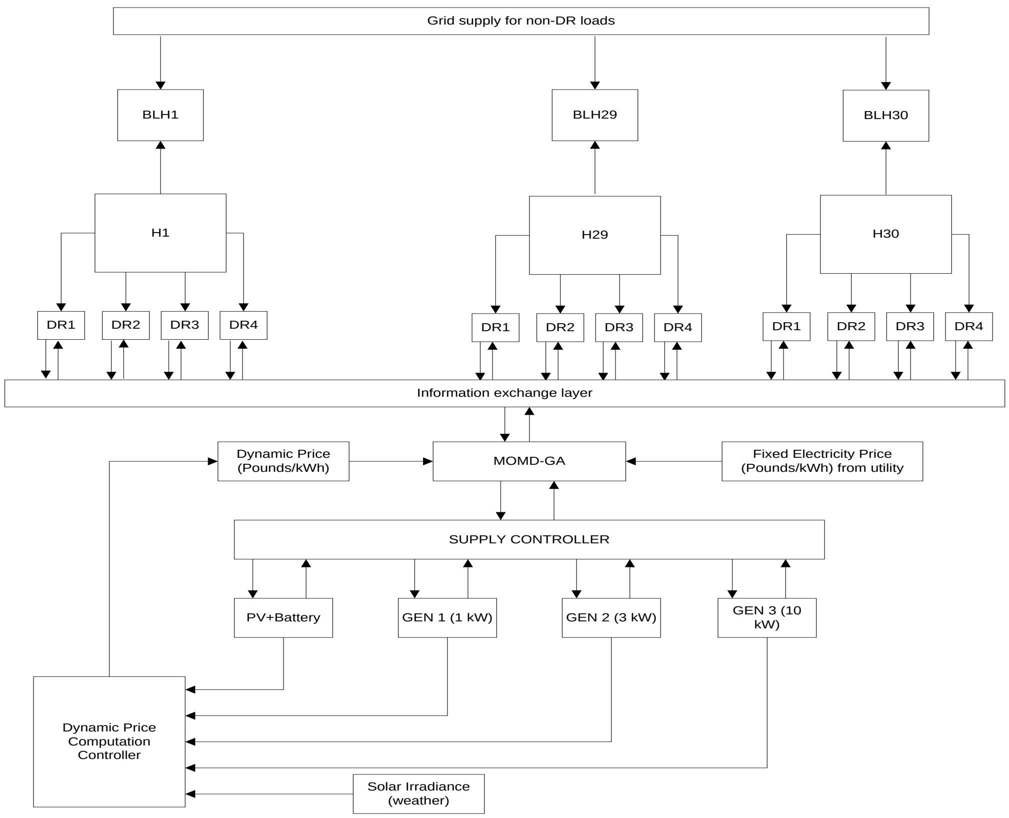

Fig.3.The proposed conceptual frame work incorporating MOMD-GA

Thus, if α_1 and α_2 are the daily limits start and end times and $\alpha_{\mathrm{p}}^{\phi,\varphi}$ and $\alpha_{\mathrm{d}}^{\phi,\varphi}$ are the dispatch time and duration for any demand response load β_{ϕ}^{φ} (where φ is the demand response load number and ϕ is the house number), then if $\alpha_{\mathrm{limit}}^{\phi,\varphi}$ is the maximum time for dispatch for any demand response load β_{ϕ}^{φ}

$$\Rightarrow \forall \beta_{\phi}^{\varphi},$$

$$1 \le \phi \le 30 \tag{2}$$

$$1 \le \varphi \le 4 \tag{3}$$

$$\alpha_{\mathrm{limit}}^{\phi,\varphi} = \alpha_2 - \alpha_{\mathrm{d}}^{\phi,\varphi} \tag{4}$$

$$\alpha_1 < \alpha_{\mathrm{p}}^{\phi,\varphi} \le \alpha_{\mathrm{limit}}^{\phi,\varphi} \le \alpha_{\mathrm{d}}^{\phi,\varphi} \le \alpha_2 \tag{5}$$

The fig. 3 further illustrates the equations (2) – (5).

Let $P_{DR} = \{H_{1DR1}, H_{1DR2}, H_{1DR3}, H_{1DR4}, ...H_{30DR1}, ...H_{30DR4}\}$ be the kW rating of participating DR loads for the 30 houses.

Let $dR_{DR} = \{y_{1DR1}, y_{1DR2}, y_{1DR3}, y_{1DR4}, ...y_{30DR1}, ...y_{30DR4}\}$ be the respective duration (in hours) for each participating DR load.

$$\Rightarrow DRR_{k1} = \sum_{\substack{i=h1k \\ j=1}}^{h2k} P_{DR_{i,j}} \,(kW) \tag{6}$$

$$\Rightarrow EDRR_{k1} = \sum_{\substack{i=h1k \\ j=1}}^{h2k} (P_{DR_{i,j}} * dR_{DR_{i,j}})(kWh) \tag{7}$$

Hence,

$$T_{DRR_{k2}} = \sum_{k1=1}^{h} \sum_{\substack{i=h1k \\ j=1}}^{h2k} P_{DR_{i,j}} \,(kW) \tag{8}$$

$$T_{EDRR_{k2}} = \sum_{k1=1}^{h} \sum_{\substack{i=h1k \\ j=1}}^{h2k} (P_{DR_{i,j}} * dR_{DR_{i,j}})(kWh) \tag{9}$$

Let $DP_{k2} = \{C_{st1}, C_{st2}, ...C_{st24}\}$ be the day-ahead dynamic electricity price in Pence/kWh for the case study.

Let fP be the fixed electricity price in Pence/kWh for the case study from an electricity vendor.

$$\Rightarrow \overline{DP_{k2}} = fP \tag{10}$$

$$CC_{stk2} = \sum\{HC_{st1}, HC_{st2}, HC_{st3}, ...HC_{st24}\} \tag{11a}$$

$$HC_{st,l} = [\sum_{k1=1}^{30} (\eta_{k1,l} * EDRR_{k1,l})] * C_{stl} \tag{11b}$$

Let $RES_{k2} = \{S_1, S_2, S_3, ..., S_4\}$ and

Let $util_l\,(kW)$ be the capacity of the generator dispatched whose value is determined by $deficit_l$

$$\Rightarrow deficit_l = [(\sum_{k1=1}^{30} (\eta_{k1,l} * DRR_{k1,l})) - S_l](kW) \tag{12}$$

The dispatch of generator follows the rule:

If $0 < \mathrm{deficit}_l < 1, \quad \mathrm{util}_l = 1\mathrm{kW}$

$1 < \mathrm{deficit}_l < 3, \quad \mathrm{util}_l = 3\mathrm{kW}$

$3 < \mathrm{deficit}_l, \quad \mathrm{util}_l = 10\mathrm{kW}$

Assumption:

$\mathrm{Max}(\mathrm{deficit}_l) \le 10\mathrm{kW} \quad \forall l$.

The objective function Z as formulated in equation (1) is subject to the following:

1. Maximizing Cutil_{k2} to minimize the under-utilization of the diesel generators.
2. Minimizing $\mathrm{Cdeficit}_{k2}$ to maximize he exploitation of the renewable energy sources.
3. Minimize CC_{stk2} which is an inherent property of MOMD-GA irrespective of the dispatch bias.
4. Minimize PC_{stk2} to obtain an overall dispatch profile with the lowest associated cost.

Where

$\eta_{k1,l}$ is the fraction of $\mathrm{EDRR}_{k1,l}$ to be dispatched for hour l and $0 < l < 1$.

Cutil_{k2} is the daily associated cost for matching $\mathrm{deficit}_l$ with util_l and is computed as follows:

$\forall \eta_l^{util} \mid \mathrm{util}_l \mid < 70\%$, $\mathrm{Cutil}_l = 5\mathrm{Pounds}$

$$\Rightarrow \mathrm{Cutil}_{k2} = \sum_{l=1}^{24} \mathrm{Cutil}_l \quad \forall \eta_l^{util} \mid \mathrm{util}_l \mid < 70\% \tag{13}$$

$\mathrm{Cdeficit}_{k2}$ is the daily associated cost/penalty for carbon emissions. Its computation assumes a standard $0.68\mathrm{kgCO_2 / kWh}$ of electricity consumed (Lau et al, 2014) and $0.14\mathrm{Pound / kgCO_2}$.
Thus,

$$\mathrm{Cdeficit}_{k2} = 0.68 * 0.14 * T_{\mathrm{EDRR}_{k2}} (\mathrm{Pounds}) \tag{14}$$

CC_{stk2} represents the associated electricity cost for the day with dynamic pricing. It is computed as

$$\mathrm{CC}_{stk2} = (\sum_{l=1}^{24} \mathrm{HC}_{st,l}) * 0.01(\mathrm{Pounds}) \tag{15}$$

PC_{stk2} represents the cumulative associated penalty allocated for any hourly dispatch $\mathrm{HC}_{st,l}$ that has a higher overall value than its corresponding fixed price value.
Thus,

Given $\mathrm{PC}_{stk2} = \sum_{l=1}^{24} \mathrm{PC}_{stl} \quad \forall l \quad \sum_{k1=1}^{30} (\eta_{k1,l} * \mathrm{EDRR}_{k1,l})(C_{stl} - fP) > 0 \quad \forall l$

$$PC_{stl} = \pm 10\%((\eta_{k1,l} * EDRR_{k1,l})(C_{stl} - fP)) \quad (16)$$

PC_{stl} is negative iff $(\eta_{k1,l} * EDRR_{k1,l})(C_{stl} - fP) < 0$ and positive iff $(\eta_{k1,l} * EDRR_{k1,l})(C_{stl} - fP) \geq 0$

5 MOMD-GA ALGORITHM

The description of the MOMD-GA is shown in the Table 2 while the nomenclature description of the variables and subscripts used are shown in the Tables 3 and 4.

Table 2: Algorithm description for MOMD-GA

Input ($P_{DR}, dR_{DR}, C_{stl}, fP, e_{cost}^{CO_2}$)
Start
Optimization part
Generate quarter hour time slot matrix S_{hDR}
Generate bit equivalent matrix BS_{hDR} of S_{hDR}
Generate maximum transfer start point matrix tst_{max} in XC for each solution in BS_{hDR}
Generate equivalent decoupling matrix tst_{dec}
Generate binary equivalent matrix tst_{dec}^{binary} of decoupling matrix tst_{dec}
Perform crossover on tst_{dec}^{binary} (see Ogunjuyigbe et al, 2015)
Perform mutation on tst_{dec}^{binary} (see Ogunjuyigbe et al, 2015)
Initialize the dispatch/population matrix XC
Appropriately fill XC based on equivalent and corresponding decimal values of tst_{dec}^{binary}
Cost computation part
Compute generator utilization cost $Cutil_{k2}$
Compute CO_2 emissions cost $Cdeficit_{k2}$ based on per unit emission costs $e_{cost}^{CO_2}(Pounds / kgCO_2 / kWh)$
Compute daily associated cost CC_{stk2} based on dynamic pricing
Compute [1]over-reaching dynamic price penalty PC_{stk2}
Compute overall cost based on equation (1)
Matrix and parameter updating
If current cost $C_{stk2,current}^{overall}$ is smaller than preceding value $C_{stk2,previous}^{overall}$, then preceding value is updated to $C_{stk2}^{overall}$ else previous value becomes current value.
Write to appropriate Excel files and plot respective graphs of supply, demand, dispatch etc.
End

[1] The over-reaching penalty is applied to any hourly allocation whose overall cost based on dynamic pricing exceeds the fixed price equivalent. The essence of this penalty is to force allocation to hours where the contribution of the renewable energy system (PV + battery) is high

Table 3: Nomenclature description for variables

DRR_{k1}	Power demand per household (kW)
$EDRR_{k1}$	Energy demand per household (kWh)
$T_{DRR_{k2}}$	Daily power demand for all households (kW)
$T_{EDRR_{k2}}$	Daily energy demand for all households (kWh)
C_{stl}	Hourly electricity dynamic price (Pence/kWh)
$HC_{st,l}$	Hourly electricity cost for all households (Pence/Pounds)
RES_{k2}	Daily renewable energy source (RES) supply (kW)
$deficit_l$	Hourly shortfall of RES in dispatching power demand
S_l	Hourly RES supply (kW)
$util_l$	Generator capacity dispatched (kW) for hour l
PC_{stl}	Hourly over-reaching penalty (Pounds)
qd_{k1i}	Participating DR load i for each household k1
t_{k1i}	Maximized start position in XC for each solution in BS_{hDR}
$BLHk1$	Base load for house $k1$
η_l^{util}	Hourly percentage utilization of $util_l$ (%)

Table 4: Description of used subscripts

$k1$	Index of each household
$k2$	Index of each day
l	Index of each hour
i	Index of each DR load
DRi	Demand response load i

6 RESULTS

The fig. 4a presents the different prices – average daily dynamic price, supplier's spot price (which guarantees at worst case a ROI), fixed price (£0.1113 from SSE) etc. The day 1 spread of electricity expenditure for house 1 for the demand response loads only using the E. Bias (environmental bias), S. Bias (supplier bias), C. Bias (consumer bias) and Z. Bias (equally weighted constraints) is shown in the fig. 4b. It is observed that the different approaches dispatch the consumer loads based on their optimization goal. While the S. Bias expenditure for the day for hose 1 demand response loads is £1.06, E. Bias achieves an expenditure of £1.00. The C. Bias and Z. Bias both achieve expenditure of £0.09 and £0.29 respectively. The start time of dispatch for two selected demand response loads – dish washer and cloth washer for the different approaches is shown in the figs. 4c and 4d respectively.

The monthly expenditure of all the houses combined using the different approaches is further presented in the Table 5. It is observed from the Tables 5 and 6 that all approach methods (except the C. Bias) guarantee the minimum income for the supply based on the quoted per unit price (SP) given by the supplier. Also worthy of note is the fact that the C. Bias approach does present the lowest expenditure for the consumers with the S. Bias approach guaranteeing the maximum profit for the supplier. The choice of the appropriate dispatch approach method is further enhanced by examining the environmental consequence (generator under-utilization, carbon emissions etc.) of the chosen dispatch approach.

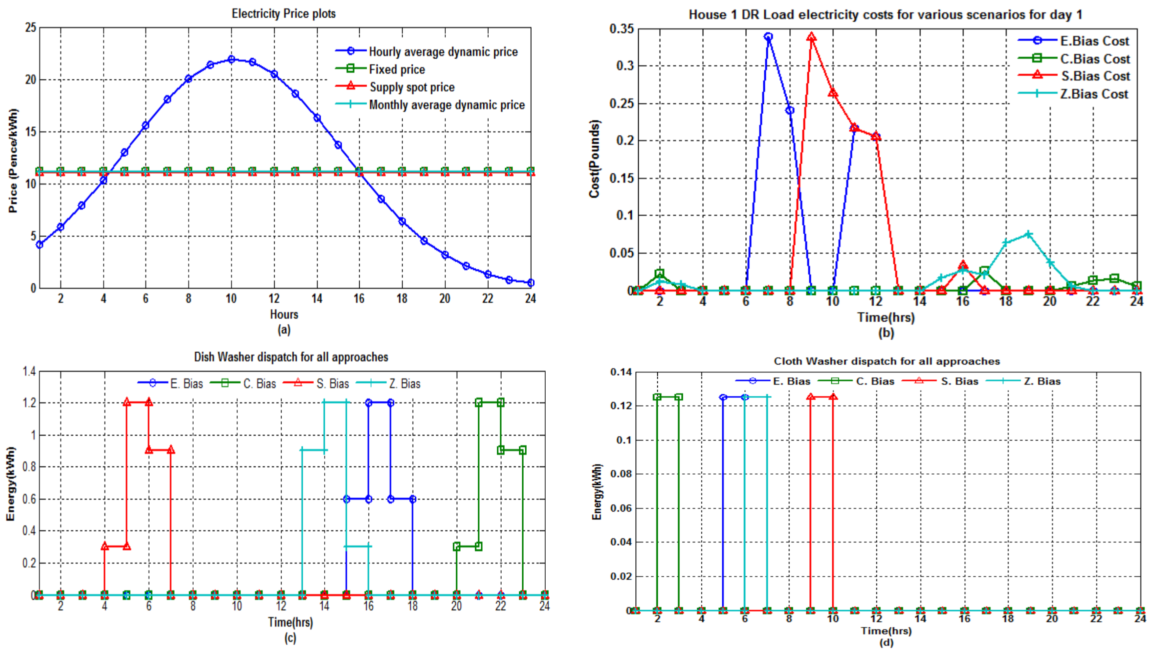

Figure 4: Daily (a) Pricing schemes, (b) electricity cost spread for house 1, (c) dish washer allocation and (d) cloth washer allocation for various pricing scenarios

Table 5: Combined monthly electricity cost (Pounds)

Cost evaluation approach (Pounds)			
C.Bias	E.Bias	S.Bias	Z.Bias
308.42	371.19	429.67	348.35

Table 6: Estimated consumer expenditure (£) and supplier minimum revenue (£) using Fixed price (FP) and supplier spot price (SP)

FP	0.1113
SP	0.11
Supplier income based on SP	346.47
Consumer expenditure using FP	350.56

7 CONCLUSION

This paper has presented MOMD-GA which is aimed at not just reducing the electricity bill of the consumer but providing options for dispatch choice based on various constraints. As a policy support algorithm, MOMD-GA offers system operators and distribution network operators a platform to harmonize the needs of the consumers with the suppliers' preferences and regulators constraints. A savings of about £42 (12% below fixed price expenditure) is obtained from the C. Bias approach while an extra income of about £83 (24% beyond spot price earnings) is obtained using the S. Bias approach. The E. Bias and Z. Bias approaches optimize dispatch and consumer monthly expenditure based on their intended purposes. While the C. Bias approach does not guarantee maximum accrual to the utility, it could however be used to encourage consumption from consumers with the deficit covered by the government in form of carbon rebates (reduced environmental penalties).

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