A Cognitive Approach to Load Balancing for Green Houses

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***Abstract*—In this paper the case study of a smart home powered by solar and wind energy is presented. The benefits of having a smart home that can control the amount of power needed, according to the context of the usage, are also shown. Simulation shows that with a good control of the load it might be possible to reduce the installation costs of the Green Energy System. Furthermore, to support the results, a load balancing algorithm is created based on the Knapsack problem. An economic analysis of the approach is also shown to demonstrate the viability of the project, and how can the intelligence in the home lower the cost.**

***Index Terms*—Smart Home, Context Reasoning, Green Energy, Multi Objective Evolutionary Algorithms**

I. Introduction

The value of oil has greatly increased over the globe during the past years. There is an urgent need to reduce energy costs. As an alternative, many green energy sources like solar energy, wind energy, geothermic energy, etc. have been proposed and studied.

This work presents a simple model to estimate the energy needed to be produced to keep a smart home running with green energy, for as long as possible. This approach benefits from the intelligence of the smart home. It establishes context awareness and keeps track of the energy being consumed, to alert the owners of energy wastage. Using a load balancing algorithm, the system can find the optimal configuration that maximizes the traditional energy independence, along with reducing the long term costs.

The rest of the paper is organized as follows: section II provides a summary of related work on green energy projects. Section III shows the important features of the study, along with some important equations needed to compute the requirements, given the location of the house. A cost analysis is presented in section IV. Sections V and VI contain the scenario generation for testing the approach, along with some simulation results over a year. Finally section VII closes the paper with the conclusions.

II. Related Work

There have been many energy studies over the past years, especially the last decade, which have served as basis and motivation for this case study. For example, [1] presents the utilization of solar and wind energy, as a alternatives to reduce energy costs.

In [2] a smart grid is defined as a network of computers and power infrastructure, with a smart meter that can monitor and control appliances. Moreover, [3] simulated a smart grid system, using agents that were compatible with TCP/IP protocols and [4] implemented it with heterogeneous peer-to-peer wireless technologies. Such approach gave a software solution to the smart grid problem, typically done in hardware, having good scalability properties. Similary [5] proposes an architecture on which the telephone serves a remote control for appliances, as well as a computer program that acts as a power meter.

On the other hand, in [6] the author enumerated the different characteristics that a smart grid should have. These characteristics included: self-healing, high reliability, energy management, and real-time pricing. This work addresses mainly the last two. Furthermore, in [7] a study for designing and integrating new smart appliances was shown.

In [8], the authors presented a solar villa which ran completely with the aid of solar energy. The particular aspect of this project is that there is a certain range of hours in the day which electricity is cheapest, and during these hours the project charges the batteries that will store the energy. The battery is charged when the state of charge (SOC) of the battery drops lower than a certain threshold.

In [9] a survey was made on the status and future of techniques to control the rotors of windmill blades, in order to reduce energy needs. Finally, on [10] the author studied the different models for solar systems (i.e. with battery, selling energy to the power grid company, stand alone, etc.). Additionally the author developed control schemes to control the speed of a motor during the whole day (daylight only) without the need of any batteries and never running out of energy.

III. Methodology

The Smart Home Energy Aware-Preserver (SHEAP) not only presents a study of green energy as an alternative to smart home energy reduction, but it provides alternatives to benefit from the intelligence of the house for controlling effectively the house appliances. The first one of these features is context awareness seen in sub-section III-A. Then an energy adviser and load balancing algorithm are presented in sub-sections III-B and III-C respectively. Finally, several equations model

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SHEAP and provide its viability depending on the location of the house around the globe. These equations are presented in the sub-sections III-D and III-E.

A. Context Awareness

Context awareness is mainly employed to control the lightning system, and other appliances such as the television and air conditioner. Basically the house is able to know what types of activities the inhabitants are doing, using image recognition and appliances monitoring. In such a way the house can predict what settings are most adequate. These settings may include tempeture and light adjustments, television status updates, coffee making, etc.

For example, consider the case where the inhabitants are watching television in the living room. Once the house realizes this event, it can reduce the lights intensity so that they dont bother the inhabitants and give the sensation of being in a cinema. In contrast, if the house notices that there are books, and/or pens on the activity being done, then the house knows that a reading or writing activity is being done. For this event, the most illumination is required. Moreover, the illumination can be complemented by the sunlight, thus by adding photo-sensors, the house can combine the light bulbs with the sunlight to acquire the desired intensity. Such intensity corresponds to the point where the power at the photo-sensor is the same as it was when the desired light setting was specified. Another easy example is to keep the house at a warmer temperature when it realizes that no one is inside; and setting it back to preffered settings when users are about to return.

Extending the context awareness into location as well yields the house with the property of monitoring the power consumption of each inhabitant. Thus at the end of the month, it can let them know who is using more energy and on what. Such a feature is useful for cases where people share the bills (e.g. student housing), since it splits the bill fairly and creates an incentive for better usage of resources, by all inhabitants and creating a better conscious of energy usage.

Another service that SHEAP can provide through context awareness is to switch all energy into the refrigerator if the power company fails to deliver energy to the house. In such way the contents inside of the refrigerator may be preserved over time until the power comes back online.

B. Energy Adviser

Consider again the example of the lighting the house. It is known that the lumens (lm) tell us how effective a bulb is. The problem comes when one wishes to establish between the lumens and the watts being consumed by the house. Such relationship depends on the material, and therefore there is no universal relation. To solve this problem, a smart home can consult the reading in a photoresistor, at an independent circuit in the same room, since it lowers its resistance as light intensity increases. Thus the current will increase and with it, the power absorbed by the photoresistor, which can be rated against the actual consumption. The probing of such relationship is done at night to prevent being affected by sunlight, and only once per month to suggest for consumption improvements, while neglecting the photoresistor consumption.

Another example is to change the television type from a CRT to an LCD or Plasma. Thus by knowing the consumption of the appliances, it can query an existent service oriented network (e.g. the one that provides connection to the outside world and remote house configuration) to find out what technology provides the same service with less consumption. With this query, the house can advise the user to change the type of appliance. The query results are shown in a table with the cost vs benefit ratio (CBR) of the change, as a function of: initial costs C in dollars, return of investment ROI in months, and lifetime L in months. The result as seen in equation 1 is dimensionless, and it shows that the lowest CBR will represent the best change and it will depend on a low C, low ROI, or high L.

$$CBR(x,y) = \frac{C_x}{C_y} \cdot \frac{ROI_x}{ROI_y} \cdot \frac{L_y}{L_x} \tag{1}$$

C. Load Balancing Algorithm

This sub-section presents a cheap solution to the load balancing problem. It is of great importance to distribute loads properly, so that one can obtain the highest profit out of the system.

Given that each appliance has a power consumption w_i, and the green sources have a total capacity of W_k, our objective turns out to be finding the best combinations of appliances a_i such that equation 2 is maximized.

$$F_k = \sum_{i \epsilon |a_i|} a_i \cdot w_i < W_k, a_i \epsilon \{0,1\} \tag{2}$$

It can be seen from equation 2 that the problem looks very similar to the well-known combinational Knapsack problem [11] if $k = 1$. However as k increases, the problems transform into a Multidimensional Knapsack problem, with the additional constrain that the capacity of the sources are not equal. Traditionally, this type of problem has a solution given by the equation 3.

$$m(i) = max\{w + w_i | a - a_i, w | a\} \tag{3}$$

Using the concept of dynamic programing, this problem is expressed as a matrix on which the equation is evaluated for $1 \leq W \leq W_k$. From here the second difference of the problem from the knapsack problem can be seen; that is, each knapsack has a different maximum capacity. The third challenge comes from the fact that the matrix grows fast, and most of its entries are computed unnecessarily.

The Binary Particle Swarn Optimization (BPSO) in [12] can serve as a mechanism to avoid these unnecessary computations. BPSO is an extension of the original PSO [13], on which the parameters to be optimized are of binary nature. In the domain of load balancing, such parameters are the selection of appliances a_i, which can be selected for a green source (i.e. $a_i = 1$) or not (i.e. $a_i = 0$). The fitness, or how well the selected parameters perform on the domain, can be seen as the addition of equation 2 for each energy source type.

For example, consider the set of appliances $\{TV, FRIDGE, AC, LIGHT, RANGE\}$ with an average power consumption of $\{125, 800, 920, 240, 12200\}$ watts respectively. If a green house with such appliances, and without any smart technology, has a solar system with maximum capacity of $2000W$ and wind system with maximum capacity of $2100W$; the BPSO can find fast enough a configuration that will maximize the profit. For the considered example, the $RANGE$ cannot be powered by any system, unless a smart reduction is applied. However the AC can be powered by wind energy, along with the $LIGHT$ system, for a total consumption of $1160W$. Simiraly the TV and $FRIDGE$ can be connected to the solar system for a total consumption of $925W$. As shown, the BPSO can also let know the user if less materials could be utilized instead. For instance, in the example shown it was sufficient to have a solar system of $1000W$ and a wind system of $1200W$; thus reducing the project costs.

D. Solar Energy

The solar energy part of the system is the most complex part. It depends mainly on the location of the house on the planet's sphere. Such location, especially the latitude, determines the length of the day λ. That is, the amount of time that the house is exposed to solar energy. On the other hand, the longitude serves to know the apparent solar time AST, which is interpreted as the hour correction related to the total solar energy actually felt. The equations that describe these relations, which also depend on the day of the year N, can be found in equation 4. In the AST, the SL and LL are the standard longitude, i.e. closest 15 degree longitude to LL which is the local longitude. DST can be 0 or 60 mins if daylight savings time is observed.

$$\begin{aligned}
\lambda &= \frac{2}{15} arccos(-tan(latitude)tan(\delta)) \\
\delta &= 23.45 sin(\frac{360}{365}(284+N)) \\
AST &= LST + ET \pm 4(SL - LL) - DST \\
ET &= 9.87 sin(2B) - 7.53 cos(B) - 1.5 sin(B) \\
B &= \frac{360}{364}(N - 81)
\end{aligned} \quad (4)$$

Given these relations, one can then estimate when the house will have solar energy or not. It is only enough to verify that AST is between $12 - \frac{\lambda}{2}$ and $12 + \frac{\lambda}{2}$. For simplicity, since the solar panels are already designed and rated under standard test conditions (i.e. $1000\frac{W}{m^2}$ at $25C$); it can be assumed that such panels can produce on a normal day an average of 85% of the power under standard conditions. For example, a panel rated for 200W will produce an average of 170W. Such assumption is enough for our approach since the interest is to demostrate a reduction in dependency of traditional power grid, and mainly reduction in installation costs. Thus the solar energy system is given by equation 5. N_s is the number of solar panels with maximum capacity P_s. An initial estimation of the number of panels can be found using equation 6.

$$E_{solar} = \begin{cases} 0.85 N_s P_s & \text{if } 12 - \frac{\lambda}{2} \leqslant AST \leqslant 12 + \frac{\lambda}{2} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

$$N_s = \lceil \frac{load}{\lambda P_s} \rceil \quad (6)$$

E. Wind Energy

Wind energy system acts as a complement to the solar energy. For some areas it may be even more powerful than solar energy. It can act as a green energy source at night time, and also provide additional energy during the day. It depends mainly on the rotor swept area A, the air density ρ (i.e. 1.255 $\frac{kg}{m^3}$), coefficient of performance C_p, generator efficiency η_g, and bearings efficiency η_b. The last three values, for good designed rotors, are taken as $0.35, 0.5, 0.95$ respectively. The remaining factor is the wind speed V_w meassured in $\frac{m}{s}$; thus the power supplied by the wind system is given by the equation 7.

$$E_{wind} = 0.5 \cdot \rho \cdot A \cdot C_p \cdot V^3 \cdot \eta_g \cdot \eta_b \quad (7)$$

F. Batteries

Batteries are not taken into account on the system to prevent additional project costs, since the goal of this paper is simply to reduce and not remove dependency from the power grid. Normally, batteries are very expensive and may have a short life span, which may lead to several replacements. However if the reader is interested, the number of batteries needed to sustain a house or some part of it for $ndays$ days, is given by equation 8 having a state of charge SOC.

$$N_{batteries} = \frac{load \cdot ndays}{SOC * Efficiency * Amps * Volts} \quad (8)$$

IV. Cost Analysis

For all energy projects to work, it is important to know the viability of it. That is, the minimum waiting time T_m in order to recover the initial investion, which can be seen in the equation 9. Equation 10 yields the project cost. η is the smart factor that will reduce the power consumption over time, and $C_\eta(t)$ is the cost of having such smart system running. Thus, it is easy to see that for a green house (with just green energy) the cost revenue will be given basically by finding the lowest installation cost (equation 11). However for a smart home, the presence of η makes it possible to obtain quicker revenues. The speed increase in revenues can be accomplished in two ways: one is by reducing the energy consumed by traditional power grid; second is by lowering the installation costs by requiring less materials to work in the same way as seen in section III-C.

$$Cost_{traditional}(T_m) - Cost_{project}(T_m) > 0 \quad (9)$$

$$
\begin{aligned}
Cost_{project} &= \sum_{i \epsilon N} \int_0^t c(t)dt \\
&= \int_0^t (\eta(t) \cdot c_{traditional}(t) + C_\eta(t))dt \\
&+ C_i \qquad (10)
\end{aligned}
$$

$$
C_i = N_s \cdot p_s + N_w \cdot p_w + p_l \qquad (11)
$$

V. Scenario Generation

In order to evaluate our case of study, a scenario was created to define the structure of a series of actions A with a duration D and units U. Following in listing 1, an example of a scenario over a period of time is presented. In general scenarios are composed of tuples of the form $(A, D, U, timestamp)$ (see equation 12).

$$
\begin{aligned}
A &= \{WORK, COOK, EAT, READ, \\
&\quad WATCH, SLEEP, TRAVEL, \\
&\quad VACATION\} \\
D &\epsilon R \\
U &= \{DAYS, HRS, MINS\} \qquad (12)
\end{aligned}
$$

Listing 1. Fragment of Scenario

```
WORK 12 HRS 08/26/2010 21:00
COOK 32 MINS 08/26/2010 21:32
EAT 25 MINS 08/26/2010 21:57
READ 107 MINS 08/26/2010 23:44
WATCH 201 MINS 08/27/2010 03:05
SLEEP 5.92  HRS 08/27/2010 09:00
```

These events are generated for a year using a stochastic process. The scenarios also include temporal and seasonal variations. That is, both the season of the year and the time of the day affect how the environment will be at an instant of time. For example, a day at 9:00am at summer will be hotter than one at winter.

Furthermore when entering either WORK or VACATION state, the probability of continuing on the same state decreases over time.

VI. Simulation

For testing our experiment, 10 one-year scenarios at the locality of the city of Orlando in the state Florida, and Mayagüez in Puerto Rico, were run using Java programming language. Each scenario was generated using different random seeds to provide different patterns. A house of 1640 square feet was used as our virtual smart home. The devices under study were the television, refrigerator, air conditioner, lighting system, and range with their average normal power consumptions listed in table I. These devices were on during the events specified also by table I, where a maximum consumption of 0W indicates that the device is off. For the green energy cases, the devices connected to solar energy were the fridge and TV.

TABLE I
Events and Appliances Maximum Consumption (Watts)

Event	AC	Fridge	Range	TV	Lights
WORK	9200	800	0	0	0
TRAVEL	9200	800	0	0	0
VACATION	9200	800	0	0	0
COOK	9200	800	12200	0	240
EAT	9200	800	0	0	240
READ	9200	800	0	0	240
WATCH	9200	800	0	125	240
SLEEP	9200	800	0	0	0

Meanwhile, the lights, AC, and range were connected to the wind energy. This configuration was obtained using the load balancing algorithm.

The return of investment for each project in Orlando is shown in figure 1. The straight line indicates the cost for having the 1640 sqft house as traditional model. Clearly, as one could have expected, if the house were to be powered by green energy (i.e. solar and wind energy); the costs would be higher at the beginning and then lower than traditional. It is shown by the *x* line, where in this case it took 7 years before some benefit was obtained. In contrast, the smart home shown by the *o* line, sees the benefit much before (e.g. 3 years) due to lower installation costs. In the figure, due to the reduction in materials, the smart home had a lower installation cost than that of the green. However, since the smart home curve has a smaller slope (around $1000\frac{\$}{yr}$ vs $2000\frac{\$}{yr}$), it would still be a better alternative, even if they both had the same initial costs. Moreover, since Mayaüez is on a tropical island at lower latitude, days have longer duration and wind blows at faster speed. This fact reflected in lowered costs; however the differnce in profit was not very significant (around $100).

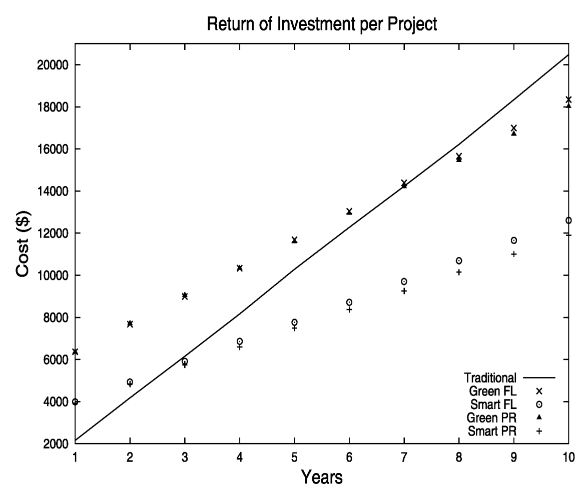

Fig. 1. Return of Investment for Projects

The rest of the presented results are only for Orlando city. Figure 2 shows the average cost on the 10 scenarios for each type of home using only operational costs (i.e. no installation costs included). The traditional bar states the average cost in dollars of the 1640 sqft home without the usage of any green energy source. The price of electricity was computed using the price at Progress Energy of Central Florida for

Fall 2010. The green bar specifies the cost for a house with green energy. This value was not close to 0 for the main reason that no batteries were simulated; thus at night solar energy didn't worked and appliances connected to it were then powered by traditional grid. Adding batteries would drastically increase the installation and maintenance costs of the project; for this reason it was decided not to disconnect completly from the traditional power grid. Finally, the smart bar states the consumption of a smart home powered by green energy. An additional decrease in cost is added mainly because appliances were intelligently turned off or dimmed when needed.

For the smart home problem, the load balancing algorithm was also run and found out that the same results obtained with 10 solar panels of 200W each, could be obtained with just 6 solar panels. The same effect occured with the wind energy, reducing the windmills from 5 to 3. In this way, a reduction was achieved on the installation cost of the project, thus reducing in the long term the return of investment time as well.

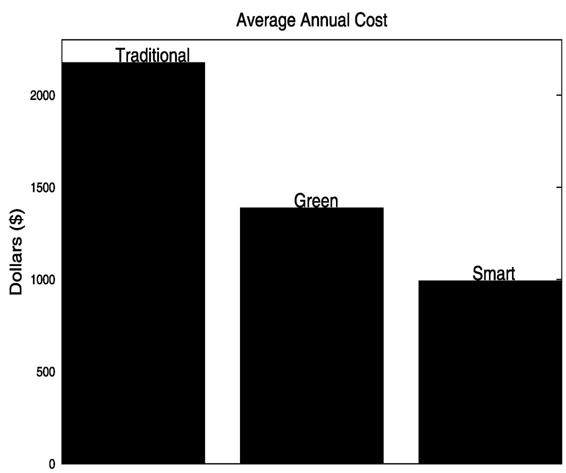

Fig. 2. Cost for Different House Types

In figure 3 one can appreaciate the average power consumption for each house type per different energy sources. Traditionally the house only depends on the power grid and achieves the total kilowatts as goal to beat. Clearly a green house alone can reduce the dependance on the power grid almost by half. However on the smart home side, one can notice that the efficiency of the system can be further improved, and with it, reduce the grid dependancy to 30%. One can notice that on the solar energy part there was no reduction in consumption. The reason for it is because the devices attached to it (i.e. fridge and tv) were not smart; hence no power adjustment was done to them. On the other hand, the devices connected to the wind energy were intelligently controlled. For this reason, the bars shown in the figure have such great difference in amplitude (around 60% less). From the same figure, it can also be noticed that the total kilowatts consumption was the same for the traditional and green homes. However, in the smart home this value was reduced, causing a greater reduction in annual energy cost.

The performance of the load balancing algorithm was compared on average of fitness and its maximum value. The results are shown in figure 4. For all the cases it took at most around 210 evaluations (i.e. 7 generations) to reach the best configuration. Hence a faster solution to our problem is yielded, which was similar in nature to that of a Multidimensional Knapsack problem.

Fig. 3. Consumption for Different House Types

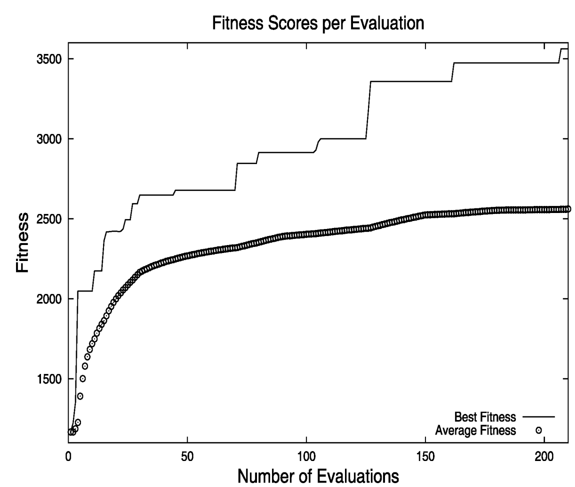

Fig. 4. Load Balancing Performance

VII. Conclusion

This paper showed an approach for adapting the idea of green smart homes. The system benefits from both solar energy and wind energy to reduce the power grid dependence. The most relevant equations were taken into account when designing the system. Load balancing of multiple energy sources was easily accomplished using the 2D-BPSO algorithm. The algorithm itself was easy, computationally cheap, and powerful to find both the best configuration as well as telling if surplus of materials existed. This fact reflected a significant cost reduction on initial payment for the system and hence made the alternative of green smart home more attractive. Moreover, by establishing context recognition, the house was able to