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Soft Computing Techniques Based Efficient Energy Storage System for HVAC Loads

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***Abstract*—This paper proposes a new strategy to meet controllable heating, ventilation, and air conditioning (HVAC) loads with a non-conventional energy source and energy storage system. It also classifies the input loads into four categories such as constant load timed schedule (CLTS), constant load variable schedule (CLVS), variable load timed schedule (VLTS), variable load variable schedule (VLVS). For classification of loads we must consider the Energy Conservation Measures (ECM) impact also. For calculation of energy saved it requires both base-line load value and post-installation value. In order to minimize cost and to increase efficiency, we use BFOA-based optimization approach together with the classification of loads. Bacterial foraging optimization algorithm (BFOA) has been widely accepted as a global optimization algorithm of current interest for distributed optimization and control. Minimizing the cost function guarantees minimum power generation through non-conventional source as well as storage capacity selection to supply the HVAC load.**

Index terms - Bacterial foraging algorithm-based optimization approach, HVAC load, energy conservation measures (ECM).

I. INTRODUCTION

The development of the smart grid will facilitate the integration of renewable energy sources into the power grid. Smart-grid applications include transmission, distribution, and distributed generation. The "smarter" monitoring and control will create a more efficient energy-management system for residential customers. Smart-grid applications in distribution systems include smart metering technologies for efficient integration of distributed renewable generation applications, fair pricing mechanisms, remote monitoring, and home automation and control of electrical power consumption.

The design, simulation, and optimization of hybrid power systems have been the subjects of several studies [8]–[13]. However, none of these investigations focused on demand flexibility and HVAC loads, in particular, or on matching HVAC loads with renewable energy sources without the need for supplementary conventional generations. Emerging smart-grid strategies can provide the distribution system with an opportunity to balance renewable generation and HVAC loads for a residential feeder using energy storage systems.

The combination of the BFOA and classification of loads for finding energy saved after taking the energy conservation measures enhances the efficiency of the renewable energy system when compared to classical optimization approaches. This paper proposes a smart-grid strategy for matching renewable energy generation with HVAC loads using renewable energy generation and energy storage.

II. RELATED WORK

A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. S. Fadali, and Y. Baghzouz [1] proposed a strategy to meet the controllable heating, ventilation, and air conditioning (HVAC) load with a hybrid-renewable generation and energy storage system. Historical hourly wind speed, solar irradiance, and load data are used to stochastically model the wind generation, photovoltaic generation, and load. Using fuzzy C-Means (FCM) clustering, these data are grouped into 10 clusters of days with similar data points to account for seasonal variations. In order to minimize cost and increase efficiency, we use a GA-based optimization approach together with a two-point estimate method. Minimizing the cost function guarantees minimum PV and wind generation installation as well as storage capacity selection to supply the HVAC load.

Tommer R. Ender and Jonathan Murphy [16] have proposed an interactive tool for energy systems portfolio planning developed through a systems engineering process that enables real-time decision making through integration with rapid modeling and simulation. A structured process that combines elements of QFD, MADM, and surrogate modeling together enable qualitative decision making based on quantitative modeling and simulation based tools. With traditional static approaches to decision-making, the decision-maker does not have access to the same fine-grained solution space.

S. Ali Pourmousavi, M. Hashem Nehrir, Christopher M. Colson and Caisheng Wang [17] have proposed a Real-time PSO-based energy management of a stand-alone hybrid wind-MT-ES system was presented in this paper. The developed EMS promotes energy sustainability in two ways: first, by ensuring an optimal balance between the attached generation sources based on the multiple constraints, and second, by incorporating desirable energy objectives into the EMS decision-making process.

Souleman Njoya Motapon Louis-A. Dessaint and Kamal Al-Haddad [18] suggested a comparative analysis of different energy management schemes for a fuel-cell-based emergency power system of a more-electric aircraft. The fuel-cell hybrid system considered in this paper consists of fuel cells, lithium-ion batteries, and supercapacitors, along with associated dc/dc and dc/ac converters. The energy management schemes addressed are state of the art and are most commonly used energy management techniques in fuel-cell vehicle applications, and they include the following: the state machine control strategy, the rule-based fuzzy logic strategy, the classical proportional–integral control strategy, the frequency decoupling/fuzzy logic control strategy, and the equivalent consumption minimization strategy. The main criteria for performance comparison are the hydrogen consumption, the state of charges of the batteries/supercapacitors, and the overall system efficiency. Moreover, the stresses on each energy source, which impact their life cycle, are measured using a new approach based on the wavelet transform of their instantaneous power. A simulation model and an experimental test bench are developed to validate all analysis and performances.

Lei Zhang and Yaoyu Li [19] have proposed a two-scale DP strategy for the optimal energy management of a WBHPS. First, an MASDP is performed for the long-term (diurnal) period, based on long-term predictions of hourly electricity price and wind energy. The battery SOC is thus obtained as the macro-scale reference trajectory, which is then used as set point for the micro-scale planning. The MISDP is then applied within a short-term (3-hour) interval, based on short-term-hour ahead prediction of hourly electricity price and wind energy. The nodal SOC values from the macro planning result are used as the terminal condition for the MISDP planning. The proposed method is tested on an exampleWBHPS with wind and electricity price data obtained for Storm Lake, IA. Significant improvement with the proposed two-scale DP was observed.

III. CLASSIFICATION OF LOADS

The classification of loads strategy provides guidance to verify energy savings for energy conservation measures (ECMs) performed on equipment or end uses. The methods outlined are useful when the savings for an ECM are too small to be resolved with whole-building or facility energy meters, or for stand-alone equipment as may be found in the commercial, industrial, and agricultural sectors. The loads are classified based on their value and their time of use into four categories such as,

- Constant Load, Timed Schedule (CLTS)
- Constant Load, Variable Schedule (CLVS)
- Variable Load, Timed Schedule (VLTS)
- Variable Load, Variable Schedule (VLVS)

A. Constant Load, Timed Schedule (CLTS)

CLTS includes equipment with constant load and constant hours-of-use. The degree to which a load or hours-of-use is constant may be defined by the user. In this category, the measured energy use rate (kW) is often used directly in calculations, after verifying that the load is constant. Based on the ECM impact the CLTS loads are classified into six types such as,

1. Changes load
$$kWh_{saved} = (kW_{base} - kW_{post})HRS_{base}$$
2. Changes hours-of-use
$$kWh_{saved} = kW_{base}(HRS_{base} - HRS_{post})$$
3. Changes load and hours-of-use
$$kWh_{saved} = (kW_{base} * HRS_{base}) - (kW_{post} * HRS_{post})$$
4. Changes load from constant to variable
$$kWh_{saved} = (kW_{base} * HRS) - \sum_i (kW_{post,i} * HRS_i)$$
Where,
$$HRS = \sum_I HRS_i$$
5. Changes hours-of-use from constant to variable
$$kWh_{saved} = (kW_{base} * HRS_{base}) - kW_{base} \sum_i HRS_{post,i}$$
Where,
$$HRS_{base} \neq HRS_{post}$$
$$HRS_{post} = \sum_i HRS_{post,i}$$
6. Changes both load and hours-of-use from constant to variable
$$kWh_{saved} = (kW_{base} * HRS_{base}) - \sum_i (kW_{post,i} - HRS$$

For each type its respective energy saving equations are given above.

B. Constant Load, Variable Schedule (CLVS)

CLVS includes equipment with constant load and varying hours-of-use. Based on ECM impact it is classified into four types such as,

1. Changes load
$$kWh_{saved} = \sum_i [kW_{base,i} * HRS_{base,i} - kW_{post,i} * HRS_{post,i}]$$
$$\sum_i HRS_{base,i} = \sum_i HRS_{POST,i}$$

2. Changes hours-of-use

$$kWh_{saved} = \sum_i [kW_{base,i}(HRS_{base,i} - HRS_{post,i}]$$

3. Changes load and hours-of-use

$$kWh_{saved} = \sum_i [kW_{base,i} * HRS_{base,i} - kW_{post,i} * HRS_{post,i}]$$

4. Changes hours-of-use from constant to variable

$$kWh_{saved} = \sum_i [kW_{base,i}(HRS_{base,i} - HRS_{post,i}]$$

For each type its respective energy saving equations are given above.

C. Variable Load, Timed Schedule (VLTS)

VLTS includes equipment with varying load and constant hours-of-use. While the total number of operation hours is constant, the equipment may spend a fixed number of hours at different loads. Based on the ECM impact it is classified into four types such as,

1. Changes load

$$kWh_{saved} = (kW_{base} - kW_{post})HRS_{base}$$

2. Changes hours-of-use

$$kWh_{saved} = kW_{base}(HRS_{base} - HRS_{post})$$

3. Changes load and hours-of-use

$$kWh_{saved} = (kW_{base} * HRS_{base}) - (kW_{post} * HRS_{post})$$

4. Changes load from constant to variable

$$kWh_{saved} = (kW_{base} * HRS_{base}) - \sum_i (kW_{post,i} * HRS_{post,i})$$

Where,

$$HRS = \sum_I HRS_{post,i}$$

For each type its respective energy saving equations are given above.

D. Variable Load, Variable Schedule (VLVS)

VLVS includes equipment with varying load and varying hours-of-use. Based on the ECM impact it is classified into three types such as,

1. Changes load

$$kWh_{saved} = \sum_i [(kW_{base,i} - kW_{post,i})HRS_{post,i}]$$

2. Changes hours-of-use

$$kWh_{saved} = \sum_i [kW_{base,i}(HRS_{base,i} - HRS_{post,i}]$$

3. Changes load and hours-of-use

$$kWh_{saved} = \sum_i (kW_{base,i} * HRS_{base,i}) - \sum_i (kW_{post,i} * HRS_{post,i})$$

For each type its respective energy saving equations are given above.

IV. BACTERIAL FORAGING OPTIMIZATION ALGORITHM

During foraging of the real bacteria, locomotion is achieved by a set of tensile flagella. Flagella help an E.coli bacterium to tumble or swim, which are two basic operations performed by a bacterium at the time of foraging [7, 8]. When they rotate the flagella in the clockwise direction, each flagellum pulls on the cell. That results in the moving of flagella independently and finally the bacterium tumbles with lesser number of tumbling whereas in a harmful place it tumbles frequently to find a nutrient gradient. Moving the flagella in the counter clockwise direction helps the bacterium to swim at a very fast rate. In the above-mentioned algorithm the bacteria undergoes chemotaxis, where they like to move towards a nutrient gradient and avoid noxious environment. Generally the bacteria move for a longer distance in a friendly environment.

When they get food in sufficient, they are increased in length and in presence of suitable temperature they break in the middle to from an exact replica of itself. This phenomenon inspired Passino to introduce an event of reproduction in BFOA. Due to the occurrence of sudden environmental changes or attack, the chemotactic progress may be destroyed and a group of bacteria may move to some other places or some other may be introduced in the swarm of concern. This constitutes the event of elimination-dispersal in the real bacterial population, where all the bacteria in a region are killed or a group is dispersed into a new part of the environment.

Let us define a chemotactic step to be a tumble followed by a tumble or a tumble followed by a run. Let *j* be the index for the chemotactic step. Let *k* be the index for the reproduction step. Let *l* be the index of the elimination-dispersal event. Also let *p*: Dimension of the search space, *S*: Total number of bacteria in the population,
Nc : The number of chemotactic steps,
Ns: The swimming length.
Nre : The number of reproduction steps,
Ned : The number of elimination-dispersal events,
Ped : Elimination-dispersal probability,
C (i): The size of the step taken in the random direction specified by the tumble.

The flow chart shown in Fig. 3.2 explains the entire process of energy management using BFOA.

The parameters related to Bacterial Foraging Optimization Algorithm such as Dimension of search space, Number of bacteria, No of chemotactic steps, No of reproduction steps, No of elimination dispersal events, No of bacteria reproduction, probability of each bacteria for elimination and dispersion is shown in Table I.

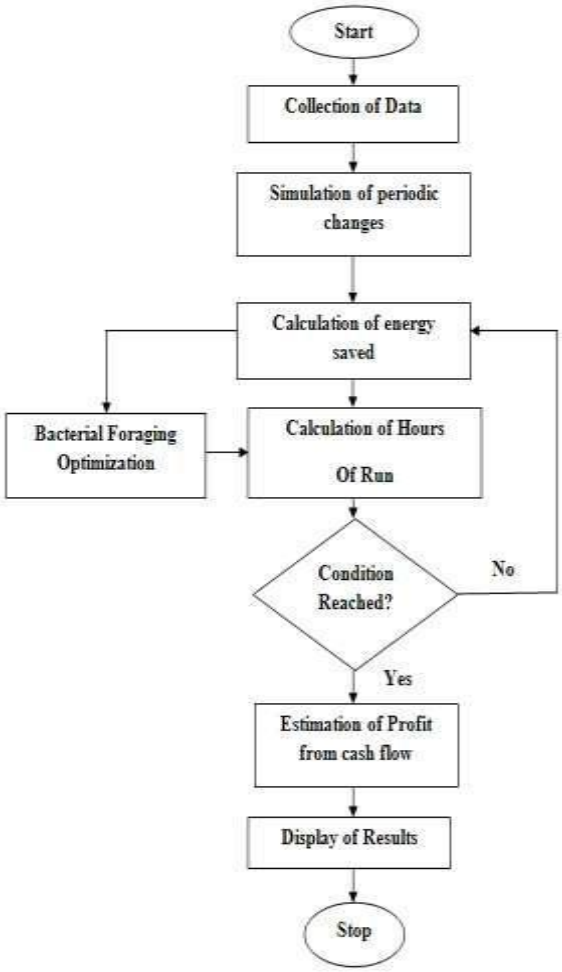

Figure 1. Flowchart for energy management using BFOA

The main aim is to minimize this cost function by maximizing the profit. So each bacteria in search space will move towards maximizing the profit and thereby minimizing the installation cost function. The installation cost for the generation of power is given by equation (1). The fitness function is given by,

$$F_T(p) = \sum_{i=1}^{NG} F_i(P_i) \quad (1)$$

TABLE I
PARAMETERS OF BFOA

Parameters	Values
N_p (Dimension search space)	1
S (Number of bacteria)	4
N_c (No of chemotactic steps)	2
N_{re} (No of reproduction steps)	6
N_{ed} (No of elimination dispersal events)	3
S_r (No of bacteria reproduction)	S/2
P_{ed} (Probabilty of each bacteria for elimination and dispersion)	0.25

Where, $F_T(p)$ indicates total installation cost for generation. NG indicates number of generators. $F_i(P_i)$ Indicates installation cost for i-th day. The constraints are given in the following equation.
The real power constraint is given by,

$$\sum_{i=1}^{NG}(P_i - P_d - P_l) = 0 \quad (2)$$

The generation cost constraint is given by,

$$P_i^{min} \le P_i \le P_i^{max} \quad (3)$$

Where, P_d is maximum demand, P_l is transmission losses, P_i is generation cost.

V. RESULTS AND DISCUSIION

In energy management we are getting solar, wind energy generation and load as the input. The installation cost function and profit function was found out. Then by using Bacterial Foraging Optimization Algorithm the installation cost funtion is minimized, profit is increased. The corresponding simulation results are given in this section.

A. Output variation

The output for generator cash-flow distribution shows that during the months of July, August and September power production is maximum. It is because of the low power production in the hybrid system (Solar and Wind power plant). The maximum profit is 82000$.

The Fig.3 indicates the expected profit and the cash-flow at 90% and 95% of risk level. The count in the Y-axis indicates that the number of days. The result indicates that for more than 100 days there will be more profit in the range of 2.5 to 2.9 M$. The expected profit is nearly 2.9M$.

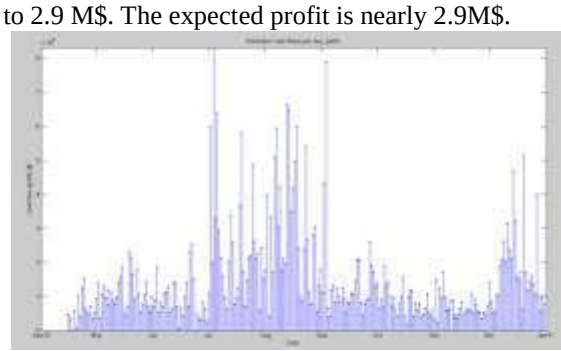

Figure 2. Simulated output for Generator cash-flow in conventional source

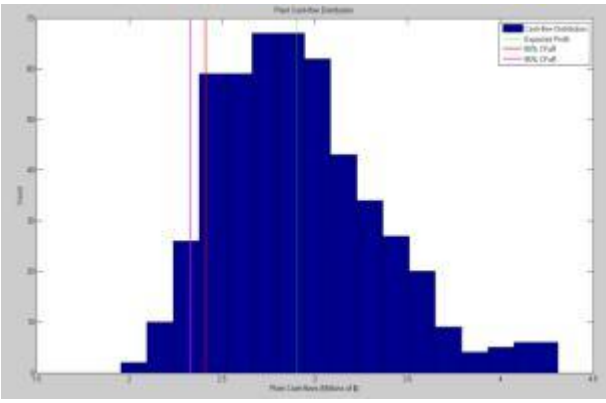

Figure 3. Simulated output for profit and cash-flow distribution

B. Results

The profit based on the percentage of risk level is shown in Table II. This indicates that the profit is high for 100% risk level.

The operating days of conventional energy source based on the renewable energy generation, percentage of time running, average hours per operating day and profit is Table III.

TABLE II
PROFIT BASED ON THE PERCENTAGE OF RISK LEVEL

% of Risk level	20	40	60	80	100
Profit in M$	0.1206	0.2411	0.3617	0.4823	0.6028

TABLE III
DETAILS RELATED TO CONVENTIONAL ENERGY SOURCE

Operating Days	**Average Hours per Operating Day**	**% of Time Running**	**Profit in M$**
253	15.31	62.14%	2.9051

VI. CONCLUSION

Simulation results show that increasing the LS percentage gives the system more flexibility and may lead to less excess energy and more efficiency. The results show the compromise between the risk of failure to meet demand and cost for different wind and PV generation levels. By comparing the results of conventional methods of energy management with the proposed method of energy management using BFOA, the proposed method is having more profit than that. The profit obtained in the proposed method is 2.9051M$.

For future work, we will apply the proposed method for matching the renewable energy sources with other controllable loads, such as plug-in electric vehicles. We can apply this strategy with other advanced soft computing techniques, so that we will decrease the execution time, iterations and able to get accurate output with high efficiency.

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