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A Genetic Evolutionary Task Scheduling Method for Energy Efficiency in Smart Homes

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Abstract – *For electricity consumers, there are power loads which need to be processed in a predefined time interval. The electricity price could vary between peak and off-peak time. In that case, the intelligent task scheduling module in a smart home can minimize the entire energy expense if the task control module could schedule the electrical equipments' start times, which are determined by their power consumptions and operation time constraints.*
In Smart Grid environments, this Advanced Metering Infrastructure (AMI) could automatically schedule the operation time of each equipment to minimize the residential overall power consumption while satisfying the equipment's operation constraint such as the equipment needs to be started at a time between two predefined time instants, and the power system is not overloaded at any time instant. In this research, the paper formulates the situation as an optimization problem and proposes a Genetic Algorithm (GA) based algorithm to find the optimum schedule arrangement for all the tasks in a smart home to reduce the energy cost. The performance of the GA based method is evaluated with the previous research works such as SA based method and greedy search method. The simulation results show that the GA based scheduling algorithm can efficiently and optimally minimize customers' electricity cost. **Copyright © 2012 Praise Worthy Prize S.r.l. - All rights reserved.**

***Keywords**: Smart Home, Genetic Algorithm, Task Scheduling, Smart Grid*

Nomenclature

TC	Total Cost
N	Total Number of the Task
i	Task Index
Si	The Earliest Time Task *i* can start
Fi	The Latest Time Task *i* must finish
SSi	The Scheduled Start Time of Task *i*
SFi	The Scheduled Finish Time of Task *i*
Li	The Running Time Length of Task *i*
Ri	The Energy Load of Task *i* on KW
SET	The total Task set of the Running Tasks
SP	The Peak hour start time
FP	The Peak hour end time
PC	The hourly energy cost rate of the peak time
OC	The hourly energy cost rate of the off-peak time
TPi	The sum of the energy cost of Task *i* in peak time
TOi	Sum of the energy cost of Taks *i* in off-peak time
LM	The Max Load the circuit can take in the house

I. Introduction

The Smart Grid is an intelligent supply and transmission power network which optimally transmits and distributes power from suppliers to consumers using information and communication technologies [1].

The Advanced Metering Infrastructure (AMI) is one of the crucial parts in the Smart Grid technologies.

AMI is an infrastructure which is advanced from Automatic Meter Reading (AMR). It provides bidirectional communication from meter and electricity applications. AMI network connects smart meters to a system, and transfers metering information to consumers or service electric power companies [2]. The power supply company can measure, collect, and analyze smart meter usage statistics wireless through AMI network, also AMI can realtimely poll the current power consumption level to adjust the equipment operation time in order to manage the energy consumption.

Demand Response (DR) in Smart Metering is a technology of notifying or automatically controlling the individual consumers to change the electricity usage pattern so that the overall demand cost on the system is reduced [3]. It can also inform consumers the consumption level and price by collecting and analyzing through AMI network. Demand Response can cut costs for securing generation assets for Peak Demand, and prepare for emergencies such as blackout [4]. As AMI has the information of each equipment's energy consumption rate, it could be used to optimize the total housing electricity cost by scheduling the duty task in advance.

The objective of the scheduling is to arrange the routine electricity tasks in order to minimize the grid electricity cost over a time horizon.

The output of the scheduling is to deliver a task running schedule when to switch on and off the loads so that

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overall of the demand cost on the system is minimized to a minimum level.

This paper formulates the situation as an optimization problem i.e. minimizing the entire power consumption while satisfying the equipments' operation time constrains and the entire power load constrain. And it then proposes a Genetic Algorithm (GA) based method to find the optimum scheduling arrangement. The contributions of the work are listed as following:

1) Formulating the electricity cost reduction problem while considering the equipments' operation time constrains and the system power load constrain which were not considered by previous methods
2) Providing a novel GA based approach to obtain the optimal scheduling arrangement for reducing the energy cost for residential customers in smart grids;
3) Satisfying the equipments' operation time constrains and the system power load constrain which were not considered by previous methods;
4) The performance of the proposed method is evaluated with other heuristic method such as the Simulated Annealing (SA) based method.

The paper is organized as follows. Section II discusses related works and motivations. Section III formulates the problem and lists all the constraints of the problem. Section IV proposes the detail of the GA approach. The proposed GA approach is compared and evaluated with the SA based method [29] in Section V through case studies.

The simulation results are further analyzed in Section V. Conclusions are drawn in Section VI. For comparisons of the proposed approach with the SA based search method, a brief description of the SA based search method is also given in the Appendix.

II. Related Works and Motivations

II.1. Related Works

As stated in Section I, the power consumption management scheduling method is defined as demand response support method. Research involves automatically scheduling for minimizing entire power load is limited. Currently, research which is similar to our topic in scheduling and providing the demand response through appropriate heuristic technologies that reduce power consumption is [6]. The research presents a multi-objective evolutionary algorithm to solve the dayahead thermal generation scheduling problem. In the proposed algorithm, the chromosome was formulated as a binary unit commitment matrix (UCM) which stored the generator on/off states and a real power matrix (RPM) which stored the corresponding power dispatch. The proposed algorithm could minimize the system operation cost and minimize the emission cost.

In [7], the demand response problem has been formulated as a combinatorial optimization problem and a simulated annealing algorithm to find the optimum schedule has been proposed.

The proposed method is applicable to different type of consumers if the interval during which a load has to be committed and the duration for which it has to be on is known at the start of the day. [8] presents an approach to the problem of planning appliance tasks in a household, taking into account the variability over time of the energy price paid by the consumer to the retailer. A mixed-integer linear programming formulation of the problem allows accommodating several issues, including the availability of power generators and storage devices. Preliminary experiments indicate that the model achieves good schedules, in very limited computation time, and without the need of sophisticated computational hardware.

Solution methods based on heuristic techniques such as Simulated Annealing algorithm (SA) in [20], [21], [22] and [30], artificial neural network (ANN) [12], particle swarm optimization (PSO) [13] and [14] which could provide promising results for solving the problem.

Besides the heuristic methods, deterministic approaches were also discussed in previous research on similar problems such as units commitment problem for energy saving. A priority list method is proposed in [15].

The research focuses on units' commitment problem, adapting extended priority list (EPL) method. The EPL method consists of two steps, in the first step, the initial unit commitment problem is scheduled by priority list (PL) method. At the step, operational constraints (System power balance, Unit minimum up/down time and so on) are disregarded. In the second step unit schedule is modified using the problem specific heuristics to fulfill operational constraints. In [16], the research presents a formulation of security constrained unit commitment (SCUC) problem based on mixed integer programming (MIP) method with considering prohibited operating zone limits of thermal and hydro units. The non-convex characteristic of generator cost function, representing prohibited operating zones is considered in SCUC. Test results with an eight-bus system show the accuracy of the model and formulations. The branch and bound method (BB) [17], and Lagrangian relaxation (LR) [18] [19] also have been used for solving the problem.

II.2. Motivations of this Work

Focusing on how to schedule the routine power demand tasks that to minimize the grid operational cost over a time horizon, a method gives better trade-offs among simplicity, far-field accuracy should be proposed.

Among previous proposed methods, the Priority List method is simple and fast but it provides poor solutions. The Dynamic Programming method is flexible but it has a poor performance on computation time because of the curse of dimensionality problem. The Mixed Integer Programming method's performance decreases when the number of unit becomes large because it requires a large memory and suffers from great computational delay. The Branch-and-Bound method exponentially increases in the computation time as the system search space grows. The

Lagrangian relaxation method provides a faster solution but it has a poor performance on numerical convergence and existence of duality gap.

The genetic algorithm (GA) is a generic probabilistic meta-algorithm for the global optimization problem, which tries to locate a good approximation to the global optimum of a given function in a large search space. It has already been used in [9], [10], [11] and [31] for power unit commitment problem. According to [23], the SA algorithm is able to provide good results in general optimization searches for task scheduling. Therefore, it is worth investigating whether or not the GA algorithm can be suitable for automatic tasks scheduling in demand response of a smart meter system. This work will give a positive answer to this question.

III. The Formulation of the Problem

This section gives the detail of the formulation of the problem and lists the equipments' operation time constrains and the system power load constrain of the problem, the notations used in the following sections are shown in the nomenclature.

III.1. Mathematical Formulation of the Problem

The objective of the DR task scheduling problem is the minimization of the total cost through peak and off-time energy consumption time. The total cost, *TC* over the entire scheduling period is the sum of the combination of peak and off-peak cost of each task *i*. Mathematically, overall objective function of the DR task scheduling problem is as follows:

$$MIN\left(TC\right)=\sum_{i=1}^{i=N}TP_i+\sum_{i=0}^{i=N}TO_i \qquad (1)$$

The sum of the energy cost of Task *i* in peak time *TPi* could be derived by:

$$TP_i=\begin{cases}\left(FP-SP\right)\cdot PC\cdot R_i & SS_i<SP,\ SF_i>FP\\ \left(SF_i-SS_i\right)\cdot PC\cdot R_i & SS_i>SP,\ SF_i<FP\\ \left(SF_i-SP\right)\cdot PC\cdot R_i & SS_i<SP,\ SF_i<FP\\ \left(FP-SS_i\right)\cdot PC\cdot R_i & SS_i>SP,\ SF_i>FP\end{cases}$$

Similarly, the sum of the energy cost of Task *i* in peak time *TOi* could be derived by:

$$TO_i=\begin{cases}0 & SS_i>SP,\ SF_i<FP\\ \left(SP-SS_i\right)\cdot OC\cdot R_i & SS_i<SP,\ SF_i<FP\\ \left(SF_i-FP\right)\cdot OC\cdot R_i & SS_i>SP,\ SF_i>FP\\ \left(SP-SS_i\right)\cdot OC\cdot R_i+ & \\ +\left(SF_i-FP\right)\cdot OC\cdot R_i & SS_i\ <SP,\ SF>FP\end{cases}$$

III.2. Constraints of the Problem

The problem subjects to several constraints for the scheduling of energy saving. These include system load constraint, the starting time constraint and so on. The object function has to subject to the constraints. The constraints that must be satisfied during the optimization process are as follows:

1) *System Load Balance:* As there is a limit of power load in the circuit, on any time *t*, the overall system load cannot be above the *LM* which is the Max power load the circuit can take in the house:

$$\sum_{i\in SET}R_i<LM \qquad (2)$$

2) *Task Start Time Constraint:* As power loads which need to be switched on for a time between two predefined time instants, there is a start time constraint for each task:

$$\forall_i\in N,\quad SS_i>S_i$$

3) *Task Finish Time Constraint:* As power loads which need to be switched off for a time between two predefined time instants, there is a finish time constraint for each task:

$$\forall_i\in N,\quad SF_i<F_i$$

4) *Task Non-preemptive Constraint:* The task which has already been started cannot be preempted by other tasks in the scheduling.

IV. The Architecture of the GA Method

The section illustrates the structure of the simulated annealing approach. Subsection IV.1 illustrates the structure and the architecture of the simulated annealing based approach.

IV.1. The Structure of the GA based Method

Section III provides the object function and constraints for the problem optimization. The optimal result could be easily derived when there are small amount of tasks for scheduling. As the number of the tasks increases, it becomes much more difficult to obtain the optimal result.

The optimization problem could be considered as a bin-packing [24] or a knapsack problem [25] if it is without the constraints III.1 and III.2. Therefore, the optimization problem for tasks scheduling with constraints is a NP-Hard problem, in which we hardly obtain the optimal result by deterministic methods.

The Genetic Algorithm (GA) is a generic probabilistic meta-algorithm for the global optimization problem, which tries to locate a good approximation to the global optimum of a given function in a large search space. It is adapted to solve many other NP-Hard problems such as

Traveling Salesman Problem [26]. Therefore, it is worth investigating whether or not the GA algorithm can be suitable for automatic tasks scheduling in demand response of a smart meter system. Fig. 1 illustrates the detail structure of the GA approach.

In Fig. 1, *Gen* is initialized as 0 in the beginning of the method. *Gen* is increased by 1 when the method finishes calculating one generation (*P* ien the algorithm). Each chromosome in the GA method is a feasible solution for the task scheduling, which is a set of the start time of each tasks, i.e. *SS(1,2,…n)*. In each generation, the best solution (the best chromosome *SS* which has the lowest energy cost) is inserted to the best solution set (*BS_set*) which records the best chromosome for each generation.

After we pick up the best chromosome from one generation, *Mutation* and *Crossover* operator are used to generate the next generation from the current generation. 50% of the chromosomes in the current generation perform mutations and the other 50% chromosomes process the crossover operation.

Fig. 2 shows the procedure of mutation. In Fig. 2, chromosome 1’ is derived from chromosome 1. The mutation operator randomly shift the scheduled start times (e.g. *SS1* and *SS2* in Fig. 2) of some tasks (e.g. Task 1 and 2 in Fig. 2) to generate a new task scheduling solution (chromosome 1’ in Fig. 2 with *SS1’* and *SS2’*). As the charge for energy is different in peak/off-peak time slot, the newly generated chromosome may have a better result in energy efficiency than the previous chromosome. The notations in Fig. 2 are explained above.

Because the shifting is random, the new scheduled finish time of a task (e.g. *SF1’* in Task 1) may be later than the required latest finish time (*SF1’ > F1* in Task 1), which will make the new chromosome an invalided solution.

Therefore, after mutation and crossover operation, all the new chromosomes in the new generation are screened with the constraints 1, 2 and 3 again to filter out the infeasible solution.

Then, steps 2 – 4 in Fig. 1 are repeated to insert new random chromosomes into the new generation if there are not enough valid chromosomes.

Fig. 3 illustrates the operation of the crossover operator. The crossover operator randomly swap some tasks’ (Task 2 in chromosome 1 and 2 in Fig. 3) scheduled start times (SS2 in chromosome 1 *SS2_c1* is swapped with SS2 in chromosome 2 *SS2_c2*; SF2 in chromosome 1 *SF2_c1* is swapped with SF2 in chromosome 2 *SF2_c2*) to generate new chromosomes.

Since the swapping of the scheduled start time is all between feasible chromosomes, the new generated chromosomes will all be valid solutions.

Therefore constraints screening is not required for the crossover generated chromosomes.

Fig. 4 shows the psedo code of the Genetic Algorithm base method. The variable names follow the notations in section III.1 and Fig. 1, 2 and 3 of GA method. The best solution is selected from the *BS_set* for all the generations.

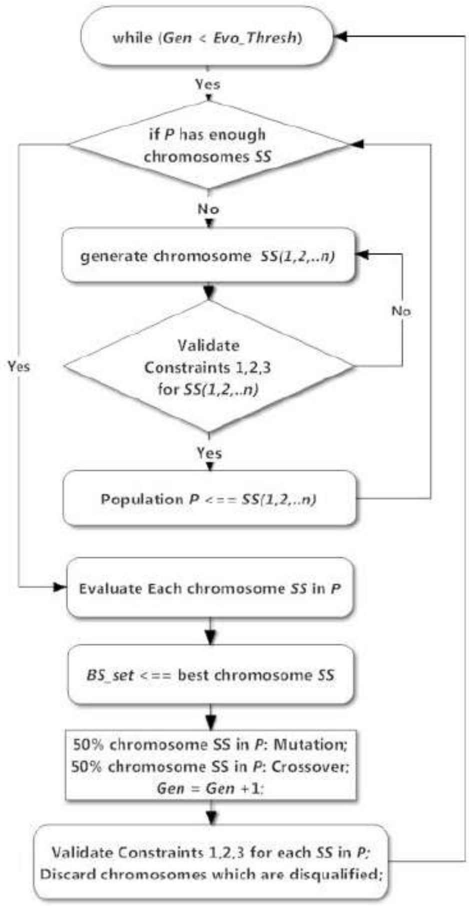

Fig. 1. Structure of the GA Algorithm

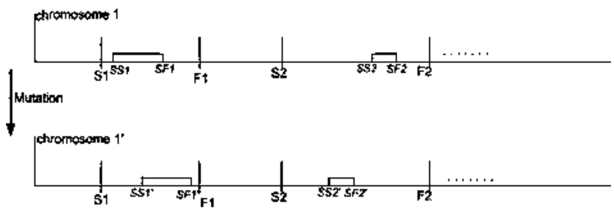

Fig. 2. Mutation Operator of the GA Algorithm

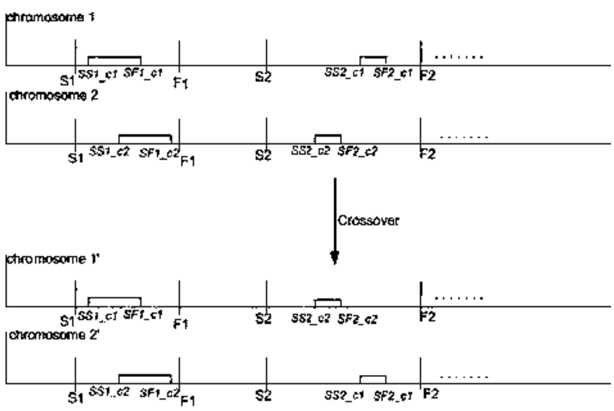

Fig. 3. Crossover Operator of the GA Algorithm

```
Algorithm: Genetic Algorithm Method
Gen = 0;
while (Gen < Evo_threshold)
    while (P does not have enough SS)
        generating a SS
        if (SS does not pass all constraints)
            continue
        endif
        insert SS to P
    endwhile
    evaluate each SS in P
    BS_set <= best SS
    randomly mutation(P)
    randomly crossover(P)
    Gen++
    constraint_validate(P)
    discard_invalid_SS(P)
endwhile
SS_best = best_solution_pick(BS_set)
return SS_best
```

Fig. 4. Psedo codes of the GA Method

V. Case Studies

The section illustrates the simulation results of the GA method. Subsection V.1 illustrates the hardware environment and parameter settings of the simulation cases. Subsection V.2 shows the simulation result and performance evaluation for each case.

V.1. Simulation Environments and Parameter Settings

Our case studies are carried in Matlab under Windows XP on a computer with 2.8GHz Pentium Core 2 Duo CPU and 2GB memory.

Ten tasks scheduling cases are designed to test the performance of the GA approaches. In each case, the whole energy cost calculation cycle is 24 hours, the time unit is defined as an hour. The task on/off constraint time window (S_i and F_i) is obtained by random generation (normal distribution with a mean value) within 24 hours.

The L_i is also randomly generated but with the constraint that it must be within the range of on/off constraint time window (S_i and F_i).

The energy load of each task is also follow a normal distribution with a 100kw mean value. The total power limit *LM* is the 80% of the sum of all tasks load. And we set Peak time energy cost rate PC = 10, Off-peak time energy cost rate OC = 5. The peak time is set for six hours from 16:00-22:00. Parameters of all ten cases are shown in Table I and Table II. For performance comparisons, the greedy search [28] and the SA based method [29] are implemented to solve the task scheduling problem.

In each test case, the GA method, the SA approach and the greedy search method were run eighty times to obtain the performance statistics.

TABLE I
TEN TASKS SCHEDULING CASES.

Task Quantity	Maximum Load(W)	Average Tasks Length (h)	Time Constraint	Average Task Load(W)
3	240	5	18	100
5	400	5	18	100
8	640	5	18	100
10	800	5	18	100
12	960	5	18	100
14	1120	5	18	100
16	1280	5	18	100
18	1440	5	18	100
20	1600	5	18	100
22	1760	5	18	100

TABLE II
PEAK/OFF-PEAK HOUR SETTINGS

Peak Hour Cost Rate	Off-peak Hour Cost Rate	Peak Hour Start (24h)	Peak Hour End (24h)
10	5	16:00	22:00

The greedy algorithm is an algorithm that follows the problem solving heuristic of making the locally optimal choice at each stage with the hope of finding a global optimum. On some problems, a greedy strategy need not produce an optimal solution.

From our previous research, the SA approaches can provide better performance than the greedy search. The brief description of the greedy method and the SA based method are given in [29].

The control parameters (such as *Evo_threshold*) of the GA approach are tabulated in Table III.

TABLE III
CONTROL PARAMETERS FOR THE GA METHOD

Max Generation Number (*Evo-threshold*)	Population Size	Mutation	Crossover
1000	10000	50%	50%

V.2. Simulation Results

The approach processing time and the obtained optimal total energy cost are evaluated among three methods. They are depicted in Table IV. Each case is run according to the parameters shown in Tables I, II and III. Table IV lists the simulation results of the GA, the SA and the greedy approach's processing time and total minimum energy cost after scheduling.

The results show that all of the approaches have similar results in processing time. In processing times, the greedy approach performs slightly better than the SA and the GA approach. This is because the greedy approach uses one-time best-fit selection which ignores the possible acceptance step.

For the results of the obtained minimum total energy cost after scheduling, the GA based method gives the best perform, and the SA approach performs better than the greedy search method.

From the above comparison results in calculation time and minimum energy cost among three approaches.

TABLE IV
QUANTITATIVE PERFORMANCE RESULTS

Cases	GA Method	SA Method	Greedy Method
Task Quantity:3			
Processing Time (s)	0.01	0.01	0.01
Total Energy Cost (KWH)	7.63	7.67	7.71
Task Quantity:5			
Processing Time (s)	0.02	0.02	0.02
Total Energy Cost (KWH)	16.41	16.73	18.93
Task Quantity:8			
Processing Time (s)	0.09	0.08	0.06
Total Energy Cost (KWH)	26.98	27.87	31.43
Task Quantity:10			
Processing Time (s)	0.15	0.13	0.101
Total Energy Cost (KWH)	31.14	33.17	39.09
Task Quantity:12			
Processing Time (s)	0.31	0.28	0.263
Total Energy Cost (KWH)	37.45	40.37	47.78
Task Quantity:14			
Processing Time (s)	0.48	0.43	0.41
Total Energy Cost (KWH)	44.32	48.03	56.37
Task Quantity:16			
Processing Time (s)	0.74	0.68	0.64
Total Energy Cost (KWH)	50.65	55.33	65.62
Task Quantity:18			
Processing Time (s)	1.01	0.93	0.90
Total Energy Cost (KWH)	55.77	60.75	71.37
Task Quantity:20			
Processing Time (s)	1.41	1.34	1.29
Total Energy Cost (KWH)	64.12	70.32	81.94
Task Quantity:22			
Processing Time (s)	1.98	1.88	1.79
Total Energy Cost (KWH)	71.95	79.05	93.84

We can conclude a complete performance review of the proposed GA approaches.

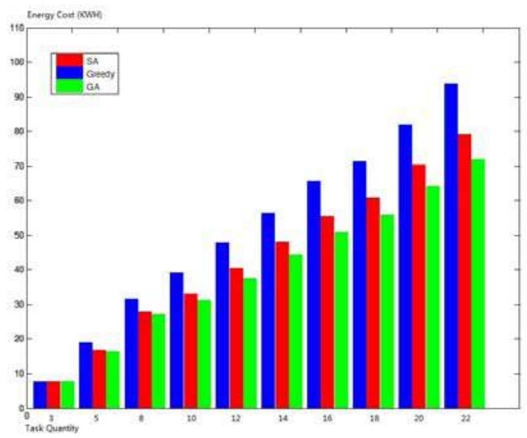

Fig. 5. Total Energy Cost for Each Case

Comparing with the greedy search method and the SA approach, the GA gives a quite optimistic performance on minimizing the energy consumption. Fig. 5 and Fig. 6 demonstrate the performance difference among the GA method, the SA approach and the greedy method. Fig. 5 and Fig. 7 show the GA approach gives better performance in obtaining the minimum energy cost in particular with the large search space cases (it is more practical in industry). According to the evaluation results, the GA approach have a good balanced trade off in calculation time and energy cost optimization (e.g. comparing with the greedy approach, in case ten, the GA approach improves the energy saving by 19.76% while it only has 6.88% calculation time increase).

Therefore, it can be concluded that the GA approach is a highly efficient method for tasks scheduling in energy saving purpose.

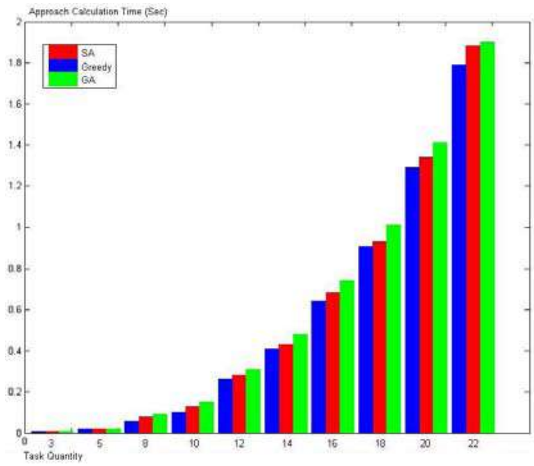

Fig. 6. Calculation Time for Each Case

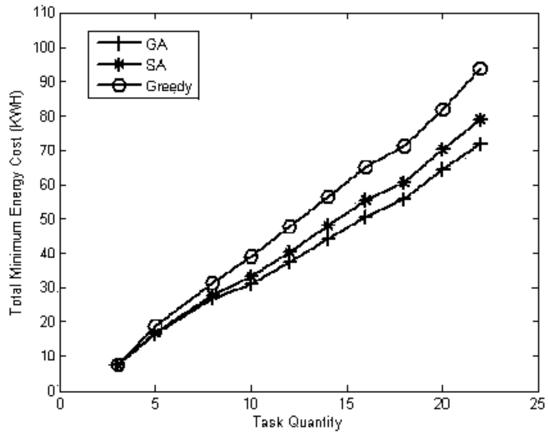

Fig. 7. Performance Comparison among Three Methods

VI. Conclusion

A GA Approach for minimizing the residential total energy cost in Demand Response (DR) services has been proposed in this research. The approach optimally schedule tasks while considering tasks on/off time constraints and the entire circuit maximum load constraint.

Compared with the SA and the greedy methods for the energy cost reduction, the proposed GA approach can obtain the optimal scheduling solution for residential customers in smart grids while satisfying the equipments' operation time constrain and the entire power load constrain which was not considered by previous methods.

The simulation results show that the GA based scheduling algorithm can efficiently and optimally minimize customers' electricity cost.

Appendix

The pseudo-code of the greedy search method and SA method are explained in Fig. 1A and Fig. 2A.

```
Algorithm: Greedy Method for Tasks Scheduling
while (SS not ready)
    Pick smallest F_i-S_i
    find SS_i which S_i - SS_i is the maximum
    (constrained by constraints)
    Add SS_i into SS
End-while
Evaluate SS, TC = f(SS);
while (count < Threshold)
    while (SS not ready)
        Pick smallest F'_i-S'_i
        find SS'_i which S'_i - SS'_i is the maximum
        (constrained by constraints)
        Add SS'_i into SS'
    End-while
    Evaluate SS', TC' = f(SS');
    If f(SS') < f(SS)
        SS = SS';
    End-if
    count ++;
End-while
SS is the optimal or near-optimal solution.
Return
```

Fig. 1A. Psedo codes of the Greedy Search Method

```
Algorithm: SA Approach for Tasks Scheduling
T = T_initial;
while (T > T_terminate)
    Randomly generate a feasible solution SS
    (constrained by constraints)
    Evaluate SS, TC = f(SS);
    count = 1;
    while (count < Threshold)
        Generate a new feasible solution SS' base on SS;
        Evaluate SS'; TC' = f(SS');
        If f(SS') < f(SS)
            SS = SS';
        Elseif rand(1) < exp((f(SS') - f(SS)) / T)
            SS = SS';
            count = count + 1;
        End-if
    End-while
    T = cool_rate * T;
    Update SS at each reduction of temperature T
End-while
SS is the optimal or near-optimal solution.
Return
```

Fig. 2A. Psedo codes of the SA Method

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