Selecting an Optimisation Algorithm for Optimal Energy Management in Grid-Connected Hybrid Microgrid with Stochastic Load

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***Abstract*— Decentralisation of the power system and the implementation of microgrids into the standard power system, leads to a complex system which requires a reliable operation and a proper energy management. Finding the right set of optimisation algorithms is the base for solving the optimisation problem. This paper overviews the usage of optimisation algorithms for microgrid energy management, with an accent on a classical optimisation algorithm (Dynamic Programming), and heuristic algorithms, such as Genetic Algorithm and Particle Swarm Optimisation. The paper also proposes a methodology for optimal energy management in a hybrid grid-connected distribution microgrid, with a storage system and stochastic load. The algorithm analyses the optimal scheduling of the installed generators considering the state of charge of the battery and electricity price for power trading with the utility grid. The optimal solution is the most economically justified solution from which the microgrid can benefit, and the one with the least impact on the nodal voltages.**

Keywords—Microgrid; Optimisation Methodology; Energy Management System; Unit Commitment

I. INTRODUCTION

The battle for nature salvation, against the fossil fuel using power plants, triggers the alarm for enhancing the operation of Renewable Energy Sources (RES) within the power system. Using clean energy is both economic and environmental friendly. Implementing the renewables for local power generation enables the consumers to become producers of electrical energy, who are independent and self-sustained. Driven by the will for providing electricity for every household and at the same time respecting nature, the number of microgrids implemented into the standard power systems increases. As far, there are some basic rules accepted by the microgrids community, regarding the proper operation and maintenance [1]. However, under the lack of regulations and technical guidelines, there are still some obstacles to the seamless operation of grid-connected microgrids.

A microgrid represents a small power system, connected to the utility grid, consisting of RES and local consumers, and, optionally, a diesel generator and storage systems for storing the unused electrical energy, for its further usage or trading with the main power grid. These components are interconnected, and they operate as a single controllable unit. That way, microgrids enable a clean and self-maintained way of power generation, meaning that they can work as a separate entity, isolated from the power system. In addition to the environmental benefits they provide, the latter is another reason microgrids are accepted worldwide [2]. Since the main sources of power in the microgrids depend on the weather conditions, their switching off and on can cause disturbance in the power system. Therefore, the microgrid has to be secured with a stable voltage and frequency.

Grid-connected microgrids can also trade electric power with the utility grid they are connected to. The price of the electricity is previously determined. For that purpose, there is a smart energy management system in the microgrids, which determines whether it is more economically justified to store the power or to sell it [3]. This is beneficial to the power system because it enhances the economy, the reliability of supply and lowers the burden that the spinning reserve carries.

The optimisation of microgrids is similar to the one for standard power systems, except that it has to take into consideration the weather conditions. The change of the weather conditions has a huge impact on the nodal voltages in the microgrid. Therefore, proper optimisation regarding the operation of the distributed generators is required.

The literature consists of many different optimisation algorithms, but the choice for a certain algorithm is based on the number of constraints and the complexity of the problem.

This paper analyses the optimisation algorithms used in the literature and proposes a methodology for enhancing the algorithms for improving the results.

II. LITERATURE REVIEW

Along with the increased microgrid implementation, the need for its optimisation increased in the last decade. The numerous research on finding the best optimisation algorithm testify to the importance of the optimisation of the microgrids. The optimal work of the microgrids means a proper and safe power system operation. That includes choosing the best location, size, and configuration of the microgrid, management, and control of the distributed generators and loads.

Depending on the aspect of view, whether the costs for generation are optimised, nodal voltage disruptions, or microgrids' impact on the power system, there are many different algorithms and mathematical methods applied for solving the microgrid optimisation problem. Researchers are constantly working on proposing novel optimisation algorithms or improving the classical algorithms which can solve the unit commitment problem of microgrids by simplifying it [4] [5] [6] [7].

For instance, paper [8] proposes a solution to the unit commitment problem in a microgrid supported with a battery system, by implementing the Most Valuable Player Algorithm (MVPA). This algorithm is a new metaheuristic optimisation algorithm inspired by actual sports events. The optimisation is subject to the operation costs. The results using the proposed method are satisfactory for the analysed microgrid configurations and operation scenarios, neglecting the power demand and power generation variations.

But, generally, there are three most applied algorithms for this problem: the Dynamic Programming Method (DP), Genetic Algorithm (GA), and Particle Swarm Optimisation (PSO) [9] [10]. In [11] these algorithms are overviewed and compared. The paper provides a clear picture of each method's usage and application.

Reference [12] presents an overview of six metaheuristic algorithms for cost minimisation of microgrids. The paper, through a comparative analysis, using different performance indicators for a microgrid, provides directions for choosing the most suitable optimisation technique for a grid-connected hybrid microgrid cost minimisation.

The unit commitment problem in microgrids is a complex problem requiring an algorithm that gathers all of the constraints. Dynamic Programming method (DP) is a classical optimisation method that can be used for solving unit commitment problems in microgrids, as presented in [13] and [14]. However, adding the nodal voltages' and distribution lines' limits, the optimisation requires a more evolutionary algorithm.

A comparison between a classical optimisation algorithm and a metaheuristic algorithm is presented in [15]. The algorithms are used for minimising the fuel costs and CO_2 emissions for a micro gas turbine in a microgrid. The results show that the PSO algorithm is applicable for solving the unit commitment problem in the microgrids, and it is more effective compared to DP.

In [16] a hierarchical GA is implemented for maximising the profit from energy exchange of a microgrid with the utility grid, assuming a Time of Use (TOU) energy policy.

The [1] presents an improved GA which minimises the costs of an islanded microgrid and maximises the benefits when it is connected to the grid. The algorithm uses a simulated annealing technique to accelerate the convergence, leaving the bad individuals in the GA in the earlier stages.

Paper [17] presents a day-ahead energy storage system scheduling in a microgrid, by using the GA and PSO. The paper gives a contribution to optimal microgrid scheduling by minimising the costs of microgrid operation, which are defined by dynamic pricing. The goal is to optimise the operation of the distributed generators and battery so that in times of high prices, the stored energy would be used. The paper compares the applicability of the two optimisation algorithms, which results in a better performance of the PSO.

The [18] proposes an improved PSO algorithm for unit commitment in microgrids. Additionally, cost functions for determining the state of charging and discharging of the battery and a dynamic penalty function are introduced. The results show improvement in cost reduction by 12 %.

In [19] wind power-based microgrid supported with fuel cells, a diesel generator, and an electrolyser is analysed. The fuel cell is used in times of energy demand which is not satisfied by the wind turbine. The paper proposes a PSO-based algorithm to minimise the operation costs. The results show nearly 70% cost reduction and economic operation of the microgrid.

The PSO algorithm is used for cost optimisation in a grid-connected microgrid, with a capability of islanded work in [20]. The proposed algorithm considers the variations of the distributed generators and power demand proposing a day-ahead forecast for overcoming this issue.

In [21] voltage disruptions caused by connected distributed generation are analysed. This is the starting point to finding the optimal placement of the distributed generation. Using PSO, the objective function of line losses, voltage stability index, and node voltage deviation of the system is optimised to determine the capacity and location of distributed generation.

Another methodology for optimisation of distributed generation considering the costs and voltage stability was introduced in [22]. The multi-objective optimisation uses two techniques: the sum-weighted Pareto front and an adapted goal programming methodology. In this paper, the voltage stability is "measured" by the load index value (*L*-index).

III. Problem Definition

The implementation of the microgrids represents a big step into a future clean energy power system and it is a big change that has come along to a very positive reaction from the people. However, it is still challenging for people to adjust their behaviour and their habits to the microgrid operation. For instance, cooking or showering during a certain part of the day. If people's habits follow the weather conditions and power generation practise, the implementation of the microgrids will be very easy and there would not be a need for a smart energy system that follows the consumption habits. However, since that practice is not very likely applicable, and power demand is a stochastic process, the microgrids' operation has to be adjusted to the consumption while respecting certain constraints.

Grid-connected microgrids can rely on the utility network, as a backup power source in times of need. However, its operation should not impact the normal operation mode of the utility grid, especially not the consumers. Therefore, it is necessary to determine the optimal schedule of distributed generators and battery systems.

The constraints usually refer to the technical limits of the installed equipment and system's balance. But, besides the technical limitations of the installed generator and battery, the microgrid operation should consider the nodal voltages, limitations of the power bought from the utility on occasions when the generators do not produce any power and the battery is empty, and the power demand. These parameters, have to be in a perfect balance, in which they can overcome the variety of uncertainties regarding the weather conditions and power demand.

In a grid-connected microgrid, additionally, the electricity prices have to be considered in order to find an optimal operation plan. This adds to the complexity of the unit commitment problem in the grid-connected microgrids, which is different from the unit commitment problem in standard power systems [1].

IV. Proposed Methodology

The optimisation of a microgrid is a complex problem consisting of multiple constraints, from the technical limits of the equipment to the balance between the production and consumption of power and the stable power supply. Grid-connected microgrids have a great advantage of being connected to the utility grid, which represents a backup in emergencies when there is an interruption in the power supply. However, being connected to the utility grid brings a big responsibility to voltage stability.

This paper proposes a methodology for creating an algorithm that considers the probability of power supply from the installed distributed generators, the uncertainty of power demand, state of charge of the battery system, and the probability of voltage sags and proposes an optimal solution by minimizing the operation costs.

Most of the microgrid optimisation research focus on the operation costs and technical constraints of the microgrid's components. However, the nodal voltages should be inspected too, in order to define one solution as the optimal one. This invokes the penalty costs for not satisfying the defined conditions for a proper microgrid's solution.

The objective function is subject to the total costs for microgrid operation:

$$F(C) = \max\left\{\sum_{i=1}^{T}(B_{DER,i} - C_{grid,i}) - C_{penalty}\right\} \quad (1)$$

where, $B_{DER,i}$ refers to the profit for selling the excess power to the utility grid in the i-th hour, and $C_{grid,i}$ refers to the costs for buying power from the grid in the i-th hour. Additionally, the penalty costs $C_{penalty}$ for not supplying quality electrical power, with stable voltage, are considered.

Adding penalty costs levels up the reliability of the power supply of the microgrids and the standards for electrical power quality and proper operation.

The constraints consider the installed power capacity of the distributed generators:

$$P_{\min,DER} \le P_{DER} \le P_{\max,DER} \quad (2)$$

Power limits of the battery:

$$0 \le P_{bat} \le P_{\max,bat} \quad (3)$$

Buying power from the grid:

$$0 \le P_{grid} \le P_{\max,grid} \quad (4)$$

Nodal voltage levels:

$$0.95 \cdot U_{r,node} \le U_{r,node} \le 1.05 \cdot U_{r,node} \quad (5)$$

The power bought from the utility grid should be enough to supply the load in the microgrid. However, if there is a legal frame that defines some of the load as a priority, then the maximum quantity of power bought from the grid can be enough to supply the priority load.

Since the weather conditions are not predictable and the forecast is not a hundred percent accurate, the algorithm should be able to follow the power production from the distributed generators and take information about the battery state of charge constantly, as often as possible. Only then it can maintain the voltage levels and optimise the microgrid operation.

Additionally, the algorithm should take information for the electrical power prices, and then decide whether the excess power from the microgrids is going to be sold to the utility grid or stored for further use. Also, this decision applies in times of power production shortage, i.e. whether the needed power should be bought from the grid or taken from the storage system. A solution to this problem was proposed in [23] and [24] by using the convex optimisation technique.

The selection for the optimal solution is based on satisfying the before mentioned constraints. That means that the optimisation algorithm should optimise the generators' operation to optimise the power losses and maximise the profit from power trading. The optimisation is described by the following steps:

- First, the data for maximum power generation for the installed generators and power demand is entered.
- Then, the values for power generated from the generators at the analysed moment are compared to the constraints.
- Additionally, each solution is applied to the network and nodal voltages are inspected. This step is very important since the microgrids are small-scale systems, whose stability depends highly on the generators' performance.

- The process continues for a limited number of iterations. The algorithm memorises the optimal solution in a way that compares it to the global best.
- In the final step, total profit from trading power with the utility grid is calculated and the penalty costs are evaluated based on the time of an outage. The solution with the highest profit is considered to be the optimal one.

V. DESCRIPTION OF THE OPTIMISATION ALGORITHMS

In this section, the Dynamic Programming (DP) method, GA and PSO basic settings will be discussed, and the comparison between the three methods will be presented.

A. *Dynamic programming*

DP method is a classical optimisation method set by Bellman in the 1950s. The method provides an optimal solution to a certain issue by dividing the main problem into many smaller sub-problems. The DP optimisation method uses a set of algorithms for finding an optimal solution to a wide range of input data. The optimisation is done by maximising or minimising an objective function.

The solution to each of the sub-problems eventually gives the optimal solution to the main problem. Although the method can be classified as a "divide and conquer" group of methods, it works opposite of them [25]. The optimisation is done by analysing the sub-problems first, which are simpler expressions. The solution of each sub-problem is memorised. The set of all conditionally optimal solutions leads to the solution of the main problem.

Many nonlinear problems, from any field, can be solved using the DP method. Its application is widely known for power system planning, optimal unit commitment in complex power systems, which cannot be solved by standard methods of nonlinear programming and energy management optimisation. In power systems optimisation, usually, the method is used for minimising the costs or maximising the profit. In energy management optimisation, the method is mostly used for the optimisation of emissions from the power plants [26].

The simple microgrid optimisation and unit commitment problem can be solved using classical optimisation techniques, such as the Dynamic Programming (DP) method, as presented in [27]. However, adding the voltage stability constraint makes the problem more complex, and therefore a different optimisation technique is required.

B. *Genetic Algorithm*

The most commonly used heuristic optimisation algorithms are the Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO). Each of these algorithms is based on natural running processes.

GA is a heuristic optimisation technique, inspired by the Darwinian principle of evolution through genetic mutation and selection. The method is an abstract version of the evolutionary process in which for a certain number of populations of chromosomes, a mutation and selection are made [28]. The chromosomes are encoded strings (usually in a binary system) that carry the information of one generation [29]. The chromosomes are tested for fitness in a certain function, which grades the solution to the analysed problem. If the solution is satisfactory, then the next generation is created.

Each generation of chromosomes has parents. The genes of the child chromosomes are created by two parent chromosomes. For that purpose, a crossover should be defined. The crossover is a point to which recombination of genes of the parent chromosomes is made. The new set of genes is the child chromosome. In the next step, a mutation of a certain gene is done.

The iterations continue for a certain population. As the number of iterations increases, eventually, the chromosomes' fitness increases and the solution improves. The process runs until the stopping criteria are reached. In this way, the optimal solution to a problem is determined [30].

C. *Particle Swarm Optimisation*

PSO is an optimisation technique inspired by the motion of bird flocks and schooling fish [31]. Similar to the GA, in PSO, the system is initialized with a population of random solutions, and the search for the optimal solution is performed by updating generations. However, this method does not have crossover and mutation steps and it requires a lower number of iterations [32].

PSO method is based on the movement of particles in space, which in the algorithm, represent the potential solutions [32]. At each point the algorithm memorises the best performance of the particle (the best solution), creating the optimal movement path. Although this might seem like an advantage, it decreases the method's accuracy.

D. *GA and PSO combination*

The comparison between GA and PSO performance on optimising a hybrid RES system presented in [33] shows that both, GA and PSO, are efficient for optimising complex problems. However, each of the optimisation methods achieves better results under well-defined objective functions and constraints. PSO is computationally more efficient than GA in terms of both speed and memory requirements. And although it is less practical, it is found to be quite applicable for unit commitment problems in microgrids [33].

Many research combine the GA and PSO, creating an even better and more efficient optimisation algorithm. In [35] a combined GA and PSO algorithm is proposed for optimisation and sizing of distributed generation. The proposed algorithm should minimise network power losses, improve voltage regulation, and improve voltage stability. The PSO algorithm is used for finding the optimal sizing of the distributed generation, and GA is used for calculating the optimal sitting of the distributed generation. The results show that the combination of these two algorithms provides a better solution than their separate usage.

This shows that for some problems, the best solution is provided by combining two optimisation algorithms. For the presented microgrid optimisation problem, we propose a combination of GA and PSO.

VI. Selection of an Optimisation Algorithm

The summary of the advantages and disadvantages of some optimisation algorithms in Table 1, shows that the DP method cannot be used for the optimisation of complex systems as the one presented in sections III and IV. However, the combination of GA and PSO can and will be used for that purpose.

TABLE I. Comparison of optimisation algorithms

Optimisation Algorithms	Advantages	Disadvantages
Dynamic Programming	- Splitting a problem into simpler sub-problems. - Solving much simpler problems gives the optimal solution. - Easy to implement to any kind of problem.	Complex problems which require multi-objective optimisation cannot be solved.
Genetic Algorithm	- The optimal solution is calculated through a selection of multiple iterations, each one better than the other. - Fast convergence. - Can be used in many fields.	Selecting true selection criteria, crossover, and mutation parameters are essential for better optimisation.
Particle Swarm Optimisation	- Does not require crossover and mutation parameters. - Memorises the previous conditional optimal solution. - Fast convergence. - Applicable for many different types of optimisation problems.	Requires complex computations.

Since GA requires a larger number of iterations and has a simpler computation algorithm, it will be used for the unit commitment problem of the microgrid. The output of the GA (the optimal solution) will be a parameter to which the voltage stability of the nodes will be computed. For that purpose, the PSO can be used.

The optimisation algorithm consisting of both, GA and PSO, will give the unit commitment and economic dispatch of the microgrid.

VII. Conclusion

Each microgrid is unique. There are many microgrid test-beds around the world and each of them defers from the others. Starting from the location and to its performance. Therefore, there is not an empirical solution to the microgrid optimisation problem. And that is what makes it challenging.

This paper presented the most used algorithms for the optimisation of grid-connected microgrids. Since it is a complex problem that requires a detailed analysis of every entity of the microgrids, at each moment, it cannot be said that the solution is unified. Each research proposes a unique solution to this problem. This means that in the planning and operation of microgrids, one can choose which optimisation algorithm suits the best for one's microgrid, according to its unique constraints.

The paper proposed a methodology for solving a complex optimisation problem, considering the uncertainties of weather conditions and power demand. The algorithm considers the penalty costs, as much stronger criteria for obtaining an optimal solution.

Dividing the problem into two different problems (unit commitment and voltage stability), which will be computed separately by GA and PSO, will simplify this problem and provide the optimal solution of the microgrid’s operation.

In future work, the implementation of the proposed methodology on a test example and the results of that case study will be presented and discussed.

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