A Formal Literature Review and Examination: Predictive Algorithms and Automated Systems within HEMS

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Abstract

With the rising demand for sustainable solutions to climate change, there has been a great deal of excitement about 'urban greening' and reducing emissions – a key factor of which resides in the control of energy distribution and usage. Across the existing research concerning HEMS[1], energy waste management, and predictive algorithms aimed at limiting net energy consumption, there is widespread agreement that the issue of excessive and uncontrolled energy wastage is highly prevalent and requires an urgent solution. As *Ref. [1]* highlights, energy wastage often results from unconscious, often habitual behaviours ingrained in daily life, implying that an effective approach must go beyond mere awareness; it must integrate a degree of automation to ensure an actual impact. This article examines the latest predictive and reactive approaches within HEMS, aiming to evaluate their success in forecasting and managing energy needs in order to determine a near-perfect technique for future designs.

The Role of Prediction in Energy Management

To address energy consumption in the first place, it is only logical to prioritise data gathering, i.e. gaining a comprehensive understanding of overall energy use within a household. As identified in *Ref. [2, 3, 4, 5, 6, 7]*, a predictive algorithm offers the optimal pathway for extracting consistent, accurate data on consumption patterns. Nevertheless, there remains considerable debate around the best practices for training and testing such algorithms.

Training Data Sources and Collection

Several models rely on raw data collected via relay modules, with Zigbee[2] emerging as a preferred tool for transmitting energy data efficiently and reliably (*Refs. [2, 3, 5]*). In particular, *Ref. [3]* details the potential of pairing Zigbee-based monitoring with RE[3]-integrated generation systems, which enables dynamic adjustments in energy use rates based on current usage and optimized estimates. This technique illustrates a tangible method for refining predictions on optimal energy consumption, yielding data that is both actionable and relevant for subsequent developments such as behavioural changes or system reforms. Similarly- albeit more simplistically - Refs. [2, 5] utilize comparable data collection frameworks, solely differing from *Ref. [3]* by avoiding RE, and including slight variations in their predictive algorithms.

It is worth pointing out that none of these systems make use of complex AI algorithms such as neural networks[4] (preferring simple regression[5]), and rather, it is their method of raw data collection that correlates so strongly with the increased accuracy of their results. Their overwhelming success should therefore be largely attributed to the use of primary sources of information, which significantly enhances the reliability of a given dataset. However, *Ref. [4]* reveals that systems relying on user-

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[1] Home Energy Management Systems
[2] A low-power, wireless module that performs data exchanges between smart home devices, ideal for energy monitoring
[3] Renewable Energy
[4] An AI model inspired by the human brain, designed to recognize patterns and make predictions by processing data through interconnected layers
[5] An AI learning method used to predict outcomes by learning basic relationships between input features and target variables

disclosed energy data sacrifice their predictive capabilities, as manual input inherently limits automation and hinders accuracy. This manual approach, while potentially useful in certain scenarios as seen previously, lacks the consistency required for scalable, sustainable energy management solutions. We can thus conclude that a balance of primary and secondary data is critical for an effective HEMS.

Advanced Algorithmic Approaches

On the other end of the spectrum, certain models emphasize advanced algorithmic precision by incorporating technical and detailed AI to predict household energy consumption (*Ref. [6 ,7]*).

Ref. [6] favours deep learning architecture[6], but critically chooses not to overly complicate their system with excessive factors, adopting a more basic yet streamlined regression technique. Boasting a 92% accuracy rate, however, it does appear to serve as a credible approach despite its lack of complexity, supports the notion that predictive precision need not always relate to lengthy, high-depth source code[7].

Conversely, *Ref. [7]* explores a more sophisticated design, involving a highly intricate, neural networks-based genetic algorithm tailored for precise energy consumption prediction. This method, while markedly more complex and time-consuming, demonstrates far superior reliability compared to simpler methods, offering a striking contrast in effectiveness. The results suggest that while simpler algorithms may achieve reasonable accuracy rates, a highly detailed neural network model will always outstrip them in performance.

Optimum Predictive Techniques

Therefore, it is evident that a robust algorithm, combining live data collection with sophisticated neural network AI technology, surpasses alternative methodologies in terms of accuracy by an unmistakeable margin. For HEMS design, this points towards a future where AI-driven predictive tools could enable a new standard in energy management, reducing the need for user input while achieving greater precision.

Subsequent Action and Energy Waste Reduction

While predictive capabilities form a fundamental aspect of HEMS, the critical issue remains the mitigation of energy wastage. It seems abundantly clear that the cause of such strong advocation for the development and research of HEMS is the climate crisis, and yet curiously, there appears to be a discernible lack of innovation regarding the actual solution to the original cause.

Non-Authoritarian Technology

Current literature identifies that intelligent, automated systems are certainly the most advantageous methods of preventing excessive consumption, but as indicated in *Ref. [2, 3 ,4 ,5 ,6]*, most studies focus on user-driven improvements, positioning the homeowner as the central actor in energy conservation. This trend is based on the assumption that users, once informed of their consumption patterns, will "instinctively" make choices to curb unnecessary energy use. Across these, *Ref. [3,5,6]* are perhaps the most in-depth analyses of energy trends, offering up charts, statistical data, and even direct suggestions to the user in *Ref. [2,6]* in order to guide users in understanding and changing their habits.

However, these are most likely suboptimal approaches , given the well-documented inconsistencies in human behaviour regarding sustainable practices. Not only have behavioural studies repeatedly shown that individuals often revert to convenience-oriented patterns, which undermines the potential for lasting change, but the complete lack of automation indicates that if a user decides to take no action, there is potential for no impact whatsoever. This provokes arguments of redundancy, questioning whether such HEMS models are a mere waste of effort.

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[6] A layered setup of neural networks that learns complex patterns from data
[7] The original text written by programmers that tells software how to work

Ref. [8] offers a real-world evaluation of user-centric HEMS, which depends on a user's willingness to prioritize energy conservation over comfort, rather than taking independent action regardless of the home-owner's behaviour. This system achieved variable results, with some households reducing energy consumption by up to 30%, yet this was very contingent on the extent to which energy-saving goals aligned with personal comfort preferences. Although positive outcomes were observed, the range of savings was deeply concerning - the extremes showing an almost negligent effect. Rationally, this leads to the conclusion that the lack of a proactive, automated system risks producing nought for a great deal of effort, supporting the case for more autonomous energy management solutions.

Integrating Automation in HEMS

By contrast, automation-focused models, as discussed in *Refs. [9,10,11,12]*, diverge significantly from user-dependent systems, with *Ref. [12]* describing an entirely independent HEMS that requires no user interaction altogether.

Seen within *Ref. [9]*, integration with solar PV and battery technology[8] presents the potential to reduce overall power demand, as well enable back-up power - a fairly advantageous asset of a HEMS. Unlike other systems, *Ref. [9,10]* both require some extent of user interaction, allowing the customization of parameters such as budget targets[9] or stipulating preset energy usage limits[10] beforehand. This approach not only instils a sense of control but also reassures users of the system's reliability and safety, an aspect that is sometimes overlooked in fully automated models.

This is certainly a major factor to consider when viewing an autonomous system, such as the one described in *Ref. [12]*. The capabilities of such a HEMS are extremely impressive, as it achieves minimum possible costs with tolerable load management wait times[11], and additionally, the technology boasts a zero human effort requirement even while promising the maintenance of grid stability[12]. Nevertheless, although this may appear highly attractive, it is somewhat deceptive, as perhaps a more balanced system which details the importance of a mix of integrated automation and user engagement, could provide a more reliable and trustworthy method.

Ref. [11] further advocates for this approach, underscoring the importance of a well-rounded HEMS design that accounts for user preferences without compromising the automated efficiency that is key to achieving optimal energy conservation.

The Future of HEMS – Combinatory Models

From the insights gained, it becomes clear that the development of HEMS should strive for a dual-strategy model, combining predictive accuracy with autonomous functionality. Such a system would offer the precision of advanced neural networks and AI-driven predictions alongside practical, automated solutions to reduce energy waste without depending on user behaviour. The path forward involves refining these hybrid approaches, balancing automated precision with accessible user controls, and creating systems that align with the varying needs and behaviours of household occupants. Embracing this model not only promises increased energy efficiency but also represents a significant step toward sustainable living, positioning HEMS as an integral component of future eco-friendly home designs. By incorporating both dynamic prediction algorithms and strategic automation, the industry could shift from passive monitoring to active management, setting new standards in residential energy sustainability – ensuring safety, user satisfaction, and maximised performance to assist in the fight against climate change.

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[8] Photovoltaic cells convert solar power into a storable format (chemical energy in batteries) to be used as needed
[9] A user-chosen cost which a HEMS must adhere to over a given period time; i.e. aim to spend less than $1000 per month on energy
[10] A maximum value for power consumption which a HEMS must adhere to over a given period time; i.e. do not exceed a threshold of 1000GW per month
[11] Delays in power allocation within energy systems to balance demand and prevent overloads
[12] The ability of an electrical grid to consistently meet demand, ensuring uninterrupted and reliable electricity flow

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