A Thesis

entitled

Nature Inspired Grey Wolf Optimizer Algorithm for Minimizing Operating Cost in Green

Smart Home

by

Srivathsan Lakshminarayanan

Submitted to the Graduate Faculty as partial fulfillment of the requirements for the

Master of Science Degree in

Engineering

Dr. Devinder Kaur, Committee Chair

Dr. Mansoor Alam, Committee Member

Dr. Srinivasa Vemuru, Committee Member

Dr. Patricia R. Komuniecki, Dean
College of Graduate Studies

The University of Toledo

August 2015

An Abstract of

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In this thesis, a new swarm intelligence based algorithm called Grey Wolf Optimizer (GWO) mimicking the social hierarchy and hunting behavior of grey wolves is used to optimally schedule the operation of Energy Storage Unit (ESU) in a green smart home to reduce the cost of power consumption and to balance the load on the grid. The smart home is primarily powered by the utility, which sends to the customer the hourly prices for the next day before the midnight when the new day rolls in. It is also integrated with local solar panels and wind turbines. Whenever the renewable energy resources are generating power, they can be used for meeting the household demand and to charge the Energy Storage Unit. The excess power generated is sold back to the utility through the grid at the same price at which the power is delivered to the customer during that hour. The GWO algorithm determines when and by how much, the ESU should be charged or discharged for each hour of the day for optimal cost saving. The proposed algorithm was tested with data obtained from the United States Department of Energy for Chicago region. The performance of the GWO algorithm is compared with the well known conventional Particle Swarm Optimization (PSO) Algorithm. The results show that the

GWO outperforms the PSO and provides higher cost saving. The proposed method does not impose any restriction on the consumer regarding when to use which appliance, thus providing total freedom and still saving money.

I dedicate this work to His Holiness Shri Kanchi Paramacharya

Acknowledgements

First and Foremost, I thank Almighty God for providing me the strength, ability and situation for carrying out this thesis work.

It gives me immense pleasure to acknowledge the people who have helped me complete my thesis successfully.

I thank my advisor Dr. Devinder Kaur for the continuous, thoughtful, diligent and meticulous guidance and encouragement, without which this work would have been impossible. It was wonderful working under her!

I thank Dr. Mansoor Alam for all the support he provided right from the beginning of my Master's Program. I thank him for the wise, calm and diligent support that he provided throughout!

I am extremely thankful to Dr. Srinivasa Vemuru for agreeing to serve on the committee. I thank him for the kind and benevolent support.

I want to thank the EECS Department, Dr.Mansoor Alam and Dr. Devinder Kaur for providing me the financial support!

I thank all the faculty and staff members of the EECS Department for their wonderful support!

Finally, I thank my family and friends for their affection and support!

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List of Abbreviations

GWO..........................Grey Wolf Optimizer
ESU............................Energy Storage Unit
PSO............................Particle Swarm Optimization
DR..............................Demand Response
TOU............................Time of Use
RTP............................Real Time Pricing
VPP............................Variable Peak Pricing
MIPSO.......................Multipass Iteration Particle Swarm Optimization
BPSO..........................Binary Particle Swarm Optimization

Chapter 1

Introduction

While the United States transportation sector emits 20% of all the carbon dioxide we produce, the generation of electricity emits 40% – clearly presenting an enormous challenge for the electric power industry in terms of global climate change [1]. According to the United States Energy Information Administration, world energy consumption will grow by 56% between 2010 and 2040 [2].

The Demand Response (DR) and the use of renewable energy resources are the two main approaches to tackle the problems of growing energy demand, depletion of fossil fuels and global climatic change. Hence, the United States Department of Energy has increased the funding for various smart grid and clean energy projects [3]. Moreover, many incentives are given to the consumers who are using renewable energy systems. For example, in the United States, a taxpayer can claim a credit of 30% of expenditures for renewable energy system [4]. The DR is used to motivate changes in the customer's power consumption behavior, in response to incentives regarding the price of electricity. It is considered as the most cost-effective and reliable solution for the smoothing of the demand curve, when the system is under stress [5].

To enforce DR, different types of time-based rate programs such as Time of Use (TOU), Real-time Pricing (RTP), and Variable Peak Pricing (VPP) have been introduced. In case of TOU, prices for the next year are forecasted based on the peak and off-peak load demand of the current year. In RTP pricing, prices are determined usually an hour before, based on the real time market conditions. In VPP, the peak price for the next day is predicted based on the peak price of the current day [6].

These days, the trend is to use the grid-connected renewable energy systems where the local renewable energy resources are connected to the grid. By using the net metering, the consumer pays to the utility only for the difference between the price of electricity drawn from the grid and the electricity supplied to the grid from renewable energy resources [7].

A great deal of research has been done in optimizing the residential load control activities of consumers in response to smart pricing. Amir-Hamed Mohsenian-Rad and Alberto Leon-Garcia used Linear Programming for Optimal Residential Load Control with Electricity Price Prediction in Real-Time [8]. In reference [9], the customer preferences are quantified using Analytic Hierarchy Process and then Multiple Knap Sack Approach is used for scheduling the appliances in the residential environment. In reference [10], Amir-Hamed Mohsenian-Rad, Juri Jatskevich, Vincent W. S.Wong and Robert Schober Leon-Garcia have used Game Theory for demand Side Management under dynamic pricing. Kumaraguruparan N. , Sivaramakrishnan H. , Sachin S. Sapatnekar, have used Multiple-Knap Sack Method to solve the problem of optimally scheduling a set of residential appliances when the hourly prices for power consumption are determined a day earlier [11].

In reference [12], Peter Van de Ven, Nidhi Hegde, Laurent Massoulie and Theodoros Salonidis have modeled threshold based battery operating strategy using Markov Decision Process for a smart home using Time of Use (ToU) Pricing Scheme. In reference [13], a dynamic programming approach is used to determine optimal charging/discharging schedule for an Energy Storage Unit. Danilo Fuselli et al. have used action dependent heuristic dynamic programming for Optimal Management of Battery in Smart Home Environment [14].

Meta-Heuristic Algorithms are being used for solving optimization problems in various engineering fields including smart grid, due to their ability to efficiently explore the search space, derivation free mechanism and problem independent nature. Yantai Huang, Lei Wang, and Qidi Wu have used Hybrid of Particle Swarm Optimization and Differential Evolution Algorithm for smart home energy management [15]. Yourim Yoon and Yong-Hyuk Kim have used Real Coded Genetic Algorithm (RCGA) for Charge Scheduling of Energy Storage System of a smart home using Time-of-Use Pricing and Demand Charge [16].

Multipass Iteration Particle Swarm Optimization (MIPSO) Algorithm is used for scheduling Battery Energy Storage Unit for Industrial user with Wind turbine Generator in [17]. Hector M. Lugo-Cordero, Abigail Fuentes-Rivera, Ratan K. Guha, and Eduardo I. Ortiz-Rivera have used Binary Particle Swarm Optimization (B-PSO) algorithm for optimally distributing the residential appliances to each of the green energy resources in a green smart home [18].

Grey Wolf Optimizer (GWO) is a new Meta-Heuristic Algorithm based on the leadership hierarchy and hunting behavior of grey wolves proposed by Seyedali Mirjalili, Seyed Mohammad Mirjalili and Andrew Lewis [19]. The GWO algorithm has been applied to various optimization problems namely training Multi-Layer Perceptron Neural Network [20], Economic dispatch problems [21], feature subset selection [22], optimal control of DC motor [23] and Blackout risk prevention in a smart grid [24].

In this thesis, an efficient and robust cost saving method for a smart home integrated with renewable energy resources is proposed by optimal scheduling of ESU using GWO Algorithm satisfying multiple constraints. The proposed method was tested on hourly power consumption data provided by the United States Department of Energy (DOE) for a residential household located in Chicago, Illinois, United States [25]. The performance of the GWO algorithm is compared with the conventional PSO algorithm.

Hourly solar energy generation data for the year 2013 was obtained from National Renewable Engineering Laboratory's web portal-PVWatts and the hourly wind velocity data was obtained from National Oceanic and Atmospheric Administration's Great Lakes Environmental Research Laboratory [26] [27]. Day ahead hourly prices for power consumption for the year 2013 was obtained from ComEd, a local utility that provides electricity to Chicago area [28].

Table I shows the snap shot of the data profile for a sample day, May 30, 2013 including hourly load demand, solar energy generated, wind turbine output and the prices predicted a day earlier.

Table 1.1: Hourly Variation of Power Consumption Cost, Load Demand, Wind Turbine Output and Solar panel Generation for a sample day (5/30/2013)

Hours	**Day Ahead Hourly Price ($/KWH)**	**Hourly Load Demand (KW)**	**Hourly Wind Turbine Output (KW)**	**Hourly Solar Panel Output (KW)**
0-1	0.0249	1.4579	1.0419	0
1-2	0.0232	1.2934	1.2271	0
2-3	0.0214	1.2634	2.7771	0
3-4	0.0216	1.2554	2.6441	0
4-5	0.0235	1.3878	2.3841	0.0371
5-6	0.0302	1.7568	1.8018	0.1281
6-7	0.0369	2.2863	2.0312	0.2576
7-8	0.0409	2.0747	2.1589	0.6322
8-9	0.0466	1.8614	1.2162	1.1946
9-10	0.0469	1.8717	1.9192	1.2695
10-11	0.0549	1.9074	1.7733	1.3104
11-12	0.0563	1.8736	2.3753	3.2244
12-13	0.0672	1.8244	3.4793	2.6888
13-14	0.0747	1.8101	3.2426	2.4762
14-15	0.0853	1.8773	4.3182	1.6375
14-16	0.0943	2.1639	4.7894	1.0934
17-18	0.0807	2.6456	4.7589	0.8074
18-19	0.0692	2.8984	4.9527	0.4310
19-20	0.0540	3.2242	4.6778	0.0845
20-21	0.0560	3.9261	4.8797	0
21-22	0.0483	4.3827	4.3425	0
22-23	0.0437	3.5779	3.0248	0
23-24	0.0353	2.7182	4.8577	0

This thesis is organized as follows: Chapter 2 discusses the infrastructure needed in the smart home to implement the algorithm. Chapter 3 discusses the social hierarchy and hunting behavior of grey wolves. Chapter 4 presents the dynamics of Grey Wolf Optimization Algorithm. The optimization problem for cost saving is formulated in Chapter 5. The simulation results are discussed in the Chapter 6 and the Chapter 7 presents the conclusion.

Chapter 2

Green Smart Home Infrastructure

This chapter discusses the infrastructure needed in the smart home to implement the proposed algorithm.

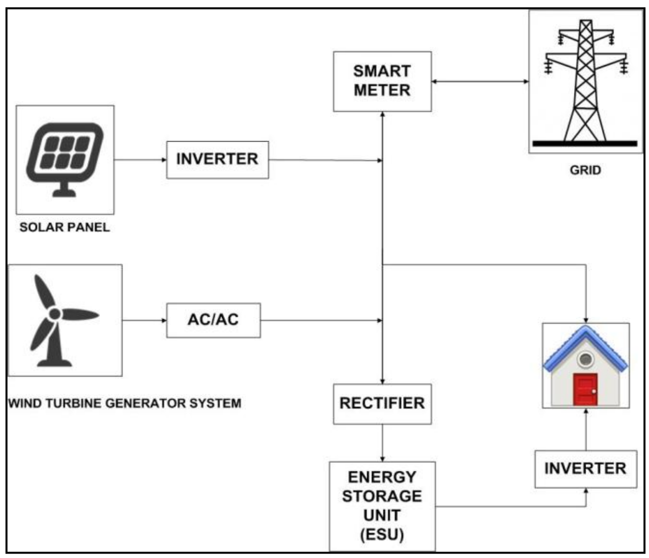

Figure 2-1: Proposed Green Smart Home Infrastructure

Figure 2-1 shows the infrastructure of the green smart home for which the proposed cost saving approach is implemented.

The specifications and functions of the components integrated to the household are explained below:

1. Energy Storage Unit: Energy Storage Unit of capacity C_B=15 KW is connected to the grid through a rectifier. Rectifier converts the power to DC to be stored in ESU.

The stored energy can be used to meet the demand of household after being converted to AC by the inverter.

2. PV Solar Panel system: A 4KW fixed array Solar Panel is connected to the grid through an inverter. Inverter converts the DC output of PV-Solar Panel to AC to supply the household demand.

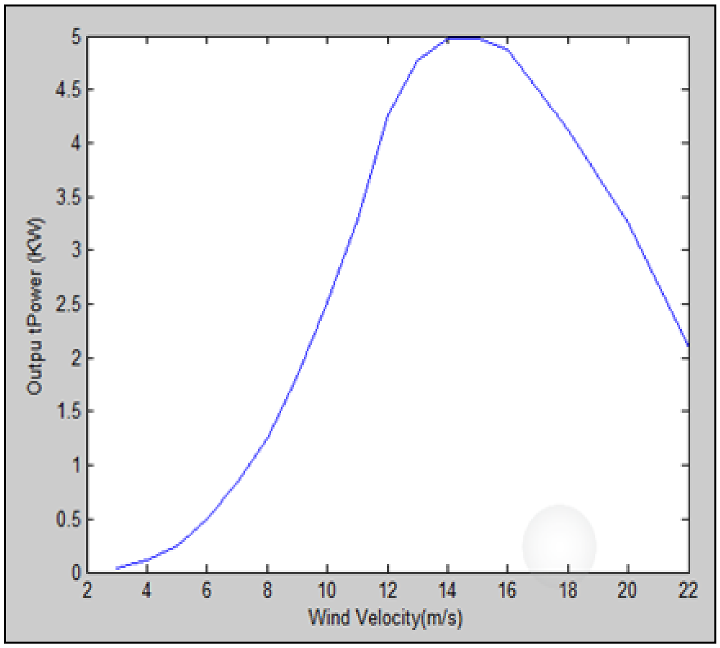

Figure 2-2: Wind Turbine Power Curve [29]

2. Wind Turbine: Figure 2-2 shows the power curve of the 5 KW wind turbine generator that is connected to the grid through AC/AC converter. The AC output of the wind turbine is not regulated. For regulating the power, AC/AC converter is used to convert the unregulated AC to direct current (DC) with a rectifier and is then converted back to AC with an inverter to match the frequency and phase of the grid.

3. Two Way Smart Meters: It is used for measuring the power consumed from the grid and the power that is delivered to the grid.

Chapter 3

Problem Formulation of Energy Cost Saving

The daily energy consumption cost (DECC) of green smart home is given by:

$$DECC = \sum_{n=1}^{24} [X(n) + L(n) - (W(n) + S(n))] * P(n)$$

(3.1)

where

X(n) is the state of charge of ESU during the hour n in Kilowatts *(KW)*.If *X(n) > 0*, the ESU is charging during the hour, else if *X(n)<0*, the ESU is discharging to supply the household demand during the hour n. When *X(n) = 0*, ESU is neither charging nor discharging.

L(n) is the household load demand during the hour *n* in Kilowatts *(KW)*.

W(n) is the wind turbine output power during the hour *n* in Kilowatts *(KW)*.

S(n) is the photo-voltaic solar panel output during hour *n* in Kilowatts *(KW)*.

P(n) is the price for electric power consumption during the hour *n* in *$/KWH*.

The objective of this research is to minimize the daily energy consumption cost (*DECC*), while satisfying the following constraints:

1. Zero Initial Charge Constraint (*ZICC*):

Energy stored in the ESU in a day must be discharged within the same day. This means, no energy should be carried forward to the next day, since the prices vary by the hour for each day. This constraint is mathematically expressed as follows:

$$\sum_{n=1}^{24} X(n) = 0 \tag{3.2}$$

2. Charging Constraint (*CC*):

At any hour *n* of the day, the ESU should not be charged above its maximum capacity C_B.

When $X(n)>0$,

$$X(n) \le (C_B) - \sum_{i=1}^{n-1} X(i) \tag{3.3}$$

For example if charged stored in ESU till the previous (n-1) hours is 7KW, then ESU can be charged up to 8KW for the nth hour.

2. Discharging Constraint (*DC*):

At any hour *n* of the day, the ESU cannot discharge power more than what has been stored in it by the previous *(n-1)* hours. This can be mathematically expressed as follows:

When $X(n)<0$,

$$|X(n)| \leq \sum_{i=1}^{n-1} X(i) \tag{3.4}$$

Violation of any of the above constraints has been added as penalty to the objective function which are defined and mathematically expressed as follows:

1. Zero Initial Charge Constraint Violation (*ZICCV*) :

This violation is added as penalty to the objective function when ESU does not drain all the power charged by it within the same day. In other words, this constraint violation is added as penalty to the Daily energy consumption cost *(DECC)* when (3.2) is false. This is explained by the following equations:

If (2) is true,

$$ZICCV = 0 \tag{3.5}$$

Else

$$\text{ZICCV} = \sum_{n=1}^{24} X(n) \tag{3.6}$$

2. The charging constraint violation (*CCV*):

This violation is added as penalty, when ESU is required to charge above its maximum capacity C_B in any hour n. For example, if the ESU is already charged to 8KW in previous (*n-1*) hours, the ESU cannot charge to 10KW at the nth hour as this would lead to a total charge of 18KW in the ESU, which is 3KW above the capacity of the 15 KW ESU. This constraint is added as penalty to the DECC when (3.3) is not satisfied.

If (3) is true,

$$CCV = 0 \tag{3.7}$$

Else,

$$CCV = X(n) - \left((C_B) - \sum_{i=1}^{n-1} X(i) \right) \tag{3.8}$$

3. Discharging Constraint Violation (*DCV*):

This constraint is violated when the demand for delivering the power is greater than what is stored in the ESU at that hour. For example, if the demand is for 10KW and if the charge on the battery is only 8KW, the ESU cannot supply the extra 2KW needed for the demand. The Discharging Constraint Violation (*DCV*) is added as penalty to the *DECC* when (3.4) is not satisfied.

If (4) is true,

$$DCV = 0 \tag{3.9}$$

Else,

$$DCV = | X(n) | - \sum_{i=1}^{n-1} X(i) \tag{3.10}$$

To increase the effect of penalties added to the *DECC*, the sum of penalties is multiplied by penalty-factor *Pv*.

Hence, the final objective function (*OF*) is to minimize the sum of *DECC* and weighted penalties. It is given by (3.11) as:

$$OF = \min\{DECC + P_V * (CCV + DCV + ZICCV)\} \tag{3.11}$$

where the penalty factor *Pv* = 5.

Penalty Factor *Pv* ensures that the solutions that do not obey the constraints are heavily penalized and in the course of evolution of GWO algorithm more solutions emerge that obey the constraints.

Chapter 4

Social Hierarchy and Group Hunting Behavior of Grey Wolves

In this chapter, the social hierarchy and group hunting behavior of grey wolf pack is presented. GWO algorithm is a nature inspired meta-heuristic algorithm which simulates the intelligent search strategy used by the grey wolves to coordinate among the pack members to locate their prey successfully during the hunting process. One of the important characteristic of grey wolves is that they have a strict social hierarchy in order to maintain stability and to mutually assist each other in hunting. The ranks of wolves based on social hierarchy and their duties are shown in Table 4.1.

Table 4.1: Social Hierarchy of Grey Wolves

Hierarchy Level	**Rank Name**	**Roles in the Pack**
1	Alpha	Leader
		Dictates Decision to the Pack
2	Beta	Advisor to alpha
		Maintains discipline in the pack
3	Delta	Watching the territory boundary
		Caretakers of ill and wounded wolves
4	Omega	Obeys other dominant wolves
		Eats after all the dominant wolves

The first level in the hierarchy and the leader of the pack is called as the alpha (α). The alpha can be either male or female. The alpha position is based on the strength and the fighting ability. The entire pack obeys the decision dictated by the alpha. Beta (β) occupies 2nd level in the hierarchy. Beta serves as the advisor to the alpha in decision making. It also commands the lower-level wolves and maintains the discipline over the pack. Delta stands 3rd in the grey wolf social hierarchy. They obey the orders of alpha and beta wolves. Deltas are the aged wolves that watch the pack's territory boundary and warn the pack in case of any danger. They also play the role of caretakers for the ill and wounded wolves. Omega wolves are at the bottom of the social hierarchy. Omegas submit to the commands of all the other dominant wolves and are allowed to eat after everyone else has eaten.

Grey wolves hunt in a group, coordinating with each other, with the alpha leading the way. Hunting of prey takes place in multiple steps.

First the pack locates the herd of prey and then surrounds them. Wolves prefer for the prey that is weak/sick/old or injured [30].

Alpha, beta and delta locate the weakened prey through its body stance, uncoordinated movements or the smell of wounds and start to chase it. Omegas follow the dominant wolves.

After the pack nears the prey, it encircles the prey and harasses it until the prey stops moving.

The pack then jumps and attacks the prey.

Chapter 5

GWO Algorithm Dynamics and Problem Encoding

In this chapter, the mapping of the cost saving problem to the GWO algorithm is described.

For each day, the cost saving problem is encoded as a pack of *'n'* wolves, searching together to find the optimum prey location. Each wolf X_i $(i=1,2,\ldots,n)$ in the pack is encoded as a 24 element vector. Each element X_{ij} $(j=1,2,\ldots,24)$ of X_i represents the state of charge of ESU for each of the 24-hours of the day. X_{ij} is initialized using the following equation:

$$X_{ij} = lower\_l + rand[0,1] \times (upper\_l - (lower\_l)) \tag{5.1}$$

where X_{ij} represents j^{th} dimension of X_i and is initialized in the interval *[upper_l lower_l],*

lower_l is the maximum power the ESU can discharge during an hour, which is -15KW for the present problem.

upper_l is the maximum power to which the ESU can be charged during an hour and is 15KW for this problem.

rand [0,1] is a random number in the interval [0,1].

Table 5.1 illustrates a sample representation of vector X_i. Each element of it corresponds to the state of charge of ESU during that respective hour of a day. For example, 1st element shows that ESU is charged to 0.8 KW from 12:00 AM to 1:00 AM.

Table 5.1: Sample ESU Schedule for a day

Time Interval	**State of Charge (KW)**	**Schedule Action**
12:00 AM to 1:00 AM	0.8	Charge
1:00 AM to 2:00 AM	11.6	Charge
2:00 AM to 3:00 AM	-0.04	Discharge
3:00 AM to 4:00 AM	-0.2	Discharge
4:00 AM to 5:00 AM	-0.02	Discharge
5:00 AM to 6:00 AM	1.6	Charge
6:00 AM to 7:00 AM	0.5	Charge
7:00 AM to 8:00 AM	0.3	Charge
8:00 AM to 9:00 AM	0	Charge
9:00 AM to 10:00 AM	-1.7	Discharge
10:00 AM to 11:00 PM	0.03	Charge
11:00 PM to 12:00 PM	1.03	Charge
12:00 PM to 1:00 PM	0.6	Charge
1:00 PM to 2:00 PM	-0.02	Charge
2:00 PM to 3:00 PM	-1.1	Discharge
3:00 PM to 4:00 PM	-0.03	Discharge
4:00 PM to 5:00 PM	-0.3	Discharge
5:00 PM to 6:00 PM	0.5	Charge
6:00 PM to 7:00 PM	-3	Discharge
7:00 PM to 8:00 PM	0.3	Charge
8:00 PM to 9:00 PM	-9.9	Discharge
9:00 PM to 10:00 PM	-0.01	Discharge
10:00 PM to 11:00 PM	-0.5	Charge
11:00 PM to 12:00 AM	-0.1	Discharge

5.1 Mathematical Modeling of Grey Wolf Pack Hunting

To mathematically model GWO for ESU Scheduling is to find the best prey location as computed by alpha in cooperation with beta, delta and omegas.

The best prey location represent the optimal ESU schedule which results in maximum cost saving.

Out of the ‘n’ wolves, the wolf with lowest daily power consumption cost becomes the alpha. The location of alpha in the search space is represented as X_α.

The wolf in the location with cost saving less than alpha but higher than remaining wolves becomes beta. Its location is represented as X_β.

Similarly, the wolf in location with cost saving less than beta but higher than remaining solutions become delta and its location is represented as X_δ.

The rest of the wolves become omega.

Omegas update their locations in the search space based on their relative positions from alpha, beta and delta. Omegas may encircle the prey whose location it estimated based on the positions of alpha, beta and delta or it may diverge from the estimated location of the prey to determine a better prey. If omega finds a prey fitter than the prey surrounded by alpha, beta and delta, it becomes the alpha. The wolves at 2nd and 3rd position from the prey become beta and delta respectively. The remaining wolves become omega.

Figure 5-1 shows how in each iteration, omega updates its location based on the location of alpha, beta and delta in a 2D search space

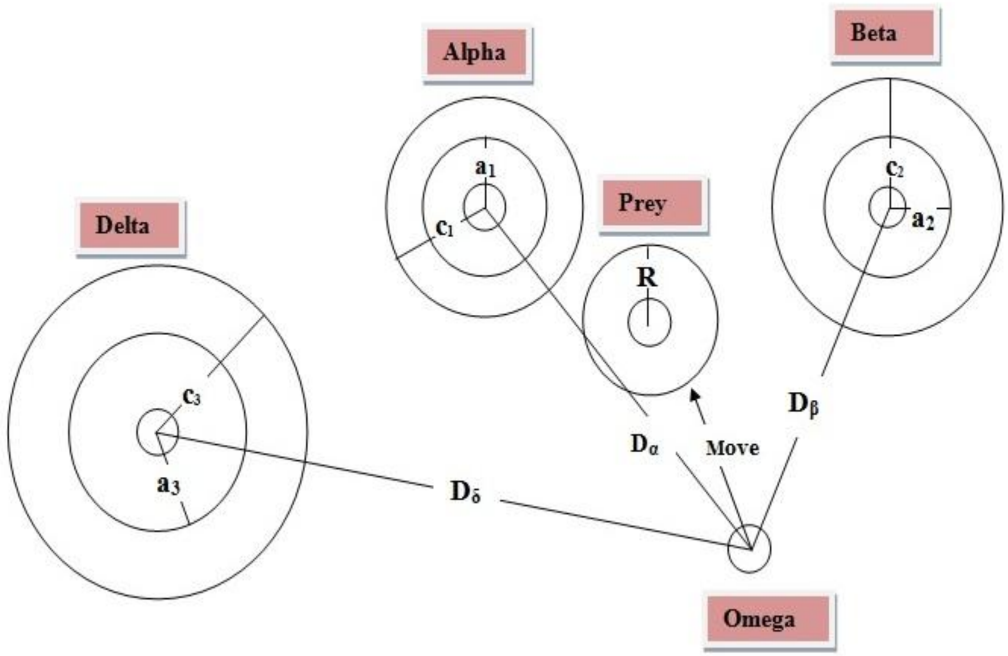

Figure 5-1: Omega updating its location in 2D search space

The location of each omega wolf is updated using the following equation:

$$X_{ij}(t+1) = \frac{X_{\omega\alpha_{ij}} + X_{\omega\beta_{ij}} + X_{\omega\delta_{ij}}}{3} \tag{5.2}$$

Where

X_{ij} *(t+1)* is the new location of j^{th} element of i^{th} omega location

$X_{\omega\alpha_{ij}}$ is the new location of j^{th} element of omega's location vector X_i based on the j^{th} element of alpha's location vector X_α.

$X_{\omega\beta_{ij}}$ is the new location of j^{th} element of omega's location vector X_i based on the j^{th} element of beta's location vector X_β.

$X_{\omega\delta_{ij}}$ is the new location of j^{th} element of omega's location vector X_i based on the j^{th} element of delta's location vector X_δ.

$X_{\omega\alpha_{ij}}$, $X_{\omega\beta_{ij}}$ and $X_{\omega\delta_{ij}}$ are calculated using the following equations:

$$X_{\omega\alpha_{ij}} = X_{\alpha j} - A_{\omega\alpha_{ij}} \cdot (D_{\omega\alpha_{ij}}) \tag{5.3}$$

$$X_{\omega\beta_{ij}} = X_{\beta j} - A_{\omega\beta_{ij}} \cdot (D_{\omega\beta_{ij}}) \tag{5.4}$$

$$X_{\omega\delta_{ij}} = X_{\delta j} - A_{\omega\delta_{ij}} \cdot (D_{\omega\delta_{ij}}) \tag{5.5}$$

where

$X_{\alpha j}$ is j^{th} element of alpha's location vector X_{α}.

$X_{\beta j}$ is j^{th} element of beta's location vector X_{β}.

$X_{\delta j}$ is j^{th} element of delta's location vector X_{δ}.

$A_{\omega\alpha_{ij}}$, $A_{\omega\beta_{ij}}$ and $A_{\omega\delta_{ij}}$ are the j^{th} element of i^{th} omega's randomization-coefficient vectors $A_{\omega\alpha}$, $A_{\omega\beta}$, $A_{\omega\delta}$.

$A_{\omega\alpha}$ models the random movement of omega wolf around the location of alpha by assuming that alpha is almost near the prey. $A_{\omega\beta}$ models the random movement of omega around the location of beta by assuming that beta is almost near the prey. $A_{\omega\delta}$ models the random movement of omega around the location of delta by assuming that delta is almost near the prey.

$A_{\omega\alpha}$, $A_{\omega\beta}$ and $A_{\omega\delta}$ are calculated using following equations:

$$A_{\omega\alpha_{ij}} = 2 * a * rand[0,1] - a \tag{5.6}$$

$$A_{\omega\beta_{ij}} = 2 * a * rand[0,1] - a \tag{5.7}$$

$$A_{\omega\delta_{ij}} = 2 * a * rand[0,1] - a \tag{5.8}$$

where

rand[0,1] is a random number in the interval *[0 1]*.

'*a*' is called decision-variable and it is uniformly decreased from 2 to 0 during the course of iterations. It is used to model the exploration and encircling behavior of wolves, which is explained in the Section 5.2 and Section 5.3.

In each iteration, each of $A_{\omega\alpha}$, $A_{\omega\beta}$ and $A_{\omega\delta}$ take a random value in the interval [-a, a]. For example, when $a=2$, each of $A_{\omega\alpha}$, $A_{\omega\beta}$ and $A_{\omega\delta}$ take a random value in the interval *[-2 2]* and when $a=1$, they take random values in the interval *[-1 1]*.

5.2 Exploration of Search Space:

For first half of iterations, '*a*' is greater than 1. During these iterations, omegas diverge from the prey location they have estimated based on the locations of dominant wolves to find a better prey. Figure 5-2 shows how omega diverges from a prey to find a better prey.

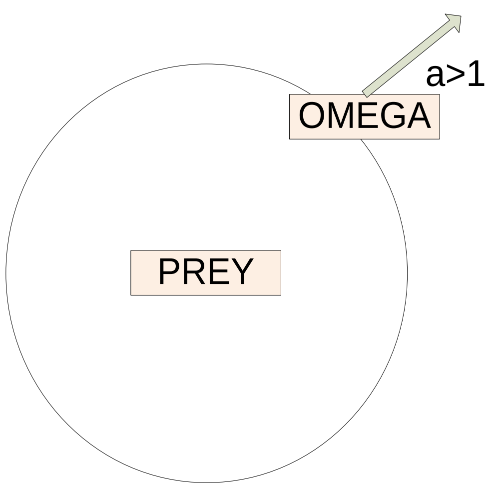

Figure 5-2: Omega diverging away from a prey to find a fitter prey

5.3 Encircling and Catching the Prey:

For the second half of iterations, *'a'* is lesser than 1. The omegas encircle the prey in smart location they have estimated based on the positions of dominant wolves in to trap and attack it. Figure 5-3 shows how omega positions around a prey for a powerful attack.

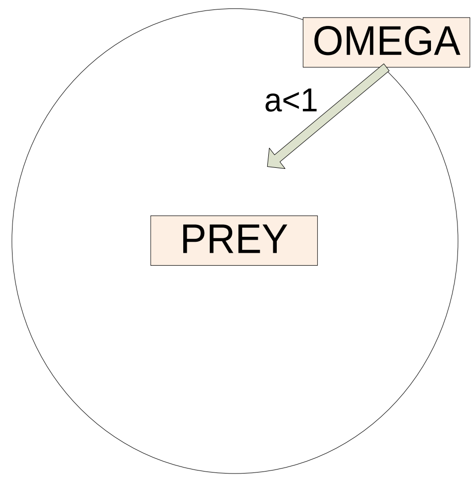

Figure 5-3: Omega finding a suitable location to encircle the prey

During the last iteration when '*a*' becomes 0, all elements of the randomization-coefficient vectors $A_{\omega\alpha}$, $A_{\omega\beta}$ and $A_{\omega\delta}$ become zero. The entire pack jumps and attacks the prey. The coordinates of all the wolves become same as the coordinate of the fittest prey.

The value of 'a' for each iteration is calculated using the following equation:

$$a = 2 - \left(\frac{2 * t}{t_{total}}\right) \tag{5.9}$$

where

t is current iteration and t_{total} is the total number of iterations.

$D_{\omega\alpha_{ij}}$ is the distance between j^{th} element of omega's location vector X_i and j^{th} element of alpha's location vector X_α.

$D_{\omega\beta_{ij}}$ is the distance between j$^{\text{th}}$ element of omega's location vector X_i and j^{th} element of beta's location vector X_β.

$D_{\omega\delta_{ij}}$ is the distance between j^{th} element of omega's location vector X_i and j^{th} element delta's location vector X_δ.

$D_{\omega\alpha_{ij}}$, $D_{\omega\beta_{ij}}$ and $D_{\omega\delta_{ij}}$ are calculated using the following equations:

$$D_{\omega\alpha_{ij}} = \left| C_{\omega\alpha_{ij}} \cdot X_{\alpha_j} - X_{ij}(t) \right| \tag{5.10}$$

$$D_{\omega\beta_{ij}} = \left| C_{\omega\beta_{ij}} \cdot X_{\beta_j} - X_{ij}(t) \right| \tag{5.11}$$

$$D_{\omega\delta_{ij}} = \left| C_{\omega\delta_{ij}} \cdot X_{\delta_j} - X_{ij}(t) \right| \tag{5.12}$$

where

X_{ij} is j^{th} element of i^{th} omega's location vector.

Due to the natural obstacles, the omega cannot find the exact locations of alpha beta and delta. There is always some error in omega's estimation of dominant wolf's location. This is modeled by obstacle-vector $C_{\omega\alpha}$, $C_{\omega\beta}$ and $C_{\omega\delta}$.

$C_{\omega\alpha_{ij}}$, $C_{\omega\beta_{ij}}$ and $C_{\omega\delta_{ij}}$ are j^{th} elements of i^{th} omega's obstacle- vectors $C_{\omega\alpha}$, $C_{\omega\beta}$ and $C_{\omega\delta}$. Elements of $C_{\omega\alpha}$, $C_{\omega\beta}$ and $C_{\omega\delta}$ are random numbers in the interval *[0 2]*.

($C_{\omega\alpha_{ij}} \cdot X_{\alpha j}$) is the approximate location of j^{th} element of alpha's location vector.

($C_{\omega\beta_{ij}} \cdot X_{\beta j}$) is approximate location of j^{th} element of beta's location vector.

($C_{\omega\delta_{ij}} \cdot X_{\delta j}$) is approximate location of j^{th} element of delta's location vector.

GWO algorithm for optimal ESU scheduling is summarized in the following steps:

1. Generate a pack of 100 grey wolves initially in the interval [-15, 15] using the equation (5.1). Set the maximum number iterations to 50.

2. Calculate the fitness of each wolf using the objective function for cost saving given in equation (3.11).

3. Sort the entire pack in ascending order based on the fitness value, which is the lowest cost. Rank the wolves based on their fitness.

4. Save the wolves with three lowest daily power consumption cost as alpha, beta and delta.

5. Set decision-variable 'a' to 2.

6. Update omega wolves locations using equations (5.2)-(5.12).

7. Decrease 'a' uniformly using equation (5.9).

8. If the iteration is lesser than the terminal count, go back to step 2. Otherwise, the alpha is returned as the optimum ESU schedule for cost saving.

Figure 5-4 shows the flow chart that summarizes the entire steps of GWO algorithm.

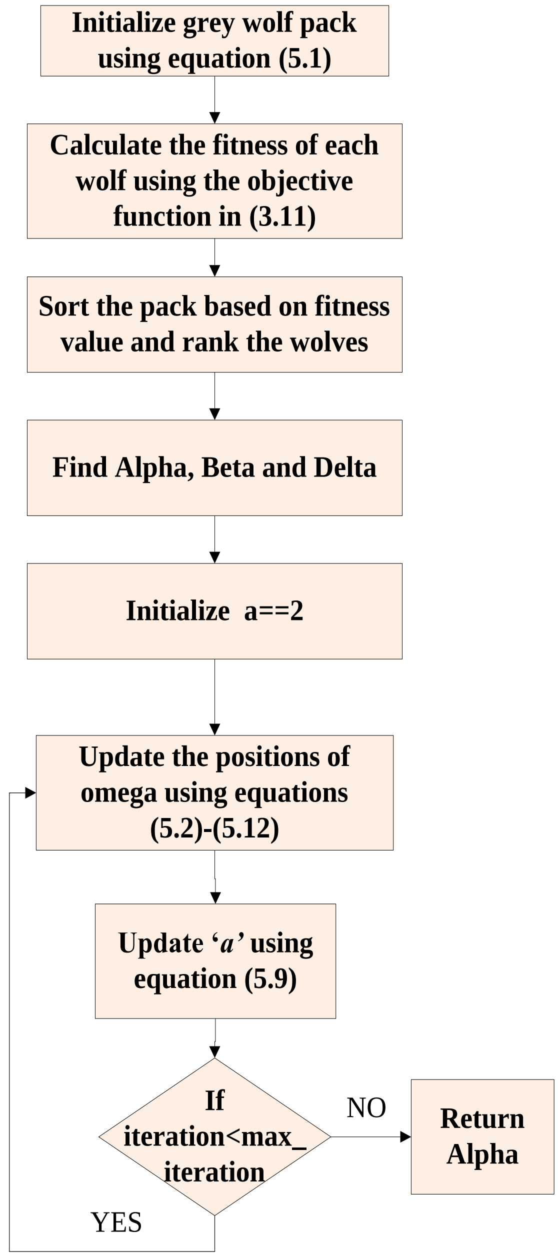

Figure 5-4: Flow-chart of GWO Algorithm

Chapter 6

Results and Discussions

In this chapter, first the results of proposed GWO method implemented on data collected by the United States Department of Energy for a typical house in Chicago, Illinois for the year 2013 is presented and the impact of hourly price variation on the performance of GWO algorithm is analyzed. Then, the results are compared with the traditional Particle Swarm Optimization (PSO) algorithm.

6.1 Results

The GWO algorithm was tested for the household under two scenarios: without green energy resources and integrated with renewable green energy resources.

6.1.1 Scenario-1: Without Green Energy Resources

In this Scenario, the smart home is powered by the utility only and it is integrated with the Energy Storage Unit (ESU).

The monthly savings obtained for Scenario-1 for the year 2013 are as shown in Table 6.1.

Table 6.1: Year 2013 Monthly Cost and Savings for Scenario-1

Months	**Original Cost($)**	**Cost With ESU scheduled by GWO ($)**	**Savings %**
January	105.4415	94.2708	10.5942
February	91.8584	83.2446	9.3772
March	94.1607	79.2054	15.8827
April	81.2736	72.5492	18.6156
May	64.5037	50.0902	22.3452
June	95.9820	83.4326	13.0747
July	195.1905	169.8639	12.9754
August	102.6765	87.3211	14.9518
September	92.9097	78.7388	15.2524
October	70.7174	58.1413	17.7835
November	82.1625	70.2770	14.4658
December	114.6652	102.0431	11.0078

To analyze the impact of hourly price fluctuation on the proposed method for cost saving, it was tested for following two extreme cases,

Case 1: A day with high fluctuations in the prices by the hour (Date: 5/31/2013).

Case 2: A day with minimal variations in the prices by the hour (Date:1/20/2013).

Figure 6-1 and Figure 6-2 show the day-ahead price variation by the hour for Case-1 and Case-2.

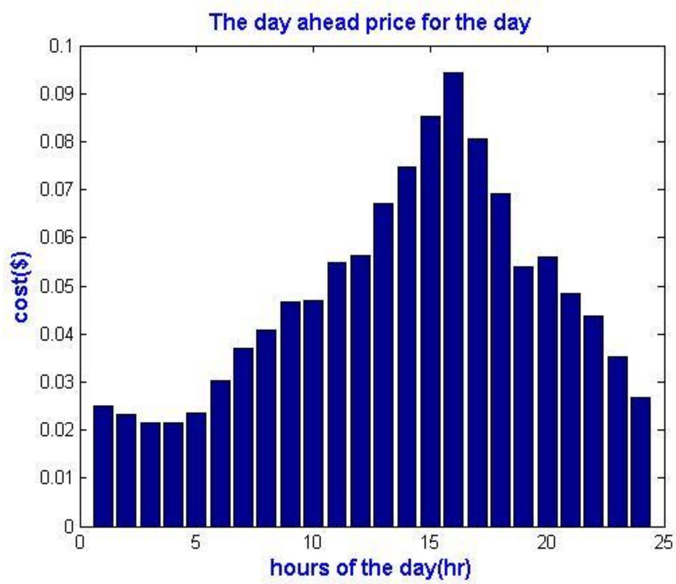

Figure 6-1: Day-ahead hourly price variation for Case-1 (Date: 5/31/2013)

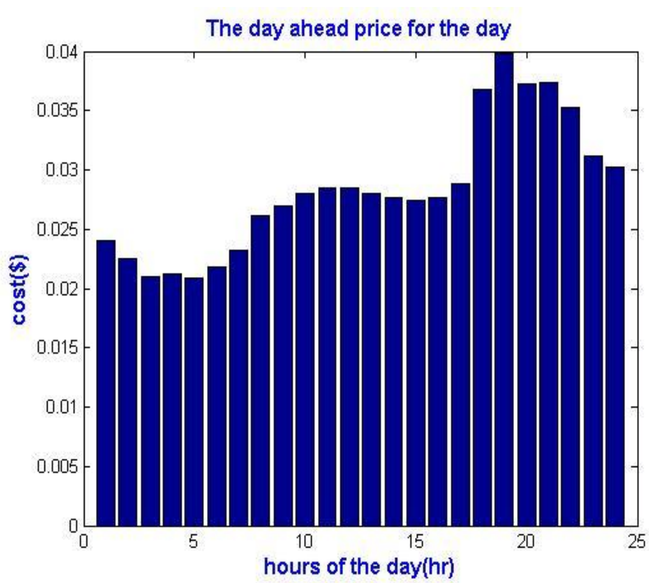

Figure 6-2: Day-ahead hourly price variation for Case-2 (Date: 1/20/2013)

It is seen from Figure 6-2 how the price varies greatly for case-1 from one hour to next with minimum of $0.02 between 3:00 AM -5:00 AM and maximum of $ 0.1 between 3:00 PM -4:00 PM. Whereas for case-2, it is seen from Fig. 7(b) that the price remains mostly static with only slight variations in hourly prices. The minimum price is $ 0.02 between 2:00 AM- 3:00 AM and the maximum price is $ 0.04 between 7:00 PM- 8:00 PM.

Table 6.1 and Table 6.2 show the original cost, cost obtained by scheduling the ESU using GWO algorithm and the percentage savings obtained for the case-1 and case-2 for Scenario-1.

Table 6.2: Result for Scenario-1 for Case-1 (Date: 5/31/2013)

Original Cost($)	**Optimized cost by Scheduling ESU with GWO($)**	**Savings %**
2.6078	1.4816	43.1850

Table 6.3: Result for Scenario-1 for Case-2 (Date: 1/20/2013)

Original Cost($)	**Optimized cost by Scheduling ESU with GWO($)**	**Savings %**
2.934	2.6391	10.0513

It is seen from Table 6.2 that saving of 43.1850% is obtained for case 1. However, it is seen from Table 6.3 that for case-2, the savings obtained is only 10.0513%.

Table 6.4 shows the optimal ESU schedule obtained using the proposed method for Case-1 for Scenario-1.

Table 6.4: Optimized ESU Schedule for Scenario-1 for Case-1

(Date: 5/31/2013)

Time Interval	**State of Charge (KW)**	**Schedule Action**
12:00 AM to 1:00 AM	0.0210	Charge
1:00 AM to 2:00 AM	- 0.0201	Discharge
2:00 AM to 3:00 AM	0.0740	Charge
3:00 AM to 4:00 AM	14.9251	Charge
4:00 AM to 5:00 AM	- 0.0007	Discharge
5:00 AM to 6:00 AM	- 0.0002	Discharge
6:00 AM to 7:00 AM	0.0008	Discharge
7:00 AM to 8:00 AM	- 0.0022	Discharge
8:00 AM to 9:00 AM	0.0022	Charge
9:00 AM to 10:00 AM	- 0.0021	Discharge
10:00 AM to 11:00 PM	- 0.0032	Discharge
11:00 PM to 12:00 PM	0.0053	Discharge
12:00 PM to 1:00 PM	- 0.0379	Discharge
1:00 PM to 2:00 PM	0.0380	Charge
2:00 PM to 3:00 PM	- 0.0028	Discharge
3:00 PM to 4:00 PM	- 14.9972	Discharge
4:00 PM to 5:00 PM	0.0000	Discharge
5:00 PM to 6:00 PM	0.0013	Charge
6:00 PM to 7:00 PM	- 0.0010	Discharge
7:00 PM to 8:00 PM	0.0024	Charge
8:00 PM to 9:00 PM	0.0094	Charge
9:00 PM to 10:00 PM	- 0.0122	Discharge
10:00 PM to 11:00 PM	0.0233	Charge
11:00 PM to 12:00 AM	- 0.0233	Discharge

Table 6.5 shows the optimal ESU schedule obtained using the proposed method for Case-2 for Scenario-1.

Table 6.5: Optimized ESU Schedule for Scenario-1 for Case-2

(Date: 1/20/2013)

Time Interval	State of Charge (KW)	Schedule Action
12:00 AM to 1:00 AM	0.0179	Charge
1:00 AM to 2:00 AM	-0.0077	Discharge
2:00 AM to 3:00 AM	0.6881	Charge
3:00 AM to 4:00 AM	0.9743	Charge
4:00 AM to 5:00 AM	13.3273	Charge
5:00 AM to 6:00 AM	- 0.0174	Discharge
6:00 AM to 7:00 AM	0.0061	Charge
7:00 AM to 8:00 AM	- 0.0475	Discharge
8:00 AM to 9:00 AM	- 0.0723	Discharge
9:00 AM to 10:00 AM	- 0.3111	Discharge
10:00 AM to 11:00 PM	-14.5578	Discharge
11:00 PM to 12:00 PM	0.2068	Charge
12:00 PM to 1:00 PM	0.6055	Charge
1:00 PM to 2:00 PM	14.1877	Charge
2:00 PM to 3:00 PM	-0.0117	Discharge
3:00 PM to 4:00 PM	0.0043	Charge
4:00 PM to 5:00 PM	0.0064	Charge
5:00 PM to 6:00 PM	-0.0139	Charge
6:00 PM to 7:00 PM	-14.9851	Discharge
7:00 PM to 8:00 PM	0.0061	Charge
8:00 PM to 9:00 PM	-0.0012	Discharge
9:00 PM to 10:00 PM	0.0026	Charge
10:00 PM to 11:00 PM	-0.0024	Discharge
11:00 PM to 12:00 AM	-0.0052	Discharge

From Figure 6-3, it can be seen that for case-1(higher fluctuation in prices), power consumption cost has reduced significantly from $2.6028 to $1.4816 by optimizing the ESU schedule using the proposed method.

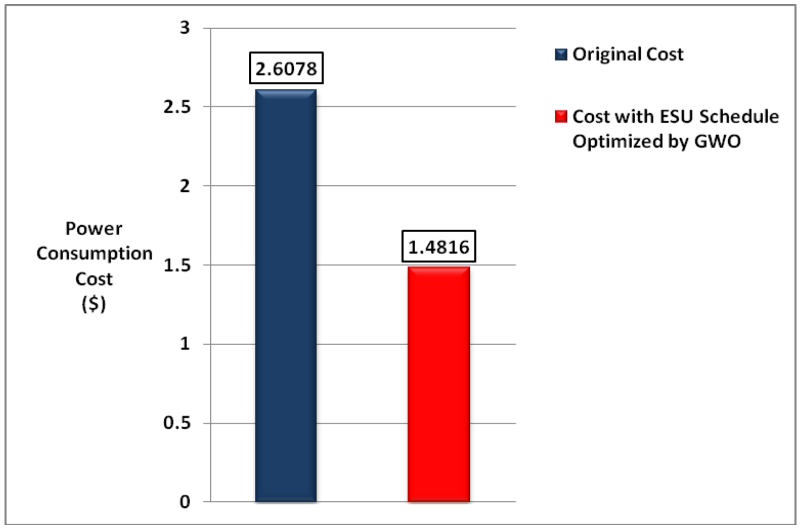

Figure 6-3: Cost Comparison for Scenario-1, Case-1

It can be observed from Figure 6-4 that for case-2 (minimal fluctuation in prices), power consumption cost reduced slightly from \$ 2.9310 to \$ 2.6391.

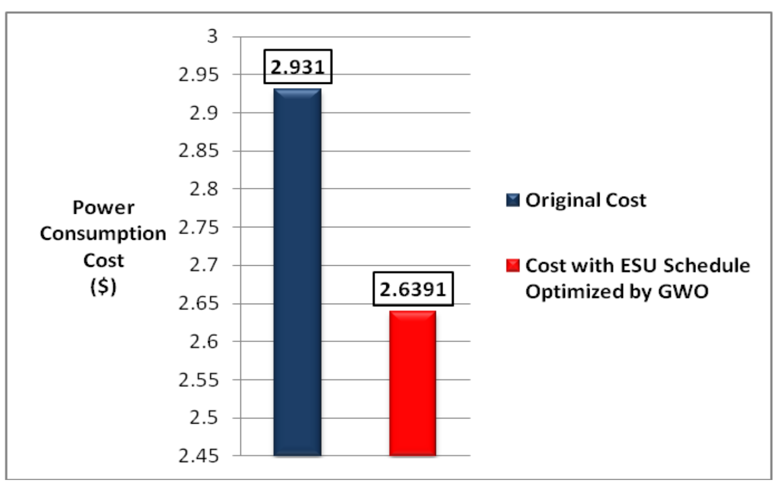

Figure 6-4: Cost Comparison for Scenario-1, Case-2

6.1.2 Scenario-2: Smart Home Integrated With Green Energy Resources

In this scenario, in addition to the supply from utility and ESU, the smart home is also powered by locally generated wind and solar power.

As mentioned before, during each hour of a day, if there is excess power from renewable energy resources after supplying power to the household, it is sold back to the utility through the grid at the same price at which the utility offers to the customer at that hour. Table 6.6 shows comparison between average monthly cost saving obtained for the year 2013 using renewable energy resources alone and by using renewable energy resources with ESU scheduled by GWO algorithm.

Table 6.6: Year 2013 Monthly Power Consumption Cost and Savings for Scenario-2

Months	Original Cost ($)	Cost with Renewable Energy ($)	Cost with Renewable Energy and GWO Optimized ESU operation ($)	Savings with Renewable Energy (%)	Savings with Renewable Energy and GWO Optimized ESU operation (%)
January	105.4415	55.1128	44.0763	47.7314	58.1983
February	91.8584	43.0630	34.7485	53.1202	62.1716
March	94.1607	37.2470	22.8795	60.4431	75.7017
April	81.2736	16.5139	1.5697	79.6811	98.0687
May	64.5307	4.5922	-9.6977	92.8807	178.5003
June	95.9820	54.3108	41.6815	43.4156	56.5736
July	195.1905	144.1589	119.2222	26.1445	38.9201
August	102.6725	69.8054	54.4850	32.0116	46.9333
September	92.9097	52.2995	38.2044	43.7094	58.8801
October	70.7174	32.9197	20.7639	53.4490	70.6382
November	82.1625	24.0393	12.7239	70.7418	84.5137
December	114.6652	72.2473	59.7632	36.9928	47.8803

Similar to scenario 1, to evaluate the impact of hourly-price fluctuation on the performance of the proposed algorithm, scenario-2 is tested for two extreme cases: Case-1(5/31/2013, a day with high fluctuations in the prices by the hour) and Case-2 (1/20/2013, a day with minimal variations in the prices by the hour).

Table 6.7 shows the cost saving obtained for household integrated with renewable energy for case 1.

Table 6.7: Result for Scenario-2 for Case-1(Date: 5/31/2013)

Original Cost ($)	**Cost With Renewable Energy ($)**	**Cost with Renewable Energy and GWO Optimized ESU operation($)**	**Savings with Renewable Energy (%)**	**Savings with Renewable Energy And GWO Optimized ESU operation (%)**
2.6078	-1.7453	-2.8618	166.9262	209.7400

It is seen from Table 6.7 that cost saving of 166.9254 % is obtained for case 1 using renewable energy resources alone and it is increased by 42.8146% to 209.7400 % by scheduling the ESU using the GWO. Table 6.8 shows the cost saving obtained for the household using green energy resources by scheduling the ESU using the GWO algorithm for Case-2.

Table 6.8: Result for Scenario-2 for Case-1(Date: 5/31/2013)

Original Cost ($)	**Cost With Renewable Energy ($)**	**Cost with Renewable Energy and GWO Optimized ESU operation($)**	**Savings with Renewable Energy (%)**	**Savings with Renewable Energy And GWO Optimized ESU operation (%)**
2.9340	1.0253	0.7439	65.0549	74.6462

It is seen from Table 6.8 that saving of 65.0549 % is obtained for case-2 by using the renewable energy resources alone and it is increased only by 9.5913 % to 74.6462 % by scheduling the ESU.

Table 6.9 shows the optimal ESU schedule obtained using the proposed method for Case-1, for Scenario-2.

Table 6.9: Optimized ESU Schedule for Scenario-2 for Case-1

(Date: 5/31/2013)

Time Interval	State of Charge (KW)	Schedule Action
12:00 AM to 1:00 AM	0.0013	Charge
1:00 AM to 2:00 AM	0.002	Discharge
2:00 AM to 3:00 AM	14.9967	Charge
3:00 AM to 4:00 AM	-0.0005	Charge
4:00 AM to 5:00 AM	0.0005	Charge
5:00 AM to 6:00 AM	-0.0005	Discharge
6:00 AM to 7:00 AM	0.0005	Charge
7:00 AM to 8:00 AM	0	Rest
8:00 AM to 9:00 AM	-0.0001	Discharge
9:00 AM to 10:00 AM	0.0002	Discharge
10:00 AM to 11:00 PM	-0.0001	Discharge
11:00 PM to 12:00 PM	-0.0003	Discharge
12:00 PM to 1:00 PM	-0.0003	Discharge
1:00 PM to 2:00 PM	0.0002	Charge
2:00 PM to 3:00 PM	0.0005	Discharge
3:00 PM to 4:00 PM	-15	Charge
4:00 PM to 5:00 PM	0	Rest
5:00 PM to 6:00 PM	0.0007	Charge
6:00 PM to 7:00 PM	0.0009	Discharge
7:00 PM to 8:00 PM	-0.0016	Charge
8:00 PM to 9:00 PM	0	Rest
9:00 PM to 10:00 PM	0.0004	Charge
10:00 PM to 11:00 PM	0	Rest
11:00 PM to 12:00 AM	-0.0004	Discharge

Table 6.10 shows the optimal ESU schedule obtained using the proposed method for Case-2, for Scenario-2.

Table 6.10: Optimized ESU Schedule for Scenario-2 for Case-2

(Date: 1/20/2013)

Time Interval	State of Charge (KW)	Schedule Action
12:00 AM to 1:00 AM	0.0055	Charge
1:00 AM to 2:00 AM	0.0140	Charge
2:00 AM to 3:00 AM	14.9805	Charge
3:00 AM to 4:00 AM	-0.0028	Discharge
4:00 AM to 5:00 AM	-0.0002	Discharge
5:00 AM to 6:00 AM	-0.0001	Discharge
6:00 AM to 7:00 AM	-0.0058	Discharge
7:00 AM to 8:00 AM	-0.0004	Discharge
8:00 AM to 9:00 AM	-0.0009	Discharge
9:00 AM to 10:00 AM	0.0067	Charge
10:00 AM to 11:00 PM	0.0031	Charge
11:00 PM to 12:00 PM	-0.1346	Charge
12:00 PM to 1:00 PM	-0.1139	Discharge
1:00 PM to 2:00 PM	-0.0124	Discharge
2:00 PM to 3:00 PM	-0.2613	Discharge
3:00 PM to 4:00 PM	-0.0004	Discharge
4:00 PM to 5:00 PM	-0.0003	Discharge
5:00 PM to 6:00 PM	-0.0155	Discharge
6:00 PM to 7:00 PM	-14.9838	Discharge
7:00 PM to 8:00 PM	0.0091	Charge
8:00 PM to 9:00 PM	-0.0087	Discharge
9:00 PM to 10:00 PM	0.0089	Charge
10:00 PM to 11:00 PM	0.0116	Charge
11:00 PM to 12:00 AM	-0.0209	Discharge

Figure 6-5 and 6-6 show the comparison between the original cost, cost with renewable energy alone and cost with renewable energy and optimized ESU scheduling for case-1 and case-2, for Scenario-2.

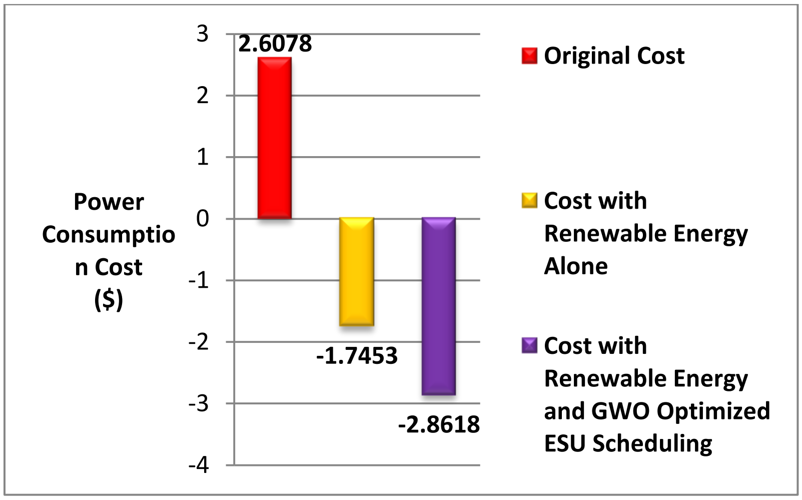

Figure 6-5: Cost Comparison for Scenario-1 for Case-1

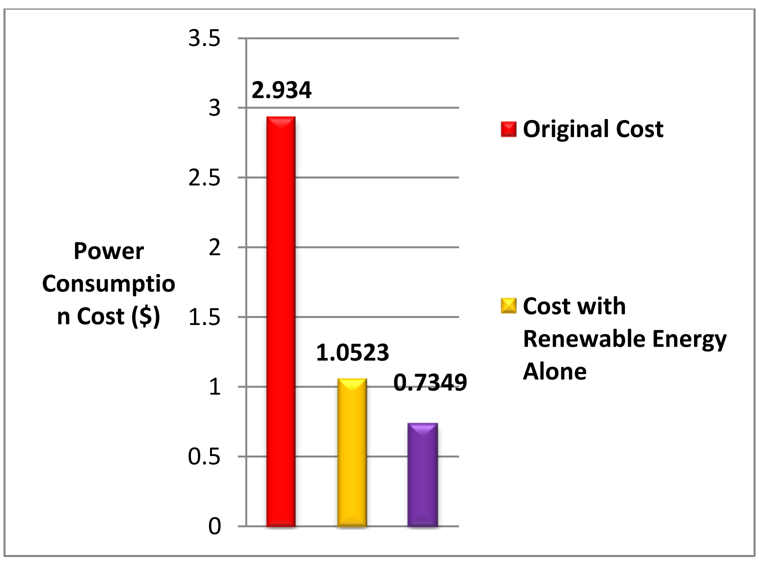

Figure 6-6: Cost Comparison for Scenario-2 for Case-2

From Figure 6-5 and Figure 6-6, it can be seen that there is great reduction in cost by optimally scheduling the ESU in case-1 whereas with case-2, there is lesser reduction in cost after optimally scheduling the ESU.

It can be seen from the results of both the scenarios that the cost saving is more when there is great deal of variation in day ahead hourly prices. This is because; high fluctuations increase non-linearity of the optimization problem and thus increase the solution space. With higher variations, there are more chances for the battery to get charged during a less demand hour and for the battery to discharge/supply the household during peak hour. Hence, for a day when the fluctuation in hourly prices is higher, the proposed method results in greater cost saving.

For the household that is powered by the utility alone and integrated with the ESU (Scenario-1), the average monthly savings obtained using the proposed method ranges from 9.3772 % in February to 22.3452 % in May. In February, the day ahead hourly price variation is smaller for most of the days, therefore the savings are comparatively lower. In May, most of the days had high fluctuation in day-ahead hourly prices, therefore the savings are higher.

For the household that is powered by the utility, renewable energy and the ESU (Scenario-2), the average monthly savings obtained using the proposed method range from 58.1983% in January to 178.5003% in May. The saving obtained in scenario-2 is the lowest for the month of January, as the locally generated solar and wind power is lesser when compared to other months of the year and most of the days in January had minimal variation in the day ahead hourly prices. Whereas in the month of May, the green energy generated locally was abundant as well as most of the days had a high variation in day-ahead price by the hour.

6.2 Comparison with PSO

The performance of the GWO is evaluated by comparing it with the conventional Particle Swarm Optimization Algorithm (PSO).

Figure 6-7 shows the comparison of average monthly savings obtained using GWO and PSO for the household that is powered by the utility alone and integrated with the ESU (Scenario-1) in the year 2013.

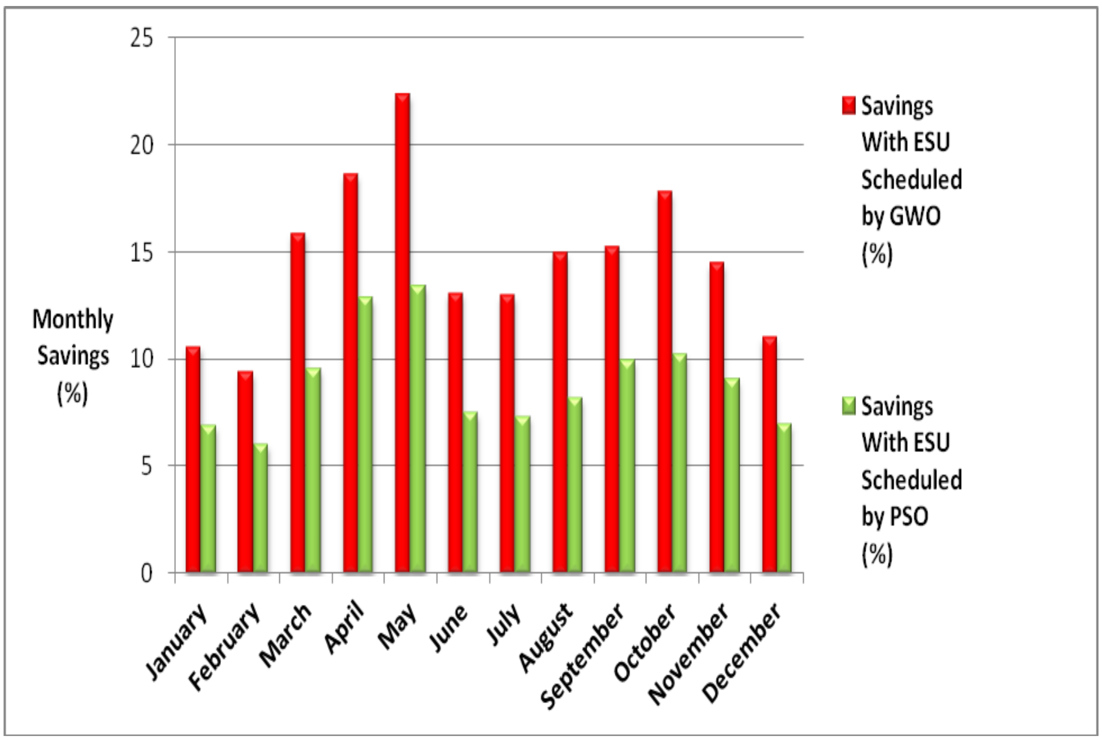

Figure 6-7: Monthly Savings Comparison between GWO and PSO for the year 2013 for Scenario-1

It can be seen from Figure 6-7 that the GWO algorithm outperforms the PSO in all the months with high average monthly savings.

Table 6.11 shows the monthly power consumption cost and savings obtained using GWO and PSO for scenario-1.

Table 6.11: Year 2013 Monthly Cost and Savings Comparison Between GWO and PSO for Scenario-1

Months	**Original Cost ($)**	**Cost With ESU scheduled by GWO ($)**	**Savings with ESU Scheduled by GWO (%)**	**Cost With ESU Scheduled by PSO ($)**	**Savings with ESU Scheduled by PSO (%)**
January	105.4415	94.2708	10.5942	98.1942	6.8733
February	91.8584	83.2446	9.3772	86.3398	6.0077
March	94.1607	79.2054	15.8827	85.1583	9.5607
April	81.2736	72.5492	18.6156	70.8306	12.8492
May	64.5037	50.0902	22.3452	55.8496	13.4164
June	95.9820	83.4326	13.0747	88.7909	7.4921
July	195.1905	169.8639	12.9754	180.8826	7.3302
August	102.6765	87.3211	14.9518	94.2711	8.1828
September	92.9097	78.7388	15.2524	83.6729	9.9417
October	70.7174	58.1413	17.7835	63.4925	10.2165
November	82.1625	70.2770	14.4658	74.7256	9.0515
December	114.6652	102.0431	11.0078	102.0431	6.9681

It can be seen from Table 6.11 that maximum cost saving of 22.3452 % is obtained for the month of May using the GWO algorithm whereas with PSO algorithm, the saving obtained for the month of May is only 13.4164%.

Figure 6-8 shows the comparison between savings obtained using GWO and PSO for case-1(Day with high fluctuation in hourly prices) and case-2(Day with lower fluctuation in hourly prices).

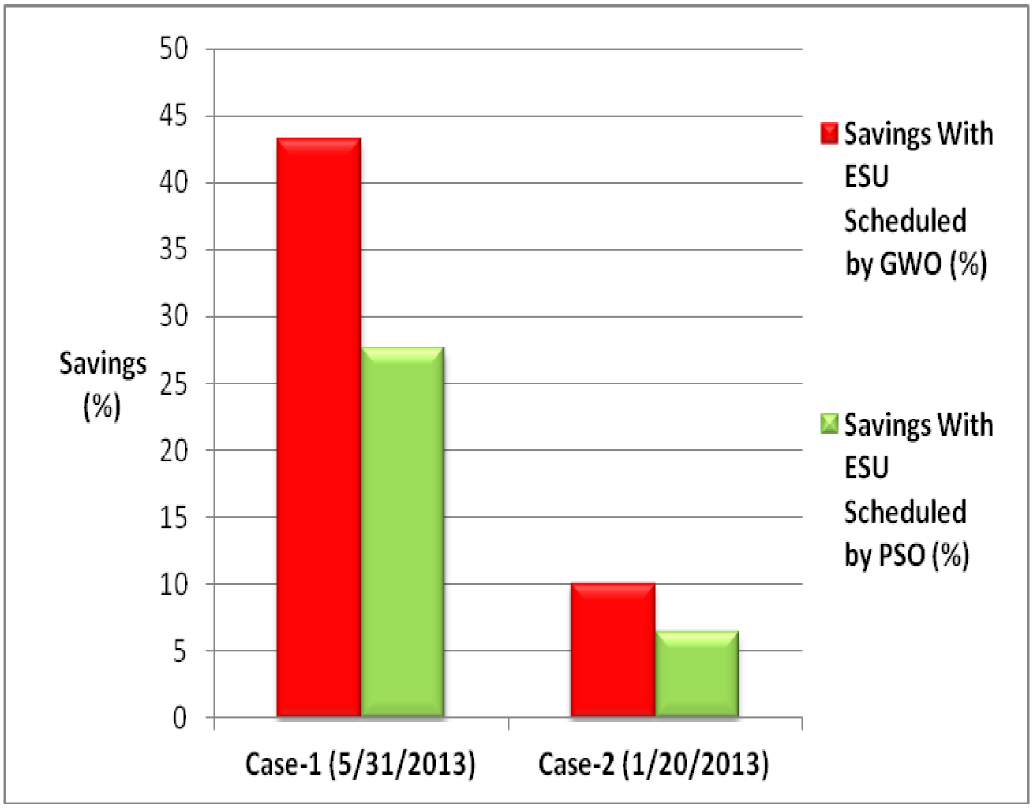

Figure 6-8: Savings Comparison between GWO and PSO
for case-1 and case-2 in Scenario-1

It can be seen from Figure 6-8 that GWO outperforms the savings obtained using PSO for both case-1 and case-2 for scenario-1.

Table 6.12 and Table 6.13 show the comparison for case-1 and case-2 numerically.

Table 6.12: Performance comparison between GWO and PSO for Scenario-1-Case-1 (Date: 5/31/2013)

Original Cost ($)	Cost With ESU Scheduled by GWO ($)	Savings With ESU Scheduled by GWO (%)	Cost With ESU Scheduled by GWO ($)	Savings With ESU Scheduled by GWO (%)
2.6078	1.4816	43.1850	1.8887	27.5740

Table 6.13: Performance comparison between GWO and PSO for Scenario-1-Case-2 (Date: 1/20/2013)

Original Cost ($)	Cost With ESU Scheduled by GWO ($)	Savings With ESU Scheduled by GWO (%)	Cost With ESU Scheduled by GWO ($)	Savings With ESU Scheduled by GWO (%)
2.934	2.6391	10.0513	2.7446	6.4537

It is seen from Table 6.12 and Table 6.13 higher cost savings is obtained by scheduling the ESU using GWO when compared to PSO for both case-1 and case-2.

Figure 6-9 shows the comparison of average monthly savings obtained for the year 2013 using GWO and PSO for the household that is powered by the utility and integrated with the green energy resources and ESU (Scenario-2).

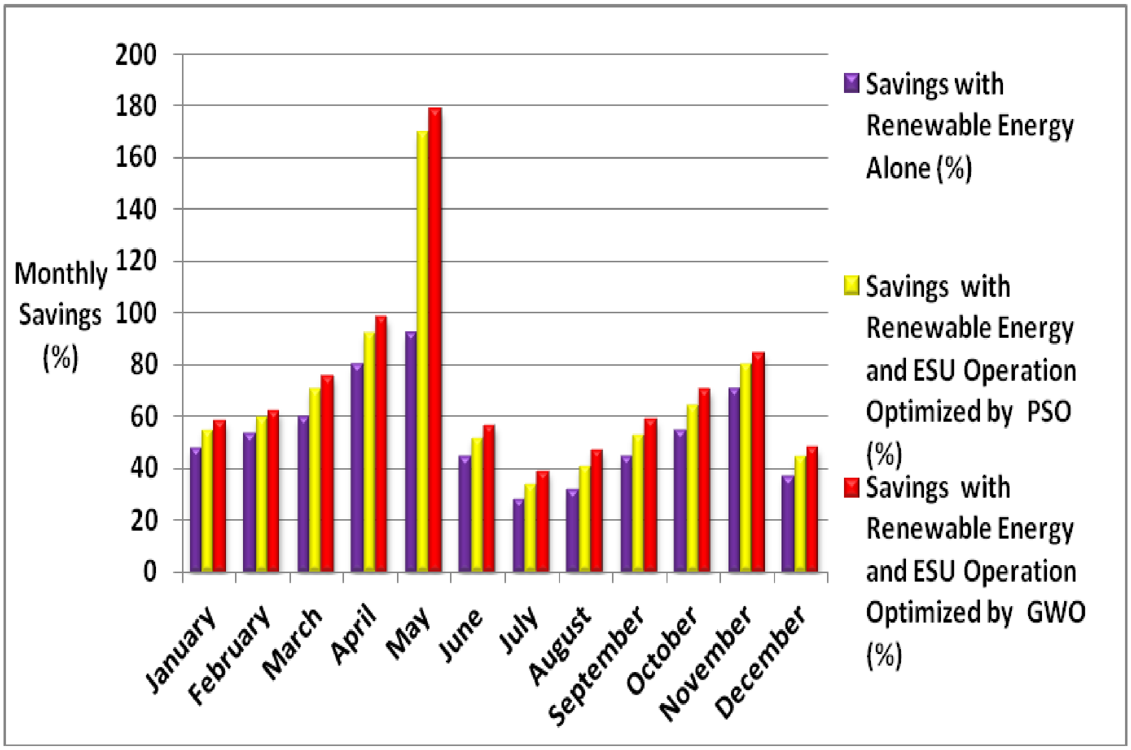

Figure 6-9: Year 2013 Monthly Cost and Savings Comparison Between GWO and PSO for Scenario-2

It can be seen from Figure 6-9 that savings obtained using the renewable energy resources with ESU scheduled by GWO algorithm is higher for all the months when compared to the savings obtained using the renewable energy resources alone and with ESU scheduled by PSO.

Table 6.14 and Table 6.15 shows the monthly power consumption cost and savings obtained using renewable energy alone and by using renewable energy with the ESU scheduled by GWO and PSO.

Table 6.14: Year 2013 Monthly Cost Comparison for Scenario-2

Month	**Original Cost($)**	**Cost with Renewable Energy ($)**	**Cost with Renewable Energy and ESU Operation Optimized by PSO ($)**	**Cost with Renewable Energy and ESU Operation Optimized by GWO ($)**
January	105.4415	55.1128	47.6738	44.0763
February	91.8584	43.0630	37.2721	34.7485
March	94.1607	37.2470	27.6934	22.8795
April	81.2736	16.5139	6.3682	1.5697
May	64.5307	4.5922	-3.7834	-9.6977
June	95.9820	54.3108	46.5150	41.6815
July	195.1905	144.1589	129.1837	119.2222
August	102.6725	69.8054	61.3758	54.4850
September	92.9097	52.2995	43.9643	38.2044
October	70.7174	32.9197	25.4566	20.7639
November	82.1625	24.0393	16.3491	12.7239
December	114.6652	72.2473	63.7153	59.7632

Table 6.15: Year 2013 Monthly Savings Comparison for Scenario-2

Month	**Savings with Renewable Energy (%)**	**Savings with Renewable Energy and ESU Operation Optimized by PSO (%)**	**Savings with Renewable Energy and ESU Operation Optimized by GWO (%)**
January	47.7314	54.7865	58.1983
February	53.1202	59.4244	62.1716
March	59.4526	70.5893	75.7017
April	79.9537	92.1645	98.0687
May	91.9994	169.3313	178.5003
June	44.1022	51.5377	56.5736
July	28.0488	33.8166	38.9201
August	31.4408	40.2218	46.9333
September	44.5499	52.6806	58.8801
October	54.5067	64.0024	70.6382
November	70.5519	80.1015	84.5137
December	36.9928	44.4336	47.8803

It can be seen from Table 6.15 that maximum cost saving of 178.5003% is obtained for the month of May by using the renewable energy resources along with ESU scheduled by GWO. In case of using renewable energy alone, the savings obtained for the month of May are 91.9994%. Savings of 169.3313% is achieved using the renewable energy resources integrated with ESU scheduled by PSO.

Figure 6-10 shows the comparative cost saving obtained for case 1 and case-2 using renewable energy resources alone, renewable energy resources integrated with ESU scheduled by GWO and PSO.

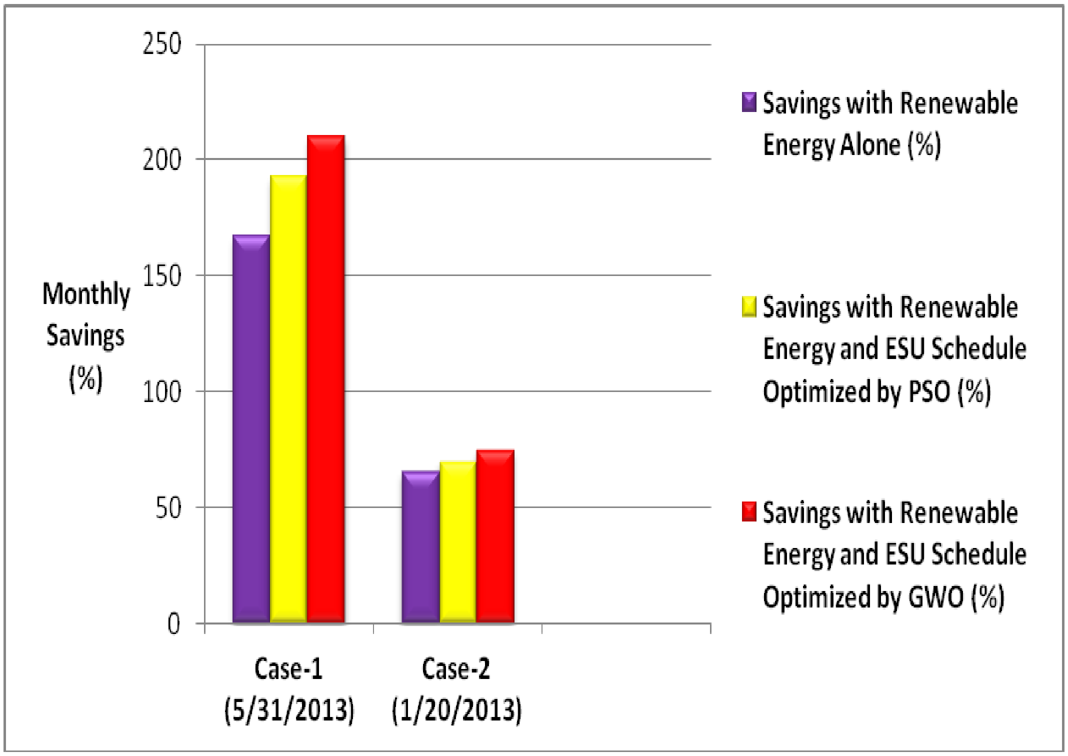

Figure 6-10: Performance comparison between GWO and PSO for Scenario-2-Case-1 and Case-2

It can be seen from Figure 6-10 that savings obtained by scheduling the ESU using the GWO is higher than savings obtained using the renewable energy resources alone and with ESU scheduled by PSO for case-1 and case-2.

Table 6.16 and Table 6.17 show the cost comparison between PSO and GWO for Case-1 and Case-2 for Scenario-2 numerically.

Table 6.16: Cost comparison between GWO and PSO for Scenario-2-Case-1

(Date: 5/31/2013)

Original Cost($)	**Cost with Renewable Energy ($)**	**Cost with Renewable Energy And ESU Operation Optimized by PSO ($)**	**Cost with Renewable Energy And ESU Operation Optimized by GWO ($)**
2.6078	-1.7453	-2.4153	-2.8618

Table 6.17: Cost comparison between GWO and PSO for Scenario-2-Case-2

(Date: 1/20/2013)

Original Cost($)	**Cost with Renewable Energy ($)**	**Cost with Renewable Energy And ESU Operation Optimized by PSO ($)**	**Cost with Renewable Energy And ESU Operation Optimized by GWO ($)**
2.9340	1.0253	0.8954	0.7439

Table 6.18 and Table 6.19 show the savings comparison between PSO and GWO for Case-1 and Case-2 for Scenario-2 numerically.

Table 6.18: Savings comparison between GWO and PSO for Scenario-2-Case-1

(Date: 5/31/2013)

Savings with Renewable Energy (%)	**Savings with Renewable Energy And ESU Operation Optimized by PSO (%)**	**Savings with Renewable Energy And ESU Operation Optimized by GWO (%)**
166.9262	192.6197	209.7400

Table 6.19: Savings comparison between GWO and PSO for Scenario-2-Case-2

(Date: 1/20/2013)

Savings with Renewable Energy (%)	**Savings with Renewable Energy and ESU Operation Optimized by PSO (%)**	**Savings with Renewable Energy and ESU Operation Optimized by GWO (%)**
65.0549	69.4801	74.6462

It can be seen from Table 6.18 and 6.19 that savings obtained using the GWO for scheduling the ESU with renewable energy resources is considerably higher than savings obtained using PSO for scheduling the ESU with renewable energy resources.

Chapter 7

Conclusion

In this thesis, the GWO algorithm was mapped to schedule an Energy Storage Unit in a household with and without renewable energy resources to reduce the cost of power consumption. It has been demonstrated that the proposed method optimizes the cost savings in the household with and without the renewable energy resources. The algorithm was tested on the data collected by the Department of Energy for a household in Chicago Illinois. Cost savings are higher for the days with high price fluctuation by the hour when compared to the days with lower price fluctuation by the hour. The performance of GWO algorithm was compared with conventional PSO algorithm. The GWO outperformed the PSO resulting in high cost savings.

This research has become very significant with the emergence of renewable energy resources such as wind and solar being integrated into the household and several companies, such as Tesla and Mercedes Benz, are showing interest in manufacturing Energy Storage Units for the households. The optimal scheduling of ESU also aids in reducing the load on the grid during peak hours thus contributing to the reliability of the grid.

This method does not put any constraints on the consumer regarding when to use certain appliances and hence does not affect the energy usage behavior of the individuals in the household. The proposed work was implemented for the household that receives the hourly prices for the next day before midnight. In the future, this work can be extended to the households that receive the prices for peak, shoulder and off-peak periods from the utility one year in advance (Time of Use Pricing). Also, this work can be implemented to real time data as and when it is available. The proposed ESU scheduling can also be incorporated into the household that schedules the shiftable residential loads for energy saving.

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