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A survey of intelligent energy management based on learning heuristic

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ABSTRACT

Human activities are dependent on energy and lifestyles that important provide services on a daily basis. Currently, polluting and energy consumption worldwide is dominated by sources non-renewable, for instance fossil fuels. Due to their environmental impact, research and investment have increased in alternative and renewable energy sources, such as photovoltaic and wind energy. Buildings use energy management systems to monitor real-time consumption and plan the operation of appliances so that the energy bill is minimized or based on other factors. The purpose of energy management systems in buildings is mainly to monitor real-time energy consumption and adjust the device's operation to minimize energy bills or achieve another specific goal. The purpose of this work is review the latest literature on energy management systems based on heuristic learning of buildings in the smart home. In addition, the literature has been updated a list of techniques that managed appliances and the planning goals and how use these techniques to in the energy scheduling.

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1. INTRODUCTION

During certain times of the day, high power consumption can be stressful for the distribution network [1]. To reduce electrical energy costs, a home energy management system controls electricity consumption [2]. It is possible to increase the balance between supply and demand using energy management systems (EMS). EMS are required to guide the flow of energy as smart grids (SGs) when more than one energy source is present in the grid [3]. The main challenge for EMS is improving its cost-effectiveness through secure and reliable communications, multi-agent systems can be developed that are hybridized with optimization algorithms, based on metaheuristics, in order to achieve energy management that meets a wide range of objectives and constraints [4], [5]. Energy management schemes, such as renewable energy sources (RES) management, battery management, and management, have been developed using different of optimization and programming methods [6]. Machine learning (ML) models are essential for predictive modeling of production, consumption, and demand in EMS because of their accuracy, efficiency, and speed [7], [8].

Furthermore, ML models can also be used to understand how energy systems function in complex human interactions [9]. In smart grids, information and communication technology (ICT) used ICT in points of generation to consumers [10]. More importantly integral the part of the SG, they can contribute to balancing production, consumption, and distribution, automatically, as shown in Figure 1, comparison of four load-forecasting models [11]. In this paper, in order to reduce electricity costs, we will used some techniques in heuristic learning to find the best pattern of energy consumption.

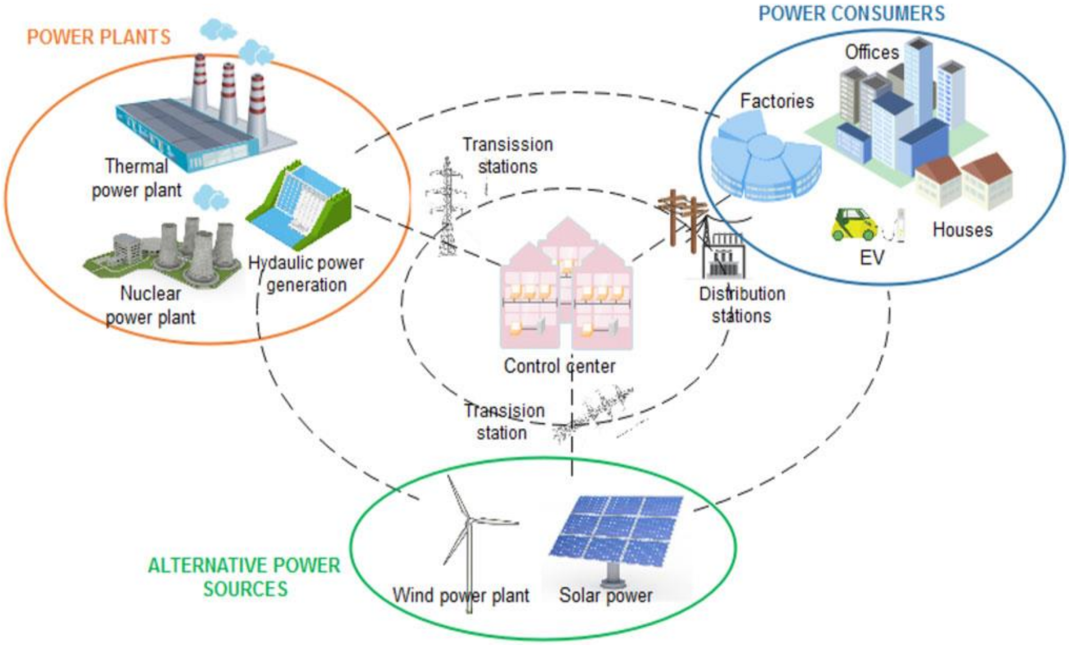

Figure 1. The concept of smart grid (SG) [11]

2. ENERGY MANAGEMENT SYSTEM

An EMS in a smart building includes internet of things (IoT) and artificial intelligence (AI) technologies that improve comfort, safety, health, and energy efficiency in buildings [12]. EMS is important of generation management in distributed power, especially in energy renewable sources such as hydro, solar and wind [13]. In addition, individual households also become participants in the production of their own electricity through local (micro) solar and wind energy systems, as shown in Figure 2 [14]. However, "when power generation exceeds local demand, the resulting surplus can be used to charge local batteries, for subsequent domestic use, or inject into the grid with a given profit" [15].

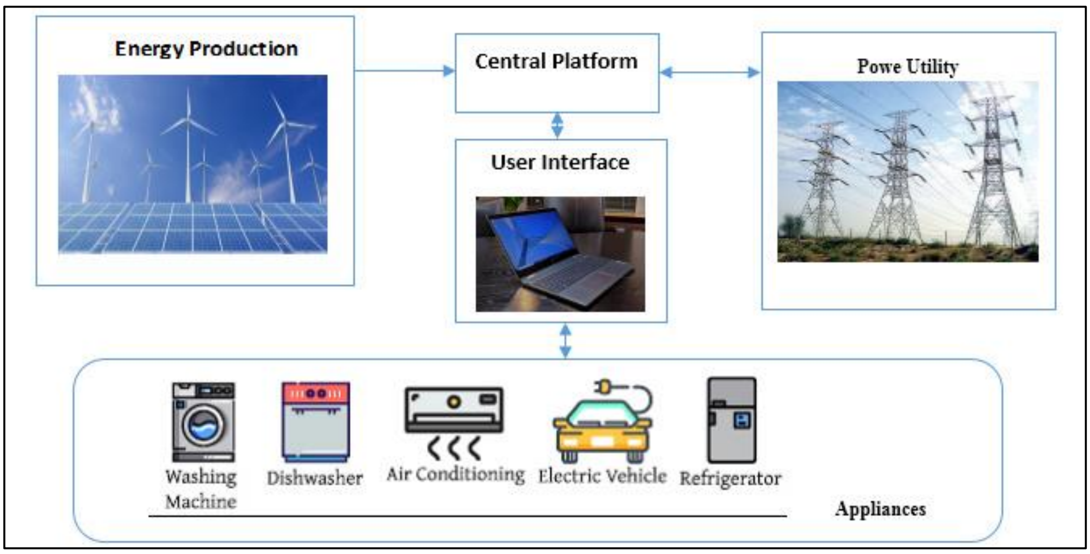

Figure 2. EMS in general [14]

2.1. EMS components (EMSC)

The following components make up the basic architecture of an EMS (Figure 2) [16]:

- Capture detailed energy consumption of individual devices and other information related to human activity using sensors and measuring devices.
- Smart appliances: consists of typical household appliances (such as dishwashers, refrigerators, or air conditioners) with computing and communication capabilities. Power generation equipment such as photovoltaic (PV) panels and wind turbines are also considered. Smart devices communicate with a central platform that manages all measurement data and coordinates device usage.
- User interface: "A device that allows residents to interact with emergency services. The interface can be used to display information such as current consumption or energy costs, and to set occupant preferences, including equipment priority, comfort parameters or planning goals".
- Central platform: designed to manage and optimize energy consumption. It receiving from smart meter information and applies scheduling mechanisms that calculated by optimization methods, assuming specific performance metrics.

In EMS, sensors continuously collect information about household activities. Typically, consumption signals are collected from individual devices, although decomposition techniques such as non-intrusive load monitoring (NILM) can being applied to extract consumption from individual devices [17].

3. MANAGEMENT IN BUILDINGS (MiB)

Energy efficiency and reduction cost can achieved in two main ways [18]; first by reducing overall energy consumption or by second shifting the operation of certain equipment with self-generation and off-peak electricity prices [19]. This can be categorized as a decrease in consumption or a change in consumption. Reducing consumption as said [20] refers to reducing overall energy use, usually by increasing consumer awareness, turning off equipment that is not in use, purchasing energy-efficient equipment, or improving buildings and building designs. The Table 1 shows a survey of management in buildings and related work on EMS.

Table 1. A survey of previous and related work on EMS

Authors	Objective
[21]	It discusses the key concepts of demand-side management (DSM) schemes in relation to consumer demand management. DSM schemes under different categories and DSM based on home energy management are also discussed along with DSM performance metrics, optimization goals, and solution methodology.
[22]	It provides a complete overview of cyber-attack vectors in traditional and intelligent measurement networks, as well as common defense and mitigation strategies to adapt to these types of events.
[23]	An overview of home energy management systems (HEMSs) "is presented, including operational goals and strategies to achieve them, appliance management", decision uncertainties, and performance metrics for HEMSs.
[24]	Described as a system that shares or exchanges energy between alternative energy sources as well as providing loads under all conditions necessary for an efficient electricity grid operation, a comprehensive energy management system integrates not just sharing and exchanging energy, but also providing safe, secure, and effective loads.
This work	It presents energy managements system using heuristic learning to ensure the distribution of energy to the buildings as well as the cost that led to reducing the bill.

4. PARAMETER TUNING (PT)

Performance optimization of ML forecasting methods is achieved by optimizing the model parameters [25]. A model's parameters are related to its training approach and the characteristics that can be altered to improve goal matching accuracy (minimizing the error between the fitted and actual goals) [26]. A non-convex optimization problem can lead to an estimation of the minimum optimal parameters rather than global parameters if an inappropriate optimization approach is chosen for training the ML forecasting system. ML models are commonly optimized using descent gradient algorithms [27]. The following section reviews some of the parameter optimization applications of ML models used to predict renewable energies are used two algorithms swarm-based optimization algorithm and an evolutionary optimization algorithm.

4.1. Tuning ML parameters using evolutionary optimization (TMLuEO)

To approximate the optimal solution, minimize evolutionary optimization techniques use a population of solutions [28]. In their working mechanism, these techniques mimic biological evolution. Evolutionary optimization approaches determine solutions by reproducing, mutationing, recombinating, and selecting [29]. Because there are no specific assumptions about fitness performance. Evolutionary optimization has therefore become a research focus and has attracted the attention of researchers [30].

4.2. Tuning ML parameters using swarm optimization (TMLuSO)

General minimization inspired by the natural motion of biological congestion, a congestion-based optimization system consists of locally interacting factors [31]. By following simple rules, the agent finds the best solution from a set of possible solutions in a given search space [32]. Density-based meta-innovations have been used to optimize performance and outcomes in a variety of engineering, medical, military, and commercial applications [33].

5. LITERATURE REVIEW AND RELATED WORK (LRaRW)

5.1. Prediction (P)

In fact, using optimization algorithms in energy planning should be supported by a suitable forecasting system [34], for example, in SGs and large micro-grids, prediction accuracy can be achieved by using large amounts of historical data on locally distributed generation and loads associated with microgrids such as photovoltaics (PV) and wind turbines [35]. This makes it possible to use statistical methods to calculate the optimal scheduling of the day ahead, which in real time using a centralized EMS, the acceptance of non-optimal solutions due to forecasting errors is applied [36]. However, day-to-day planning of small microgrids, especially for residential use, smart homes (SHs) or monolithic buildings, can be dangerous due to the high random behavior of local and load production [37]. To circumvent this problem, mathematically programmed EMS are often equipped with appropriate prediction systems that can work with alternative optimization methods, possibly in multi-stage designs [38].

5.2. Scheduling (S)

To improve efficiency in energy for residents, EMS monitors consumption and coordinates equipment operations [39]. In this way can be achieved by reducing consumption or changing consumption, the latter being more popular in residential construction. Changes in consumption depend on optimal planning of timing technology and appliance performance [40]. The equipment can be managed, planning criteria, operational constraints, and planning techniques must be considered before accepting and deploying them in real-world scenarios. Optimizing load management, potential storage, and ultimately energy exchange with the grid is possible via prediction of local loads and renewable energy production [41].

The home appliance-scheduling problem in Table 2 can be solved by a variety of techniques, many of which are based on the common goals of minimizing carbon emissions and cost. To improve energy consumption through load scheduling, a variety of methods and techniques have been proposed [48]. There are two types of methodologies: mathematical optimization, appliance scheduling [49], [50].

Table 2. EMS techniques used in buildings

Authors	Techniques	Objective
Chen *et al*. [42]	Home Energy Management (HEM)	Cost reduction, Peak to average ratio (PAR)
Bayram and Ustun [43]	HEM	Cost minimizing, PAR
Hu and Xiao [44]	GA	Cost reduction, PAR reduction
Yang and Shami [45]	GA	Cost reduction, PAR, UC
Li *et al*. [46]	ACO	Cost reduction, PAR reduction
Tian *et al*. [47]	EMC	PAR reduction, Cost minimizing
This work	HL	Cost minimizing and scheduling appliances.

5.2.1. Mathematical and heuristic (MaH)

Mathematical optimization methods are computationally intensive for large problems [51]. Because mathematical optimization relies on high-level procedures to find good solutions, it is less accurate than heuristic and meta-heuristic approaches [52]. Those algorithms are especially attractive for problems in which finding a good solution is usually easier than finding a non-optimal solution [53]. Examples include genetic algorithms, swarm intelligence algorithms, particle swarm optimizations (PSOs), Tabu Search algorithms [54].

5.2.2. Scheduling appliance (AS)

The use of supervised training can teach artificial neural networks to solve scheduling problems [55]. It is usually the feed architectures that are chosen among artificial neural network (ANN) topologies, and inputs such as demands and production forecasts in time of every day, and occupation information are taken into account. Multiple devices can be managed simultaneously using two strategies. Using one approach, one ANN is trained for each device, while using another approach; one ANN is trained for multiple devices [55].

6. OPTIMIZATION (O)

In EMS, optimization methods are mainly divided into mathematical programming, computational intelligence and hybrid techniques. The optimization of the performance that achieved through optimizing, the model parameters to EMS based on heuristic learning. In Table 3, a group of meta-heuristic techniques used in the energy management system [56].

Table 3. Literature review of using a heuristic algorithm in EMS

Author's	Meta-heuristic	Objective	Advantage	Disadvantage
Liemthong *et al*. [57]	Ant colony optimization (ACO)	Operating cost reduced	To schedule smart appliances optimally to attain our desired objectives	High computational time, difficult real-time implementation
Hassan *et al*. [58]	Artificial bee Colony (ABC)	Operating cost of MG reduced	Robust population-based algorithm, easy to implement. Adequate convergence speed.	Complex process.
Ghiasi *et al*. [59]	Binary particle swarm optimization algorithm (BPSO)	Techniques to minimize cost Operating	EMSs using to reduce the electricity bill in residential building and Minimization of carbon emissions	Difficult real-time implementation
Chamandoust *et al*. [60]	Genetic Algorithm (GA)	The operation, the cost of emissions have minimized and increased commercial profit	Scalable population-based algorithms including operations such as crossing, mutation and selection at find the optimal solution. Convergence at the right speed. Widely used in many fields.	It is necessary to define crossing and mutation parameters, as well as population parameters and stopping criteria.
Dwijendra *et al*. [61]	Greedy algorithm	Operating cost of MG reduced	Solve schedule problem is considered to schedule multi-energy systems in the microgrid to satisfy the electricity load.	Don't solve problem deal with the large state.
Albogamy *et al*. [62]	Particle swarm algorithm	Reduces the MG operating cost	Derivative-free, simple in implementation, required limited inputs	High computational time, difficult real-time implementation
Sarker *et al*. [63]	Tabu search	VPP operating cost reduced	Require less computational time	Verification of the optimality of the result requires other methods such as branching and binding
This Work	Genetic algorithm, Harmony, Swarm algorithm.	Reduces cost energy	Use Multi-objective to solve predication and scheduling of used energy.	High computational time and complex process.

7. CONCLUSION

EMSs can monitor household electricity consumption at the home level in real time. These systems add "smart" functionality to traditional homes and play on active role in a new grid. This survey provides an in-depth review of EMSs based on heuristic learning, including goals and strategies to achieve goals, as well as appliance management, uncertainty in level HEMs decision-making, and performance indicators. Furthermore, this work presents the reader with current challenges facing these systems, namely in terms of resource energy management consumption, dynamic scheduling in this approach of dual distributed energy sources, and consumer clusters, one of these challenges is how to predict energy use based on weather information and schedule it for home appliances so that it is sufficient for use. Energy prediction based on deep learning is used by some researchers, while scheduling based on deep learning is used by others, but both techniques aren't used in smart homes. After reviewing the literature and previous work, we find that most researchers use single-objective algorithms, but the recommended to use a hybrid (multi-objective) system to tune the parameters between them and to achieve the goal of predict energy consumption through weather information and reduce electricity bills through appliance scheduling, and reduce carbon emissions in the environment.

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