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AI-Driven Swarm Intelligence Optimization Framework for Scheduling Of Renewable-Rich Microgrid: A Comparative Study of MILP, PSO, GWO and ABC

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ABSTRACT

Microgrids offer a good platform for incorporation of distributed renewable energy generation, energy storage, local loads, and interaction with the grid. The challenge is, though, that solar and wind energy are intermittent, electricity demand is variable, and the price of electricity is dependent on time – making microgrid scheduling an optimal constrained optimization problem. In this study, a comparative optimization approach for renewable energy dominant micro-grid scheduling is proposed, which is based on Mixed Integer Linear Programming (MILP), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO) and Artificial Bee Colony (ABC). The load demand, solar generation, wind generation, and electricity-price profiles are combined to create a common 24-hour scheduling framework.

A battery energy storage system is built into it with defined capacity and SOHC limits, charging/discharging power limits and round trip operating efficiencies. The MILP is a deterministic optimization benchmark and the PSO, GWO and ABC are population-based swarm-intelligence techniques. Under the corrected common formulation, the reported objective costs are 3079.2245, 3112.4667, 3081.2892, and 3084.4690 for MILP, PSO, GWO, and ABC, respectively. The closest approach to the MILP benchmark is the three swarm-intelligence approaches, where the GWO approach is the closest. The corresponding total grid imports are 11.4676, 11.4400, 11.4302, and 11.4662 kWh, respectively. The results show the feasibility of using swarm-intelligence techniques for scheduling a renewable-rich microgrid with keeping the optimization problem formulation the same for every size of microgrid for easy comparison.

Not only are the four methods compared in terms of finding a low objective value, but all the methods are compared under the same physical and operating conditions. The common formulation is identical in terms of the power-balance relation, the battery energy terms, the state-of-charge limits, the charging/discharging limits, the terminal state-of-charge condition, the no-export condition and the storage operating-cost term.

When the costs are compared to a deterministic optimization technique, it is important that the consistency is maintained as otherwise the difference in the mathematical problem reported could give false results. As a consequence, the study considers MILP to be the definitive reference and the results obtained by the metaheuristic algorithms approximate solutions to the same scheduling problem.

Keywords: Microgrid; Renewable Energy; Energy Management System; MILP; Particle Swarm Optimization; Grey Wolf Optimization; Artificial Bee Colony; Battery Energy Storage; Microgrid Scheduling; Swarm Intelligence.

I. INTRODUCTION

Renewable-Rich Microgrid Architecture

A microgrid is a small-scale power generation system comprising distributed renewable energy resources, energy storage, electrical loads, power conversion, monitoring and control and an interface with the main electricity grid, where the generation resources are renewable. This architecture allows for local renewable electricity to be used locally, and offers more flexibility when local renewable electricity generation is not adequate to cover local demand [1, 2]. In the considered microgrid, the integration of solar photovoltaic (PV) and wind power generation with a battery energy storage system (BESS), household load demand and the utility grid. Renewables add operational variations due to the variability of the availability of the resources. If there is a high proportion of renewable energy generation, excess energy can be fed to the load and stored in the battery. If there is insufficient renewable generation the battery can discharge to meet the demand whilst the remaining demand can be met from the main grid [1], [6], [14].

Therefore, the Battery is a balancing element between the renewable surplus and renewable deficit. These components are time coupled from an energy-management point of view. Charging and discharging the battery during one scheduling period, has an impact on the energy available during the next scheduling period.

Likewise, the electricity demand of the grid is influenced by the instantaneous demand, renewable generation, price of electricity and available battery energy [1] and [14]. Hence, the need of synchronized scheduling of renewable resources, battery operation and energy exchange within the grid is critical for economical operation of a renewable-rich microgrid [3] [6]. For the present study, the microgrid is assumed to be a grid connected system, which includes battery energy storage, wind generation, solar PV generation, household load demand, and the utility grid, where renewable energy is utilized.

The problem of scheduling is based on averaged hourly profiles for the load demand, solar generation, wind generation and electricity price over a given 24-hour period of operation. The same system operating parameters and setup are applied to the various optimization methods to facilitate comparison of these methods. The building also shows why it is not possible to make the energy management decisions at an hourly basis. The relationship between the battery state and renewable availability and load demand is through the scheduling horizon. An economic choice made in one hour can impact the amount of energy available during a high price time. Therefore, the optimization problem has to take into account both intra-temporal and inter-temporal power balance. In this research this property will be taken up as a time coupled characteristic which plays an important role in the formulation.

Renewable Generation and Load Variability

Most microgrid installations are typically comprised of distributed renewable generators, local electrical loads, energy storage systems, power-conversion equipment, measurement and control devices and an interface with the utility grid, with renewable generators being the dominant component. This can enable electricity to be generated locally and used locally and also allow for flexibility if local resources are not enough. Importantly, from an energy-management point of view, it's the way these resources relate to each other over time. The charge of the battery in one period impacts the energy that will be available in other periods, and the purchase of the grid relies on the present demand as well as past energy storage in the battery [1], [2], [14].

This variability is clearly illustrated in the renewable profiles used in the study. Solar PV generation is highest in the light of day and wind generation is more constant across the full 24 hour period. The load profile and the electricity price profile are two more sources of variation. Battery scheduling is a key way to achieve a balance between local generation and demand as a result of these profiles. When the entire hourly profiles are investigated, the resulting scheduling problem is therefore more informative, as only aggregate daily values are investigated.

Importance of Day-Ahead Scheduling

As the PV and Wind get more and more into the grid, so does their influence on the operating parameters of a micro grid. The solar output is generally of a diurnal nature while the wind output can change in accordance with wind conditions. Meanwhile, electricity demand varies on a daily basis. The net-load profile that is generated then has times when renewable energy can meet a high percentage of demand, and times when there is a need for extra energy from the grid.

Scheduling of renewable resources, battery storage, and grid exchange is an important energy-management problem that is challenging given this variability [3, 10, 19]. The time varying inputs are useful to be converted to a finite scheduling problem by the day-ahead framework. For the present work, the 24 hour time frame is used, making a bed of common operating conditions for all algorithms. This allows for comparison of the battery schedules and SOC trajectories produced by the different optimization methods, as well as the objective values.

Economic Operation of Renewable-Rich Microgrids

Day-ahead scheduling offers a useful solution for scheduling resources over a fixed time horizon. While having a 24-hour time scale, the 24-hour optimization problem can include hourly changes in load, renewable generation, electricity price, and battery state. Day-ahead scheduling for coordinating the distributed generation, energy

storage, demand response, and energy interaction with the grid has been applied to previous microgrid studies [3], [6], [14].

In the present study this time coupled view is taken. In the current formulation, there are two parts of the economic goal: the part associated with acquiring electric power from the grid, and the storage operating-cost part. Thus, it is not the case that a schedule that has a slightly lower grid import is a schedule with the lowest total objective. The term for the battery operation also has an influence on the final value. This difference should be kept in mind when analysing results, especially when comparing the overall objective with MILP, as this objective is the lowest for GWO and the most distant from MILP.

Environmental and Operational Perspective

The main goal of economic scheduling is to meet the electrical load and maintain the operating restrictions of the resources available while minimizing operating costs. The cost benefit of a grid connected renewable microgrid is dependent on the availability of renewable, electricity rates, grid imports and battery performance. Storage can store energy for future use and so help to cut back purchases during relatively expensive times. This flexibility, however, is limited by the energy capacity of the battery, its charging and discharging limits, the range of state of charge and efficiency [6, 14]. While the environmental objectives are applicable to microgrids based on renewable energy, the present corrected formulation focuses mainly on the modeled operating cost and the interaction of the grid. Emission-aware optimization is thus not considered as a new objective in the results presented here, but an extension. To maintain objective formulation to be focused also helps comparing the three swarm-intelligence methods with MILP.

Motivation for Comparative Optimization

Microgrids are becoming more and more popular with the addition of renewable resources like wind and solar PV technologies, which can make generation unpredictable and cause a requirement for good energy scheduling. When renewable energy is available to meet the load requirement, the operation of battery storage and grid energy are not always coordinated, so the economical and reliable supply of renewable energy is crucial. Furthermore, the price differences for electricity may affect the most suitable time to use the grid and/or the battery [1], [6], [14]. Various optimization techniques may be sensitive towards the same scheduling problem as they employ different search and solution mechanisms. A structured mathematical programming approach is provided by deterministic methods like Mixed Integer Linear Programming (MILP), while the population-based search techniques like Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO) and Artificial Bee Colony (ABC) are based on swarm intelligence-based methods [3], [7], [8], [12]. Hence it is necessary to compare these methods in the same operating conditions. To evaluate the MILP, PSO, GWO, and ABC methods in this study, the load demand, the solar generation, the wind generation, the electricity-price profile, the 24-hour scheduling horizon, and the battery operating conditions are the same.

Their performance is evaluated using the objective cost, energy imported from the grid, battery state of charge and schedule behavior. This is a widely used assessment tool that will give a common ground to understand how well the selected optimization techniques are working for scheduling the microgrid with renewable resources. This is therefore a methodological, as well as a numerical, motivation. The objective value is meaningful only if it's computed on the same constrained optimization problem. In the corrected study this is done in a deliberate manner, with a common evaluator and by comparing the MILP schedule with this evaluator. This helps to justify the comparison and helps avoid the perception that the algorithms are superior due to different constraint handling.

II. LITERATURE REVIEW

Microgrid Energy Management and Scheduling Context

Economic dispatch, renewable energy utilization, battery energy management, demand response, reliability, and uncertainty have been some areas of research on microgrid EMS. Zia et al. did a critical review of the different methods of microgrid EMS and highlighted the coordinated decision making under renewable and load fluctuations [1]. They also identified uncertainty quantification and the use of optimization/metaheuristic techniques in microgrid energy management as areas of uncertainty. The last few studies have started to incorporate more recent concerns such as the integration of electric vehicles, demand response, renewable utilization, environmental sustainability, and economic objectives, to reflect a broader paradigm transition from

cost minimization to multi-dimensional decision making [9, 11]. Analytically, this literature helps to set the foundation that the scheduling of microgrids is not a merely a generator dispatch problem. The addition of storage adds temporal coupling and intermittability in the supply from renewables adds variability. There is, therefore, a good basis in the literature for comparing optimisation approaches, based on common constraints rather than comparing individual algorithm implementations, using the same operating data.

Deterministic MILP-Based Scheduling

One of the known scheduling methods for microgrids is MILP which can be used to model both continuous and binary variables in one mathematical optimization model. Tenfen and Finardi formulated a MILP model for energy management problem of microgrids [3]. Mashayekh et al. [4] performed optimization, sizing and placement of DERs in multi-energy micro-grid using MILP. Nicolosi et al. also performed unit commitment of generation technologies in a micro-grid with consideration to emissions using MILP [5]. The main feature of MILP is the representation of the constraints in an explicit manner and the optimization using deterministic approach. More complex systems and more complex uncertainty models can significantly increase the CPU requirements, however. In the current study, the primary importance of MILP is as a deterministic benchmark. The resulting solution includes a representation of the battery state, limits for charging/discharging and binary operating status of the battery, so it serves as a reference to compare approximate population-based solutions to the problem. The role is especially useful after correcting the often-used formulation, as then the costs of the metaheuristics can be considered deviations from an exact benchmark and not results from another model.

Swarm-Intelligence Approaches

Kennedy and Eberhart proposed PSO as a population-based optimization method that is based on social behavior [12]. The use of PSO in microgrid applications has resulted in battery charging and discharging schedules and a reduced operating cost. Hossain et al. presented a modified PSO method for real time energy management in grid integrated microgrids and particularly studied the cost functions related to batteries and a dynamic penalty function [6]. Mquqwana and Krishnamurthy used PSO for optimizing the performance of a hybrid renewable-energy microgrid management in uncertainty, which included battery reserve margins [10]. Guan et al. proposed an improved model for multi-objective microgrid scheduling based on PSO, taking into account both the operational costs and environmental costs [9]. Artificial Bee Colony (ABC) is a method that is based on the foraging behaviour of honeybee colonies. It takes advantage of the ‘exploit’ features of employed bees, ‘explore’ features of onlooker bees, and scout bees to explore and exploit candidate solutions. Karaboga and Basturk introduced a numerical optimization method called ABC [13].

Ullah et al. used ABC to optimize the optimal power sharing in microgrids and showed the validity of ABC for the optimization problem of the energy system [7]. Grey Wolf Optimization (GWO) is a novel optimization algorithm proposed by Mirjalili et al. that is based on their leadership hierarchy and hunting process [8]. This method is based on alpha, beta and delta solutions to direct the population. The search mechanism of it is different from PSO and ABC so that it can be used for comparison analysis of population base optimization methods [8], [16], [23]. The merit of using three different swarm-intelligence methods is that they imbibed with different search methodologies. PSO updates candidate solutions based on the velocity and individual/global best information, GWO employs the concept of leadership hierarchy and ABC employs the following phases: employed, onlooker, scout. Thus, their comparison is not, in this case, an evaluation of one of the metaheuristics themselves but rather an indicator of the population-based search behavior with respect to the same physical scheduling problem.

Hybrid, Multi-Objective, and Uncertainty-Aware Scheduling

Hybrid optimization has been studied to incorporate constraint-handling capability of mathematical programming and search capability of metaheuristics. Kim et al. suggested a MILP-PSO hybrid scheduling strategy for the islanded microgrid, which includes the detailed model of energy-storage efficiency of the battery system [14]. Another critical direction is multi-objective scheduling as there could be conflicts between operating cost, environmental, reliability and renewable utilization [9], [15]. New research has also investigated hybrid optimization techniques which are a mixture of mathematical solution and metaheuristic search [14].

The Energies base paper illustrates this way with a multi-objective microgrid scheduling model based on the improved PSO algorithm [9]. Forecasts of renewable generation and electricity demand, as well as electricity

prices, have errors. This uncertainty is represented in the case of stochastic scheduling by scenarios or probability distributions, in the case of robust optimization by solutions that are robust in a given uncertainty set [17,19]. More recently, some work merged the methods of probabilistic scheduling with swarm intelligence to solve flexibility and resilience issues [25]. The current study is based on representative hourly profiles and, therefore, provides a benchmark for comparison of the algorithms, rather than a complete stochastic formulation. Demand response offers another source of flexibility and flexibility options, and it is to change selected loads to more favorable operating periods. It can be used in conjunction with battery storage and renewable generation to help minimise the mismatch between the local generation and demand at a particular instant. In the microgrid energy-management research reviews, coordinated demand-side flexibility is recognized as a key research area that needs to be further pursued [1, 18]. The increased amount of electric vehicles in the grid fosters more flexibility for scheduling charging loads and in V2G mode can offer further flexibility for the microgrid optimization. Recent research based on the swarm intelligence approach has integrated distributed energy resources, EVs and energy trading [11].

Analytical Comparison of the Reviewed Studies

Study / approach	Primary focus	Main contribution identified in the reviewed paper	Implication / limitation for the present comparison
Zia et al. [1]	Microgrid EMS	Coordinated EMS decisions under renewable/load variability; highlights uncertainty and optimization methods.	Provides broad EMS context but does not provide the controlled MILP–PSO–GWO–ABC comparison used here.
Tenfen & Finardi [3]	MILP energy management	Explicit mathematical formulation for microgrid EMS.	Shows the strength of deterministic constraint representation; motivates a benchmark for metaheuristics.
Hossain et al. [6]	Modified PSO EMS	Battery-related cost functions and dynamic penalty mechanisms in grid-connected microgrids.	Supports PSO use for battery scheduling, but uses a different model and therefore is not a direct algorithm-to-algorithm benchmark.
Ullah et al. [7]	ABC power sharing	Demonstrates ABC applicability to microgrid energy-system optimization.	Provides evidence for ABC but not a common constrained scheduling comparison with MILP, PSO and GWO.
Mirjalili et al. [8]	GWO	Defines the alpha–beta–delta leadership mechanism used by GWO.	Provides the algorithmic basis; application performance remains problem-dependent.
Guan et al. [9]	Improved PSO scheduling	Multi-objective scheduling considering operational and environmental costs.	Shows the broader multi-objective direction; the present study uses a common economic benchmark.
Kim et al. [14]	MILP–PSO hybrid	Combines mathematical programming and swarm search with detailed battery efficiency modeling.	Supports hybrid approaches and detailed storage modeling, while the present work compares methods under one common formulation.

Hosseini et al. [17]	Robust EMS	Addresses uncertainty in demand and renewable generation.	Highlights an extension beyond the deterministic profiles used in the present benchmark.
Akter et al. [22]	Metaheuristic review	Reviews scopes, trends and recommendations for metaheuristic microgrid optimization.	Supports systematic comparison and motivates evaluating multiple algorithms under common conditions.
Present study	MILP, PSO, GWO and ABC	Uses the same 24-hour inputs, battery framework, power balance, SOC limits, terminal-SOC condition, no-export condition and storage operating cost for all methods.	Directly addresses the identified gap through a controlled method comparison.

Table 1. Analytical comparison of representative studies and the present research framework.

The literature reviewed indicates that there is sufficient evidence supporting the use of the individual optimization techniques, but the literature generally varies in system configuration, objectives, battery assumptions, how the battery uncertainty is treated, or how the battery constraints are handled. It is therefore not easy to make direct comparisons between different published studies. The current study addresses this problem by fixing the scheduling issue and modifying just the optimization method. Differences of the final values of the objectives can be interpreted as a difference in the capability of the algorithms to explore the same feasible solution space mainly. Battery modeling is also known to have an impact on battery scheduling as per the literature. The efficiency, reserve margin, degradation or other storage costs may be included in studies in various ways. To this end, the author explicitly writes that the coefficient used in the current objective is a part of the cost of operation for the storage and is not an independent model of battery ageing. This clarification considers the results as preliminary ones, and not evidence of any electrochemical degradation or battery lifetime.

Research Gap

From the reviewed literature, there are many that analyze one optimization method or one algorithm that has been slightly adapted for a specific microgrid configuration. There is relatively less focus on a comparative study of deterministic optimization and multiple swarm-intelligence methods on the same scenario. Furthermore, it is necessary to evaluate the performance of the algorithms, not just by objective cost, but also by the fact that they can be imported to the grid, the behaviour of the batteries, convergence, and computational performance.

In the current work, this is filled by developing a common 24-hour scheduling framework and a comparison of four different optimization methods (MILP, PSO, GWO, and ABC) with the same system-level inputs and battery framework. Based on the studies reviewed, none of the reviewed optimization techniques can be considered as the best optimization technique for all microgrid scheduling problems.

The combination of MILP and PSO, ABC, GWO and other metaheuristics provides flexible population based search with structured mathematical representation. More recent evaluations have highlighted the need for hybrid solutions, the management of uncertainty and for systematic comparison of algorithms under the same circumstances [22, 23]. These observations are in favor of the current study which focused on a controlled comparison between MILP, PSO, GWO and ABC via the same renewable-rich microgrid scheduling framework.

III. PROBLEM STATEMENT

Addition of SPs and WPs to microgrids results in variability in available generation. The microgrid needs to determine the electricity demand and what percentage it will draw from the renewable energy sources, how the battery will be utilized, and what percentage of electricity will be received from the main grid. Given that

electricity costs fluctuate throughout the year, it might be beneficial to shift energy use to lower-cost times, if possible.

The problem under investigation is thus formulated as a constrained scheduling problem where the goal is to reduce the operating cost of the modeled cost function while meeting the load demands, battery operating boundaries and energy balance of the microgrid. Furthermore, the corrected common formulation has a terminal-SOC condition and no-export condition so the algorithms are not given any advantage by an artificial change in the stored energy at the end of the day or by exporting energy beyond the modeled objective. The major method requirement is that the deterministic and stochastic methods must consider the same feasible schedules. All four approaches are thus evaluated based on the same hourly renewable and load inputs, same electricity-price profile, same battery equations and same operational limits.” This is what will form the basis for a meaningful algorithmic comparison.

IV. RESEARCH OBJECTIVES

The objectives of this research are:

1. To develop and implement a Mixed Integer Linear Programming (MILP) based optimization model for microgrid scheduling using Python and a MILP solver, ensuring optimal utilization of distributed energy resources under system constraints.
2. To implement a Particle Swarm Optimization (PSO)-based approach for microgrid scheduling and extend the framework by incorporating additional swarm-intelligence algorithms for comparative optimization.
3. To conduct a comprehensive comparative analysis between MILP and swarm intelligence-based optimization techniques in terms of operational cost, emission reduction, computational efficiency, and convergence performance.

V. SYSTEM DESCRIPTION AND DATA PREPARATION

The proposed framework takes into account a microgrid with high share of renewables (solar, wind, battery energy storage) and a household load demand with grid connection. Implementation involves the use of heterogeneous time-series datasets of electricity consumption per household, PV generation, weather information, PV generation information based on wind and electricity market prices. These data sets are cleansed, synchronized and converted to representative hourly profiles that are scheduled for 24 hours.

The last input to the schedule at every hour is load demand, solar generation, wind generation and price of electricity. A common input set guarantees the four optimization approaches have the same scheduling problem. It is especially beneficial for day-ahead scheduling since each decision variable can be connected to a distinct operating interval.

System could be regarded as a series of hour-by-hour energy-balance decisions. Renewable generation is applied to meet demand when available and the battery is applied to shift the load between excess and deficit. The remainder of the power demand is met by the grid. The battery charging/discharging control, which not only involves the amount of energy purchased, but also the timing of buying and selling, needs to be optimized due to the price volatility.

Component	Role	Scheduling relevance
Solar PV	Renewable generation	Supplies local demand and reduces grid dependence
Wind generation	Renewable generation	Complements solar generation
Battery ESS	Energy storage	Stores surplus energy and supplies demand during deficit periods
Load	Electricity demand	Defines the energy requirement
Grid	External energy source	Supplies remaining demand

Table 2. Components of the considered renewable-rich microgrid.

VI. MATHEMATICAL FORMULATION

Power Balance

For each scheduling interval t , the microgrid must satisfy the power balance:

$$P_{PV}(t) + P_{WT}(t) + P_{grid}(t) + P_{dis}(t) = P_L(t) + P_{ch}(t)$$

where P_{PV} and P_{WT} represent renewable generation, P_{grid} represents grid import, P_{dis} and P_{ch} represent battery discharge and charge power, and P_L represents load demand.

This balance equation makes sure that each scheduling interval's electrical demand is met. It also sets relationships between the renewable generation and storage operation. If renewable does not meet the demand, then the battery discharge and grid import covers the rest of the demand. If renewable energy generation is available in excess of the immediate demand, charging can take up some of the surplus subject to the constraint of the battery.

Battery Energy Model

The battery state is represented using stored energy and state of charge (SOC). During charging:

$$E_t = E_{(t-1)} + \eta_{ch} P_{ch,t}$$

During discharging:

$$E_t = E_{(t-1)} - P_{dis,t} / \eta_{dis}$$

The battery operates within its defined energy and power limits:

$$E_{min} \leq E_t \leq E_{max} \quad 0 \leq P_{ch,t} \leq P_{ch,max} \quad 0 \leq P_{dis,t} \leq P_{dis,max}$$

$P_{dis,max}$

The battery configuration implemented is 5kWh nominal capacity with 20% minimum SOC, 90% maximum SOC, 1 kW maximum charge/discharge power and 95% charge/discharge efficiencies with 50% initial SOC. The equations for the battery allows for a realistic scheduling comparison: energy stored at the end of one interval is the energy available for the next interval. It is important to note that the present study does not include a separate electrochemical degradation state. The storage-cost coefficient in the objective is an operating cost related to charging/discharging. It should not therefore be construed as a battery life model, cycle-aging model or degradation-health state.

Economic Objective

The scheduling objective is based on electricity procurement cost together with a storage operating-cost component:

$$J = \sum_t [P_{grid,t} \times Price_t + c_s (P_{ch,t} + P_{dis,t})]$$

where $c_s = 0.045$ is the storage operating-cost coefficient used in the implementation. This coefficient is an operating-cost term; it is not a separate battery degradation or battery-aging model. No independent degradation state, cycle-aging equation, or degradation-life model is included in the present formulation. The objective is minimized subject to the system and battery operating constraints.

The objective formulation is also the reason why the cost of each grid and the total objective cost must be reported separately. Charging and discharging can be part of the storage operating-cost term, which can lead to a slightly higher total objective, but at the same time the grid import can be slightly lower. The corrected results show this behaviour for GWO with respect to PSO.

VII. OPTIMIZATION APPROACHES

MILP

The deterministic benchmark is used for MILP. There are continuous variables representing the power on the grid, the charging/discharging of the batteries, and the amount of energy stored in the batteries, as well as binary variables representing the operating status of the devices. This enables the limitations of operations to be explicitly represented. Since the solver is deterministic, the MILP solution is a good benchmark to test the quality of approximate solutions obtained with approximate metaheuristic algorithms.

PSO

In PSO, the particles are the candidates of 24 h battery schedules. The position of each particle is updated based on its own best solution and the best solution (global best solution) obtained. Here, 25 particles and 75 optimization iterations have been used. The inertia weight is reduced linearly from 0.9 to 0.4, the cognitive coefficient is reduced linearly from 2.5 to 0.5 and the social coefficient is increased linearly from 0.5 to 2.5. These parameter schedules are designed to help make the shift from exploration to exploitation. Early generations help to explore the search space more widely, later generations are more interested in the information of the particle's

most promising solution and the population's most promising solution. The feasibility is checked on the same physical restrictions as for the common scheduling problem.

GWO

For GWO, each wolf is a candidate 24 hour schedule. The remaining population is directed by the alpha, beta and delta solutions. The corrected implementation has the number of wolves set to 100, and the number of iterations set to 500, with the control parameter (α) decreasing linearly from 2 to 0 over the iterations of the algorithm. The control parameter is slowly decreased, which slowly modifies the search behavior in the optimization horizon. “The algorithm first lets out the exploration and then concentrates the population on the good solutions. It is tested under the same objective and feasibility factors as PSO, ABC and MILP.

ABC

Each candidate program is a different food source - represented by ABC. The search process involves the following phases: employed-bee, onlooker-bee and scout-bee. The corrected implementation uses the following: 60 food sources, 60 bees employed, 60 bees onlookers, 700 iterations and a trial limit of 80. The neighbor coefficient ϕ is sampled randomly from the range of $[-1, 1]$ and solutions are selected that are feasible. The common physical optimization problem is not modified and a feasibility-aware repair mechanism is used. The algorithm has three stages: employed, onlooker and scout and each one has a distinct search behavior. When a candidate who is not improving is found, the trial limit decides when he or she will be replaced by another candidate using the scout mechanism. The handling is important as it is feasibility-aware, the candidate battery schedule has to be consistent with the common power-balance and battery constraints.

VIII. EXPERIMENTAL SETUP

Parameter	Value
Scheduling horizon	24 hours
Battery capacity	5 kWh
Initial SOC	50%
Minimum SOC	20%
Maximum SOC	90%
Initial energy	2.5 kWh
Maximum charge power	1 kW
Maximum discharge power	1 kW
Charge efficiency	95%
Discharge efficiency	95%
Storage operating-cost coefficient	0.045 per kWh
PSO population	25 particles
PSO iterations	75
PSO inertia weight	0.9 to 0.4
PSO c_1	2.5 to 0.5
PSO c_2	0.5 to 2.5
GWO population	100 wolves
GWO iterations	500
GWO α parameter	2 to 0
ABC food sources	60
ABC employed bees	60
ABC onlooker bees	60
ABC iterations	700
ABC trial limit	80
ABC ϕ range	$[-1, 1]$

Table 3. Corrected experimental and algorithm parameters used in the implementation.

MILP Solver Details

The deterministic benchmark is solved with the `scipy.optimize.milp` call to the HiGHS mixed-integer optimization solver. The implementation is based on SciPy 1.16.3, Python 3.13.15 and has 300 seconds for the solver! The MILP has 120 variables: 24 grid-import variables, 24 charging variables, 24 discharging variables, 24 battery-energy variables and 24 binary variables that represent the charging status of the batteries. The objective is the cost of the grid electricity plus the storage operating-cost component as described in Section 6.3. The description of the explicit solver is provided to enable reproducing the deterministic benchmark and differentiating it from the stochastic ones. A comparative optimization study is important since two factors are crucial for the solver: the solver chosen and the size of the model; the benchmark is the deterministic reference solution with which the metaheuristic schedules are compared. The common formulation check, described in the following section, is an additional check that the MILP schedule can be analysed using the same objective function as the stochastic approaches.

IX. RESULTS AND DISCUSSION

The optimized results were corrected and are presented in Table 4. The objective cost is the common scheduling objective that is used by the MILP as well as the three stochastic methods. The same power balance, the same battery dynamics, the same SOC limits, the same charge/discharge limits, the same terminal-SOC condition, the same no-export condition and the same storage operating-cost coefficient are used for all four approaches to ensure that the results are directly comparable.

Algorithm	Objective Cost	Grid Import (kWh)	Final SOC (%)
MILP	3079.2245	11.4676	50.00
PSO	3112.4667	11.4400	50.00
GWO	3081.2892	11.4302	50.00
ABC	3084.4690	11.4662	50.00

Table 4. Comparative results from the corrected common microgrid scheduling formulation.

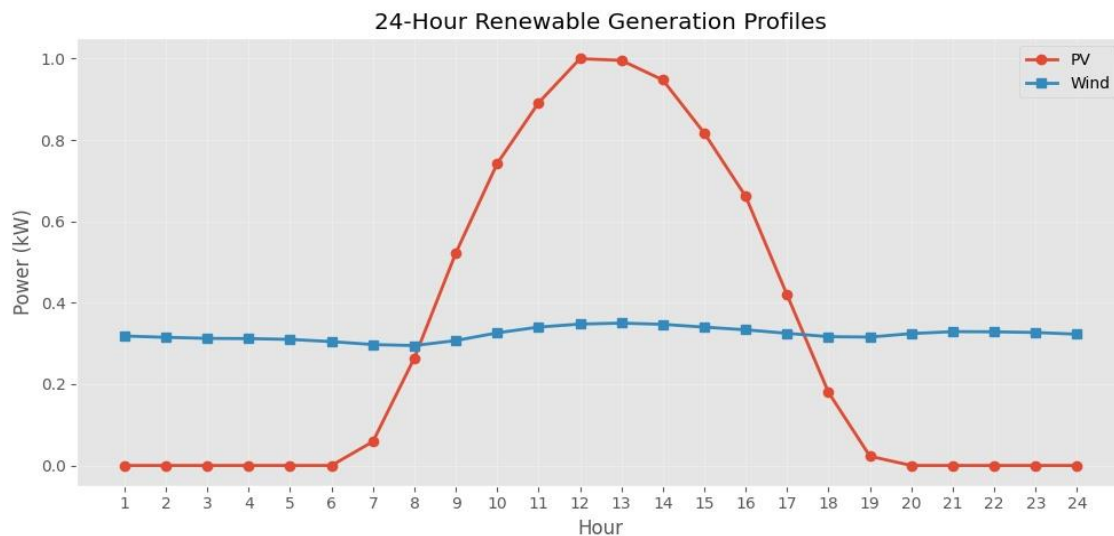


Figure 1. 24-hour photovoltaic and wind generation profiles.

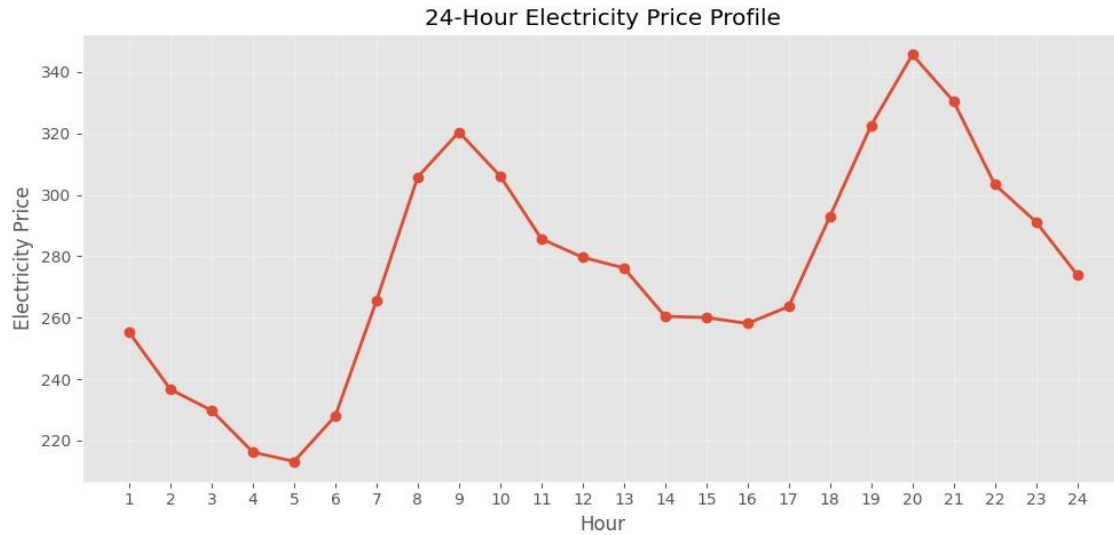


Figure 2. 24-hour electricity price profile.

The price and renewable profile combination offers a chance for time shifting of energy, via storage. When renewable energy is available, charging can be used to store energy, and when renewable energy is low, discharge from the battery can help to decrease the reliance on the grid. Meanwhile, the price of electricity impacts on the economic value of stored electricity. The optimization thus aims to find a schedule that optimises these competing effects within the battery constraints.

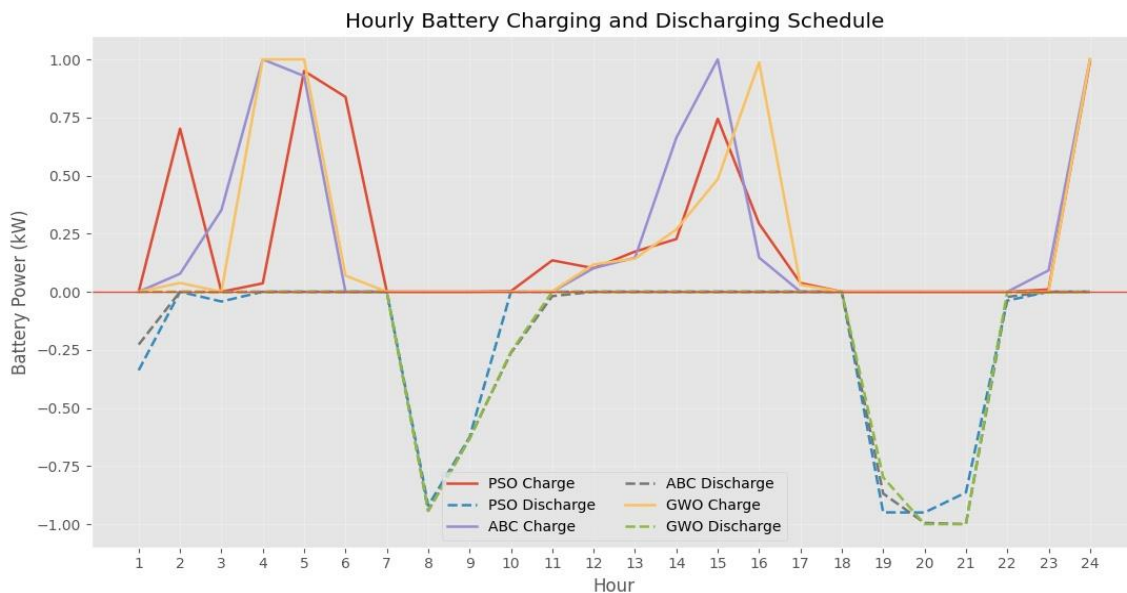


Figure 4. Hourly battery charging and discharging schedules for the best feasible solutions of PSO, ABC and GWO.

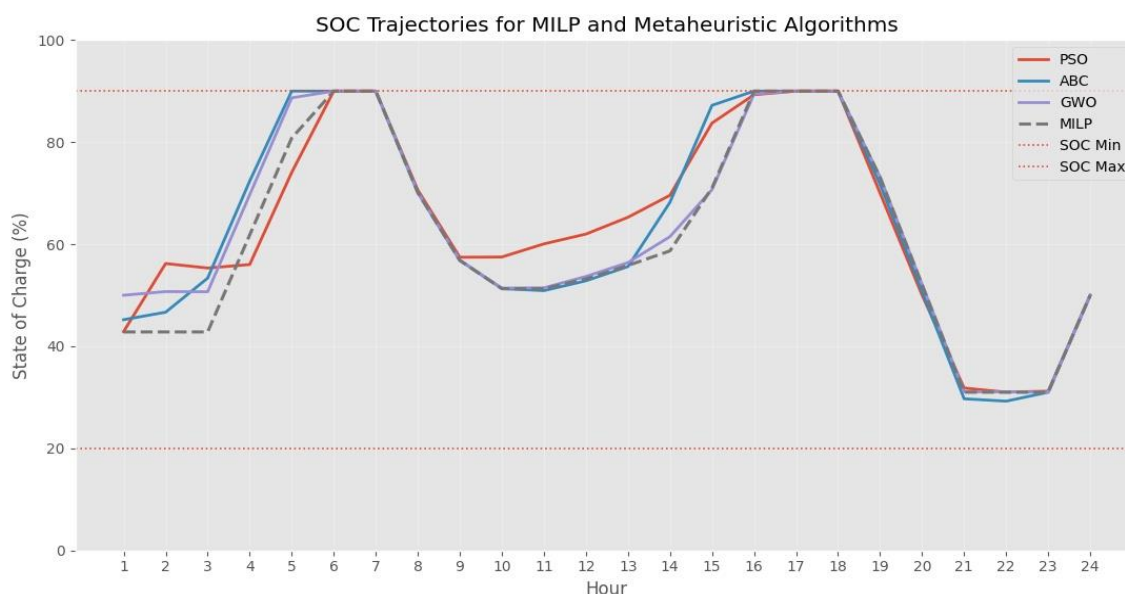


Figure 5. SOC trajectories for MILP and the three metaheuristic approaches.

The numerical results are also able to be physically interpreted by the SOC trajectories. The trajectories are drawn rather than the objective values at the end of the algorithms are evaluated, as to see when the stored energy is being increased and when it is being decreased. The large similarity in the overall SOC pattern suggests that the methods are reacting to the same conditions regarding the renewables and prices, whereas the slightly different time paths are due to the different search strategy of the algorithms.

MILP–Metaheuristic Formulation Consistency

This direct equivalence check has been carried out by using a common metaheuristic representation by mapping the MILP battery schedule. The MILP objective is 3079.22452414869, as is the common evaluator, so there is no objective difference. The difference in the grid schedule and in the charging schedule is around 4.44×10^{-16} and the difference in the battery-energy trajectory is 0.0, respectively. So there is common-formulation equivalence and the common-formulation equivalence check passes.

The consistency is crucial as the MILP and metaheuristics need to solve the same constrained optimization problem in order to be compared meaningfully in terms of cost. This validation directly tackles the main methodology question in the comparison. But if the optimization method could be blamed on this lower cost, then the other would have been allowed to employ a different battery constraint, terminal condition or objective term. The equivalence check is to determine that the schedule generated by the MILP is taken under the same mathematical objective as the metaheuristic solutions.

Interpretation of Objective Costs

The MILP has the exact benchmark objective of 3079.2245. PSO obtains 3112.4667, which is 1.0796% above the MILP optimum. GWO obtains 3081.2892 and ABC obtains 3084.4690. Consequently, in the stochastic ones, GWO is the more similar algorithm to the deterministic one and in the second place is ABC, and thirdly is PSO. As a consequence, the corrected results keep the direction of the heuristic solutions which have no advantage over the exact MILP-based solutions. The slight difference between the PSO and MILP is especially significant in comparison. It proposes a feasible schedule which is very close to the deterministic optimum for the current 24-hour problem. The objective values of GWO and ABC are also close to the benchmark, but slightly higher. The differences should be viewed in the context of this data set and formulation and not as a sole ranking of the algorithms.

Grid Import and Battery Behavior

The grid-import values are close across the four methods: 11.4676 kWh for MILP, 11.4400 kWh for PSO, 11.4302 kWh for GWO, and 11.4662 kWh for ABC. The four methods have different grid import, with GWO showing the lowest. The four methods also have different stochastic objective, with the lowest being for GWO. The PSO objective is set high because the furthest solution that can be obtained with the PSO is still further away from the deterministic solution.

The common formulation guarantees the end-of-day energy equality, and is therefore 50% on the final SOC for all four methods. This finding is proof of the value of using several performance indicators. Objective cost is the full modelled economic criterion while the grid import is only a small part of the scheduling behavior. The battery numbers give a third angle because they indicate the energy that is transferred around the day using each method. Reporting these measures together gives a better sense of how they relate to one another than does presenting a single bar chart of objective measures.

X. RESULT VALIDATION

Corrected schedules were checked for accuracy and feasibility by independent objective checks. The common evaluator reproduced the objective values for the best stochastic solutions the objective values stored during the simulation. The solution for MILP also passed checks for the power-balance, battery-limit, terminal-energy, grid non-negativity and objective-formulation. The conversion of the MILP and common objectives was successful, and they were found to be equivalent within the numerical precision.

Algorithm	Stored / benchmark objective	Recalculated / common objective
MILP	3079.224524	3079.224524
PSO	3112.466711	3112.466711
GWO	3081.289223	3081.289223
ABC	3084.468966	3084.468966

Table 5. Objective consistency between stored optimization results and the corrected common evaluator.

Consistency between the objective values stored and the objective values calculated gives another way of verifying the consistency of the reporting of the implementation to the paper. For specific values, especially the numerical values in Table 4, these are not only obtained from the output of the algorithms, but can also be reproduced using the common evaluation formulation. This gives added confidence in the reported comparison, and may help identify the source of any optimization performance as opposed to any differences in objective calculation.

XI. DISCUSSION

The comparison results show that the optimization strategy can have a certain impact on the microgrid schedule. The objective value is the most objective result of the three different formulations from GWO, PSO and ABC, respectively, with the most value coming from GWO and the least coming from PSO, under the same common formulation. The observed ranking is best viewed as a result for the current set of data and model setup and not as a general comparison of the ranking of optimization algorithms.

The findings also highlight the significance of battery energy storage systems (BESS) in the context of microgrids with renewable energy sources. The battery is able to move energy through time, which means it can decrease the electricity demand during peak net use time. These are also important aspects that have been highlighted in the previous research on microgrid energy management, namely battery charging/discharging control and modeling of the battery storage [6, 10, 14].

A comparison of deterministic and swarm-intelligence methods is useful because the former type excel at some tasks, while the latter type excel at others. MILP gives an explicit formulation of the operational constraints while the swarm-intelligence methods, give flexible population-based search. It is important to note that the same constrained optimization problem is used to formulate the problem in both cases, and, hence, the costs that the stochastic methods yield are close to the deterministic benchmark and not seemingly ‘better,’ as a result of the

formulation differences. The most suitable approach to a practical application, thus, will depend on the size of the system, complexity of the formulation, the required solution time, and the importance of the exact representation of the constraints.

Practically, the outcome implies that the selection of algorithm should take into account two factors: numerically, the quality of the results; and modelling, the requirements. MILP is suited to a formulation which can be written using simple linear relationships and binary choices for operating. When the search space becomes more complicated or another component of the problem is nonlinear, it may be helpful to use a metaheuristic. The current comparison will thus serve as a starting point for future investigations where the fundamental physical meaning of the microgrid will remain unchanged.

XII. LIMITATIONS AND FUTURE SCOPE

This study is conducted on a representative 24-hour time schedule. Other considerations that were not included in the current analysis include environmental optimization, scenarios incorporating uncertainty, integration of electric vehicles, demand response, and annual scheduling over the course of the year; these are topics for future work. Further studies could be conducted on hybrid optimisation techniques such as MILP-PSO, and multi-objective formulations that take into account various cost, emissions, renewable utilisation and battery degradation. The current formulation does not include a separate model for the degradation/aging of the battery. If degradation is included as an explicit optimization parameter, future work can include a model of cycle-depth-dependent degradation, battery lifetime cost or electrochemical aging model. An extension would be able to account for the short term operating cost as well as the long term economic impact of battery cycling, under the storage objective.

Another limitation will be the deterministic nature of the input profiles of the present. Forecast errors may exist in the real operation in solar generation, wind generation, loads and electricity price. The common framework could be extended in the future, keeping the same principle of common constraints, to the scenario-based stochastic optimization or robust optimization, while keeping the same principle of common constraints for all algorithms to be compared. Other evaluations may also provide further details of computational time and convergence statistics, for repeated stochastic runs.

Last, but not least, the present study is designed for algorithm comparison in the context of a controlled environment, and not to be considered as a model for an actual deployment. A higher dimension of the optimization problem would be achieved with larger scheduling horizons, more generators, more flexibility in loads, EV charging, energy trading, or network problems. These extensions would be more useful in assessing the advantages and disadvantages of deterministic and metaheuristic approaches in terms of practical differences, as well as their scalability.

XIII. CONCLUSION

This paper provided comparison among the four aforementioned algorithms (MILP, PSO, GWO and ABC) for scheduling renewable-rich microgrids. The framework integrates load demand, solar generation, wind generation, electricity prices and battery energy storage in a shared (24-hour) scheduling problem. As shown in the comparative results, the objective value of solver 3079.2245 is obtained by correcting the parameters of the algorithm, solver description, interpretation of the storage cost, figures, synthesis of literature and reference list, while the PSO, GWO and ABC solvers get the objective value of 3112.4667, 3081.2892, and 3084.4690, respectively.” The study illustrates the applicability of swarm-Intelligence optimization solution in microgrid scheduling and establishes a structured and systematic framework for comparing the effectiveness of both the optimization methods.

The proposed framework can be expanded to multi-objective cost-emission optimization, uncertainty modelling, demand response and integration of electric vehicles and hybrid mathematical-metaheuristic optimization. This could be helpful to residential microgrids, institutional campuses, commercial facilities, remote microgrids, and community energy systems. While the components and market rules differ across individual applications, the key scheduling problem is always to meet the demand, utilise the renewable energy sources optimally, operate the storage within its limits and manage the grid interaction economically.

Perhaps, it's also helpful to compare from the algorithm-selection point of view. If it can be modeled accurately with tractable linear constraints, mathematical programming is still attractive when the system can be modeled accurately. Metaheuristics are appealing if the problem has some nonlinearities, has a complex search space, or does not have an objective function which can be conveniently formulated in a conventional solver. A combination of both types is increasingly studied to take advantage of properties of both [14, 21, 24]. The corrected results provide a consistent standard for evaluation of extensions in the future.

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