



Comprehensive Review of AI-Based Energy Management Systems for Renewable Microgrids

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Abstract: Microgrids are viewed as a distributed power generation system, made up of renewable power resources such as PV, wind, battery storage, shiftable loads, etc., to make a system more sustainable and resilient. But owing to the bi-directional intrinsic properties of renewable energy sources and their intermittent flow, and the randomness of renewable energy demand, energy management under a renewable intermittent system is much more complicated than that in traditional distribution systems. This investigation focuses on reviewing energy management systems based on AI for renewable microgrids, covering forecasting, scheduling, real time control, managing uncertainty and implementation challenges. The paper covers optimization techniques, machine learning, deep learning, reinforcement learning and composite methods. In line with the review, AI can also enhance the accuracy of predictions and operation cost and optimize storage utilization and adaptive control. But there are some obstacles to the path of implementing AI: Data quality, complexity, cyber security risk, the absence of hardware validation and the lack of understanding of how the black box decision making process works. Further work with models and forecasting via physics-driven models, probabilistic forecasting, edge implementation, cyber-resilient control and reproducible benchmark testing should be included in future studies to provide reliable implementation for real-world applications.

Index Terms: Artificial intelligence, energy management systems, microgrids, renewable energy.

1 INTRODUCTION

A microgrid is a distribution network that includes embedded generation resources, power electronic converters, storage subsystems and dispatchable loads that are all renewable. They can be grid-connected or islanded, and can be useful for rural electrification, campus, industrial facilities, and resilient community energy systems. Initial research on microgrids identified the need for islanded control requirements [1] and the need for hierarchical control layers [2] and coordinated operation between sources and storage and loads [3], [4], [5], [6].

The energy management system (EMS) is the supervisory layer whereby determines the amount of energy to be generated, stored, bought, sold or curtailed. The ideal microgrid EMS will have to consider VPP, wind generation fluctuations, fluctuating demands, battery SoC, price signals and reliability constraints from the grid. Rule-based control is easy to understand and implement but may be ineffective in a highly nonlinear and uncertain system. Optimization-based control can enhance scheduling quality, and artificial intelligence (AI) can learn from hidden relationships from operational data and give guidance for adaptive decision

making [7], [8], [9], [10].

The size of data collected by microgrids has increased, making its use in research with AI-based EMS possible. The amount of data collected by microgrids has grown so much that they can be used in researching and applying AI-based EMS. Non-linear load and generation behavior can be modeled by machine learning, time dependent behavior by deep learning and learning sequential control policies by reinforcement learning or the hybrid approach of optimization and data driven prediction. The study seeks to this review examine explore the utilization of these AI techniques for forecasting, scheduling and real-time control in renewable microgrids, as well as to highlight the significant challenges that remain before the widespread implementation of these technologies.

2 REVIEW SCOPE AND METHOD

This paper presents a review of AI-based EMS methods for renewable microgrids with a focus on publications and foundational methods that enable the prediction, optimization, reinforcement learning, communication-based operation and cybersecurity of renewable microgrids. The review is structured into five themes: Microgrid EMS architecture, Scheduling and dispatch optimization, Forecasting based on statistical learning and DL methods, trial-and-error learning for instantaneous control and Implementation challenges.

Both classical and AI oriented studies are included. This is because the physical structure of the microgrid cannot be considered independent from the AI-based EMS [1], [3], [4], [5], [6] and hence these papers are included. Forecasting and AI references are included where they explain methods that are directly transferable to renewable energy forecasting and demand response, [11]. The elements of reinforcement learning and cyber-physical security have also been included as modern EMS designs are increasingly adaptive and networked.

3 ARCHITECTURES OF AI-BASED EMS IN RENEWABLE MICROGRIDS

A typical EMS for renewable microgrid is composed of four levels. The initial stage is the physical energy module, which is made up of photovoltaic arrays, wind turbines, and diesel backup systems (if available), battery energy buffering systems, electric vehicles and local demand units. The second layer is the measurement and communication layer, which gathers measurement data from the meters and sensors, as well as weather data and inverter measurements. The third layer is the decision layer, where forecasting, optimization, and AI based control are carried out. The last layer sets points for converters, batteries, and controllable loads and grid-interconnection equipment.

AI should be seen not as a replacement for protection and low-level converter control, but rather as a decision support tool to back up the protection. Deterministic, fast and safe operation is still needed for inner voltage and current control loops. AI models can help the EMS predict renewables generation and demand, forecast battery performance, advise economic schedules, and adjust operating decisions when conditions change. This layered design is summarized in Fig. 1, and the relationship between data acquisition, forecasting, optimization and control is demonstrated.

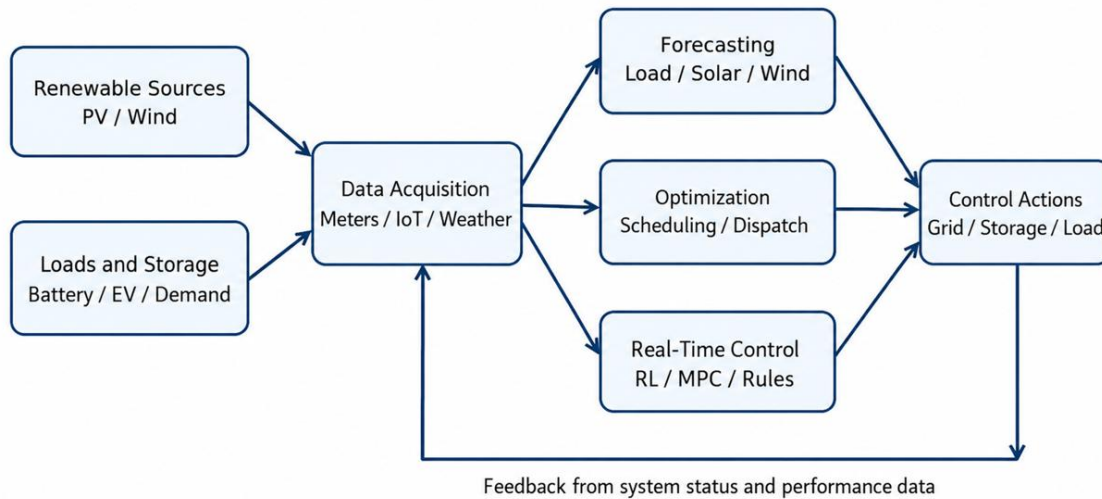


Fig. 1. Architecture of an AI-based energy management system in a renewable microgrid.

4 OPTIMIZATION-BASED SCHEDULING AND DISPATCH

Optimization is one of the earliest and most significant EMS approaches. The EMS could optimize the total operating costs, emissions, degradation of battery systems, renewable utilization or reliability within a microgrid. When constraints need to be imposed explicitly, namely battery level constraints, energy equilibrium, generation limits, limits on the import/export of power into the grid, mixed-integer and model-predictive approaches are useful [10], [12], [13]. The model predictive control is particularly useful due to the iterative nature of the control decisions as they are updated as new forecasts and measurements are obtained [12], [13].

With the EMS problem being nonlinear, nonconvex or hard to solve exactly using mathematical programming algorithms, metaheuristics are widely used. For dispatch problems, sizing and scheduling problems, the particle swarm optimization, genetic algorithms, Pareto-based particle swarm optimization, grey wolf optimization and ant-colony methods have been implemented [14], [15], [16], [17], [18], [19], [20]. These methods are appealing due to their flexibility and their ability to combine practical constraints. They can take many iterations, however, may converge towards suboptimal solutions and may need careful tuning the algorithm settings.

Optimization is not only solution for actual time renewable microgrids. Forecasts and uncertainty models strongly influence the accuracy of schedule. A deterministic optimal schedule might be unsuccessful, attributed to the unexpected fluctuation of solar radiation, or sudden rise of demand. In this context, recent studies in EMS are increasingly using optimization and machine learning forecasting, probabilistic scenarios and reinforcement learning policies.

5 MACHINE LEARNING AND DEEP LEARNING FOR FORECASTING

Forecasting is one of the fundamental applications of AI in an EMS, since the decision on dispatching will rely on the forecast load, the renewable energy production, and market signals. curved associations among weather observables, historical demand and harvested power can be learned by classical data-driven techniques comprising maximum-margin classifiers, bagging-based tree models and gradient-boosted topologies [21], [22], [23]. The models are useful when the available data is of moderate size and interpretability and training speed are important.

Where the EMS needs to learn patterns in large time-series datasets, deep learning is useful. Long short-term memory networks (LSTM) exist to created aimed at inferring long-range correlations in sequential data, have been extensively applied in load forecasting [24], [25]. In addition, a broader deep learning foundation is applicable for energy representation learning [26], [27]. When data is abundant and computational resources are plentiful, modern time-series architectures can capture complex multivariate patterns, and can be extended to enable multi-horizon prediction, such as attention-based models and temporal fusion models [28].

Weather and location and seasonal conditions affect the output of renewable energy, which is why solar and wind forecasting are of particular interest. The results of the review on solar radiation and PV forecasting reveal that statistical, machine learning, and hybrid forecasting techniques have the potential to enhance short-term forecasting accuracy. However, the performance of these models varies with the forecast horizon, input quality, and the validation technique applied [29], [30]. The stochastic nature of wind and its spatial variation are also difficulties in wind forecasting [31]. Point prediction is not the only focus in load forecasting competitions and probabilistic forecasting tutorials, uncertainty estimates are also important [11], [32].

6 REINFORCEMENT LEARNING FOR REAL-TIME EMS

EMS operation is modeled as a step-by-step policy selection scenario, utilizing reinforcement learning. Entities watch the state of the system, decide on what action to take, and then get a reward depending on the cost, reliability, comfort or battery operation. The functional unit then acquires knowledge of the framework's strategy through playing repeatedly against an environment [33]. This formulation can also be appropriate for microgrids as the choice of energy management decision for one period affects the energy inventory available for the next period: a choice of battery discharge at one time alters the available battery stored energy for the next time.

Deep reinforcement learning (deep RL) relies on representation of a policy or worth procedure with a neural network, which serves to control a system with many states and actions [34], [35], [36]. Within the microgrid EMS, DRL has been used in flexible demand management, storage scheduling and multi-agent coordination [37], [38], [39]. The advantage of reinforcement learning is that it is flexible to change prices, renewable output and load behavior, and it does not require solving a complete optimization problem at each time step.

But there are significant dangers associated with the RL-based EMS, too. Learning can be non-stable, negative side effects of reward functions can be introduced, and safe exploration is not possible in a real power system. Most RL models are trained in a simulated environment, but a policy that works in a simplified simulated environment may not be successful in actual hardware. Hence, RL must be used together with safety constraints, offline validation, model predictive supervision or rule-based fallback control before practical use.

7 COMPARATIVE DISCUSSION

No universal solution exists AI global solution EMS functions. Forecasting models work best in predicting future loads or renewable production. When it is necessary to meet explicit operational constraints, optimization methods work best. Reinforcement learning is most appropriate in situations where the EMS is required to learn adaptive sequential decision making. Designs in hybrid EMS are thus more realistic than designs based on one of the above methods.

Table 1. Comparison of AI methods for renewable microgrid EMS

Method	Main EMS use	Strength	Limitation	Typical citation
PSO / GA / metaheuristics	Scheduling and dispatch	Flexible for nonlinear problems	May need many iterations and tuning	[14], [15], [40]
MPC / mathematical optimization	Constrained scheduling	Handles operational constraints clearly	Depending on forecast and model quality	[10], [12], [13]
SVM / RF / XGBoost	Forecasting and classification	Good with moderate data	Feature engineering may be required	[21], [22], [23]
LSTM / deep learning	Time-series forecasting	Learns temporal dependencies	Need larger datasets and computation	[24], [25], [26]
DRL / multi-agent RL	Adaptive real-time control	Learns sequential decisions	Safety and hardware transfer remain difficult	[33], [34], [37], [38]
IoT and edge-enabled EMS	Implementation layer	Supports local decisions	Cybersecurity and interoperability risks	[41], [42], [43]

Table 1 illustrates that each method has a distinct EMS requirement. In a practical EMS, deep learning is adopted to estimate the state of the system, mathematical optimization techniques can be used to schedule the system in advance, and a constrained reinforcement agent or a rule-based controller can be employed to adjust the instant-processing system. Architecture that works best depends on the microgrid size, available measurements, communication network, computing platform and acceptable level of risk.

8 RESEARCH GAPS

Practical applications are one of the gaps found in literature. Most EM studies performed based on AI rely on a simulation approach; using a simulated and idealized battery model, linearized converter behavior, and noise-free datasets. This may not be a complete reflection of measurement error, delay in communications, data missing, limits or protection requirements on the system, but can be very useful for preliminary research. Further research is required to include hardware in the loop testing or microgrid test beds (where applicable) or field validation.

Uncertainty management is the second gap. Traditional point forecasts are not adequate for microgrids because the errors in the forecasts affect their storage scheduling and reliability. The use of probabilistic forecasting and scenario-based scheduling should be increased, especially in high PV and wind penetration systems. By using uncertainty-aware EMS design, the number of reserves can be lowered, and the cycling of batteries can be prevented.

The third gap is cybersecurity. Communication networks, IoT devices, smart meters and cloud and edge computing provide power to microgrids. All of these are avenues for Data manipulation attacks, command manipulation and Resource exhaustion attacks. Some studies on smart grid cyber security suggest that the state estimation and control decisions as well as the reliability of the system can be jeopardized by cyber-physical attacks [44], [45], [46]. Thus, anomaly detection, secure communication and fail-safe control logic are crucial for AI-based EMS.

The fourth gap is explainability and operator trust. Difficult economic verification may result in an action performed by a black-box EMS that seems attractive. For critical power systems, decisions should be explainable, traceable and in line with engineering constraints. To bridge the performance to engineering

acceptance gap, explainable AI, physics-informed learning and transparent optimization layers are used.

9 FUTURE RESEARCH DIRECTIONS

The advancement of future AI-based EMS should take steps toward hybrid architectures of forecasting, optimization and safe adaptive control. Uncertainty-aware forecasts, physical constraints and economic constraints, safe operating boundaries for reinforcement learning. This kind of hybrid architecture facilitates boosting the adaptability and robustness of the system.

Another key trend is that of edge computing. Local execution of AI models can lower communication latency, safeguard data privacy, and enable the microgrid to function with poor cloud connectivity. The following studies are useful background for distributed sensing and local decision support for the IoT and the edge-computing area [41], [42], [43], [47], [48]. But when it comes to deployment on the edge, lighter models and more robust data preprocessing and secure update capabilities are required.

Continuing research should also center on the common benchmarks systems and evaluation that could be made reproducible. Various EMS papers report cost savings but employ a variety of datasets, price profiles and battery assumptions. It is hard to make a comparison of them. A more robust review culture should document the test system used, the data set used, the time to the forecast, the uncertainty model, the computing time and whether the test is validated, as well as assumptions made about battery degradation.

9.1 PRACTICAL IMPLEMENTATION CONSIDERATIONS

Choosing an accurate algorithm is not enough for practical implementation. The synchronized measurements should be received by the EMS, and the EMS should ignore measurements that are not normal and should run even if some communications links are delayed or lost. The data pretreatment, missing value filling and time alignment should therefore be considered as a part of the EMS design and not as a second step. If these functions are missing, a high performing AI model will be unable to make a good decision as the input data will no longer be the real-time state of the microgrid.

Another important implementation question is the deterioration of the battery. A common model of scheduling constraint is the simple constraint on the battery state of charge, but deep cycling can shorten battery life and lead to higher costs of long-term operation. The reward or objective function should reflect cycle aging in the future AI-based EMS, and account for the effects of temperature and replacement cost. This will render the final schedule more realistic for renewable microgrids with storage facilities, on which PV and wind variations need to be stored daily.

9.2 EVALUATION INDICATORS

Technical, economical and reliability indicators should be used for evaluation. Operating cost, renewable utilization, loss of load probability, voltage and frequency deviation, battery cycling, computational time and cybersecurity response are some indicators that are useful. You need to report only the prediction errors or cost reductions if it is a low-cost schedule, but not safe or may reduce storage life. A well-balanced evaluation framework will improve future papers for comparison and be more valuable in the design of a practical microgrid.

10 DATA REQUIREMENTS AND MODEL EVALUATION

The effectiveness of an AI-driven EMS is rigorous standards, resolution, and reliability from the results. Historical load, photovoltaic power, wind speed, irradiance, temperature, electricity price, battery state of charge, inverter limits and Load control instructions are useful supply variables. Forecasting errors can result

from missing data, sensor drift and communication failures, potentially resulting in unsafe dispatch decisions. These tasks of data cleaning, synchronization, outlier detection and feature selection should be considered as integral parts of the EMS design and not as preprocessing [21], [22], [23], [29], [30].

There is no single metric for evaluating EMS models. Average Prediction Deviation, root means square Deviation and means absolute percentage error are typical benchmarks used for forecasting. Most significant measures for operational EMS studies are total operating cost, renewable energy utilization, battery throughput, unserved energy, peak reduction, voltage deviation, frequency deviation, and computation time. A forecasting model that has a small forecasting error is not necessarily the optimal EMS model if it results in higher battery cycling or operating constraints are violated.

A fair comparison also requires realistic train-test separation. If the sample time-series data is randomly mixed, some information in the data can leak into the testing set as future patterns affect the training set. Chronological validation, taking multiple seasons and varying weather conditions, are more reliable studies. It is also important to have probabilistic evaluation as renewable microgrids need more than just a point forecast [11], [31], [32]. These practices increase the trustworthiness of the study results and help produce more practical and useful microgrid plan results.

11 BATTERY STORAGE AND DEMAND-SIDE FLEXIBILITY

One of the controllable assets in renewable microgrids is the batteries. It can alleviate the fluctuation of PV and wind power, adjust the price, supply islanded operation, achieve high-quality power, etc. With batteries, however, the temptation is to take a short-term profit but risk a long-term loss. An EMS with frequent cycling of the battery may not reduce energy cost in simulation but it can reduce battery life in service operations. So, battery state of charge (SOC), battery depth of discharge (DOD), temperature and cycle-aging should be bearing in mind for the plan of AI based scheduling models. [10], [11], [12], [14].

Demand-side flexibility can help to alleviate the stress on storage. Water pumps, heating and cooling systems, electric-vehicle chargers and industrial processes can be moved to other locations during reasonable time frame. Demand response has value while there is an abundance of renewable energy generation accessible, but limited storage. There are similar approaches to scheduling flexible demand that have been adopted using reinforcement learning and optimization methods that consider user comfort, price signals and grid constraints. [37], [38], [39].

Optimization of storage and demand response should not be split within a practical EMS but should be coordinated. In one instance, the EMS can postpone the charging of batteries and shift flexible loads to solar at a high time of day, for instance. It can store energy on the island for reliability, not just to take advantage of price arbitrage, when the risk of islanding is high. These decisions need to be made jointly through a combination of constraint and adaptive control and within a single EMS framework.

12 PRACTICAL IMPLEMENTATION CONSIDERATIONS

To implement AI-based EMS, communication architecture, computing platform and fail-safe operation must be considered. Cloud-based EMS can leverage on the large computing power and centralized data storage but requires reliable communication. While the Edge-based EMS can make decisions with low latency and good privacy, it is necessary to adopt lightweight models and limited hardware resources. Internet-of-Things and edge-computing technologies are helpful to support distributed monitoring, but also raise cybersecurity and interoperability needs [41], [42], [43], [47], [48].

Security needs to be built into the EMS design from the outset. AI models can mislead due to fake data,

tampering with meters, or sending malicious commands that lead to unsafe control actions. The literature on cyber-physical security indicates that these cyber-attacks can impact on the state estimation and control components of modern power systems [44], [45], [46]. For trustworthy operation of an AI-based microgrid, therefore, anomaly detection, authentication, encrypted communication, and redundancy and manual override mechanisms are required.

Another implementation issue is operator understanding. Operators should know why the EMS recommends charging, dispatch or curtailment decisions. Decisions made with no explanation of the reasoning can lead to decreased trust particularly under abnormal operating conditions. The EMS will be more acceptable to the operators and easier to validate by integrating data-driven models with engineering constraints, with the addition of rule-based safety checks and visual decision-support dashboards.

Lastly, future papers must be clearly reporting details on the implementation. Some of the key information comprises sampling interval, hardware platform, solver or training time for the simulation, data source, communication assumptions, battery type, islanding conditions, and if hardware-in-the-loop or a real microgrid was used. Review papers are more useful if they can compare methods (algorithmically as well as practically) and it is possible to do this by means of clear reporting [46], [49].

Technical indicators should be carefully documented along with economic assumptions. The benefit of EMS may change based on the kind of tariff, feed-in price, demand charge, fuel cost, and battery replacement cost. What works well at one price level may not work at others if export restrictions are added to the mix, or if time of use prices or ancillary-service pricing are added. It is useful to use sensitivity analysis when comparing scheduling and control strategies.

Social and operational acceptance are other factors to consider in the design of a microgrid EMS. In residential/community microgrids, DR responses can impact the comfort/daily life of the users. Load shifting can have an impact on production schedules in industrial microgrids. Consequently, constraints for energy cost optimization should instead account for acceptable operating windows, user preferences and critical load priorities for the EMS.

Another key area of focus is standardization and interoperability. Microgrids are generally a mix of materials from various manufacturers, such as inverters, meters, protection relays, weather stations and battery controllers. The data formats and communication protocols may be inconsistent, which means that the EMS may have to do some expensive integration work. By adopting open communication standards, modular software applications and data models that are understandable, this barrier can be lowered and scalability enhanced [49], [50].

In the case of islanded operation, the EMS must also comply with the resilience criteria. When the grid goes down, the objective is not just to reduce costs, but ensure an adequate supply of critical loads, maintain battery reserves and coordinate local generation. Therefore, the evaluation of the AI models should be done in outage scenarios, sudden drops in renewables and peaks in demand. These resilience tests are necessary since microgrids are typically deployed to enhance the reliability of the electricity supply during extreme weather events or weak-grid conditions.

Additionally, electric vehicles are playing an important role in renewable energy microgrids. Depending on the charger capability and user availability, EVs can be Usable as flexible loads, mobile containments, vehicle-to-grid resources. They are difficult to schedule because they are unpredictable in their arrival and departure times and can offer flexibility if they can be managed in conjunction with PV generation and battery reservoir [47], [50].

Diesel generators or fuel cells can be used to provide backup power for hybrid renewable microgrids. These sources should not be used exclusively as emergency power sources but should receive optimization of their operation to minimize fuel consumption, emissions and start-stop stress from the use of AI-based EMS. In this case, multi-objective optimization becomes useful as it will accommodate the trade-off between different operating costs, emissions, degradation, and reliability metrics.

The importance of environmental goals in EMS design is increasing. While some studies only consider financial costs, a renewable microgrid can also aim to decrease carbon emissions, renewable curtailment, and fossil fuel usage. Environmental indicators need to be reported along with economic indicators in future EMS to clearly evaluate sustainability benefits.

Another issue is the availability of the datasets. This is because many AI papers rely on private or simulated datasets making it challenging to replicate. Publicly available data, open data pre-processing and public shared code can contribute to increased scientific reliability. Use of private data should be described as fully as possible so other investigators can appreciate the experimental conditions, including the sampling rate, period, feature list, and how missing data were treated [39], [47], [48].

Post deployment model maintenance is also crucial. Model drift can occur due to changes in load patterns, tariffs, and equipment user behavior. An EMS trained in the past data can slowly start losing its reliability. Careful implementation of periodic retraining, online learning and performance monitoring can ensure accuracy, but will need to be carefully implemented to prevent the introduction of unsafe behavior in an operating microgrid [50].

In terms of engineering, sometimes it is better to have a simple model than a complex one. If large computing resources are needed, explanation is desired or if the highly accurate deep network fails in the face of missing data, it is not appropriate for use. The choice of AI methods should be made with a focus on balancing accuracy, stability, interpretability, and computational cost, not simply choosing the most complex. A good EMS should not just use the most complex AI method, but balance things out: accuracy, stability, interpretability and computational cost [49].

13 CONCLUSIONS

By enabling accurate forecasting, economic scheduling and adaptive real-time control of renewable microgrid resources, AI-based EMS technology can help optimize their operation. The techniques used for optimization are still relevant for constraint handling and machine learning and deep learning are relevant for load and renewable forecasting. Sequential control is a field where reinforcement learning is a useful framework and must be carefully used due to safety and reliability requirements, as well as the need for explainability in power systems.

The review reveals that there are non-algorithmic barriers. Data quality, hardware validation, cybersecurity, computing resources and operator trust will play a role when it's put into practice. The most realistic future EMS will be hybrid; will be physics-aware, uncertainty-aware, cyber-resilient, and will run on local edge platforms. These systems could be useful in improving the reliability, economy and scalability of prospective smart grids in context of renewable microgrids.

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