Planning and management strategies of direct current microgrids for cost optimization and improvement of operating conditions

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Doctoral Thesis

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Manizales, Colombia
2020
Dedicated to

To God...

To my family. Thanks for your patience and support

In loving memory of my father Fernando (1966 - 2000)

To my advisors Carlos Ramos and Daniel Gonzalez...Thanks a lot

To my partner and friend Danilo Montoya...Thanks for the support

A Dios...

A mi familia. Gracias por su paciencia y apoyo

En amoroso recuerdo de mi padre Fernando (1966 - 2000)

A mis asesores Carlos Ramos y Daniel Gonzalez...Gracias por todo

A mi compañero y amigo Danilo Montoya...Gracias por el apoyo
Abstract

This thesis develops planning and management strategies of direct current microgrids for improving the operating conditions and optimization cost. The first part of this work addresses the power flow problem in direct current grids, where five different solutions are proposed. In the particular case of the radial topology, three methods are proposed based on the triangular matrix formulation, graph theory and sweep methods. In addition, two iterative approaches are proposed for solving the power flow problem in direct current grids with mesh or radial grids, those based on Taylor series expansion and successive approximations, respectively. The second part of this thesis proposes three master–slave methodologies for sizing distributed generators in direct current microgrids. The master stage is in charge to size the generators by using three continuous methods: a continuous version of the genetic algorithm, the black hole optimization method and the particle swarm optimization algorithm. The slave stage use the successive approximation power flow method by adopting as objective function the minimization of the power loss. The main objective of this part of the thesis is to find the methodology that provides the best balance between solution quality and processing time. The third part of the thesis focuses on the technical impact of the optimal integration of distributed energy resources on direct current microgrids. This is addressed by proposing a hybrid methodology for optimal location and sizing of distributed generators in direct current networks, which consists on a hybrid methodology between the parallel population-based incremental learning and the particle swarm optimization method, where the objective function is the reduction of the power losses. Finally, this thesis proposes two energy management systems for standalone and grid–connected direct current microgrids which considers, as main objective, the improvement of the technical aspects (voltage and currents bounds, state of charge of the batteries, power and energy capabilities, among other) and the reduction of the operational costs. The first energy management system is propose for a standalone direct current microgrid by considering the control of the photovoltaic generation and battery storage system. Such an energy management system enables the photovoltaic system to control the power generation and ensures that the power storage element does not exceed the technical limits of the state of charge. The second energy management system is aimed at reducing the energy cost purchased to the utility grid by a direct current microgrid formed by distributed generators, battery storage systems and electrical loads. This solution takes into account the state-of-charge of the battery storage systems and the variable production of the renewable generators, in particular of wind and photovoltaic technologies, and the variations in the power consumption and energy costs.

All the methods, methodologies and strategies in this thesis are based on sequential programming to avoid the use of software with undesired requirements, such as high cost (commercial software), or the requirement of prepossessing of the input and/or output data. In addition,
those solutions are validated through different simulations, where other methods proposed in literature are used as comparison references. All simulations are carried out in the software Matlab and in the Power Electronics Simulator PSIM.

Keywords: Direct current networks, distributed generation, energy storage systems, parallel processing; optimal power flow, cost optimization, combinatorial optimization.
Estrategias de planeamiento y gestión de microrredes de corriente continua para optimización de costos y mejora de las condiciones operativas

Resumen

Esta tesis desarrolla estrategias de planeación y gestión para microrredes de corriente continua con el objetivo de mejorar las condiciones y costos operativos. La primera parte de esta tesis aborda el problema de flujo de potencia en redes de corriente continua, donde cinco soluciones son propuestas. En el caso particular de las redes de topología radial, son propuestos tres métodos basados en la formulación triangular, teoría de grafos y métodos de barrido. Adicionalmente, dos enfoques iterativos son propuestos para resolver el problema de flujo de potencia en redes de corriente continua con topología radial o enmallada, los cuales son basados en expansiones de series de Taylor y aproximaciones sucesivas. La segunda parte de esta tesis propone tres metodologías maestro–esclavo para dimensionar generadores distribuidos en redes de corriente continua. La etapa maestra es encargada de dimensionar los generadores empleando tres métodos continuos: Una versión continua del algoritmo genético, el algoritmo de optimización basado en agujeros negros y el algoritmo de optimización por cálculo de partículas. La etapa esclava utiliza el método de flujo de potencia basado en aproximaciones sucesivas adoptando como función objetivo la reducción de pérdidas de potencia. El objetivo principal de esta parte de la tesis es encontrar la metodología que proporciona el mejor balance entre calidad de la solución y tiempos de procesamiento. La tercera parte de esta tesis se enfoca en el impacto técnico de la integración óptima de recursos energéticos distribuidos en microrredes de corriente continua. Lo cual se aborda al proponer una metodología híbrida para la ubicación y dimensionamiento óptimo de generadores distribuidos en microrredes de corriente continua, la cual emplea una versión paralela del algoritmo basado en aprendizaje incremental y el algoritmo de optimización por cálculo de partículas; implementando como función objetivo la reducción de las pérdidas de potencia. Finalmente, esta tesis propone dos estrategias de gestión de la energía para redes de corriente continuas aisladas y conectadas a la red, las cuales consideran como objetivos principales la mejora de aspectos técnicos de la red (límites de corriente y tensión, estado de carga de las baterías, límites de potencia y energía, entre otros) y la reducción de costos operacionales. La primera estrategia de gestión de energía se propone para una red aislada de corriente continua, la cual considera el control de la generación fotovoltaica y los sistemas de almacenamiento de energía. Dicha estrategia de gestión permite a los sistemas de generación fotovoltaica controlar la generación de potencia y asegurar que los elementos almacenadores no excedan los límites de estado de carga. La segunda estrategia de gestión de la energía busca reducir los costos de compra de energía a el operador de red para una microrred formada por generadores distribuidos, almacenadores de energía y cargas eléctricas. Esta solución
considera el estado de carga de los sistemas de baterías y la producción de energía variable de los generadores a base de energías renovables, en particular de las tecnologías eólicas y fotovoltaicas, como también, la variación del consumo de potencia y costos de la energía.

Todas las metodologías y estrategias propuestas en esta tesis son basadas en programación secuencial para evitar el uso de software con requerimientos indeseados, como altos costos (software comerciales), o la necesidad de pre–procesar los datos de entrada y/o salida. Adicionalmente, estas soluciones fueron validadas a través de diferentes simulaciones, donde otros métodos propuestos en la literatura fueron usados como referencias de comparación. Todas las simulaciones fueron llevadas a cabo en el software Matlab y el simulador de electrónicos de potencia PSIM.

**Palabras clave:** Redes de corriente continua, generación distribuida, sistemas de almacenamiento de energía, procesamiento paralelo, flujo de potencia óptimo, optimización de costos, optimización combinatorial.
Preface

This thesis reports the results of my PhD studies at the Departamento de Ingeniería Eléctrica, Electrónica y Computación, Facultad de Ingeniería y Arquitectura, Universidad Nacional de Colombia. This work was carried out between August of 2017 to June of 2020. This thesis was supported by the Universidad Nacional de Colombia and Colciencias under the project: Estrategia de transformación del sector energético Colombiano en el horizonte de 2030 - Energética 2030 - ”Generación distribuida de energía eléctrica en Colombia a partir de energía solar y eólica” (Code: 58838, Hermes: 38945).

The results reported in this thesis were published in six international journals and two conference proceedings (See appendix A). However, the thesis format makes it easier for the reader to understand the overall work and to identify the improvements in the state of the art. Moreover, the publications significantly improve the diffusion of the thesis results.

The thesis follows common publishing guidelines given by international journals. Similarly, the bibliographical citations, the equations, figures and tables have been numbered in order of appearance. Both roman and italic fonts are used in the text, the latter being used to highlight important issues, differentiate nouns and mark non-English words. Finally, the simulations developed in this work have been carried out by using Matlab, while some simulations which include power electronics circuits have been carried out by using PSIM software.
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Abbreviations and nomenclature

This section presents the abbreviations and nomenclature employed along the thesis.

Abbreviations

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<tr>
<td>PSIM</td>
<td>Power Electronics Simulation</td>
</tr>
<tr>
<td>SG</td>
<td>Smart Grid</td>
</tr>
<tr>
<td>MG</td>
<td>Microgrid</td>
</tr>
<tr>
<td>MGs</td>
<td>Microgrids</td>
</tr>
<tr>
<td>DG</td>
<td>Distributed Generator</td>
</tr>
<tr>
<td>DGs</td>
<td>Distributed Generators</td>
</tr>
<tr>
<td>ESS</td>
<td>Energy Storage Systems</td>
</tr>
<tr>
<td>RES</td>
<td>Renewable Energy Resources</td>
</tr>
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<td>Alternating Current</td>
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<tr>
<td>DC</td>
<td>Direct Current</td>
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<td>DERs</td>
<td>Distributed Energy Resources</td>
</tr>
<tr>
<td>EMS</td>
<td>Energy Management System</td>
</tr>
<tr>
<td>SOC</td>
<td>State-of-Charge</td>
</tr>
<tr>
<td>PF</td>
<td>Power Flow</td>
</tr>
<tr>
<td>OPF</td>
<td>Optimal Power Flow</td>
</tr>
<tr>
<td>BSS</td>
<td>Battery Storage Systems</td>
</tr>
<tr>
<td>PSO</td>
<td>Particle Swarm Optimization algorithm</td>
</tr>
<tr>
<td>PV</td>
<td>Photovoltaic</td>
</tr>
<tr>
<td>PVS</td>
<td>Photovoltaic System</td>
</tr>
<tr>
<td>SPVS</td>
<td>Standalone Photovoltaic System</td>
</tr>
<tr>
<td>MPP</td>
<td>Maximum Power Point</td>
</tr>
<tr>
<td>MPPT</td>
<td>Maximum Power Point Tracking</td>
</tr>
<tr>
<td>SA</td>
<td>Successive Approximations</td>
</tr>
<tr>
<td>PPBILL</td>
<td>Parallel Population-Based Incremental Learning</td>
</tr>
<tr>
<td>TBM</td>
<td>Taylor’s Series Based Approximation</td>
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<td>TM</td>
<td>Triangular Matrix</td>
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<tr>
<td>SMBGT</td>
<td>Sweep Method Based on Graph Theory</td>
</tr>
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<td>Abbreviations</td>
<td>Description</td>
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<td>---------------</td>
<td>-------------</td>
</tr>
<tr>
<td>BF</td>
<td>Backward Forward Sweep Method</td>
</tr>
<tr>
<td>P</td>
<td>Constant Power Load</td>
</tr>
<tr>
<td>R</td>
<td>Resistive Load</td>
</tr>
<tr>
<td>NR</td>
<td>Newton Raphson</td>
</tr>
<tr>
<td>GJ</td>
<td>Gauss - Jacobi</td>
</tr>
<tr>
<td>GS</td>
<td>Gauss - Seidel</td>
</tr>
<tr>
<td>BH</td>
<td>Black hole</td>
</tr>
<tr>
<td>CGA</td>
<td>Continuous genetic algorithm</td>
</tr>
<tr>
<td>STD</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>PBIL</td>
<td>Population Based Incremental Learning</td>
</tr>
<tr>
<td>PMC</td>
<td>Monte Carlo Algorithm</td>
</tr>
<tr>
<td>GPU</td>
<td>Graphics Processing Units</td>
</tr>
<tr>
<td>PM</td>
<td>Probability Matrix</td>
</tr>
<tr>
<td>PPT</td>
<td>Paralleling Processing Time</td>
</tr>
<tr>
<td>NEC</td>
<td>National Electrical Code</td>
</tr>
<tr>
<td>MTRP</td>
<td>Maximum Time Required to Evaluated the Fitness Function</td>
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<tr>
<td>PMC</td>
<td>Parallel Monte-Carlo</td>
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<tr>
<td>P&amp;O</td>
<td>Perturb and Observe Algorithm</td>
</tr>
<tr>
<td>SVE</td>
<td>Square Voltage Error</td>
</tr>
<tr>
<td>PVSs</td>
<td>Photovoltaic Systems</td>
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<tr>
<td>PDT</td>
<td>Power Demand Tracking</td>
</tr>
<tr>
<td>ESD</td>
<td>Energy Storage Device</td>
</tr>
<tr>
<td>CV</td>
<td>Constant Voltage mode</td>
</tr>
<tr>
<td>OR</td>
<td>Operating Regions</td>
</tr>
<tr>
<td>OR1</td>
<td>Operating Region 1</td>
</tr>
<tr>
<td>OR2</td>
<td>Operating Regions 2</td>
</tr>
<tr>
<td>OR3</td>
<td>Operating Regions 3</td>
</tr>
<tr>
<td>SMC</td>
<td>Sliding Mode Controller</td>
</tr>
<tr>
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<td>Constant Power Load</td>
</tr>
<tr>
<td>CIL</td>
<td>Constant Impedance Load</td>
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<td>SR</td>
<td>Solar Radiation</td>
</tr>
<tr>
<td>STC</td>
<td>Standard Conditions</td>
</tr>
<tr>
<td>PPSO</td>
<td>Parallel PSO</td>
</tr>
<tr>
<td>PS</td>
<td>Particle Swarm</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial Neuronal Network</td>
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Nomenclature
## Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v$</td>
<td>Bus voltage in all buses of DC grid</td>
</tr>
<tr>
<td>$i$</td>
<td>Net injected currents in all buses of the DC grid</td>
</tr>
<tr>
<td>$p$</td>
<td>Power in all buses of the DC grid</td>
</tr>
<tr>
<td>$D(v)$</td>
<td>Diagonal positive definite matrix</td>
</tr>
<tr>
<td>$G$</td>
<td>Nodal admittance matrix of the DC grid</td>
</tr>
<tr>
<td>$G_B$</td>
<td>Conductance matrix associated to the branches of the DC grid</td>
</tr>
<tr>
<td>$G_n$</td>
<td>Conductance matrix associated to the resistive loads connected to the DC grid</td>
</tr>
<tr>
<td>$G_{gg}$</td>
<td>Conductance matrix associated to the generators connections</td>
</tr>
<tr>
<td>$G_{dd}$</td>
<td>Conductance matrix associated to the load connections</td>
</tr>
<tr>
<td>$G_{dg}$</td>
<td>Conductance matrix that relating the generators and loads</td>
</tr>
<tr>
<td>$i_g$</td>
<td>Current at the voltages buses</td>
</tr>
<tr>
<td>$i_d$</td>
<td>Current at the demand buses</td>
</tr>
<tr>
<td>$v_g$</td>
<td>Voltage at the voltages buses</td>
</tr>
<tr>
<td>$v_d$</td>
<td>Voltage at the demand buses</td>
</tr>
<tr>
<td>$p_g$</td>
<td>Power generation at the voltages buses</td>
</tr>
<tr>
<td>$p_d$</td>
<td>Power consumed or injected at demand buses</td>
</tr>
<tr>
<td>$i_k$</td>
<td>Net Current at the $k^{th}$ bus</td>
</tr>
<tr>
<td>$v_k$</td>
<td>Voltage at the $k^{th}$ bus</td>
</tr>
<tr>
<td>$p_k$</td>
<td>Power at the $k^{th}$ bus</td>
</tr>
<tr>
<td>$v_0^d$</td>
<td>Initial voltage profiles at the demand buses</td>
</tr>
<tr>
<td>$v_d^t$</td>
<td>Voltage profiles in $t$ iteration at the demand buses</td>
</tr>
<tr>
<td>$t_{max}$</td>
<td>Maximum iterations number</td>
</tr>
<tr>
<td>$n$</td>
<td>Number of buses at the DC grid</td>
</tr>
<tr>
<td>$b$</td>
<td>Number of branches at the DC grid</td>
</tr>
<tr>
<td>$R_p$</td>
<td>Primitive resistance matrix</td>
</tr>
<tr>
<td>$R_{ij}$</td>
<td>Resistive parameter of the branch that connects the buses $i$ and $j$</td>
</tr>
<tr>
<td>$i_B$</td>
<td>Branch currents</td>
</tr>
<tr>
<td>$T$</td>
<td>Triangular incidence matrix</td>
</tr>
<tr>
<td>$\Delta v_B$</td>
<td>Vector of voltage drops in all the branches</td>
</tr>
<tr>
<td>$v_0$</td>
<td>Voltage at the slack bus</td>
</tr>
<tr>
<td>$R_{bus}$</td>
<td>Equivalent impedance matrix</td>
</tr>
<tr>
<td>$A$</td>
<td>Incidence matrix</td>
</tr>
<tr>
<td>$A_0$</td>
<td>Incidence matrix associated at the bus 0</td>
</tr>
<tr>
<td>$R$</td>
<td>Resistive loads</td>
</tr>
<tr>
<td>$v_s$</td>
<td>Voltage on the main generator</td>
</tr>
<tr>
<td>$P_{loss}$</td>
<td>Power loss</td>
</tr>
<tr>
<td>$min$</td>
<td>Minimum</td>
</tr>
<tr>
<td>$max$</td>
<td>Maximum</td>
</tr>
<tr>
<td>$p_{dg}$</td>
<td>Power supplied by DGs</td>
</tr>
</tbody>
</table>
## Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_L$</td>
<td>Power demanded by the loads at the buses</td>
</tr>
<tr>
<td>$P_{min}^g$</td>
<td>Minimum power that the slack bus can supply</td>
</tr>
<tr>
<td>$P_{max}^g$</td>
<td>Maximum power that the slack bus can supply</td>
</tr>
<tr>
<td>$P_{min}^{dg}$</td>
<td>Minimum power that the DGs can supply</td>
</tr>
<tr>
<td>$P_{max}^{dg}$</td>
<td>Maximum power that the DGs can supply</td>
</tr>
<tr>
<td>$P_{max}^{DG}$</td>
<td>Maximum distributed generation level</td>
</tr>
<tr>
<td>$V_{min}$</td>
<td>Minimum allowable voltage at the buses of the DC grid</td>
</tr>
<tr>
<td>$V_{max}$</td>
<td>Maximum allowable voltage at the buses of the DC grid</td>
</tr>
<tr>
<td>$\text{Ones}$</td>
<td>Vector filled with ones</td>
</tr>
<tr>
<td>$z$</td>
<td>Fitness function</td>
</tr>
<tr>
<td>$\beta_n$</td>
<td>$n^{th}$ penalization factor</td>
</tr>
<tr>
<td>$P_t$</td>
<td>Population at the iteration $t$</td>
</tr>
<tr>
<td>$n_i$</td>
<td>Number of stars</td>
</tr>
<tr>
<td>$n_{dg}$</td>
<td>Number of DGs</td>
</tr>
<tr>
<td>$o(n_i, n_{dg})$</td>
<td>Rectangular matrix filled with ones</td>
</tr>
<tr>
<td>$r(n_i, n_{dg})$</td>
<td>Rectangular matrix filled with random numbers</td>
</tr>
<tr>
<td>$P_{dg(l,k)}$</td>
<td>Active power generated by the generator $k$ at the $l$ solution individual</td>
</tr>
<tr>
<td>$P_{BH}^t$</td>
<td>Black hole in population $t$</td>
</tr>
<tr>
<td>$P_i^t$</td>
<td>$i^{th}$ individual of the population at the iteration $t$</td>
</tr>
<tr>
<td>$f(P_{t+1})$</td>
<td>best fitness function value of all individuals</td>
</tr>
<tr>
<td>$R_{EH}$</td>
<td>Event horizon radius</td>
</tr>
<tr>
<td>$D_{BH}$</td>
<td>Euclidean distance</td>
</tr>
<tr>
<td>$r$</td>
<td>Random number</td>
</tr>
<tr>
<td>$r_p$</td>
<td>Recombination probability</td>
</tr>
<tr>
<td>$m_p$</td>
<td>Mutation probability</td>
</tr>
<tr>
<td>$\text{bestsol}_i$</td>
<td>Best solution for each particle</td>
</tr>
<tr>
<td>$\text{bestpos}_i$</td>
<td>Best position for each particle</td>
</tr>
<tr>
<td>$\text{bestsol}_g$</td>
<td>Best solution of the particle swarm</td>
</tr>
<tr>
<td>$\text{bestpos}_g$</td>
<td>Best position of the particle swarm</td>
</tr>
<tr>
<td>$x_t$</td>
<td>Position of the particle swarm at the iteration $t$</td>
</tr>
<tr>
<td>$MS^t$</td>
<td>Movement speed of the particle swarm at the iteration $t$</td>
</tr>
<tr>
<td>$MS_{min}^{\text{t}}$</td>
<td>Minimum value allowed for the movement speed of each particle</td>
</tr>
<tr>
<td>$MS_{max}^{\text{t}}$</td>
<td>Maximum value allowed for the movement speed of each particle</td>
</tr>
<tr>
<td>$o(P, n_{dg})$</td>
<td>Rectangular matrix filled with ones</td>
</tr>
<tr>
<td>$r(P, n_{dg})$</td>
<td>Rectangular matrix filled with random numbers</td>
</tr>
<tr>
<td>$MS_t^i$</td>
<td>Movement speed of the $i^{th}$ particle at the iteration $t$</td>
</tr>
<tr>
<td>$\Omega^t$</td>
<td>Inertia factor at the iteration $t$</td>
</tr>
<tr>
<td>$\Omega_{min}^t$</td>
<td>Minimum inertia factor value</td>
</tr>
<tr>
<td>$\Omega_{max}^t$</td>
<td>Maximum inertia factor value</td>
</tr>
<tr>
<td>Nomenclature</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>-------------</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>Cognitive factor</td>
</tr>
<tr>
<td>$\phi_2$</td>
<td>Social factor</td>
</tr>
<tr>
<td>$N$</td>
<td>Set of buses of the DC grid</td>
</tr>
<tr>
<td>$G_{ij}$</td>
<td>$ij^{th}$ component of the matrix of conductances</td>
</tr>
<tr>
<td>$G_{i0}$</td>
<td>Conductance associated to the resistive load connected at bus $i$</td>
</tr>
<tr>
<td>$v_i$</td>
<td>Voltage at the bus $i$</td>
</tr>
<tr>
<td>$v_j$</td>
<td>Voltage at the bus $j$</td>
</tr>
<tr>
<td>$p_i^g$</td>
<td>Power generated at the bus $i$</td>
</tr>
<tr>
<td>$p_i^d$</td>
<td>Power consumed at the bus $i$</td>
</tr>
<tr>
<td>$i_{ij}$</td>
<td>Current of the branch that connects the buses $i$ and $j$</td>
</tr>
<tr>
<td>$I_{ij}^{max}$</td>
<td>Maximum current allowed in that branch that connects the buses $i$ and $j$</td>
</tr>
<tr>
<td>$B$</td>
<td>Set of branches that form the electrical network</td>
</tr>
<tr>
<td>$x_{i^d}^g$</td>
<td>Binary variable that indicates the location of a DG at the bus $i$</td>
</tr>
<tr>
<td>$D$</td>
<td>Set of buses selected for locating DGs</td>
</tr>
<tr>
<td>$NDG_{max}$</td>
<td>Maximum number of DGs</td>
</tr>
<tr>
<td>$PS$</td>
<td>Population size</td>
</tr>
<tr>
<td>$P(i,j)$</td>
<td>Probability of the option $j$ to be selected on element $h$</td>
</tr>
<tr>
<td>$P(i,j)_{Old}$</td>
<td>Non-updated probability of position $(i,j)$</td>
</tr>
<tr>
<td>$P(i,j)_{Act}$</td>
<td>Updated probability of position $(i,j)$</td>
</tr>
<tr>
<td>$P(i,j)_{New}$</td>
<td>New probability of position $(i,j)$</td>
</tr>
<tr>
<td>$LR$</td>
<td>Learning rate</td>
</tr>
<tr>
<td>$LR_{min}$</td>
<td>Minimum learning rate value</td>
</tr>
<tr>
<td>$LR_{max}$</td>
<td>Maximum learning rate value</td>
</tr>
<tr>
<td>$W$</td>
<td>Number of workers of the processor</td>
</tr>
<tr>
<td>$E_n$</td>
<td>Entropy of the $PM$</td>
</tr>
<tr>
<td>$E_{TOL}$</td>
<td>Tolerance error assigned to $E_n$</td>
</tr>
<tr>
<td>$FF$</td>
<td>Fitness Function</td>
</tr>
<tr>
<td>$P_{ESD}$</td>
<td>Power supplied or stored by the ESD</td>
</tr>
<tr>
<td>$P_{PV}$</td>
<td>Power generated by the PVS</td>
</tr>
<tr>
<td>$P_{Load}$</td>
<td>Power demanded by the load</td>
</tr>
<tr>
<td>$SOC_{Max}$</td>
<td>Maximum state of charge of the battery</td>
</tr>
<tr>
<td>$SOC_{Min}$</td>
<td>Minimum state of charge of the battery</td>
</tr>
<tr>
<td>$SOC_{Rec}$</td>
<td>Recovery level assigned to the state of charge of the battery</td>
</tr>
<tr>
<td>$V_{PV-REF}$</td>
<td>Voltage reference of the PVS</td>
</tr>
<tr>
<td>$i_{pv}$</td>
<td>PV current</td>
</tr>
<tr>
<td>$v_{pv}$</td>
<td>PV voltage</td>
</tr>
<tr>
<td>$i_{ph}$</td>
<td>PV photo-induced current</td>
</tr>
<tr>
<td>$i_o$</td>
<td>Inverse saturation current</td>
</tr>
<tr>
<td>$R_s$</td>
<td>Series resistance</td>
</tr>
</tbody>
</table>
## Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_h$</td>
<td>Shunt resistances</td>
</tr>
<tr>
<td>$q$</td>
<td>Electron charge</td>
</tr>
<tr>
<td>$k$</td>
<td>Boltzmann constant</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Quality factor</td>
</tr>
<tr>
<td>$N_c$</td>
<td>Number of cells</td>
</tr>
<tr>
<td>$T_c$</td>
<td>Temperature in Kelvin</td>
</tr>
<tr>
<td>$C_{pv}$</td>
<td>Capacitor in parallel with the PV</td>
</tr>
<tr>
<td>$L_{pv}$</td>
<td>Inductance of the unidirectional DC/DC converter of the PV</td>
</tr>
<tr>
<td>$i_{L_{pv}}$</td>
<td>Current of the unidirectional DC/DC converter of the PV</td>
</tr>
<tr>
<td>$v_{dc}$</td>
<td>Bus voltage</td>
</tr>
<tr>
<td>$u_{pv}$</td>
<td>Activation signal of the converter MOSFET of the PV</td>
</tr>
<tr>
<td>$P_c$</td>
<td>Maximum allowable power for the capacitor</td>
</tr>
<tr>
<td>$V_{Bat}$</td>
<td>Battery nominal voltage</td>
</tr>
<tr>
<td>$\Delta V$</td>
<td>Maximum voltage drop allowed at the capacitor</td>
</tr>
<tr>
<td>$v_{ESD}$</td>
<td>ESD voltage</td>
</tr>
<tr>
<td>$L_{ESD}$</td>
<td>Inductor of the bidirectional DC/DC converter of the ESD</td>
</tr>
<tr>
<td>$i_{L_{ESD}}$</td>
<td>Current of the bidirectional DC/DC converter of the ESD</td>
</tr>
<tr>
<td>$u_{ESD}$</td>
<td>Activation signal of the MOSFETs of the ESD</td>
</tr>
<tr>
<td>$V_c$</td>
<td>Capacitor voltage</td>
</tr>
<tr>
<td>$V_{cMax}$</td>
<td>Maximum allowable voltage at the capacitor</td>
</tr>
<tr>
<td>$V_{cMin}$</td>
<td>Minimum allowable voltage at the capacitor</td>
</tr>
<tr>
<td>$V_{oc}$</td>
<td>Open circuit voltage at the PV</td>
</tr>
<tr>
<td>$SW_{Load}$</td>
<td>Switch that connect and disconnect the load</td>
</tr>
<tr>
<td>$SW_{Bat}$</td>
<td>Switch that connect and disconnect the battery</td>
</tr>
<tr>
<td>$V_{Bat}$</td>
<td>Battery voltage</td>
</tr>
<tr>
<td>$cg$</td>
<td>Conventional generator</td>
</tr>
<tr>
<td>$Ec_{cost_{cg}}$</td>
<td>Total energy purchasing costs associated to the $cg$</td>
</tr>
<tr>
<td>$\Omega_H$</td>
<td>Set that contains the time horizon of operation</td>
</tr>
<tr>
<td>$\Omega_{cg}$</td>
<td>Set that contains the buses with conventional generators installed</td>
</tr>
<tr>
<td>$cost_{s_{cg}^{i,h}}$</td>
<td>Energy purchasing costs by $cg$ installed at the bus $i$ at the operation period $h$</td>
</tr>
<tr>
<td>$P_{cg}^{i,h}$</td>
<td>Power generated by $cg$ installed at the bus $i$ in the operation period $h$</td>
</tr>
<tr>
<td>$\Delta t$</td>
<td>Length of the period under analysis</td>
</tr>
<tr>
<td>$P_{dg}^{i,h}$</td>
<td>Power generated by $dg$ installed at the bus $i$ in the operation period $h$</td>
</tr>
<tr>
<td>$P_{i,h}^{B}$</td>
<td>Power supplied or stored by the BSS installed at the bus $i$ in the period $h$</td>
</tr>
<tr>
<td>$P_{i,h}^L$</td>
<td>Power consumed by the loads installed at the bus $i$ on the period $h$</td>
</tr>
<tr>
<td>$\Omega_N$</td>
<td>Set that contains all the buses of the system</td>
</tr>
<tr>
<td>$v_{i,h}$</td>
<td>Voltages of the bus $i$ at the period $h$</td>
</tr>
<tr>
<td>$v_{j,h}$</td>
<td>Voltages of the bus $j$ at the period $h$</td>
</tr>
<tr>
<td>$\Omega_{dg}$</td>
<td>Set that contains all buses with distributed generators installed</td>
</tr>
</tbody>
</table>
## Nomenclature Description

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Omega_B$</td>
<td>Set that contains all buses with BSS installed</td>
</tr>
<tr>
<td>$P_{\text{min}}^{cg}$</td>
<td>Minimum generation power allowed for each $cg$</td>
</tr>
<tr>
<td>$P_{\text{max}}^{cg}$</td>
<td>Maximum generation power allowed for each $cg$</td>
</tr>
<tr>
<td>$P_{\text{disch}}^{\text{max}}_i$</td>
<td>Maximum power of discharge allowed for the BSS installed at the bus $i$</td>
</tr>
<tr>
<td>$P_{\text{charg}}^{\text{max}}_i$</td>
<td>Maximum power of charge allowed for the BSS installed at the bus $i$</td>
</tr>
<tr>
<td>$E_{n_i}^B$</td>
<td>Energy capability of the BSS installed at the bus $i$</td>
</tr>
<tr>
<td>$t_{d_i}^B$</td>
<td>Discharge time of the BSS installed at the bus $i$</td>
</tr>
<tr>
<td>$t_{c_i}^B$</td>
<td>Charge times of the BSS installed at the bus $i$</td>
</tr>
<tr>
<td>$SOC_{i,h}^{B}$</td>
<td>SOC of the BSS installed at the bus $i$ at the period $h$</td>
</tr>
<tr>
<td>$SOC_{i,\text{Max}}^i$</td>
<td>Maximum state of charge of the battery installed at the bus $i$</td>
</tr>
<tr>
<td>$SOC_{i,\text{Min}}^i$</td>
<td>Minimum state of charge of the battery installed at the bus $i$</td>
</tr>
<tr>
<td>$\phi_i^B$</td>
<td>Charge coefficient of the battery connected at the bus $i$</td>
</tr>
<tr>
<td>$\Delta SOC_{i,\text{charg}}^{\text{max}}$</td>
<td>Max. charge slew-rate of the SOC for the battery installed at the bus $i$</td>
</tr>
<tr>
<td>$\Delta SOC_{i,\text{discharg}}^{\text{max}}$</td>
<td>Max. discharge slew-rate of the SOC for the battery installed at the bus $i$</td>
</tr>
<tr>
<td>$NI$</td>
<td>Number of iterations</td>
</tr>
<tr>
<td>$v_{g,h}^t$</td>
<td>Voltage at the ideal generators on the period $h$</td>
</tr>
<tr>
<td>$v_{d,h}^t$</td>
<td>Voltage at the demand buses on the period $h$</td>
</tr>
<tr>
<td>$P_{d,h}$</td>
<td>Power of the loads and DERs connected to the different buses on the period $h$</td>
</tr>
</tbody>
</table>
1. Introduction

Electrical power grids are an indispensable part of the human infrastructure \[1, 2\]; nevertheless, conventional electrical power systems have also produced harmful effects mainly evidenced as global warming, which is caused by the consumption of fossil fuels (transportation systems and thermo-electric plants) producing tons of greenhouse effect gases \[3\]. In addition, due to the complexity and high costs of the traditional electrical systems, many people around the world live in not interconnected zones.

![Figure 1-1: Microgrid components.](image)

To deal with those problems, new paradigms in electrical systems have been developed in recent decades, as are the cases of Smart Grids (SG) and Microgrids (MGs), by employing a combination of Distributed Generators (DGs), Energy Storage Systems (ESS) and loads \[4\]. Such solutions are intended to replace the dependence on fossil fuels for electricity generation \[5\]. A Microgrid (MG) is an electrical system located close to the final user which integrates different ESS and Renewable Energy Resources (RES) existing in the region, and the electrical network (Grid); while the SG, are autonomous MGs that are operated through smart control techniques. In Fig. [1-1] is presented an example of a Microgrid, where the red and blue arrows represent the devices that generate and demand power, respectively.

The planning and operation of MGs on electrical power systems is a topic widely studied on the world, focusing the efforts in making use of the energy resources in the best possible way \[6\]. Those solutions present as main objectives: the reduction of the environmental
impact associated to the energy generation, increase the coverage of the electrical network and improve the life conditions of the population on the not interconnected zones [7]. The MGs can operate in standalone or grid connected mode and can be of Alternating Current (AC) or Direct Current (DC); however, nowadays DC MGs have been intensively studied and used for power supply due to their advantages over the AC counterparts; some of those advantages are: 

i) no need of synchronizing generators, 

ii) less number of power converters, 

and 

iii) simpler implementation since reactive power and frequency analyses are not required [8]. In the case of AC MGs, multiple works have been developed to select, locate and operate the Distributed Energy Resources (DERs) on the MGs [9] using different solution methods: stochastic, linear and nonlinear, metaheuristic techniques, convex optimization, among others [10, 11]. Those works are focused on improving both the solution quality and the processing times. It is important to note that processing times increase as the electrical systems expand, hence several authors adopt parallel processing tools for reducing the computational time [12]. In this sense, the methods based on sequential programming are widely adopted to avoid the use of software with undesired requirements such as high cost (commercial software) or prepossessing of the input and output data [13, 14]. However, the planning and operation of DC MGs is a topic under development, which is identified in this doctoral thesis as a gap in the state-of-the-art.

For obtaining an optimal planning and operation of a DC MG, two stages are required: the first stage is in charge of the selection, location and sizing the different devices that compose the MG; which are the distribution electrical system, the DGs and the ESS. The second stage corresponds to the energy management of the devices of the MG, which defines the control strategies for each device, and the local or global Energy Management System (EMS). Both stages aim at satisfying the objective functions imposed by the user or operator of the grid, which can be associated to technical, economical or environmental criteria [15]. Some of the different technical constrains of the DC MGs are: global power balance, maximum and minimum State-of-Charge (SOC) allowed for the ESS, currents and voltages bounds, power capacity on DGs, among others [16, 17]. An adequate planning and management of the DC MG allow obtaining different benefits as: reduction of the pollution caused by fossil fuels generation [18, 19], reduction of power losses (due to transport of energy), improvement of voltage profiles and stability index, increased line loadability, reduction of costs, among others [20]. However, wrong planning or management of a MG may result in voltage profiles out of conventional ranges, voltage fluctuations, line capacity violation, increased failure levels due to intermittent generation, higher investment and operational costs, reduction of the lifetime of the DERs and in the worst case, the collapse of the MG [21]. In this doctoral thesis, communication elements will not be included.
In the particular case of the planning of DC MGs, it is necessary to start identifying the types of DGs technologies based on RES that can be used in the region where the MG is going to be localized; as well as the hourly generation and power demanded. This is achieved by employing historical data and forecasting methods [22, 23]. Then, it is necessary planning the electrical system for transporting the energy from the generators to the loads, and locate the main generators, which in most cases, corresponds to the electrical grid and/or generators based on fossil fuels [24]. This stage is neglected in the particular case that the electrical network exist, considering on the planning stage, the location and sizing of DGs and ESS only, which is the case analyzed on this doctoral thesis. For optimal integration of DERs on DC microgrid, it is necessary to consider three different steps (See Figure 1-2): the first step corresponds to the selection and location of the DERs on the MG, the second step sizes the DERs and the third step is responsible for evaluating the impact on the microgrid (branches currents and voltages profiles) of the possible configurations proposed by steps 1 and 2, with the aim to evaluate the objective function fixed by the designer or operator, and to ensure the constraints of the DC MG. In addition, the last step is used to evaluate the different operative states considered on the EMS [25].

Note that, the optimal integration of DERs in DC microgrids is obtained through a cascade strategy that sends and receives information between the steps that form the planning stage, as illustrated in Figure 1-2. For an adequate interpretation of this stage is necessary to start by describing step 3, that addresses DC power flow analysis, which is in charge to evaluating the power values assigned by step 2 (sizing of the DERs); for the type of devices and locations into the DC grid assigned by step 1.

The process to solve the set of quadratic equations that model the DC power flow (PF) in the third step of the planning stage is not a trivial task, which is mainly due to the non-convex characteristic of the solution space [26]. Therefore, to determine the steady state solution of the DC MG with radial or mesh structure, iterative methods have been used, they are based on convex approximations [27, 28] and conventional numerical methods [29]. In this
sense, recently semidefinite programming [27], as well as second-order cone programming models [28]; have been extensively studied for solving optimal power flow problems in DC power grids. Nevertheless, those models take long processing times and increase, in quadratic form, the number of variables of the problem; which may be non-efficient for large scale DC power grids [30]. On the other hand, Gauss–Seidel and Newton–Raphson methods are classical solutions used [17], [31] for solving power flow problems. The main advantage of the Gauss–Seidel method lies in that it does not require any linearization strategy and it is easily implementable for radial and mesh grids with multiple slack nodes. Additionally, its convergence was demonstrated by [31] using Banach space theorems; nevertheless, this method requires many iterations to find the power flow solution, making it less efficient in comparison with the Newton–Raphson method. In case of the Newton–Raphson method, it works with linearization of the power flow equations around the well-defined starting point by using Taylor’s series expansion methods for multi-variable problems; the main advantage of this method lies in the few calculations required to solve the power flow. Besides, in [17] were presented the sufficient conditions to guarantee the convergence of this method for DC power flow problems. Notwithstanding, the recursive updating of the Jacobian matrix for each iteration reduces its computational performance. The previous problems denote the need to propose solution methods for solving the DC power flow with short processing times, but with a satisfactory quality solution. Such a solution is needed to improve the efficiency of the planning and management stages.

In step 2 of the planning stage are evaluated different sizes for the DGs and ESS assigned by the step 1. For analyzing the impact of the sizes of the DERs, it is employed a DC optimal power flow (OPF) to find the power configuration to be injected or stored by the different distributed energy resources in the DC MG; this for obtaining technical, economical and environmental benefits [32]. Those problems are closely related to step 3 because they depend on each other to determine the viability of the network (the OPF depends on the PF). For solving the OPF problem in DC power grids have been proposed equivalent convex formulations as presented in [27] and [28]. The first case proposes a convex reformulation of the OPF equations that to use semidefinite programming by relaxing the non-convex constraint associated to rank one of the matrix of variables, then, after solving the OPF problem, the voltage profiles are recovered using eigenvalues and eigenvectors decomposition [33]. In the second case, a second-order cone programming model is proposed, the authors apply the same relaxing concept of the previous case to solve and recover the solution variables, and both approximations use commercial optimization packages. In microgrid’s control theory the OPF problem is solved for hierarchical controllers [34] or consensus algorithms [35]; they concentrate their power analysis on a global power balance or PF methods [36, 37, 38], according to the topology of the MG used: a single or multiple nodal representation of the grid. In terms of optimization, some approximations of the OPF problem for DC power grids have been presented, and their corresponding OPF equations are solved through optimizing
packages and optimization techniques [27, 39, 40] considering the possible interconnection of distributed energy resources, including wind and photovoltaic generation as well as battery energy storage systems [16, 41, 42]. It is important to stand out that in the revision of the state-of-the-art made in this doctoral thesis was found that the sizing of DERs in DC grids is a research topic in progress, for this reason in the specialized literature exists few documentation about this topic. This situation highlights the importance of exploring such a problem to propose new methodologies in this research line, those aimed to obtain the best performance in terms of quality solution and processing time.

To locate and select the devices that form a DC MG (Step 1), some solutions have been proposed to provide an optimal integration and operation on DC MGs. Commercial tools, intelligent control methods, and metaheuristics optimization approaches have been used for the integration of DGs [43, 44, 42]. For the integration of ESS, no works were found in the literature review made in this thesis, that addressing the problem of location and selection of ESS in DC grids only. However, there are works that aim to integrate, simultaneously; Battery Storage Systems (BSS) and DGs, e.g. the methodology proposed in [45], which is based on a convex mathematical formulation for the day-ahead to improve the economic dispatch of distributed generators and BSS in DC grids. Such work solves the mathematical model by using semidefinite programming methods with the aim of reducing the energy purchasing costs from conventional generators (economic dispatch). Moreover, that solution uses an artificial neuronal network for forecasting both solar and wind resources. The main problem of this method concerns the adoption of semidefinite programming methods, which increase the complexity and computational cost. Other solution is proposed in [16], which is based on the Particle Swarm Optimization algorithm (PSO) for obtaining the optimal size and dispatch of the energy resources in DC networks. That work adopts an objective function aimed at reducing costs of investment and operation of the energy resources. The main problems of this work are, first, the consideration of a single nodal representation of the grid, i.e. neglecting both branch connections and multiple DERs located in different buses of the electrical grid; and second, the DERs impact on the electrical grid was analyzed without power flow methods. In addition, the selection of the solution method and its parameters is not described in detail, and there is not provided any comparison with other existing methods in terms of solution quality and processing time, which is required to evaluate the performance of the solution. As can be observed in the previous paragraphs, the works proposed to plan the DC microgrids are scarce and the researches mainly uses specialized packages as solution methods. These characteristics demonstrate the need to propose methodologies based on sequential programming, that allow to reduce the cost and complexity of the solution methods; by ensuring quality solutions with short processing times. This will allow the operator or designer of the DC MG exploring different alternatives and scenarios in shorter times.
With respect to the operation of DC MGs (energy management stage), different control techniques and optimization methodologies have been proposed for this purpose in the literature for both connected and standalone DC MGs; by using methods based on droop control, fuzzy control, multi-agent based control and hierarchical control; being the last control strategy the most widely used in the last years (See Figure 1-3). In this type of control strategy, the primary control is in charge of direct control of the devices (i.e. power, voltage and current control), the secondary control is responsible of guaranteeing the technical conditions (current, voltage and power limits, SOC limit of the ESS, among other) and satisfy the constraints imposed to the MG, and the tertiary control defines the energy management in the MG; this with the aim to achieve the goals fixed by the operator of the MG. All control stages are communicated for analysing the operatives stages of the MG, to take decisions that allow to the MG operating in the desired energy, power, voltage and current levels. The energy management stage represents a non-linear, multi-variable and complexity problem, which requires control strategies to operate the DC MG in the desired conditions.

For DC MGs connected to the electrical grid, several works have been proposed with the main objective of reducing the operational costs. An example of this is the work presented in [47], which proposes a power management system for a MG composed of a photovoltaic system (PVS), a battery and the electrical network. The paper focuses on power balancing, with load shedding and PVS constrained power generation, considering also the grid power availability. A methodology that uses a real-time rule-based algorithm for the power management of a MG for electric vehicle charging stations is presented in [48]. That MG is formed by a PVS, an ESS, the electrical network and the DC loads, which are associated to the electric vehicle charging stations, it taking into account the variation in the energy cost. With respect to the optimization methods, a methodology based on the PSO technique for optimal operation of DERs in DC networks is presented in [16], which has the aim of reducing the purchasing cost the energy. The main problem of that work is that it considered a MG with a single bus; which does not represent the topologies of the microgrids with
branch connections and multiple buses. Other works have been reported in the last years; e.g. the methodology proposed in [44], which uses the Linprog function of Matlab to impose an optimal operation to a DC Microgrid based on photovoltaic generation. In that work the authors do not consider the variation of the power generated and demanded, and also do not compare the proposed methodology with other works reported in literature. In [45] the problem of economic dispatch of energy storage systems in DC microgrids is addressed by using a semidefinite programming model, considering the variation in the PV and wind generation, power demand and energy cost. The semidefinite problem was solved with a software specialized for convex optimization problems. In conclusion, few works have been devoted to DC grids with multiple buses, loads, DGs and BSS. Moreover, it is detected the need to use methodologies not based on specialized tools to reduce the complexity and costs. Therefore, it is necessary to propose control strategies and EMS, based on simple and free tools for controlling the DC grids; which provide solutions of high quality and short processing times in comparisons with methods proposed in literature.

DC MGs for standalone applications are commonly formed by renewable DG, ESS and electrical loads. As ESS can be used: batteries, capacitors, ultracapacitors, batacitors, among others [49]; its selection is based on the requirements of power and energy density. This type of MGs do not include the electrical network or a buck-up DG (e.g. diesel, fuel cells, etc.) [50] [51], allowing to eliminate the purchase of energy to the utility grid, fossil fuels costs, and also reduce the operational complexity of the system. In particular, PVS are commonly included in this type of MGs due to the wide availability of solar energy [52]. The integration of a PVS, an ESS, and loads is known as a Standalone Photovoltaic System (SPVS) [53]. SPVSs are used in multiple applications for non-critical loads, such as plug-in chargers for electrical vehicles, lighting systems, television sets, data centers, air-conditioning, and home.

**Figure 1-4.** Conventional Standalone DC microgrid.
applications, among others [54] 55 56.

SPVS devices must be integrated into the DC-bus of the MG by using DC/DC converters, which enable the operation of each device in the corresponding safe and optimal operating condition [57]; this is possible measuring the current and voltages of the different elements that compose the MG and assigning the control signal through control strategies and EMS (See Figure 1-4). For example, the DC/DC converter associated with the PVS is regulated using algorithms and/or control strategies, both of them aim to track the PVS maximum power point (MPP); hence, such algorithms are known as MPP tracking (MPPT) solutions [58] 48. The integration of the ESS with the DC-bus is achieved using bidirectional converters and control strategies [59] to regulate the DC-bus voltage and guarantee the global power balance. However, additional conditions can also be considered; for example, a limitation to the power generated by the PVS [60] 61 62, which is applied when the ESS reaches the maximum SOC during low power demand; or a load disconnection when the ESS is operating in the minimum SOC during high power demand [60] 63. Those considerations and the regular constraints imposed to the standalone DC MGs must be considered into the control strategies and EMS to prevent an accelerated reduction of the ESS lifetime [64] 65 66, hence reducing the maintenance and operational costs.

In order to propose solutions to the different problematic presented in the previous paragraphs: DC power flow analysis, optimal power flow problem, optimal integration and operation of DERs in DC grids; this thesis presents some methodologies and control strategies applied to the different stages and steps that composes the planing and management of DC microgrids; with the main objective of optimizing the costs and improving the operating conditions. The proposed methodologies are based on sequential programming and parallel processing tools, this to prevent the use of specialized software and to reduce the processing times. In this way, Chapter 2 proposes five different solutions for solving the power flow problem in DC MGs with radial or mesh topologies. Then, Chapter 3 addresses the problem of sizing DERs in DC grids by proposing three methodologies for solving the OPF problem: a continuous genetic algorithm, a Black Hole optimization method and a particle swarm optimization algorithm, all of those using the successive approximations power flow method for solving the PF problem. The aim of that chapter is to find the hybrid methodology that provides the best performance in terms of solution quality and processing time. In Chapter 4, a hybrid method for both optimal location and sizing of DGs in DC MGs is proposed, which is based on the Parallel Population-Based Incremental Learning (PPBIL) and the PSO algorithm. This method uses as objective function the reduction of the power losses considering also the set of restrictions associated to the power flow analysis in DC grids. Chapter 5 proposes two EMS for connected and standalone DC MGs. The first EMS is designed for SPVS, which enable controlling the power generation on the photovoltaic system and ensures that the battery does not exceed the limits of the state of charge; this guarantees the global power
balance at all times and the operation of the system within allowable technical limits, thus expanding the lifetime of the devices that compose the MG. The results obtained shown the effectiveness of the methodologies proposed in this work. The second EMS considers a DC MG connected to the electrical grids with a master-slave strategy, which is formed by a parallel implementation of the PSO and a multi-period power flow method based on successive approximation. This EMS has the aim of achieving the optimal daily operation of the BSS with lower energy purchasing costs, also including the power balance, devices capabilities and voltage regulation. Finally, in Chapter 6 are presented the conclusions and future lines of researching derived from this doctoral thesis.
2. Power Flow Analysis in DC Grids with Mesh and Radial Structure

This chapter presents the mathematical formulation and five new solution methods for solving the DC power flow problem, considering both resistive and constants power loads, for electrical networks with radial or mesh structure. The first section presents the modeling procedure of the DC power flow problem, where it is observed its non-lineal and non-convex nature. Then, the second section proposes two iterative methods for solving the DC PF problem in both radial and mesh topologies: the first method based on a Taylor series expansion by using a set of decoupling equations to linearize around the desired operating point. The second method manipulates the set of non-linear equations that represents the DC PF problem to transform them into a conventional fixed point form, which is used to develop a successive approximation methodology. For the particular case of the radial topology, the third section proposes three methods based on triangular matrix formulation, graph theory and sweep algorithms. The literature review made in this doctoral thesis shows that those solution methods have not been applied for solving the PF problem in DC grids.

The objective of this chapter is to select the method with the best performance in terms of quality solution and processing time. The performance was evaluated using six test systems and three additional comparison methods: Gauss-Jacobi, Gauss-Seidel and Newton Raphson; all used in literature for this same application. The simulation results shown the good performance of the solution methods proposed in this work, and allow to select the best solution method for radial and mesh structures.

The analysis and results reported in this chapter have been published in the Electric Power Systems Research paper “Linear power flow formulation for low-voltage DC power grids” [67], in the IEEE Transactions on Circuits and Systems II: Express Briefs in the papers “Power flow analysis in DC grids: Two alternative numerical methods” [68] and “Triangular Matrix Formulation for Power Flow Analysis in Radial DC Resistive Grids with CPLs” [69]; and in the Journal of Physics: Conference Series, in the paper “Application of the backward/forward sweep method for solving the power flow problem in DC networks with radial structure” [70].
2.1. Introduction

The power flow analysis is an essential tool in the design and operation of AC and DC composed by passive components, active sources and nonlinear loads [71]. Those loads are typically modeled as constant power loads (CPLs), which introduce hyperbolic non-convexities on the power flow model [72, 73]. The main objective of power flow analysis is the calculation of the voltage profiles in all the buses of the network under steady-state conditions [31]. The power flow analysis on AC grids has been one of the most studied topics since the 1960s [74]; however, the power flow analysis in DC grids was recently explored due to the adoption of DC grids, this caused by the advances on power electronics, renewable generation and energy storage technologies [46, 4]. The solution of the power flow problem in DC grids requires numerical methods due to the non-convexities of the model, which makes difficult to obtain its analytical solutions [17].

Classical methods have been proposed to face the DC PF problem in DC networks, such as Gauss-Seidel [31] and Newton-Raphson methods [17]. In the first case, the convergence of the Gauss-Seidel method for power flow analysis in DC grids was demonstrated using fixed point theorems, while the convergence of the Newton-Raphson has been demonstrated by using the Kantorovichs theorem. In addition, power flow formulations based on semidefinite programming [27] and second-order cone programming [28] have been proposed in literature to solve the problem here discussed. Although those methods are also used in optimal power flow analysis, each one of them transforms the power flow problem in DC grids in a convex equivalent problem by using positive semidefinite matrices. The previous programming methods are able to solve power flow problems using interior point methods, but they generate a quadratic increment in the number of variables to be analyzed, which negatively impact the processing times required to solve the power flow problem [30]. In AC grids this problem has been studied during the last decades, where solutions based on numerical methods, linear approximations, convex approximations, have been proposed [75] for solve the PF problem with any topology or structure, presenting as main objective the improvement of the solution quality and the processing time. In addition, in AC grids with radial structure it is possible to propose power flow methods faster than those previous works; which are based on the sweep iterative algorithms as the triangular matrix formulation [76], graph theory [77] and backward/forward methods [78]. Those faster methods take advantage of the radial structure of the grid, to reduce the mathematical complexity and processing time.

Therefore, it is required to develop efficient methods to solve the PF problem in DC grids. Those new solutions could be based on linear approximations, successive approximations, triangular matrix formulation, graph theory and backwar/forward methods; which have been used for solving the PF problem in AC grids. In such away, this Chapter proposes five methodologies based on the methods previously described; which are aimed at solving the
DC PF problem in DC grids with radial or mesh structures. Finally, in order to demonstrate the effectiveness and robustness of the proposed solutions, other solution techniques reported in literature are used as reference for comparison purposes.

2.2. Mathematical formulation problem

The DC power flow equations are the set of nonlinear non-convex algebraic expressions that allow determining the steady-state behavior of the electrical circuits under the presence of constant power loads [79]. Those equations are obtained by applying the Kirchoff’s laws and the Tellegen’s theorem to any electrical grid that fulfills the following assumptions [31]: the DC power grid has at least one constant voltage bus; the graph is connected, this is, there are not islanded buses on the DC power grid; the voltage profiles are strained within the interval $V_{\text{min}} \leq v \leq V_{\text{max}}$, where $V_{\text{min}} > 0$. Finally, the DC power grid is operating under steady-state conditions, this is, there are not external perturbations or topological modifications. Considering the previous operative conditions, the power flow problem for power grids is represented as follows [80]:

$$[p = D(v)i, \quad i = Gv] \leftrightarrow p = D(v)Gv, \quad (2-1)$$

$$G = (G_B + G_n) = \begin{pmatrix} G_{gg} & G_{gd} \\ G_{dg} & G_{dd} \end{pmatrix}, \quad G_{dg} = G_{gd}^T$$

(2-2)

where $v \in \mathbb{R}^n$, $i \in \mathbb{R}^n$ and $p \in \mathbb{R}^n$, represent the bus voltages, and both net injected currents and power in all buses of the network. $D(v) \in \mathbb{R}^{n \times n}$ is a diagonal positive definite matrix such that $D_{ii} = v_i; \quad i = 1, 2, ..., n$ and $D_{ij} = 0; \quad i \neq j$. Finally, $G \in \mathbb{R}^{n \times n}$ is the nodal admittance matrix, which is composed by the addition of the conductance matrix, that represents the conductivity effects of each branches that interconnected the different buses of the electrical system ($G_B \in \mathbb{R}^{n \times n}$), and the conductance matrix associated to the resistive loads connected the DC MG ($G_n \in \mathbb{R}^{n \times n}$), respectively. In addition, $G$ can be decomposed in four components as it is shown in equation (2-2); where, $G_{gg}$ represents the component of the conductance matrix associated to the generators connections, $G_{dd}$ is the component of the conductance matrix associated to the load connections, and $G_{gd} = G_{dg}^T$ corresponds to the component of the conductance matrix that relating the generators and loads. Finally, in this doctoral thesis, $n$ and $b$ represent the number of buses and branches, respectively.

The set of equations defined by equation (2-1) has both linear and nonlinear equations, which can be rewritten as follows [80]:

$$[p = D(v)i, \quad i = Gv] \leftrightarrow p = D(v)Gv, \quad (2-1)$$

$$G = (G_B + G_n) = \begin{pmatrix} G_{gg} & G_{gd} \\ G_{dg} & G_{dd} \end{pmatrix}, \quad G_{dg} = G_{gd}^T$$

(2-2)
13. Solution methods for the DC power flow problem

\[ i_g = G_{gg} v_g + G_{gd} v_d, \quad (2-3) \]
\[ -i_d = G_{dg} v_g + G_{dd} v_d, \quad (2-4) \]
\[ p_g = D(v_g) [G_{gg} v_g + G_{gd} v_d], \quad (2-5) \]
\[ -p_d = D(v_d) [G_{dg} v_g + G_{dd} v_d], \quad (2-6) \]

In those equations \( i_g \in \mathbb{R}^s, i_d \in \mathbb{R}^{n-s}, v_g \in \mathbb{R}^s \) and \( v_d \in \mathbb{R}^{n-s} \) correspond to the currents and voltage profiles at the ideal generators (known voltage buses) and demand buses (unknown voltages), respectively. \( p_g \in \mathbb{R}^s \) and \( p_d \in \mathbb{R}^{n-s} \) represent the power generation at the ideal voltage buses and the power consumed at the load buses, respectively. \( D(v_g) \in \mathbb{R}^{s \times s} \) and \( D(v_d) \in \mathbb{R}^{(n-s) \times (n-s)} \) have the same interpretation of \( D(v) \). In this representation \( s \) defines the number of ideal generators, which implies that \( s \geq 1 \). Moreover, in this formulation the power generated by the DGs and ESS located in buses different to the constant voltage buses are considered as negative loads into the mathematical model.

It is observed that equation (2-5) is formed by a set of linear equations, since the variables of the problem are \( p_g \) and \( v_d \). Notwithstanding, equation (2-6) remains as a set of nonlinear equations due to the product between different voltages contained on \( v_d \). Therefore, since the voltage profiles of the ideal generators are known, equation (2-5) is not required into the mathematical formulation. For this reason, equation (2-6) represents the conventional power flow problem for DC power grids [81]. It is worth to highlight that the power flow solution using numerical methods only makes sense when the grid has at least one CPL; because such a condition transforms the power flow equations into a set of nonlinear non-convex equations [71].

2.3. Solution methods for the DC power flow problem

This section proposes five methods for solving the power flow problem in DC grids. Two methods based on Taylor series expansion and successive approximations are proposed to solve the PF problem in radial and mesh structures. Moreover, three additional methods are proposed for solving the PF problem in radial DC grids only, which are based on triangular matrix formulation, graph theory and backward/forward methods.

2.3.1. Power flow solution methods for DC grids with radial or mesh structure

The solution for the power flow equations given in (2-6) is addressed in this subsection with two different iterative techniques. The first method generates a linearization using a Taylor’s
series expansion while the second one works with the original set of nonlinear equations. Both solution methods are explained in the following subsections.

2.3.1.1. Taylor’s series based approximation (TBM)

To obtain a linear approximation of the power flow equations, it is necessary to obtain an equivalent linear form for expression (2-6). Therefore, for linearization purposes, the inverse value of the voltage profile at the \( k^{th} \) bus was considered as a nonlinear term, this taking into account the alternative form of (2-1) given in (2-7).

\[
\frac{p_k}{v_k} = i_k
\]  \hspace{1cm} (2-7)

The nonlinear term \( \frac{1}{v_k} \) in (2-7) is approximated using a first-order (linear) Taylor’s series expansion around the operating point \( v_k^0 \). Such a term is selected to be linearized because \( v_k \) does not take zero values; this is not the case of the current variable, which can take zero values in all step-buses. Moreover, \( v_k \) is limited as it was described in the mathematical formulation. The linearization of the term \( \frac{1}{v_k} \) is based on the general form of the Taylor’s formula for a continuous nonlinear function \( f(x) \) around \( x_0 \) presented below:

\[
f(x) = \sum_{n=0}^{\infty} \frac{1}{n!} \left( \frac{d^n}{dx^n} f(x_0) \right) (x - x_0)^n
\]  \hspace{1cm} (2-8)

Applying the definition given in (2-8) for a first-order expansion, i.e. \( n = \{0, 1\} \), the nonlinear term \( \frac{1}{v_k} \) around \( v_k^0 \) is approximated as follows:

\[
\frac{1}{v_k} \approx \frac{1}{v_k^0} - \left( \frac{1}{v_k^0} \right)^2 (v_k - v_k^0)
\]  \hspace{1cm} (2-9)

Finally, the linear approximation of the active power balance given in (2-10) is obtained by substituting (2-9) into (2-7).

\[
\left( 2 - \frac{1}{v_k^0} \right)^2 v_k p_k = i_k
\]  \hspace{1cm} (2-10)

It must be noted that the Taylor’s linearization is applied only to the buses with unknown voltage, therefore the buses with generators exhibiting voltage control capability are not included in the linearization process because their voltages are known [81]. Under the light of the previous analysis, the net injected current, power and the voltage profile in the \( k^{th} \) bus are equal to the current \( (i_k = i_d) \), voltage \( (v_k = v_d) \) and power \( (p_k = -p_d) \) on the demand
buses, hence the linear approximation of the active power balance (2-10) is rewritten as it is given in (2-11), in which $p_d$ is a vector including all constant power loads and $v_0^d$ denotes the initial voltage profiles compose by a vector filled by ones with dimensions $b \times 1$ (plane voltage profiles).

$$-2D(v_0^d)^{-1}p_d + \left(D(v_0^d)^{-1}\right)^2 D(v_d)p_d = i_d$$

Taking advantage of the diagonal operator property, expression (2-12) is obtained:

$$-2D(v_0^d)^{-1}p_d + \left(D(v_0^d)^{-1}\right)^2 D(p_d)v_d = i_d$$

Finally, replacing the $i_d$ definition given in (2-4) into (2-12) leads to the linear approximation of the $v_d$ solution given in (2-13).

$$v_d = \left(D(v_0^d)^{-1}\right)^2 D(p_d) - G_{dd}^{-1} \left(G_{dg}v_g + 2D(v_0^d)^{-1}p_d\right)$$

Expression (2-13) enables the explicit calculation of the voltage profile in the demand buses of a DC power grid. Moreover, this linear approach can be applied to both radial and mesh dc power grids. Finally, by replacing $v_0^d$ by $v_t^d$ (that corresponds to iteration $t$) in (2-13) and rearranging some terms, an iterative method for obtaining the unknown voltage is derived based on an alternative Taylor’s series expansion method as follows:

$$v_{d}^{t+1} = \left[D^{-2} \left(v_0^d\right) D \left(p_d\right) - G_{dd}^{-1}\right]^{-1} \left[2D^{-1} \left(v_0^d\right) p_d + G_{dg}v_g\right]$$

### 2.3.1.2. Successive approximation (SA)

This method works directly from expression (2-6), which is rearranged as follows:

$$G_{dd}v_d = -D_d^{-1} (v_d) p_d - G_{dg}v_g,$$

where $G_{dd}$ and $G_{dg}$ are positives definite symmetric matrices, which entails that its inverse always exists allowing to obtain the conventional expression for solving nonlinear problems using fixed point theorems with the following structure:

$$v_d = -G_{dd}^{-1} \left[D_d^{-1} (v_d) p_d + G_{dg}v_g\right]$$

An iterative process for calculating $v_d$ is obtained from (2-16) by adding the iterative counter $t$ as follows

$$v_{d}^{t+1} = -G_{dd}^{-1}D_d^{-1} \left(v_0^t\right) p_d - G_{dd}^{-1}G_{dg}v_g$$

The convergence of the successive approximated method was detailed in [31]; nevertheless, it is important to stand out that expression (2-17) is different from the conventional Gauss
Seidel reported in power systems analysis books, which corresponds to an important contribution of this thesis.

Finally, the iterative process is executed until an acceptable convergence error or maximum number of iterations ($t_{\text{max}}$) are reached. In this sense, the most common stopping criterion is the variation of the voltage profile during two consecutive iterations; that is, $\max (|V^{t+1} - V^t|) \leq \epsilon$, where $\epsilon$ is the minimum convergence rate. In this chapter both stopping criteria are used in all iterative methods proposed. Finally, Algorithm 1 presents the iterative procedure designed to solve the power flow problem in DC grids by using TBM or SA.

**Algorithm 1** Proposed iterative power flow method for DC resistive networks with radial or mesh structures

**Data:** Define the DC system

Construct the conductance matrix $G$

Define $v_{d}^t$ (with $t = 0$), $\epsilon$ and $t_{\text{max}}$

for $t = 0 : t_{\text{max}}$ do

Evaluate $v_{d}^{t+1}$

if $\max (|v_{d}^{t+1} - v_{d}^t|) \leq \epsilon$ then

Result: Return $v_{d} = v_{d}^{t+1}$

break

else

$v_{d}^{t+1} = v_{d}^t$

end

end

2.3.2. Power flow solution methods for DC grids with radial structure

In AC grids, multiple authors have proposed solution methods focused on electrical systems with radial structure, those aimed at reducing the complexity and processing times. These solution methods are known as sweep iterative power flow methods [77, 76], which are based on a simple mathematical formulation and iterative processes, where the most widely adopted are based on triangular matrix formulation [76], graph theory [77] and backward-/forward methods [78]. In the literature review made in this doctoral thesis, it was not found works addressing the DC power flow problem in grids with radial topology; therefore, this subsection proposes three solution methods based on the sweep iterative power flow methods most widely used in AC grids, it considering both resistive and constant power loads (See Figure 2-1).
2.3 Solution methods for the DC power flow problem

To formulate the mathematical problem describing a DC grid with radial structure is necessary to consider two additional assumptions on the DC grids: a DC network is radial if it has \( n \) buses and \( b \) branches, such that \( b = n - 1 \), where there is one, and only one, route between each pair of buses, as it illustrated in Figure 2-1. In a radial grid, a unique ideal power generator with voltage control capabilities is considered on the DC grid, which allows the voltage output of the whole grid to be controlled. Figure 2-1 presents a typical radial DC grid, composed of a unique main generator (an ESS formed by multiples batteries in this example), branches, resistive and CPLs loads. Those Batteries can be replaced by the electrical grid or DGs; provided that those devices have sufficient power to achieve the global power balance on the DC network.

2.3.2.1. Power flow method based on triangular matrix formulation (TM)

This subsection proposes an iterative sweep method based on the upper triangular relationship between bus and branch currents, it also uses a primitive impedance matrix. The main advantage of this method lies in the possibility of avoiding inversions of non-diagonal matrices.

For a general DC grid, the primitive resistance matrix \( \mathbf{R}_p \) is defined in equation (2-18); where \( R_{ij} \) is the resistive parameter of the branch that connects the buses \( i \) and \( j \), respectively. Note that \( \mathbf{R}_p \in \mathbb{R}^{b \times b} \) is a positive definite matrix. The branch currents \( \mathbf{i}_B \in \mathbb{R}^{b \times 1} \) can be related to the bus injected currents \( \mathbf{i}_d \in \mathbb{R}^{(b) \times 1} \) by using a triangular incidence matrix \( \mathbf{T} \in \mathbb{R}^{b \times (n-1)} \) at it is reported in equation (2-19). In this equation \( \mathbf{i}_d \) denotes the net current.
demanded at the load buses; which is a function of the power demanded or generated by CPLs and resistive loads. \( i_d \) is calculated in equation (2-20).

\[
\mathbf{R}_p = \text{diag} ([R_{01}, ..., R_{ij}, ..., R_{mn}]),
\]

\( i_B = \mathbf{T}i_d, \)

\[
i_d = -\mathbf{D}_d^{-1}(v_d)p_d - \mathbf{G}_n v_d
\]

The construction of the triangular incidence matrix \( \mathbf{T} \) can be made if the DC network is previously ordered by layers (ordering nodal) as it is reported in [83], hence, \( \mathbf{T} \) can be calculated as follows:

- \( \mathbf{T}(k, l) = 1 \) if branch \( k \) is located upstream the \( l \) bus.
- \( \mathbf{T}(k, l) = 0 \) if branch \( k \) is located downstream the \( l \) bus.

To illustrate the structure of \( \mathbf{T} \), consider the radial DC test feeder depicted in Figure 2-1 where there are 6 buses (excluding the voltage controlled bus 0) and 6 branches marked with letters from \( a \) to \( f \), respectively. Then, using equation (2-19), the triangular incidence matrix takes the following form:

\[
\begin{pmatrix}
  i^a_B \\
  i^b_B \\
  i^c_B \\
  i^d_B \\
  i^e_B \\
  i^f_B
\end{pmatrix}
= \begin{pmatrix}
  1 & 1 & 1 & 1 & 1 & 1 \\
  0 & 1 & 1 & 1 & 1 & 1 \\
  0 & 0 & 1 & 1 & 0 & 0 \\
  0 & 0 & 0 & 1 & 0 & 0 \\
  0 & 0 & 0 & 0 & 1 & 1 \\
  0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix}
\begin{pmatrix}
  i_1 \\
  i_2 \\
  i_3 \\
  i_4 \\
  i_5 \\
  i_6
\end{pmatrix}
\]

(2-21)

The voltage drop at each branch can be formulated by using the relation between the voltage in the branches and their respective currents reported in equation (2-22), where \( \Delta v_B \in \mathbb{R}^{b \times 1} \) denotes the vector of voltage drops in all the branches.

\[
\Delta v_B = \mathbf{R}_p \mathbf{i}_B
\]

(2-22)

Now, by applying the second Kirchhoff’s law for each closed loop between the voltage controlled bus (bus 0 in Figure 2-1) and the bus of interest, it is obtained equation (2-23). In such an expression \( v_0 \) is the voltage at the slack bus and \( \mathbf{1} \in \mathbb{R}^{(n-1) \times 1} \) is a vector filled by ones.

\[
v_d = \mathbf{1}v_0 - \mathbf{T}^T \Delta v_B,
\]

(2-23)
Finally, by combining expressions (2-19), (2-20), and (2-22) with (2-23), it is obtained the next equation:

\[ v_d = \mathbf{1}v_0 + \mathbf{T}^T\mathbf{R}_p\mathbf{T}(\mathbf{D}^{-1}(v_d)p_d + \mathbf{G}_n v_d), \]  

(2-24)

Expression (2-24) is a nonlinear non-convex formulation for power flow analysis in radial DC resistive networks, therefore, this set of equations must be solved with iterative numerical methods [17]. The matrix operation \( \mathbf{T}^T\mathbf{R}_p\mathbf{T} \) produces a constant matrix that depends only on the grid structure (i.e. bus contentions and branch parameters), which implies that in comparison with power flow methods based on admittances, this term can be defined as the equivalent impedance matrix; that is \( \mathbf{R}_{bus} = \mathbf{T}^T\mathbf{R}_p\mathbf{T} \). To solve the power flow formulation defined in (2-24) it is necessary only to add an iterative counter \( t \), which produces:

\[ v_{d}^{t+1} = \mathbf{1}v_0 + \mathbf{R}_{bus}(\mathbf{D}^{-1}(v_{d}^{t})p_d + \mathbf{G}_n v_{d}^{t}), \]  

(2-25)

Finally, Algorithm 2 presents the iterative procedure used to solve the power flow problem in DC grids by using the proposed triangular representation.

**Algorithm 2** Proposed iterative power flow method for DC resistive networks based on triangular matrix formulation

**Data:** Define the DC radial system

- Apply the nodal ordering method [83]
- Construct the triangular incidence matrix \( \mathbf{T} \)
- Construct the conductance matrix \( \mathbf{G}_n \)
- Construct the primitive resistance matrix \( \mathbf{R}_p \)
- Build and store the \( \mathbf{R}_{bus} \) matrix
- Define \( v_0, v_{d}^t \) (with \( t = 0 \)), \( \epsilon \) and \( t_{max} \)

**for** \( t = 0 : t_{max} \) **do**

- Evaluate \( v_{d}^{t+1} \) with (2-13)
  - if \( \text{max} \left( |v_{d}^{t+1} - v_{d}^t| \right) \leq \epsilon \) then
    - **Result:** Return \( v_d = v_{d}^{t+1} \)
    - break
  - else
    - \( v_{d}^{t+1} = v_{d}^t \)
  - end

**end**

### 2.3.2.2. **Sweep method based on graph theory (SMBGT)**

This subsection addresses the power flow calculation for DC networks with radial structure, considering both resistive and constant power loads. The proposed SMBGT correlates the
branch currents and nodal currents through an incidence matrix by using an iterative procedure, which provides simplicity in its mathematical formulation and shorter convergence times. The basic concept of the branch-to-bus incidence matrix is described below [76].

The incidence matrix $A$ for radial electrical networks is always square and invertible. This matrix is constructed as follows:

- $A(k,l) = 1$ if the branch $k$ is connected to the bus $l$ and the current is leaving of the $l$ bus.
- $A(k,l) = -1$ if the branch $k$ is connected to the bus $l$ and the current is arriving to the $l$ bus.
- $A(k,l) = 0$ if branch $k$ is not connected to the bus $l$.

Moreover, in radial distribution networks the current can be assumed flowing from the substation to the load buses, i.e. the direction of the current through the branch $k$, connected between buses $i$ and $j$, is from $i$ to $j$ if the bus $i$ is upstream of the bus $j$; otherwise, the current flows from $j$ bus to $i$ bus.

To provide a numerical example of the branch-to-bus incidence matrix, the radial DC grid depicted in Figure 2-1 is considered, which is represented by the incidence matrix $A$ given in (2-26).

$$
\begin{align*}
A_0 &= \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \\
A &= \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 1 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix} \\
&= \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 1 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix}
\end{align*}
$$

(2-26)

The rows of $A$ are the branches $(a,b,c,d,e,f)$ and the columns represent the buses $(1, 2, 3, 4, 5, 6)$. The slack bus (bus 0 in Figure 2-1) is not contained in the incidence matrix, instead it is represented in an additional matrix $A_0$. The voltage drop in each branch of the network is calculated by equation (2-27), where $v_s$ represents the voltage on the main generator (voltage controlled bus).

$$
\Delta v_B = A_0 v_s + A v_d,
$$

(2-27)

The relation between branch currents is also established:

$$
i_B = -A^{-T}i_d,
$$

(2-28)
Moreover, the relation between voltage drops and currents in all the branches is obtained by applying Ohm’s law:

$$\Delta v_B = R_p i_B,$$

where $R_p$ is the primitive resistance matrix, described in the last subsection. In the case of the example depicted in Figure 2-1 this matrix takes the following form:

$$R_p = \begin{bmatrix}
R_{01} & 0 & 0 & 0 & 0 & 0 \\
0 & R_{12} & 0 & 0 & 0 & 0 \\
0 & 0 & R_{23} & 0 & 0 & 0 \\
0 & 0 & 0 & R_{43} & 0 & 0 \\
0 & 0 & 0 & 0 & R_{25} & 0 \\
0 & 0 & 0 & 0 & 0 & R_{56}
\end{bmatrix}$$

Combining expressions (2-27) to (2-29), and rearranging some terms, it is obtained the equation (2-31).

$$v_d = A^{-1}R_p A^{-T}i_d - A^{-1}A_0 v_s$$

$$v_{d}^{t+1} = -A^{-1}R_p A^{-T} (D^{-1}(v_d^t)^T p_d + G_n v_d^t) - A^{-1}A_0 v_s$$

The formula defined in (2-31) relates the bus voltages and currents; nevertheless, an iterative procedure is needed to solve this set of equations, since $i_d$ depends of the bus voltages $v_d$, see equation (2-20). Finally, by replacing (2-20) in (2-31), and adding an iterative counter $t$, the equation that allows to solve power flow problem in DC grids by using the SMBGT is presented in equation (2-32).

The formulation of the power flow method based on SMBGT requires a recursive actualization of the variables; this process is described in Algorithm 3. Finally, the SMBGT does not require admittance bus calculations in its iterative procedure to estimate all the voltage profiles in all the buses of the network, which is a clear difference with other methods reported in literature [31, 67] and proposed in this doctoral thesis.

### 2.3.2.3. Backward/Forward sweep method (BF)

The BF power flow method is a well-known strategy for solving power flow problems in AC grids with radial structure. The mathematical foundation is supported by graph theory applied to grids with tree or radial structure [84]. This method uses a nodal ordering stage, the Kirchhoff’s laws and a simple iterative process for solving the power flow problem; presenting as main advantage the avoidance of matrix inversions. The literature review made for this thesis shows that the BF has not been applied for solving the power flow problem in DC
Algorithm 3 Iterative procedure for power flow analysis in radial DC networks by using SMBGT.

**Data:** Define the DC radial system
Apply the nodal ordering method
Construct $A$ and $A_0$
Obtain the inverse of $A$
Construct the primitive resistance matrix $R_p$
Define $v_s$, $v_0^d$, $\epsilon$ and $t_{\text{max}}$

for $t = 0 : t_{\text{max}}$

<table>
<thead>
<tr>
<th>Evaluate $v_{d}^{t+1}$ in (2-32)</th>
</tr>
</thead>
<tbody>
<tr>
<td>if $\max(</td>
</tr>
<tr>
<td>Result: Return $v_d = v_{d}^{t+1}$.</td>
</tr>
<tr>
<td>break</td>
</tr>
<tr>
<td>else</td>
</tr>
<tr>
<td>$v_{d}^{t+1} = v_{d}^t$</td>
</tr>
<tr>
<td>end</td>
</tr>
</tbody>
</table>

end

The general formulation of the BF method is based on the relation between nodal and branch currents. To perform the PF analysis in DC grids with radial structure, it is proposed an iterative procedure based on equations (2-28) and (2-29), which represent the branch current and voltages, respectively.

The BF method starts assuming that the voltages in all the buses are defined as:

$$v_d^t = [v_2^t, ..., v_{f-1}^t, v_{f+1}^t, ..., v_n^t]^T,$$  \hspace{1cm} (2-33)

where $t$ is the iterative counter. Then, condition $t = 0$ corresponds to the initial solution $v_d^0$ (typically plane voltages in per-unit representation). The slack bus was removed from this vector since its voltage is known (voltage controlled bus). Then, by applying the Kirchhoff’s laws for each closed loop between the slack bus and other buses, and by using the equations (2-28) and (2-29), it is possible to find the recursive equation that allows calculating the voltage profiles in the buses different to the voltage controlled bus:

$$v_d^{t+1} = 1v_0 + A^{-1}\Delta v_B^t$$  \hspace{1cm} (2-34)

Finally, starting from the initial solution (i.e. $v_d^0 = 1 \rightarrow$ vector filled by ones with dimensions $b \times 1$), the Algorithm 3 enables to implement the BF approach for PF solutions in DC grids. Algorithm 4 was based on a compact formulation for power flow analysis that was initially proposed in [85] for AC grids. The algorithm starts by reading the parameters that define the
Algorithm 4 Backward forward power flow method.

Data: Define the DC radial system
Apply the nodal ordering method
Construct $A$
Obtain the inverse of $A$
Define $v_0$, $v_0^d$, $\epsilon$ and $t_{max}$

for $t = 0 : t_{max}$ do
    Calculate the nodal currents ($i_d$) by using (2-20)
    Calculate the branch currents ($i_B$) by using (2-28) → Backward sweep
    Calculate the branch voltages ($\Delta v_B$) by using (2-3)
    Evaluate $v_{d}^{t+1}$ by using (2-34) → Forward sweep
    if $\max(\|v_{d}^{t+1} - v_{d}^{t}\|) \leq \epsilon$ then
        Result: Return $v_{d} = v_{d}^{t+1}$
        break
    else
        $v_{d}^{t+1} = v_{d}^{t}$
    end
end

2.4 Test systems and comparison methods

To verify the effectiveness and robustness of the proposed methods six test systems are used. Four radial test system with 10, 21, 33 and 69 buses. The test systems with 10 and 69 buses were modified by adding multiples branches for obtaining its equivalent mesh structure. The test systems with 10 and 21 buses were taken from the literature [31, 86]. The test systems with 33 and 69 buses are modifications of test systems used in AC networks [87, 88, 13]. For obtaining the DC equivalent systems the reactance in the lines and the reactive power consumed by loads were eliminated. The electrical configuration and the data corresponding to the test systems are described in the following subsections.
2.4.1. 10 bus test system

The traditional electrical configuration associated to the 10 bus test system is presented in Figure 2-2. This electrical system is formed by 10 buses and 9 branches [31], with a unique generator and radial structure. The parameters of this system are shown in Table 2-1.

![Image of electrical configuration for the 10 bus test system]

In Table 2-1 the first, second and third columns report the sending and receiving bus, and the resistance in p.u associated to the branch that connects those buses, respectively. The fourth column specifies the type of the receiving bus, which can be a step bus, or load connected bus: constant power load (P) or resistive load (R). Finally, the fifth column corresponds to the load value. In this thesis, the power supply is considered positive (+) and the power demanded is considered negative (-).

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>R [pu]</th>
<th>Type of bus</th>
<th>P [pu]</th>
<th>- R [pu]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (slack)</td>
<td>2</td>
<td>0.0050</td>
<td>Step-bus</td>
<td>- -</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>0.0015</td>
<td>P</td>
<td>-0.8</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>0.0020</td>
<td>P</td>
<td>-1.3</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>0.0018</td>
<td>P</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>0.0023</td>
<td>R</td>
<td>2.0</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>7</td>
<td>0.0017</td>
<td>Step-bus</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>8</td>
<td>0.0021</td>
<td>P</td>
<td>0.3</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>9</td>
<td>0.0013</td>
<td>P</td>
<td>-0.7</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>0.0015</td>
<td>R</td>
<td>1.25</td>
<td></td>
</tr>
</tbody>
</table>

In addition, this test system was selected to validate the capability of applying the proposed power flow methods to both radial and mesh configurations: the radial topology is evaluated by preserving the configuration described in [31]; the mesh topology is evaluated by adding two lines to the test system following the connections and parameters given in Table 5-2. This modified test system is identified in this thesis as “10 buses mesh test system”. In Figure 2-2 the branches added for obtaining the mesh test systems are present in red color.

2.4.2. 21 bus test system

The 21 bus test system was presented in [86]. This electrical DC network is formed by 21 buses and 20 branches, presenting as main characteristic that it only considers constant
2.4 Test systems and comparison methods

Table 2-2.: Proposed connections for testing the mesh grid case in the 10 bus test system

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>R [pu]</th>
<th>From</th>
<th>To</th>
<th>R [pu]</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>10</td>
<td>0.0035</td>
<td>8</td>
<td>10</td>
<td>0.0025</td>
</tr>
</tbody>
</table>

power loads into the system. The electrical configuration of this test system is presented in Figure 2-3. Table 5-3 shows the data of this test system, presenting the following information from left to right: sending bus, receiving bus, resistance in p.u of the branch connecting those buses, and the power supplied or demanded y the sending bus. The base voltage and base power of this system are 1 kV and 100 kW, respectively. The voltage at the slack node (Node 1) is considered to be flat, i.e., 1 p.u. The last condition is applied in all test systems used in this doctoral thesis.

![Figure 2-3.]: Electrical configuration for the 21 bus test system

2.4.3. 33 bus test system

This test system is formed by 33 buses and 32 branches, presenting an unique slack bus and multiple buses with constant power loads. The AC electrical system of 33 buses was proposed in [89], and its electrical configuration is shown in Figure 5-24. This section neglects the values corresponding to the reactance and reactive power demanded in the AC system to
obtain the DC equivalent network with 33 buses. The parameters of this test system are consigned in Table 2-4, which contains real values and not p.u values as in the last test system. For this reason, base values of voltage (12.66 kV) and a power (100 kVA) were used to obtain p.u values.

Table 2-4.: Electrical parameters of the 33 bus test system

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>R [Ω]</th>
<th>P [kW]</th>
<th>From</th>
<th>To</th>
<th>R [Ω]</th>
<th>P [kW]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>0.0922</td>
<td>100</td>
<td>17</td>
<td>18</td>
<td>0.7320</td>
<td>90</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>0.4930</td>
<td>90</td>
<td>2</td>
<td>19</td>
<td>0.1640</td>
<td>90</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>0.3660</td>
<td>120</td>
<td>19</td>
<td>20</td>
<td>1.5042</td>
<td>90</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>0.3811</td>
<td>60</td>
<td>20</td>
<td>21</td>
<td>0.4095</td>
<td>90</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>0.8190</td>
<td>60</td>
<td>21</td>
<td>22</td>
<td>0.7089</td>
<td>90</td>
</tr>
<tr>
<td>6</td>
<td>7</td>
<td>0.1872</td>
<td>200</td>
<td>22</td>
<td>23</td>
<td>0.4512</td>
<td>90</td>
</tr>
<tr>
<td>7</td>
<td>8</td>
<td>1.7114</td>
<td>200</td>
<td>23</td>
<td>24</td>
<td>0.8980</td>
<td>420</td>
</tr>
<tr>
<td>8</td>
<td>9</td>
<td>1.0300</td>
<td>60</td>
<td>24</td>
<td>25</td>
<td>0.8900</td>
<td>420</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
<td>1.0400</td>
<td>60</td>
<td>25</td>
<td>26</td>
<td>0.2030</td>
<td>60</td>
</tr>
<tr>
<td>10</td>
<td>11</td>
<td>0.1966</td>
<td>45</td>
<td>26</td>
<td>27</td>
<td>0.2842</td>
<td>60</td>
</tr>
<tr>
<td>11</td>
<td>12</td>
<td>0.3744</td>
<td>60</td>
<td>27</td>
<td>28</td>
<td>1.0590</td>
<td>60</td>
</tr>
<tr>
<td>12</td>
<td>13</td>
<td>1.4680</td>
<td>60</td>
<td>28</td>
<td>29</td>
<td>0.8042</td>
<td>120</td>
</tr>
<tr>
<td>13</td>
<td>14</td>
<td>0.5416</td>
<td>120</td>
<td>29</td>
<td>30</td>
<td>0.5075</td>
<td>200</td>
</tr>
<tr>
<td>14</td>
<td>15</td>
<td>0.5910</td>
<td>60</td>
<td>30</td>
<td>31</td>
<td>0.9744</td>
<td>150</td>
</tr>
<tr>
<td>15</td>
<td>16</td>
<td>0.7463</td>
<td>60</td>
<td>31</td>
<td>32</td>
<td>0.3105</td>
<td>210</td>
</tr>
<tr>
<td>16</td>
<td>17</td>
<td>1.2890</td>
<td>60</td>
<td>32</td>
<td>33</td>
<td>0.3410</td>
<td>60</td>
</tr>
</tbody>
</table>
2.4.4. 69 bus test system

This test system is obtained in the same manner as the 33 bus test system previously described, i.e. making some modifications in the electrical configuration, which can be observed in Figure 2-5. The original AC 69 bus test system was proposed in [90], and the data used in this thesis are presented in Table 2-5. The base values used in this test system for obtaining the p.u values are 12.66 kV and 100 kVA, respectively.

Figure 2-5.: Line diagram the 69 bus test system

Four branches were added to the traditional 69 bus test system [91], to obtain an equivalent mesh system. The data of these branches are described in Table 2-6 and presented in red color on Figure 2-5.

2.4.5. Comparison methods

To validate the performance of the solution methods proposed in this chapter, in terms of both solution quality and computational effort, three comparison methods proposed in literature are used. The first comparison method is the Newton-Raphson method (NR) [92], which finds the voltage profiles by using an iterative process based on a Jacobian matrix formed by partial derivatives of the voltages variables. The second and third methods correspond to the Gauss-Jacobi (GJ) and Gauss-Seidel (GS) [93], respectively; which use a simple iterative process to find the voltages profiles.

2.5. Simulations results

In this section were compared the simulations results obtained with the proposed methods. A first scenario compares all solution methods that allow to solve the PF problem in DC grids with mesh structure. A second scenario evaluates the performance of the methods proposed for solving the DC problem in networks with radial structure. The main idea of those scenarios is to find the methods with the best performance for solving the DC PF in each type of structure. The comparison methods were considered in both scenarios since those methods can solve the DC PF problem in mesh and radial networks.
To ensure a fair comparison between all the solution methods, it is considered a $\epsilon = 1 \times 10^{-10}$, $t_{max} = 1 \times 10^3$ iterations and $1 \times 10^5$ consecutive executions to obtain the average time required. Furthermore, NR was selected as base case for analyzing the performance of the solution methods in terms of quality solution and processing time. The NR method was selected since in [17] it was demonstrated that the method converge to the power flow solution in DC grids. The adopted criteria for comparing all solution methods here used are: the average voltage error ($\text{VoltageError}$), power loss error ($\text{PlossError}$) and the average
2.5 Simulations results

Table 2-6.: Proposed connections for testing the mesh grid case in the 69 bus test system

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>R [pu]</th>
<th>From</th>
<th>To</th>
<th>R [pu]</th>
</tr>
</thead>
<tbody>
<tr>
<td>35</td>
<td>52</td>
<td>0.0022</td>
<td>27</td>
<td>69</td>
<td>0.0025</td>
</tr>
<tr>
<td>50</td>
<td>53</td>
<td>0.0057</td>
<td>46</td>
<td>60</td>
<td>0.0275</td>
</tr>
</tbody>
</table>

processing time. Finally, all simulations of this chapter were carried out on a Dell Precision T7600 Workstation with 32 GB of RAM memory and with an Intel(R) Xeon(R) CPU ES-2670 at 2.50 GHz, it using the software MATLAB.

2.5.1. Simulation results for DC MGs with mesh structure

In this subsection are analyzed the results obtained by the NR, GJ, GS, and the proposed TBM and SA; when those were applied on the mesh test systems used in this thesis. Table 2-7 shows the numerical results, from left to right: the method used, the VoltageError, $P_{\text{loss}}$ Error and the average processing time required by each method defines as “Time”.

By analyzing the VoltageError and $P_{\text{loss}}$ Error of the solution methods, with respect to the NR, it is appreciated that those error values can be neglected for both mesh test systems due to the small values achieved. With respect to the VoltageError, the maximum and minimum average error were obtained by GJ ($1.59 \times 10^{-5}$) and TBM ($1.89 \times 10^{-12}$), respectively. In addition, with respect to the power loss error, the worst case is presented by GJ with an error of ($1.93 \times 10^{-7}$), and the lower error was presented by TBM ($2.38 \times 10^{-13}$). Based on the previous values, it is possible to affirm that all solution methods proposed in this doctoral thesis are adequate for solving the DC PF problem in grids with mesh structure.

Due to the analysis presented in the last paragraph, the selection of the method with the best performance will be based only on the average processing time. Figure 2-6 presents the processing time required by each method with respect to the NR in percent, where the time...
required by the NR method corresponds to 100 %. By analysing the information presented in this figure, the worst methods in terms of processing time are the GJ and GS, which presented an average increasing of a 51247 % and 28154 % with respect to NR, respectively. The other two methods provide a considerable reduction of the average processing time, where TBM requires 43 % and SA requires only the 18 % of the time used by the NR method. In fact, the SA exhibits the shorter processing time in all test systems, hence the SA is the solution method with the best performance for solving the PF problem for DC grids with mesh structure, this in comparison with the methods proposed and used for comparison in this doctoral thesis.

2.5.2. Simulation results DC MGs with radial structure

In this subsection are analyzed the results provided by the methods used for solving the DC PF problem in grids with radial structure, which are presented in Table (2-8). By observing the values show in this table for VoltageError and $P_{\text{loss}}$Error in the four radial test systems, it can be appreciated the same condition than in the case of the mesh structure: the errors are small enough to be neglected. In that way, the minimum and maximum values of VoltageError were $3.88 \times 10^{-15}$ and $1.44 \times 10^{-8}$, respectively; and the minimum and maximum values for $P_{\text{loss}}$Error were $1.77 \times 10^{-12}$ and $2.12 \times 10^{-5}$. Therefore, all the adopted methods provide solutions with similar quality.

With the aim to obtain the method with the best performance for solving the DC PF in radial grids, Figure 2-7 represents the processing time of the methods in percent with respect to the NR in percent. By analysing those results it is appreciated that the GJ and GS provide an average increasing of 40933 % and 32804 % with respect to the NR. However,
2.6 Conclusions

The other methods provide an average reduction with respect to the base case: 82\% (TBM), 22\% (SA), 32\% (TM), 24\% (SMBGT) and 11\% (BF). Therefore, the BF provides the best performance in terms of processing time, with an average reduction of 91.22\% (NR), 95.60\% (GJ), 95.59\% (GS), 90.72\% (TBM), 51.66\% (SA) and 83.14\% (TM); when it is compared with the other methods.

![Figure 2-7: Processing time performance for all solution methods with respect to the base case (NR) in radial test systems.](image)

**Table 2-8:** Results obtained for test system with radial structure.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
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<td>- - - - - - - - - -</td>
<td>1.48 x 10^{-7}</td>
</tr>
<tr>
<td>GJ</td>
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<td>1.47 x 10^{-1}</td>
</tr>
<tr>
<td>GS</td>
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<tr>
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<tr>
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</tr>
<tr>
<td>BF</td>
<td>2.42 x 10^{-13}</td>
<td>1.77 x 10^{-12}</td>
<td>1.47 x 10^{-1}</td>
</tr>
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</table>

**Table 2-8:** Results obtained for test system with radial structure.

<table>
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</table>

2.6 Conclusions

In this chapter the calculation of the power flow in DC grids considering both radial and mesh structures was addressed. To understand this problem, in section 2.2 was made the mathematical formulation, where the assumptions and equations that represent the problem were presented. This formulation allows to identify the non-linear and non-convex nature of
the DC PF problem, for which in this thesis was necessary to employ solution methods of high level for solving it.

In the review of the state of the art made in this doctoral thesis, was found the need to provide efficient methods for solving the DC PF problem, that present an adequate performance in terms of solution quality and processing time. For this reason, five different methods were proposed in section 2.3 of this chapter: two methods based on Taylor’s series expansion and successive approximations, both able to be used on radial and mesh grids with multiple ideal buses; and three methods based on triangular matrix formulation, graph theory and backward/forward methods for DC grids with radial structure of any size. Those methods provide the following main characteristics:

- Taylor’s series based method used a linearization principle similar to the Newton Raphson method; nevertheless, it do not require a Jacobian matrix, which accelerates its convergence’s time in comparison to the NR.

- The successive approximation method uses the nonlinear set of equations with the same philosophy applied to the Gauss–Seidel method, but providing faster convergence and accurate results in comparison with the GS.

- The method based on the triangular matrix do not require any non-diagonal matrix inversion during the iterative process, which make it faster in comparison with the conventional methods.

- The sweep method based on graph theory correlates the branch currents and nodal currents through an admittance matrix, which provides simplicity in its mathematical formulation and faster convergence times.

- The backward/forward method is implement by calculating currents in the backward stage and recovering voltages in the forward stage using an iterative procedure.

To verify the effectiveness and robustness of the proposed methods, four radial test system were used: 10, 21, 33 and 69 buses. The test systems with 10 and 21 buses were taken from [31, 86]. Test systems with 33 and 69 buses are modified versions of systems used in AC networks [87, 13]. Furthermore, two mesh adaptations of the 10 and 69 buses test systems were defined by adding branches to the radial versions. The performance of each method was evaluated in terms of solution quality and processing time, by using three methods reported in literature as comparison methods: Gauss-Jacobi, Gauss-Seidel and Newton-Raphson [93, 31]. The comparison was based on the average voltage error, the power loss error and the average processing time. Finally, the NR was selected as base case for the comparison due to in [17] it was demonstrated that this method converge in DC grids with any structure.
In addition, this chapter compared two test scenarios: the first scenario adopts grids with mesh structure only, by using the NR, GJ, GS, TBM and SA. The second scenario evaluates the performance of all methods in networks with radials structure. It is important highlight that, in both scenarios, the average voltage and power loss error are neglected due to the lower values achieved. For this reason, this thesis concludes that all proposed methods are adequate for solving the DC PF problem in grids by considering mesh and radial structure, this in terms of the solution quality.

Due to the previous conditions, the selection of the methods with the best performance was based on the average processing time. The simulation results obtained in the mesh test systems demonstrated the robustness and effectiveness of the proposed methods in comparison with the other solution reported in literature. From those results, the SA is the power flow method with the best performance for mesh DC grid. For the second scenario, the sweeps iterative methods provided the best results, and as the size of the DC network increases, the BF method provides the best performance. Therefore, the BF method is the best option for solving power flow problem in DC microgrids with radial structure, specially for large systems.

Finally, as future work, can be considered to improve the efficiency of the mathematical methods inside the solution methods that require matrix inversions. Furthermore, parallel processing tools can be used to improve the efficiency of the solution methods in terms of processing times.
3. Optimal Power Flow in DC grids

In the previous chapter different solution methods for solving the power flow problem were proposed, which are responsible to evaluate the impact on the electrical variables of the MG (branches currents and voltages profiles) of the power generated and demanded by the DERs located on the DC grid at steady-state conditions [31]. However, for obtaining the size of the DERs, in the planning stages, it required a method to find the power values providing the highest technical, economical or environmental benefits; it requiring short processing times. Therefore, this chapter is devoted to develop the mathematical formulation that describe the OPF problem in DC grids and to propose a solution method that provides satisfactory results, in this particular case in terms of power loss reduction and processing time. Such a solution is focused on DGs.

For solving the DC OPF problem, this chapter adopts a sequential programming perspective, which eliminates the need of using specialized software to solve the mathematical formulation of the OPF. For this purpose, this doctoral thesis proposes a master-slave solution. The master stage defines the total power output of each generator, while the slave stage solves the power flow equations and compute the fitness function of the problem (i.e. power loss minimization). The master stage could be composed by three continuous optimization methods: the Particle Swarm optimization Algorithm (PSO), a Continuous version of the Genetic Algorithm (CGA) and the Black Hole Optimization method (BH); which are selected due to satisfactory results reported in solving the OPF problem in AC grids [87, 94, 95]. The slave stage is designed to solve the power flow by using the successive approximation method, described in chapter (2), which works with both radial and mesh grids considering multiple buses. The aim of this chapter is to select the master-slave solution, formed with one of the proposed continuous methods and with the SA, which provides the best performance in terms of solution quality and processing time.

Part of the analyses and results reported in this chapter have been published in the international journal Advances in Electrical and Electronic Engineering in the paper: “Optimal power flow in direct-current power grids via black hole optimization” [96] and in the journal WSEAS Transactions on Power Systems in the paper “Optimal power dispatch of DGs in DC power grids: a hybrid Gauss-Seidel-Genetic-Algorithm methodology for solving the OPF problem” [97].
3.1. Introduction

Due to the importance of the DC networks, and the need of integrating renewable resources on the electrical systems for reducing the negative impact of fossil fuels and improving different economical and technical aspects [31], several authors have evaluated the integration of distributed generators in DC grids. For analysing the impact of the power supplied by the DGs into the DC grid (sizing problem), in literature have been proposed optimal power flow methods to find the power level to be injected by each generator, with the purpose of improving different technical indicators, such as power loss, voltage profiles, among others [45]. An example of this is presented in [28], where a second order cone programming formulation is proposed to solve the OPF problem in standalone DC MGs. In addition, in [98] is proposed a convex quadratic model for solving the OPF problem, which uses as fitness function the reduction of the power loss. In [44] was used the Linprog function for solving the DC OPF problem in a radial DC MG, the authors in this work do not compare the obtained results with other solution methods reported in literature. The main problem of the methods previously cited, is the use of specialized optimization software for solving the DC OPF problem.

With the aim of not using specialized software to solve the DC OPF problem, the authors of [95] proposed a methodology based on the PSO algorithm. The main problem of this work is that the authors consider a MG with an unique bus that neglected the branches and multiples buses existing in regular DC MGs, as shown in Chapter 2. Within the review carried out in this doctoral thesis, other works addressing the OPF in DC grids without using specialized software were not found, which demonstrates the need to propose techniques based on sequential programming that allow to obtain solutions with high quality and with shorter processing times. However, in AC grids have been proposed multiple works based on sequential programming that not require commercial or special software, by using different optimization techniques such as numerical methods, heuristics and methaheuristics techniques, stochastic methods, among others [99]. In the review made in this thesis, it was observed that for AC grids is commonly adopted the power loss reduction as fitness function; and many works are aimed to reduce the processing times required by the solution methods.

Based on that situation, in this chapter a master-slave methodology based on sequential programming was proposed. For the master stage three different continuous optimization methods are tested (BH, CGA and PSO), which are in charge of sizing the DGs located on DC grid. In the slave stage was used the SA, described in the previous chapter, which calculates the fitness function of the possible solution proposed by the master stage. By combining the continuous optimization methods with the SA, three different master-slave methodologies are obtained: BH/SA, CGA/SA and PSO/SA. To validate the effectiveness and robustness of the different solution methodologies, the test systems of 21 and 69 nodes were used. In addition, three different scenarios of maximum distributed power generation
were considered: 20%, 40%, and 60% of the total power generated by the slack bus; which enable to evaluate the impact of the distributed power generation on the electrical system. The simulations were conducted in MATLAB to select the master-slave methodology with the best performance for solving the OPF problem in DC grids.

This chapter is organized as follows: Section 3.2 presents the mathematical formulation of the optimal power flow problem in DC networks with a nonlinear and non-convex structure. Section 3.3 defines the proposed methodology based on the master-slave strategy. Section 3.4 presents the main characteristics of the test systems and shows the numerical validation of the three different master-slave optimization algorithms, with the corresponding analysis and discussion. Finally, Section 3.5 presents the concluding remarks derived from this chapter.

### 3.2. Mathematical Formulation

The OPF problem is formulated through a mathematical model composed of an objective function related to a set of constraints of the power flow in DC networks [67]. This mathematical model can be used to satisfy different technical, economical and environmental objectives fixed by the proprietary or operator of the DC grid; e.g. the power loss, which is the variable in this chapter as the objective function.

#### 3.2.1. Objective function

The objective function is defined as a value to be minimized applying optimal flow; in this particular case, the minimization of power loss in a DC MG associated to the energy transport by the branches. To represent that function, it is used Equation (3-1), where $P_{\text{loss}}$ represents the power loss (the variable to be minimize), which is a function of $v$ and $G_B$, those representing the bus voltages and conductivity matrix associated to the branches.

$$

\text{min } P_{\text{loss}} = \text{min} \ (v^T G_B v), \quad (3-1)

$$

#### 3.2.2. Constraints

Constraints refer to limits of the OPF and PF problems. They are represented by the following equations:
3.2 Mathematical Formulation

\[ p_g + p_{dg} - p_L = D(v)Gv \]  \hspace{1cm} (3-2)

\[ P_{g}^{\min} \leq p_g \leq P_{g}^{\max} \]  \hspace{1cm} (3-3)

\[ P_{dg}^{\min} \leq p_{dg} \leq P_{dg}^{\max} \]  \hspace{1cm} (3-4)

\[ V_{\min} \leq v \leq V_{\max} \]  \hspace{1cm} (3-5)

\[ Ones^T p_{dg} - P_{DG}^{\max} \leq 0 \]  \hspace{1cm} (3-6)

This is the mathematical interpretation of Equations (3-2) to (3-6): In Equation (3-2) \( p_g, p_{dg} \) and \( p_L \) refer to the power generated by the slack node, the power supplied to the network by the DGs, and the power demanded at the network nodes, respectively. This Equation expresses the power balance of the network. In Equations (3-3) and (3-4) \( P_{g}^{\min} \) and \( P_{g}^{\max} \) denote the minimum and maximum power that the slack node can deliver to the network. Likewise, \( P_{dg}^{\min} \) and \( P_{dg}^{\max} \) define the minimum and maximum power that the DGs can supply. Those Equations are used to determine the generation capacity of both the slack node and the DGs. Equation (3-5) includes \( V_{\min} \) and \( V_{\max} \), which define the maximum and minimum allowable voltage, those representing the voltage regulation limits. Finally, Equation (3-6) defines the maximum generation of the DGs allowed in the DC grid, where \( P_{DG}^{\max} \) represents the allowable distributed generation with respect to the power generated by the slack bus, without considering the location of distributed generator on the electrical system. In this Equation \( Ones^T \) is a vector filled with ones transposed , that allows made the mathematical operation between \( p_{dg} \) and \( P_{DG}^{\max} \).

3.2.3. Fitness function:

The fitness function \((z)\), is composed of the original objective function value as well as constrains added using penalties. The fitness function value proposed in this chapter to guide the master optimization problem is:

\[
\min z = \left( \begin{array}{c}
  p_{loss} + \beta_1 Ones^T \max \{0, v - V_{\max}^\}\ \\
  + \beta_2 Ones^T \min \{0, v - V_{\min}^\} \\
  + \beta_3 Ones^T \max \{0, p_{dg} - P_{dg}^{\max} \} \\
  + \beta_4 Ones^T \min \{0, p_{dg} - P_{dg}^{\min} \} \\
  + \beta_5 \max \{0, Ones^T p_{dg} - P_{DG}^{\max} \}
\end{array} \right)
\]  \hspace{1cm} (3-7)

where \( \beta_1 \) to \( \beta_5 \) correspond to penalization factors, which are typically higher than zero. In this chapter, each penalization factor is equal to 1000 in order to force the optimization methods to fulfill all the conditions imposed over the OPF problem formulated from (3-1) to (3-6). Such a value was obtained through trial and error, when all the constrains are fulfilled, all the penalization factors must be annulled by \( \max \{\cdot\} \) and \( \min \{\cdot\} \) functions, which turns the fitness function value into an objective function, since in that case \( z \) is equal to \( P_{loss} \).
3.3. Proposed methodology

The set of equations introduced in the previous section, require nonlinear methods to find the solution. In that sense, this study proposes to divide the optimal power flow problem in DC networks into two stages: The first stage (master) uses three different continuous optimization methods to find the optimal power injection of the DGs. The second stage (slave) uses the SA to evaluate the fitness function in each one of the possible solutions proposed by the master stage. The following subsections describe the master-slave methodology adopted in this chapter:

3.3.1. Master stage: continuous optimization methods

The master stage is used for dimensioning the DGs. This process is performed with three different continuous optimization techniques: BH, CGA and PSO. Those methods were selected since they have been used in literature for OPF analysis in AC grids networks, obtaining satisfactory results [87, 94, 95]. On the other hand, with the objectives to reduce the processing time and provide a fair comparison between the continuous methods used, the successive approximation method, presented in Chapter 2 of this thesis, was used for solving the power flows required in the evaluation of each continuous optimization method, due to that this solution method is highly effective in DG grids with both radial and mesh structure. The continuous methods are presented below.

3.3.1.1. Black hole optimization method (BH):

This is a nature-inspired optimization technique based on the dynamic interaction between stars and black holes [100]. This technique has been used for solving nonlinear optimization problems by implementing a particle swarm (stars) as well as a criterion of elimination and generation of stars through a heuristic approach (event horizon radius). The BH method is briefly introduced below by highlighting the main steps in its computational implementation.

Stars are born:

The BH approach is a population-based optimization algorithm derived from conventional particle swarm optimization [101]; in that sense, the initial population ($P_t$) corresponds to the first set of stars randomly distributed over the solution space, i.e., as a cumulus of stars in the universe [102]. During the generation of this set of stars, the number of stars ($n_i$), possible solutions, is the number of rows; while number of DGs ($n_{dg}$) is the number of columns, as formulated in Equation (3-8).

$$P_t = P_{dg}^{min} o(n_i, n_{dg}) + (P_{dg}^{max} - P_{dg}^{min}) r(n_i, n_{dg})$$  (3-8)
3.3 Proposed methodology

In the previous expression, $P_t$ represents the star population matrix, $o(n_i, n_{dg})$ is a rectangular matrix filled with ones, and $r(n_i, n_{dg})$ corresponds to a rectangular matrix filled with random numbers from zero to one with normal distribution properties. Note that $P_t$ corresponds to the current population and each individual (star) inside it represents the total power generation at all nodes that contain DGs. Furthermore, the best solution (lower fitness function for minimization problems) inside the initial population $P_t$ is selected as a black hole location. In the case of the DC power flow problem, $P_t$ is represent by the following equation:

$$P_t = \begin{bmatrix}
p_{dg(1,1)} & p_{dg(1,2)} & \cdots & p_{dg(1,k)} & \cdots & p_{dg(1,n_{gd})} \\
p_{dg(2,1)} & p_{dg(2,2)} & \cdots & p_{dg(2,k)} & \cdots & p_{dg(2,n_{gd})} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
p_{dg(1,1)} & p_{dg(l,2)} & \cdots & p_{dg(l,k)} & \cdots & p_{dg(l,n_{gd})} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
p_{dg(n_i,1)} & p_{dg(n_i,2)} & \cdots & p_{dg(n_i,k)} & \cdots & p_{dg(n_i,n_{gd})}
\end{bmatrix}_{n_i \times n_{gd}}$$  (3-9)

Where $p_{dg(l,k)}$ represents the active power generated by the generator $k$ at the $l$ solution individual.

Movement of stars:

The dynamic behavior of stars in the proximity of a black hole is highly influenced by the intense gravitational force of the latter. In that sense, the movement of any star may have a particular behavior as a function of its location with respect to the position of the black hole [100]. Such behavior is emulated by the mathematical relationship presented in Equation (3-10).

$$P_{t+1}^i = P_t^i + (P_t^{BH} - P_t^i)r(n_{dg}); \quad i = 1, 2, \ldots, n_i$$  (3-10)

where $P_t^{BH}$ represents the black hole in population $t$, and $P_{t+1}^i$ denotes the $i^{th}$ individual after its movement. Remarkably, after this process the location of the black hole remains unaltered.

Black hole updating:

After generating the descending population of stars $P_{t+1}$, the location of the black hole must be changed if the $i^{th}$ individual among the descending population exhibits a lower fitness function value than the current black hole, i.e., $P_t^{BH} = P_{t+1}^i$; otherwise, the location of the black hole remains constant, i.e., $P_t^{BH} = P_t^{BH}$.
Star replacement:

The survival of a star in the neighborhood of a black hole depends on its current position with respect to black hole’s location. In theoretical physics, any object that crosses the event horizon around a black hole is destined to destruction. Nevertheless, this catastrophic scenario generates stellar material that enables the formation of new stars. To emulate the possibility that an arbitrary star in the descending population is absorbed by the black hole, the event horizon radius is defined as:

\[ R_{EH} = \frac{f(P_{BH}^t + 1)}{\sum_{i=1}^{n_i} f(P_i^t + 1)} \]

(3-11)

where \( f(P_{BH}^t + 1) \) represents the best fitness function value of all individuals contained in the current population (black hole fitness function value), while the denominator of (3-11) corresponds to the sum of the fitness function of all individuals in the same iteration.

To determine if any star crosses the event horizon, the euclidean distance of such star with respect to the black hole’s location is defined in Equation (3-12).

\[ D_{BH-i} = \| P_{BH}^t + 1 - P_i^t + 1 \| \]

(3-12)

If \( R_{EH} > D_{BH-i} \), a new star is randomly generated to replace the one absorbed by the black hole; otherwise, the star continues in the current population. Notice that the birth of new stars increases the possibility of expanding the exploration of the algorithm over the solution space, which would be considered global exploration [102].

Stopping criterion:

To halt the exploration of the BH over the solution space, one of the following stopping conditions must be satisfied:

- The maximum number of iterations (\( t_{max} \)) has been reached.
- After \( k \) consecutive iterations the black hole’s location has not been updated.

Finally, the Algorithm 5 shows the application of the master-slave solution method proposed in this study to solve OPF problems in DC power grids via a hybrid BH–SA approach.

3.3.1.2. Continuous genetic algorithm (CGA)

This proposed optimization method is a continuous approach of the conventional GA proposed by Chu & Beasley in [103]. It uses the selection, recombination and mutation operators with a continuous representation in order to generate the population representing the sizes
Algorithm 5 Proposed pseudo-code for the hybrid BH–SA approach.

Data: Initialization parameters

for $t = 1 : t_{\text{max}}$ do
  if $t == 1$ then
    Generate initial population
    Solve slave problem
    Evaluate fitness function
    Assign black hole location
  else
    Generate descending population
    Solve slave problem
    Evaluate fitness function
    Black hole updating
    Star replacement
    if Has any stopping criteria been met? then
      Finish optimization process
      Optimal solution found
      Print results
      Break
    else
      Continue
    end
  end
end

of the DGs. The genetic algorithm has four main characteristics to know: generation of the initial population, genetic operators for generating the descending population, new population calculation and stopping criteria. All of them are important to solve any optimization problem, each one of them is explained below.

**Initial population:**

This is the first step of the iterative process of the CGA, equal to the BH, it is proposed a population with a size of $n_i$ rows and $n_{gd}$ columns, by using the Equation (3-8) to obtain the individuals that composes the initial population. After generating the initial population, the slave stage evaluates the fitness function of all individual that form $P_t$, selecting the individual with the lower fitness function value as best solution (incumbent).

**Descending population:**
The genetic algorithm corresponds to an iterative optimization process, hence it is necessary to generate new potential solutions to replace the bad solutions the current population. To generate those new individuals, the classical selection, recombination and mutation operators are adapted to solve continuous optimization.

**Selection:** the descending population starts selecting an arbitrary subset of individuals contained in the current population, in this selection a random number \( r \) between 1 to \( n_i \) is chosen, i.e., \( r = 1 + (n_i - 1) \text{rand} \), where \( \text{rand} \) corresponds to a random number between 0 to 1. If \( r < n_i \), an additional \( (n_i - r) \times n_{gd} \) matrix with potential solutions are generated by using the same strategy adopted for the initial population. The total set of selected individuals are conformed by the combination of both strategies.

**Recombination:** this process alters the descending population through the following principle. If the recombination probability \( r_p \) is higher than 50\% (this value has been arbitrary selected), then, two arbitrary individuals (randomly selected) are recombined in an arbitrary position selected via random number between 1 to \( n_{gd} \). If \( r_p \) is lower than 50\%, then two arbitrary individuals (randomly chosen) are averaged to generate a new potential individual. This operation always generates feasible individuals, since the initial population and the random solutions are generate inside of the admissibility region of the distributed generators. This process continues to obtain descending population with \( n_i \) potential solutions.

**Mutation:** In this point the mutation probability \( m_p \) is explored, i.e., if \( m_p \) is higher than 50\% (this value has been arbitrary selected), an arbitrary position of the potential solution between 1 to \( n_{gd} \) is modified by an arbitrary power generation value guaranteeing that (3-4) be satisfied. If \( m_p \) is lower than 50\%, the potential solution is not modified. This process continues until all descending individuals are analyzed. Once the descending population has been, generated its fitness function values are calculated by using the slave stage.

**New population:**

In the new population will be saved the set of best solutions found by the genetic algorithm up to the current iteration \( t \). Then, a new population is generated by combining the current and descending set of individuals, which produces a population with \( 2 \times n_i \) potential solutions; if, two potential solutions are identical, then, one of them is eliminated. This procedure is repeated until guaranteeing that all potential solutions are different (diversity criterion). After that process, the resulting potential solution list is ascending ordered in terms of the fitness function values, and the first \( n_i \) potential solutions are selected as the new population for the next iteration cycle \( t + 1 \). Finally, the incumbent is update.

**Stopping criteria:**
3.3 Proposed methodology

The proposed CGA finishes its optimization process with the same conditions proposed for the BH. Finally, Algorithm 6 presents the iterative process of the CGA/SA hybrid methodology.

Algorithm 6 Proposed pseudo-code for the hybrid CGA/SA approach.

Data: Initialization parameters

for $t = 1 : t_{max}$ do
  if $t == 1$ then
    Generate initial population
    Solve slave problem
    Evaluate fitness function
    Select the incumbent
  else
    Generate descending population by using selection, recombination and mutation
    Solve slave problem
    Evaluate fitness function
    Generate the new population
    Update the incumbent
  if Has any stopping criteria been met? then
    Finish optimization process
    Optimal solution found
    Print results
    Break
  else
    Continue
  end
end

3.3.1.3. Particle swarm optimization (PSO)

The PSO is a bio-inspired meta-heuristic algorithm based on the behavior of the flocks of fish and birds, and it was proposed by Eberhart and Kennedy in 1995 [104]. This method takes advantage of the mode used by the groups of animals for exploring a region to find a common source of food for all individuals of the group. By modeling each individual as a particle, it is possible to transform the group of individuals in a particle swarm dispersed over a solution space. This particle swarm is limited by a set of constraints associated with each problem. In the PSO algorithm each step or iteration takes into account the information of each particle, as well as the particle swarm information, for generating the next movement. The application of PSO for solving the OPF problem in DC grids is summarized in the
Algorithm and explained below.

**Generate the particle swarm:**

In the first iteration, the particle swarm is generated in a random way, by assigning the active power to be supplied by DGs as in the BH and CGA solutions (using Equation (3-4)). In the PSO, each individual of the population is known as particle and the population as particles swarm. In this optimization method, the number of particles depends on the particular problem [95]. Subsequently, the power flow is solved and the fitness function for each particle is evaluated by using the slave stage. Finally, the best solution and best position for each particle are selected: bestpos\(_i\) and bestsol\(_i\), respectively; and the best solution and the best position of the particles swarm (incumbent) are also detected: bestpos\(_g\) and bestsol\(_g\).

**Movement of the particles:**

The PSO uses a velocity vector to control the movement of the particles swarm in the solution space. For each particle, the movement in the iteration \(t\) (\(x^t\)) is a function of the position of the particle swarm in the last iteration (\(x^{t-1}\)) and its movement speed at the current iteration \(t\) (\(MS^t\)), see Equation (3-13).

\[
x^t = x^{t-1} + MS^t
\]

In the first iteration of the optimization process, the movement speed for all particles swarm (MS) is obtained using Equation (3-14); where, \(MS^{\text{min}}\) and \(MS^{\text{max}}\) correspond to the minimum and maximum values allowed for the movement speed of each particle, \(o(P, n_{dg})\) and \(r(P, n_{dg})\) represent a rectangular matrix filled with ones and random numbers between zero to one. From the second iteration on, Equation (3-15) is used to calculate the movement speed of the \(i^{th}\) particle in the iteration \(t\) (\(MS^t_i\)), which is a function of the inertia factor at the iteration \(t\) (\(\Omega^t\)), the movement speed of the particle in the previous iteration (\(MS^{t-1}_i\)), the position of the particle in the last iteration (\(x^{t-1}_i\)), a cognitive and social factors (\(\phi_1\) and \(\phi_2\)) controlling the direction of the movement of the particle, which points to the best particle and swarm position; and two random values (\(r_1\) and \(r_2\)) that prevent the technique from being trapped in a local optima [95].

\[
MS = MS^{\text{min}} o(P, n_{dg}) + (MS^{\text{max}} - MS^{\text{min}}) r(P, n_{dg})
\]

\[
MS^t_i = \Omega^t MS^{t-1}_i + \phi_1 r_1 (\text{Bestpos}_i - x^{t-1}_i) + \phi_2 r_2 (\text{Bestpos}_g - x^{t-1}_i)
\]
The inertia factor is in charge to control the convergence of the PSO, this value is update in each iteration by using the current iteration value \( t \), the maximum number of iterations proposed for the algorithm \( t_{\text{max}} \) and the maximum and minimum limits fixed to \( \Omega \). Equation (3-16) allows calculating the value of the inertia factor \( \Omega^t \) in the iteration \( t \).

\[
\Omega^t = \Omega^{\text{max}} - \left( (\Omega^{\text{max}} - \Omega^{\text{min}}) / \Omega^{\text{max}} \right) \ast t
\]

Evaluation of the fitness function and update of the best solution and position:

After the movement of the particles, the fitness function for each particle is evaluated; and with this information the best solution and position for each particle and the swarm are update (best solution of the problem).

Stopping criterion:

The same stopping criteria used for the BH and CGA solutions are adopted for the PSO algorithm.

3.3.2. Slave Stage:

The slave problem is used to calculate the fitness function associated with the possible solution proposed by the master stage. In other words, the slave stage calculates the electrical variables needed to estimate the power loss of the system. For that purpose, this thesis proposes to solve the power flow problem through the iterative method based on Successive Approximation presented in chapter 2, which allows solving the DC power problem in grids with radial and mesh structure; providing short processing times. This characteristics improves the performance of the master-slave methodologies proposed in this chapter.

3.4. Simulation results

In order to validate the solution methodologies proposed in this chapter, two tests of 21 and 69 buses, described in chapter 2 were used. Since the objective of those methodologies is to find the optimal size of the DGs, the test systems were modified by changing the generation buses with constant power loads, but keeping the same power level assigned in the traditional test system for the generation. In this work, the location of the DGs on the electrical grid were based on the locations reported in literature for both test systems, which are reported in the analysis of each test system given in subsection 3.4.1 and 3.4.2. The parameters selected for the sizing techniques are shown in Table 3-1. The main parameters of those
Algorithm 7 Pseudo-code for the PSO algorithm

Data: Assign initial conditions

for \( t = 1 : t_{\text{max}} \) do

if \( t = 1 \) then

Generate the particles swarm
Solve slave stage
Evaluate the fitness function
Select \( \text{bestpos}_i \) and \( \text{bestsol}_i \) for each particle
Select \( \text{bestpos}_g \) and \( \text{bestsol}_g \) of the particle swarm

else

Calculate the velocity vector
Update the position of the particles swarm
Solve the slave stage
Evaluate fitness function
Update \( \text{bestpos}_i \) and \( \text{bestsol}_i \) for each particle
Update \( \text{bestpos}_g \) and \( \text{bestsol}_g \) of the particle swarm

if Have any stopping criteria been met? then

Solution found
Finish optimization process
Break

else

Continue

end

end

end

Techniques are selected equal, or equivalent, to provide a fair comparison. Those parameters are: the number of particles in the swarm or the population size, the total number of iterations, and the maximum number of iteration without improving the fitness function. These parameters were found through trial and error to provide a satisfactory balance between the number of iterations, the size of the population, and the total processing time required by the master technique (location of the generators). This is important because the relation between the exploration vs exploitation (i.e. exploration/exploitation) could be decreased dramatically and the real improvements in the objective function related to the power loss minimization could be negligible \[13\]. The stopping criterion based on the 50 iterations without improvements corresponds to the 25\% of the total iterations, which was considered as an adequate criteria for finishing the exploitation process, because it allows identifying if the solution is a local or a global optimum. The selection of this percent was made through trial and error. This can take different values according to the problem analyzed \[105, 106\].
3.4 Simulation results

Table 3-1.: Parameters of the sizing techniques

<table>
<thead>
<tr>
<th>Method</th>
<th>CGA</th>
<th>BH</th>
<th>PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of particles</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Selection method</td>
<td>Tournament</td>
<td>Event horizon radius</td>
<td>Cognitive and social component: 1.4</td>
</tr>
<tr>
<td>Update population method</td>
<td>Cross over: averaging</td>
<td>Cognitive and social component</td>
<td>Speed/Inertia (max-min): (0.1-0.1)/(0.7-0.001)</td>
</tr>
<tr>
<td>Mutation</td>
<td>Random population</td>
<td>Random population</td>
<td>R1 = R2: Random</td>
</tr>
<tr>
<td>Stopping criterion</td>
<td>Max. iterations: (200)</td>
<td>Max. iterations: (200)</td>
<td>Max. iterations: (200)</td>
</tr>
<tr>
<td></td>
<td>Iteration without improving: (50)</td>
<td>Iteration without improving: (50)</td>
<td>Iteration without improving: (50)</td>
</tr>
</tbody>
</table>

Additionally, three different levels of maximum DG generation in both test systems were considered: 20%, 40%, and 60% of the total power demanded at the slack node, in order to evaluate the impact of the distributed power injected on the DC grid. In this thesis, each distributed generator installed in the electrical network can exploit the maximum allowable generation, as long as the other generators are not injecting power into the network. As parameters for the slave stage, it was assigned a maximum number of iterations equal to 2000, and a convergence error equal to $1 \times 10^{-10}$ (the same adopted in Chapter 2).

Finally, to calculate the average processing times and the minimum, mean and standard deviation of the solution obtained by the solution methods, each test scenario was executed 1000 times. The simulations were carried out on a Dell Precision T7600 Workstation with 32 GB of RAM memory and with an Intel(R) Xeon(R) CPU ES-2670 at 2.50 GHz.

### 3.4.1. 21 bus test system

In the modified version of the 21 bus system, the slack bus generates a power equivalent to 5.8160 p.u., which represents a power loss equal to 0.27603 p.u; that value corresponds to the base case (without DGs installed on the electrical system). In this test system, the same base values proposed in chapter 2 for the original test system were adopted. Furthermore, the locations of the generators in the 21 bus system are nodes 9, 12, and 16, as it is reported in [107].

Table 3-2 presents the results obtained by the proposed methodologies to solve the OPF problem in the 21 bus test system. The information presented in this table is organized as follows: The first column reports the method; the second column shows the DG location.
Table 3-2: Results in the 21-node system

<table>
<thead>
<tr>
<th>Method</th>
<th>DG location /Size</th>
<th>Power Loss</th>
<th>Time [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[p.u]</td>
<td>[µ [p.u]]</td>
<td>[σ [%]]</td>
</tr>
<tr>
<td>20 % generation = 1.1632 [p.u.]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BH</td>
<td>9/0.0063</td>
<td>0.1321</td>
<td>0.1431</td>
</tr>
<tr>
<td></td>
<td>12/0.1932</td>
<td>0.1320</td>
<td>0.1344</td>
</tr>
<tr>
<td></td>
<td>16/0.9616</td>
<td>0.1318</td>
<td>0.1330</td>
</tr>
<tr>
<td>CGA</td>
<td>9/0.0069</td>
<td>0.1320</td>
<td>0.1344</td>
</tr>
<tr>
<td></td>
<td>12/0.1752</td>
<td>0.1320</td>
<td>0.1344</td>
</tr>
<tr>
<td></td>
<td>16/0.9805</td>
<td>0.1318</td>
<td>0.1330</td>
</tr>
<tr>
<td>PSO</td>
<td>9/0.0069</td>
<td>0.1320</td>
<td>0.1344</td>
</tr>
<tr>
<td></td>
<td>12/0.1781</td>
<td>0.1320</td>
<td>0.1344</td>
</tr>
<tr>
<td></td>
<td>16/0.9851</td>
<td>0.1318</td>
<td>0.1330</td>
</tr>
<tr>
<td>40 % generation = 2.3264 [p.u.]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BH</td>
<td>9/0.2341</td>
<td>0.0614</td>
<td>0.0675</td>
</tr>
<tr>
<td></td>
<td>12/0.7789</td>
<td>0.0612</td>
<td>0.0622</td>
</tr>
<tr>
<td></td>
<td>16/1.3117</td>
<td>0.0612</td>
<td>0.0622</td>
</tr>
<tr>
<td>CGA</td>
<td>9/0.3124</td>
<td>0.0612</td>
<td>0.0622</td>
</tr>
<tr>
<td></td>
<td>12/0.7085</td>
<td>0.0612</td>
<td>0.0622</td>
</tr>
<tr>
<td></td>
<td>16/1.3050</td>
<td>0.0612</td>
<td>0.0622</td>
</tr>
<tr>
<td>PSO</td>
<td>9/0.3058</td>
<td>0.0612</td>
<td>0.0623</td>
</tr>
<tr>
<td></td>
<td>12/0.7296</td>
<td>0.0612</td>
<td>0.0623</td>
</tr>
<tr>
<td></td>
<td>16/1.2910</td>
<td>0.0612</td>
<td>0.0623</td>
</tr>
<tr>
<td>60 % generation = 3.4896 [p.u.]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BH</td>
<td>9/0.8948</td>
<td>0.0288</td>
<td>0.0319</td>
</tr>
<tr>
<td></td>
<td>12/1.0584</td>
<td>0.0280</td>
<td>0.0288</td>
</tr>
<tr>
<td></td>
<td>16/1.4754</td>
<td>0.0280</td>
<td>0.0288</td>
</tr>
<tr>
<td>CGA</td>
<td>9/1.0005</td>
<td>0.0280</td>
<td>0.0288</td>
</tr>
<tr>
<td></td>
<td>12/1.0667</td>
<td>0.0280</td>
<td>0.0288</td>
</tr>
<tr>
<td></td>
<td>16/1.4219</td>
<td>0.0280</td>
<td>0.0288</td>
</tr>
<tr>
<td>PSO</td>
<td>9/0.9330</td>
<td>0.0279</td>
<td>0.0283</td>
</tr>
<tr>
<td></td>
<td>12/1.0739</td>
<td>0.0279</td>
<td>0.0283</td>
</tr>
<tr>
<td></td>
<td>16/1.4827</td>
<td>0.0279</td>
<td>0.0283</td>
</tr>
</tbody>
</table>

and the power injected by each DG. Between columns third to the fifth are presented the minimum value (min [p.u.]), mean value (µ [p.u]) and standard deviation (σ [%]) of the fitness function (power loss reduction). Finally, the sixth column presents the average time required by each methodology. Figure 3-1 presents the minimum and mean reduction of the power loss obtained by the solution methods. In subfigure 3-1(a) is presented the minimum reduction of power loss obtained by each method for all levels of maximum DG generation allowed. In this illustration it can be appreciated that the PSO method provides the best solution, with an averaged reduction of 73.32% in the $P_{loss}$ when it is compared with the base
case. Moreover, it is obtained an improvement on the average minimum reduction of the $P_{\text{loss}}$ of $0.18\%$ and $0.04\%$ with respect to BH and CGA, respectively. The subfigure 3-1(b) shows the mean reduction in the $P_{\text{loss}}$. In the particular case when it is considered a maximum DG generation of 20\%, the PSO obtained the best results with a mean reduction equal to 51.8\%; which is 3.65\% and 0.5\% higher than the BH and CGA, respectively. For the case of a maximum DG generation of 40\%, the CGA presents the best solution with a reduction of 77.46\%, obtaining an improvement in the mean reduction of 1.93\% and 0.05\% with respect to BH and PSO, respectively. Finally, for a value of 60\% on DG generation, the best solution is achieved by the PSO (89.74\%), the second and third best solutions are the CGA (89.57\%) and BH (88.45\%). Analyzing the previous results, the PSO algorithm provides the best average results in terms of minimum (0.11\%) and mean (1.24\%) reduction of power loss for the 21 bus test system; when it is compared with the CGA and BH, respectively. Moreover, the standard deviation of the solutions, given in Table 3-2, shows that all the methods exhibit high consistency in the results, since $\sigma$ is lower than 8\% in all test scenarios. In addition, when the maximum DG generation allowed increases, the $\sigma$ decreases for all methods.

Figure 3-2 analyzes the processing times required by the solution methods, where the BH
3.4.2. 69 bus test system

For the adaptation made to the 69 bus test system in this chapter, the power generation of the slack node is 40.4311 p.u., and the power loss is 1.5385 p.u (base case for this scenario). In addition, the slack bus operates with a voltage of 1 p.u, with the same base values reported by the radial system described in chapter 2. In this DC grid, the generators are located at nodes 26, 61, and 66, as it is reported in [13].

Table 3-3 presents the results of the solution methods applied to the 69 bus test system. In this way, Figure 5-23 shows the minimum and mean power loss reduction, where the PSO presents the best results in all test scenarios, presenting an improvement of 0.03 % and 0.33 % in the minimum power loss reduction when it is compared with the CGA and BH, respectively. In the same way, for the mean power loss reduction, the PSO presents a mean reduction of 0.02 % and 3.03 % higher than CGA and BH, respectively. With respect to the $\sigma$, similar to the 21 bus test system, the average value obtained does not exceed 7 %. It is important highlight that, as the maximum DG generation level increase, the $\sigma$ for the BH and CGA also increases; while the $\sigma$ associated to the PSO decreases. The previous results confirm that the PSO provides the best solution for both the 21 and 69 bus test systems, and the BH achieved the worst results in terms of quality solution.

Figure 3-4 shows the processing times required by the solution methods. In this figure it can be observed that the BH is in the first place, and the CGA and PSO are in the second and third place in terms of processing time, respectively. The BH presents an average processing time reduction of 45.72 % and 69.11 % with respect to the CGA and PSO, respectively. The processing time required by all methods for the 21 and 69 bus test systems allows to identify
Table 3-3.: Results in the 69 bus test system

<table>
<thead>
<tr>
<th>Method</th>
<th>DG location / Size</th>
<th>Power Loss</th>
<th>Time [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>( \text{min} ; \text{[p.u.]} )</td>
<td>( \mu ; \text{[p.u.]} )</td>
</tr>
<tr>
<td>BH</td>
<td>26/0.1618</td>
<td>0.5745</td>
<td>0.6298</td>
</tr>
<tr>
<td></td>
<td>61/4.5862</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>66/3.2877</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CGA</td>
<td>26/0.0040</td>
<td>0.5655</td>
<td>0.5798</td>
</tr>
<tr>
<td></td>
<td>61/5.7967</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>66/2.2798</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PSO</td>
<td>26/0.0002</td>
<td>0.5649</td>
<td>0.5757</td>
</tr>
<tr>
<td></td>
<td>61/5.5722</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>66/2.5139</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

20% generation = 8.0862 [p.u.]

<table>
<thead>
<tr>
<th>Method</th>
<th>DG location / Size</th>
<th>Power Loss</th>
<th>Time [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>( \text{min} ; \text{[p.u.]} )</td>
<td>( \mu ; \text{[p.u.]} )</td>
</tr>
<tr>
<td>BH</td>
<td>26/1.6018</td>
<td>0.1440</td>
<td>0.1928</td>
</tr>
<tr>
<td></td>
<td>61/12.8098</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>66/1.6554</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CGA</td>
<td>26/1.7335</td>
<td>0.1407</td>
<td>0.1462</td>
</tr>
<tr>
<td></td>
<td>61/12.1362</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>66/2.2840</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PSO</td>
<td>26/1.5487</td>
<td>0.1399</td>
<td>0.1426</td>
</tr>
<tr>
<td></td>
<td>61/12.1981</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>66/2.4256</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

40% generation = 16.1724 [p.u.]

<table>
<thead>
<tr>
<th>Method</th>
<th>DG location / Size</th>
<th>Power Loss</th>
<th>Time [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>( \text{min} ; \text{[p.u.]} )</td>
<td>( \mu ; \text{[p.u.]} )</td>
</tr>
<tr>
<td>BH</td>
<td>26/4.0141</td>
<td>0.0575</td>
<td>0.0913</td>
</tr>
<tr>
<td></td>
<td>61/15.3273</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>66/2.3043</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CGA</td>
<td>26/3.7186</td>
<td>0.0556</td>
<td>0.0571</td>
</tr>
<tr>
<td></td>
<td>61/16.0335</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>66/2.3446</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PSO</td>
<td>26/3.7511</td>
<td>0.0556</td>
<td>0.0556</td>
</tr>
<tr>
<td></td>
<td>61/15.8844</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>66/2.4575</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

60% generation = 24.2586 [p.u.]
that the methods with the best (faster method) and worst (slower method) performance in terms of processing times are the BH and the PSO; this is the opposite to the result obtained in terms of quality solution.

Figure 3-3: Power loss reduction in 69 bus test system.

Figure 3-4: Processing time performance for the 69 bus test system.

Figure 3-5 presents the different trade-off provided by each methodology in terms of power loss and processing time for all network size and maximum DG generation level considered in this thesis. In this figure, the Y-axis presents the average value of mean power loss, in
3.5 Conclusions

In this chapter was studied the optimal power flow problem in DC grids using test scenarios with three maximum distributed power generation levels: 20%, 40%, and 60% of the total power generated by the slack bus, which are modified versions of the test systems of 21 and 69 buses. Those test scenarios were proposed with the aim of evaluating the impact of the distributed power generation on the electrical system in terms of power loss and processing times required by the solution methods.

In the review made in this chapter, it was found the need of proposing solution methods based on sequential programming to avoid the use of specialized software to solve the mat-
Mathematical formulation of the OPF problem. In this sense, a master-slave methodology that combines three continuous optimization methods was proposed: BH, CGA and PSO, those with the power flow method based on successive approximation; to solve the OPF problem in DC grids. The master stage is in charge to define the optimal power that each DG should inject to reduce the power loss. The slave stage is responsible to evaluate the fitness function of each possible solution provided by the master stage, solving the power flow problem through the SA. The selection of the SA was based on the performance provided in Chapter 2.

The methods selected for the master stage include the following contributions in the state-of-the-art:

- A new application for the BH was proposed, which offer an adequate performance for OPF in DC networks, it was confirmed by the numerical results reported in this work.

- A modification of the conventional binary GA was proposed (CGA) to solve nonlinear continuous optimization problems through modified methods of selection, recombination and mutation.

- A new approach for the PSO was presented in this chapter, which allows to solve the OPF problem in DC grids with multiple buses, branches, load and distributed generators.

The results obtained by the solution methods in both test feeders show that the PSO offers the best solution in terms of power loss reduction. However, the PSO requires the longer processing times in comparison with the BH and CGA. The BH presented the shortest processing times in all the cases under analysis, but also the worst solution in terms of power loss reduction. The trade-offs provided by each methodology in terms of power loss and processing time were analyzed. Concluding that the BH/SA methodology proposed in this work offers the best balance between power loss reduction and processing time. For that reason, among the approaches analyzed in this study, BH/SA is considered the most adequate method to solve the optimal power flow problem in direct current networks of any size and DG generation level.

As future investigation, the optimal location and dimensioning of distributed energy resources, such as renewable generation and energy storage systems, can be addressed by using similar hybrid algorithms. In addition, the hybrid methodologies proposed in this chapter can be used in MG control applications to determine the set point of the controllers depending on the loads and distributed energy resources operation conditions.
4. Optimal location and sizing of distributed generators in DC networks

This chapter addresses the problem of optimal integration of distributed energy resources in DC grids. This chapter proposes a hybrid method for optimal location and sizing of DGs in DC networks, which is based on sequential programming and parallel processing tools. The solution is based on the Parallel Population-Based Incremental Learning (PPBIL), for solving the location problem, and the Particle Swarm Optimization algorithm to solve the sizing problem. For comparison purposes, two additional location methods reported in literature, and two additional sizing methods were used to form eight additional hybrid methods; which enable to evaluate the performance of the proposed solution. Such an evaluation is illustrated with test systems formed by 10, 21 and 69 buses simulated in MATLAB. Finally, the simulation results demonstrate that the proposed PPBIL/PSO method provides the best balance between power loss reduction and processing time.

Part of the analyses and results achieved in this chapter have been published in the Communications in Computer and Information Science book series in the paper: “Hybrid Metaheuristic Optimization Methods for Optimal Location and Sizing DGs in DC Networks” [108].

4.1. Introduction

The DGs in DC networks are usually interconnected to the electrical system by using power electronics interfaces, which are intended to control the operation condition of the generator. Those power electronics interfaces could use batteries to guarantee a given power flow from non-predictable renewable generators (e.g. photovoltaic and wind based) [109, 110], or be controlled to dispatch a required power from predictable sources such as fuel cells (using a dc/dc converter) [111] or diesel generators (using a rectifier) [112]. The operation conditions of those devices in the DC grid, have been evaluated using multiple strategies such as the ones discussed in Chapters 2 and 3 of this doctoral thesis.

With respect to the location and sizing of distributed generators in DC grids, the authors of [113] proposed a methodology to integrate those DGs into DC grids, which used a heuristic approach to locate the generators and a mathematical method for sizing the photovoltaic
generators. Such a solution considers the reduction of the installation and operation costs as the objective function, which is optimized using the linear programming tool *linprog* available for MATLAB [114]; however, no comparison with other methods is provided, and the processing times are not analyzed. Similarly, in [10] the PSO algorithm is used to calculate the optimal size and dispatch of DGs and batteries in DC grids. That work uses an objective function aimed at reducing the costs of both investment and operation for the energy resources. Such a work considers an unique-nodal representation of the grid, neglecting both branch connections and multiple distributed energy resources located in different buses of the electrical system. In addition, the impact of the DERs on the electrical grid was analyzed without using power flow methods, and any comparison with other existing methods is provided. Another approach is proposed in [115], where an exact mixed-integer nonlinear programming method is used to represent the problem of location and sizing of DGs in DC grids, considering the minimization of the total power losses as the objective function. To solve that problem, a convex relaxation of the mathematical formulation is performed using a Taylor series expansion and the transformation of binary variables into continuous equivalents. The main problem of that approach is the high possibility to converge into a local optima instead of a global one.

Then, it is needed to propose mathematical formulations for the problem of location and sizing of DGs in DC networks, which considers multiple buses, loads and DGs. Such a model can be used to develop optimization techniques able to find the configuration of the generators with the best impact into the technical aspects of the network, and with short processing times; which guarantees an adequate exploration of the solution space within the time restrictions of the project. In this sense, a correct selection of the method used to solve the power flow problem is critical. In particular, the processing time required by such a method is very important, since the power flow must be solved for each configuration evaluated by the optimization algorithm. To the best of the author knowledge, the optimal location and sizing of distributed generators in DC grids have not been addressed using parallel processing tools; hence such a topic must be studied to provide faster implementations.

However, the problem of location and sizing of DGs has been extensively studied in AC networks [116, 117, 118, 119], then, it is possible to evaluate some of the solutions applied in AC networks to DC networks. For example, in [87] it is proposed a hybrid method for location and sizing of DGs in electrical systems based on a GA and the Particle Swarm Optimization algorithms. In that work, the objective function corresponds to the reduction of the active power loss, validating the proposed method in two test systems with 33 and 69 buses. Moreover, despite the authors compare the performance of the method with other solutions, the processing times required by the optimization methods are not discussed. Similarly, in [120] is proposed a hybrid methodology, based on the sine-cosine algorithm and chaos map theory, for solving the problem of location and sizing of distributed generators. This methodology
was validated in two test systems of 33 and 69 buses, by comparing the results obtained with other optimization techniques; however, the processing times were not discussed. Other approach is reported in [121], in which a master-slave strategy is implemented using a modified PSO algorithm to locate DGs and capacitors, and the Monte-Carlo algorithm is used for defining the size of the generators. In that work, the main objectives are reducing the power loss and improving the voltage profiles, but the authors do not provide a comparison with other techniques or an analysis of the processing time.

Another approach for AC networks is presented in [122], which is aimed at maximize the profit generated by the energy exchange with the grid by using a hierarchical GA, where the time of use and the energy price policy are imposed. In [13] is proposed an approach based on the Population-Based Incremental Learning algorithm, which has the aim of locating DGs using a parallel processing system to improve the calculation speed. In that work, the objective function is based on the active power loss and the voltage square error, and the authors provide comparisons with other techniques only for the location step, using the same sizing method for all the tests. Finally, an example of a parallel processing system, applied to the problem of location and sizing of DGs in AC grids, is addressed in [123]. That work uses a parallel implementation of the Monte-Carlo algorithm (PMC), using the processing time as performance indicator, but comparison with other methods is not provided. In conclusion, the previous references put into evidence the interest of performing the location and sizing of DGs in AC networks to reduce the power loss, using also the processing times as efficiency indicator.

This chapter proposes a methodology for optimal location and sizing of DGs in DC networks, which is performed under peak load conditions to determine the size of the DGs that enables to reduce the total power losses of the electrical network in the worst operation scenario. The solution is based on the Parallel Population-Based Incremental Learning and the PSO algorithms, which enable to improve the quality of the solution and reduce the processing time. The selection of the PBIL method for a parallel implementation is motivated by the low memory consumption and low computational complexity of that algorithm [124]. Furthermore, the PBIL computational characteristics makes simple to perform the parallel implementation aimed at reducing the processing time. On the other hand, the PSO has been widely adopted in literature to calculate the size of DGs, in both AC and DC grids [87, 121, 95], providing satisfactory results in terms of solution quality and processing time. Therefore, based on the results reported in those works and the results reported in Chapter 3, the PSO was selected in this chapter to calculate the size of the DGs.

It is important to highlight that this hybrid solution has been previously proposed in [13] for AC distribution networks (which is an additional contribution of this doctoral thesis), but it has not been applied to DC systems. Furthermore, the work reported in [13] only eva-
Optimal location and sizing of distributed generators in DC networks

This chapter evaluates the performance of the location technique, hence it has not been demonstrated that the PSO algorithm is the most suitable solution to develop the hybrid methodology for DC networks. This chapter, instead, considers two additional location techniques and two additional sizing techniques, which are used to demonstrate the improvement provided by the proposed solution. The two additional location techniques are the GA \[87\] and PMC \[123\] algorithms. The selection of those solution methods was based on the satisfactory results reported in literature for the same problem \[125, 126, 127, 128\]. The two additional sizing techniques are based on a continuous GA proposed in \[97\] and the black-hole optimization method proposed in \[100\], and as in the previous case, those methods were selected based on the satisfactory results reported in literature and in Chapter 3 of this doctoral thesis.

The study performed in this chapter considers the combination of the three location techniques with the three sizing techniques, obtaining nine hybrid solutions, where the proposed PPBIL/PSO method is one of them. The evaluation of those solutions is performed in three test systems with 10, 21 and 69 nodes, respectively, in which three DGs can be located. Those simulations were carried out in MATLAB by using the successive approximation method reported in Chapter 2 for running the power flows inside the sizing methods. The rest of the chapter is organized as follows: Section 4.2 presents the mathematical formulation of the optimal location and sizing of DGs in DC microgrids, which is formed by the objective function and the set of restrictions of the problem. Then, Section 4.3 presents the master-slave solution, based on both PPBIL and PSO algorithms, proposed in this chapter. The performance evaluation and practical tests are provided in Section 4.4. Finally, the conclusions derived from the work and the possible future works are described in Section 4.6.

4.2. Mathematical Formulation

The problem of optimal location and sizing of DGs in DC networks is formulated by means of a mono-objective optimization problem, where the objective function considers the reduction of the power loss in the whole system. This optimization problem is subjected to a set of technical constraints associated to the power flow in DC networks \[67\]. The power loss are selected as objective function due to the widely use of such an index, in AC networks, for the same problem \[129, 130, 97\]. The mathematical model that describes the problem of location and sizing of DGs in DC networks, presented in this chapter, was made in terms of the nodal components, unlike the previous chapters where the mathematical model were described in vectorial way.

Objective function:

\[
\min P_{Loss} = \min \sum_{i \in N} \left[ \left( \sum_{j \in N} G_{ij} v_i v_j \right) - G_{i0} v_i^2 \right]
\]  \tag{4-1}

In such an objective function \( P_{Loss} \) represents the total power loss associated to the resistive
components in the branches of the network. \( \mathcal{N} \) is the set of buses forming the system, \( G_{ij} \) is the \( ij^{th} \) component of the matrix of conductances, \( G_{in} \) is the conductance associated to the resistive load connected at bus \( i \), \( v_i \) and \( v_j \) are the voltages at buses \( i \) and \( j \), respectively.

**Set of constraints:**

\[
p_i^g - p_i^d = \sum_{j \in \mathcal{N}} G_{ij} v_i v_j \quad \forall i \in \mathcal{N} \tag{4-2}
\]

\[
V^\text{min} \leq v_i \leq V^\text{max} \quad \forall i \in \mathcal{N} \tag{4-3}
\]

\[
I_{ij} \leq I_{ij}^{\text{max}} \quad \forall ij \in \mathcal{B} \tag{4-4}
\]

\[
P_{\text{dg}} x_i^{\text{dg}} \leq p_i^{\text{dg}} \leq P_{\text{dg}}^{\text{max}} x_i^{\text{dg}} \quad \forall i \in \mathcal{D} \tag{4-5}
\]

\[
\sum_{i \in \mathcal{N}} x_i^{\text{dg}} \leq NDG_{\text{max}} \tag{4-6}
\]

\[
\sum_{i \in \mathcal{N}} p_i^{\text{dg}} x_i^{\text{dg}} \leq P_{\text{DG}}^{\text{max}} \tag{4-7}
\]

\[
x_i^{\text{dg}} \in \{0, 1\} \quad \forall i \in \mathcal{N} \tag{4-8}
\]

The mathematical model defined from (4-1) to (4-8) considers the minimization of the objective function defined in (4-1), hence the minimization of the total power loss of the DC grid. Equation (4-2) imposes the power balance at each bus, where \( p_i^g \) and \( p_i^d \) are the power generated and consumed at bus \( i \), respectively. Equation (4-3) imposes the maximum \( (V^{\text{max}}) \) and minimum \( (V^{\text{min}}) \) limits for the nodal voltages. Expression (4-4) shows the thermal current bound of each branch in the DC system, were \( I_{ij} \) is the current of the line \( ij \) within the set of branches that form the electrical network \( (\mathcal{B}) \), and \( I_{ij}^{\text{max}} \) is the maximum current allowed in that line. The maximum and minimum power to be injected by the DG connected at bus \( i \) are defined in (4-5), where \( x_i^{\text{dg}} \) is a binary variable that takes the value of 1 when a DG is located at bus \( i \), and it takes a value of 0 otherwise; the binary nature of \( x_i^{\text{dg}} \) is defined in (4-8), and \( \mathcal{D} \) represents the set of buses selected for locating DGs. Finally, constraint (4-6) limits the maximum number of DGs that can be introduced \( (NDG_{\text{max}}) \), while constraint (4-7) imposes the maximum level of penetration \( (P_{\text{DG}}^{\text{max}}) \) allowed into the DC network.

Finally, this optimization problem is nonlinear and non-convex, hence this chapter adopts a master-slave structure to decouple the DGs location problem (discrete optimization) from the DGs sizing problem (continuous optimization).
4.3. Proposed hybrid method

The location and sizing of DGs in electrical networks is traditionally divided in two subproblems [87, 129, 130]: the location of DGs on the electrical network and the calculation of the size of those generators. This chapter adopts a master-slave structure for connecting the proposed PPBIL and PSO techniques, where the PPBIL is in charge of solving the discrete optimization problem of locating the DGs, while the PSO algorithm is in charge of solving the continuous problem of sizing the DGs.

4.3.1. Codification of the solution

The codification scheme for the location and sizing problems is depicted in Fig. 4-1. The location and size of the DGs is performed with two vectors of \(|\mathcal{N}| - 1\) columns, where each element of the vector corresponds to a particular bus of the electrical system, excluding the voltage controlled node, i.e. the slack bus. \(|\mathcal{N}|\) represents the cardinality of the set \(\mathcal{N}\), i.e the number of nodes of the DC grid. Fig. 4-1(a) shows the binary codification for the location of the DGs, in which it is assigned a value of 1 when a bus is candidate for locating a generator, and 0 is assigned in the opposite case. For example, the vector in Fig. 4-1(a) reports that buses 1, 3 and \((|\mathcal{N}| - 2)\) were selected for locating DGs. Fig. 4-1(b) presents the continuous codification for sizing the DGs, where each candidate bus has an assigned value of active power to be injected between \(P_{\text{min}}^{\text{dg}}\) and \(P_{\text{max}}^{\text{dg}}\). The example of Fig. 4-1(b) reports that buses 1, 3 and \((|\mathcal{N}| - 2)\) will supply 0.85 p.u, 1.25 pu and 0.75 p.u, respectively. Finally, both vectors are used in the master and slave processes, which are described in the next subsections.

![Figure 4-1.](image)

(a) Location of distributed generation

(b) Sizing of distributed generation

4.3.2. Master stage: Optimal location of distributed generators using PPBIL

The location of the generators is performed, in the master stage, using the PPBIL algorithm; such an algorithm was selected due to the satisfactory results obtained in AC networks [13].
This optimization algorithm includes a modification of the iterative processing of the traditional PBIL [131] to enable parallel processing, which reduces the computation time required by the algorithm.

The PBIL algorithm is an estimation of distribution algorithm [132], and it uses probabilistic methods to find a solution with a given value on the objective function. This algorithm has been widely used for solving combinatorial optimization problems [133, 134], which is the case of the location of DGs. The main advantages of using the PBIL algorithm are the low memory consumption, low computational complexity and, mainly, the capability of modifying the learning rate, which enables to increase or decrease the exploration in the solution space in agreement with the application [135]. The PPBIL is implemented by evaluating, in parallel, the objective function of all the individuals of the population [13]. Similar approaches have been used in literature to reduce the computation times of optimization and simulation processes, it taking advantage of graphics processing units (GPU) or processors with parallel cores [123, 136, 137]. Algorithm 8 describes the PPBIL algorithm. Each step of the algorithm is explained in detail below.

**Algorithm 8** Pseudo-code for the PPBIL algorithm

**Data:** Step 1 → Assign initial conditions

**Step 2** → Initialize probability matrix

while \( E_n \leq E_{Tot} \) do

**Step 3** → Generate the population

**Step 4** → Evaluate fitness function

**Step 5** → Select the best individual

**Step 6** → Update the probability matrix

**Step 7** → Update the learning rate

**Step 8** → Calculate the entropy

**Step 9** → Evaluate the stopping criteria

end

**Step 10** → Extract the best individual from the probability matrix

**Step 11** → Evaluate fitness function

- **Step 1. Assign initial conditions:**

  In this step are selected the four main parameters to start the iterative process of PBIL. First, it is assigned the population size \((PS)\), which affect the exploration of the solution space and the processing time. To ensure the evaluation of the complete population in one cycle of the parallel units, \(PS\) is selected equal to the number of cores of the processor. The second parameter is the initial probability of each option into the probability matrix. To guarantee an adequate exploration of the solution space, the PBIL algorithm starts the iterative process with the same probability for all the
possible options. For this application, the initial probability is equal to 0.5 since each node has two options: locate (50%) or not (50%) a generator. The third parameter includes the type of learning rate (LR), e.g. linear, exponential, sigmoidal, bell shape; and the maximum and minimum bounds of LR, which are into the range of 0 to 1 [13]. For the location of DGs, it was found that the best type of LR is sigmoidal, while best values for the maximum and minimum bounds are 0.25 and 0.50, respectively [13]. The fourth parameter is the stopping criterion, which corresponds to the entropy tolerance, and it is selected as 0.1 following the work reported in [13].

- **Step 2. Initialize probability matrix:**

  The probability matrix (PM) is formed by \((n)\) columns, representing the elements to be considered on the solution of the problem, and \((m)\) rows, which are the possible solutions for each element. For the location of DGs, \(n\) is equal to \((|\mathcal{N}| - 1)\), hence excluding the slack bus; and \(m = 2\) since only two options are available for each node. Fig. 4-2 presents an example of the probability matrix.

  \[
  \begin{array}{cccccc}
  & 1 & 2 & 3 & \ldots & n \\
  \text{Option 1} & P(1,1) & P(1,2) & P(1,3) & \ldots & P(1,n) \\
  \text{Option 2} & P(2,1) & P(2,2) & P(2,3) & \ldots & P(2,n) \\
  \vdots & & & & & \\
  \text{Option m} & P(m,1) & P(m,2) & P(m,3) & \ldots & P(m,n) \\
  \end{array}
  \]

  \text{Figure 4-2.: Structure of the probability matrix}

  At the start of the algorithm, all the components of PM start with the same probability \(1/m = 0.5\). Moreover, the PM must to satisfy the constraint given in (4-9), where \(P(j, h)\) is the probability of the option \(j\) to be selected on element \(h\). Such a restriction ensures that the accumulative probability of the options for a single element is 100%.

  \[
  \sum_{j=1}^{m} P(j, h) = 1 \quad \forall h = 1, 2, \ldots, n \quad (4-9)
  \]

- **Step 3. Generate the population:**

  The population is generated using the PM data. The objective is to create individuals using the information of each option into each element of the PM, avoiding identical individuals to guarantee an adequate exploration of the solution space. Hence, when an individual is repeated, it is replaced by a randomly generated one.

- **Step 4. Evaluate the fitness function:**
4.3 Proposed hybrid method

The evaluation of the fitness function of each individual is the step that takes more time in the PBIL process. Therefore, the solution proposed in this work uses the parallel processing structure reported in [13], which enables to evaluate the fitness function of all the individuals at the same time. If the population size is not equal to the number of cores of the processor \(W\), the time required by the paralleling processing \(PPT\) is equal to \(PPT = \text{CEIL}(PS/W) \cdot MTRP\), where \(MTRP\) is the maximum time required to evaluated the fitness function of an individual and \(\text{CEIL}(\cdot)\) returns the integer that is higher than or equal to a real number. In this chapter, the evaluation of the fitness function is performed by the slave stage, which optimizes the size of the distributed generators for each individual of the PPBIL population.

- **Step 5. Select the best individual:**

  The individual with the best fitness value is selected. In this case, the individual with the minimum power loss that fulfills the set of constraints discussed in Section 4.2.

- **Steps 6 and 7. Update the probability matrix and the learning rate:** The values of the probability matrix are updated using equation (4-10), where \(P(i,j)_{\text{Old}}\) is the non-updated probability of position \((i,j)\) and \(P(i,j)_{\text{Act}}\) is the updated probability.

\[
P(i,j)_{\text{Act}} = P(i,j)_{\text{Old}} + (1 - P(i,j)_{\text{Old}}) \cdot LR
\]

(4-10)

Then, assigning the index \(k\) to the option with the highest fitness value of the element \(j\), the update of the probability matrix is performed using equation (4-11): the probability of the option with the highest fitness value is increased, while the probability of the other options (different to \(k\)) are reduced. In such an equation \(P(i,j)_{\text{New}}\) is the new value of the probability at position \((i,j)\). Finally, all the elements must to satisfy restriction (4-9) after updating the probability matrix.

\[
P(i,j)_{\text{New}} = \begin{cases} 
P(i,j)_{\text{Act}} & \text{if } i = k \\ (1 - P(i,j)_{\text{Act}}) \cdot \frac{P(i,j)_{\text{Old}}}{1 - P(i,j)_{\text{Old}}} & \text{if } i \neq k
\end{cases}
\]

(4-11)

Algorithm 8 reports that the learning rate must be also updated. The value of LR is updated using equation (4-12), where \(LR_{\text{min}}\) and \(LR_{\text{max}}\) are the bounds assigned in Step 1. Moreover, \(E_n\) is the entropy of the \(PM\); in the first iteration of the algorithm \(E_n = 1\), hence the probability matrix exhibits a high dispersion of the data since all the options have the same probability in each element [131, 135].

\[
LR = LR_{\text{max}} - \frac{LR_{\text{max}} - LR_{\text{min}}}{1 + e^{-10 \cdot (E_n - 0.5)}}
\]

(4-12)
Steps 8 and 9. Calculate the entropy and evaluate the stopping criteria:

The entropy $E_n$ enables to quantify the probabilities distribution of the solution. In that way, the probabilities in $PM$ are completely dispersed when $E_n = 1$, and they converge to a single solution when $E_n = 0$. However, a particular tolerance $E_{TOL}$ is used as an approximation to $E_n = 0$, which enables to converge to a solution in a finite time. Equation (4-13) describes the mathematical formulation of the entropy, which is calculated by adding all the probabilities in $PM$, and using the total number of elements $n$ to normalize the entropy into $0 \leq E_n \leq 1$. The stopping criterion for the PPBIL algorithm is $E_n < E_{TOL}$, with $E_{TOL} = 0.1$. The selection of the $E_{TOL}$ value is discussed in [13].

$$E_n = - \sum_{i=1}^{m} \sum_{j=1}^{n-1} P_{(i,j)} \cdot \log [P_{(i,j)}]$$

(4-13)

Steps 10 and 11. Extract the best individual of the probability matrix and evaluate the fitness function:

When the PPBIL algorithm reaches the stopping criterion, the best solution is extracted from $PM$ by selecting the options on each element with the highest probability. Finally, the fitness function of the best configuration is calculated, which enables to evaluate the impact of the solution into the DC grid.

4.3.3. Slave problem: Optimal sizing of distributed generators using PSO

In the slave stage is used the PSO reported in Chapter 3, and the methodology proposed in that optimization method is used, for solving the OPF problem (See Algorithm 7). Such a method is aimed at determining the optimal size of the generators present in each individual produced by the master stage.

Finally, the flowchart reported in Fig. 4-3 summarizes the master-slave method based on both PPBIL and PSO algorithms. The figure put into evidence that the parallel processing is used to evaluate the objective function of all the PPBIL individuals at the same time. This is performed by the PSO algorithm to obtain the optimal size of each generator in each configuration.
4.4 Test systems

In this chapter three different test systems are used for validating the hybrid method proposed for optimal location and sizing of DGs in DC networks. The test systems are adapted from the 10, 21 and 69 bus systems presented in Chapter 2. The modifications made to those test systems consist on replacing the distributed generators and batteries by loads with the

Figure 4-3.: Proposed method based on the PPBIL and PSO algorithms
same power magnitude. Therefore, the resulting test systems are only formed by a main
generator and electrical loads. The objectives of the previous modifications is to increase
the technical problems on the grids (increase power loss, reduce voltage profiles, etc.) and
to eliminate the presence of distributed elements to provide a base case.

The base cases values are obtained by using the base values reported in Chapter 2 for each
test system, and solving the power flow problem without considering the installation of DGs
on the electrical systems. The 10 bus test system produce an initial power loss of 0.1436 p.u.
for a total demand of 4.82 p.u. The 21 bus test system presents a total power demanded of
5.54 p.u and a power loss of 0.2760 p.u. Finally, the 69 bus test system presents a power loss
of 1.5385 p.u for a total power consumption of 38.8925 p.u.

4.5. Results

The simulations were carried out on a Dell Precision T7600 Workstation with 32 GB of
RAM memory and with an Intel(R) Xeon(R) CPU ES-2670 at 2.50 GHz, which provides 12
processing cores. Moreover, the following conditions are imposed to provide a fair comparison
between the different optimization solutions:

- All the nodes, except the slack node, are candidates for locating DGs.
- It is considered $N_{DG_{max}} = 3$, hence a maximum of three generators can be installed.
  Such a limit is in agreement with the test scenarios adopted literature for the same
  problem [129] [138] [13].
- The maximum level of power able to supply by each generator is 1.2 p.u for the 10 bus
  system, 1.5 p.u for the 21 bus system, and 12 p.u for the 69 bus system. The minimum
  level of power for each generator is 0 p.u. for all the cases [98].
- The maximum allowable current in the DC lines of the test systems were calculated
  through a power flow analysis without considering the integration of DGs. Based on
  those base values of the branches currents, and using the Electrical National Code
  (NEC), the maximum currents levels were defined: 5.2 p.u. for the 10 bus system, 5.2
  p.u. for the 21 bus system, and 42.11 p.u for the 69 bus system. Finally, the same type
  and caliber were selected for all electrical conductors of the DC grids.
- For all test systems, the maximum penetration allowed for distributed generation was
  40% of the power injected by the slack bus without considering the integration of DGs.
  This limit of the level of penetration was defined following the recommendation given
  in [88]. Such a constraint was considered to account for the restriction of distributed
  generation present in some national electrical regulations; hence the proposed mathe-
  matical formulation provides a general solution because such a limit could be set to
zero when it is not needed. Moreover, this consideration enables to analyze the impact of the DG penetration level on the electrical system.

Metaheuristic techniques used to solve constrained optimization problems can adopt a fitness function ($FF$) that enables the exploration outside of the feasible solution space [97, 139], which increases the probability of finding solutions located near the boundaries. The $FF$ adopted in this chapter is formed by the original objective function value and all the constraints introduced as penalties:

$$
FF = \min \left\{ \begin{array}{l}
  p_{\text{loss}} + \beta_1 \max \left\{ 0, \sum_{i \in \mathcal{N}} (v_i - V_{i}^{\text{max}}) \right\} \\
  + \beta_2 \min \left\{ 0, \sum_{i \in \mathcal{N}} (v_i - V_{i}^{\text{min}}) \right\} \\
  + \beta_3 \max \left\{ 0, \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}} (I_{ij} - I_{ij}^{\text{max}}) \right\} \\
  + \beta_4 \max \left\{ 0, \sum_{i \in \mathcal{N}} (P^g_i - P_{i}^{g,\text{max}} x_{i}^{	ext{DG}}) \right\} \\
  + \beta_5 \min \left\{ 0, \sum_{i \in \mathcal{N}} (P^g_i - P_{i}^{g,\text{min}} x_{i}^{	ext{DG}}) \right\} \\
  + \beta_6 \max \left\{ 0, \sum_{i \in \mathcal{N}} (P_{i}^{x_{i}^{	ext{DG}} DG} - P_{DG}^{\text{max}}) \right\} \\
  + \beta_7 \max \left\{ 0, \sum_{i \in \mathcal{N}} (x_{i}^{	ext{DG}} - N\text{DG}_{\text{max}}) \right\} \end{array} \right. 
$$

(4-14)

In the previous $FF$, the constants $\beta_1$ to $\beta_7$ correspond to penalization factors. In this work, all penalization factors are set to 1000, using trial and error, in order to force the optimization methods to satisfy all the constraints imposed in the mathematical formulation defined in Section 4.2.

Two additional binary optimization methods are used to locate the DGs in the master stage, which enable to evaluate the performance of the PPBIL solution. Those binary methods are GA and PMC. The GA is widely used in literature to locate DGs in electrical grids [87, 140, 141]; this technique uses selection, recombination and mutation methods to find a combination of generators with lower power loss. The second binary method (PMC) implements a parallel Monte-Carlo algorithm, which performs several random samples of the different possible locations for the DGs, evaluating the $FF$ of all the configurations in parallel to detect the locations with lower power loss [123]. The adoption of PMC, for evaluation purposes, enables to compare the proposed solution with another parallel processing method. The parameters of PPBIL, GA and PMC methods used for the master stage are given in Table 5-3. The size of the population for both the PPBIL and PMC was defined equal
to the number of workers available in the PC processor, otherwise the processing time is significantly increased since all the population can not be evaluated at the same time. Instead, the size of the genetic algorithm population was defined using trial and error, selecting the number of individuals providing the best balance between power losses and processing time. Finally, the other parameters of the binary methods were obtained using an heuristic method following the methodology reported in reference [13].

Table 4-1.: Parameters of the location techniques

<table>
<thead>
<tr>
<th>Method</th>
<th>GA</th>
<th>PMC</th>
<th>PPBIL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>12</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>Selection method</td>
<td>Tournament</td>
<td>Repeated random sampling</td>
<td>Initial probability: 0.5</td>
</tr>
<tr>
<td>Rate learning</td>
<td>Cross over: simple</td>
<td>- - -</td>
<td>Sigmoidal LRmin: 0.25 LRmax: 0.50</td>
</tr>
<tr>
<td>Mutation</td>
<td>Binary simple</td>
<td>- - -</td>
<td>Random population</td>
</tr>
<tr>
<td>Stopping criterion</td>
<td>Maximum generational cycles: (40)</td>
<td>Maximum iterations: (10)</td>
<td>Entropy: (0.1)</td>
</tr>
</tbody>
</table>

For evaluating the slave stage also two additional optimization methods were considered. The CGA and BH optimization algorithms, which were explained in Chapter 3. These algorithms were implemented in MATLAB using the SA power flow formulation method reported in Chapter 2, which enables to find the best size of the DGs.

With the aim of validating the proposed PPBIL/PSO method, the four additional algorithms are combined with both PPBIL and PSO algorithms to form eight additional techniques, which will be used to evaluate the performance of the proposed solution. The validation was carried out by testing the same cases with each hybrid optimization technique. Those simulation results are presented in Tables 5-5, 4-3, and 4-4 which report, from left to right, the following information: the hybrid method, the DGs location and size, the mean power loss, the relative mean reduction of the power loss in relation with the base case, the mean square error of the voltage profile and its relative reduction in relation with the base case, the worst voltage profile and its location into the system, the maximum current on the branches, and the averaged processing time. Those averaged values were obtained from 1000 continuous executions for each solution method on each test scenario.
4.5.1. 10 bus test system results

Table 4-2.: Results 10 bus test system

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Table 5-5 and Fig. 4-4 present the impact and processing time of the different optimization methods for the 10 bus test system. From Fig. 4-4(a) it is observed that the proposed met-
hod provides the best solution with a reduction of 66.21% of the power loss, exhibiting an additional reduction of 1.68% over the other techniques. In contrast, the PMC/BH solution produces the minimum reduction of active power loss (60.47%), hence exhibiting the worst performance. Moreover, in column 6 of Table 5-5 is observed that all hybrid solutions satisfy the maximum allowable current in the branches of this test system.

Fig. 4-4(b) shows the processing time required by all optimization techniques, where the proposed solution exhibits the second lower processing time, which is 33.71% longer than the time required by the faster PMC/BH solution. However, despite the PMC/BH technique is faster, it produces the worst solution in terms of power loss. Finally, excluding PMC/BH, the proposed PBIL-PSO exhibits a processing time 53.61% lower, in average, in comparison with the other optimization techniques.

Furthermore, for analyzing the impact of each optimization technique on the voltage profile, the square voltage error (SVE) is calculated with respect to the voltage base \( V_{base} \) using expression (4-15) [87]. Fig. 4-4(c) shows the reduction of the square error voltage profiles in percentage, where the maximum reduction is obtained by the PPBIL/PSO (67.85%), while the minimum reduction is provided by the GA-BH (63.82%). Therefore, the proposed method provides a better voltage profiles in comparison with both the base case and the other techniques. In this way, Fig. 4-4(d) shows the worst voltage nodes given by each

Figure 4-4.: Results obtained with the 10 bus test system.
solution, which exhibit a deviation from the nominal voltage (1 p.u.) lower than 2%. Such a deviation is acceptable according to the load and type of network, hence it guarantees a secure and reliable operation of the grid \[132,143,13\]. In any case, the best operation condition, concerning the voltage profiles, is provided by PPBIL/PSO since the worst voltage node is closer to 1 p.u., in comparison with the other solutions; in contrast, the worst operation condition is provided by the PMC/BH technique.

\[
SVE = \sum_{i \in N} (V_i - V_{base})^2
\]

Finally, the standard deviation (STD) of the mean power loss obtained by each hybrid solution is presented in Figure 4-5, where the PPBIL/PSO presents the minimum STD (0.26%), which put into evidence the precision and repeatability of the solution provided by that method. The PPBIL/GA method also provides a low STD (0.29%), while the other hybrid methods exhibit high STD values.

![Figure 4-5: Mean standard deviation of the power loss for the 10 bus test system.](image)

### 4.5.2. 21 bus test system results

The results obtained with the 21 bus system are presented in Table 4-3 and illustrated in Fig. 4-6. Figure 4-6(a) shows that the higher reduction in power loss is achieved again by the PPBIL/PSO (78.37%), while the lower impact is given by PMC/BH (52.36%). In comparison with the other techniques, the proposed method provides an averaged reduction in the power loss of 11.76%. Moreover, column 6 of Table 4-3 reports the maximum branch currents obtained by each solution method, which fulfill the maximum allowable current in the 21 bus test system.

Concerning the processing time, the proposed method takes the second place, it requiring 39.58% more time than the PMC/BH method; in any case, the proposed PPBIL/PSO is, in average, 50.35% faster than the other seven solutions. Fig. 4-6(c) and 4-6(d) analyze the
square error voltage profile, where the PPBIL/PSO method provides the best performance with a reduction of 87.61% with respect to the base case, and with an average reduction of 13.80% in comparison with the other techniques. Similar to the previous case, the solution with the worst reduction in the square voltage error is the PMC/BH (51.22%).

Fig. 4-6(d) reports that the method with the best nodal voltage is the PPBIL/PSO (0.9760 p.u at bus 9), while the worst voltage is obtained by PMC/BH (0.9383 p.u at bus 17). In addition, the figure also shows that all the methods provide an operation around ±10% of the nominal voltage, which ensures a safe grid operation. This limit is selected according to the load and type of network in order to guarantee a secure and reliable operation [142, 144]. Finally, Figure 4-7 presents the STD of the power loss obtained for the 21 bus test system. As in the previous case, the PPBIL/PSO method provides the lower STD value (1.42%), followed by the PPBIL/GA (2.38%); while the other methods exhibit higher STD values.

4.5.3. 69 bus test system results

The results obtained with the 69 bus system are reported in Table 4-4 and Fig. 4-8. Fig. 4-8(a) shows the impact of the nine methods on the 69 bus system, where again the proposed PPBIL/PSO provides the higher reduction on the power loss with respect to the base case (90.99%). Moreover, the PPBIL/PSO provides an additional average reduction on the
4.5 Results

Table 4-3.: Results 21 bus test system

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power loss of 24.83% with respect to the other approaches; this shows that, for both small and large systems, the proposed method provides the best location and size for the DGs. Moreover, all the solution methods fulfill the maximum allowable current in the branches of
Figure 4-7.: Mean standard deviation of the power loss for the 21 bus test system.

the 69 bus test system, which is reported in column 6 of Table 4-4.

The effectiveness of the proposed method, in terms of speed, is shown in Fig. 4-8(b), which reports that the PPBIL/PSO is in third position; while the faster method is PPBIL/BH (39.79% faster) and the second one is PMC/BH (39.23% faster). Finally, PPBIL/PSO is 52.46% faster than the other six methods.

Figure 4-8.: Results obtained with the 69 bus test system.

The impact of the nine methods on the voltage profiles is illustrated in both Fig. 4-8(c) and
4.5 Results

Table 4-4: Results 69 bus test system

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<th>Method: Location/ Sizing</th>
<th>DG Location/ Size [kW]</th>
<th>$P_{loss}$ [kW]/ %$P_{loss}$ reduction</th>
<th>$V_{error}$ [p.u]/ %$V_{error}$ reduction</th>
<th>Worst voltage profile [p.u]/ Bus</th>
<th>Maximum current [p.u]</th>
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<tr>
<td>PMC/BH</td>
<td>2/189.23</td>
<td>122.71/20.23</td>
<td>0.0548/28.68</td>
<td>0.9339/69</td>
<td>29.18</td>
<td>135.00</td>
</tr>
<tr>
<td></td>
<td>10/1042.66</td>
<td></td>
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<td></td>
<td>33/51.06</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GA/PSO</td>
<td>14/179.33</td>
<td>17.4946/88.62</td>
<td>0.0084/89.04</td>
<td>0.9804/69</td>
<td>22.89</td>
<td>839.67</td>
</tr>
<tr>
<td></td>
<td>58/237.90</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>62/1200</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GA/CGA</td>
<td>59/446.07</td>
<td>19.0251/87.63</td>
<td>0.0090/88.25</td>
<td>0.9779/27</td>
<td>22.91</td>
<td>1611.72</td>
</tr>
<tr>
<td></td>
<td>63/1170.76</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>GA/BH</td>
<td>8/60.85</td>
<td>55.8518/72.65</td>
<td>0.0210/72.65</td>
<td>0.9596/61</td>
<td>28.04</td>
<td>305.31</td>
</tr>
<tr>
<td></td>
<td>14/406.04</td>
<td></td>
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<td></td>
<td>67/673.68</td>
<td></td>
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</table>

(d). As in the previous cases, the proposed PPBIL/PSO provides the higher reduction in the square error voltages, with a reduction of 91.91%. Moreover, the worst voltage profile provided by this method is 0.984 p.u at bus 64. Instead, the worst solution, in terms of voltage profiles, was obtained by the PMC/CGA with a reduction of the square error voltage of
28.68\%, followed closely by the PMC/BH with a reduction of 34.27\%. Finally, both methods also provide the worst node voltages: 0.9333 p.u for PMC/CGA and 0.9339 p.u for PMC/BH.

Figure 4-9 presents the STD values for the power loss exhibited by the different solution methods in the 69 bus system. The figure shows that the PBIL/PSO achieved again the lower STD value (5.25\%), followed by the PPBIL/GA (5.37\%) and PPBIL/BH (5.98\%) methods, while the other ones exhibit higher STD values. Finally, based on the previous STD results, it is concluded that the PBIL/PSO method provides the highest precision and repeatability of the solution for any size of the electrical system.

Figure 4-10 shows the impact of the different hybrid methods used to find the optimal
location a size of the DGs. Such a figure enables to analyze the different trade-offs provided by each method in terms of power loss and processing time for any network size: the vertical axis reports the average value of the power loss, in percentage, with respect to the base cases (without DGs) for all test systems; while the horizontal axis reports the average processing time required by each method, also in percentage, with respect to the hybrid method requiring the longest processing time in all test systems, i.e. GA/CGA. This figure shows that PMC/BH is the faster method, with an average processing time of 9.08%, but with the worst average power loss (55.64% of the power loss in the systems without any DG). Similarly, the worst solution in terms of processing time is the GA/CGA method, with an average processing time of 791.73 s. The PPBIL/PSO is the second faster method with an average value of 14.46%, but obtaining the best results in terms of power loss, with an average value 21.50%. In this figure, the trade-off between power loss and processing time corresponds to the distance to the origin (0,0), which represents the ideal solution for the problem in study: power loss and time processing equal to zero. The figure reports that the proposed PPBIL/PSO solution provides the best trade-off, between power loss and speed, since it exhibits the shorter distance to the origin. In practical terms, the proposed solution provides the lowest power loss with an acceptable processing time.

4.6. Conclusions

In this chapter was proposed a hybrid method, formed with the PPBIL and the PSO algorithms, for the optimal location and sizing of distributed generators in DC networks. The method uses a mathematical formulation to analyze the impact of the distributed generation into the grid. In particular, the objective function is based on reducing the power loss, but accounting for the set of restrictions required in this type of systems. Finally, the performance of the proposed solution was contrasted with other eight options based on optimization algorithms widely adopted in literature.

The proposed PPBIL/PSO hybrid method provides the location and size of the DGs that produce the highest reduction in the power loss for small, medium and large DC grids. In terms of location, the GA provides similar results, but requiring a higher processing time. In terms of size, the fastest method was the BH, but providing much less efficient solutions, i.e. higher power loss than PSO. Moreover, the processing time and power loss of all the methods were normalized for the three test cases, which put into evidence that the proposed PPBIL/PSO solution provides the best trade-off between speed and power loss for any grid size. In addition, the PBIL/PSO exhibits the lower standard deviation for the power loss in all test scenarios; hence the proposed PBIL/PSO provides the highest precision and repeatability for the solution when it is compared with the other hybrid approaches; which were obtained by combining the location methods PPBIL, PMC and GA, with the sizing methods PSO, CGA and BH.
Future improvements to this solution consider the inclusion, into the mathematical model, of renewable generation curves and hourly power demand, which could provide a more accurate solution for a particular geographic region. Moreover, the solution can be further developed to integrate energy storage devices on the electrical network, which could be used for improving the electrical behavior and profitability of the grid. In addition, it is possible to propose an optimal tuning strategy for the parametrization of the binary and continuous optimization techniques, this aimed at balancing the exploration and exploitation of the solution space, which will enable to find the best compromise between the number of iterations and the population sizes.

After obtaining an optimal integration of DGs in the DC MG, is necessary to propose energy management systems that allow operating in an optimal way different DERs into the DC grid. By guarantying the technical constraints and improving the technical and economical criteria used as objective function by the grid operator. In order to offer a solution to the aforementioned problematic, the next chapter proposes two different energy management strategies to operate the DC microgrid by considering the main grid, distributed generators, energy storage systems and electrical loads located into DC grid.
5. Energy management in DC microgrids for improving the operation conditions and cost optimization

In the previous chapters, different methods for solving the power flow, optimal power flow and location and sizing of DG were proposed; with the main objective to obtain a methodology that allows planning in an optimal form the DC network, with the compromise to obtain the best results in technical and computational terms. Consecutively, to the design process of the MG is necessary to propose energy management strategies that provide the best results in the technical and economical indexes. For the previous reasons, this chapter proposes energy management systems for DC grids, which enable to integrate and operate batteries into DC grids to improve the operating conditions of the DC grid in technical and economic terms.

To carry out this task, in this chapter two energy management strategies, described in figure 5-1 are proposed, which are based on a hierarchical topology. The first energy management strategy (EMS 1 in Figure 5-1) is focused in the secondary and primary hierarchical control levels. This is applied to a stand-alone DC microgrid formed by a Photovoltaic System, a...
battery, a non-critical DC load, and a capacitor as a backup storage element. That strategy is aimed at controlling the voltage, current and power on the different generation and storage devices (primary control), which is based on the sliding mode control technique. Such a control strategy was selected due to the stability, robustness against variation in parameters, and robustness against input and load uncertainties provided, which are common MGs [145, 146]. In addition, sliding mode controllers are easier to implement compared with other types of non-linear controllers [147]; hence those controllers are widely used and studied in specialized literature [148, 149, 150, 145, 146].

The main contribution of the first energy management strategy concerns a secondary control level that manages the connection and disconnection of the battery and the load, as well as the generation of the photovoltaic system and to ensure charge/discharge process of the battery. Being the control objective guarantee the power balance and the operation of the system within the allowable technical limits. To control the generation of the photovoltaic system, two operating modes based on the Perturb and Observe (P&O) algorithm are implemented. The first one performs a maximum power point tracking action, while the second one regulates the power generated by the PVS to match the load requirement (power demand tracking mode, PDT). The management strategy also considers different operating states for ensuring the battery safety.

The second energy management system (EMS 2 in Figure 5-1) proposed in this chapter is focuses on the tertiary control. This EMS is focused on an economic dispatch strategy, which assigns to the batteries the optimal power levels to supply or store in each operational hour of a distributed generation environment. The main objective is to reduce the energy purchasing costs, satisfying the set of constraints of the DC grid operation: the SOC bounds of the batteries, the variation in the photovoltaic and wind generation systems, the power demand, and the energy purchasing cost. The solution is based on a master-slave topology formed by a parallel implementation of a PSO algorithm, and by a multi-period power flow method based on the successive approximations method presented in Chapter 2. In addition, to forecast the PV and wind generation, this chapter adopts an artificial neural network. In order to demonstrate the effectiveness of the proposed methodology, three different metaheuristic optimization methods, based on sequential programming, are used: the BH and CGA described in Chapter 3, and the traditional Chu & Beasley genetic algorithm, which has been used for solving the optimal operation of BSS in AC grids [151]. Furthermore, two operative scenarios for the BSS are considered: in the first operative scenario the BSS can operate between its maximum and minimum SOC, hence without imposing a final SOC. The second scenario imposes a final SOC equal to the 50% of the nominal capacity of each battery. Finally, the energy purchasing costs of keeping energy stored into the batteries is evaluated, using the data of generation and power demand of a regular day and week in Colombia. The results obtained in two simulation scenarios demonstrate that the proposed methodology
achieved the best results in terms of quality solution and processing time, and demonstrated that forcing a final SOC equal to 50% for each day reduces the energy purchasing cost for a day and week of operation under the Colombian conditions, this compared with the case when no SOC restriction is adopted.

Part of the analyses and results reported in this chapter have been published in the international journal Sustainability, in the paper: “Energy management in PV based microgrids designed for the Universidad Nacional de Colombia” [152]; and in the Journal of energy storage, in the paper “An energy management system for optimal operation of BSS in DC distributed generation environments based on a parallel PSO algorithm” [153].

5.1. Energy management in standalone DC microgrids with controlled PV generation, battery storage and load connection

Stand-alone electrical DC microgrids require power management strategies to extend the lifetime of their devices and to guarantee the global power balance of non-critical loads. This section proposes an EMS for an isolated DC microgrid formed by a photovoltaic system, an energy storage system (battery), and a noncritical load. This configuration enables the photovoltaic system to control the power generation and ensures that the storage element does not exceed the safe limits of the state of charge. To control the generation of the photovoltaic system, two operating modes based on P&O algorithm are implemented in this thesis. The first one performs a maximum power point tracking action, while the second one regulates the power generated by the PVS to match the load requirement (power demand tracking, PDT). The management strategy also considers different operating states for ensuring the battery safety: normal operation, overcharge (at the maximum state of charge), and bulk charge (at the minimum state of charge); in those states the disconnection/connection of both the battery and the load is also considered.

The main contribution of this section is to design and test a control strategy for an EMS aimed at regulating a standalone microgrid based on a PV system and an energy storage device. This solution is validated using detailed MG circuitual simulations, which includes the PV source model (single-diode model), lithium-ion battery model, constant power load model and the DC/DC converters equations; moreover, realistic power generation and demand from Medellín-Colombia, are considered. The results obtained demonstrate the effectiveness of the energy management strategy, and in this way, enable to improve the battery operation conditions and reduce the costs associated to the maintenance and disconnection of the microgrid in educational buildings or other applications focused on this type of DC microgrid.
5 Energy management in DC microgrids for improving the operation conditions and cost optimization

5.1.1. Introduction

As presented in [154, 155], the integration of ESS into a microgrid mitigates the energy production intermittency of renewable sources caused by the night and weather conditions (cloudy operation, solar radiance, temperature, wind speed, etc.); moreover, the ESS helps to control the power flows inside the MG to achieve the global power balance and maximize the benefits for the operator or proprietary. In addition, to manage the intermittency of renewable energy resources and load demand characteristics, an EMS is an essential part of the MGs for optimal use of the distributed energy resources in reliable and coordinated ways [154, 155].

DC MGs are formed by DGs, ESS, and electrical loads [50, 51, 156, 157]. In particular, photovoltaic systems (PVSs) are commonly included in DC MGs as DGs due to the wide availability of solar energy [52]; and the integration of a PVS, an ESS, and loads is known as a stand-alone photovoltaic system [53]. Those SPVSs are used in multiple applications for attending non-critical loads, such as plug-in chargers for electrical vehicles, lighting systems, television sets, data centers (facility lighting or non-critical workstations used for log files inspection), air-conditioning, home applications, among others [54, 55, 56, 158, 159]. In this sense, a correct energy management of the SPVS allows to reduce the operational cost and improves the quality of the electrical service of the DC grids; thus improving the life conditions of the users in those spaces [160]. For example, in [161] an EMS for stand-alone DC microgrid based on a photovoltaic source, electrochemical storage, a supercapacitor, and a diesel generator was proposed. That strategy allows to control the system to balance the power injection accounting the slow start-up characteristic of the diesel generator by means of a supercapacitor. A similar solution was published in [162], where an EMS is proposed for a stand-alone hybrid AC/DC microgrid formed by a PV system, a fuel cell as a secondary power source, and a battery and a supercapacitor as hybrid ESS. The proposed EMS allows to manage the system under different modes and SOC limits when all devices are connected to the DC bus. For the reasons discussed above, this section is aimed to design an energy management strategy for PV based microgrids that consider the environmental conditions and power demand of Medellín-Colombia.

SPVS devices must be integrated using a DC-bus interfaced with DC/DC converters, which enable the operation of each device in the corresponding safe and optimal operating condition [57]. For example, the DC/DC converter associated with the PVS is regulated using algorithms and/or control strategies aimed at tracking the maximum power point; hence, such algorithms are known as MPPT solutions. The ESS integration with the DC-bus is performed using bidirectional converters and control strategies [163, 59] to regulate the DC-bus voltage and to guarantee the global power balance in the standalone MG when excess or shortage power exists. However, additional conditions can also be considered; for example,
5.1 Energy management in standalone DC microgrids with controlled PV generation, battery storage and load connection

a limitation to the power generated by the PVS \[60, 61, 62\], which is applied when the ESS reaches the maximum SOC during low power demand, or a load disconnection when the ESS reaches the minimum SOC during high power demand \[60, 63\]. Those protections are needed to prevent an accelerated reduction of the ESS lifetime \[64, 65, 66\], hence reducing costs.

EMSs used in SPVSs consider a load shedding strategy for preventing the ESS from violating the minimum SOC only when noncritical loads are connected to the MG \[164, 165, 166\]. However, this requires an over sizing of both the generators and the ESS when critical loads are present. The main challenge in EMS design concerns the limitation of the maximum SOC condition because traditional control techniques are unable to supply power to the load without using the ESS; therefore, ESS are constantly discharged and charged with small amounts of power. This situation produces charge/discharge sub-cycles, which are integrated as full cycles that reduce the lifetime of the battery \[167\]. Therefore, this section proposes a new EMS based on operation states for controlling a SPVS without violating both the maximum and minimum SOC of the ESS. For that purpose, the EMS considers three operating regions for the ESS: overcharge, normal operation, and bulk charge; and two operating modes for the PVS are also defined: MPPT and PDT \[47\]. The proposed EMS also includes a capacitor connected in parallel with the battery as backup ESS. The function of this capacitor is to enable the disconnection of the battery in both overcharge (high SOC) and bulk charge (low SOC) conditions, hence avoiding charge/discharge sub-cycles in the battery.

Therefore, the main contribution of this section is the design and test of a control strategy for an EMS aimed at regulating a microgrid based on a PV system and ESS. The solution is also intended to avoid the sub-cycles problem present in power demand tracking operation, which causes an accelerated aging of the battery pack due to the integration of charge/discharge sub-cycles into full charge/discharge cycles. This is done by inserting an auxiliary capacitor into the ESS to support the PDT operation, which enables to disconnect the battery to avoid the sub-cycles problem. Moreover, the EMS also considers all the states needed to protect the battery, including the load disconnection when the power balance is not achievable due to both low SOC and low PV power production. This section is organized as follows: subsection 5.1.2 presents the background of SPVSs based on DC microgrids. Then, subsection 5.1.3 introduces the structure, control strategies, and energy management system used in the proposed solution. The results and simulations analysis are reported in subsection 5.1.4.

5.1.2. Background of SPVSs

Figure 5-2 shows the SPVS architecture adopted in this section, which is formed by a PVS, an ESS (lithium-ion battery in parallel with a capacitor), the controlled DC/DC converters, and the load \[168, 169\]. Such microgrid structure is commonly used in several applications.
5 Energy management in DC microgrids for improving the operation conditions and cost optimization

that require a global power balance \[170, 171, 172].

![Conventional stand-alone DC microgrid.](image)

Equation (5-1) formalizes the global power balance of the SPVS, where \( P_{ESD} \) represents the power supplied or stored by the Electric Storage Device (ESD), \( P_{PV} \) is the power generated by the PVS, and \( P_{Load} \) is the power demanded by the load. In this balance, the supplied power is positive and the consumed power is negative.

\[
P_{ESD} + P_{PV} + P_{Load} = 0
\]  

(5-1)

EMSs should consider the fact that batteries have two SOC limits: a maximum state of charge (\( SOC_{Max} \)), i.e. overcharge, and a minimum state of charge (\( SOC_{Min} \)), i.e. bulk charge. If the battery operates outside those limits, the ESS lifetime could be significantly reduced \[173, 174, 175\]. Therefore, EMSs should also integrate two operating modes: (1) constraining the power generated by the PVS so that it is equal to the power demanded by the load (\( P_{PV} \approx P_{Load} \)), which is needed when \( SOC_{Max} \) is achieved; and (2) disconnecting the load when the ESS reaches the \( SOC_{Min} \). In the second mode, the PVS must be operated at the MPP until the battery reaches an acceptable SOC value to reconnect the load \[47\].

An example of this kind of EMSs is presented in \[171\], where a multi-loop and multi-segment adaptive droop-controller is used to manage the energy flow in a PV/battery hybrid system for a stand-alone DC MG. That solution controls the power generated by the PVS to regulate the charge/discharge battery power. However, since the battery is used to regulate the voltage in the DC-bus, such an action produces charge/discharge sub-cycles, which reduce the lifetime of the battery. Similarly, in \[58\] the authors proposed a double-layer hierarchical controller to ensure the global power balance of a DC MG. In such EMS, both the generators and the ESS can operate as voltage source converters or current source converters, which
5.1 Energy management in standalone DC microgrids with controlled PV generation, battery storage and load connection

enable both types of devices to regulate the DC-bus voltage. This solution requires a virtual battery disconnection when the $SOC_{\text{Max}}$ is reached, which is performed by controlling the power generated by the PVS. Such a strategy may cause voltage instability due to the absence of a storage device, hence no device is capable of storing the small amount of power excess that could be produced by the PVS due to quantization or controller errors.

Other solutions have been focused on regulating the power generation of the PVS to prevent the batteries from operating outside the $SOC$ limits. This is the case in [47], where PVS generation is constrained depending on battery $SOC$ and grid availability. Similarly, in [48] is reported a real-time rule-based algorithm for the power management of a MG that considers a constraint to the power generated by the PVS. Different authors [176] have also proposed an EMS based on multiple MG operating states: MPPT mode and constant voltage (CV) mode. The CV mode is used when the battery $SOC$ reaches the maximum limit; hence the PVS power generation is constrained to ensure a constant battery voltage. The same strategy has been applied by other authors to avoid an excessive $SOC$ condition [17,171,58,48]. However, in those solutions the batteries are not disconnected; therefore, the small amount of power excess that could be produced by the PVS (due to quantization or controller errors) is stored or supplied by the battery, hence generating charge/discharge sub-cycles, which reduce the battery’s lifetime.

The problem associated with the charge/discharge sub-cycles of the ESS is illustrated in Figure 5-3, which considers the control of PVS generation reported in [47]. That control strategy was implemented following the flowcharts reported in [47], but modifying the power profiles reported in that paper since those profiles do not illustrate the sub-cycles problem. Such solution has MPPT and PDT modes, where both modes are based on the P&O algorithm. This simulation includes a single BP585 PV module with a constant irradiance of 1000 W/m², a constant power load of 40 W, and an initial battery $SOC$ equal to 0.99995, which is near $SOC_{\text{Max}}$. The simulation considers constant power profiles for both the photovoltaic source and load to illustrate the sub-cycles problem in an easy way: those constant profiles enable to visualize the source of the sub-cycles problem without the action of other controller transitions. The results presented in Figure 5-3 show that the PVS operates in MPPT mode at the beginning of the simulation to provide the power required by the load, while charging the battery. The MPPT mode is active for 0.34 s; at that moment, the battery $SOC$ reaches $SOC_{\text{Max}}$. From that moment on, the system operates in PDT mode to reduce the power generated by the PVS. In PDT mode, two different waveforms can be observed in the PVS power curves: (1) when the battery $SOC$ is higher than $SOC_{\text{Max}}$ (between 0.34 s and 0.63 s) and (2) when the $SOC$ is almost equal to $SOC_{\text{Max}}$ (from 0.63 s on). In the first part of this PDT operation, the control strategy uses the power excess from the battery to supply part of the load power, thus discharging the battery to respect the $SOC$ limit. However, when the $SOC$ is almost equal to $SOC_{\text{Max}}$ small errors of the PDT
control produce small charge/discharge sub-cycles in the battery (observed in Figure 5-3(b)), which are integrated as full charge/discharge cycles that reduce the battery’s lifetime. In this simulation, the PDT errors are caused by the discretization of the P&O algorithm that is used to track the load power, which is an unavoidable condition. Similar errors will occur in other tracking solutions, such as incremental conductance, extremum seeking or linear and non-linear controllers.

The following subsection proposes both a circuital structure and a control strategy to address this problem.

5.1.3. Circuital Structure and Control Strategy for the EMS

To solve the problem described in Section 5.1.2, this section proposes an EMS for a SPVS that considers battery SOC limits, PVS power generation control, and the integration of a backup capacitor to avoid charge/discharge sub-cycles in the battery. The backup ESS (capacitor) is used to support the power balance when the main ESS (battery) is disconnected, which occurs when the battery SOC falls outside safe limits. Such procedure avoids charge/discharge sub-cycles in the battery and, hence, artificial battery degradation.

The EMS proposed in this section is based on three operating regions (OR), defined by the SOC limits, and two control modes for the PVS; a graphic representation of those regions is provided in Figure 5-4. Region 1 (OR1) covers the normal battery operation and PVS; hence, the PVS works in MPPT mode and the battery is connected to the EMS.
5.1 Energy management in standalone DC microgrids with controlled PV generation, battery storage and load connection

The second operating region (OR2) occurs when the battery SOC reaches the maximum limit \((SOC \geq SOC_{\text{Max}})\), which forces the PVS to operate in PDT mode and disconnect the battery. OR2 uses the capacitor as backup ESD to ensure a correct power balance, thus eliminating the charge/discharge sub-cycles described in the previous section. The EMS remains in OR2 while the MPP of the PVS is higher than the power demanded by the load.

The third operating region (OR3) occurs when the battery SOC reaches the minimum limit \((SOC \leq SOC_{\text{Min}})\), which forces the battery disconnection and the use of the backup capacitor for ensuring the global power balance. Moreover, if the capacitor is discharged (hence the capacitor voltage reaches a safe minimum value), the load is disconnected to force the capacitor to charge until the voltage reaches the battery voltage level, which enables the EMS to reconnect the battery. Finally, the load is reconnected when the battery has been charged to a safe SOC value.

**Figure 5-4.** Proposed methodology.

### 5.1.3.1. Devices and Control Strategies

The components of the proposed EMS are depicted in Figure 5-5: PV panel, battery, capacitor, DC/DC converters, control strategies, and common DC-bus. The PVS is connected to the DC-bus using an unidirectional DC/DC boost converter, which is regulated using the sliding-mode controller (SMC) proposed in [145]. Such a SMC regulates the DC/DC converter to impose a desired PV voltage despite the environmental and DC-bus voltage conditions, hence the voltage of the PV source is always equal to the voltage reference \((V_{PV-REF})\); the design and stability proof of the SMC are reported in [143]. The reference of such a SMC is provided by the P&O algorithm proposed in [47], which has two operation modes: the MPPT mode tracks the optimal PV voltage that ensures the maximum power generation, while the
PDT mode tracks the PV voltage to produce a given power reference. Therefore, the strategy used to control the power generation of the PVS does not require the implementation of forecasting methods, since the combined action of the P&O and SMC algorithms ensures the production of the maximum power possible (MPPT mode) or a lower power level to match the load demand (PDT mode) depending on the microgrid requirements. In addition, the proposed structure also has adjustable parameters to control the power generated by the PV sources, with one limitation: the maximum power that can be delivered is constrained by the environmental conditions, while the minimum power is controllable. This section of the power system is modeled using the electrical equations of both the PV panel and the unidirectional DC/DC converter given in Equations (5-2)–(5-4):

\[ i_{pv} = i_{ph} - i_o \left[ \exp \left( \frac{q \left( v_{pv} + i_{pv} R_s \right)}{(N_c \eta k T_c)} \right) - 1 \right] - \frac{(v_{pv} + i_{pv} R_s)}{R_h} \]  
\[ \frac{dv_{pv}}{dt} = \frac{i_{pv} - i_{L_{pv}}}{L_{pv}} \]  
\[ \frac{di_{L_{pv}}}{dt} = \frac{v_{pv} - v_{dc} (1 - u_{pv})}{L_{pv}} \]

Equation (5-2) describes the PV current \( i_{pv} \) and voltage \( v_{pv} \) imposed by the unidirectional DC/DC converter, the photo-induced current \( i_{ph} \), which is almost proportional to the irradiance level, the inverse saturation current \( i_o \), the series and shunt resistances \( R_s \) and \( R_h \), the electron charge \( q \), the Bolzmann constant \( k \), the quality factor \( \eta \), the number of cells \( N_c \) and the temperature in kelvins \( T_c \). Equation (5-3) describes the dynamic behavior of the PV voltage, where \( C_{pv} \) is the capacitor in parallel with the PV source, \( L_{pv} \) is the inductance of the unidirectional DC/DC converter and \( i_{L_{pv}} \) is the current of that inductor. Finally, Equation (5-4) describes the dynamic inductor current behavior, where \( v_{dc} \) corresponds to the bus voltage and \( u_{pv} \) is the activation signal of the converter MOSFET, which is generated by the SMC.

The backup capacitor \( C \) of the structure is used in OR2 and OR3 for supporting the power balance and, at the same time, enabling the control of the DC-bus voltage in both OR2 and OR3. The capacitor is always connected to the EMS, while the battery is disconnected in OR2 and OR3 using the switch \( SW_{Bat} \). It must be noted that, independent of the size or the selected technology of the battery bank, the sub-cycles problems will remain; the quantization errors of the PDT control strategy will produce small charge/discharge sub-cycles, which are integrated as full charge/discharge cycles. The solution to avoid that problem is to disconnect the battery bank when the PV system must operate in PDT mode. A larger battery bank will suffer a small impact of the sub-cycles problem, since each sub-cycle will be divided into the batteries forming the bank, but the solution proposed in this section is intended to remove the sub-cycles degradation independent of the battery size or selected technology.
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The capacitor size is calculated using the average power values obtained when the system operates in PDT. Equation (5-5) calculates the average current in the capacitor, where $P_c$ is the maximum allowable power for the capacitor, and $V_{Bat}$ is the battery nominal voltage. Equation (5-6) can be used to calculate the capacity of the capacitor, where $t$ represents the selected discharging time and $\Delta V$ is the maximum voltage drop allowed for those $t$ seconds; both values are assigned by the MG designer according to the generator and load characteristics.

\[
I_C = \frac{P_c}{V_{Bat}} \quad \text{(5-5)}
\]

\[
C = \frac{I_C}{\Delta V} \ast t \quad \text{(5-6)}
\]

The hybrid ESS is connected to the DC-bus using the bi-directional converter depicted in Figure 5-5, which is controlled to regulate the DC-bus voltage. The control strategy adopted for that converter was proposed in [146]; it consists in a SMC for the charger/discharger that ensures a stable DC-bus voltage in any operating condition: charging, discharging, or stand-by. This control strategy is active in all the operating regions by using the battery or capacitor as ESS, thus ensuring the global power balance of the system. This section of the model is represented by Equation (5-7), where $v_{ESD}$ corresponds to the ESD voltage, $L_{ESD}$ denotes the inductor of the bidirectional DC/DC converter and $i_{ESD}$ is the current of that...
inductor; finally, $u_{ESD}$ is the activation signal of the MOSFETs generated by the SMC of this charger/discharger.

$$\frac{di_{ESD}}{dt} = \frac{v_{ESD} - v_{dc}(1 - u_{ESD})}{L_{ESD}}$$ (5-7)

To evaluate the proposed EMS, constant power load [177] models were selected due to their widely use in DC MGs analyses [178, 179, 180, 181, 182]. That representation has the main characteristic of changing both the load current and voltage to keep the load consumption constant; therefore, when the bus voltage exhibited perturbations, the load current changed accordingly. This is different from the constant impedance load (CIL) representation, in which perturbations in the bus voltage causes a different load power consumption. In practical applications of DC Microgrids, CPL is an accurate representation of the loads due to the presence of DC/DC converters interfacing the loads with the DC bus: the load current changes according to the perturbations in the bus voltage (load voltage) to consume the power requested by the load [178, 179, 180]. Therefore, CIL is not an accurate representation of the loads in DC Microgrids with commercial loads. In any case, CPL models can be used to represent loads interfaced with DC/DC converters having variable power consumptions. In that case the power requested by the load is just updated in the model, but the load keeps behaving as a CPL: the current changes according to the bus voltage perturbations to ensure the desired power consumption.

In addition, the load voltage was considered equal to the DC-bus voltage; hence, there was no need for an additional DC/DC converter for the load interface. Finally, since the load was disconnected in OR3, a switch $SW_{load}$ was included in the EMS circuit to disconnect and reconnect the load from the DC-bus.

### 5.1.3.2. Energy Management System Proposed to Control the SPVS

Figure 5-4 presents the operating regions defined around the technical operating limits established for the battery $SOC$. Such regions should consider the different operating modes of the PVS (MPPT and PDT) and the battery and load connection/disconnection depending on the requirements of each operating region.

The following subsections explain the types and operating ranges of the battery $SOC$, and the control strategies applied to the regions proposed in this section: overcharge, normal charge, and bulk charge. It also describes the requirements to move from one region into another, and to connect/disconnect the battery and the load so that voltage fluctuations are as small as possible. To provide a better explanation of the EMS, the three regions are described in the following order: Region 1 (normal operation); Region 2 (overcharge); and
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Region 3 (bulk charge).

**Region 1** (*Normal*: $SOC_{Min} < SOC < SOC_{Max}$):
In this region, the PVS should always operate in MPPT in order to utilize its maximum power generation. Because the battery is responsible of the global power balance at all times, it should always be connected ($SW_{Bat} = 1$). Moreover, the load is always connected in this region ($SW_{Load} = 1$) because the PVS and the battery, combined, can produce sufficient power to supply the load demand. The restrictions and considerations to enter this operating region are detailed in the subsections describing Regions 2 and 3. To leave this operating region, the battery needs to reach its $SOC$ limits. The state diagram in Figure 5-6 provides a better interpretation of those interactions.

![Figure 5-6: Flowchart of the control strategy in Region 1.](image)

**Region 2** (*Overcharge*: $SOC \geq SOC_{Max}$):
This operating region occurs when the power generated by the PVS is higher than that consumed by the load and the battery reaches $SOC_{Max}$. For that reason, the backup ESS (in this case, the capacitor) must replace the battery and take control of the power balance and the voltage at the DC-bus, keeping the load connected at all times ($SW_{Load} = 1$). It should be noted that, for the EMS to operate in this region, the battery $SOC$ should be equal to, or higher than, the maximum limit ($SOC \geq SOC_{Max}$). In this OR, there are different operating scenarios depending on the values of the power generated by the PVS, the power demanded by the load, and the maximum and minimum voltage limits assigned to the capacitor, which are explained below and presented in the state diagram of Figure 5-7.

- $(P_{pv} \geq P_{Load})$: In this operating state, the battery must be disconnected ($SW_{Bat} = 0$) and, at the same time, the PVS should operate in PDT. As a result, the capacitor is in charge of supplying and storing the power required by the system to perform the PDT and to control the DC-bus voltage. In order to prevent the capacitor from fully discharging and the system from collapsing due to the lack of power to control the
5 Energy management in DC microgrids for improving the operation conditions and cost optimization

DC-bus, the system operates in PDT mode until the capacitor reaches a voltage below ($V_c < V_{Bat} - \Delta V_c$), being $\Delta V_c$ the maximum allowable voltage drop for the capacitor. In the case that this limit is violated, the PVS should change to MPPT mode so that the capacitor is charged until it reaches the battery voltage ($V_{Bat}$), thus exploiting the excess of power generated by the PVS. Note that, in the management system, the voltage of both the capacitor and the battery should always be sensed to perform this control action. Additionally, the capacitor should be protected against over voltage conditions. For that reason, if during the operation in PDT mode the capacitor reaches the maximum allowable voltage ($V_{cMax}$), then the PVS is operated in open circuit voltage ($Voc$) until the capacitor reaches a safe voltage ($V_c = V_{cMax} - \Delta V_c$). This is achieved because the capacitor is forced to supply the power required by the load, thus enabling the reduction of its voltage. When the capacitor reaches a safe voltage, the PVS starts to operate in MPPT mode to provide power. As a result, the operating mode can change to PDT if the power conditions are met ($P_{pv} \geq P_{Load}$); otherwise, the PVS continues operating in MPPT in Region 1 as long as the power generated by the panel is lower than that required by the load ($P_{pv} < P_{Load}$), and the capacitor’s voltage is lower than, or equal to, that of the battery ($V_c \leq V_{Bat}$). This forces the capacitor to discharge before changing operating regions (from 2 to 1), thus reducing the voltage fluctuations at the DC-bus when the battery is connected.

- ($P_{pv} < P_{Load}$): In this state, the PVS power reaches a lower value than that of the load. This is due to the decrease in Solar Radiation (SR), the variation of T, or higher power demanded by the load; therefore, the PVS should increase the delivered power and start to operate in MPPT, maintaining the battery disconnected ($SW_{Bat} = 0$). The system continues operating in Region 2 as long as the condition to change to OR1

![Flowchart of the control strategy in Region 2.](image-url)
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(described in the previous paragraph) is not met. If that condition is not satisfied and the condition \( P_{pv} \geq P_{Load} \) remains, the capacitor is charged up to the battery nominal voltage and the PVS operates in PDT once again.

Region 3 \((\text{Bulkcharge} : \text{SOC} \leq \text{SOC}_{Min})\):

When the battery reaches the minimum allowable \( \text{SOC} \), it should not supply power to the load. For that reason, the battery is disconnected when the operating state \( \text{SOC} \leq \text{SOC}_{Min} \) is reached, while the capacitor is in charge of supplying the demanded power in such a way that the global power balance is satisfied and the voltage level at the DC-bus is controlled. The previous condition will be fulfilled as long as the capacitor does not reach the minimum voltage level established for its operation \( (V_{cMin}) \). At the same time of the battery disconnection, a warning signal is sent to indicate that the system is operating in Region 3 and the load might be de-energized. Such signal takes a value of one \((\text{Warning} = 1)\) when the battery reaches its minimum \( \text{SOC} \) and continues that way until the \( \text{SOC} \) achieves a safe operating level, at which point it changes to zero \((\text{Warning} = 0)\). That warning signal is adapted in the management system to alert users that the system will stop supplying power for a period of time.

When the system is operating in Region 3, two operating conditions can be created: (1) the generated power is higher than, or equal to, the power demanded by the load \( (P_{PV} \geq P_{Load}) \); therefore, the system should charge the capacitor until its voltage reaches or exceeds the battery voltage in order to connect the battery \((W_{Bat} = 1)\), and charging the battery until it reaches a safe recovery level \( (\text{SOC}_{Rec}) \). Only when this condition is met, the warning is off \((\text{Warning} = 1)\) and the system starts to operate in Region 1. (2) the generated power is lower than the power demanded by the load \( (P_{PV} < P_{Load})\): if the capacitor reaches its minimum voltage in this condition, the load is disconnected, while the battery is kept disconnected until the capacitor reaches a voltage level equal to, or higher than, the battery voltage. When this condition is satisfied, the battery is connected, and its charge cycle is started until its \( \text{SOC} \) is equal to, or higher than, \( \text{SOC}_{Rec} \). Only when this condition is met, the load is reconnected, the warming signal is off and the system can start to operate in OR1. It is important to highlight that, by using the hysteresis band generated between \( \text{SOC}_{Min} \) and \( \text{SOC}_{Rec} \), it is possible to avoid the connection and disconnection of the battery for short periods of time, and the load connection and disconnection when the second operating condition is fulfilled. In an operating state of variable demand, this prevents fluctuations and continuous transients in the system. Moreover, in OR3 the PVS operates in MPPT mode at all times so that the maximum power is generated. The state diagram in Figure 5-8 is a graphic representation of this strategy.
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5.1.4. Simulation Results

This section describes the simulations that were conducted to make sure that each one of the regions and operating states in the EMS are satisfied and enable the SPVS to operate adequately. In order to simulate the components of the SPVS and the control strategies, it was employed the specialized software PSIM. The BP585 mono-crystalline PV panel, formed by 36 cells in series, was selected. Table 5-1 presents the module characteristics in standard conditions (STC-radiance, 1 kW/m²; and cell temperature, 25 °C). To estimate the module parameters, the mathematical formulation proposed in [183] and the data in standard conditions were used. Changes in the radiance and temperature are also considered by changing the photo-induced current of the PV source model, which is a common simulation practice as it is reported in [183]. It must be highlighted that the adopted PV model is also valid for representing modules currently available at the market, which exhibit characteristics similar to the ones of the PB585 module, e.g. M36PCS (85 W), P36PCS (85 W), among others. The nominal voltage of the lithium-ion battery (used to form the ESS) was 12V, with three cells in series, one set of cells in parallel, and a nominal capacity of 5.2 Ah. The limits $SOC_{Max} =0.9$ and $SOC_{Min} =0.1$ were defined in the management strategy to extend the lifetime of the device [181]. Additionally, for an adequate transition from Region 3 to Region 1, the EMS implemented a $SOC_{Rec}$, which is specified in each test scenario.

Figure 5-8.: Flowchart of the control strategy in Region 3.
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### Table 5-1: Parameters of the BP585 panel.

<table>
<thead>
<tr>
<th>Parameters (STC)</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open circuit voltage (Voc, STC)</td>
<td>22.1 V</td>
</tr>
<tr>
<td>Short circuit current (Isc, STC)</td>
<td>5 A</td>
</tr>
<tr>
<td>MPP voltage (V_{MPP}, STC)</td>
<td>18.0 V</td>
</tr>
<tr>
<td>MPP current (I_{MPP}, STC)</td>
<td>4.70 A</td>
</tr>
<tr>
<td>Voc temperature constant (α_{Voc})</td>
<td>−0.088 V/°C</td>
</tr>
<tr>
<td>Isc temperature constant (α_{Isc})</td>
<td>0.047 %/°C</td>
</tr>
<tr>
<td>Number of cells (Ns )</td>
<td>36</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Estimated Parameters (STC)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Iph (A)</td>
<td>5</td>
</tr>
<tr>
<td>Isat (nA)</td>
<td>2.808</td>
</tr>
<tr>
<td>Ideality factor of diode (η)</td>
<td>1.121</td>
</tr>
<tr>
<td>Rs (Ω)</td>
<td>0.227</td>
</tr>
<tr>
<td>Rp (kΩ)</td>
<td>2.029</td>
</tr>
</tbody>
</table>

The parameters of the different elements that formed the control strategies and the converters used to design this SPVS are described in the references cited in Section 5.1.3. For a better understanding and analysis of the results obtained by the proposed EMS, this subsection starts with the validation of each one of the operating regions considering the variation in photovoltaic generation and the power demanded by the load. For that purpose, short simulation times and an analysis of the transients of each OR and their transitions, as well as the DC-bus voltage were used. Finally, a 24-h test scenario was defined (with load and solar irradiation variations sensed in Medellín-Colombia) to evaluate the behavior of the SPVS in all the operation regions.

#### 5.1.4.1. Simulation and Validation of the Proposed Operation Regions

This subsection analyzes each operating region in order to validate all the conditions and constrains considered in the proposed EMS. For that purpose, the EMS parameters were adjusted as follows.

The capacitor was calculated by analyzing the behavior of the PVS when PDT was applied in the presence of the battery and an irradiance of 1000 W/m²; thus, obtaining the scenario of maximum power in which the capacitor will operate. After analyzing the results of this scenario (see Figure 5-3), $P_c = 10$ W was defined so that the capacitor had sufficient power to assume the power excess generated in this operating mode. The maximum voltage drop of 1 V was also considered for a time of 1 s, which requires a 0.833 F capacitor. Based on the capacitor calculation, the values $V_{C_{\text{max}}} = 18$ V, $V_{C_{\text{min}}} = 5$ V, and $ΔV_C = 1$ V were assigned. It is considered a margin of 60 % (upper limit) and 50 % (lower limit) of the
nominal voltage of the battery in order to establish the voltage levels in this EMS and offer an adequate power level in the capacitor. It is important to highlight that the capacitor voltage limits vary depending on the specific equipment and manufacturer. In addition, it was considered $\Delta V_{PV} = 0.2V$ as the voltage rate in the power control strategy of the PVS and assigned a value of $SOC_{Rec} = 0.10005$ as the recovery $SOC$ of the battery. Those values were selected in order to validate the operating states in a short period of time and analyze the transients generated by the fulfillment of the conditions, as well as transitions from one OR to the next. Finally, each one of the proposed scenarios has an initial load, PVS power generation, and variable power demanded by the load so that all the states and regions in the EMS can take place. Note that all the test scenarios in this section use the same minimum and maximum $SOC$ limits previously defined.

**Region 1 (Normal: $SOC_{Min} < SOC < SOC_{Max}$):**

This subsection describes different test cases in the same scenario, in which power generation and demand in the SPVS are changed to test the conditions established for the system operation in Region 1 (normal) and Region 2 (overcharge). Figure 5-9 presents this test scenario, describing the system dynamics under the proposed EMS. PVS power generation was divided into three levels. The first level was generated by a solar irradiance of 1000 W/m$^2$, which resulted in approximately 84 W produced by the PVS. At $t = 6.2$ s, a 40% reduction (400 W/m$^2$) was applied, and the PV generated 50 W after that. Finally, another 40% reduction (400 W/m$^2$) was applied at $t = 6.5$ s, which generated a total drop of 80% in the maximum irradiation from the start of the test scenario until the time under analysis. Thus, the final power delivered by the PVS was approximately 16 W. Additionally, this scenario considered the variation in the power demanded by the load, which was 20 W at $t = 0$ s, 90 W at $t = 2$ s, and, finally, 30 W at $t = 3$ s. The time interval between seconds 4 and 5 presents a load increase with positive slope from 30 W to 50 W, which is maintained until $t = 6$ s. Finally, the load drops to 30 W from $t = 6$ s to the end of the period under analysis. The previous scenario of PVS generation and power demand is defined in such way that transitions between ORs 1 and 2 occur and the PVS operates in PDT and MPPT. The test simulation was divided into 5 time intervals for a correct interpretation of the test scenario as well as the PVS behavior based on the different variations. The intervals represent a scenario where power generation and demand change, one exceeding the other.

To validate the operation of the proposed EMS in OR1, the battery $SOC$ started at 0.5 so that, during the entire simulation time, the EMS stayed within the ranges assigned to operate in this region. Figure 5-10 presents the behavior of the system when load and demand variations were applied. Remarkably, the PVS operated in MPPT at all times, keeping the battery and load connected throughout the simulation, while the battery was in charge of supplying and storing the power excess generated by the PVS so that a global power balance could be achieved. The subfigure that presents the voltage assigned to the PVS by the DC/DC converter shows the way the EMS modified that voltage as the irradiation on the
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Figure 5-9.: Power demanded and generated by the SPVS test system in OR1 and OR2.

Panel varied (fell), always staying in MPPT mode. This validates the correct operation of the external control strategy applied to obtain the maximum power from the PVS. Moreover, it was proved that the management strategy selected to control the ESS could be used to control the DC-bus voltage, always keeping the voltage near its nominal value ($V_{DC} = 48$ V), while the power demanded by the load is supplied and absorbed without affecting the MG operation. In this test system, the power flow supplied by the ESD is provided by the battery, since the switch of the ESD is closed (please refer to Figure 5-5 to check the switch). The voltage peaks in DC bus are associated with strong variations in the demand, which are mitigated by the control strategy. This test scenario does not consider the transition to other ORs such a condition is validated in ORs 2 and 3.

Region 2 (Overcharge: $SOC \geq SOC_{Max}$):

In order to validate the conditions proposed for OR2, the same test system presented in Figure 5-9 was used. The validation of the correct operation of the EMS is presented in Figure 5-11, which details the control actions performed by the EMS in different operating and demand scenarios of OR2 divided into time intervals based on variations in load and PVS generation. The waveforms of battery $SOC$ and voltage demonstrate that, during most of the simulation time, the system operated with $SOC \geq SOC_{Max}$ and the battery was disconnected, while the capacitor was in charge of supplying and storing the power excess required by the system to achieve the global power balance. As a result, the sub-cycles of the battery associated with the operation in PDT in this OR are eliminated. In Interval 1, the generated power was higher than the demand of the system and, because the $SOC$ level was lower than the maximum established limit, 0.9 ($SOC = 0.89995$), the system started operating in OR1. As the simulation progressed, the battery was charged until it reached the maximum allowable limit for the $SOC$ at $t = 0.36$ s. When this happened, the operation of the system changed to OR2, the battery was disconnected, and the PVS system was operated in PDT.
This can be observed in the voltage of the battery and the voltage assigned by the converter to the PVS (PV voltage). This operation mode continued until Interval 2. The capacitor voltage shows that this device was in charge of supplying and storing the power excess associated with the PDT during Interval 1. In Interval 2, the power state in the SPVS changed: the demanded power was higher than the power generated by the PVS. For that reason, the photovoltaic system changed to operate in MPPT at \( t = 2 \) s, reducing the PV voltage so that the power required by the load was delivered. Because the power generated by the PVS was not sufficient to cover the load demand, the capacitor should have compensated for that deficit. During this entire interval the battery was disconnected because the system did not meet the conditions to change operating regions.

In Interval 3, the load conditions led the system to operate in PDT once again, increasing the voltage of the PVS until it reached an adequate power level. Because the capacitor should have delivered the power difference in this operating mode, its voltage started to drop (as can be seen from the voltage waveform), keeping the battery disconnected. Interval 4 presents different load levels, which were correctly managed by the EMS. In the simulation, the \( 4 \text{ s} \leq t \leq 5 \text{ s} \) interval exhibited a step-shaped load increase during which the PDT adapted to such an increase. This produces a voltage drop in \( V_{pv} \) and, as a result, the power generated by the PVS rose in a controlled manner. In that interval, the DC-bus presented
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higher voltage fluctuations than in other intervals of the test scenario. After $t = 5$ s, the load was constant ($P_{\text{Load}} = 50$ W) until $t = 6$ s, while the system was operating in PDT with a disconnected battery. At $t = 6$ s, the demanded power dropped to 30 W, because the PDT conditions were maintained, and the system continued operating in this OR. Additionally, Interval 4 presented a drop in Solar irradiance (SR), which had an impact on the power generated by the PVS and resulted in a reduction in the power produced by the PV panel. During the first power reduction, which occurred in the $6.2 \leq t \leq 6.4$ s interval, the power generation stayed above the power demanded by the load; for that reason the PVS operated in PDT mode at all times. Note that, although the reduction in power generated by the PVS was important, the EMS correctly responds by reducing the reference voltage of the PVS. Nevertheless, charge and discharge power fluctuations were produced in the capacitor, although smaller than those generated during the step-shaped increase in the load during the $4 \leq t \leq 5$ s interval. Finally, a second drop in SR took place between Intervals 4 and 5, $6.5 \leq t \leq 6.7$ s, which caused the power generated by the PVS to drop below the power demanded by load at $t = 6.6$ s. The PVS then changed from PDT to MPPT mode. The EMS maintained the system in OR2 until the capacitor reached the battery voltage at $t = 6.8$ s, satisfying the condition for battery reconnection in Interval 5. For that reason, the

Figure 5-11.: Energy Management System: test system in OR2.
SPVS started to operate in OR1, while the battery SOC fell from $t = 6.8$ s until the end of the simulation. Remarkably, in the entire test scenario, the operating voltage of the DC-bus was maintained near its nominal voltage ($V_{DC} = 48$ V), with a maximum variation of 0.72%.

The test scenario in Figure 5-11 does not show the charge/discharge action of the capacitor when the maximum and minimum limits are reached. For that reason, Figures 5-12 and 5-13 present the behavior of the system when into those two operation states in order to demonstrate the adequate operation of the system. Figure 5-12 illustrates a scenario where the capacitor reaches $V_{C_{Max}}$ when the PVS is operating in PDT. Thus, an initial voltage ($V_c = 18.1$), $SOC \geq SOC_{MAX}$, and the power demanded by the load (40 W) were assigned. Those conditions forced the system to discharge the capacitor to a safe voltage level ($V_c = 17$ V in this case). For that purpose, the EMS operated the system in Voc until the capacitor voltage reached the safe level established by the control strategy, thus generating $P_{PV} = 0$ W and forcing the capacitor to supply all the power required by the load. When the capacitor reached the safe voltage level, the system switched modes to operate in MPPT at $t = 0.388$ s until it reached the required power level to continue operating in PDT at $t = 0.397$ s, which can be observed in the waveforms PVS, load, and capacitor power. Figure 5-12 presents the voltage levels assigned by the control strategy (reference) and the converter to the PVS, as well as the stabilization of the capacitor voltage in the levels assigned by the EMS.

![Figure 5-12](image)

**Figure 5-12:** Control strategy to reduce the power generation in the PVS in order to discharge the capacitor when $V_c \geq V_{C_{Max}}$ in PDT mode.

Figure 5-13 illustrates the test scenario in which the capacitor reaches the minimum voltage limit allowable in OR1, with the PVS operating in PDT. In this scenario, the load power
was 40 W and $SOC = 0.91$, thus generating $V_{Bat} = 11.94 V$. In order to violate the minimum voltage limit ($V_c < V_{Bat} - \Delta V_c$), an initial voltage of 10.92 V was assigned to the capacitor so that the system charged it. Due to the previous conditions, the power graph of the devices in Figure 5-13 shows that the system, when the simulation started, operates in MPPT until the capacitor reached the minimum allowable voltage level to operate in PDT in OR2 at $t = 0.242$ s, when it changes to PDT ($V_c \geq V_{Bat}$). Importantly, the power to charge the capacitor was extracted from the power excess of the PVS generation. At the start of the simulation, the capacitor voltage was under the allowable level, i.e., a volt below that of the battery voltage ($\Delta V_c = 1 V$). For that reason, the voltage assigned to the PVS by the control strategy forced the system operation in MPPT until the capacitor voltage reaches the battery at the moment of the disconnection. After that point, the system operated in PDT again until the load and generation conditions in the SPVS changed.

**Figure 5-13.**: Control strategy to increase the power generation in the PVS in order to charge the capacitor when $V_c = V_{Bat} - \Delta V_c$ in PDT mode.

**Region 3 (Bulkcharge : $SOC \leq SOC_{Min}$)**: In order to validate the correct system operation in OR3, this subsection proposes two test scenarios to study the conditions that can exist when the SPVS works in that region. Figure 5-14 shows the test scenario that represents the operating condition in which the battery reached the $SOC_{min}$ and the power of the PVS changed to $P_{PV} \geq P_{Load}$. Such a scenario considered an initial $SOC = 0.100025$ and $SOC_{Rec} = 0.10005$, and the system started to operate in OR1. Moreover, the power generated by the PVS ($P_{PV} = 84 W$) was constant and the power demanded by the load was variable: the load started with a demand of 120 W and, as a result, the system changed from OR1 to OR3 at $t = 0.104$ s. When the SPVS changed to OR3, the warning signal took
a value of 1, which indicated that the system may close to a load disconnection. After $t = 0.2$ s, the power demanded by the load decreased ($P_{Load} = 60$ W) until $t = 1.6$ s. Due to that drop in the load, the power state of the system changed ($P_{PV} \geq P_{Load}$), and as a result, the capacitor started to charge. When the condition $V_{c} \geq V_{Bat}$ was satisfied at $t = 0.806$ s, the EMS reconnected the battery and started the charging process. Importantly, only when the $SOC$ reached the recovery level at $t = 1.446$ s the system started to operate in OR1. At that point, the warning signal took a value of zero, which indicated there was no risk of load disconnection anymore. Finally, in OR1 there was a load increase ($P_{Load} = 60$ W), where, the generated power excess is stored in the battery. Note that, during the entire test scenario, the system operated in MPPT to take advantage of the power generated by the PVS and to escape from the bulk charge condition.

In this simulation the EMS maintained the voltage level of the DC-bus approximately equal to the nominal voltage ($V_{DC} = 48$ V), presenting maximum variations of 4.5% and 0.2% on average. The strongest voltage fluctuations were caused by variations in the power demanded by the load, where the sliding-mode controller provides a satisfactory performance, as it is observed in Figure 5-15.

Figure 5-16 presents a test scenario to validate the operating conditions when the load is disconnected. Such a scenario considers an initial $SOC$ of 0.100025 and $SOC_{Rec} = 0.10005$. As in the previous scenario, the power generated by the PVS ($P_{PV} = 84$ W) was considered to be constant and the power demand by the load, variable. The system started its operation in OR1, with a power demand of $P_{Load} = 120$ W; for that reason, it changed to OR3 at $t = 0.036$ s. After the SPVS changed operating regions, the battery was disconnected and the warning signal took a value of 1, indicating load disconnection risk. At the same time, the capacitor started its discharge process, which was accelerated at $t = 0.4$ s due to an increase in the power demanded by the load ($P_{Load} = 140$ W). At $t = 0.507$ s, the capacitor reached its minimum voltage limit ($V_{c} \leq V_{CMin}$); for that reason, the load was disconnected and the charging process of the capacitor was started. When the capacitor reached the battery voltage at $t = 1.021$ s, the battery was reconnected and its charging process was started until it reaches the $SOC_{Rec}$. When the recovery $SOC$ was reached at $t = 1.28$ s, the load was reconnected with a value of $P_{Load} = 140$ W, thus forcing the system to operate in OR1. At that time the warning signal took a value of zero, indicating the end of the disconnection risk. During the remaining simulation time, the SPVS operated in OR1 while the battery was supplying the missing power to the load. In addition, the power excess produced by the reduction in the power demanded by the load ($P_{Load} = 80$ W) at $t = 1.6$ s was stored. In this test scenario (as in the previous one), the PVS operated in MPPT all the time, correctly following the reference voltage assigned by the control strategy of the DC/DC converter. Regardless of the load and battery disconnection, the voltage level in DC-bus was correctly regulated.
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![Figure 5-14](image): Test system in OR3 (operating condition \( P_{PV} \geq P_{Load} \)).

![Figure 5-15](image): Voltage of the DC-bus test system in OR3 (operating condition \( P_{PV} \geq P_{Load} \)).
Figure 5-16.: Test system in OR3 (with disconnected load).

5.1.4.2. 24-h Test Scenario

After the correct operation of the SPVS was validated in each one of the operating regions defined in the proposed EMS, a 24-h test scenario was defined using the irradiation values reported by NASA for Medellín- Colombia [185], and the same PVS and operating conditions adopted for the previous tests. Moreover, such scenario uses a power curve of the typical behavior of a residential building in Medellín- Colombia [186]. The power levels were adjusted to observe the different operating regions proposed in this section; Figure 5-18 presents those values. The simulation times in this scenario were longer than in the previous subsection, hence the EMS parameters were adjusted: for the calculation of the capacitor, $P_c = 10\, W$ was considered, as well as a maximum voltage drop of 1 V, and a discharge time $t = 60\, \text{s}$. Those values result in a 49.9 F (approximated to 50 F) capacitor. In addition, a $V_{C_{\text{Max}}} = 18\, \text{V}$, $V_{C_{\text{Min}}} = 5\, \text{V}$, and $\Delta V_c = 1\, \text{V}$ were defined. For the PVS voltage rate, the control strategy considered $\delta V_{PV} = 1\, \text{V}$. Finally, $SOC_{Rec} = 0.2$ was established to create an adequate hysteresis band (10\% of the $SOC$) and to avoid multiple transitions between OR1 and OR3.
5.1 Energy management in standalone DC microgrids with controlled PV generation, battery storage and load connection

Figure 5-17.: Voltage of the DC-bus test system in OR3 (with disconnected load).

Figure 5-18.: PV generation and power demanded by the load in a 24-h scenario.

Figure 5-19 presents the results obtained when the EMS was applied in the power and demand scenario described in Figure 5-18. The analysis begins at hour 6, when the system started with $SOC = SOC_{Min}$ and, for that reason, it entered in OR3, disconnecting the battery and producing the load disconnection. Because the solar irradiance was not available, power was not generated at that time. Nevertheless, the PVS operated in MPPT mode waiting for an increase in the irradiance. The previous operating condition was set until hour 7, when the PVS started to generate power due to an increase in the irradiance. First, it charged the capacitor and then connected the battery when $Vc \geq V_{bat}$ at $t = 7.67$ h. The
voltage waveforms of both the battery and the capacitor show that the battery charging process started after that point. At $t = 8.64$ h the battery reached $SOC_{Rec} = 0.2$; therefore, the load was connected and the SPVS moved into OR1, keeping the PVS operating in MPPT. In this state, the power excess and power requirements were managed by using the battery. At $t = 12.10$ h the battery reached $SOC_{Max} = 0.9$; for that reason, the system moved to OR2, which caused the PVS to switch to PDT mode and the immediate disconnection of the battery, while the capacitor was in charge of supplying and absorbing the power excess of the PDT mode. At $t = 12.60$ h the capacitor reached the maximum voltage limit allowable in OR2; as a result, the EMS set the PVS to operate in open-circuit voltage so that the capacitor was forced to supply the power required by the load to reach the desired operating voltage level based on the $\Delta Vc$ previously defined. This can be observed in the sub-figures of both battery and capacitor voltage and the power. In the $13.07 \leq t \leq 13.93$ h interval, it is observed that the EMS did not allow the capacitor to violate the voltage drop limit, $(\Delta Vc = 1)$ V, forcing the capacitor to charge up to the battery voltage every time that limit was reached. This was achieved using the transition of the PVS from PDT to MPPT, which led to an increase in the power generation, and the power excess was injected into the capacitor to charge it. In the $13.93 \leq t \leq 16.09$ h interval, the system operated in PDT, while the capacitor was responsible for guaranteeing the global power balance in agreement with the conditions defined for OR2. Due to the reduction in generation after hour 13, the system met the conditions to change to OR1 at $t = 16.10$ h; and in that instant the capacitor reached the voltage level of the battery, hence the battery was reconnected. From that moment on, the PVS operated in MPPT, while the battery was responsible of supplying the power excess needed to support the load due to the reduction in PVS generation. The battery $SOC$ started to decrease until $t = 18.53$ h, when it reached the minimum allowable limit; consequently, the system changed to OR3. Due to the amount of power demanded by the load at that time, the capacitor was taken to the minimum allowable voltage limit and, as a result, the load was disconnected. After that instant, the capacitor started to charge by absorbing the small amount of energy generated by the panel, reaching the voltage of the battery at $t = 19.23$ h, when the battery was reconnected. At that moment, the power generated by the PVS was limited by the low irradiance, and the battery did not reach the $SOC_{Rec}$; for that reason, the load remained disconnected until hour 6. The bottom sub-figure in Figure 5-19 presented the warning signal of the system, which was activated every time the system entered OR3 and deactivated when the recovery $SOC$ was reached, it forced the system to enter in OR1. The simulation demonstrated the correct operation of the EMS in the scenario under analysis.
This section proposes an energy management system for the day-ahead dispatch of battery storage systems under a distributed generation environment for DC networks, with the main objective of reducing the cost of the energy purchased to the utility grid. This EMS uses a master-slave strategy formed by a parallel implementation of the particle swarm optimizer and a multi-period power flow method based on successive approximation presented in Chapter 2, with the aim of achieving the optimal daily operation of the BSS. The objective function selected for the optimization was the reduction of the total energy purchasing costs, also including the power balance, devices capabilities and voltage regulation. The effectiveness of the EMS was evaluated in a test system of 21 buses, comparing the solution quality and speed with three optimization techniques published in literature: a black hole optimizer, a continuous genetic algorithm with matrix structure, and a traditional Chu & Beasley genetic algorithm. In addition, two simulation scenarios were used to identify the optimal final SOC conditions for the BSS. The results show that the proposed EMS provides the best trade-off between quality solution and speed.

Figure 5-19: 24-h test scenario.
5.2.1. Introduction

Different control techniques and optimization methodologies have been proposed for regulating the operation of DC MGs (energy management stage) for both connected and standalone DC applications in the last years. The most common ones are droop control [187], fuzzy control [188], multi-agent based control [170] and hierarchical control. In particular, the hierarchical control been widely used in the last years [46]. In this type of control strategy, which structure is depicted in Fig. 5-1, the primary control is in charge of directly control the power devices, the secondary control is responsible of guaranteeing the technical conditions and constraints imposed to the MG, and the tertiary control defines the energy management strategy of the MG. Such an energy management strategy is designed depending on the goals imposed by the operator of the MG, e.g. operating cost reduction, power availability for emergency, among others. In the hierarchical structure, the control stages are communicated to exchange set points and measurements needed to take decisions that forces the desired operating conditions in the MG (i.e. power outputs/inputs, voltage and current references). The energy management stage represents a non-linear, multi-variable and complex problem, which requires a correct operation of both the primary and secondary control strategies to set the MG in the desired conditions. Therefore, this section is focused exclusively on the tertiary control by proposing an economic dispatch strategy, which assigns to the storage systems the power levels to supply or store in each hour. Hence, the proposed economic dispatch strategy assumes that the other control stages achieved the assigned operational references.

Concerning the energy management system proposed for the tertiary control, in the particular case of the distributed generators, some solutions have been proposed to provide an optimal integration and operation on DC MGs. Those works use commercial tools [189], intelligent control methods [43, 119], and metaheuristics optimization approaches [44, 190]. For the particular case of BSS, the operation methodology proposed in [45] is based on a convex mathematical formulation for the day-ahead, which improves the economic dispatch of distributed generators and BSS in DC grids. Such a work solves the mathematical model by using semidefinite programming methods with the aim of reducing the energy purchasing costs to the conventional generators (economic dispatch). Moreover, that solution uses an artificial neuronal network for forecasting both solar and wind resources. The main problem of this method concerns the adoption of semidefinite programming methods, which increases the number of variables that represent the problem, hence increasing the complexity and computational cost. Other solution is proposed in [16], which is based on the PSO algorithm for obtaining the optimal size and operation of the energy resources in DC networks. The work adopts an objective function aimed at reducing the energy resources costs of investment and operation. The main problems of this work are the consideration of a unique-nodal representation of the grid, i.e. neglecting both branch connections and multiple distributed
energy resources located in different buses of the electrical grid; furthermore, DERs impact on the electrical grid was analyzed without power flow methods. In addition, the selection of the solution method and its parameters is not described in detail, and there is not provided any comparison with other existing methods in terms of solution quality and processing time, which is required to evaluate the performance of the solution.

In the case of AC MGs, multiple works have been proposed to select, locate and operate distributed generators and BSS on the MGs [9] using different solution methods: stochastic methods, linear and nonlinear methods, metaheuristic techniques, convex optimization methods, among others [10, 11]. Those works are focused on the solution quality and the processing times. It is important to note that processing times increase as the electrical systems expand, hence several authors adopt paralleling processing tools for reducing the computational time [12]. In this sense, the methods based on sequential programming are widely adopted to avoid the use of software with undesired requirements such as high cost or prepossessing of the input and output data [13, 14].

Recognizing the current needs in the state-of-the-art about EMS for the BSS in DC grids, this section proposes a master-slave methodology, formed by a parallel implementation of a PSO algorithm and a multi-period power flow method based on successive approximations solution proposed in Chapter 2, for obtaining the optimal operation scheduling of BSS in DC grids with high penetration of distributed generators under a day-ahead economic dispatch environment. The proposed mathematical model considers an objective function based on the reduction of the energy purchasing costs, including also the set of constraints representing the physical operation of a DC grid, i.e. the \( \text{SOC} \) bounds of the batteries and the variation in the photovoltaic and wind generation systems, the power demand and the energy purchasing cost. To forecast the PV and wind generation, this work adopts an artificial neural network using the parameters reported in [45].

In order to demonstrate the effectiveness of the proposed method, three different metaheuristic optimization methods, based on sequential programming, are used: the black hole optimization [96]; the continuous genetic algorithm with matrix structure [191], which has been used for solving the optimal power flow in DC grids; and the traditional Chu & Beasley genetic algorithm, which has been used for solving the optimal operation of BSS in AC grids [151]. In addition, the following two operative scenarios for the BSS are considered: first, the operation of the BSS between the maximum and minimum \( \text{SOC} \), hence without imposing a final state-of-charge; and second, the operation of the BSS must to have a defined final state-of-charge equal to the 50 % of the nominal capacity of each battery. To evaluate the energy purchasing costs of keeping energy stored into the batteries, the data of generation and power demand of a regular week in Colombia were used.
Section 5.2.2 presents the mathematical model used to represent the problem of scheduling the charge and discharge the BSS in DC grids under a distributed generation environment, which is formed by the objective function and the set of linear and nonlinear constraints. Then, Section 5.2.3 presents the master-slave strategy used to scheduling the charge and discharge the BSS. The test system, considerations and comparison methods are described in Section 5.2.4. Section 5.2.5 reports the simulation results, analysis and discussion.

5.2.2. Mathematical Formulation

This subsection presents the mathematical formulation of the optimal scheduling of BSS for a day-ahead operation in DC grids under a distributed generation environment. The model considers, as objective function, the reduction of the total energy purchasing costs associated to the conventional generators (the grid or generators based on fossil fuels), and it takes into account the set of constraints associated to the operation of the BSS, distributed generators and the DC grid [45]. The mathematical formulation follows the traditional form used in literature to describe the problem of optimal BSS operation in electrical systems, which presents the equations for both the objective function and the set of constraints of the problem [192, 151, 193].

5.2.2.1. Objective function

\[
\min \ E_{\text{cost}_c} = \min \ \left( \sum_{h \in \Omega_H} \sum_{i \in \Omega_{cg}} \text{costs}_{i,h}^c \ P_{i,h}^c \Delta t \right), \quad \{ \forall i \in \Omega_{cg} \text{ & } \forall h \in \Omega_H \} \tag{5-8}
\]

Equation (5-8) presents the objective function used in this chapter, which aims at reducing the total energy purchasing costs, for the next day of operation, associated to the conventional generators (\(E_{\text{cost}_c}\)). In this equation, \(\Omega_H\) and \(\Omega_{cg}\) represent the sets that contain the time horizon of operation (24 hours in this case) and the buses with conventional generators installed, respectively. \(\text{costs}_{i,h}^c\) and \(P_{i,h}^c\) represent the energy purchasing costs and the power generated by conventional generators (\(cg\)) located at bus \(i\) in the operation period \(h\). Finally, \(\Delta t\) is the length of the period under analysis, which is equal to 1 hour for this work.

In the particular case that the energy of the conventional generators is being produced using fossil fuel, the energy purchasing costs must be replace by the fuel and maintenance costs in each generator.
5.2 EMS 2: An energy management system for optimal operation of battery storage systems in DC distributed generation environments

5.2.2.2. Set of constraints

The set of constraints considered in this study are show from equation (5-9) to (5-22):

\[ P_{cg}^{i,h} + P_{dg}^{i,h} + P_{B}^{i,h} - P_{d}^{i,h} = \sum_{j \in \Omega_N} G_{i,j}v_{i,h}v_{j,h}, \quad \forall (i, j) \in \Omega_N \quad \forall h \in \Omega_H \]  

Equation (5-9) represents the power balance at each bus of the DC grid, where \( P_{cg}^{i,h} \) and \( P_{dg}^{i,h} \) are the power generated by the conventional and distributed generators based on renewable energy, both located at the bus \( i \) on the period \( h \), respectively; and \( P_{d}^{i,h} \) is the power consumed by the loads located at the bus \( i \) on the period \( h \). \( \Omega_N \) is the set that contains all the buses of the system, and \( P_{B}^{i,h} \) is the power supplied or stored in the period \( h \) by the BSS located at the bus \( i \). In this analysis the power supplied by the BSS is assumed to be positive, while the power stored is assumed to be negative. Finally, \( G_{i,j} \) is the admittance of the branch connecting the buses \( i \) and \( j \), while \( v_{i,h} \) and \( v_{j,h} \) are the voltages of the buses \( i \) and \( j \) at the period \( h \), respectively.

It is also necessary to include into the mathematical formulation the constraints of the distributed generators and the BSS, which are reported in Equations (5-10), (5-11) and (5-12). In those equations \( \Omega_{dg} \) and \( \Omega_{B} \) are the sets of buses with distributed generators and BSS installed, respectively. \( P_{cg}^{\min} \) and \( P_{cg}^{\max} \) represent the minimum and maximum generation power allowed for each conventional generator, while \( P_{dg}^{\min} \) and \( P_{dg}^{\max} \) are the power generation limits for each distributed generator.

\[ P_{cg}^{\min} \leq P_{cg}^{i,h} \leq P_{cg}^{\max}, \quad \forall i \in \Omega_{cg} \quad \forall h \in \Omega_H \]  
\[ P_{dg}^{\min} \leq P_{dg}^{i,h} \leq P_{dg}^{\max}, \quad \forall i \in \Omega_{dg} \quad \forall h \in \Omega_H \]  

In the particular case of the BSS, those devices have a range of operation defined by the maximum power of discharge \( P_{i}^{\text{disch max}} \) and charge \( P_{i}^{\text{charg max}} \) allowed, which are taken from the manufacturer datasheet; such a constraint is given in Equation (5-12). \( P_{i}^{\text{disch max}} \) and \( P_{i}^{\text{charg max}} \) are obtained using equations (5-13) and (5-14), which depend on the energy capability \( En_{B}^{i} \), and both the discharge \( td_{B}^{i} \) and charge \( tc_{B}^{i} \) times of the BSS installed at bus \( i \).

\[ P_{i}^{\text{charg max}} \leq P_{i}^{B} \leq P_{i}^{\text{disch max}}, \quad \forall i \in \Omega_{B} \quad \forall h \in \Omega_H \]  
\[ P_{i}^{\text{disch max}} = \frac{En_{B}^{i}}{td_{B}^{i}}, \quad \forall i \in \Omega_{B} \]  
\[ P_{i}^{\text{charg max}} = -\frac{En_{B}^{i}}{tc_{B}^{i}}, \quad \forall i \in \Omega_{B} \]
Equation (5-15) is introduced for calculating the impact on the SOC of the power $P_{i,h}^B$ supplied or stored in the period $h$ by the BSS located at the bus $i$. In such an equation $SOC_{i,h}^B$ represents the SOC of the BSS in the same bus and period, $SOC_{i,h-1}^B$ represents the SOC of the BSS at the previous period, and $\phi_i^B$ is the charge coefficient of the battery connected at the bus $i$, which is a function of the charge or discharge data of the BSS as it is reported in Equation (5-16). In addition, equations (5-17) and (5-18) define both the initial and final SOC desired for the battery, and Equation (5-19) defines the minimum and maximum bounds allowed for the SOC of the BSS located at the bus $i$.

\[
SOC_{i,h}^B = SOC_{i,h-1}^B - \phi_i^B P_{i,h}^B \Delta t, \quad \forall i \in \Omega_B \& \forall h \in \Omega_H \tag{5-15}
\]

\[
\phi_i^B = \begin{cases} 
\frac{1}{td_i^B P_{i}^{\text{dischmax}}} & \text{for } \forall i \in \Omega_B \& \forall h \in \Omega_H \\
\frac{1}{tc_i^B P_{i}^{\text{chargmax}}} & \text{else}
\end{cases} \tag{5-16}
\]

\[
SOC_{i,h=1} = SOC_i^0, \quad \forall i \in \Omega_B 
\]

\[
SOC_{i,h=24} = SOC_i^f, \quad \forall i \in \Omega_B 
\]

\[
SOC_{i}^{\text{min}} \leq SOC_{i,h}^B \leq SOC_{i}^{\text{max}}, \quad \forall i \in \Omega_B \& \forall h \in \Omega_H \tag{5-19}
\]

The maximum slew-rate of the SOC are calculated from $P_{i}^{\text{chargmax}}$ and $P_{i}^{\text{dischmax}}$ using equations (5-20) and (5-21) for both charge ($\Delta SOC_{i}^{\text{chargmax}}$) and discharge ($\Delta SOC_{i}^{\text{dischmax}}$) conditions, respectively.

\[
\Delta SOC_{i}^{\text{chargmax}} = \phi_i^B P_{i}^{\text{chargmax}} \Delta t, \quad \forall i \in \Omega_B \tag{5-20}
\]

\[
\Delta SOC_{i}^{\text{dischmax}} = \phi_i^B P_{i}^{\text{dischmax}} \Delta t, \quad \forall i \in \Omega_B \tag{5-21}
\]

Finally, Equation (5-22) defines the voltage profile limits, where $v_{i,h}$ is the voltage profile in the bus $i$ on the period $h$. $V^\text{min}$ and $V^\text{max}$ correspond to the maximum and minimum voltage allowed on the electrical network, respectively.

\[
V^\text{min} \leq v_{i,h} \leq V^\text{max}, \quad \forall i \in \Omega_N \& \forall h \in \Omega_H \tag{5-22}
\]

The mathematical model described from (5-8) to (5-22) is a nonlinear and non-convex optimization model due to the non-affine characteristics of the power balance constraints defined by (5-9), which introduce a hyperbolic relation between voltage and power in all buses \[190\]. Therefore, it is required to use convexification techniques or sequential quadratic programming models to deal with this problem. This section adopts the second option to avoid the use of software with undesired requirements, which is the case of the first option.
5.2.3. Proposed methodology

The problem of optimal scheduling of BSS dispatch for the day-ahead, considering a distributed generation environment, can be divided into two sub-problems [151, 45]: the first problem is to find the optimal level of power to be stored or provided by the BSS in each operation period, with the aim of minimizing the objective function; the second problem is to evaluate the objective function for each power configuration of the BSS obtained by solving the first problem. Solving the second problem requires the hourly power flow to identify the impact of the different DERs and loads located into the DC grid.

For solving those problems, this section proposes an energy management system designed with a master-slave methodology, which uses a Parallel PSO (PPSO) algorithm and an hourly power flow method based on successive approximations described in Chapter 2. Those components are described below.

5.2.3.1. Master stage: Optimal scheduling of the BSS operation

This stage is implemented using a parallel implementation of the particle swarm optimization (PPSO) method, which is aimed at finding the best solution with the shortest processing time. This solution is based on the traditional PSO technique [104] and parallel processing tools developed with multi-core structures [14, 13]. The PSO algorithm was selected due to the satisfactory results provided in the operation of distributed energy resources for both AC and DC grids reported in [87, 13, 16] and in the previous chapters.

The proposed PPSO algorithm starts reading the data of the electric system (buses, branch data, operative bounds, etc.) and the initial conditions of the optimization method: number of particles, the inertia and velocity limits, the cognitive and social components values, and the stop-criteria. In this particular implementation the stop-criteria are the maximum number of iterations and the number of iterations in which the solution is not improved. Then, using those parameters, the particles swarm (PS) is generated in a random way, where each particle contains the power to be provided or stored by the batteries located into the DC grid for the periods considered under the analysis. Fig. 5-20 summarizes the PPSO algorithm.

The codification of the particles adopted in this master stage uses a vector with length $|\Omega_B| \times |\Omega_H|$, which contains the power absorbed or provided by each battery during the different periods considered into the analysis. Those power values must be within the safe ranges of operation for both charge and discharge, moreover the minimum and maximum SOC of the batteries must be always fulfilled. Fig. 5-21 presents an example of a grid with four buses and three generators: the main grid is connected to the bus 0, a wind generator is located at bus 2 and a PV generator is located at bus 3. In this figure the blue arrows represent the power injection to the microgrid; in this section it is considered that the main
The microgrid can inject the power needed for the system balance, while the DGs inject the maximum power generated in each hour. The red arrows represent a power demand to the microgrid, which is observed in bus 4, where a load is located. Furthermore, the example considers three batteries located at buses 1, 3 and 4, respectively; which are identified in the figure as battery
1, 2 and \( k \), the last one used for generality purposes. Since the batteries have the capability to supply and demand (store) power, those have both red and blue arrows. The connection of all the active elements to the DC microgrid require power electronic converters, and their conversion topology depends on the type of energy resource. For example, the connection of the photovoltaic array presented in Fig. 5-21 can be performed using a buck-boost or a Ćuk converter, since those topologies support input-output voltage differences lower, equal or higher than one [194]. Similarly, the batteries can be connected using buck-boost topologies but adopting bidirectional structures [195]. In the case of wind turbines, the connection is performed using voltage source converters, which are commonly used to interface synchronous machines, and those converters enable to provide a dc output [196]. A similar topology, based on a voltage source converter, is used to interface the grid. Finally, those power converters are regulated by primary control strategies.

Taking into account that the aim of this section is to find the optimal power that the batteries must supply or store in each hour, such an information is codified as it is presented in Fig. 5-22; each battery has 24 values, one for each hour; hence, the vector has \( 24 \cdot k \) elements for \( k \) batteries. In the example of Fig. 5-22, battery 1 is discharged during periods 1 (0.8 pu) and 3 (0.2 pu), and it is charged during the periods 2 (-1.1 pu) and 24 (-0.5 pu). Similarly, the \( k \)-th battery is charged during the periods 1 (-0.7 pu), 2 (-0.1 pu), and 3 (-1 pu), while such a battery is discharged during the period 24 (1 p.u).

**Figure 5-21.** Example proposed for the codification used for the particles representing the BSS operation.
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Figure 5-22.: Codification used for the particles representing the BSS operation.

The next step of the PPSO iterative process (depicted in Fig. 5-20) evaluates the objective function for each particle of the PSO using the slave stage. This work adopts a multi-worker parallel system [13] to evaluate several particles at the same time. Therefore, the number of iterations $NI$ needed to evaluate the swarm is given by Equation (5-23), in which $W$ is the number of workers (cores, processors, etc.) available and $N$ is the number of particles of the swarm. This parallel-processing step is finished when all the particles of the swarm are evaluated.

$$NI = \frac{N}{W}$$ (5-23)

The best solution and position for each particle are selected with the lowest value for the objective functions, which provides the best local solution. Then, the best swarm solution and position are obtained, which corresponds to the global solution. In the case that some of the stopping criteria is reached, then the iterative process stops; otherwise the velocity vector is calculated to update the positions of the particles forming the swarm, which are used for a new iteration of the algorithm.

5.2.3.2. Slave stage: hourly power flow calculation based on successive approximations

For calculating the value of the objective function of each particle generated by the master stage, it is necessary to evaluate the hourly power flow, which enables to quantify the energy purchasing cost and to verify that all constraints are fulfilled. Such an hourly power flow must to consider the variation in both the generation and power demand during the period under evaluation. This section uses an adaptation of the iterative power flow calculation method presented in Chapter 2, which uses successive approximations for calculating all the voltage at the load terminals by solving Equation (5-24).

$$v_{d,h}^{t+1} = -G_{dd}^{-1}\text{diag}^{-1}(v_{d,h}^t)p_{d,h} - G_{dd}^{-1}G_{dg}v_{g,h}^t$$ (5-24)
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In such an equation \( v_{g,h} \) and \( v_{d,h} \) correspond to vectors that contain all the voltages in the generation and load buses on the period \( h \), and \( t \) represents the index of the current iteration. \( P_{d,h} \) denotes the power of the loads and DERs (DGs and BSS) connected to the different buses on the period \( h \). Finally, \( G_{dd} \) are the components of the conductance matrix corresponding to the load interconnections, while \( G_{dg} \) are the components relating the generators and loads. Moreover, \( \text{diag() \ } \) is the diagonal operator that enables converting the voltages vector \( v_{d,h}^t \) into a diagonal square matrix. After calculating the voltage profiles of the electrical system, the other variables of the electrical grid can be calculated: the currents on branches, power loss, energy purchasing cost, among others.

The power flow calculation method presented in Chapter 2 was modified to include the variations of the power demanded by the loads, the variation in the generation of the DGs, and the bi-directional power flow of the BSS. Such a modification leads to a multi-period power flow method, which considers the hourly variation in both power generation and demand. In addition, it is proposed a fitness function to penalize the violation of the problem constraint as it is described in Equation (5-25): \( FF \) stores the fitness function value, which corresponds to the algebraic sum of the daily operating costs and the penalties associated to the power generated by the conventional and distributed generators, and voltage deviations from the limits; where \( \beta_1 \) to \( \beta_6 \) are a positive real numbers related to those penalties. This section adopted a value for each penalization factor equal to 1000, based on an heuristic search [191] and the results of previous chapters. Finally, when all constraints related to power generators and voltage profiles are fulfilled, the fitness function value corresponds to the objective function value, i.e. \( FF = E_{cost_{cg}} \).

\[
FF = \min \begin{pmatrix}
E_{cost_{cg}} + \beta_1 \max \left\{ 0, \sum_{h \in \Omega_H} \sum_{i \in \Omega_c} \left( p_{i,h}^{cg} - P_{c}^{max} \right) \right\} \\
+\beta_3 \min \left\{ 0, \sum_{h \in \Omega_H} \sum_{i \in \Omega_c} \left( p_{i,h}^{cg} - P_{c}^{min} \right) \right\} \\
+\beta_3 \max \left\{ 0, \sum_{h \in \Omega_H} \sum_{i \in \Omega_dg} \left( p_{i,h}^{dg} - P_{d}^{max} \right) \right\} \\
+\beta_4 \min \left\{ 0, \sum_{h \in \Omega_H} \sum_{i \in \Omega_dg} \left( p_{i,h}^{dg} - P_{d}^{min} \right) \right\} \\
+\beta_5 \max \left\{ 0, \sum_{h \in \Omega_H} \sum_{i \in \Omega_N} \left( v_{i,h} - V_{i}^{max} \right) \right\} \\
+\beta_6 \min \left\{ 0, \sum_{h \in \Omega_H} \sum_{i \in \Omega_N} \left( v_{i,h} - V_{i}^{min} \right) \right\} 
\end{pmatrix}
\] (5-25)
Algorithm 9 Slave stage algorithm

Data: Read data and assign the SA parameters

for $h = 1 : 24$ do
  Load the power demanded by the loads during the period $h$
  Load the power generated by the DGs during the period $h$
  Load the power provided/stored by the BSS during the period $h$
  Solve the DC power flow for the period $h$ using Equation (5-24)
  Calculate objective function for the period $h$
  Evaluate the constraints for the period $h$
  Calculate the fitness function for the period $h$
end

Adding the fitness function values of all periods

The constraints associated to the power and SOC of the batteries installed in the DC grid do not were included inside the $FF$, since those were satisfied inside the construction of the vector that represents each possible solution for the master stage, by using the codification proposed in Figure 5-22. The previous fitness function (5-25) accounts for those restrictions into the $Ecost_{cg}$ component.

Algorithm 9 describes the iterative process used to execute the proposed multi-period power flow method. The algorithm starts by reading the parameters for the successive approximations (SA): number of iterations, convergence error and initial voltages. Then, the power demanded by the loads, the power generated by the DGs and the power provided/stored by the BSS are loaded into the algorithm; such an information is used to calculate the DC power flow using the SA algorithm. Then, the objective function, the constraints and the fitness function are calculated in each period. Finally, when all periods have been evaluated, the fitness functions of each period are added to obtain the total energy purchasing costs and the penalties associated to the violation of the constraints for each possible solution.

5.2.4. Test system

The performance evaluation of the proposed solution is carry out using a modified version of the system of 21 buses presented in Chapter 2. This version was modified by changing the generation buses with constant power loads, but keeping the same power level assigned in the traditional test system for the generation. It was also added a photovoltaic generator located at bus 21 with a maximum power of 140.79 kW, and a wind generator located at bus 12 with a maximum power of 105.76 kW. In addition, three batteries are located in buses 7, 10 and 15. The line diagram of the test system is shown in Figure 5-23. The modified version exhibits a total power demand of 5.54 p.u. The base values of both voltage and power of this test system are 1 kV and 100 kW, respectively. Finally, the minimum and maximum safe
5.2 EMS 2: An energy management system for optimal operation of battery storage systems in DC distributed generation environments

Table 5-2.: BESS location and parameters

<table>
<thead>
<tr>
<th>Location</th>
<th>( E_{Bi} ) [pu]</th>
<th>( tc_{Bi} ) [h]</th>
<th>( td_{Bi} ) [h]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus 7</td>
<td>5</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Bus 10</td>
<td>4</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Bus 15</td>
<td>4</td>
<td>5</td>
<td>4</td>
</tr>
</tbody>
</table>

limits for the bus voltages are defined as 0.9 and 1.1 p.u, i.e. ±10 % around the nominal voltage (1 p.u).

Figure 5-23.: Line diagram 21 bus test system (taken from [45])

5.2.4.1. BSS parameters

The test system considers two types of BSS, which location and parameters are shown in Table 5-2. The rest of the BSS parameters are calculated using the mathematical formulation presented in Section 4.2. In addition, three scenarios are considered for validating the proposed master-slave solution:

- **Scenario 1 (S1):** This scenario does not consider the integration of the BSS into the DC grid, hence this is designated as a base scenario for comparison.

- **Scenario 2 (S2):** This scenario considers the integration of the BSS, with a SOC variation from 10 % to 90 % during the operation day. Moreover, this scenario does not impose any restriction for the final SOC value.

- **Scenario 3 (S3):** This scenario considers the integration of the BSS, with a SOC variation from 10 % to 90 % during the operation day. However, this scenario imposes a final SOC value equal to 50 %.
Scenario $S_2$ enables the EMS to take advantage of the total energy stored into the BSS during the operation day. Instead, scenario $S_3$ forces the BSS to finalize the day with a defined SOC to attend unexpected energy demands at the beginning of the next day.

### 5.2.4.2. Input data for the proposed EMS

The input data used in the optimization are: energy purchasing cost, power produced by both the PV and wind generators, and the power demand. This section considers the typical load demand of tropical countries, like Colombia, used for day-ahead economic dispatch problems. Such a consideration includes a base energy cost of 0.208 $/kWh, which was taken from a Colombian energy distribution company. In addition, the analysis considers periods of 1 hour with a time-horizon of 24 hours. Those data were taken from [45], and they are reported in both Fig. 5-24 and Table 5-3.

![Figure 5-24: Input data for EMS proposed.](image)

The stochastic behavior of the power production of PV and wind generators is simulated by using an artificial neuronal network (ANN) for forecasting the next day power generation of those devices. The ANN was trained with the 70% of the data, and the remaining data was used to evaluate the ANN performance, obtaining an error of 3%. The ANN has 2 inputs (time, temperature), 6 delay and 18 hidden neurons for simulating the PV generation; the ANN also has 4 inputs (time, temperature, humidity, pressure), 4 delay and 18 hidden neurons for simulating the wind generation. The input and output data, and the previous parameters, were taken from [45, 197, 198], which correspond to the generation conditions of tropical countries like Colombia.
5.2 EMS 2: An energy management system for optimal operation of battery storage systems in DC distributed generation environments

### Table 5-3: Energy purchasing cost and hourly demand.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.80</td>
<td>0.47</td>
<td>13</td>
<td>0.95</td>
<td>1.45</td>
</tr>
<tr>
<td>2</td>
<td>0.74</td>
<td>0.34</td>
<td>14</td>
<td>0.94</td>
<td>1.32</td>
</tr>
<tr>
<td>3</td>
<td>0.73</td>
<td>0.32</td>
<td>15</td>
<td>0.95</td>
<td>1.34</td>
</tr>
<tr>
<td>4</td>
<td>0.74</td>
<td>0.25</td>
<td>16</td>
<td>0.95</td>
<td>1.36</td>
</tr>
<tr>
<td>5</td>
<td>0.78</td>
<td>0.27</td>
<td>17</td>
<td>0.99</td>
<td>1.36</td>
</tr>
<tr>
<td>6</td>
<td>0.86</td>
<td>0.36</td>
<td>18</td>
<td>1.00</td>
<td>1.36</td>
</tr>
<tr>
<td>7</td>
<td>0.93</td>
<td>0.47</td>
<td>19</td>
<td>0.97</td>
<td>1.30</td>
</tr>
<tr>
<td>8</td>
<td>0.95</td>
<td>0.68</td>
<td>20</td>
<td>0.95</td>
<td>1.47</td>
</tr>
<tr>
<td>9</td>
<td>0.94</td>
<td>0.98</td>
<td>21</td>
<td>0.91</td>
<td>1.47</td>
</tr>
<tr>
<td>10</td>
<td>0.96</td>
<td>1.15</td>
<td>22</td>
<td>0.86</td>
<td>1.32</td>
</tr>
<tr>
<td>11</td>
<td>0.96</td>
<td>1.30</td>
<td>23</td>
<td>0.87</td>
<td>1.09</td>
</tr>
<tr>
<td>12</td>
<td>0.96</td>
<td>1.38</td>
<td>24</td>
<td>0.71</td>
<td>0.83</td>
</tr>
</tbody>
</table>

#### 5.2.4.3. Comparison methods

Three published solution methods, based on sequential programming, were used to evaluate the performance of the proposed approach. The first and second methods correspond to the black hole optimizer and the continuous genetic algorithm proposed for the optimal power dispatch of DGs in DC power grids presented in Chapter 3. The third method is the traditional the Chu & Beasley genetic algorithm, which was used in [151] for providing an optimal operation of BSS in AC networks. In that method the BSS can supply or store the maximum charging or discharging power limit, hence continuous power values are not allowed.

The parameters of those comparison methods were optimized using an additional PSO algorithm with the following parameters: 30 particles, a cognitive and social component value equal to 1.4, a minimum and maximum inertia range from 0.1 to 0.7, a maximum number of iterations equal to 300 and a number of iterations without improvement equal to 50. The parameters of the methods were optimized by considering as objective function the minimization of the purchasing cost. Moreover, the maximum number of individuals (or particles) for both the proposed and comparison methods was set to 100, the maximum number of iterations was set to 1000 and the maximum number of iterations without improvement was set to 1000. The proposed PSO solution includes two additional parameters: maximum inertia (range from 0 to 1) and the cognitive and social components (range from 0 to 2). Furthermore, the maximum number of iterations of the GA was set to 2000 because this algorithm does not use a population inside its iterative process, hence it requires a bigger solution space in comparison with the other methods. The parameters of the proposed PSO and comparison methods, obtained with this process, are reported in Table 5-4.
Table 5-4.: Parameters of the different optimization methods used

<table>
<thead>
<tr>
<th>Method</th>
<th>PSO</th>
<th>BH</th>
<th>CGA</th>
<th>GA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of individuals</td>
<td>95</td>
<td>92</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Selection method</td>
<td>Cognitive component:</td>
<td>2</td>
<td>Event horizon radius</td>
<td>Tournament</td>
</tr>
<tr>
<td></td>
<td>Social component:</td>
<td>0.63</td>
<td></td>
<td>Tournament</td>
</tr>
<tr>
<td>Update Population method</td>
<td>Speed (max-min):</td>
<td>(0.1-0.1)</td>
<td>Cognitive and social component</td>
<td>Cross over: promedio</td>
</tr>
<tr>
<td></td>
<td>Inertia (max-min):</td>
<td>(0.63-0.001)</td>
<td></td>
<td>Cross over: simple</td>
</tr>
<tr>
<td>Mutation</td>
<td>R1=R2</td>
<td>Random population</td>
<td>Random population</td>
<td>Binary simple</td>
</tr>
<tr>
<td>Stopping criterion</td>
<td>Maximum iterations:</td>
<td>(1000)</td>
<td>Maximum iterations:</td>
<td>(795)</td>
</tr>
<tr>
<td></td>
<td>Iterations without improvement:</td>
<td>(88)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(961)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1500)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.2.5. Simulation results

The simulations results of this section were carried out on a Dell Precision T7600 Workstation with 32 GB of RAM memory and an Intel(R) Xeon(R) CPU ES-2670 running at 2.50 GHz, which provides 12 parallel processing cores. MATLAB software was selected to implement the energy management systems based on the multiple optimization methods. Such a selection was based on the language simplicity, the powerful matrix manipulation capabilities, and the automatic management of the parallel workers (including data distribution and output recollection for each worker memory). Such a characteristic enables a simple implementation of the proposed parallel PSO algorithm. Finally, the evaluation of the proposed PPSO solution is performed in two simulation cases described below.

5.2.5.1. Simulation case 1

This simulation case considers both $S_1$ and $S_2$ scenarios to evaluate the performance of the different solution methods. In order to provide a fair comparison, all the methods used the SA algorithm to calculate the hourly power flow. In addition, the renewable generators are considered operating at the maximum capacity available depending on the irradiance
5.2 EMS 2: An energy management system for optimal operation of battery storage systems in DC distributed generation environments

and wind hourly-profiles. Both BH and CGA methods were parallelized to provide a fair comparison with the proposed PPSO solution; instead, the GA was not parallelized since the evolution of an individual requires the information of the previous state, hence no parallel implementation is possible [151]. Finally, 1000 consecutive executions were carried out to determine the average performance of each method.

Table 5-5.: Performance of the solution methods in the simulation case 1

<table>
<thead>
<tr>
<th>Method</th>
<th>Total energy purchasing costs</th>
<th>(t_{avg}) [s]</th>
<th>(pt_{avg}) [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(min) [$]</td>
<td>(max) [$]</td>
<td>(\mu) [$]</td>
</tr>
<tr>
<td>Scenario 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base case</td>
<td>2064.19</td>
<td>- -</td>
<td>- -</td>
</tr>
<tr>
<td>Scenario 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PPSO</td>
<td>2003.25</td>
<td>2021.56</td>
<td>2008.33</td>
</tr>
<tr>
<td>BH</td>
<td>2025.38</td>
<td>2045.03</td>
<td>2038.80</td>
</tr>
<tr>
<td>CGA</td>
<td>2036.94</td>
<td>2048.37</td>
<td>2043.82</td>
</tr>
<tr>
<td>CA</td>
<td>2038.62</td>
<td>2063.19</td>
<td>2060.67</td>
</tr>
</tbody>
</table>

Table 5-5 reports the simulation results for this case, presenting from left to right: the method; the minimum \((min)\), maximum \((max)\) and mean \((\mu)\) energy purchasing costs in dollars \([\$]\); the standard deviation \((\sigma)\); the average time for the sequential \((t_{avg})\) and parallel processes \((pt_{avg})\).

Figure 5-25.: Reduction of energy purchasing costs obtained by the different optimization methods with respect to the base case

Fig. 5-25 summarizes the reduction of the energy purchasing costs obtained with the different solution methods. The figure shows that the proposed PPSO solution provides the best results: the minimum, maximum and mean reduction, with respect to the base case \((S_1)\),
5 Energy management in DC microgrids for improving the operation conditions and cost optimization

Figure 5-26: Averaged processing time required by the different optimization methods using both sequential and parallel implementations

are equal to 2.95%, 2.06% and 2.7%, respectively. Similarly, the PPSO solution provides an improvement of 1.24%, 1.56% and 2.09% with respect to BH, CGA and GA, respectively. Moreover, the standard deviation of the solutions given in Table 5-5 shows that all the methods exhibit high consistency and repetitibility in the results.

Fig. 5-26 reports the average processing times required by the solution methods. Concerning the sequential implementation, the fastest result was achieved by the GA, however, this method provides the worst reduction of the energy purchasing cost. Therefore, the performance vs speed relation of the GA option is unsatisfactory. The proposed PSO provides the second shorter processing time: it provides an average reduction of the processing time equal to 87.65% and 55.31% when it is compared with the BH and CGA in sequential implementations, respectively. Concerning parallel implementations, the PPSO provides a processing time 74.89% shorter than the BH and 45.98% shorter than the CGA. Moreover, those parallel implementations are faster than the sequential ones, as it is expected: the PPSO is 58.32% than a classical PSO, the parallel BH is 15.23% faster than the sequential BH, and the parallel CGA is 46.61% faster than the classical CGA. Those results put into evidence the positive compromise between speed and cost reduction provided by the proposed PPSO, and at the same time, the effectiveness of the parallel implementations are also demonstrated.

Fig. 5-27 presents the SOC of the BSS generated by the four optimization methods during a day for scenario S2, which considers the power profiles and energy cost previously reported in Fig. 5-24. Fig. 5-27(a) depicts the SOC produced by the PPSO, where all batteries were charged from period 1 to 5 respecting the $\Delta SOC_i^{charg_{max}}$. This occurs because both the power demanded by the loads and energy cost during those periods are low. From period 6 to 10 the PPSO keeps the batteries unused, thus saving the energy for periods with low renewable generation and high power demanded. Then, from period 11 to 13 the batteries
provide a small part of the load since the distributed generators produce a high amount of energy. After period 15 the power generated by the renewable sources decrease, hence the EMS uses all the available energy in the BSS to supply the power requested by the load. Finally, from period 18 to 20 the BSS reach the minimum SOC allowed, therefore, in the rest of the periods the power consumed by the loads is purchased to the main grid.

Fig. 5-27(b) presents the operation of the BSS imposed by the BH, where it is observed that the BH solution forces the BSS discharge in periods of low power demand, high renewable generation, and low energy cost; at the same time, the BH also enables battery charge in periods of high power demand and high energy costs, which produce a negative impact on the objective function. The operation imposed by the CGA is reported in Fig. 5-27(c), which shows that CGA does not use the complete capacity of the BSS; moreover, the charge and discharge operations of the BSS are not in agreement with the renewable generation and load demand (e.g. BSS charge when demand is low and production is high, and BSS discharge when demand is high and production is low). The previous analysis leads to conclude that CGA is trapped in a local optimum. Figure 5-27(d) reports the BSS SOC imposed by the GA, which shows that the hard discretization of this method make it get trapped in a local optimum. Finally, all the solution methods satisfy the voltage bounds established in the scenario.

5.2.5.2. Simulation case 2:

This simulation case is intended to identify the final condition of the SOC, between $S_2$ and $S_3$, which provides the strongest reduction of the energy purchasing costs for the operation of the next day. Such an analysis is performed by considering a week of operation, the input data of the analysis are described below.

Fig. 5-28 presents the power provided by both PV and wind generators in this simulation for the different days of the week. Those profiles were generated by using the ANN described in the previous section, and considering the weather conditions for a regular week of tropical countries like Colombia [45]. Moreover, the data of the power demand of a week in an electrical distribution company of Colombia is reported in Fig. 5-29 which considers four types of curves for a week: regular day (Monday, Tuesday, Thursday and Friday), Wednesday, Saturday and Sunday. Those curves were selected since they are the most representative ones in Colombia to describe the power demand. Finally, the EMS also takes into account the energy purchasing costs given in Fig. 5-24.

Fig. 5-30(a) presents the SOC of the BSS in a week of operation using $S_2$. In such a case the batteries always start and finalized the days at the minimum SOC, they presenting a similar behavior in the different days of operation in comparison with the profile generated by the
PPSO in the simulation case 1: charging the BSS in the first periods, keeping the power stored during the periods of high renewable generation, and discharging the BSS in the periods with maximum power demanded and low renewable generation. Moreover, the SOC limits
5.2 EMS 2: An energy management system for optimal operation of battery storage systems in DC distributed generation environments

are always fulfilled; and the total energy costs of such an operation is 10,461.36$ for the week.

Fig. 5-30(b) presents the SOC of the BSS in a week of operation using $S_3$. In this case the BSS always starts and finalizes the days at SOC = 50%, therefore the batteries are charged in a shorter time at the start of every day. Then, the batteries are discharged during periods with the low renewable generation, low energy demand and high purchasing costs, reaching the minimum SOC allowed. However, since the batteries must to finalize the days with SOC = 50%, the BSS are charged during the last periods of the day, when the power demand and the energy cost have been decreased. Finally, during the week of operation simulated with $S_3$, the total energy purchasing cost was equal to 10,428.00$, which is a reduction of 0.31% on energy costs when it is compared with the scenario $S_2$ (i.e. without any limitation in the final SOC value).

The previously results show that using the conditions of $S_3$ reduced the energy costs when it is compared with the conditions of $S_2$: starting and finishing each day at an SOC equal to 50%; moreover, $S_3$ ensures that the BSS have stored energy to mitigate unexpected increments of the power demand. Therefore, it is recommended to use the proposed master-
Energy management in DC microgrids for improving the operation conditions and cost optimization

![Power demand graph](image1)

**Figure 5-29:** Behavior of hourly power demand.

![SOC graphs](image2)

**Figure 5-30:** SOC of the BSS for scenarios $S_1$ and $S_2$ during a week of operation.

slave methodology with the conditions of $S_3$, which enables to achieve the optimal operation of the BSS for day-ahead dispatch in DC electrical networks.

### 5.3. Conclusions

In this chapter two EMS for the optimal operation of stand-alone and grid connected microgrids were proposed.
The first energy management strategy (Section 5.1) was designed for a stand-alone DC microgrid formed by a PVS, a battery, a non-critical DC load, and a capacitor as a backup storage element. Such EMS manages the connection and disconnection of the battery and the load, as well as the generation of the photovoltaic system and the ESD charge/discharge process, in order to guarantee the power balance and the operation of the system within allowable technical limits, thus increasing the lifetime of the devices that form the MG.

The validation of the proposed EMS demonstrated that, by implementing a backup energy storage element (in this case a capacitor) and PVS generation control, load disconnections and inappropriate use of the main storage device can be reduced. Furthermore, using the auxiliary capacitor, the charge and discharge sub-cycles produced by the PDT control strategy can be eliminated. Those advantages enable to extend the battery lifetime and reduce the costs associated with the maintenance and disconnection of the microgrid.

In addition, the installation of SPVSs with the proposed EMS allow to reduce the energy purchasing from the utility grid, decreases the dependency of fossil fuels to reduce the environmental impact, and also reduces the operational complexity of the solution in comparison with systems based on other renewable resources, e.g., wind generation, small scale hydro-electric, among others.

The main limitation of the first EMS proposed in this chapter, is the total load disconnection; hence as future work, the fragmentation of the load or the integration of multiple critical and non-critical loads into the microgrid will be considered. Those considerations allow the implementation of more complex load shedding strategies, multiple generation and storage systems integration to improve the energy storage capacity of the MGs. Moreover, microgrids could be connected to the electrical grid where possible, thus enabling a cheaper energy dispatch that enhances the financial impact of the microgrid and improves the quality of the service provided to final users.

A second EMS (Section 5.2) was proposed based on a master-slave methodology, which is formed by a parallel implementation of the PSO algorithm and an hourly power flow method based on successive approximations. Such an EMS was designed for obtaining the optimal operation scheduling of the BSS in DC grids under a distributed generation environment. To test the performance of the proposed solution, an artificial neural network was used to forecast the hourly power generation of the renewable generators, while the variation in power demand and energy purchasing costs were taken from the Colombian power system.

The results obtained in two simulation scenarios demonstrate that the proposed PPSO/SA
methodology achieved the best results in terms of quality solution: an average reduction in the total energy purchasing costs of 1.63% with respect to the comparison methods (BH, CGA and GA). In terms of processing time, the fastest method was the GA, but the poor performance of the solution in comparison with the other methods makes it unusable. The second faster method, with sequential implementation, was the proposed solution based on PSO, which achieved an average reduction in the processing times of 71.48% with respect to the BH and CGA. Similarly, when the PSO, BH and CGA methods were parallelized, their processing times were strongly reduced, those obtaining and average reduction of the processing time equal to 40.05%. However, the proposed PPSO method exhibited the lower processing times, it providing a reduction of 55.89% and 55.89% when it is compared with the parallel versions of the BH and the CGA, respectively. Therefore, the proposed PPSO/SA method provides the best trade-off between quality solution and processing time.

In addition, the results demonstrated that forcing a final SOC equal to 50% for each day reduces the energy purchasing cost for a week of operation under the Colombian conditions, this compared with the case when any SOC restriction is adopted.

Finally, the extension of the proposed EMS for location and operation of distributed energy resources in DC grids, considering the reduction of the initial investment and operation costs as objective function, could be a future improvement to this solution.
6. Conclusions and Future Works

In this doctoral thesis were identified the main problems related to the planning and management of DC MGs, which have been addressed by proposing multiple solutions. Those new solution have as main objective the reduction of the operational cost and the improvement of different operation conditions of the DC MGs.

The second chapter addresses the power flow problem in DG grids to calculate the voltage profiles in all the buses of the network under steady-state conditions; such information is required to evaluate the technical and economical indicators, as well as the set of constraints that represents the DC grids. That problem is typically modeled by using a set of nonlinear, non-convex, algebraic expressions that allow determining the steady-state behavior of the electrical circuits under the presence of constant and resistive power loads. Those equations are obtained by applying the Kirchoff’s laws and the Tellegen’s theorem; which requires to adopts high level solution methods. For the particular case of the DC grids, classical methods have been proposed to solve the power flow problem, such as Gauss-Seidel, Gauss-Jacobi and the Newton-Raphson method; as well as new methodologies based on semidefinite programming and second-order cone programming. The main problems of the previous solution methods are the use of specialized software, which increase the cost and the complexity of the solution.

Analyzing the previous problems, it was found that it is necessary to develop efficient methods for solving the power flow problem in DC grids; which allow to guarantee the solution quality and to reduce the processing times, this in comparison with classical solution methods reported in literature. In addition, the proposed methodologies must to avoid the use of specialized software. In this way, in Chapter 2 were proposed five solution methodologies for solving the power flow problem in DC networks by considering both mesh and radial topologies. For the particular case of the radial topology, three methods based on triangular matrix formulation, graph theory and a Backward-Forward sweep process were proposed. Furthermore, two iterative approaches for solving the power flow problem in DC grids with mesh or radial grids were also developed, which are based on a Taylor series expansion method and successive approximations. For comparison purposes, this chapter considers three classical techniques: Gauss-Seidel, Gauss-Jacobi and Newton-Raphson method. The techniques were tested in four radial systems with 10, 21, 33 an 69 buses; and on two mesh test systems, which are modified versions of the 10 and 69 bus systems.
The performances of the methods were evaluated in terms of solution quality (voltage error and the power loss) and average processing time, by selecting the NR as base case for the comparison of the results because in literature it was demonstrated that such a method converges in DC grids with any structure. The results show that the average voltage and power loss errors are negligible due to the lower values achieved. For this reason, this thesis concludes that in terms of the solution quality all the proposed methods are adequate for solving the DC PF problem in grids with mesh and radial structures.

Therefore, the selection of the methods with the best performance was based on the average processing time. The simulation results demonstrated the robustness and effectiveness of the proposed methods in comparison with the other solutions reported in literature. In the particular case of the grids with radial topology, the Back-Forward sweep method provided the best results for any size of radial grid, it improving its performance as the size of the DC network increases. The method based on Successive Approximations was in second place for grids with radial structure. For the test systems with mesh structure, the simulations results demonstrated that the SA is the power flow method with the best performance. Based on the satisfactory performance of the SA for solving the power flow problem in DC grids with mesh or radial structure, this doctoral thesis adopted this solution method for solving the power flows in the planing and management strategies proposed for DC grids. The aforementioned allowed satisfied the main objective of the Chapter 2, which was to obtain an efficient method in terms of quality solution and processing times for solving the power flow problem; since this directly affects the performances of the optimal power flow methods used inside the planning strategies of DC grids. Finally, the solution of the power flow problem in DC grids can be improved by considering faster mathematical methods for matrix inversions. Furthermore, parallel processing tools can be used inside the iterative process to reduce the processing times.

The third chapter proposed three master–slave methodologies for solving the problem of optimal power flow in DC MGs, which is needed for sizing the DGs of the electrical system. In the proposed methodologies, the master stage was in charge of sizing the generators by using three different continuous methods: the black hole optimization method, a continuous version of the genetic algorithm and the particle swarm optimization algorithm. The slave stage was based on the successive approximation power flow method proposed in Chapter 2, which is used to solve the power flow problem. By combining the different continuous methods used in the master stage with the slave stage were obtained three hybrid solution methodologies: BH/SA, CGA/SA and PSO/SA.

Since the main objective of Chapter 3 was to select the methodology that provides the best balance between objective function (minimization of the power loss) and processing
time, Two modified versions of the systems with 21 and 69 buses were proposed to test the solutions. Those tests considered the location of three distributed generators proposed in literature. In addition, the impact of the power level injected by the DGs was evaluated by using three different maximum distributed power generation levels: 20%, 40%, and 60% of the total power generated by the slack bus.

The results obtained by the hybrid methodologies in both test systems shown that the PSO/SA provided the best solution in terms of power loss reduction. However, this methodology requires the longer processing times in comparison with other solution methods. With respect to the processing times, the BH obtained the best results in all the cases under analysis, but also the worst solution in relation to the power loss reduction. In addition, the trade-offs provided by each methodology in terms of power loss and processing time were analyzed: the BH/SA methodology provided the best balance between power loss reduction and processing time. For that reason, this methodology is considered as the most adequate for solving the optimal power flow problem in DC grids for any size and DG generation level.

The results presented in Chapter 3 demonstrated that the aim of this part of the thesis was fulfilled, which was to find the optimal power flow methodologies that provide the best trade-offs between solution quality and processing time; in order to improve the performance of the methodologies used for the location and sizing of DERs in DC grids (planning strategies), addressed in Chapter 4 of this thesis. As future improvement for the solutions proposed for solving the optimal power flow problem, it must be considered the integration of batteries inside the DC grids, and the implementation of parallel processing tools for reducing the processing times. In addition, the proposed hybrid methodologies can be used in microgrid control applications to determine the set point of the controllers depending on operation conditions of the loads and distributed energy resources.

The fourth chapter is focused on the technical impact of the optimal integration of distributed energy resources on DC microgrids. For AC grids multiple works have been proposed to solve this problem. However, it was found that, in DC grids, this is a topic in develop and a lot of solutions proposed do not analyze the effectiveness and robustness of the proposed approaches with respect to other solutions reported in literature, in terms of both solution quality and processing times.

The previous problems were addressed by proposing a hybrid methodology for optimal location and sizing of distributed generators, which is based on the PPBIL and the PSO. This solutions uses as objective function the reduction of the power losses, and considers the set of constraints associated to the direct current grids. The study, performed in Chapter 4, considered the combination of two additional location (Genetic algorithm and parallel Monte-Carlo) and two additional sizing methods (the BH and CGA proposed in chapter 3),
obtaining nine hybrid solutions, where the proposed PPBIL/PSO method is one of them. The evaluations of those solutions were performed in three test systems with 10, 21 and 69 nodes, respectively, in which three DGs were located and dimensioned. The results demonstrated the effectiveness and robustness of the proposed methodology in terms of solution quality and processing times. However, all test scenarios were executed 1000 times with the aim to evaluate the precision and repeatability for each hybrid solution.

The results obtained in Chapter 4, demonstrated that the proposed PPBIL/PSO hybrid method provided the solution with the highest reduction in the power loss for small, medium and large DC grids. In terms of location, the GA obtained similar results, but requiring a higher processing time. In relation to the sizing of the distributed generators, the fastest method was the BH, providing the less efficient solutions in terms of quality (minimum power loss reduction). Moreover, the processing time and power loss of all the methods were normalized for the three test systems, which allow to observe that the PPBIL/PSO solution obtained the best trade-offs between speed and power loss for any grid size. In addition, the PBIL/PSO exhibited the lower standard deviation for the power loss in all test scenarios; hence the proposed PBIL/PSO provided the highest precision and repeatability for the solution when compared with the other hybrid solutions. Furthermore, by analyzing the results obtained by the proposed methodology it is identified the importance of adopting parallel processing tools for reducing the processing times. Finally, it can be appreciated that the Chapter 4 of this thesis allowed to obtain a planning methodology of DC grids, that satisfies all technical requirements that represent this type of electrical network by improving at the same time the operating conditions of the grids.

For the problem of optimal integration of distributed energy resources in DC grids, future improvements of the proposed solutions may include the integration of hourly curves of power generation and demand into the mathematical model, and consider the installation of energy storage systems into the electrical network. In addition, it is possible to propose an optimal tuning strategy for the parametrization of the binary and continuous optimization techniques, which allow balancing the exploration and exploitation of the solution space to find the most adequate parameters for each solution method.

In Chapter 5 were proposed two energy management systems for DC grids, with the aim of improving different technical and economic conditions. The first strategy is proposed for the first and second level of the hierarchical control, and the second one is focused on the tertiary level. The first energy management system was designed to control the photovoltaic generation and battery storage systems in a standalone DC MG. Such an energy management system enabled the photovoltaic system to control the power generation and ensures that the power storage element does not exceed the technical limits of the state of charge. This was achieved by developing a control methodology based on multiple control states,
which allowed the connection and disconnection of the energy storage system and the load installed inside the microgrid. The proposed EMS also considered a capacitor connected in parallel with the battery as backup ESS. The function of this capacitor was enabled the disconnection of the battery in both overcharge (high state of charge) and bulk charge (state of charge) conditions, hence avoiding charge/discharge sub-cycles in the battery. This EMS was validated using detailed MG circuitual simulations, which include the PV source model (single-diode model), a lithium-ion battery model, a constant power load model and the DC/DC converters equations; moreover, realistic power generation and demand profiles from Medellín-Colombia were used.

The results demonstrated that the proposed EMS reduced the charge sub-cycles on the energy storage system, hence avoiding an accelerated aging. Therefore the proposed EMS can to extend the battery lifetime and reduce the costs associated to the maintenance and disconnection of the microgrid. Furthermore, those results enable to conclude that using SPVSs with the proposed EMS reduces the energy purchasing from the utility grid, reduce the dependency of fossil fuels and the environmental impact, and also reduce the operational complexity of the system in comparison with systems based on other renewable resources, e.g. wind generation, small scale hydroelectric, among others.

A future improvement of the previous EMS, may consider the integration of multiples loads (critical and non-critical) to develop a load shedding strategy. In addition, multiple generation and storage systems integration to improve the energy storage capacity of the MGs could also be considered. Finally, the EMS can be integrated to a grid-connected environments, with the aim of reducing the energy purchasing cost.

The second EMS, also proposed in Chapter 5, had the aim of providing an optimal daily operation to the BSS with the lower energy purchasing costs, including the constraints imposed by the power balance, devices capabilities and voltage regulation. For this purpose it was proposed a master-slave strategy formed by a parallel implementation of the PSO (PPSO) and a multi-period power flow method based on the successive approximation method, proposed in Chapter 2.

The performance evaluation of this EMS, in terms of solution quality and processing times, was performed in a modified version of the 21 bus test system, which considered a wind and a PV generator, and three batteries located into DC grid. Moreover, an artificial neural network was used to forecast the hourly power generation of the renewable generators, while the variation in power demand and energy purchasing costs were taken from the Colombian power system. Furthermore, the solution quality and speed of the proposed solution was contrasted with three optimization techniques published in literature: a black hole optimizer, a continuous genetic algorithm with matrix structure, and a traditional Chu & Beasley
genetic algorithm; which were parallelized to provide a fair test scenario. In addition, two simulation scenarios were used to identify the optimal SOC conditions for the batteries: the first scenario considered the operation of the batteries between the maximum and minimum SOC, hence without imposing a final state-of-charge; and second test scenario included in the operation of the batteries a defined final state-of-charge equal to the 50% of the nominal capacity of each battery.

The results obtained in the different test scenarios demonstrated that the proposed PP-SO/SA methodology achieved the best results in terms of quality solution. In terms of processing time, the fastest method was the GA, but the poor performance of the solution in comparison with the other methods makes it unusable. The second faster method, with sequential implementation, was the proposed solution based on PSO. Similarly, when the PSO, BH and CGA methods were parallelized, their processing times were strongly reduced, being the PPSO the faster method; which demonstrated again the effectiveness of using parallel processing tools in planning and operation of DC grid. Furthermore, the proposed PP-SO/SA method provided the best trade-offs between quality solution and processing time. Finally, the results demonstrated that forcing a final SOC equal to 50% for each day reduces the energy purchasing cost for a week of operation under the Colombian conditions, this compared with the case when any SOC restriction is adopted. As future improvement, the evaluation of the optimal location of the different energy resources used, as well as including inside the objective function the reduction of emissions of $CO_2$ related to the distributed generators based on fossil fuels can be considered. Finally, analyzing the results obtained for the two energy management systems proposed was possible the cost optimization in the DC grid, and improving the operational conditions of the DERs, which allows to reduce the costs associated with the maintenance, the disconnection of the microgrid and replacement of the batteries.

In general terms, this thesis presented different mathematical models, solution methodologies and management strategies for the optimal planning and operation of DC grids, which are based on sequential programming methods and hierarchical control techniques. Finally, Table 6-1 reports the most important contributions provided in this thesis with the corresponding sections and publications.
<table>
<thead>
<tr>
<th>Contributions</th>
<th>Section</th>
<th>Publication</th>
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<tbody>
<tr>
<td>A Taylor’s series based approximation for solving the power flow problem in DC grids</td>
<td>Section 2.3.1.1</td>
<td>Power flow analysis in DC grids: two alternative numerical methods with both mesh and radial structure. Journal: IEEE Transactions on Circuits and Systems II, 2019 (Q1).</td>
</tr>
<tr>
<td>A linear approximation based on successive approximations method for solving the power flow problem in DC grids with both mesh and radial structure</td>
<td>Section 2.3.1.2</td>
<td>Linear power flow formulation for low-voltage dc power grids. Journal: Electric Power Systems Research, 2018 (Q1).</td>
</tr>
<tr>
<td>A Triangular matrix formulation for solving the power flow problem in DC grids with radial structure</td>
<td>Section 2.3.2.1</td>
<td>Triangular matrix formulation for power flow analysis in radial dc resistive grids with cpls. Journal: IEEE Transactions on Circuits and Systems II, 2019 (Q1).</td>
</tr>
<tr>
<td>The application of the Backward/Forward sweep method method for solving the power flow problem in DC grids with radial structure</td>
<td>Section 2.3.2.3</td>
<td>Application of the backward/forward sweep method for solving the power flow problem in DC networks with radial structure. Journal: Journal of Physics: Conference Series, 2020 (Q3).</td>
</tr>
<tr>
<td>A hybrid methodology for solving the optimal power flow problem in DC grids</td>
<td>Section 3.3.1.1</td>
<td>Optimal power flow in direct current power grids via black hole optimization. Journal: Advances in Electrical and Electronic Engineering, 2019 (Q3).</td>
</tr>
<tr>
<td>Hybrid metaheuristic approaches for optimal integration of distributed generators in DC grids</td>
<td>Section 4</td>
<td>Hybrid metaheuristic optimization methods for optimal location and sizing DGs in dc networks. Journal: Applied Computer Sciences in Engineering, 2019 (Q3).</td>
</tr>
<tr>
<td>Energy management systems for standalone DC grids</td>
<td>Section 5.1</td>
<td>Energy management in pv based microgrids designed for the Universidad Nacional de Colombia. Journal: Sustainability, 2020 (Q2).</td>
</tr>
<tr>
<td>Energy management systems for connected DC grids</td>
<td>Section 5.2</td>
<td>An energy management system for optimal operation of BSS in DC distributed generation environments based on a parallel PSO algorithm. Journal: Journal of energy storage, 2020 (Q1).</td>
</tr>
</tbody>
</table>
A. Publications

The main results of this doctoral research have been published in international journal papers and conference proceedings.

The following papers are published and they contribute to the divulgation of the results achieved in this work:


O. D. Montoya, W. Gil-Gonzalez, and L. F. Grisales-Noreña, “Triangular matrix formulation for power flow analysis in radial dc resistive grids with cpls,” IEEE Transactionson Circuits and Systems II: Express Briefs, pp. 1–1, 2019. This journal was indexed A1 by Publindex and Q1 by Scopus at the moment of publication.


L. F. Grisales-Noreña, O. D. Garzon-Rivera, O. Danilo Montoya, and C. A. Ramos-Paja,


The following publications were supported by partial results of this thesis:


References


