A Concise Review of Energy Management Strategies for Hybrid Energy Storage Systems

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***Abstract* — In this work, relevant literature with regards to energy management strategies was reviewed and discussed. The energy management strategies were grouped into forecast/historical, heuristic logic, ANN-fuzzy logic, and reinforcement learning (machine learning) based methods. From the literature, it is clear that energy management strategies are imperative if the optimal operation of hybrid energy storage systems and assets is to adequately counteract uncertainty due to intermittent renewable energy sources. The Reinforcement learning-based algorithm which uses an agent-based approach to optimally control the system offers an optimal solution for energy management.**

***Keywords* — Control; Energy management; Hybrid Energy storage systems; Optimisation; Reinforcement learning.**

I. Introduction

Hybrid energy storage systems are simply the combination of complementary heterogenous energy storage technologies. The heterogeneity of the ESs technology, which portends certain benefits (such as prolonged lifetime and energy reliability of the assets) when exploited, imposes the need for a more evolved energy management strategy (EMS) at the system level in contrast to a conventional EMS suitable for a homogeneous ESs [1]. Despite the benefits, HESS foretells, such as an better reliability and energy uncertainty mitigation, if the system's design (including inter-dependencies) is not adequately considered a performance improvement cannot be guaranteed compared to homogeneous ESs.

Therefore, an EMS which can orchestrate the most vital decision-making process is required for the optimal operation of HESS. The EMS must control and coordinate the systematic distribution of energy amongst the heterogeneous energy storages with regards to dis/charging schedules while serving the load demand [1].

This paper seeks to concisely present a summary of existing EMSs for HESS in order to serve as informative literature for researchers.

II. Literature Review on EMS for HESS

In this paper, several EMS for optimal control and decision-making have been investigated, especially to negate the effects of energy resources uncertainty in HESS. These approaches range from the use of historical data to better improve the forecast of RE energy to dynamic expert rule-based intervention strategies.

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A. Forecast/Historical based Energy Management Strategies

The work presented in [2] employed game theory for the first time in an adaptive model predictive framework for demand-side response management in a grid-connected RE network and shows superiority over the day ahead scheme when forecasting error is significantly large (>10%). In [3] to achieve an accurate DA forecast, learning tools; self-organising map (SOM) and Learning vector quantisation (LVQ) are combined and used to classify historical PV power, and weather data patterns for training by Support vector regression (SVR), a Bayesian machine learning method. During the classification, the historical data is loaded as an input vector, representing the pattern of the hourly PV power generation. A minimisation of the Euclidean norm is used to adjust the weight of the selected neuron during the classification with a learning rate. The SVR consists of 5 SVR models and 6 sub-models each having 5 inputs and 3 outputs. The input data correspond to weather elements such as precipitation, temperature, and solar irradiance. The SVR machine learning is a technique that is selected based on its proven forecasting accuracy and learning competency. After that, a fuzzy logic inference system was utilised as an intermediary switch for mapping any given input to output via the learned models for forecasting.

In [4], an adaptive model predictive control (MPC) is used to negate the effects caused by forecast uncertainties for optimal operation in a smart residential microgrid. The Microgrid comprised both Renewable/non-Renewable energy resources such as PV solar panels and WTS, as well as combined heat and power (CHP) as well as energy storage such as batteries and water tanks. A mixed-integer programming optimisation technique is used iteratively at each sampling time to minimise a cost function, formulated using a day's short-term forecast of solar radiation wind, load demands, and electricity price. The optimal solution is derived using feasible power balance constraints on the MG for the thermal, electricity supply, and demand-side energy capacity. The adaptive MPC which combined a receding horizon and forecast error compensation showed superiority with a lower cost of operation, compared to the Day-ahead programming technique. This is chiefly due to a lack of state feedback and correction while using the rolling horizon optimisation method. Additionally, the erroneous forecast is modelled as a deviation from the actual forecast trajectory by summing the actual forecast and a Gaussian noise distribution for all-time. Furthermore, work done in [5] concerning sensitivity analysis reinforced the superiority of the recursive MPC over the Day-ahead strategy implemented in the residential MG home energy management system. In [6] a review work on optimal control techniques, mixed-integer linear programming (MILP) an optimisation technique that makes use of both binary or integer values, as well as non-integer values for selected variables, is utilised. A centralised controller integrating load and generation forecasting via two days ahead neural network is used to proffer an online trajectory for the system sub-components, users, and water flow while guaranteeing minimal operating cost and power balance over time [7].

In [8] a nonlinear model predictive control (NMPC) algorithm is used on a standalone Microgrid for load shedding and optimal control of voltage stability within the acceptable ±5% deviation recommended by the ANSI C8.1-1989 standard while balancing the energy in the Microgrid. The NMPC algorithm performs a binary type continuous optimisation (mixed-integer nonlinear programming) for an optimal decision concerning load dispatch based on predicted power imbalance. In [9], the thermal overload limits of a transmission line were considered and incorporated into a linearised AC loss transmission network model for more realistic handling of voltage magnitude and reactive power in an adaptive MPC framework. The constraints for the optimisation problem are selectively made minimal to improve the incurred unacceptable polynomial-time caused by the high dimension of the problem.

In [10] an adaptive intelligence technique (AIT) for EMS a battery (BAT) – ultracapacitor (UC) based HESS was proposed to maximise self-consumption while minimising the effects of forecast error which consequently impact the deviation of load shaving and the corresponding threshold for dispatchable power. The AIT method, after computing techno-economic feasible fixed power and energy thresholds, incorporates robustness to forecast error by updating these fixed thresholds at every iteration with information derived from the previous day's optimal trend. Thus, AIT which did not require an accurate RES and Load data was shown to have superior performance over the PSO algorithm. However, a limitation is that the AIT algorithm depends on the averaging method which requires a fixed number of samples to determine the energy state of charge in the battery and only the UC will function as energy storage if this condition is not met. The AIT method guaranteed high self-consumption and mitigated potential reverse power dynamics amongst RES, load, and ESs assets. In [11], an ANN architecture is used for prediction and to realise a feed-forward control, and a conventional state of charge energy management strategy which uses feed-forward control was compared. Furthermore, the authors, through a cost function sensitivity analysis showed that in HESS, the key contributors to the total asset's cost are the battery and hydrogen assets. Also, the fractional cost of combining hydrogen–battery technologies, was 48% and 9% compared with hydrogen or battery-only system respectively. In [12], to control the deviation in dc-link voltage arising from the variable load and RES uncertainty in a grid-connected HESS MG which comprised a BAT and ultra-capacitor, a dynamic EMS was proposed. In [13] a multivariate quadratic optimisation was formulated to solve a real-time optimal control energy management operational task relating to a dual-mode split HEV. An offline approach is used to solve the multivariate quadratic optimisation problem to obtain the control decision, which is thereafter, imposed on the HEV in real-time as in a traditional MPC fashion. The method which was compared to a traditional MPC approach achieved 97.46% computational efficiency and 23.3% in fuel savings. In HESS the concept of hybridisation is even so very often harnessed especially in electrical vehicles (EV), where a super-capacitor (SC) with high efficiency and power density properties is combined with a conventional battery which lacks such properties but has a relatively lower cost and a high energy density which the SC lacks. Hence, the exploitation of the SC and Battery in a complementary mode enhances the life cycle of the battery at a lower design cost.

B. Heuristic Logic-based Method with Forecast Prediction

An energy management power regulation system was proposed in [14] for a standalone HESS comprising WTS, PV FC, EL, BAT, and Load. The proposed logic-based EMS employed three stages to guarantee the continuous operation of the HESS. The first stage involved predicting the wind speed and load demand profile. In the second stage, the predicted variables and the available energy in the ES are used to estimate and schedule the maximum load demand, which can be supplied. After that, in the third stage, each subsystem was coordinated with eight dynamic operation modes generated based on the predicted variables and parameters associated with the net power flow and the intrinsic limitations of the subsystem. The allowable range for the SOC of the ES during an emergency and normal operation was 40–95% and 75–95%, respectively. ESs are generally categorised based on specific characteristics of interest such as high energy and power density, and life cycle ramp rate. Regrettably, no one ES has all these characteristics of interest. Thus, while ESs are generally suited for mitigating generation and consumption mismatches in a DC MG, their practicality and performance, will perhaps largely depends on their characteristics and the dynamics of the mismatch [15].

C. ANN-Fuzzy Optimisation

In [16] an expert energy management system based on an artificial neural network was proposed for grid-connected hybrid energy storage systems, specifically integrating WTS, ES, and several DERS. The framework presented consisted of three stages; the first trained an ANN with historical data to forecast wind speed within a probabilistic error confidence interval to incorporate robustness in the prediction. Hence, negating the difficulty imposed by wind speed uncertainty in energy scheduling and optimal operation of the assets. Secondly, a modified bacteria Foraging Optimisation (MBFO) technique was used to minimise cost and emission objectives. Thirdly, an interactive Fuzzy satisfying approach was simulated to resolve the trade-off between the multi-objectives.

In [17], Artificial intelligence AI (ANN and FLC) based energy management techniques were used to optimise the efficiency and operation of hybrid power systems, HPS. The HPS consisted of both primary RESs such as PV and WTS, and backup sources such as FC and Gas micro-turbine.

Furthermore, the study underscored the role and importance of Hydrogen as a long-term ES employed to buffer RESs intermittency. In addition, hydrogen is considered a clean renewable energy carrier that may perhaps be transformed into various forms such as liquid, gaseous, or metal hydride for convenient storage or use.

D. Reinforcement Learning-based Energy Management Strategy

Research on temporal difference (TD) learning, an experience-based technique acquired by investigating and exploiting, was suggested for predictive decision making for unknown systems in [18]. This was in contrast to the traditional method, which relied solely on the difference between the actual and expected outcomes.

In [16], a novel Markov decision process technique is proposed for solving the prioritised discharging problem in a HESS with two energy storages (ESs): a 22KWh Lead Acid (LA) and 20 KWh Vanadium (VR) battery system linked with a PV, which is simulated in SIMULINK using a MATLAB MDP toolbox. With one 16 KWh rapid charging (Lithium-ion battery) Peugeot electric vehicle, the HESS placed in a residential residence in Wolfenbüttel, Germany, meets the electrical load need of four residents. In the absence of a test case, the domestic load demand model for North-West Germany is employed. Load demand profile based on charging the EV's LI BAT at home and aggregating the resulting demand to the annual load demand. The ESs' charge states and net power flow were discretized and normalized within a 0–1 range, respectively.

Afterwards, they're merged to form a tuple that describes the MDP's model state space, from which only one discrete action space (specified as overcharge/discharge or null of the ESs) can be selected at any time interval. Then, based on the next transition condition, in which the LA depth of discharge is 50% and the VR is maintained between 33% and 74% of the nominal capacity, a reward is given. The authors proposed a real-time energy management system for a hybrid (battery and ultracapacitor) tracked vehicle to optimize performance and energy economy with power split control for varied road driving circumstances [19]. The convergence of a multiple transition probability matrix is accelerated using a fast Q-Learning algorithm, which is also updated anytime the error norm exceeds the given criteria. The suggested technique outperformed a stochastic dynamic programming approach and a traditional RL with two driving cycles in terms of fuel efficiency. A Dyna-H RL was recently proposed in [20] for real-time optimisation of fuel usage in a PHEV. Using two clutch states and a braking state, the agent was employed to optimally regulate four traction configuration modes. Furthermore, energy management strategies for hybrid electric vehicles are generally dependent on optimization, necessitating explicit system knowledge.

Furthermore, the authors in [21] proposed a real-time based RL power management for plug-in hybrid electric vehicles aimed at optimally distributing power between a battery and an ultracapacitor. The results validated using different driving conditions and vehicle parameters showed the RL based approach reduced total energy loss by 16.8% compared to a rule-based strategy. The authors in [22] proposed for the first-time applied reinforcement learning technique to minimise the fuel consumption of a hybrid electric vehicle. The formulation required only a partial model of the system without the need for an explicit model or TPM.

The application of RL based energy management for HESS has mostly been considered in the literature concerning hybrid Electric vehicles while only a few have considered hybrid MG.

Deep RL EMS is presented in [23] to handle stochastic power production in residential microgrids by using a convolution neural net to extract useful time-series information from a vast continuous non-handcrafted feature space. To avoid overfitting and positive bias, the neural net is validated on historical features of observation at regular intervals throughout training. The algorithm's performance is assessed using the Levelized energy cost economic criterion for maximising operation revenue.

The approach in [24] describes an EMS based on a cooperative multi-agent strategy, in which different learning agents ranging from simple to complex jointly monitor and control the assets (such as RES, ES) of integrated homes/buildings and MGs. The authors of [25] present an EMS for a freestanding microgrid that uses a decentralized cooperative multi-agent enabled Fuzzy Q-learning. The continuous input states are formulated using five membership functions and an action space that includes a fuzzy set of each microgrid asset, as well as two fuzzy sets, which work together to create the agent's continuous action policy.

For a grid-connected RES microgrid with ES and consumer load, [26] presented a two-steps-ahead RL EM method. The learning agent can optimally use the WTS, independent of the grid, to charge the ES and, on the other hand, maximize the utilization of the ES during peak demands, thanks to the RL's use of a two-step-ahead prediction of available wind power via an MCM, which solves a multi-criteria decision process. As a result, intelligent consumer uses learned stochastic scenarios to help them perform experience-based optimal control actions.

Multi-agent-based RL was used in [27] to achieve optimal control of a micro-grid with unpredictability while lowering the average electricity cost sourced from an external grid. The importance of RL as a potential solution for many decision and control problems in electric power systems is highlighted by the authors in their comprehensive review [28]. Furthermore, control system techniques for power system applications, which are largely based on advances in certain fields such as applied mathematics, control theory, telecommunication, computer science, and operational research, have continued to evolve to meet dynamic challenges and requirements, particularly with the availability of more powerful computationally efficient resources. As a result, learning algorithms like RL, which allows controllers to learn a goal-oriented task, should be included in the control architecture so that controllers can learn and update their decision-making based on experience [28].

III. Conclusion

This paper presented a concise review of existing energy management strategies. Recent EMS research has largely focused on forecast/historical and heuristic logic-based EMS that leverage A.I. and optimization. As shown in [29], these approaches are not only computationally costly but also essentially heuristic, limiting available possibilities and omitting satisfactory yet intermediate solutions that could increase HESS performance. Power Pinch analysis (PoPAS) [30] - [32], a graphical EM technique that helps minimize the computing cost of optimisation strategies, has recently been applied for EM of HESS. The PoPA, on the other hand, was created using a DA method that ignored the impact of uncertainty.

Furthermore, using a robust optimization method that takes uncertainty into account is thought to be a pessimistic strategy. As a result, over-budgeting resources can lead to waste, which can be a problem in real-world applications [33]. Similarly, for EM of MGs, stochastic and chance-constrained based optimisation, as used in [34]–[37], were shown to be computationally inefficient and intractable. Hence, an alternative has been the use of approximate solutions which extensively depend on the accuracy of probabilistic distribution or explicit modelling of the underlying uncertainty in parameters, which can be practically limiting in real-world applications as the distribution might be unavailable [38], [39].

Interestingly, an intelligent agent-based algorithm, RL which can learn an MDP has been exploited mostly in literature for hybrid Electric vehicles while only a few have considered MGs. Nevertheless, the RL has often been used in conjunction with computationally cumbersome optimisation strategies. Therefore, future work would propose a deep reinforcement learning-based adaptive power pinch analysis energy management strategy to integrate the advantages of the methods while limiting their shortcomings. The RL approach in [40] excludes the use/build-up and as well as update of a Markov chain to model a stochastic transition matrix (TPM) in contrast with [19], [20], [41].

Furthermore, the optimal control strategy which is often derived from a stepwise non-linear optimisation as in [19] is replaced by a backwards-looking optimisation in [22] and further replaced by the heuristic graphical-based adaptive power pinch analysis MPC framework in [40]. Thus, the computational cost of ensuring a TPM offline and solving a complex non-convex optimisation EMS for HESS (especially with heterogeneous energy and flow mix which must deal with the intrinsic interaction of power, hydrogen, and water flow between subsystems) will be avoided.

Most interestingly, in the aforementioned RL papers excluding [21], the evaluation and formulation of a scalar reward for the performance of the RL agent have been based on a backwards-looking optimisation, which has been implemented subjectively and without recourse to a systematic approach that determines the ideal optimal action strategy as in the use of a corrected adaptive PoPA. As a result, these rewards were based on a local maximization, which can potentially raise the operational costs and result in extra energy losses, as opposed to the global maximum insight provided by a corrected adaptive PoPA.

Hence, future EMS designs with accurate predictive models or forecast error correction mechanisms such as deep RL and PoPA will not only minimise resources wastage but also curtail asset degradation.

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