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Gestión de microrredes eléctricas basadas en fuentes renovables en Colombia.

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A Dios por mi madre Mariela a quién debo todo lo que soy, A mi familia y mi esposa...

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1. Introducción

En esta tesis se aborda el problema de la gestión de la energía de microrredes híbridas con energía renovable, en un país en vía de desarrollo como es el caso de Colombia, que cuenta con una posición geográfica privilegiada por la disponibilidad de recursos renovables para la generación de energía, pero donde aún es incipiente la gestión y optimización de estas microrredes si tenemos en cuenta que cerca de la mitad de su territorio se encuentra en la zona no interconectada (ZNI)([1]–[4]), donde no es posible tener redes eléctricas convencionales. Se abre entonces una enorme posibilidad de analizar el tema de gestión y optimización energética de microrredes, principalmente en el entorno rural colombiano que mayoritariamente se encuentra ubicado en la zona no interconectada, la cual cuenta con gran cantidad de recursos para la generación de energía renovable (fotovoltaica, eólica etc.), con posibilidades de conexión prácticamente nulas, hecho que las condiciona a operar como microrredes aisladas; Además, se encuentran en regiones donde las cargas (consumos eléctricos) se encuentran "dispersas", con suministro básicamente mediante grupos electrógenos que funcionan principalmente con combustible diésel. Por tanto, la gestión de una microrred en las zonas rurales en un entorno como el colombiano se convierte en un problema de optimización que integra el dimensionamiento de fuentes de energía renovable y no renovable (híbridos), así como un suficiente y adecuado sistema de almacenamiento para suplir el déficit de suministro causado por la variabilidad de recursos como irradiación y viento, con un coste financiero aceptable (costes operativos de la microrred) y que puedan ser gestionadas de forma óptima cuando se integran en un modelo que incluye carga dispersa como las encontradas en la zona no interconectada de Colombia (ZNI). Por lo anterior se deduce que el problema de gestión energética de microrredes para esta zona se enfoca en microrredes aisladas, donde pocos autores han incluido el tema de confiabilidad, incluyendo la localización óptima de generadores distribuidos dentro de la microrred. Pese a que este es un problema de planificación y no se relaciona directamente con los costes, sí tiene una repercusión en el dimensionado de componentes, arquitectura de la microrred y pérdidas de energía.

En este documento se describen los 4 trabajos que permitieron presentar esta tesis doctoral en formato de compendio de artículos.

En primer lugar, se realizó una revisión del estado del arte de la gestión de energía en microrredes con energía renovable, donde se encontró una gran cantidad de trabajos de gestión energética en microrredes híbridas que usan tecnologías de generación no compatibles necesariamente con el desarrollo y planeación energética de países en vías de desarrollo como Colombia. Se abre entonces una enorme posibilidad de abordar el tema de optimización y gestión de la demanda de microrredes, principalmente en el entorno rural colombiano ubicado en la zona no interconectada (ZNI), que dispone de elevada irradiación (y en algunas localizaciones, también viento), con posibilidades de conexión prácticamente nulas y por tanto obligando a las microrredes a operar en modo aislado.

En la segunda parte de esta tesis, se estudió el problema de optimización de microrredes aisladas híbridas con energía renovable considerando diferentes modelos y tecnologías de baterías. Se consideraron datos reales de una microrred localizada en la ZNI. Los parámetros que se tuvieron en cuenta en la optimización fueron perfiles reales de consumo, generación diésel y temperaturas reales de operación que inciden en el desempeño y duración de las baterías.

En la tercera parte se analizaron desde el punto de vista técnico y económico varias microrredes localizadas en diferentes regiones geográficas de Colombia. En este análisis se tuvo en cuenta que estas microrredes cuentan con diferentes recursos energéticos tales como irradiación, viento y agua (microcentrales hidroeléctricas). Se consideraron microrredes con diferentes perfiles reales de consumo, desde una casa aislada, hasta una pequeña población, teniendo en cuenta el efecto del desplazamiento horario de los consumos, que permite considerar su coincidencia con mayor generación de energía por parte de recursos renovables y de esta manera disminuir los costes en la optimización.

2. Gestión de energía en microrredes con fuentes de energía renovable

En este trabajo se realizó una extensa revisión literaria del estado del arte relacionado con la gestión de energía en microrredes con energía renovable. Se tuvieron en cuenta tanto microrredes conectadas a red como aisladas, así como las que pueden funcionar en ambas modalidades. Este trabajo se publicó en la revista Applied Sciences en 2019 [5].

2.1 Objetivos y Metodología

Los objetivos planteados en este trabajo fueron:

1. Revisar el estado del arte de la gestión de energía en microrredes con energía renovable.
2. Realizar un análisis comparativo de los diferentes métodos y técnicas de optimización en microrredes con energía renovable.

La metodología empleada fue:

1. Revisión bibliográfica de diferentes metodologías de gestión de energía en microrredes.
2. Análisis comparativo de las técnicas de optimización, incluyendo modelos matemáticos, modos de operación de microrred, herramientas, algoritmos y softwares de simulación.

2.2 Revisión bibliográfica y principales aportaciones

La creciente demanda exponencial del consumo de energía en el mundo es la principal causa del agotamiento de combustibles fósiles como petróleo, gas y carbón. Esto ha traído como consecuencia el aumento de gases de efecto invernadero (GEI). Para mitigar estos problemas a nivel mundial los sistemas de energía han incorporado a pequeña y gran escala fuentes provenientes de recursos renovables tales como solar, eólica, biomasa, mareomotriz etc. [6], organismos como la agencia internacional de la energía IEA [7] y el acuerdo de París promueven el uso de este tipo de energías, a nivel mundial fijan como metas la descarbonización energética y la limitación del aumento de la temperatura global para el año 2050.

Las microrredes híbridas con fuentes de energía renovable surgen como solución para responder a la demanda de energía en aréas remotas que cuentan con diversos recursos energéticos. Una microrred se caracteriza por tener un conjunto de cargas, equipos de almacenamiento de energía y sistemas de generación a pequeña escala ([8], [9]). En un concepto más amplio se define como una red de distribución en media o baja tensión, que contiene generación distribuida que puede incluir fuentes renovables y convencionales (sistemas híbridos) junto con unidades de almacenamiento que suministran energía a usuarios con cargas eléctricas (y en algunos casos también térmicas). Estas microrredes poseen sistemas de comunicación necesarios para ser gestionadas en tiempo real [10], además pueden operan tanto conectadas a red como de forma aislada [11]. Las microrredes a su vez se clasifican de acuerdo con el tipo de tensión en que se acoplan: microrredes de corriente continua (o directa, CC o DC), alterna (CA o AC) o híbridas.

Debido a la fuerte dependencia de las condiciones climáticas y meteorológicas, en muchos casos el sistema óptimo es un sistema híbrido de energía renovable (considerando una o más fuentes renovables) con sistemas de almacenamiento de baterías (y en algunos casos incluyendo generador diésel) [12].

En una microrred, es fundamental el equilibrio entre la oferta y la demanda de energía para mantener la estabilidad, esto ocurre porque la generación de las fuentes distribuidas intermitentes como la fotovoltaica y las turbinas eólicas son difíciles de predecir y su generación puede fluctuar significativamente dependiendo de la disponibilidad de las fuentes primarias (irradiación solar y viento). El problema del equilibrio entre la generación y el consumo se vuelve aún más importante cuando la microrred funciona en modo aislado, donde la generación disponible es limitada para equilibrar la demanda [13]. La optimización de la gestión de la energía en una microrred se considera un problema de optimización offline [14].

La gestión de la energía en las microrredes implica un software de control que permite el funcionamiento óptimo del sistema [15], esto se logra considerando el coste mínimo requerido y dos modos de operación de la microrred (aislado e interconectado, en su caso). La variabilidad de recursos como la irradiación solar y la velocidad del viento deben tenerse en cuenta al considerar las microrredes con fuentes de energía renovables [16].

En la referencia [17] los autores realizaron una revisión de los estudios relacionados con la gestión energética de las microrredes. Algunos autores han resuelto el problema de la gestión energética utilizando diferentes técnicas para lograr un funcionamiento óptimo de la microrred. Sin embargo, estas técnicas deben incorporar mejores estrategias de control debido a la integración de generación distribuida, elementos de almacenamiento y vehículos eléctricos.

Otros autores [18] han revisado varios métodos de integración para sistemas de energía renovable basados en el almacenamiento y en la respuesta a la demanda. Estos métodos cubren dos áreas principales: (1) el uso óptimo del almacenamiento de energía y (2) la mejora de la participación de los usuarios a través de mecanismos de respuesta a la demanda y otros métodos de gestión colaborativa. Los autores de la referencia [19] revisaron las estrategias de gestión energética para microredes hibrídas con enegías renovables, diferentes configuraciones de microrredes aisladas y conectadas a red. Otros artículos de revisión [20] han mostrado los objetivos de los controladores de supervisión de microrredes (*microgrid supervision controllers* MGSC) y los sistemas de gestión de energía (*energy management systems* EMS) para microrredes.

En la tabla 1 se muestra las contribuciones principales de los artículos de revisión relacionados con la gestión energética de las microrredes.

Tabla 1. Publicaciones de revisión de gestión de energía en microrredes.

Referencia	Principales Contribuciones
[17]	Los autores presentaron un análisis comparativo sobre estrategias de toma de decisiones para sistemas de gestión energética de microrredes. Estos métodos se seleccionan en función de su idoneidad, practicabilidad y manejabilidad, para un funcionamiento óptimo de las microrredes.
[18]	Se revisan los métodos de integración de la gestión energética, la respuesta a la demanda y los sistemas de almacenamiento. Los autores utilizaron modelos más precisos para el almacenamiento, incluidos factores clave como los factores de reducción debido a la tasa de carga / descarga de temperatura y el envejecimiento.
[19]	Los autores presentaron una revisión de las estrategias y enfoques utilizados para implementar la gestión energética en sistemas híbridos de energía renovable conectados y aislados de la red.
[20]	Se muestra una extensa revisión sobre las metodologías de gestión energética aplicadas en microrredes. Se revisa la gestión de energía para regulación de potencia a corto y largo plazo.
[21]	Los autores mostraron enfoques de técnicas de optimización y herramientas usadas para la solución del problema de la gestión energética. Se incluyen métodos heurísticos, métodos basados en agentes, métodos basados en control predictivo y otros métodos.
[22]	Se realizó una descripción general de los últimos desarrollos de investigación utilizando algoritmos de optimización en la planificación de microrredes y se revisaron las distintas metodologías de planificación.
[23]	Los autores presentaron una descripción general de las microrredes híbridas actuales y los métodos y aplicaciones de optimización.
[24]	Se mostró en detalle la optimización de las microrredes con generación distribuida, tanto en el modo conectado a la red como en el modo autónomo.

Las microrredes apoyadas con energías renovables se pueden entender como un caso de redes inteligentes "*smartgrids*", ofreciendo un conjunto de soluciones tecnológicas que permiten intercambiar información entre los consumidores y los centros de generación distribuida, de tal manera que necesitan ser gestionadas de forma óptima. Una microrred está compuesta por diferentes recursos de generación distribuida que se conectan a la red pública a través de un punto común. La Figura 1 muestra un modo de gestión de energía de una microrred, detallando sus distintos módulos: interfaz hombre-máquina (HMI), control y adquisición de datos, pronóstico de carga, optimización, etc [25].

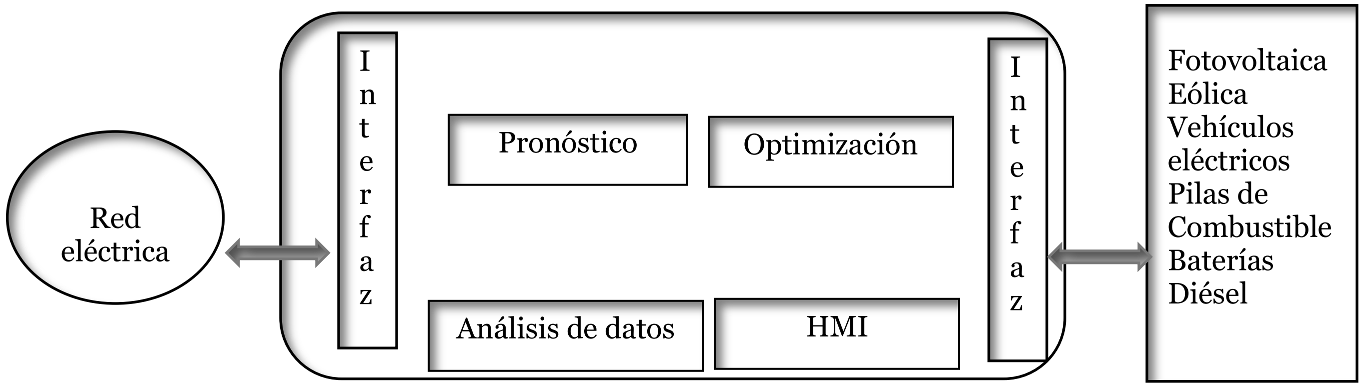

Figura 1. Gestión de energía en microrredes.

La gestión energética de una microrred implica un sistema automatizado integral que tiene como objetivo principal lograr una programación óptima de los recursos [21]–[24], basándose en tecnologías de información avanzada, pudiendo optimizarse tanto la gestión de las fuentes de energía distribuidas como el sistema de almacenamiento de energía.

La gestión de la energía en microrredes busca generalmente resolver los siguientes objetivos:

- Maximizar las potencias de salida de los generadores en un instante particular
- Minimizar los costes operativos de la microrred
- Optimizar los sistemas de almacenamiento de energía
- Minimizar costes ambientales

Algunos de los métodos de optimización clásicos incluyen programación mixta de enteros lineales y no lineales ([26], [27]). La función objetivo y las restricciones utilizadas en la programación lineal son funciones lineales con variables de decisión reales y enteras [28]. Los métodos de programación dinámica se utilizan para resolver problemas más complejos que se pueden discretizar y secuenciar [29]. El problema generalmente se divide en subproblemas que se resuelven de manera óptima para, posteriormente, superponer las soluciones parciales con el fin de desarrollar una solución óptima para el problema original [30].

La metaheurística es otra alternativa importante en la optimización de microrredes. Distintas técnicas heurísticas se utilizan para aproximar la mejor solución utilizando algoritmos genéticos, evolución biológica y mecanismos estadísticos para lograr un funcionamiento y control óptimos de la energía de la microrred ([31], [32]).

Las técnicas de control predictivo se utilizan en aplicaciones donde es necesario predecir la generación y la carga para garantizar una gestión eficaz de la energía almacenada, esto típicamente combina programación y control estocástico ([33], [34]). Entre estas técnicas, las más destacables son las que permiten predecir el deterioro de elementos de la red, principalmente sistemas de almacenamiento [35].

Los métodos de optimización basados en multiagentes utilizados en microrredes, permiten una gestión descentralizada de la microrred y consisten en secciones que tienen un comportamiento autónomo para ejecutar las tareas con objetivos definidos ([36], [37]). Estos agentes, que incluyen cargas, generadores distribuidos y sistemas de almacenamiento, se comunican entre sí para obtener un coste mínimo.

Los métodos estocásticos y la programación robusta se utilizan para resolver las funciones de optimización cuando los parámetros tienen variables aleatorias, particularmente en redes neuronales artificiales, lógica difusa y teoría de juegos [38].

Existen otros métodos derivados de la combinación de técnicas mencionadas anteriormente, tales como métodos estocásticos y heurísticos y algoritmos de enumeración ([39], [40]). La Figura 2 presenta un resumen de las metodologías de gestión de la energía utilizada en microrredes basados en la literatura revisada en este trabajo [21]. Diferentes investigaciones han propuesto varias metodologías relacionadas con la gestión energética en microrredes ([15], [41]–[43]). Muchos métodos se basan en enfoques clásicos, como la programación lineal y no lineal de enteros mixtos ([27], [44]). La programación lineal puede considerarse un buen enfoque en función del objetivo y las limitaciones, mientras que los métodos de inteligencia artificial están orientados a abordar situaciones en las que otros métodos conducen a resultados insatisfactorios, incluida la previsión de generación renovable y el funcionamiento óptimo del almacenamiento de energía, teniendo en cuenta los modelos de envejecimiento de la batería, entre otros ([45], [46]).

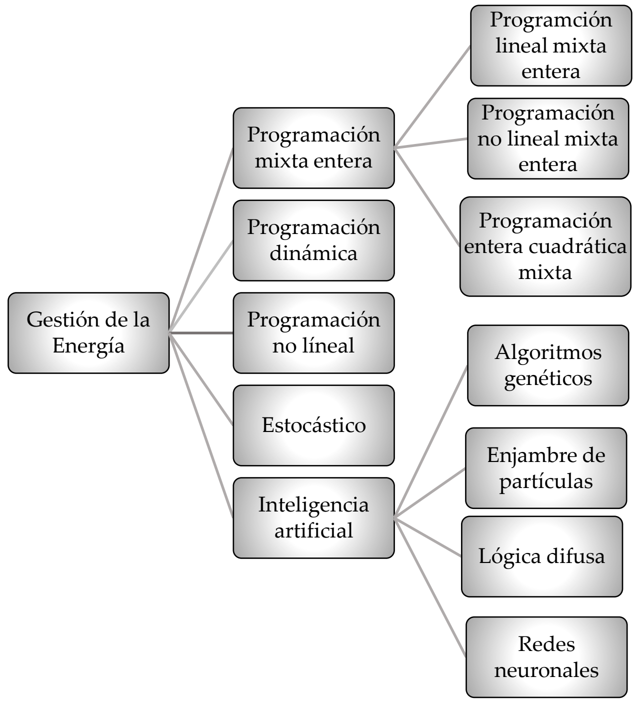

Figura 2. Metodología de gestión en microrredes.

De acuerdo con la literatura revisada, se encontró un gran número de publicaciones relacionadas con gestión de la energía en microrredes interconectadas ([23]–[29]). Por su parte, la operación en modo aislado es considerada por otros autores como alternativa de solución de suministro principalmente en zonas rurales de difícil acceso o simplemente donde no existen redes convencionales ([53]–[56]), en estos sistemas algunos autores incluyen el modelo de la batería en la optimización del sistema([57]–[60]). También existen trabajos que plantean la optimización para microrredes que operan tanto de forma aislada como interconectadas ([1], [61], [62]).

En cuanto a las técnicas de optimización, en las microrredes híbridas se aplican diferentes métodos para maximizar la producción de energía de cada fuente en particular, minimizar los costes de electricidad u optimizar los sistemas de almacenamiento. En la figura 3 se presentan las técnicas y algoritmos de optimización más comúnmente empleados, derivados de la revisión literaria realizada en este trabajo. Por otra parte, en la tabla 2 se resumen algunas ventajas y desventajas de los modelos matemáticos de optimización.

Diferentes investigadores ([31], [32], [63]–[67]) han propuesto técnicas metaheurísticas para resolver el problema de optimización con multirrestricciones, problemas combinatorios multidimensionales y altamente no lineales. Otros autores ([29], [68]–[72]) presentaron métodos de programación dinámica estocástica para optimizar el problema de la gestión energética con objetivos multidimensionales. Algunos trabajos ([38], [73]–[75]) han propuesto la teoría de juegos para resolver problemas con funciones objetivo que presentan conflictos que no se resuelven satisfactoriamente con otros métodos.

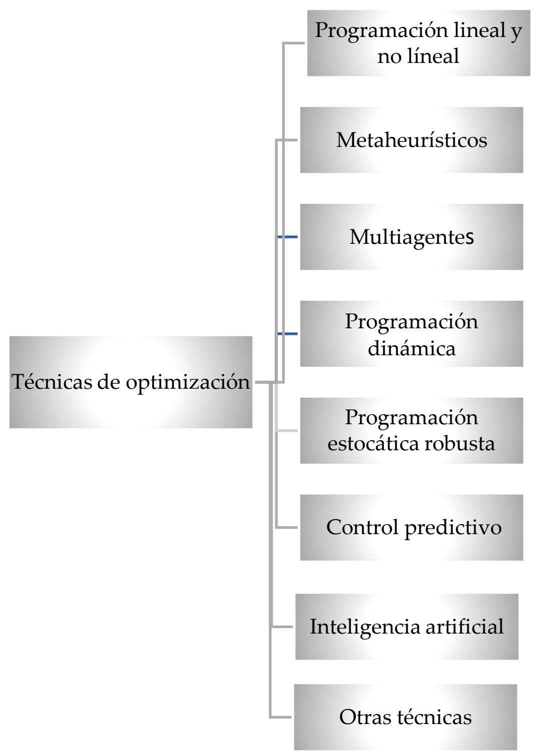

Figura 3. Técnicas de optimización en gestión de energía en microrredes.

Tabla 2. Análisis comparativo de modelos matemáticos de optimización en microrredes.

Referencias	**Modelo matemático de optimización**	**Ventajas**	**Desventajas**
([28], [54], [76], [77])	Programación lineal de enteros mixtos (*mixed integer lineal programming* MILP)	La programación lineal *(lineal programming* LP) es una forma rápida de resolver los problemas y las restricciones lineales, dando como resultado una región factible convexa, garantizándose en muchos casos la obtención de la solución óptima global	Capacidades limitadas para aplicaciones con funciones continuas y no diferenciables
([26], [62])	Programación no lineal de enteros mixtos entera (*mixed-integer non-linear programming* MINLP)	Utiliza operaciones simples para resolver problemas complejos. Puede obtener más de una solución óptima para elegir, lo cual es una ventaja sobre la formulación MILP	Alto número de iteraciones (alto esfuerzo computacional)
([68], [69])	Programación dinámica	Puede dividir el problema en subproblemas, optimizando cada subproblema y, por lo tanto, resolviendo problemas secuenciales.	Implementación compleja debido al gran número de funciones recursivas.
([78], [79])	Algoritmos genéticos	Algoritmos evolutivos basados en poblaciones que van mejorando con las generaciones, que incluyen operaciones como cruce, mutación y selección para encontrar la solución óptima. Velocidad de convergencia adecuada. Ampliamente utilizado en muchos campos	Se deben configurar los parámetros de cruce y mutación, y los parámetros de población y de criterio de parada
([31], [55], [80])	Enjambre de partículas	Buen desempeño en problemas de dispersión y optimización	Alta complejidad computacional
([56], [81])	Colonia artificial de abejas	Algoritmo robusto basado en poblaciones, fácil de implementar. Velocidad de convergencia adecuada	Formulación compleja
([82], [83])	Cardumen de peces artificiales	Pocos parámetros, rápida convergencia, alta exactitud y flexibilidad	Iguales desventajas que los algoritmos genéticos, pero sin problemas de cruces ni mutaciones.
([84], [85])	Algoritmo de forraje bacteriano	El tamaño y la no linealidad del problema no afectan mucho. Convergencia hacia la solución óptima donde los métodos analíticos no convergen	Espacio de búsqueda grande y complejo

En cuanto a las herramientas de simulación usadas en la gestión de energía en microrredes, las más conocidas son programas como Matlab/Simulink (MathWorks, Natick, MA, EE. UU.) [86], Matlab es un entorno informático numérico del lenguaje de programación de cuarta generación, que puede interactuar con otros lenguajes como C, C ++, C #, Java, Fortran y Python. MATPOWER [87], es una herramienta de código abierto que se utiliza para simular flujos de energía óptimos, que utiliza Monte Carlo para evaluar el rendimiento de las microrredes. Alternativamente, muchos autores han utilizado otras herramientas como GAMS [88], que es un lenguaje de optimización para programación lineal, no lineal y mixta, para resolver el problema de la incertidumbre en la gestión de la energía y para el dimensionamiento óptimo de la microrred. Se han empleado otras herramientas como CPLEX [89], que es un optimizador basado en el lenguaje C y es compatible con otros lenguajes como C ++, Java y Python.

La simulación y modelado de microrredes se realiza con programas como Simulink y otros como PSCAD/ EMTDC [90], se destaca también el uso de softwares como HOMER [91], HOGA (o su versión actual improved Hybrid Optimization by Genetic Algorithms iHOGA) [92] y otros como HYBRID2 [93], usados para la optimización de sistemas híbridos con energías renovables. iHOGA es un software basado en algoritmos genéticos que incluye estrategias de control, modelos más complejos que consideran factores como el envejecimiento de las baterías y cálculos económicos más precisos, pudiendo realizarse análisis de probabilidad y de sensibilidad de los parámetros utilizados en la optimización.

2.3 Conclusiones

La gestión de la energía en una microrred se puede considerar como la solución de un problema de optimización, que suele tener un criterio económico, técnico y ambiental, este corresponde a una función de optimización de objetivos múltiples que se satisface resolviendo simultáneamente problemas técnicos, económicos y medioambientales en una microrred.

La gestión de energía en microrredes con energía renovable integra habitualmente una estrategia de optimización que asegura la continuidad del suministro y reduce los costes de producción de energía, el problema de gestión de la energía o el control de optimización en una microrred se convierte en un modelo de gestión/optimización mono-objetivo cuando se presenta una única función de coste, esta función normalmente corresponde al coste operativo de las microrredes y multi-objetivo cuando simultáneamente se presenta una solución a los problemas técnicos, económicos y/o ambientales.

Con base en la literatura revisada, se ha encontrado que diferentes autores han abordado el problema de gestión en microrredes utilizando métodos que manejan técnicas de optimización como programación lineal y no lineal. Otros investigadores al aumentar la complejidad (elevado número de combinación de componentes, restricciones y estrategias de control) optan por utilizar métodos metaheurísticos, control predictivo, programación dinámica, multiagentes y metodos basados en inteligencia artificial. Estos métodos se eligen en función de su practicidad, confiabilidad y la disponibilidad de recursos en el entorno de la microrred.

Se ha realizado una descripción de las técnicas y métodos matemáticos de optimización y gestión de la energía, tanto para micrrorredes conectadas a red como aisladas, identificando la ventajas y desventajas de cada uno de ellos, sin embargo, para microrredes aisladas híbridas que utilizan sistemas de almacenamiento basados en baterías, es necesario realizar más investigaciones que conduzcan a mejorar la fiabilidad de estos dispositivos, considerando modelos de envejecimiento que estimen los tiempos exactos de duración y por lo tanto optimizen el sistema considerando reemplazos y nuevas tecnologías como las basadas en iones de litio.

Se han desarrollado muchas herramientas y software que se usan para optimizar microrredes híbridas que integran energías renovables. Algunos de estos se ofrecen como código abierto y otros se están desarrollando comercialmente y adaptado para solucionar un problema predeterminado. Los requisitos y especificaciones del sistema son la base para la selección de la herramienta adecuada.

Se han encontrado una gran cantidad de trabajos de gestión de la energía que usan tecnologías de generación no compatibles necesariamente con el desarrollo y planeación energética de países en vía de desarrollo como Colombia, se abre entonces una importante posibilidad de abordar el tema de optimización y gestión de energía de microrredes, principalmente en el entorno rural colombiano con gran cantidad de recursos renovables, pero sin posibilidades de conexión a la red principal (microrredes aisladas).

3. Optimización de microrredes aisladas con energía renovable considerando modelos y tecnologías de baterías

Las microrredes híbridas son una nueva solución en áreas remotas de difícil acceso, o en zonas en las que no se tiene acceso a la red eléctrica convencional. En las microrredes híbridas basadas en energías renovables, uno de los principales elementos que sustentan el suministro energético, debido a la intermitencia de variables como la irradiación o el viento, son las baterías [94].

Las baterías constituyen elementos esenciales en microrredes híbridas con energía renovable, debido a la madurez de tecnologías como el plomo-ácido y la aparición de tecnologías como las baterías de litio. Esta última representa una opción atractiva debido a su alta densidad energética, mayor vida útil y mejor sostenibilidad ambiental.

Fundamentado en lo anterior, se realizó un segundo trabajo publicado en la revista Energies [95]. En este trabajo se presenta la optimización de una microrred híbrida aislada con energías renovables, considerando tecnologías y modelos de envejecimiento de baterías. La microrred representada se encuentra localizada en la ZNI de Colombia, que se caracteriza por tener una baja cobertura de suministro de energía, pese a su ubicación privilegiada para la generación de energía mediante recursos como irradiación solar y viento.

3.1 Objetivos y Metodología

Los objetivos planteados en este trabajo son:

1. Optimizar la microrred considerando los modelos de envejecimiento de baterías, teniendo en cuenta la temperatura y las condiciones reales de funcionamiento.
2. Analizar la influencia del modelo de batería utilizado en la optimización de una microrred híbrida con energía renovable.

3. Determinar los costes de la microrred comparando tecnologías y modelos de baterías de plomo-ácido y de litio.

La metodología aplicada fue la siguiente:

1. Revisión bibliográfica de optimización de microrredes aisladas con energía renovable.
2. Localización geográfica de la microrred considerada utilizando datos reales de consumo y datos meteorológicos de irradiación y velocidad promedio de viento.
3. Modelado y simulación de la configuración existente de la microrred considerada.
4. Optimización de la microrred considerando modelos de envejecimiento de baterías de plomo-ácido y de litio.

3.2 Revisión bibliográfica y principales aportaciones

El calentamiento global y el aumento de los gases de efecto invernadero provocados por la generación de energía basada en combustibles fósiles han generado preocupación en todo el mundo sobre el suministro energético futuro [7]. Estos inconvenientes se han convertido en una oportunidad para el uso de energías renovables como la solar, eólica, mareomotriz, geotérmica y biomasa, entre otras. Se estima que las energías renovables podrían cubrir alrededor del 80% de la demanda mundial de energía para 2050, reduciendo la dependencia de combustibles fósiles y mitigando los efectos causados por el cambio climático [96]. Sin embargo, uno de sus inconvenientes es su carácter relativamente impredecible y su intermitencia. Para superar estos inconvenientes, una solución atractiva es combinar dos o más fuentes de energía en un sistema híbrido gestionado como microrred, que puede resolver problemas de fiabilidad y proporcionar una solución respetuosa con el medio ambiente.

Las microrredes híbridas son una nueva solución en áreas remotas de difícil acceso o que no tienen acceso a la red eléctrica convencional [5]. En las microrredes híbridas basadas en energías renovables, uno de los principales elementos que sustentan el suministro energético debido a la intermitencia de las variables, como la radiación o el viento, son las baterías. Las baterías son los dispositivos de almacenamiento más utilizados en los sistemas híbridos debido a su facilidad de transporte y montaje, bajo mantenimiento en general, bajo precio comparado con otras tecnologías de almacenamiento, gran capacidad energética, modularidad y escalabilidad, así como madurez de tecnologías como el plomo-ácido [97]. Las nuevas baterías de litio representan una opción atractiva debido a su alta densidad energética, mayor vida útil y mejor sostenibilidad ambiental. Además, las baterías de litio han tenido una reducción de precio del 8 al 16% anual [60].

Con la reducción de costes de los paneles fotovoltaicos, las baterías representan en general el mayor coste de las microrredes, considerando el coste total a lo largo de la vida útil (donde se incluyen los reemplazamientos cuando finaliza la vida útil de los componentes). La duración de las baterías depende principalmente de la tecnología y de las condiciones de operación de la microrred. La estimación de la vida útil de las baterías es crucial ya que influye en los costes de reemplazamiento de las mismas y, por lo tanto, en el coste total del sistema [98].

La optimización de los sistemas híbridos aislados depende principalmente de la predicción de la duración de la batería, ya que una predicción errónea o demasiado optimista puede conducir a una estimación deficiente de los costes del sistema. La importancia de estas consideraciones se ha destacado en publicaciones recientes [99]. Es muy importante utilizar modelos precisos de estimación de la vida útil de las baterías en sistemas donde las condiciones reales y climáticas de funcionamiento difieren considerablemente de la hoja de datos y la vida útil esperada de la batería según las pruebas de laboratorio.

3.2.1. Modelos de envejecimiento de baterías de plomo-ácido

Los modelos de envejecimiento de baterías de plomo-ácido representan aspectos esenciales como corrosión anódica, degradación de la masa activa, pérdidas de agua y estratificación del electrolito [100]. A continuación, se describen los modelos de baterías de plomo-ácido usados en este trabajo:

Modelo de ciclos equivalentes

Los modelos de baterías basados en ciclos equivalentes son utilizados por programas de optimización como HOMER [101]. Este modelo supone que el final de la vida útil de la batería se alcanza con un número determinado de ciclos completos equivalentes de carga y descarga, que generalmente se muestra en la hoja de datos de la batería. La IEC 60896-1: 1987 [102] establece las condiciones para determinar este número de ciclos. Sin embargo, no considera las condiciones reales en que se realizan los ciclos de carga/descarga en las aplicaciones donde funcionan las baterías, que en muchos casos son muy distintas a las condiciones de los ensayos de laboratorio. El número completo de ciclos de carga Z_n es representado en la ecuación 1:

$$Z_n(t + \Delta t) = Z_n(t) + \frac{|I_{dischbat}(t)| \times \Delta t}{C_n} \qquad (1)$$

Donde $|I_{dischbat}(t)|$ (A) es el valor absoluto de la corriente de descarga.

C_n corresponde a la capacidad nominal de la batería (Ah).

En el caso que $Z_n(t) = Z_{\text{IEC}}$ (cuando el número de ciclos completados desde el inicio de la vida útil hasta el momento *t*(h) es el mismo que el número de ciclos IEC proporcionado por el fabricante), entonces es alcanzado el final de la vida útil de la batería.

Las variables relacionadas con el estado de operación real de la batería afectan significativamente a su vida útil, como el estado de carga (*state of charge*, SOC)([103], [104]), la profundidad de descarga (*depth of discharge*, DOD) la temperatura, la corriente, la tensión, el tiempo que lleva la batería sin alcanzar la carga completa ([105]–[107]).

Modelo de conteo de ciclos de Rainflow

El modelo de conteo de ciclos (*Rainflow)* ([108], [109]), considera distinto número de ciclos equivalentes en función de la profundidad de descarga (DOD), el ciclo de vida de la batería es calculado mediante la ecuación 2:

$$Life_{bat} = \frac{1}{\sum_{i=1}^{m} \frac{Z_i}{CF_i}} \quad (2)$$

Donde Z_i es el conteo de ciclos correspondiente a cada rango de profundidad de descarga (DOD), que se divide en m intervalos para 1 año (un año promedio o toda la vida). Para cada intervalo, hay varios ciclos hasta la falla (*CFi*). En la figura 4 se observa una gráfica típica de los ciclos de vida frente a la profundidad de descarga de una batería de plomo-ácido [110].

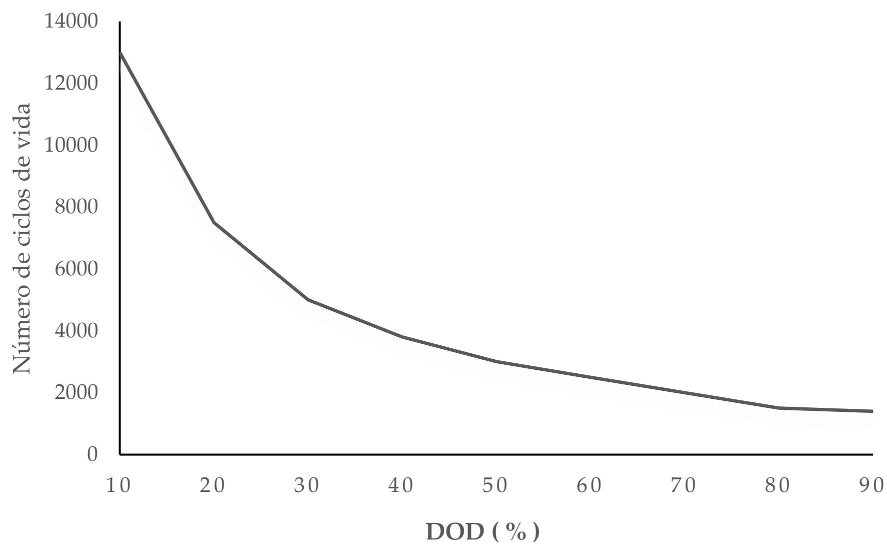

Figura 4. Ciclos de vida vs Profundidad de descarga (batería de plomo-ácido).

El modelo de *Rainflow* sin embargo tampoco considera el resto de los parámetros que afectan a la vida útil de la batería tales como estratificación del ácido, corriente y temperatura.

Modelo de Schiffer *et al*

Los parámetros relacionados con el envejecimiento por degradación y corrosión de baterías han sido estudiados por autores como Schiffer *et al*. [111], cuyo modelo de ciclos ponderados es aplicado a baterías de plomo-ácido. La carga cíclica real en amperios-hora (Ah) se multiplica continuamente por un factor de peso que representa completamente las condiciones reales de funcionamiento de la batería, tales como el SOC, estratificación del ácido, corriente y el tiempo que tarda sin alcanzar la carga completa durante la vida útil de la batería.

El número de ciclos nominales Z_N se calcula dividiendo los amperios-hora Ah descargados por la capacidad nominal de la batería, esta relación se determina mediante la ecuación 3:

$$Z_N = \int_0^t \frac{|I_{dch}(\tau)|}{C_N} d\tau \tag{3}$$

Donde I_{dch} es la corriente de descarga, C_N es la capacidad nominal de la batería

En cuanto a la pérdida de capacidad por degradación, el rendimiento Ah es ponderado mediante el impacto en el SOC, la corriente de descarga y la estratificación del ácido. El número ponderado de ciclos se estima mediante la ecuación 4:

$$Z_{W(t)} = \frac{1}{C_N} \int_0^t |I_{DCH}(\tau)|\, fSOC(\tau) fAcid(\tau) d\tau \tag{4}$$

Donde *fSOC* es un factor para la influencia del SOC, el cual también incluye el impacto de la corriente nominal y *fAcid* es un factor que representa el impacto de la estratificación del ácido.

Por su parte la tensión de la batería puede determinarse en cada paso de tiempo dependiendo de los estados de carga, para $I_{ba}(t)>0$ (cargando) se usa la ecuación 5, y para $I_{ba}(t)<0$ (descargando), la ecuación 6, estas ecuaciones se basan en el modelo de Shepherd [112].

$$U_{(b)} = V_0 - gDOD(t) + \rho_c(t)\left(\frac{I_{bat}(t)}{C_N}\right) + \rho_c(t)M_c\left(\frac{I_{bat}(t)}{C_N}\right)\left(\frac{SOC_t}{C_C - SOC_{(t)}}\right) \tag{5}$$

$$U_{(b)} = V_0 - gDOD(t) + \rho_d(t)\left(\frac{I_{bat}(t)}{C_N}\right)\rho_d(t)M_d\left(\frac{I_{bat}(t)}{C_N}\right)\left(\frac{SOC_t}{C_d - SOC_{(t)}}\right) \tag{6}$$

Donde U(V) es la tensión en terminales de la celda, V_0 (V) es la tensión de equilibrio de la celda en el estado de carga completa, g(V) es una constante de proporcionalidad del electrolito, $\rho_c(t)$ y $\rho_d(t)$ (ΩAh) representan la resistencia interna agregada durante la carga y descarga, y C_C y C_d representan la capacidad normalizada de la batería durante carga y descarga.

Por su parte las pérdidas de capacidad debido a la degradación C_{deg} se calcula mediante la ecuación 7:

$$C_{deg}(t) = C_{deg,limit}e^{-cZ(1-Z_{W(t)})/1.6Z_{IEC})} \quad (7)$$

Donde, $C_{deglimit}$ corresponde al final de la vida útil de la batería (80%) y cZ es igual a 5. La cantidad de ciclos algo mayor que las consideradas por el IEC.

Los cálculos para determinar la pérdida final de la capacidad de la batería debido a la corrosión y degradación se determinan mediante la ecuación 8:

$$C_{rest}(t) = C_d(o) - C_{corr}(t) - C_{deg}(t) \quad (8)$$

Donde C_{corr} es la pérdida de capacidad de corrosión, C_{deg} es la pérdida de capacidad de degradación y C_d *(o)* es la capacidad inicial normalizada de la batería. En la figura 5 se muestra una simulación de una batería de plomo-ácido considerando las pérdidas por corrosión y degradación para una vida útil de 3,2 años [113].

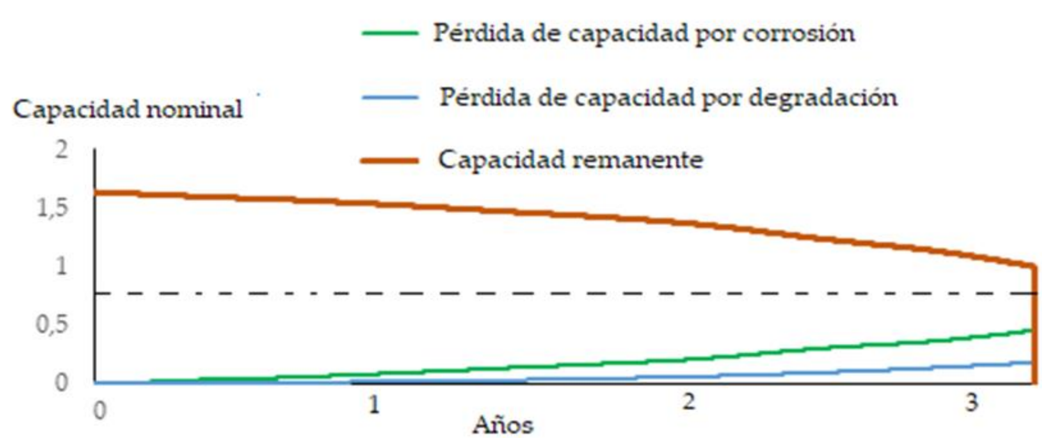

Figura 5. Pérdidas de capacidad por corrosión y degradación en una batería durante una simulación.

3.2.2. Modelos de envejecimiento de baterías de litio

De todos los materiales químicos disponibles para la fabricación de baterías, el litio es uno de los más prometedores; una de sus principales ventajas sobre otros químicos es su alta densidad de energía y alta eficiencia de carga y descarga[114]. Las diversas variantes de baterías de iones de litio se clasifican además de acuerdo con las químicas empleadas, la densidad de energía, el voltaje de la celda, la vida útil, el coste y la capacidad [115]. Dentro de las químicas más reconocidas de las baterías de litio se encuentran: LMO (óxido de litio y manganeso), LCO (oxido de litio y cobalto), NCA (litio níquel-cobalto aluminio), NMC (óxido de litio-níquel-manganeso-cobalto), LFP (litio fosfato de hierro), LMO / LTO (cátodo de óxido de manganeso y litio), NMC / LTO (cátodo de óxido de litio-níquel-manganeso-cobalto) y LFP / LTO (cátodo de fosfato de hierro y litio) [116]. Esta variedad de materiales da como resultado características de batería significativamente diferentes.

En la literatura existen una gran cantidad de trabajos relacionados con modelos de baterías de litio, estos modelos se refieren a aspectos físicos, químicos, eléctricos, o muchos que son resultado de combinar estos factores [117]. Los modelos de envejecimiento tienen la finalidad de reproducir la degradación de la batería, esta degradación se debe a dos fenómenos diferentes: el envejecimiento por “calendario” que ocurre cuando la batería no se está usando y que depende de factores como temperatura, estado de carga de la batería SOC y el paso del tiempo t, mientras que el envejecimiento por “ciclado” está relacionado con factores como profundidad de descarga DOD, tasa de carga y descarga, C-rate y temperatura [118]. Los modelos de baterías de litio seleccionados en este trabajo corresponden a ensayos acelerados realizados con baterías comerciales, sin embargo, pese a tratarse de baterías de una misma química ($LiFePO_4$), existen numerosos modelos de diferentes fabricantes, de manera que cada modelo puede tener una vida útil distinta, ya que depende de sus características fisicoquímicas y de construcción. Por lo tanto, cada modelo funciona exactamente para la batería que se ha ensayado.

Las baterías de litio consideran en sus modelos de envejecimiento, entre otros factores: Pérdidas de capacidad y potencia, incremento de la impedancia y efectos causados por la temperatura; a continuación, describiremos los modelos de envejecimiento de baterías de litio considerados en este trabajo:

Modelo de Wang *et al*

En cuanto a modelos de baterías de litio, el modelo de Wang *et al.* [119] proporciona un modelo de ciclo de vida para baterías LiFePO4/grafito litio-ferrofosfato considerando parámetros como pruebas de carga/descarga aceleradas bajo diferentes condiciones de temperatura y profundidades de descarga. Este modelo subestima la pérdida de capacidad a 60 °C y la sobreestima a 45 °C. Los autores obtuvieron un porcentaje de pérdida de capacidad representado por la Ecuación 9:

$$Q_{loss}(\%) = 30{,}330 \times exp\frac{-31{,}500}{8.314 \times T}\,A_h^{0.552} \tag{9}$$

Donde T es la temperatura absoluta en kelvin y Ah es la cantidad de carga en amperios-hora involucrada en el proceso de carga desde el inicio de la operación de la batería.

Esta ecuación es válida para tasas de carga equivalentes a C/2; es decir, tiempos de carga y descarga completos de 2 h. Las tasas de carga se evalúan desde este valor hasta 10 C; es decir, la batería se cargará por completo en un décimo de hora. En este trabajo es usada esta ecuación durante el año promedio o durante toda la vida de la batería.

Modelo de Groot *et al*

Por su parte el modelo de Grot *et al.* [120], está basado en una ecuación empírica para baterías de litio de 2,3 Ah. Se muestra que el ciclo de vida de las baterías LiFePO4/grafito de litio-ferrofosfato no solo depende de las tasas de carga y descarga (corriente), la temperatura y la profundidad de descarga, sino también se ve afectado por las pausas entre los tiempos de carga y descarga y esas dependencias son altamente no lineales, la ecuación 10 describe este modelo.

$$Q_{EOL} = \left(a \times e^{b \times I} \times T^{(C \times I^2 + d \times I + e)}\right) + f \tag{10}$$

Donde Q_{EOL} es la carga que la batería puede entregar durante su vida útil (kAh), I es la tasa de carga, T es la temperatura en °C y a, b, C, d, e y f son las constantes de ajuste. En este trabajo es usada esta ecuación durante el año promedio o durante toda la vida de la batería.

El modelo de Saxena *et al*. [121] cuantifica el ciclo de vida de las baterías de óxido de litio y cobalto $LiCoO_2$ /grafito sometidas a estados de carga entre 0 y 60%. Desarrolla un modelo que estima la pérdida de capacidad de las baterías y la influencia del SOC y la tasa de carga. El porcentaje de pérdida de capacidad se modela mediante la Ecuación 11:

$$Q_{loss}(\%) = K1 \times \mathrm{SOC}_{mean} \times (1 + K2 \times \Delta\mathrm{SOC} + K3 \times \Delta\mathrm{SOC}^2 \times \left({}^{EFC}/_{100}\right)^{0.453} \qquad (11)$$

Donde SOC_{mean} es el SOC promedio (30–50%), ΔSOC es la variación del SOC (100–60%), *EFC* son los ciclos completos equivalentes y K1, K2, K3 = 3,25, 3,25 y 2,25, respectivamente. En este trabajo se usa esta ecuación durante el año promedio o durante toda la vida de la batería.

Modelo de Petit *et al*

El modelo de envejecimiento de Petit *et al*. [122], combina dos modelos de envejecimiento, uno por calendario y otro por ciclado. Usa una ecuación basada en la ley de Arrhenius considerando factores como el estado de carga (SOC), la temperatura y el tiempo.

Envejecimiento por ciclado:

Para el envejecimiento por ciclado se usa una ecuación similar a la empleada por Wang *et al*. [123] que tiene en cuenta la pérdida de capacidad de la batería por dos factores: corriente y temperatura. En la ecuación 12 se representa este modelo:

$$Q_{loss}^{cyc}(\%) = B_{cyc} \times exp\left(\frac{-Ea_{cyc} + \gamma \times |I|}{R \times T}\right) Ah^{Z_{cyc}} \qquad (12)$$

Donde B_{cyc} es un factor pre-exponencial en $Ah^{1-Z_{cyc}}$, que depende de la corriente, Ea_{cyc} es la energía de activación expresada en J mol^{-1}, γ es un coeficiente para determinar la aceleración en el envejecimiento debido a la corriente J mol^{-1} A^{-1},

| I | (A) es el valor absoluto de la corriente, R es la constante del gas (8,314 J · mol^{-1} · K^{-1}), T es la temperatura absoluta (K) y Z_{cyc} es una constante con un valor cercano a 0,5.

Envejecimiento por calendario:

Los dos principales factores considerados en envejecimiento por calendario corresponden a la temperatura y al estado de carga (SOC) [124]. Se representa mediante una ecuación empírica mostrada en la ecuación 13:

$$Q_{loss}^{cal} = B_{cal}\,(SOC) exp\left(\frac{-Ea_{cal}}{RT}\right) t^{z_{cal}} \quad (13)$$

Donde B_{cal} es un factor pre-exponencial que depende de *SOC,* expresado en $\frac{Ah}{s^{z_{cal}}}$, Ea_{cal} es la energía de activación, expresada en J mol^{-1}, el cual evalúa la dependencia del envejecimiento por calendario de la temperatura.

Petit *et al.* [122] postulan que el envejecimiento por ciclado ocurre solo cuando la batería está cargada y la corriente está por encima de cierto valor I_{limt} (A), en este caso usa la ecuación de Wang *et al.* (ecuación 12), por el contrario, si la corriente se encuentra por debajo de este valor, el modelo usado es envejecimiento por calendario (ecuación 13), de esta manera, intercambia los dos modelos. El límite de esta corriente I_{limt} (A), depende de la habilidad de la batería para manejar altas tasas de carga.

Modelo de Swierczynski *et al*

Por su parte, Swierczynski *et al.* [125] presentaron un modelo semiempírico para baterías de iones de litio con nanofosfatos dependiente de la temperatura de almacenamiento y *SOC,* en la ecuación 14 se muestra el modelo de envejecimiento por calendario, en el cual se define como la pérdida irreversible de capacidad de la batería y las pérdidas de potencia durante su almacenamiento:

$$Q_{loss}(\%) = (0.019 \times SOCst^{0.823} + 0.5195) \times (3.528 \times 10^{-9} \times T^{5.087} + 0.295)) \times tm^{0.8} \quad (14)$$

Donde *SOCst* corresponde al estado de carga de la batería en condición de almacenamiento, *T* es la temperatura de almacenamiento, y *tm* es el tiempo de almacenamiento en meses**.**

3.2.3. Cálculos económicos

El software iHOGA realiza la simulación de diferentes combinaciones de componentes (generador fotovoltaico (FV), aerogenerador/es, banco de baterías, generador diésel, etc.) durante todo un año, en pasos horarios, excepto en los casos en que se selecciona el modelo avanzado de baterías propuesto por Shiffer *et al.* [111].

Para cada combinación de componentes y estrategias de control del sistema, se deben calcular el valor actual neto (*Net Present Cost*, NPC) y el coste normalizado de generación de energía (*Levelized Cost of Energy*, LCOE) de manera que el algoritmo genético [126] utilizado por iHOGA puede calcular la función fitness de cada combinación y finalmente después de varias generaciones alcanza un sistema óptimo.

El NPC (€) de una combinación de componentes i y estrategia de control k ($NPC_{i,k}$) se obtiene considerando el coste de adquisición de todos los componentes, los costes de instalación y reemplazo de los componentes, el coste de operación y mantenimiento *(O&M),* y el coste del combustible durante la vida útil del sistema, $Life_{system}$ (años). Todos los flujos de efectivo se convierten al momento inicial del sistema (hora 0, año 1) [127], considerando las tasas de interés y la inflación mediante la ecuación 15:

$$\begin{aligned}\mathrm{NPC}_{i,k} = \sum_{j} \Bigg[& Cost_j + \mathrm{NPC}_{rep_j} \\ & + \sum_{t_y=1}^{Life_{system}} \left(Cost_{O\&M_j} \times \frac{(1+Inf_{general})^{t_y}}{(1+I)^{t_y}} \right) \Bigg] \\ & + \sum_{t_y=1}^{Life_{system}} \left(Cost_{fuel} \times \frac{(1+Inf_{fuel})^{t_y}}{(1+I)^{t_y}} \right) + Cost_{INST}\end{aligned} \tag{15}$$

Donde *j* son los diferentes componentes, t_y es un año de la vida útil del sistema, $Cost_j$ es el coste de adquisición del componente *j*, NPC_{repj} es la suma de los costes de reemplazo del componente *j* durante la vida útil del sistema menos el coste residual del componente *j* al final de la vida útil del sistema, $Cost_{O\&Mj}$ es el coste anual de operación y mantenimiento del componente *j*, $Inf_{general}$ es la inflación anual esperada general, *I* es la tasa de interés anual, $Cost_{fuel}$ es el coste anual del combustible usado por el generador diésel, Inf_{fuel} es la inflación anual esperada del combustible diésel y $Cost_{INST}$ es el coste de instalación.

El LCOE (€/kWh) de una combinación de componentes i y estrategia de control k ($LCOE_{i,k}$) se calcula de la siguiente manera:

$$\mathrm{LCOE}_{i,k} = \frac{\mathrm{NPC}_{i,k}}{E_{load} \times Life_{system}} \tag{16}$$

Donde E_{load} (kWh/año) es la carga anual esperada del sistema.

3.2.4. Ciclo de vida de las emisiones

Existen diferentes métodos de valoración que se aplican en los análisis de evaluación del ciclo de vida, uno de los más utilizados es el método del panel internacional sobre cambio climático (IPCC), que expresa el impacto en términos de emisiones de CO_2 equivalente[128]. Las emisiones de CO_2 equivalente incluyen las emisiones de la energía utilizada para fabricar, transportar y reciclar los componentes del sistema y también las emisiones de la quema de combustible del generador diésel o gasolina, la extracción, refinación y el transporte de combustible [129].

La mayoría de los trabajos de investigación previos consideran las emisiones por kWh generada por cada fuente de energía. Para calcular el ciclo de vida de las emisiones, es preferible estudiar las emisiones (kg de CO_2 equivalente) por kW o kVA de potencia nominal o pico de cada componente del sistema.

En una investigación anterior [129], se utilizaron para evaluación del ciclo de vida de las emisiones los siguientes valores en kg de emisiones equivalentes de CO_2: generador fotovoltaico de 700 a 2000 kgCO_2/kWp de potencia máxima (para diferentes tecnologías), generador eólico dividido en la turbina eólica y torre, 510

$kgCO_2/kW$ de la potencia nominal (turbina eólica) y 35 $kgCO_2/m$ de longitud (torre), baterías (plomo-ácido) 55,3 $kgCO_2/kWh$ de la capacidad de almacenamiento, controlador de carga 19,1 $kgCO_2/kW$ de potencia nominal, inversor 26,3 $kgCO_2/kVA$ de potencia nominal, para el consumo de generador diésel 3,15 $kgCO_2/l$, para el consumo del generador a gasolina 3,1 $kgCO_2/l$ y en la fabricación del generador diésel se consideraron 215 $kgCO_2/kVA$ de potencia nominal.

3.2.5. Módulos fotovoltaicos

Cuando un módulo fotovoltaico de una potencia pico (Wp) y corriente de cortocircuito I_{sc} (A) no cuenta con seguidor del punto de máxima potencia MPPT, este es afectado por una irradiancia global sobre su superficie $G_{(t)}$ (kW/m^2) e inyecta corriente al cargador de baterías durante un tiempo t, $I_{PV(t)}$ (A) [58], donde el efecto de la temperatura del módulo fotovoltaico es insignificante (excepto para temperaturas extremadamente altas), esta corriente es calculada mediante la ecuación 17:

$$I_{PV(t)} = I_{SC} \cdot G_{(t)} \tag{17}$$

Cada string del generador fotovoltaico inyecta una corriente $I_{PV(t)}$, entonces la potencia de salida del generador fotovoltaico en (W) que tienen N_{PVp} strings en paralelo se calcula mediante la ecuación 18.

$$P_{PV(t)} = N_{PVp} \cdot I_{PV(t)} \cdot V_{DC(t)} \cdot f_{PVloss} \tag{18}$$

Donde $V_{DC(t)}$ (V) es el voltaje de corriente continua del generador fotovoltaico durante el paso de tiempo t, en los sistemas acoplados de corriente continua es el voltaje del banco de baterías, que depende del estado de carga de la batería (*SOC*), la corriente que entra o sale del banco de baterías y otros factores; f_{PVloss} es un factór que incluye el desajuste del módulo fotovoltaico o la tolerancia de potencia, las pérdidas debidas a la suciedad en los módulos fotovoltaicos y las pérdidas en los conductores.

Cuando el cargador de baterías o el inversor incluyen el MPPT, el módulo fotovoltaico siempre trabaja en el punto de máxima potencia de la curva $I = f(V)$ de tal manera que la potencia de salida del generador se calcula con la ecuación 19, en esta la temperatura no es despreciable:

$$P_{PV(t)} = N_{PVp} \cdot N_{PVS} \cdot \ P_{STC} \cdot G_{(t)} \cdot f_{PV\_loss} \cdot [1 + \alpha/100 \cdot (T_{c(t)} - 25)] \qquad (19)$$

donde N_{PVS} es el número de módulos fotovoltaicos en serie, P_{STC} es la potencia de salida estándar de cada módulo (Wp), α es el coeficiente de temperatura de potencia del módulo fotovoltaico (%/ºC), normalmente en el rango de -0,43 a -0,47 %/ºC y $T_{c(t)}$ (ºC) es la temperatura de la celda fotovoltaica durante el tiempo t, que se puede calcular mediante la ecuación 20:

$$T_{c(t)} = T_{a(t)} + \frac{NOCT - 20}{0.8} \cdot G_{(t)} \qquad (20)$$

Donde T_a es la temperatura ambiente (ºC) y *NOCT* es la temperatura nominal de la celda de funcionamiento (°C).

Los datos de la irradiancia global sobre la superficie fotovoltaica *($G_{(t)}$)* para cada paso de tiempo durante todo el año se pueden medir o se pueden descargar en diferentes sitios web gratuitos de internet, por ejemplo, en pasos de tiempo por hora en PVGIS [130] o renewable Ninja [131]. Estos datos horarios también pueden ser generados por medio del índice de claridad, promedio mensual o con la irradiación promedio mensual sobre superficie horizontal obtenidos de [132]. Cuando se utilizan datos de irradiación promedio mensual, estos se deben transformar en el índice de claridad promedio de cada mes utilizando la ecuación de Rietveld [133], calculando el índice de claridad de cada día. La irradiación horaria global sobre la superficie del generador fotovoltaico se obtiene mediante el método de Graham y Hollands [134], utilizando los modelos de Liu y Jordan [135] o de Hay y Davies [136].

3.2.6. Combustible Diésel

El consumo de combustible del generador diésel FG, $F_{(t)}^{FG}$ en litros hora l/h se puede interpretar mediante una relación lineal de generación de energía [137]. El consumo de combustible en cada paso de tiempo se estima mediante la ecuación 21:

$$F_{(t)}^{FG} = \left(c_1^F \left(\frac{P_{(t)}^{FG}}{1000} \right) + c_2^F \left(\frac{P_{rated}^{FG}}{1000} \right) \right) \Delta t \qquad (21)$$

Donde c_1^F y c_2^F (l/kWh) son los parámetros del consumo de combustible, $P_{(t)}^{FG}$ es la potencia de salida del generador durante un tiempo t (W), P_{rated}^{FG} es la potencia nominal del generador y Δt is the paso de tiempo medido en horas (h).

Skarstein and Uhlen [137] sugirieron c_1^F = 0,246 l/kWh y c_2^F= 0,08415 l/kWh, los cuales son valores apropiados para los generadores diésel. Para generadores de baja potencia a gasolina Dufo-López *et al.* [129] proponen c_1^F = 0,5 l/kWh y c_2^F= 0,2 l/kWh.

La potencia de salida de los generadores debe ser superior al mínimo recomendado por los fabricantes (usualmente un 30% [138]). Para evitar fallas prematuras debido a un mal proceso de combustión; Se puede aplicar una carga ficticia cuando esta se encuentre por debajo del límite inferior [139].

La vida útil de los generadores eléctricos depende de su tecnología y tamaño (1.000 horas para generadores de gasolina de baja potencia y hasta 40.000 horas para generadores diésel de alta potencia). En la simulación de una microrred híbrida, puede ser agregada una penalización por cada arranque del generador (5 minutos por arranque), considerando que con cada arranque se consume ese tiempo de vida extra.

Los costes de operación, mantenimiento y envejecimiento son más altos cuando el generador funciona por debajo de su potencia óptima (50-80% de su potencia nominal) [140]. Durante cada paso de tiempo, se usa un factor multiplicador para obtener el tiempo de operación equivalente que es aplicado a los costes de operación, mantenimiento y vida útil [33]. Los costes de operación y mantenimiento son de 0,1-0,4 €/h.

3.2.7. Datos de los componentes usados en la optimización

Este el caso de la microrred considerada en este trabajo, esta se encuentra localizada en el departamento de la Guajira, zona norte de Colombia, en la comunidad de

Nazareth. El consumo promedio diario es de 30 kWh, estos datos fueron obtenidos de los informes de la referencia [141]. En las tablas 3-8 se muestran los datos de entrada considerados en la simulación de la microrred Nazareth [142].

Tabla 3. Irradiación y velocidad de viento para Nazareth.

Mes	**Irradiación (kWh/m^2/día)**	**Velocidad media del viento(m/s)**
Enero	5,86	7,04
Febrero	6,51	7,24
Marzo	7,02	7,1
Abril	6,92	6,93
Mayo	6,72	6,86
Junio	7	7,64
Julio	7,13	7,39
Agosto	7,17	6,62
Septiembre	6,66	5,7
Octubre	5,99	5,25
Noviembre	5,57	5,75
Diciembre	5,39	6,7

Tabla 4. Módulo fotovoltaico considerado en la optimización (microrred Nazareth).

Parámetros	**Datos**
Potencia nominal	380 Wp
Corriente de cortocircuito (I_{sc})	10,11 A
Temperatura de operación de la celda (NOCT)	47°
Coeficiente de temperatura (α)	−0,37%/°C
Coste de adquisición	220 €
Vida útil	25 años
Emisiones	800 $kgCO_2$/kWp
Angulo de inclinación	15°
Azimuth	0°
Tensión nominal (2 en serie)	24 V
Máximo número permitido	2 en serie/50 en paralelo

Tabla 5. Datos de las turbinas eólicas (microrred Nazareth).

Parámetros	**Modelo 1: WT600**	**Modelo 2: WT3000**
Potencia máxima	660 W	3471 W
Altura del buje	13 m	15 m
Coste de adquisición	4255 €	7555 €
Vida útil	15 años	15 años
Emisiones	600 kgCO2	1800 kgCO2
Coste de operación y mantenimiento (O&M)	85 €/año	50 €/año
Máximo número permitido en paralelo	3	3

Tabla 6. Datos de las baterías (microrred Nazareth).

Parámetros	Plómo-ácido 1 OPZS	Plómo -ácido 2 OPZS	Litio 1 BYD B-Box 5.0	Litio 2 LG Chem
Capacidad	1865 Ah	3360 Ah	106,6 Ah	63 Ah
Coste de adquisición	820 €	1010 €	3390 €	3400 €
Coste de operación y mantenimiento (O&M) una celda)	8,2 €/año	10,1 €/año	20 €/año	30 €/año
Coste de operación y mantenimiento (O&M) (banco completo) *	50 €/ año	50 €/ año	50 €/ año	50 €/ año
Tensión nominal	2 V	2 V	48 V	48 V
Vida flotante 20 °C	20 años	18 años	10 años	10 años
Ciclos equivalentes completos	1500	1600	6000	3200
SOC_{min}	20%	20%	20%	20%
Auto -descarga	3%/ mensual	3%/ mensual	2%/ mensual	2%/ mensual
Número de Baterías en serie	24	24	1	1
Máximo número de baterías en paralelo	6	6	6	6

* Coste de una jornada de mantenimiento

Tabla 7. Datos del generador Diésel (microrred Nazareth).

Parámetros	Datos
Potencia nominal	1,9 kVA
Potencia mínima	30%
Coste de adquisición	800 €
Vida útil	10.000 h
Emisiones	3,5 $kgCO_2$/ud
Coste de operación y mantenimiento O&M	0,14 €/h
Coste de combustible diésel (incluyendo transporte)	1,13 €/l
Máximo número permitido en paralelo	2

Tabla 8. Inversor/Cargador (microrred Nazareth)

Potencia nominal	5 kVA
Eficiencia	90%

Los datos económicos para calcular el valor actual neto (NPC) se resumen en la tabla 9:

Tabla 9. Datos económicos de la microrred Nazareth para el cáculo del NPC.

Parámetros	Datos económicos
Coste de adquisición del banco de baterías	30.960 €
Coste de adquisición de generador fotovoltaico	9.680 €
Vida útil esperada del generador fotovoltaico	25 años
Coste de adquisición del generador diésel	800 €
Vida útil esperada del generador diésel	10.000 h

Coste de adquisición del inversor	2.915 €
Coste de la turbina eólica	4.255 €
Vida útil esperada de la turbina eólica	15 años
Coste de adquisición del controlador	2215 €
Vida útil esperada del inversor	10 años
Vida útil del sistema	25 años
Tasa anual de interés/ tasa de inflación	4%/4%
Costes de instalación	500 €

3.2.8. Resultados

Los resultados de la simulación del sistema actual se resumen en la tabla 10, con baterías de plomo-ácido y tres modelos de envejecimiento de baterías con una temperatura promedio de 27° C. Se observa que con el modelo de Schiffer *et al.* [111] (el modelo más realista), la vida útil de la batería es más corta, y por lo tanto son necesarios más reemplazos a lo largo de la vida útil del sistema (25 años), de tal manera que tanto el NPC y el LCOE son mayores que en los casos donde se predice la duración de las baterías con los otros modelos menos realistas.

Tabla 10. Resultados de la simulación del sistema actual, usando tres modelos de envejecimiento de baterías y una temperatura promedio de 27º C.

Modelo de envejecimiento de la batería	**Duración estimada (años)**	**NPC (€)**	**LCOE (€/kWh)**
Rainflow conteo de ciclos	9,23	98.891	0,36
Ciclos equivalentes completos promedio	9,23	99.061	0,36
Schiffer	7,05	119.458	0,49

En la optimización también se buscará la estrategia de control óptima, entre las dos preseleccionadas por el software iHOGA. Estas estrategias globales son dos:

- Seguimiento de la demanda: En esta estrategia, en sistemas que incluyen baterías y generador ya sea diésel o a gasolina, cuando la energía procedente de las fuentes renovables no es suficiente para cubrir la demanda, el resto de energía la cubrirán las baterías. Si las baterías no pueden cubrir toda la demanda, el generador funcionará para cubrir el resto de la demanda.
- Carga cíclica: Se diferencia de la estrategia anterior en que, en caso de que en un intervalo temporal se requiera que funcione el generador, este funcionará a su potencia nominal, satisfaciendo no solo la demanda sino también

cargando las baterías. Esta estrategia puede tener una variación llamada carga cíclica hasta el "SOC *setpoint*", que significa que el generador seguirá funcionando a su potencia nominal hasta que el banco de baterías alcance un valor específico de estado de carga (SOC), que por defecto es un 95%.

La tabla 11 muestra los resultados para la optimización de la microrred considerando los tres modelos de envejecimiento para baterías de plomo-ácido (modelo de ciclos completos equivalentes, modelo *Rainflow* y modelo de Schiffer *et al.*). Los modelos clásicos como el de los ciclos completos equivalentes y el modelo de *Rainflow* presentan resultados similares, tanto en la vida útil esperada como en el NPC y LCOE. Estos costes son más altos cuando se considera el modelo de envejecimiento de Schiffer *et al.*, que es más realista, ya que al reducir la vida útil de las baterías se requiere más reemplazos durante la vida útil del proyecto, por lo tanto, aumenta el coste total del sistema.

También se observa que usando los modelos de ciclos completos equivalentes y *Rainflow*, la vida útil de la batería es la de la vida flotante ya que se realizan pocos ciclos por año. Existe una reducción en la vida útil de las baterías debido a un aumento de temperatura del 39,2% utilizando la temperatura media real (27 °C en el lugar de instalación) frente al caso de 20 °C (la reducción de la vida flotante es del orden del 50% por cada 8,3 °C de aumento de temperatura [143]). Esta reducción es mucho menor en el caso de utilizar el modelo de Schiffer ya que considera muchos más parámetros, además de la temperatura y los ciclos.

Considerando el modelo más realista (Schiffer *et al.*) a la temperatura media real (27ºC), el mejor sistema estaría compuesto por: generador fotovoltaico (FV) de 31,9 kWp, generador diésel de 1,9 kVA de potencia nominal, aerogeneradores de 66 kW de potencia nominal, baterías de 89.520 kWh de capacidad, inversor de 5 kVA de potencia nominal, con el seguimiento de la demanda como estrategia de control óptima. Los resultados principales son: vida útil de la batería de 5,52 años, NPC de 104.690 € y LCOE de 0,36 €/kWh. Se comparan el resultado del óptimo con el resultado del sistema actual, considerando el modelo de Schiffer *et al.* (tabla 10), donde el NPC es de 119.458 € y el LCOE de 0,49 €/kWh, observando que el sistema actual no es óptimo.

Tabla 11 . Resultados de las optimizaciones del sistema en el caso de baterías de plomo-ácido, utilizando los tres modelos de envejecimiento de baterías (micorred Nazareth).

Modelo de envejecimiento de la batería¹	Temperatura ambiente	Configuración óptima del sistema² (En todos los casos la potencia del generador diésel es = 1,9 kVA, Capacidad del banco de baterías = 89,52 kWh, y una potencia del Inversor= 5 kVA)	Estrategia de control³	Vida útil baterías (años)	NPC (€)	LCOE (€/kWh)
PCCE	20°	12,16 kWp / 0 kW	SD	20	52.544	0,19
PCCE	27°	12,16 kWp / 0 kW	SD	12,31	59.413	0,21
CCR	20°	34,2 kWp / 0 kW	SD	20	52.013	0,19
CCR	27°	33,4 kWp / 0 kW	SD	12,31	59.413	0,21
Schiffer	20°	32,68 kWp / 0 kW	SD	7,73	91.573	0,32
Schiffer	20°	32,68 kWp / 0 kW	CC	7,59	92.195	0,32
Schiffer	20°	32,44 kWp / 0 kW	CC	7,36	92.650	0,32
Schiffer	27°	31,9 kWp / 66 kW	SD	5,52	104.690	0,36
Schiffer	27º	29,64 kWp / 66 kW	CC	5,67	104.730	0,36
Schiffer#	27º	29,64 kWp / 66 kW	CC	5,63	105.307	0,36

¹ Promedio completo de ciclos equivalentes= PCCE. Conteo de ciclos de Rainflow = CCR. Schiffer# = Schiffer sin Seguimiento continuo de SOC setpoint

² Potencia fotovoltaica (kWp) / Potencia turbina eólica (kW)

³ Seguimiento de la demanda = SD. Carga cíclica = CC.

Las optimizaciones resultantes considerando baterías de litio en lugar de baterías de plomo-ácido se muestran en la tabla 12. Se considera que las baterías de litio utilizadas pueden ser LiFePO4/grafito o LiCoO2/grafito. El modelo de Wang *et al.* [119] demostró ser más pesimista respecto a la vida útil de las baterías en comparación con el modelo de Groot *et al.* [120] para incrementos considerables de temperatura, mientras que el modelo utilizado por Saxena *et al.* [121] depende principalmente de los rangos de estados de carga de las baterías .

Se observa en los resultados de la tabla 12 que incluso con el modelo más pesimista, los NPC y LCOE son muy inferiores a los de las optimizaciones de baterías de plomo-ácido utilizando el modelo realista de Schiffer (Tabla 11), concluyendo que las baterías de litio son adecuadas para este caso.

Tabla 12. Resultados de las optimizaciones del sistema en el caso de baterías litio, utilizando los tres modelos de envejecimiento de baterías (micorred Nazareth).

Modelo de envejecimiento de la batería[1]	Temperatura ambiente	Configuración óptima del sistema[2] (En todos los casos la potencia del inversor es = 5 kVA)	Estrategia de control[3]	Vida útil baterías (años)	NPC (€)	LCOE (€/kWh)
Wang	20°	14,44 kWp/1,9 kVA/0 kW/15,35 kWh	SD	10	47.889	0,17
Wang	20°	15,2 kWp/1,9 kVA/0 kW/20,46 kWh	CC	10	52.657	0,18
Wang	27°	14,44 kWp/1,9 kVA/1,66 kW/15,35 kWh	SD	6,15	56.204	0,20
Wang	27°	13,68 kWp/1,9 kVA/1,66 kW/15,35 kWh	CC	6,12	64.796	0,23
Groot	20°	14,44 kWp/1,9 kVA/0 kW/15,35 kWh	SD	10	47.934	0,17
Groot	20°	15,2 kWp/1,9 kVA/0 kW/20,4 kWh	CC	10	52.657	0,19
Groot	27°	14,44 kWp/1,9 kVA/0 kW/15,35 kWh	SD	6,15	56.204	0,20
Groot	27°	15,2 kWp/1,9 kVA/0 kW/ 20,4 kWh	CC	6,15	63.747	0,23
Saxena	20°	13,68 kWp/1,9 kVA/0 kW/15,35 kWh	SD	3	78.427	0,29
Saxena	27°	19 kWp/1,9 kVA/3,32 kW/15,35 kWh	SD	3,03	84.742	0,22
PCCE	20°	20,52 kWp/1,9 kVA/1,66 kW/10,2 kWh	SD	10	54.216	0,19
PCCE	27°	13,68 kWp/3,8 kVA/3,32 kW/5,1 kWh	SD	6,15	58.216	0,20
PCCE	27°	15,2 kWp/1,9 kVA/0 kW/20.4 kWh	CC	6,15	63.747	0,23
CCR	20º	14,44 kWp/1,9 kVA/0 kW/15.3 kWh	SD	9,88	48.455	0,18
CCR	20º	15,2 kWp/1,9 kVA/0 kW/20.4 kWh	CC	9,88	53.461	0,19
CCR	27º	14,44 kWp/3,8 kVA/3,32 kW/5.1 kWh	SD	6,15	57.162	0,2

[1] Promedio completo de ciclos equivalentes= PCCE. Conteo de ciclos de Rainflow = CCR. Schiffer# = Schiffer sin seguimiento continuo de SOC setpoint

[2] Potencia del generador fotovoltaico (kWp) / Potencia del generador diésel (kVA)/ Potencia turbina eólica (kW)/Capacidad del banco de baterías(kWh)

[3] Seguimiento de la demanda = SD. Carga cíclica = CC.

La Figura 6 muestra la distribución anual de la energía generada en este caso por el sistema durante un año. El porcentaje de energía generada por renovables es del 96,81%. De la generación renovable, 9.703 kWh/año son suministrados por el generador fotovoltaico, 6.705 kWh/año por aerogeneradores, mientras que un menor aporte lo realiza el generador diésel de 541 kWh/año. El exceso de energía fue de 3.496 kWh / año (parte de la energía generada por las fuentes renovables que sobra puesto que se genera en períodos en que el consumo ya está cubierto y las baterías cargadas al 100%).

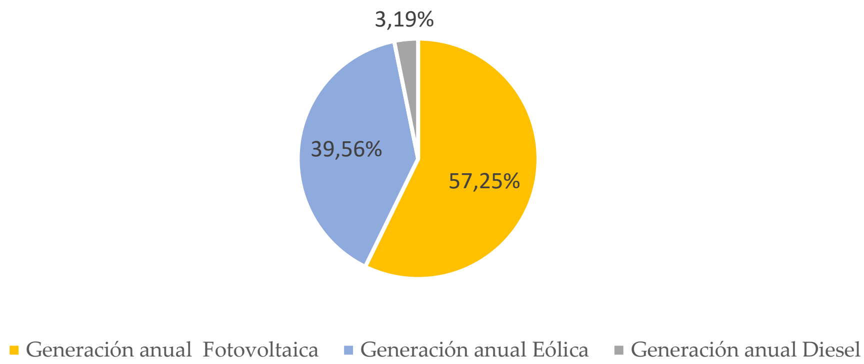

Figura 6. Distribución de energía anual (micorred Nazareth).

3.3 Conclusiones

En este trabajo se han comparado diferentes modelos y tecnologías de baterías en la optimización de una microrred híbrida. Los modelos clásicos de envejecimiento de baterías de plomo-ácido utilizados por diferentes investigadores, como el modelo de ciclos completos equivalentes y el modelo de conteo de ciclos *Rainflow*, generalmente tienden a sobreestimar la vida útil de la batería hasta 3 veces su duración actual. Sin embargo, el modelo de ciclos ponderados de Schiffer *et al*. [111], que tiene en cuenta las condiciones reales de operación de las baterías, ha demostrado tener mejores resultados ya que sus predicciones son más cercanas a las reales. Los resultados de las diferentes optimizaciones muestran que se obtienen menores costes de valor actual neto (NPC) y menores costes normalizados de energía (LCOE) para los modelos de baterías de plomo-ácido y de litio; por tanto, se concluye que el sistema actual no está optimizado.

En cuanto a las baterías de ferrofosfato de litio $LiFePO_4$/grafito, el modelo de envejecimiento de Wang *et al*. presenta resultados más pesimistas en cuanto a la duración de la batería que el de Groot *et al*, ante aumentos importantes de temperatura. Por otro lado, el modelo de Saxena *et al*., se basa principalmente en los estados de carga de la batería (SOC). Finalmente, comparando las dos tecnologías (plomo-ácido vs. litio), los resultados muestran menores costes para el caso del litio tanto en NPC como en LCOE (en comparación con el modelo realista de Schiffer para plomo-ácido), lo que permite tener una visión más optimista sobre el conocimiento y la exploración de nuevos modelos de envejecimiento para tecnologías emergentes como las baterías de litio, ya que pueden representar una alternativa para su incorporación en microrredes híbridas.

Como resultados más relevantes de este trabajo tenemos:

- El óptimo dimensionamiento y gestión de los elementos que componen una microrred dan lugar a importantes beneficios energéticos y económicos.
- Los modelos clásicos para estimar la duración de la batería proporcionan resultados demasiado optimistas, por lo que es recomendable utilizar modelos más realistas.
- El efecto de la temperatura en la estimación de la vida útil de la batería puede ser significativo, por lo que los modelos precisos deben considerar este parámetro.
- Las baterías de iones de litio pueden ser adecuadas como sistemas de almacenamiento en una microrred, ya que pueden dar lugar a un menor coste a lo largo de la vida de la instalación debido a que su vida útil es más larga que las baterías de plomo-ácido y a su menor coste de mantenimiento.

4. Optimización y viabilidad de una microrred híbrida aislada fotovoltaica-diésel considerando la tecnología de la batería.

Dentro de la zona no interconectada (ZNI) de Colombia se encuentran algunas islas localizadas en la zona norte del país. Esta zona tiene un servicio de energía deficiente soportado en muchas localidades principalmente con generadores diésel. Algunas localizaciones pertenecientes a esta zona corresponden a territorios insulares, entre ellas se encuentra la isla de Múcura que pertenece al distrito de Cartagena, esta localidad actualmente dispone de un sistema híbrido Diésel-Fotovoltaico-baterías, el cual recientemente ha incorporado el uso de paneles solares, pero el sistema en conjunto no funciona de manera óptima y mucho menos optimizada.

En este trabajo se dimensionó y optimizó una microrred híbrida compuesta por generador diésel, generador fotovoltaico y almacenamiento con baterías para el suministro de energía en la isla Múcura. En la simulación y optimización se consideraron baterías de plomo-ácido y litio combinadas con la estrategia de desplazamiento de consumos. Este trabajo se presentó en [113].

4.1 Objetivos y metodología

Los objetivos planteados en este trabajo fueron:

1. Diseñar y optimizar un sistema óptimo híbrido Diésel-fotovoltaico para la isla de Múcura.
2. Optimizar la microrred considerando las tecnologías de las baterías y el desplazamiento de consumos.

   La metodología empleada fue:

1. Revisión bibliográfica de optimización de microrredes híbridas Diésel-fotovoltaico.
2. Identificación y localización de la microrred propuesta.
3. Obtención del perfil de consumo y de los datos meteorológicos de la microrred.
4. Simulación y optimización de la microrred mediante el programa iHOGA.

5. Evaluación técnico-económica de la microrred considerando el desplazamiento de consumos.

4.2 Revisión bibliográfica y principales aportaciones

La integración de microrredes es uno de los desafíos que tienen países como Colombia donde cerca del 52 % del territorio se encuentra en la llamada zona no interconectada (ZNI). En esta región el suministro de energía aún sigue siendo deficiente, en algunos poblados el promedio de servicio se encuentra inclusive por debajo de las 6 horas al día. Estas localidades se encuentran por lo general en zonas de difícil acceso, lo que prácticamente las condiciona a no tener conexión al sistema interconectado [144]. Sin embargo, la localización de la mayoría de estos poblados es en zonas con abundante recurso solar y viento, biomasa, ríos, etc, siendo esta la hoja de ruta para la integración de estos recursos a través de microrredes híbridas aisladas integradas con energías renovables [145].

En la actualidad la electrificación para estas localidades básicamente se desarrolla a través de tres soluciones energéticas principalmente: sistemas fotovoltaicos individuales, microrredes con grupos diésel y microrredes híbridas [146].

En las microrredes híbridas aisladas las baterías representan uno de los principales costes de todo el sistema, esto hace que su dimensionamiento y la estimación de su duración sea un desafío importante [22]. Algunos estudios recientes han analizado la electrificación de zonas remotas utilizando sistemas híbridos ([80], [147]), considerando principalmente los costes de degradación de las baterías. Otros estudios se enfocan a la optimización de la microrred teniendo en cuenta modelos de envejecimiento de las baterías de plomo-ácido y litio [116].

En el caso de isla Múcura, actualmente cuenta con 43 usuarios registrados [148], cuya actividad económica principal es la pesca y el turismo. Sin embargo, en la actualidad esta localidad tiene problemas de acceso al agua potable. En cuanto al suministro de energía, esta localidad actualmente dispone de una instalación híbrida descrita en la tabla 13:

Tabla 13. Estado actual del sumistro de energía en Múcura.

Promedio anual de consumo de electricidad	Factor de potencia	Capacidad instalada	Promedio de servicio de electricidad (h/día)
322 kWh	0,92	Diésel 116 kW Fotovoltaica 30 kW Baterías 480 kWh[1]	11,45

[1] 96 Baterías 2500 Ah/2 V

4.2.1. Datos de entrada de los componentes usados en la optimización

Los datos de entrada de los componentes utilizados en la microrred Múcura se describen en las tablas 14-17.

Tabla 14. Datos de los módulos fotovoltaicos (microrred Múcura).

Parámetros	Datos
Potencia nominal	380 Wp
Corriente de cortocircuito (I_{sc})	10,11 A
Temperatura de operación de la celda (NOCT)	47°
Coeficiente de temperatura (α)	−0,37%/°C
Coste de adquisición	220 €
Vida útil	25 años
Emisiones	800 kgCO_2/kWp
Angulo de inclinación	10°
Azimuth	0°
Tensión nominal (2 en serie)	24 V
Máximo número permitido	2 en serie/13 en paralelo

Tabla 15. Datos de las baterías (microrred Múcura).

Parámetros	Plómo- ácido 1 OPZS	Plómo -ácido 2 OPZS	Litio 1 BYD B-Box 5.0	Litio 2 BYD B-Box 7.5
Capacidad	546 Ah	3.500 Ah	106,6 Ah	160 Ah
Coste de adquisición	216 €	1.457 €	3.390 €	4.700 €
Coste de operación y mantenimiento (O&M) una celda)	2,16 €/año	14,57 €/año	20 €/año	20 €/año
Coste de operación y mantenimiento (O&M) (banco completo) *	50 €/ año	50 €/ año	50 €/ año	50 €/ año
Tensión nominal	2 V	2 V	48 V	48 V
Vida flotante 20 °C	15 años	15 años	10 años	10 años
Ciclos equivalentes completos	1.500	1.600	6.000	6.000
SOCmin	20%	20%	20%	20%
Auto -descarga	3%/ mensual	3%/ mensual	2%/ mensual	2%/ mensual
Número de baterías en serie	150	150	7	7
Máximo número de baterías en paralelo	3	3	51	51

Tabla 16. Datos de los generadores diésel (microrred Múcura).

Parámetros	Datos	
Potencia nominal	82 kVA	150 kVA
Potencia mínima	30%	30%
Coste de adquisición	14.000 €	18.000 €
Vida útil	30.000 h	30.000 h
Emisiones	3,5 kgCO2/ año	3,5 kgCO2/ año
Coste de operación y mantenimiento	0,42 €/año	0,52 €/año
Coste de combustible (incluido el transporte	0,8 €/l	0,8 €/l
Máximo número permitido en paralelo	2	2

Tabla 17. Datos del inversor/cargador (microrred Múcura).

Parámetros	Datos	
Potencia nominal	30 kVA	50 kVA
Eficiencia	90%	90%
Coste de adquisición	38.240 €	42.940 €
Vida útil	10 años	10 años
Coste de operación y mantenimiento	0,42 €/año	0,52 €/año
Coste de combustible (incluido el transporte)	0,8 €/l	0,8 €/l
Máximo número permitido en paralelo	2	2

La simulación de la microrred actual sin optimizar se presenta en la tabla 18: se ha usado el modelo de envejecimiento de Schiffer *et al.* y una temperatura media de 27,5° [132].

Tabla 18. Simulación de la microrred Múcura.

Modelo de envejecimiento de la batería	Vida útil (años)	NPC (€)	LCOE
Schiffer et al.	0,8	3.407.944	1,16

El consumo para la localidad se muestra en la figura 7 basado en datos del [148], donde se observa la curva de consumo actual y la modificada haciendo coincidir los consumos con las horas más altas de irradiación.

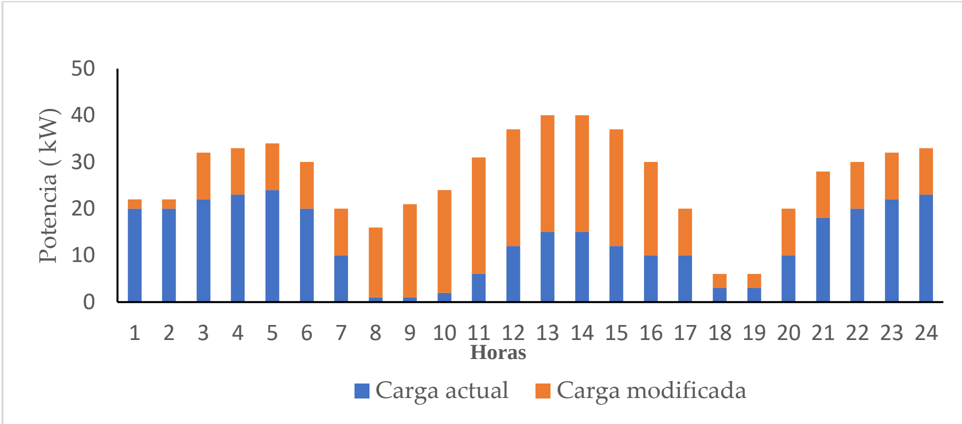

Figura 7. Perfil de consumo diario microrred Múcura.

4.2.2. Resultados

El sistema fue simulado y optimizado mediante el software iHOGA 2.5. La configuración usada para la microrred Múcura es mostrada en la figura 8, y los resultados de los sistemas óptimos, tanto para baterías de plomo-ácido como de litio incluyendo desplazamiento de consumos, son presentados en las tablas 19-22. Para esta simulación se optó por la estrategia de control de carga cíclica mencionada en el capítulo 3 y los modelos de envejecimiento Schiffer *et al.* para baterías de plomo-ácido [111] y e l modelo de Wang *et al.* para baterías de litio [119].

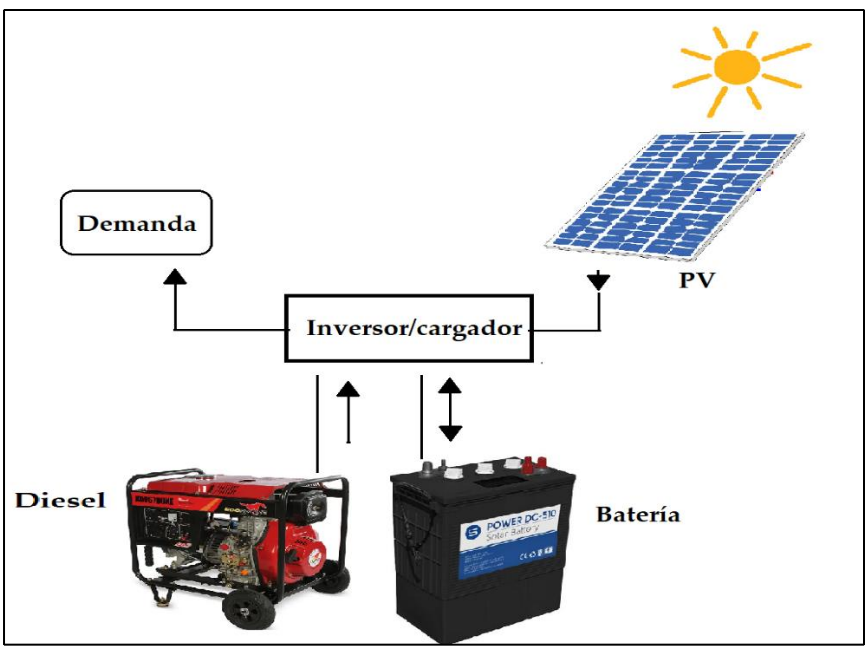

Figura 8. Sistema híbrido aislado microrred Múcura.

Tabla 19. Resultados de optimización para la microrred Múcura (considerando baterías de plomo-ácido y el perfil de carga actual).

Tipo de optimización	Configuración óptima del sistema (En todos los casos la potencia del inversor es = 30 kVA)[1]	Estrategia de control[2]	Vida útil batería (años)	Emisiones (kgCO2/año)	NPC (€)	LCOE (€/kWh)
Mono-objetivo	192,66 kWp/30 kVA/327,6 kWh	SD	4,51	76.778	1.041.148	0,35
	281,58 kWp/30 kVA/1000,8 kWh	CC	7,57	63.831	1.242.545	0,42
Multi-objetivo	192 kWp/30 kVA/327,6 kWh	SD	4,52	76.742	1.041.148	0,35
	291,46 kWp/30 kVA/1000,8 kWh	CC	7,55	63.264	1.414.566	0,42

[1] Potencia generador fotovoltaico (kWp)/ Potencia del generador diésel (kVA)/ Capacidad del banco de baterías (kWh)

[2] Seguimiento de la demanda = SD. Carga cíclica = CC

Tabla 20. Resultados de optimización para la microrred Múcura (considerando baterías de plomo-ácido y el desplazamiento de consumos).

Tipo de optimización	Configuración óptima del sistema (En todos los casos la potencia del inversor es = 50 kVA)[1]	Estrategia de control[2]	Vida útil batería (años)	Emisiones (kgCO2/año)	NPC (€)	LCOE (€/kWh)
Mono-objetivo	187.7 kWp/82 kVA/327,6 kWh	SD	4,23	11.102	563.168	0,19
	192,6 kWp/82 kVA/327,6 kWh	CC	4,2	11.016	565.880	0,19
Multi-objetivo	187,7 kWp/82 kVA/327,6 kWh	SD	4,26	11.126	561.228	0,19
	187,7 kWp/82 kVA/327,6 kWh	CC	4,26	11.543	564.297	0,19

[1] Potencia generador fotovoltaico (kWp)/ Potencia del generador diésel (kVA)/ Capacidad del banco de baterías (kWh)

[2] Seguimiento de la demanda = SD. Carga cíclica = CC

Tabla 21. Resultados de optimización para la microrred Múcura (considerando baterías de litio y el perfil de carga actual).

Tipo de optimización	Configuración óptima del sistema (En todos los casos la potencia del inversor es = 30 kVA)[1]	Estrategia de control[2]	Vida útil batería (años)	Emisiones (kgCO2/año)	NPC (€)	LCOE (€/kWh)
Mono-objetivo	79,04 kWp/82 kVA/96 kWh	SD	5,56	136.315	1.421.978	0,48
	83,98 kWp/82 kVA/96 kWh	CC	4,75	131.625	1.403.436	0,48
Multi-objetivo	79,04 kWp/82 kVA/96 kWh	SD	5,72	136.016	1.426.620	0,48
	79,04 kWp/82 kVA/96 kWh	CC	4,89	130.449	1.399.265	0,48

[1] Potencia generador fotovoltaico (kWp)/ Potencia del generador diésel (kVA)/ Capacidad del banco de baterías (kWh)

[2] Seguimiento de la demanda = SD. Carga cíclica = CC

Tabla 22. Resultados de optimización para la microrred Múcura (considerando baterías de litio y el desplazamiento de consumos).

Tipo de optimización	Configuración óptima del sistema (En todos los casos la potencia del inversor es = 50 kVA)[1]	Estrategia de control[2]	Vida útil batería (años)	Emisiones (kgCO2/año)	NPC (€)	LCOE (€/kWh)
Mono-objetivo	202,54 kWp/82 kVA/192 kWh	SD	6,08	43.182	969.041	0,33
	202,54 kWp/82 kVA/63,9 kWh	CC	5,02	91.925	1.105.344	0,38
Multi-objetivo	128,44 kWp/82 kVA/144 kWh	SD	5,73	57.269	1.003.063	0,39
	128,4 kWp/82 kVA/144 kWh	CC	5,77	88.857	1.193.716	0,41

[1] Potencia generador fotovoltaico (kWp)/ Potencia del generador diésel (kVA)/ Capacidad del banco de baterías (kWh)

[2] Seguimiento de la demanda = SD. Carga cíclica = CC

El desplazamiento de consumos es una técnica de gestión de la demanda que busca reducir los costes operativos de la microrred trasladando el consumo a las horas de máxima irradiación y reduciendo el aporte de los generadores diésel en la generación de energía, reduciendo así costes del sistema y combustible [149]. En la figura 9 se muestran los costes de la energía obtenidos con la optimización, los LCOE más bajos se obtienen usando desplazamiento de consumos.

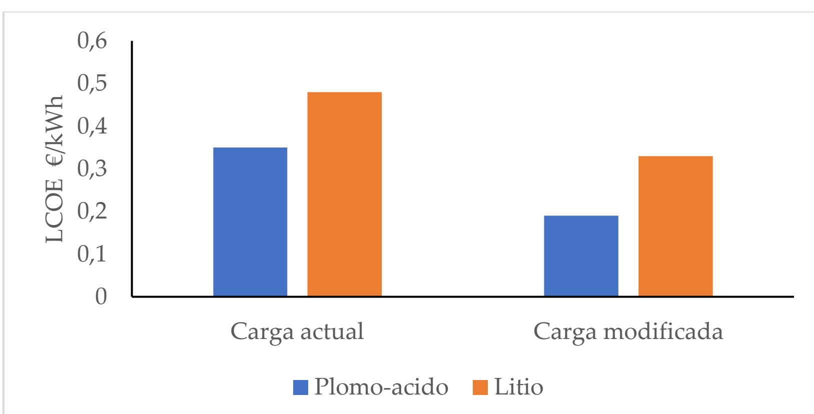

Figura 9. Coste normalizado de energía (LCOE) microrred Múcura.

En la figura 10 se observan los costes actuales netos (NPC) para la carga actual y la carga modificada, donde se logra una reducción significativa cuando se desplazan consumos para ambos tipos de baterías. Esta disminución se acerca al 46% en el caso de las baterías de plomo-ácido y al 32% en las baterías de litio.

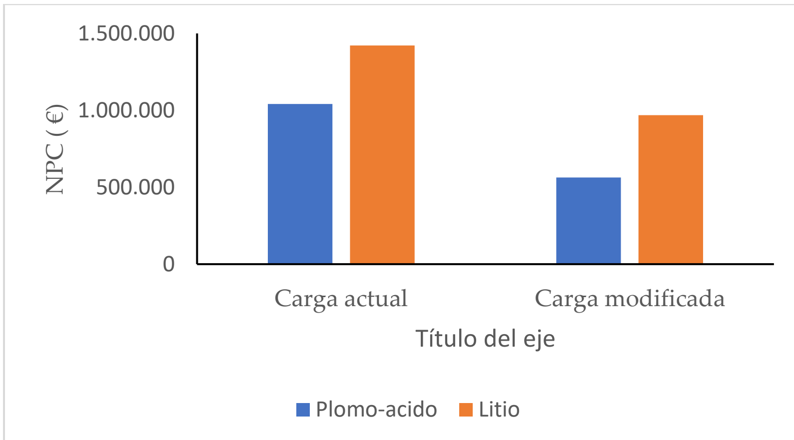

Figura 10. Coste actual neto (NPC) microrred Múcura.

El nivel de emisiones también tuvo un descenso significativo como se puede apreciar en la figura 11, un 85% menos de emisiones para el caso de baterías de plomo-ácido y un 68% para baterías de litio.

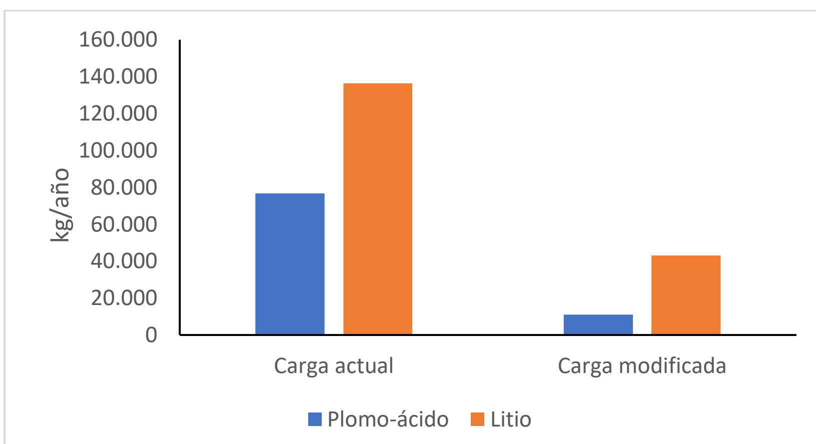

Figura 11. Emisiones CO_2 microrred Múcura.

4.3 Conclusiones

En este artículo se presentó la optimización de una microrred aislada basada en Fotovoltaica-Diésel-Baterías para la isla Múcura en Colombia. El principal aporte de este trabajo es que se ha estudiado la viabilidad de este sistema teniendo en cuenta los datos de consumo real, los recursos renovables y los costes de todos los componentes durante la vida del proyecto. Los resultados de la simulación muestran que es posible reducir los costes operativos de una microrred reduciendo el uso de combustible diésel, haciendo un uso óptimo de las energías renovables locales y garantizando el suministro de energía durante todo el año.

Debido al alto potencial de la energía solar en la zona geográfica donde se localiza la isla de Múcura, se verifica que el desplazamiento de consumos es una técnica viable que permite reducir tanto los costes como las emisiones medias. Los resultados de la simulación presentan una reducción promedio del 40% en el LCOE, 35% en el NPC y 80% en las emisiones para cualquiera de las tecnologías de baterías.

Como trabajo futuro se deja abierta la posibilidad de explotar otro tipo de energías renovables para integrarlos en la microrred, dentro de este tipo de energía se encuentra la mareomotriz debido al potencial que se tiene en la zona.

5. Factibilidad Tecno-económica en microrredes aisladas con energías renovables en la zona no interconectada de Colombia (ZNI)

En este trabajo se estudió la factibilidad desde el punto vista tecno-económico de 6 microrredes de la ZNI de Colombia. Estas microrredes se localizan en diferentes puntos geográficos, tienen diferentes condiciones climáticas y disponibilidad de recursos renovables. Actualmente 2 de estas 6 microrredes combinan grupos electrógenos como diésel y energía solar fotovoltaica. En las demás se dimensionaron y optimizaron los sistemas de acuerdo con la disponibilidad de recursos locales y se usaron diferentes perfiles reales de consumo tanto actuales como desplazados en el tiempo. Este trabajo fue publicado como artículo en la revista Energies el 23 de Noviembre de 2020 [150].

5.1 Objetivos y Metodología

Los objetivos planteados en este trabajo fueron:

1. Diseñar y dimensionar 6 microrredes aisladas.
2. Optimizar 6 microrredes aisladas con almacenamiento mediante baterías.
3. Evaluar técnica y económicamente las microrredes teniendo en cuenta los modelos de baterías de plomo-ácido y litio.
4. Evaluar y comparar las microrredes usando como estrategia el desplazamiento de consumos.

La metodología usada fue:

1. Localización y caracterización de 6 diferentes microrredes aisladas ubicadas en la zona no interconectada de Colombia.
2. Obtención de curvas de consumo para cada microrred.
3. Modelado y optimización de las microrredes mediante el software iHOGA,

improved Hybrid Optimization by Genetic Algorithms

5. Utilización de curvas de consumo diarias desplazadas en el tiempo.
6. Comparación de sistemas optimizados con curvas de consumo actuales y desplazadas en el tiempo.

5.2 Revisión bibliográfica y principales aportaciones

En Colombia, como en el resto de los países de América Latina, el acceso a la electricidad en zonas remotas es muy limitado debido a la falta de infraestructura necesaria para llevar la electricidad a estos lugares y debido a las precarias condiciones económicas de los potenciales usuarios, por lo que no es rentable para las empresas eléctricas invertir en estas áreas. En la denominada zona no interconectada (ZNI), que corresponde al 52% del territorio de Colombia, aproximadamente el 92% de la energía eléctrica es generada por generadores diésel, y el resto es generado por pequeñas centrales hidroeléctricas. En estas zonas, la población vive en lugares de difícil acceso, lo que eleva el precio del combustible (diésel), se emiten gases contaminantes y generan contaminación acústica [151], por lo que este sistema de generación no es el más recomendable [152]. Además de este suministro eléctrico insuficiente y limitado, no se han mejorado ni utilizado los recursos energéticos autónomos, lo que ha provocado un pobre desarrollo social y económico de la población de estas zonas.

El Gobierno de Colombia, mediante la Ley 697 de 2001, estableció que el uso racional de la energía era una cuestión de carácter social y de interés nacional. La Ley 1715 de 2014 [153] propugnó el uso de fuentes no convencionales para la generación de energía. Programas como PROURE [154] (Programa de Uso Racional y Eficiente de Energía y fuentes de energía no convencionales) promovieron la financiación de proyectos de generación de energía en la ZNI. Todas estas iniciativas tienen el objetivo de fomentar la generación distribuida y las microrredes, ya que permiten generar y suministrar electricidad cerca de los lugares donde se consume.

La optimización de las microrredes aisladas depende principalmente del coste y la vida útil de las baterías. Existen varios estudios centrados en el análisis técnico y económico de sistemas que utilizan baterías de plomo-ácido [97], ya que esta es la tecnología más utilizada en estos sistemas. Otros estudios se centran en el análisis tecno-económico de microrredes en zonas rurales, como el realizado por López-González *et al.* [155], donde se proponen 13 microrredes para áreas remotas en Venezuela, incluyendo sistemas de generación FV-eólica con baterías de plomo-ácido.

En el caso de Colombia, un estudio reciente realizó un análisis tecno-económico de sistemas fotovoltaicos [156] para una localidad perteneciente a la ZNI de Colombia. En otro estudio, Guacaneme *et al.* [157] presentaron varias soluciones utilizando microrredes para áreas rurales de Colombia.

Considerando todos estos trabajos previos, se puede afirmar que es necesario realizar más estudios para determinar las características que deben tener las microrredes aisladas en los países en desarrollo como Colombia. Así será posible estudiar su comportamiento desde un punto de vista técnico, económico y ambiental en las condiciones climáticas actuales y en situaciones en las que ocurren cambios en el consumo, determinando el coste actual neto (NPC) del sistema, el coste nivelado de energía (LCOE) y el nivel de emisiones.

Teniendo en cuenta todos estos estudios previos, se realizó este estudio considerando 6 microrredes aisladas, teniendo en cuenta diferentes localizaciones, diferentes tamaños y perfiles de consumo, así como disponibilidad de recursos renovables. Como primer criterio para la selección de microrredes, se tuvo en cuenta la disponibilidad de recursos renovables. Los datos de entrada para la optimización corresponden a los datos de irradiación y velocidad del viento para cada ubicación [158]. El modelado y la simulación se realizaron considerando sistemas de almacenamiento basados en baterías de litio y plomo-ácido. Las simulaciones resultantes proporcionan el coste óptimo del sistema, los niveles de emisiones, el coste de la electricidad y la vida útil de la batería.

Las microrredes consideradas se muestran en la figura 12, la mayor parte de la demanda energética de estas comunidades corresponde a iluminación, pequeños electrodomésticos y equipos de refrigeración. La demanda de energía durante las horas del día es baja porque las principales actividades en estas comunidades son la agricultura y la pesca, que naturalmente se realiza fuera del hogar[159]. Para la preparación de comidas se utiliza principalmente leña y, en algunos casos, gas propano líquido (GLP) [160].

Figura 12. Localización geográfica de las 6 microrredes.

La tabla 23 muestra la situación actual de la demanda de energía y los sistemas de generación de las 6 localidades. En el caso de Providencia se seleccionó el consumo promedio de una vivienda aislada y en el caso de Puerto Estrella se consideró el consumo de 20 viviendas y no se incluyó la generación eólica porque los aerogeneradores actualmente instalados no estaban en servicio.

Tabla 23 . Estado actual de los sistemas de generación para las 6 microrredes.

Localización	Consumo (kWh/día)	Factor de potencia	Fuente de Generación	Capacidad instalada (kW)	Promedio diario de servicio de electricidad (h)
Titumate	245	0,92	Diésel/Fotovoltaico	250	6,2
Tarapacá	890	0,93	Diésel	280	10,3
Santa Rosa	105	0,97	Diésel	175	1,5
Guacamayas	394	0,89	Diésel/PCH	150	20,2
Puerto Estrella [1]	52	0,90	Diésel/Fotovoltaico/Baterías	425	7,3
Providencia [2]	6	0,95	Diésel	4300	24

[1] Promedio de electricidad para 20 viviendas, [2] Promedio de electricidad para 1 vivienda

La Figura 13 muestra 2 de los sistemas optimizados en este trabajo y que actualmente operan como sistemas híbridos en las localidades de Titumate y Puerto Estrella.

Figura 13. Fotografías de Titumate (izquierda) y Puerto estrella (derecha).

Para las 6 ubicaciones, se simularon los sistemas actuales. En los seis casos, teniendo en cuenta que la generación de energía se lleva a cabo básicamente por generadores diésel, se podrían esperar altos costes de generación, sin embargo, se obtuvo un LCOE muy bajo en la localidad de Guacamayas porque en este caso, además de la generación de diésel, hay una pequeña central hidroeléctrica (PCH). La tabla 24 muestra un resumen de los resultados de la simulación de los sistemas actuales.

Tabla 24. Simulación de los sistemas de generación actual para las 6 microrredes.

Localización	(NPC) (€)	Emisiones $kgCO_2$/año	(LCOE) (€/kWh)
Titumate	2.963.765	414.571	1,32
Tarapacá	5.542.385	564.205	0,68
Santa Rosa	1.409.383	121.216	1,46
Guacamayas	106.506	9.098	0,03
Puerto Estrella	361.235	33.741	0,77
Providencia	156.015	9.491	2,85

5.2.1. Datos de entrada de las optimizaciones

Los datos de entrada para las simulaciones se resumen en las tablas 25-29, Para los generadores diésel y las turbinas eólicas se usaron modelos de [40]. Por su parte para las baterías de plomo-ácido se utilizó el modelo de Schiffer *et al.* [111], mientras que para baterías de litio el modelo de Wang *et al* [119]. Los cálculos del ciclo de vida de las emisiones se basaron en la referencia[129], para las tasas de inflación e interés se obtuvieron datos de [161].

Tabla 25. Datos de los módulos fotovoltaicos.

Parámetros	Datos
Potencia nominal	380 Wp
Corriente de cortocircuito (Isc)	10,11 A
Temperatura de operación de la celda (NOCT)	47°
Coeficiente de temperatura (α)	−0,37%/°C
Coste de adquisición	220 €
Vida útil	25 años
Emisiones	800 kgCO2/kWp
Angulo de inclinación	10°
Azimuth	0°
Tensión nominal (2 en serie)	24 V
Máximo número permitido	2 en serie/13 en paralelo

Tabla 26. Datos de las turbinas eólicas usadas en la optimización.

Parámetros	Modelo 1: WT600	Modelo 2: WT1500	Modelo 3 WT3000
Potencia máxima	660 W	1.660 W	3.471 W
Altura de buje	13 m	15 m	15 m
Coste de adquisición	4.255 €	4.875 €	7.555 €
Vida útil	15 años	15 años	15 años
Emisiones	600 kgCO2	900 kgCO2	1800 kgCO2
Costes de operación y mantenimiento	85 €/año	98 €/año	150 €/año

Tabla 27. Baterías consideradas en la optimización.

Parámetros	**Plomo-ácido 1**	**Plomo-ácido 2**	**Plomo-ácido 3**	**Litio 1**	**Litio 2**	**Litio 3**
	OPZS	**OPZS**	**OPZS**	**BYD B-Box 5.0**	**BYD B-Box 7.5**	**BYD B-Box 10**
Capacidad	162 Ah	546 Ah	3500 Ah	106,6 Ah	160 Ah	213 Ah
Coste de adquisición	110 €	216 €	1.457 €	3.390 €	4.700 €	6.400 €
Coste de operación y mantenimiento Una celda	1,1 €/año	2,16 €/año	14,57 €	20 €/year	20 €/year	40 €/year
Tensión nominal	2 V	2 V	2 V	48 V	48 V	48 V
Vida flotante a 20 ◦C	15 años	15 años	15 años	10 años	10 años	10 años
Ciclos equivalentes completos	1.600	1.600	1.600	6.000	6.000	6.000
SOCmin	20%	20%	20%	10%	10%	10%
Auto descarga	2%/mensual	2%/ mensual	2%/ mensual	2%/ mensual	2%/ mensual	2%/ mensual
N° de baterías en serie para una tensión de 300 V DC	150	150	150	7	7	7
N° de baterías en seria para una tensión de 48 V DC	24	24	24	1	1	1

Tabla 28. Generadores diésel considerados en la optimización.

Parámetros	Datos				
Potencia nominal	1.9 kVA	3 kVA	31 kVA	82 kVA	150 kVA
Potencia mínima	30%	30%	30%	30%	30%
Coste de adquisición	800 €	1.050 €	8.850 €	14.000 €	18.000 €
Vida útil	10.000 h	10.000 h	20.000 h	30.000 h	30.000 h
Coste de operación y mantenimiento	0,14 €/h	0,17 €/h	0,35 €/h	0,42 €/h	0,52 €/h
Coste del diésel (incluyendo transporte)	0,8 €/l	0,8 €/l	0,8 €/l	0,8 €/l	0,8 €/l
Máximo número permitido de generadores en paralelo	2	2	2	2	2

Tabla 29. Inversores/cargadores considerados en la optimización.

Potencia nominal	0,9 kVA	8 kVA	50 kVA	100 kVA	150 kVA
Eficiencia	90%	90%	90%	90%	90%
Coste de adquisición	800 €	3.840 €	38.000 €	55.000 €	65.000 €
Vida útil	10 años	10 años	10 años	10 años	10 años

5.2.2. Resultados

La microrred aislada más adecuada para la demanda energética de la población de Titumate correspondió a una combinación de FV-Diésel-Batería. La Figura 14 muestra la curva de carga diaria para esta ubicación considerando la carga actual y la carga modificada con gestión de la demanda. La carga modificada se obtuvo cambiando el tiempo de algunos de los consumos, para coincidir con las horas de alta irradiación.

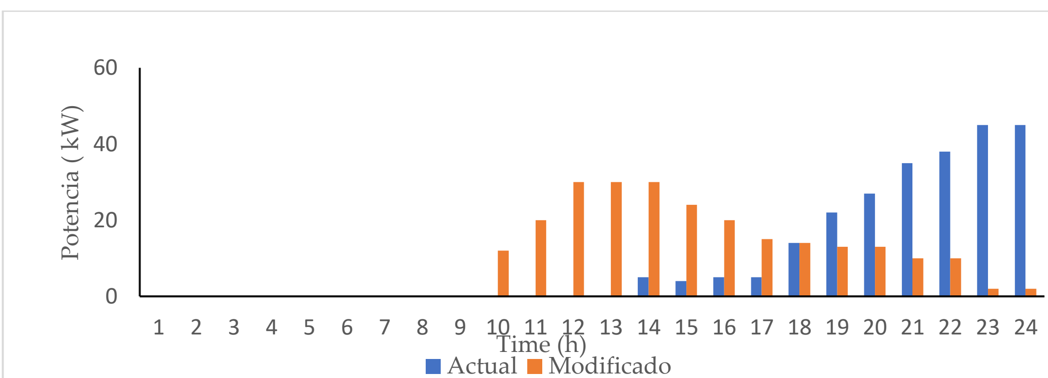

Figura 14. Perfil de consumo diario Titumate.

Los resultados se muestran en la tabla 30, donde se observa una reducción considerable del NPC en sistemas con baterías de plomo-ácido (52%) y en sistemas que usan baterías de litio (56%). De manera similar, el coste de producción de cada kWh se reduce en un 75-90% en comparación con el sistema actual mostrado en la tabla 24.

Tabla 30. Optimización para Titumate (Temperatura ambiente promedio de 27 °C).

En todos los casos la potencia del generador diésel = 31 kVA									
Perfil de Consumo	**Estrategia de control[1]**	**Potencia del generador fotovoltaico (kWp)**	**Tipo de Batería**	**Capacidad del banco de baterías (kWh)**	**Inversor (kVA)**	**Tiempo de vida da la batería (años)**	**NPC (€)**	**Emisiones (kgCO2/yr)**	**LCOE (€/kWh)**
Actual	SD	153	Plomo-ácido	491	100	3,38	792.873	20.713	0,35
	CC	133,4	Plomo-ácido	491,4	100	4,1	861.882	30.244	0,39
	SD	143,2	Litio	288	100	6,08	830.833	7.187	0,37
	CC	143,2	Litio	288	100	6,08	830.833	7.574	0,37
Modificado	SD	138,32	Plomo-ácido	163,8	50	4,3	357.241	8.015	0,16
	CC	138,32	Plomo-ácido	163,8	50	4,25	367.657	9.783	0,16
	SD	138,2	Litio	63,39	50	6,08	361.712	6.761	0,16
	CC	138.32	Litio	96	50	6,08	403.540	5.058	0,18

[1] SD = seguimiento de la demanda. CC = carga ciclica

Se ha seleccionado el caso de la microrred de Titumate, en la figura 15 se muestra la simulación del resultado óptimo para los primeros 4 días del año de esta localidad, considerando los casos de carga actual y de carga modificada. Se observa como el SOC del banco de baterías aumenta al utilizar el perfil de carga modificado, permaneciendo prácticamente por encima del 60%. Esto puede extender la vida útil de las baterías y simultáneamente reducir el tiempo de operación del generador diésel.

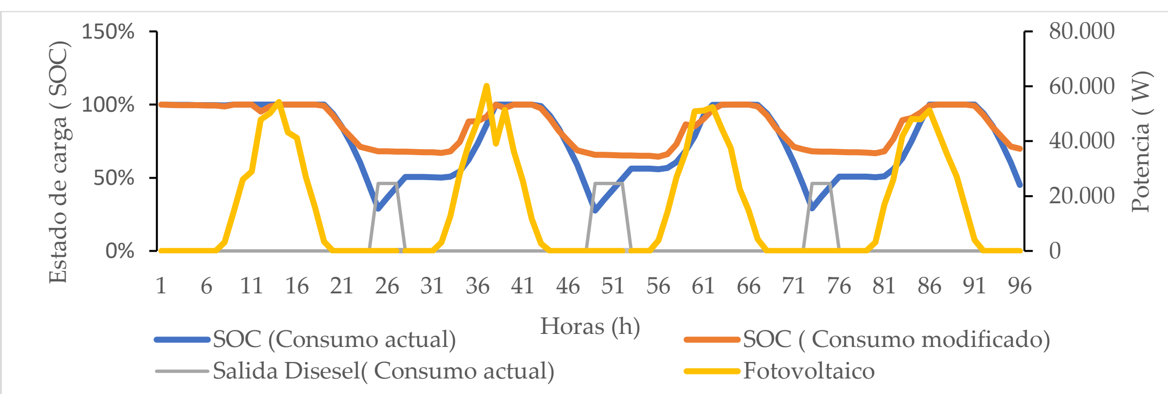

Figura 15. Estado de carga de baterías vs Generación fotovoltaica (Titumate).

La figura 16 muestra los diferentes costes energéticos obtenidos con los perfiles de carga actuales y modificados para las 6 microrredes que utilizan baterías de plomo-ácido y la estrategia de seguimiento de la demanda. Un precio de energía más bajo es observado en 5 de las ubicaciones utilizando un perfil de carga modificado, con excepción de la localidad de Guacamayas que tiene un LCOE bajo debido a su generación mediante una pequeña central hidroeléctrica (PCH).

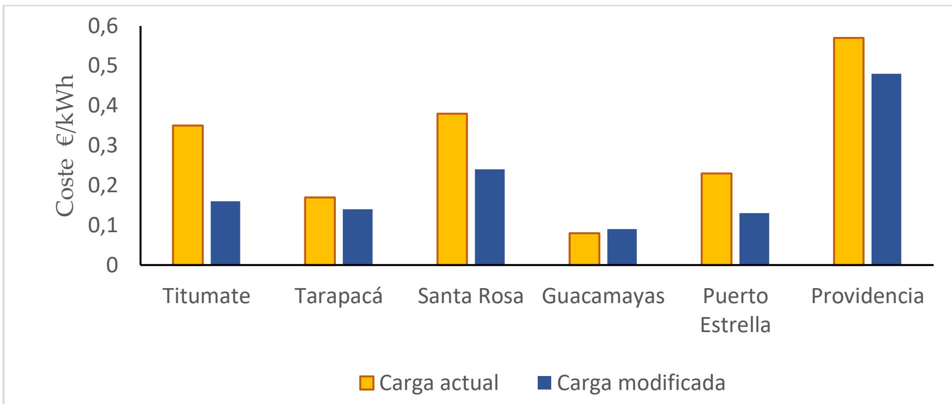

Figura 16. Coste normalizado de energía (LCOE) para las 6 microrredes.

La Figura 17 muestra los NPC de los sistemas óptimos de las 6 ubicaciones, realizando la optimización usando baterías de litio y con la estrategia de seguimiento de la demanda, observándose una disminución en costes en 5 de las 6 microrredes que utilizan perfiles de carga modificados. En tres localidades (Titumate, Santa Rosa y Puerto Estrella) la reducción de costes ronda el 50% con el perfil de carga modificado.

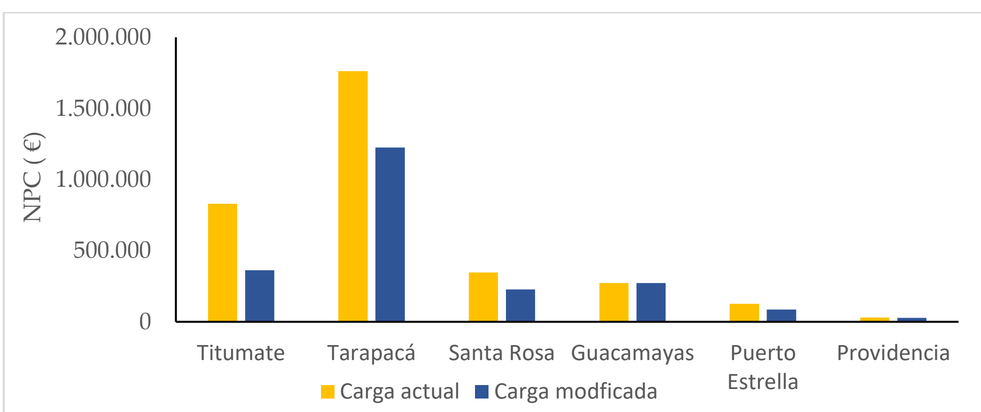

Figura 17. Coste actual neto (NPC) del óptimo obtenido para cada microrred, baterías de litio, estrategia seguimiento de la demanda.

En la figura 18 se observan los resultados de las emisiones del sistema óptimo obtenido para cada una de las 6 microrredes usando baterías de litio y utilizando como estrategia de control carga cíclica (CC). El nivel de emisiones según los resultados presentados en la figura 18 descendieron para 5 de las 6 microrredes optimizadas, en Guacamayas el valor es similar debido a su sistema de generación mediante pequeña central hidroeléctrica.

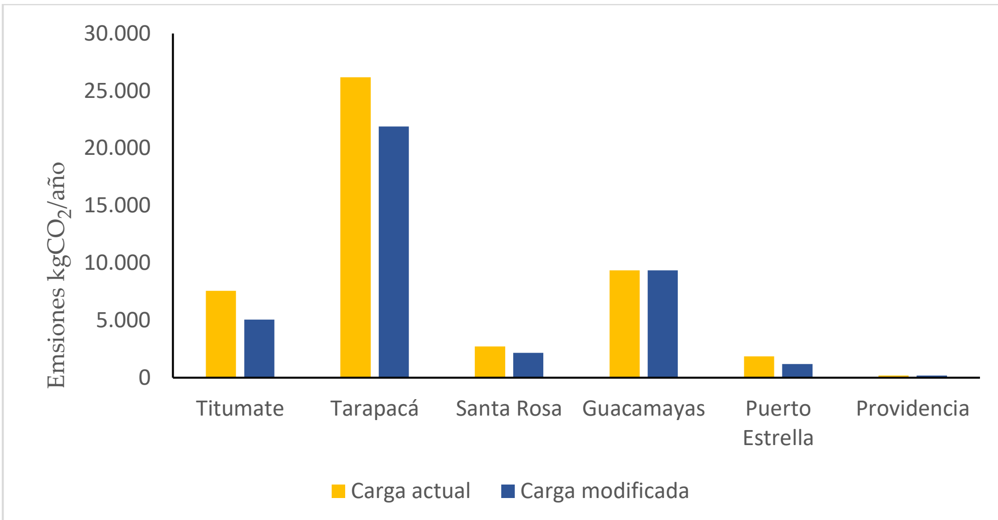

Figura 18. Emisiones totales equivalentes de CO_2 (kg/año) del óptimo obtenido para cada microrred, baterías de litio, estrategia seguimiento de la demanda.

5.3 Conclusiones

Este artículo ha presentado un estudio tecno-económico de 6 microrredes aisladas, todas ellas localizadas en la zona no interconectada de Colombia. Se han obtenido sistemas híbridos de generación óptima para 6 localizaciones, considerando la posibilidad de utilizar generadores diésel, paneles solares, turbinas hidráulicas, aerogeneradores y baterías. Los resultados muestran que en casi todos los escenarios se pueden conseguir valores de NPC inferiores a los actuales (cuyo suministro principalmente es con diésel), de igual manera es posible lograr una reducción significativa tanto para los LCOE, principalmente en el caso de la localidad de providencia en la cual prácticamente toda la generación actual corresponde a generadores diésel, el nivel de emisiones es otro factor importante que también se ha visto reducido en forma considerable por el aprovechamiento de fuentes de energías renovables locales, combinado con la reducción del número de horas de funcionamiento de los generadores diésel y la gestión por el lado de la demanda.

Sin embargo, esta gestión del lado de la demanda se ve limitada, en gran medida, por la dificultad de cambiar los hábitos de consumo de los usuarios. Los resultados también han demostrado que las baterías de litio pueden ser una buena alternativa a las baterías de plomo-ácido, considerando la vida útil y los costes del sistema.

En trabajos futuros sería interesante realizar una estimación precisa del precio del diésel en la optimización de microrredes híbridas aisladas, considerando que el coste promedio del diésel en la zona no interconectada de Colombia es altamente variable debido a que, en dicha zona, se tienen inconvenientes asociados con el transporte en áreas de difícil acceso. Es importante señalar que las estrategias de optimización podrían incluir un programa de gestión del lado de la demanda que puede reducir el coste de operación. Además, el desarrollo de microrredes con energías renovables en zonas rurales también ayudará a afrontar el reto del suministro energético de zonas remotas y reducir la dependencia de los combustibles fósiles. Los resultados del estudio proporcionan una base para explorar la optimización de las microrredes con otras tecnologías como las pilas de combustible y la biomasa. Sin embargo, el gobierno colombiano tendrá que jugar un papel crucial para el desarrollo de las microrredes híbridas aisladas en áreas remotas.

6. Conclusiones

En un primer trabajo, se ha realizado una extensa revisión del estado del arte de la gestión energética en microrredes con energías renovables, tanto en microrredes conectadas a la red eléctrica como aisladas. En la literatura revisada, la gestión de la energía en microrredes con energías renovables se trata como un problema de optimización, que puede ser mono-objetivo, cuando se tiene una sola función de coste que representa el coste operativo de la microrred y multi-objetivo, cuando de manera simultánea se resuelven problemas económicos, técnicos y ambientales.

Diferentes autores han abordado el problema con múltiples enfoques y propuesto distintas soluciones utilizando diversos métodos. Muchos de estos métodos se basan en técnicas clásicas tales como programación lineal y no lineal de enteros mixtos, mientras que otra gran cantidad de trabajos se basan en técnicas de optimización heurísticas, metaheurísticas y de control predictivo, debido al número elevado de combinaciones posibles entre componentes y estrategias de control cuya evaluación con los métodos tradicionales resulta inadmisible en un tiempo de computación moderado. Existen otros trabajos que utilizan métodos que están basados en combinación de métodos heurísticos, estocásticos, algoritmos evolutivos e inteligencia artificial que están enfocados a abordar situaciones en las que otros métodos conducen a resultados insatisfactorios, incluida la previsión de la generación renovable y el óptimo funcionamiento del sistema de almacenamiento de energía (generalmente baterías en sistemas híbridos aislados).

En un segundo trabajo se han comparado diferentes modelos y tecnologías de baterías en la optimización de una microrred híbrida en la zona no interconectada de Colombia (ZNI). Por los resultados obtenidos se observa que los modelos clásicos de envejecimiento de baterías de plomo-ácido utilizados por varios investigadores, como el modelo de ciclo equivalentes y el modelo de recuento de ciclos de *Rainflow*, generalmente tienden a sobreestimar la vida útil de la batería, incluso hasta tres veces su duración real. Sin embargo, el modelo de carga ponderada de Schiffer *et al.* ha mostrado mejores resultados ya que sus predicciones son más cercanas a las reales. Los resultados de las diferentes optimizaciones muestran que se obtienen menores costes de valor actual neto (NPC) y menor coste nivelado de la energía (LCOE) para distintas configuraciones de baterías de litio comparadas con las configuraciones de las tradicionales baterías de plomo-ácido; por tanto, se concluye que los sistemas actuales no están optimizados. En cuanto a las baterías de ferrofosfato de litio $LiFePO_4$/grafito, el modelo de envejecimiento de Wang *et al* presenta resultados más pesimistas en cuanto a la duración de la batería que el de Groot *et al*, ante aumentos importantes de temperatura.

Estos resultados permiten concluir que es necesario optimizar los diseños de microrredes no conectadas a la red eléctrica, ya que los beneficios económicos pueden ser significativos. Un diseño adecuado permitirá un mejor aprovechamiento de la generación renovable, e incluso aprovechar el excedente de energía que se puede utilizar en vehículos eléctricos, o en el caso de islas, para desalación de agua. Además, la utilización de tecnologías de almacenamiento de litio frente a las baterías tradicionales de plomo-ácido, puede conllevar un menor coste total a lo largo de la vida útil del sistema, aunque los costes iniciales sean mayores, ya que su vida útil en determinados casos puede ser muy superior. Por lo tanto, el uso de otras tecnologías de almacenamiento, como las baterías de iones de litio, debe considerarse en el diseño, aunque su coste inicial puede ser mayor, y teniendo en cuenta que cada modelo de envejecimiento está relacionado directamente con la tecnología usada en su construcción, ya que cada modelo de envejecimiento es válido solo para una determinada tecnología de baterías de litio.

En un tercer trabajo se presenta una optimización para una microrred aislada compuesta por un sistema fotovoltaico-diésel-baterías. Este sistema actualmente no está optimizado y se encuentra en una pequeña isla del Caribe Colombiano en el distrito de Cartagena. En este trabajo se estudia la factibilidad técnica y económica de esta microrred híbrida considerando datos reales de consumo, recursos renovables locales y desplazamiento de consumos aprovechando la radiación solar local. Los resultados demuestran que es posible obtener sistemas optimizados con modelos de batería de plomo ácido (modelo de Schiffer *et al*) y de litio (modelo de Wang *et al*), reduciendo los costes hasta en un 40% en LCOE, 35% en NPC y un 80% en emisiones de CO_2 considerando ambas tecnologías de baterías. Se deja abierta la posibilidad de integrar otro tipo de fuente renovable (maremotriz) puesto que se trata de una isla y potencialmente se dispone de este recurso.

Para finalizar, se presenta un estudio tecno-económico para 6 microrredes aisladas de la zona no interconectada de Colombia. Se han obtenido sistemas híbridos de generación óptima para 6 localidades, considerando la posibilidad de utilizar generadores diésel, paneles solares, turbinas hidráulicas, aerogeneradores y baterías. Los resultados muestran que en casi todos los escenarios se pueden conseguir valores de NPC inferiores a los actuales (que funcionan principalmente con diésel) gracias a la reducción del número de horas de funcionamiento de los generadores diésel y al uso de la gestión por el lado de la demanda.

Es importante señalar que las estrategias de optimización podrían incluir un programa de gestión del lado de la demanda que puede reducir el coste de operación. Además, el desarrollo de microrredes con energías renovables en zonas rurales también ayudará a afrontar el reto del suministro energético de zonas remotas y reducirá la dependencia de los combustibles fósiles. Los resultados del estudio proporcionan una base para explorar la optimización de las microrredes con otras tecnologías como las pilas de combustible y la biomasa. Sin embargo, el gobierno colombiano tendrá que jugar un papel crucial para el desarrollo de las microrredes híbridas aisladas en áreas remotas.

7. Aportaciones y trabajos futuros

7.1 Aportaciones

Las principales aportaciones de esta tesis doctoral fueron:

- Una completa revisión del estado del arte relacionado con la gestión de energía en microrredes con energía renovable, que trajo como resultados la publicación: *García Vera, Yimy E.; Dufo-López, Rodolfo; Bernal-Agustín, José L. 2019. "Energy Management in Microgrids with Renewable Energy Sources: A Literature Review" Appl. Sci. 9, no. 18: 3854*, este artículo fue publicado el día 13 de septiembre de 2019.
  La revista *Applied Sciences* se encuentra indexada en JCR Q1 (en el área de ingeniería) y Q2 en otras 4 categorías en el 2019, el artículo tiene a la fecha de depósito de esta tesis 34 citaciones (*Web of Science*), hecho que marca tendencia como referencia de artículos de revisión en el área de microrredes y energías renovables. También es parte de la edición del libro "*Standalone Renewable Energy Systems: Modeling and Controlling*" de la revista *Applied Sciences*. Editorial MDPI, 2020 ISBN 978-3-03936-184-7.
- En un segundo trabajo se presenta la optimización de una microrred híbrida aislada con energías renovables considerando tecnologías y modelos de envejecimiento de baterías. La microrred representada se encuentra localizada en la zona no interconectada de Colombia (ZNI). El trabajo fue presentado como la siguiente publicación: *García-Vera, Yimy E.; Dufo-López, Rodolfo; Bernal-Agustín, José L. 2020. "Optimization of Isolated Hybrid Microgrids with Renewable Energy Based on Different Battery Models and Technologies" Energies 13, no. 3: 581*. El artículo fue publicado el 20 de enero de 2020. La revista *Energies* se encuentra indexada en JCR como Q2 en todas sus categorías, y a la fecha de hoy este artículo ha sido citado en 8 ocasiones según la base de datos *Web of Science*.
- Un tercer trabajo relacionado con la factibilidad técnica en microrredes

aisladas usando técnicas de optimización fue publicado como: *Y. Edisson García Vera, R. Dufo-López and O. Daniel Diaz Castillo, "Optimization and Feasibility of Standalone Hybrid Diésel-PV-Battery Microgrid Considering Battery Technologies," 2020 IEEE ANDESCON, Quito, 2020.* Este trabajo se encuentra en la base de datos IEEE Explorer y se presentó en la Conferencia Técnica y Científica bianual del Consejo Andino del IEEE (*ANDESCON*) realizado en Quito Ecuador del 13 al 20 de octubre de 2020.

- En el cuarto trabajo se analizó la viabilidad técnico-económica de 6 diferentes microrredes de la zona no interconectada de Colombia, para ello se consideraron diferentes perfiles reales de consumo, localizaciones geográficas diferentes y configuraciones según disponibilidad de fuentes de energía, así como tecnología y tipo de baterías. Se aplicó la gestión de energía usando desplazamiento de consumos. Este trabajo se presentó como: *García-Vera, Yimy E.; Dufo-López, Rodolfo; Bernal-Agustín, José L. 2020. "Techno-Economic Feasibility Analysis through Optimization Strategies and Load Shifting in Isolated Hybrid Microgrids with Renewable Energy for the Non-Interconnected Zone (NIZ) of Colombia" Energies 13, no. 22: 6146.* Este artículo fue publicado el 23 de noviembre de 2020, y ha sido citado a fecha de hoy en 1 ocasión. La revista *Energies* se encuentra indexada en JCR como Q2 en todas sus categorías.

7.2 Trabajos futuros

Como trabajos futuros se platean:

- Se requiere investigar sobre la gestión óptima de la energía y la gestión de las baterías de litio en las microrredes, a la vez que se consideran modelos de degradación más precisos (incluyendo modelos de envejecimiento por calendario y por ciclado) para predecir con precisión la vida útil de la batería en las condiciones reales de funcionamiento.
- Se deben realizar más trabajos para la estimación precisa del precio del diésel,

considerando que el coste del diésel en la ZNI de Colombia es muy variable debido a sus inconvenientes asociados con el transporte hacia áreas de difícil acceso. La investigación adicional también podría incluir análisis de sensibilidad considerando factores como: variación de carga, precio del combustible, subsidios a las energías renovables, tasas de interés y coste de adquisición de los componentes del sistema.

- Diseñar y gestionar microrredes con cargas flexibles que puedan ser gestionadas de forma óptima en la zona no interconectada de Colombia, especialmente que incorpore recursos renovables locales (fotovoltaica, eólica, biomasa, minihidráulica), reduciendo la dependencia de combustibles como el diésel, de esta manera se reducirían sus costes y podrán ser ambientalmente más sostenibles.

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Energy Management in Microgrids with Renewable Energy Sources: A Literature Review

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Review

Energy Management in Microgrids with Renewable Energy Sources: A Literature Review

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Abstract: Renewable energy sources have emerged as an alternative to meet the growing demand for energy, mitigate climate change, and contribute to sustainable development. The integration of these systems is carried out in a distributed manner via microgrid systems; this provides a set of technological solutions that allows information exchange between the consumers and the distributed generation centers, which implies that they need to be managed optimally. Energy management in microgrids is defined as an information and control system that provides the necessary functionality, which ensures that both the generation and distribution systems supply energy at minimal operational costs. This paper presents a literature review of energy management in microgrid systems using renewable energies, along with a comparative analysis of the different optimization objectives, constraints, solution approaches, and simulation tools applied to both the interconnected and isolated microgrids. To manage the intermittent nature of renewable energy, energy storage technology is considered to be an attractive option due to increased technological maturity, energy density, and capability of providing grid services such as frequency response. Finally, future directions on predictive modeling mainly for energy storage systems are also proposed.

Keywords: microgrids; energy management; renewable energy; optimization; photovoltaic; energy storage

1. Introduction

The exponential demand for energy has led to the depletion of fossil fuels such as petroleum, oil, and carbon. This, in turn, increases the greenhouse effect gases. Energy systems have incorporated small-scale and large-scale renewable sources such as solar, wind, biomass, and tidal energy to mitigate the aforementioned problems on a global scale [1]. Global energy demand will grow by more than a quarter to 2040, when renewable sources are expected to represent 40 percent of the global energy mix. The reliability of the renewable sources is a major challenge due mainly to mismatch between energy demand and supply [2]. Renewable energy resources, distributed generation (DG), energy storage systems, and microgrids (MG) are the common concepts discussed in several papers [3]. The increase in the demand for energy and the rethinking of power systems has led to energy being generated near the places of consumption. This energy is derived from renewable sources, which are becoming increasingly competitive due to a drop in prices, especially in the case of photovoltaic solar and wind energies [4].

Due to strong dependency on climatic and meteorological conditions, in many cases the optimal system is a hybrid renewable energy system (considering one or more renewable sources) with battery storage systems (and in some cases including diesel generator) [5]. The hybrid energy systems are typically used for electricity supply for several applications such as houses or farms in rural areas without grid extension, telecommunication antennas, and equipment, and many other stand-alone systems [6,7]. In many cases these hybrid systems imply the highest reliability and lowest costs compared to systems with only one energy source [8,9].

A microgrid consists of a set of loads, energy storage equipment, and small-scale generation systems [10]. It can be defined in a broader sense as a medium or low distribution grid, which has distributed generation including renewable and conventional sources (hybrid systems) with storage units that supply electrical energy to the end users. The reliability of the microgrid is improved by the storage and it is used to complement the intermittency of the PV and wind output power [11–13]. These microgrids have communication systems that are necessary for real time management [14]. Microgrids can also operate either in isolation or when connected to a grid [15]. Based on the type of source they manage, microgrids can be classified as direct current line (DC), alternating current line (AC), or hybrid (shown in Figure 1).

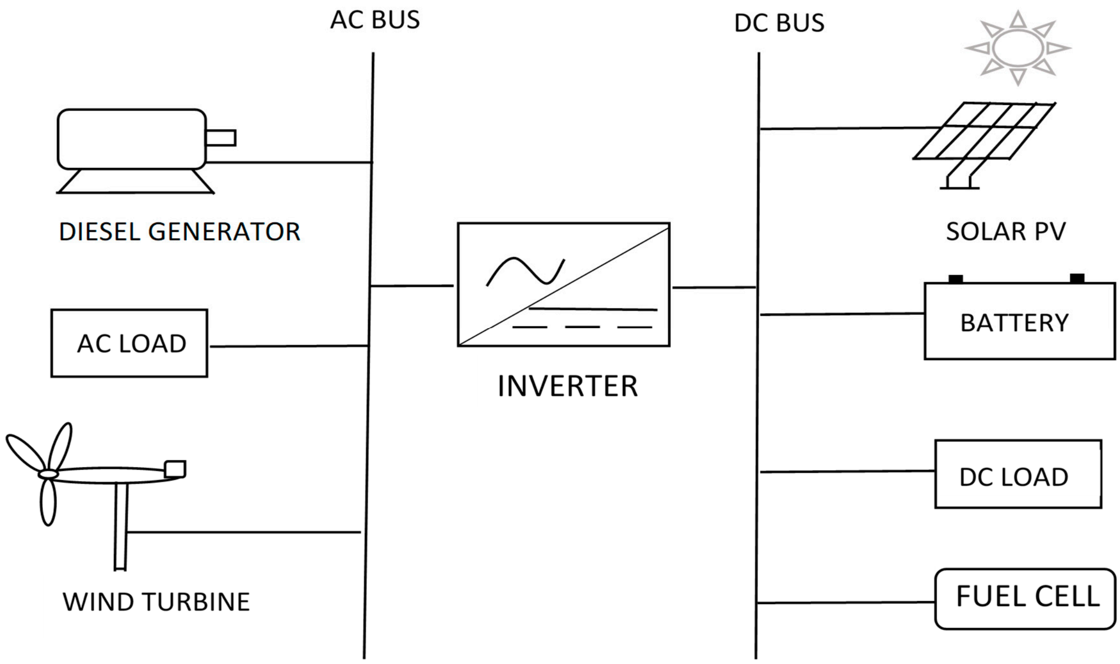

Figure 1. A hybrid isolated microgrid scheme.

In a microgrid, it is essential to maintain the power supply-demand balance for stability because the generation of the intermittent distributed sources such as photovoltaic and wind turbines is difficult to predict and their generation may fluctuate significantly depending on the availability of the primary sources (solar irradiation and wind). The supply-demand balancing problem becomes even more important when the microgrid is operating in stand-alone mode where only limited supply is available to balance the demand [16]. Energy management optimization in microgrids is usually considered as an offline optimization problem [17].

Microgrids supported with renewable energies can be classified as smartgrids, which provide a set of technological solutions to allow information exchange between the consumers and the distributed generation. An energy management system (EMS) is defined as an information system, which provides the necessary functionality when supported on a platform to ensure that generation, transmission, and distribution supply energy at minimal cost [18]. Energy management in the microgrids involves a control software that permits the optimal operation of the system [19]. This is achieved by considering the minimal required cost and two microgrid operation modes (isolated and interconnected). The variability of resources such as solar irradiation and wind speed must be accounted for when considering microgrids with renewable energy sources [20].

A review on the studies related to the energy management of microgrids can be found in [21]. A few authors have solved the problem of energy management using different techniques to achieve an optimal microgrid operation. However, these techniques must incorporate better solution strategies due to the integration of distributed generation, storage elements, and electric vehicles.

Other recent papers [22] have reviewed various integration methods for renewable energy systems based on storage and demand response. This covers two main areas, namely (1) the optimal usage of storage, and (2) improvement of user participation via demand response mechanisms and other collaborative methods. The authors in [23] reviewed energy management strategies for hybrid renewable energies. The above review covered different configurations of stand-alone and grid-connected hybrid systems. Other review papers [24] have shown the control objectives of the microgrid supervisory controllers (MGSC) and energy management systems (EMS) for microgrids. Table 1 shows the contributions of the review papers related to the energy management of microgrids. Unlike the cited papers, this paper focuses on the incorporation of better strategies for the control of energy (both heat and electrical) flow between the hybrid system sources and load. Furthermore methods of energy management in stand-alone hybrid microgrid considering the battery degradation are also discussed.

Table 1. Microgrids energy management review papers.

Reference	Contributions
[21]	Authors presented a comparative analysis on decision making strategies for microgrid energy management systems. These methods are selected based on their suitability, practicability, and tractability, for optimal operation of microgrids.
[22]	Energy management integration methods, demand response, and storage systems are reviewed. Authors used more accurate models for storage including key factors such as the derating factors due temperature charge/discharge rate and ageing.
[23]	Authors presented a review on strategies and approaches used to implement energy management in stand-alone and grid-connected hybrid renewable energy systems.
[24]	Authors showed an extensive review on energy management methodologies applied in microgrids. EMS for real-time power regulation and short-/long-term energy management are reviewed.
[25]	Authors showed previous solutions approaches, optimization techniques, and tools used to solve energy management problem in microgrids. It includes heuristic, agent-based, MPC, evolutionary algorithms, and other methods.
[26]	Authors showed an overview of the latest research developments using optimization algorithms in microgrid planning and planning methodologies.
[27]	Authors presented an overview of current hybrid microgrids and optimization methods and applications.
[28]	Authors showed in detail the optimization of distributed energy microgrids in both the grid-connected and stand-alone mode.

2. Microgrid Optimization Techniques

Energy management of a microgrid involves a comprehensive automated system that is primarily aimed at achieving optimal resource scheduling [25–27]. It is based on advanced information technology and can optimize the management of distributed energy sources and energy storage system [28]. The microgrid optimization problem typically involves the following objectives:

Maximize the output power of the generators at a particular time;
Minimize the operating costs of the microgrid;
Maximize the lifetime of energy storage systems;
Minimize the environmental costs.

Some of the classic optimization methods include mixed integer linear and non-linear programming. The objective function and constraints used in linear programming are linear functions with real-valued and whole-valued decision variables. Dynamic programming methods are used to solve more complex problems that can be discretized and sequenced. The problem is typically broken down into sub-problems that are optimally solved. Then, these solutions are superimposed to develop an optimal solution for the original problem.

Metaheuristics is another important alternative in microgrid optimization. Heuristic techniques are combined to approximate the best solution using genetic algorithms, biological evolution, and statistical mechanisms for achieving optimal operation and control of microgrid energy.

Predictive control techniques are used in applications where predicting the generation and loading is necessary to guarantee effective management of stored energy. This typically combines stochastic programming and control. The most remarkable among these techniques are the ones to predict the deterioration of elements of the grid, mainly storage systems.

Optimization methods based on a multi-agent used on microgrids allow a decentralized management of the microgrid and consist of sections having autonomous behavior to execute the tasks with defined objectives. These agents, which include loads, distributed generators and storage systems, communicate with each other to achieve a minimal cost.

Stochastic methods and robust programming are used to solve the optimization functions when the parameters have random variables, particularly in artificial neural networks, fuzzy logic, and game theory.

A few more methods can be derived from a combination of the aforementioned techniques such as stochastic and heuristic methods and enumeration algorithms.

3. Microgrid Energy Management with Renewable Energy Generation

A microgrid is composed of different distributed generation resources that are connected to the utility grid via a common point. Figure 2 shows a microgrid energy management mode along with several features that are modules of human machine interfaces (HMI), control and data acquisition, load forecast, optimization, etc. [29].

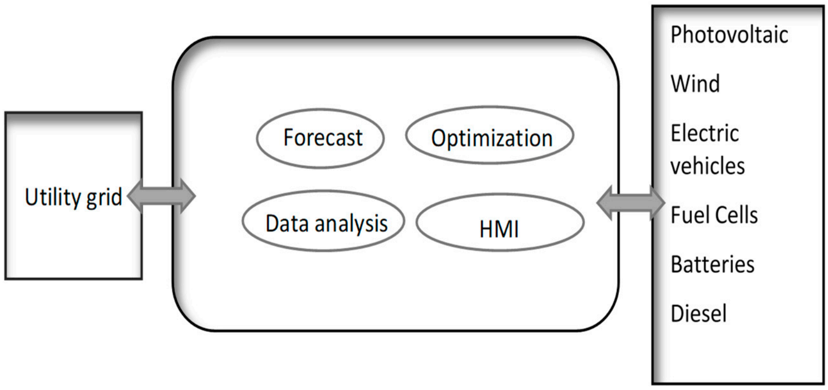

Figure 2. Microgrid energy management [29].

Many researchers have addressed energy management by implementing different approaches. However, all approaches have focused on determining the most optimal and efficient microgrid operation. The following sub-sections discuss and classify these strategies and solutions.

3.1. Energy Management Based on Linear and Non-Linear Programming Methods

Ahmad et al. [30] presented a technical and economic method to optimize a MG based on mixed integer linear programming (MILP). This paper presents the advantages of programming the generation of distributed sources, managing the intermittency and volatility of this type of generation, and reducing load peaks. The cost function is solved via linear programming based on a general algebraic modeling system (GAMS). Simulations to optimize MG size are performed via software called HOMER. Taha and Yasser [31] presented a robust algorithm based on a predictive control model for an isolated MG. The model incorporates multi-objective optimization with MILP, which minimizes the cost, energy consumption, and gas emission due to diesel generation in the MG.

Sukumar et al. [32] proposed a mixed method for MG energy management. This was achieved by combining the utility grid and fuel cell power. The problem is solved using linear optimization methods, and the on/off states of the utility grid are solved via MILP. A particle swarm optimization (PSO) method was used to obtain an optimal energy storage system size.

Tim et al. [33] proposed a system for energy management in an interconnected MG that adopted a centralized approach based on the concept of flexibility for the final users. An optimal economic dispatch was obtained using quadratic programming. This grid was integrated with a photovoltaic system and the constraints must satisfy the demand. The algorithm was tested on an IEEE 33 node modified grid.

Delgado and Domínguez-Navarro [34] presented an algorithm based on linear programming for MG energy management that allowed the optimal operation of either generators or controllable and non-controllable loads. The optimization problem involves the optimal dispatch of generators (diesel) while meeting the operational and economic constraints imposed by the purchase and sale of energy corresponding to each component (generators, storage systems, and loads).

Helal et al. [35] analyzed an energy management system for a hybrid AC/DC MG in an isolated community that employs a photovoltaic system for desalination. The proposed optimization algorithm was based on the mixed integer non-linear programming, wherein the objective function minimizes the daily operating costs.

Umeozor and Trifkovic [36] researched the energy management of a MG based on MILP via the parametrization of the uncertainty of solar and wind energy generation in the MG. The optimization is achieved at two levels. First, the parametrization scheme is selected; second, the operational decisions are made the problem considers the variation in market prices and the disposition of the storage systems.

Xing et al. [37] presented an energy management system based on multiple time-scales. The optimization problem considers two aspects: A diary static programming and dynamic compensation in real time. This is solved via a mixed-integer quadratic programming method using optimal load flows, and the load state of the batteries are predicted using wind and solar radiation data.

Correa et al. [38] proposed an energy management system based on a virtual power plant (VPP). The studied MG has solar panels and storage systems and works in an interconnected manner. These elements are programmed/modeled using linear programming methods to minimize the operating costs. Renewable energies are incorporated into an energetic model, similar to the Colombian one, and are mainly based on hydric resources.

Cardoso et al. [39] analyzed a new model to observe the battery degradation of a MG. The problem is solved using stochastic mixed-integer linear programming, taking several factors such as loads and different sources of energy generation, costs, constraints, grid topology, and local fees for energy into consideration.

Behzadi and Niasati [40] analyzed a hybrid system that consists of a photovoltaic (PV) system, battery, and fuel cells. Performance analysis was conducted using the TRNSYS software, and the sizing was determined either using the genetic algorithm in the HOGA software (now called iHOGA), manual calculations, or the HOMER software. Three energy management strategies were tested for energy dispatch in this hybrid system. The excess energy was checked in each system and a decision was taken to either produce hydrogen or charge the battery or both.

3.2. Energy Management Based on Metaheuristic Methods

Dufo-López et al. [41] proposed a control strategy for the optimal energy management of a hybrid system based on genetic algorithms. The system is composed of renewable sources (PV, wind, and hydro), an AC generator, electrolyzer, and fuel cells. Energy management is optimized to minimize the operating costs, which enables the use of the excess energy generated by the renewable sources to charge the batteries or produce hydrogen in the electrolyzer. The load that cannot be supplied by the renewable sources can be obtained by either discharging the battery or using fuel cells.

Das et al. [42] studied the effect of adding internal combustion engines and gas turbines to a stand-alone hybrid MG with photovoltaic modules. A multi-objective genetic algorithm was used to optimize this system based on the energy costs and overall efficiency. Two strategies, both electric and thermal, were used to track the load. All the analyzed systems satisfied the electrical demand when combined with both heating and cooling.

Luna et al. [43] presented an energy management system that operates in real time. Three cases were studied considering the perfect, imperfect, and exact predictions. The employed optimization model was tested in both a connected and an isolated MG, with large imbalances between the generation and load.

An economic dispatch and battery degradation model has been proposed in [44], wherein genetic algorithms were used for energy supply options via a diesel generator. The results showed that an increase in the battery lifespan decreases the operational costs of a MG. This method was validated in a hybrid MG composed of a diesel generator and photovoltaic system.

Chaouachi et al. [45] proposed a multi-objective, intelligent energy management system for a MG that minimizes the operational costs and environmental impact. An artificial neural network has been developed to predict the photovoltaic and wind power generation 24 and 1 h in advance, respectively, along with the load demand. The multi-objective intelligent energy management system is composed of multi-objective linear programming. The battery scheduling is obtained using a fuzzy logic-based expert system.

Li et al. [46] presented a study on MG optimization based on the particle swarm algorithm that can operate a connected or isolated MG. The proposed approach considers the fluctuations in the renewable sources and load demands in the MG, with appropriate advance (24 h) forecasts available to overcome these fluctuations.

Nivedha et al. [47] analyzed a MG containing/supporting wind power generation, fuel cells, a diesel generator, and an electrolyzer. A fuel cell is used when the energy demand is not covered by the wind turbine, to ensure energy balance when operating diesel generators to reduce the operational costs. The fuel cell operates to meet the high load demand, resulting in economic MG operation with a ~70% cost saving using the particle swarm optimization algorithm.

Abedini et al. [48] presented an energy management system for a photovoltaic/wind/diesel stand-alone hybrid MG, which is optimized using a particle swarm algorithm with Gaussian mutation. This study minimizes both the capital and fuel costs of the system.

Nikmehr et al. [49] studied an optimal generation algorithm applied to a MG based on optimization via the imperial competitive algorithm. This algorithm solves the load uncertainty and distributed generators, along with the economic dispatch of the generating units. This algorithm is comparable to methods such as the Monte Carlo method, and has been tested in interconnected MGs.

Marzband et al. [50] presented an energy management system for an isolated MG using the artificial bee colony algorithm (ABC). A stochastic approach is required to analyze the economic dispatch of the generating units inside a MG, given the intermittent nature of solar energy resources and wind generation. The results showed a 30% decrease in costs. The non-dispatchable generation and load uncertainty are managed using neural networks and Markov chains.

Kuitaba et al. [51] presented a new method to optimize an interconnected MG, which combines an expert system based on fuzzy logic and a metaheuristic algorithm known as Grey Wolf optimization. This method involves minimizing both the costs of the generating units and the emission levels of the fossil fuel sources. This method lowers MG costs by considering the optimal capacity of the batteries and reducing the consumption of fossil fuels.

Papari et al. [52] analyzed energy management in a MG connected to a direct current utility grid. The optimization is implemented using the crow search algorithm (CSA), which is a metaheuristic optimization method that imitates the behavior of a crow to store and hide food.

Wasilewski [53] presented a metaheuristic optimization method to optimize a MG. The methods include the evolutionary and particle swarm algorithms. These methods account for the fact that the deterministic conditions assumed in the problem impose an important limit on the employed methodology. However, it also recognizes the uncertainty of using renewable energies.

Ogunjuyigbe et al. [54] presented a technique based on a genetic algorithm for the optimal location of both renewable generation and batteries in a stand-alone MG. The proposed multi-objectives are to reduce operational and life cycle costs, and dump energy. The optimization allows variations in the radiation and wind sources, and extracts data from a load profile to optimize the MG.

Kumar and Saravanan [55] proposed an algorithm based on the demand prediction over 24 h in a MG using the artificial fish swarm optimization method. Thus, the demand can be planned in advance, considering both renewable and non-renewable generation. The algorithm is used to program the sources, load, and storage elements. They system includes a wind turbine, two photovoltaic generators, a fuel cell, a micro-turbine, and a diesel generator.

A particle swarm algorithm has been proposed in a recent paper by Hossain et al. [56] for energy management in a grid-connected MG. A model for charging and discharging a battery has been formulated. The proposed cost function reduces costs by 12% over a total time horizon/period of 96 h, with time intervals of one hour. These results can be adjusted in real time.

Azaza and Wallin [57] studied energy management in a MG with a hybrid system consisting of wind turbines, photovoltaic panels, diesel generator, and battery storage. A multi-objective particle swarm optimization is used, which evaluates the probability of losing energy supply over a time horizon/period of 6 months each during summer and winter.

Motevasel and Seifi [58] presented an expert system for energy management (EEMS) in a MG that contains wind turbines and photovoltaic generation. Neural networks are used to predict wind turbine generation. The bacterial foraging algorithm is used for the optimization, while the optimization of the multi-objective problem is obtained by the EEMS module by applying an improved bacterial foraging-based fuzzy satisfactory algorithm.

Rouholamini and Mohammadian [59] proposed optimal energy management for a grid-connected hybrid generation system, including PV generator, wind turbine, fuel cell, and electrolyzer. This system trades power with the local grid using real time electricity pricing over a 24-h time horizon/period based on the simulation results. The interior search algorithm was used to optimize the energy management in the above case.

3.3. Energy Management Based on Dynamic Programming Techniques

Shuai et al. [60] proposed an energy management system for a MG based on dynamic programming and mixed-integer non-linear programming optimization. The MG is interconnected to the grid and decisions are made using the Bellman equation. Historical data are used off-line, while considering the power flow and battery storage as constraints. Using the algorithm in multiple MGs simultaneously is a feasible possibility.

Almada et al. [61] proposed a centralized system for energy management of a MG either in the stand-alone or interconnected modes. In the stand-alone mode, the fuel cell only works if the battery is less than 80%. In the interconnected mode, a 60% threshold is required to ensure reliable behavior.

Wu et al. [62] proposed an algorithm based on dynamic programming for the management and control of stand-alone MGs. The deep learning algorithm works in real time, which permits intra-day scheduling to obtain a control strategy for MG optimization, while sending information from local controllers within the framework of centralized management.

Zhuo [63] proposed an energy management system using dynamic programming to manage a MG with renewable generation sources and batteries. The objective was to maximize the benefits from the sale of renewable energy and minimize the cost required to satisfy the energy demand. The author used a non-regulated energy market where electricity prices fluctuate and the battery control actions are determined by dynamic programming.

Choudar et al. [64] presented an energy management model based on the battery state of charge and ultra-capacitors. The hierarchic structure of optimal MG management has four states or operating modes: Normal operating mode, photovoltaic limitation mode, recovering, and stand-alone modes.

Marabet et al. [65] proposed an energy management system for a laboratory scaled hybrid MG with wind, photovoltaic, and battery energy. The control and data acquisition system are operated in real time. The energy management system is based on a set of rules, and optimizes the MG performance by controlling and supervising the power generation, load, and storage elements.

Luu et al. [66] presented a dynamic programming method and methodology based on the rules applied to a stand-alone MG containing diesel and photovoltaic generators, and a battery. The constraints are governed by the power balance between generation and consumption, along with the capacity of each distributed generator. Dynamic programming is used to minimize the operational and emission costs. The constraints are the power balance between offer and demand, along with the operating capacity of each distributed generator.

3.4. Energy Management Based on Multi-Agent Systems

Boudoudouh and Maâroufi [67] proposed an energy management system in a MG with renewable energy sources. Simulations were run using the Matlab-Simulink and java platform for agent developers (JADE) software. The reliability of this model was validated by fulfilling requirements such as autonomy and adaptability in the MG management system with load variation.

Raju et al. [68] studied energy management in a grid outage divided into two MGs, which contains two photovoltaic and wind generators each and a local load. A multi-agent management system based on the differential evolution algorithm in JADE was used to minimize the generation costs from the intermittent nature of the solar resource and randomness of load. This system also addressed the price variation in the grid, and the critical loads were considered while selecting the best solution.

Bogaraj and Kanakaraj [69] presented an energy management proposal based on intelligent multi-agents for a stand-alone MG, which maintains the energetic balance between the loads, distributed generators, and batteries. The agents consist of photovoltaic systems, wind turbines, fuel cells, and battery banks. Loads are divided in three groups based on their priority. The auto-regressive moving average models (ARMA) were used to predict the generation. Cases covering high and low irradiation, and low wind were analyzed. The system used a dynamic compensator to balance the reactive power.

Anvari-Moghaddam et al. [70] presented an energy management system for a microgrid that includes houses and buildings. The optimization process for the energy management system involves the coordination of management in distributed generation (DG) and response to the demand. The main objectives of the cost function are to minimize the operating costs and meet the thermic and electrical needs of the clients. The communication platform used by the agents is based on the hypertext (HTPP) communication protocol.

In the study investigated in [71], Nunna and Doolla used an energy management system based on multi-agents, which considers different types of load patterns and the energy available from the distributed energetic resources. They proposed a novel mechanism that encouraged clients to participate. This proposal was validated in interconnected grids using the JADE programming language. The management system reduces the consumption peaks and offers the clients an attraction benefit–cost ratio.

Dou and Liu [72] presented a decentralized multi-objective hierarchical system based on the agents in an interconnected smart MG, minimizing the operating and emission costs and line losses.

The authors in [73] researched decentralized energy management based on the multi-agents contained in a MG, using cognitive maps with fuzzy logic. The intelligent agents refer to the distributed generators, batteries, electrolyzer, and fuel cells. Centralized and decentralized approaches were compared and it showed that the decentralized approach offers the advantage of partial operation under certain circumstances such as during a system malfunction or failure.

Mao et al. [74] presented a hybrid energy management system for a MG based on multi-agents, which incorporates both the centralized and decentralized approaches and optimizes the economic operation of the MG. A novel simulation platform for energy management systems was designed based on the client-server framework and implemented in the C++ environment.

Netto et al. [75] developed a real time framework for energy management in a smart MG in the islanded mode using a multi-agent system. The RSCAD software was used to simulate the MG using the TCP/IP protocol for the purposes of testing and real time operation.

3.5. Energy Management in Microgrids Based on Stochastic Methods and Robust Programming

Che Hu et al. [76] showed an energy management model for a MG wherein the uncertainty in the supply and energy demand are taken into account. Uncertainty in wind and photovoltaic generation, and demanded energy is considered. The stochastic programming of two states was formulated using the GAMS and was tested on a real grid at the Nuclear Energy Research Centre in Taiwan. The battery capacity was optimized in the first stage, while an optimal operation strategy for the MG was evaluated in the second stage.

The author in [77] presented an optimization system for a hybrid MG using a multi-objective stochastic technique. The objective function presented in this study minimizes the system losses and reduces the operating cost of the renewable resources, which were used at different points of the MG. The problem was formulated using the weighting sum for the total operating cost and losses of the feeding systems. The proposed scheme was solved using mixed integer linear programming and tested on the IEEE 37 node distribution system.

Lu et al. [78] proposed a dynamic pricing mechanism that achieves an optimal operating performance. This mechanism was applied to a grid composed of multiple MGs, to evaluate the uncertainty of renewable energy integration on a large scale. An optimization scheme was developed at two levels: The pricing mechanism guaranteed the market operator's energy operation in the upper level, while in the lower level the MG transactions were developed.

Xiang et al. [79] proposed an optimization model for an interconnected MG based on a model using the Taguchi orthogonal matrices. The uncertainty in the renewable energy and load demand were determined by an interval based on error prediction.

Hu et al. [80] introduced an optimization method for an interconnected grid that is divided in two stages. A conventional generator is used in the first stage, while the second stage ensures an economical dispatch of the conventional and distributed generation using hourly marketing. This combination permits management of the uncertainty in renewable generation using the Lyapunov optimization method.

Shen et al. [81] presented a stochastic energy management model for an interconnected MG. The uncertainty level is managed using Latin hypercube sampling based on the Monte Carlo method, which generates various scenarios for the distributed resources, load, and electricity price. A sensitivity analysis is performed to determine the standard deviation of the expected price and level of reliability.

Rezai and Kalantar [82] proposed a stochastic energy management system for a stand-alone MG based on the minimization of frequency deviations. Operating costs of the MG include conventional and distributed generation, and reserves and incentives for generation using renewable sources. The outputs of the conventional generators were also analyzed for various contingencies to demonstrate the robustness of the proposed approach.

Su et al. [83] studied a model for the efficient programming of an interconnected MG, which minimizes the operating costs of the conventional generators, battery degradation, and commercial costs corresponding to the energy from the utility grid. This model follows two stages.

The first stage involves optimization of the MG, while the second stage involves analysis of the power output to calculate the MG energy losses in real time.

Farzin et al. [84] proposed an energy management system for an isolated MG. The islanding event was treated as a normal probability distribution of the failures in the utility grid. The objective was to minimize the MG operating costs. This included costs associated with the microturbine operation, wind turbines, batteries, and load disconnection.

Liu et al. [85] proposed an energy management system for an interconnected MG considering renewable energies and load uncertainties. The energy management is divided in two sub-problems: The first involves scheduling within the defined energy boundaries for system protection, while the second evaluates the real time energy capacity deviation limit for frequency regulation. The presented approach was found to be more cost effective.

Kuztnesova et al. [86] proposed a decentralized energy management system for an interconnected MG using agent-based modeling and robust optimization. The MG performance was evaluated in terms of the cost from the power imbalances associated with the uncertainty of renewable generation and load power demand.

Zachar and Daoutidis [87] proposed a hierarchic control mechanism to regulate and supervise the loads and dispatchable energy inside a MG. Stochastic optimization was used on a low scale to avoid errors in the forecast of renewable energies. Deterministic optimization was realized on a fast scale to update the optimal dispatch conditions.

Battistelli et al. [88] proposed an energy management system for a remote hybrid AC/DC MG, which ensures economical dispatch in spite of the uncertainties associated with the use renewable energy sources. A load control is determined (thermic and electric vehicles) based on the demand, while taking the limits of the generators, controllable loads, and charge and discharge of batteries into consideration.

Lujano et al. [89] developed an optimal load management method for hybrid systems composed by the wind tubine, battery bank, and diesel generator. The autoregressive moving average (ARMA) was used to predict the wind speed.

The results showed that the load management strategy improved wind power usage by shifting the controllable loads to the wind power peaks, thus increasing the charge in the battery bank. This research contributed strategies for the energy management of hybrid MGs.

3.6. Energy Management Using Predictive Control Methods

Zhai et al. [90] proposed a predictive robust control that can be applied to a stand-alone MG. The management model employed mixed integer programming. The MG is composed of wind and PV generators, batteries, and loads.

Zhang et al. [91] presented a model predictive control (MPC) method to manage a MG that integrates both distributed and renewable generation. The model's objective is to reduce the costs and constraints in both generation and energy demand.

Minchala Ávila et al. [92] proposed a methodology based on predictive control for energy management in a stand-alone MG. The controller operates the battery energy in a centralized manner and performs a load elimination strategy to ensure balance in the MG power output.

Ju et al. [93] investigated an energy management system for a hybrid MG taking the degradation costs of the energy storage systems into consideration. The proposal consists of a two-layer predictive control for the hybrid MGs, which use batteries and supercapacitors as storage systems. An important contribution of this work is that the degradation costs of the supercapacitors and batteries were modeled, which allows more accurate assessment of the MG operating costs.

Valencia et al. [94] proposed an energy management model for a MG that uses predictive control, which involves the prediction of the intervals using fuzzy logic. This allows the representation of the non-linearity and dynamic behavior of the renewable sources.

Genesan et al. [95] presented an energy management system for a MG based on a control algorithm to integrate and manage various types of generation such as the PV, distributed generation, energy storage systems, and UPS from the supply grid and different loads. The transition problem between the storage systems and PV generation is solved via control and communication, which functions on a TCP/IP protocol.

García Torres and Bordons [96] introduced optimal programming in a hybrid MG, based on a predictive control model that is solved using mixed integer quadratic programming. They integrated the operating costs and MG optimization, which includes the degradation costs of all the components of the hybrid system, mainly the hydrogen-based storage systems.

Solanki et al. [97] presented a mathematical model of the smart loads and energy management of a stand-alone MG. Loads are modeled using neural networks. Energy management is realized with the predictive control method, which performs an optimal power dispatch taking the elements and controllable loads into consideration.

Oh et al. [98] proposed a multi-step predictive control model for a MG over a time horizon/period of 180 min in 15 min steps. This includes conventional and renewable energy generators, energy storage elements, and both critical and non-critical loads. The cost function was formulated considering the costs associated with fuel consumption, renewable energy reduction, battery state of charge, and amount of load shedding.

A proposal has been presented by Prodan et al. [99] for the energy management of a MG based on a fault-tolerant predictive control design. One of their many contributions includes the extension of the useful battery life by decreasing the charge and discharge cycles.

Wu et al. [100] presented an optimal solution for the operation of a hybrid system using solar energy and battery storage. The battery plays a significant role in the storage of grid power during off-peak periods and supply of power to the customers during peak demand. Thus, scheduling the hybrid system leads to the minimal power consumption from the grid and reduces a customer's monthly cost.

Thirugnanam et al. [11] proposed a battery strategy management. The main objective tries to reduce the fuel consumption in DG, reduce fluctuating PV power, and control the battery charge and/or discharge rate to improve the battery life cycle. The battery charge/discharge rate control model considers the battery SOC limits, wherein the batteries are not charged or discharged beyond the specified limits.

Dufo-López et al. [101] presented a technique to optimize the daily operation of a diesel-wind-PV hybrid, using MPC with forecast data of the irradiation, wind speed, temperature, and daily load. The main contribution of this work is daily optimization that accounts for the degradation of the lead-acid battery by corrosion and capacity losses, using the advanced model presented by Schiffer et al. [102]. This parameter is important when considering the operating costs of the MG, as the useful life and replacement of the batteries can be estimated more accurately. The optimization is executed using genetic algorithms.

3.7. Energy Management Based on Artificial Intelligence Techniques

Elseid et al. [103] defined the role of energy management in a MG as a system that autonomously performs the hourly optimal dispatch of the micro and utility grids (when interconnected) to meet the energy demand. In the above study, the authors used a CPLEX algorithm developed by IBM.

Mondal et al. [104] proposed an energy management model for a smart MG based on game theory, using a distributed energy management model. In this scheme, the MG selects a strategy to maximize its benefits with respect to the cost and adequate use of energy.

Prathyush and Jasmín [105] proposed an energy management system for a MG using a fuzzy logic controller that employs 25 rules. The main objective is to decrease the grid power deviation, while preserving the battery state of charge.

Leonori et al. [106] proposed an adaptive neural fuzzy inference system using an echo state network as a predictor. The objective was to maximize the income generated from energy exchange with the grid. The results showed that the energy management performance improved by 30% over a 10 h prediction horizon/period.

De Santis et al. [107] introduced an energy management system for an interconnected MG using fuzzy logic based on the Mamdani algorithm. The main objective is to take decisions on the management tasks of the energy flow in the MG model, which is composed of renewable energy sources and energy storage elements. The optimization was realized in a scheme that combines fuzzy logic and generic algorithms.

Venayagamoorthy et al. [108] proposed an energy management model for a MG connected to the main power grid. The MG maximizes the use of renewable energies and minimizes carbon emissions, which makes it self-sustainable. The management system is modeled using evolutionary adaptive dynamic programming and learning concepts using two neural networks. One of the neural networks is used for the management strategy, while the other used to check for an optimal performance. The performance index is evaluated in terms of the battery life, use of renewable energy, and minimization of the controllable load.

Ma et al. [109] proposed an algorithm using game theory based on the leaders and followers for energy management. This approach aims at maximizing the benefits available to active consumers of the MG, while keeping the Stackelberg balance to ensure an optimal distribution of benefits.

Jia et al. [110] formulated an adaptive intelligence technique for the energy management of an interconnected MG, which uses energy storage elements. The objective is to minimize any load fluctuations due to uncertainties in the renewable energy generation. The load profile is managed by storage elements and ultra-capacitors.

Arcos-Avilés et al. [111] presented an energy management algorithm based on low-complexity fuzzy logic control for a residential grid-connected MG, which includes renewable distributed generation and batteries.

Aldaouab et al. [112] proposed an optimization method using genetic algorithms for residential and commercial MGs. The MG uses PV-solar energy, microturbines, a diesel generator, and an energy storage system.

Liu et al. [113] proposed a Stackelberg game approach for energy management in a MG. A management system model that takes the fee for the PV energy into account was introduced, which includes the profits from the MG operator and a utility model for the PV consumers.

Nnamdi and Xiaohua [114] proposed program consisting on an incentive-based demand response for the operations of the grid connected MG. The game theory based demand response program (GTDR) was used to investigate the grid connected operational mode of a MG. The results showed that lower costs could be achieved in the MG when the DG benefit of the grid operator is maximized at the expense of minimizing the fuel/transaction costs.

3.8. Energy Management Based on Other Miscellaneous Techniques

Astaneh et al. [115] proposed an optimization scheme to find the most economic configuration for a stand-alone MG, which has a storage system with lithium batteries, and considered different control strategies for energy management. The lifetime of lithium batteries is estimated using an advanced model based on electrochemistry to evaluate the battery longevity and its lifetime.

Neves et al. [116] presented a comparative study on the different objectives of the optimization techniques for the management of stand-alone MGs. This approach is primarily based on linear programming and genetic algorithms. The results showed that the optimization of the controllable loads could result in an operating cost reduction and inclusion of renewable energies.

Wei et al. [117] proposed an iterative and adaptive algorithm based on dynamic programming to enable optimal energy management and control a residential MG. The charge/discharge level of the battery is treated as a discreet problem in hourly steps. The decisions on the energy supply for a residential load with respect to the energy fee are made in real time.

Yan et al. [118] studied the design and optimization of a MG using a combination of techniques such as mixed integer programming for the optimization of energy management, and the probabilistic Markov model to represent the uncertainty of PV generation. The design included a linear model to evaluate the MG lifetime.

Akter et al. [119] proposed a hierarchic energy management model for an interconnected residential MG serving prosumers, which includes a local control mechanism that shares information with a central controller for energy management.

In the research presented in [120], an energy management system was designed for a hybrid system combining wind, PV, and diesel generation. The system operates both on- and off-grid. Thus, there exists a control mechanism within the inverter for transfers between the micro and utility grids.

Lai et al. [121] proposed a techno-economic analysis of an off-grid photovoltaic with graphite/LiCoO2 storage used to supply an anaerobic digestion biogas power plant (AD). The main contribution is the economical study of the hybrid system including the battery degradation costs. An optimal operating regime is developed for the hybrid system, followed by a study on the levelized cost of electricity (LCOE).

Figure 3 presents a summary of the energy management methodologies used for the MGs based on the above-reviewed literature. Different researches have proposed several methodologies related to energy management in MGs. Many methods are based on classical approaches such as mixed integer linear and nonlinear programming. Linear programming can be considered a good approach depending on objective and constraints, while artificial intelligence methods are focused to approach situations where other methods lead to unsatisfactory results, including renewable generation forecasting and optimal operation of energy storage considering battery aging, among others.

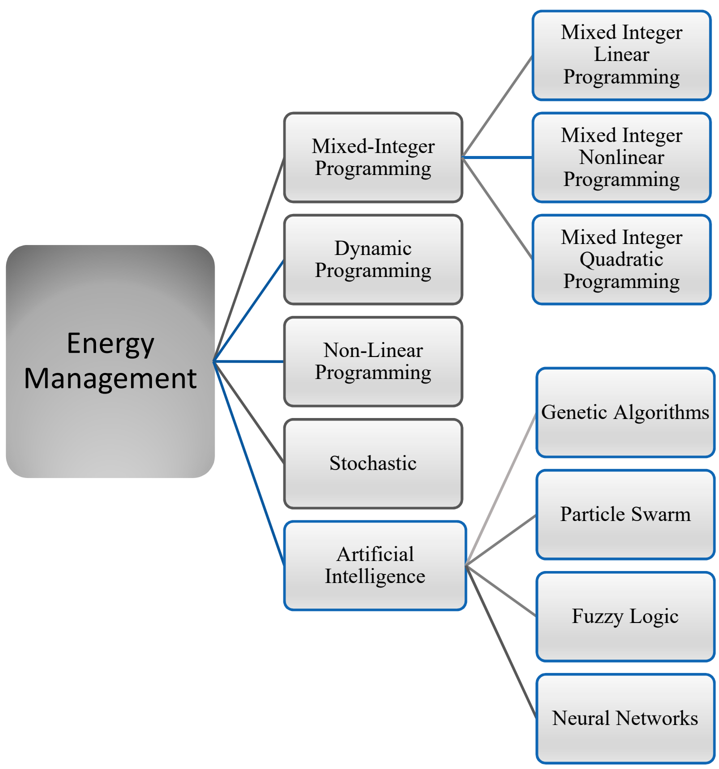

Figure 3. Energy management methodologies in microgrids (MGs) [25].

3.9. Optimization Techniques

Different optimization techniques are generally applied to maximize the power output of each particular source, minimize electricity costs, or maximize storage systems. Figure 4 presents the most commonly employed optimization techniques and algorithms presented in the literature review. Main advantages and disadvantages are briefly presented in Table 2.

Various techniques have been used by different researches. Energy management and the optimization of control in a MG can have one or more objective functions. These functions can vary depending on the optimization problem presented. This can result in a mono-objective or multi-objective problem, which can include the minimization of costs (operation and maintenance cost, fuel cost, and degradation cost of storage elements such as batteries or capacitors), minimization of the emissions and minimization of the unmet load. Table 3 shows a comparison between the different optimization and management methods used in the MGs. Different researchers have proposed metaheuristic techniques to solve the problem of optimization due to multi-constraints, multi-dimensional, and highly nonlinear combinatorial problems. Other authors presented stochastic dynamic programming methods for optimizing the energy management problem with multidimensional objectives. Game theory has been proposed for some researchers to solve problems with conflicting objective functions.

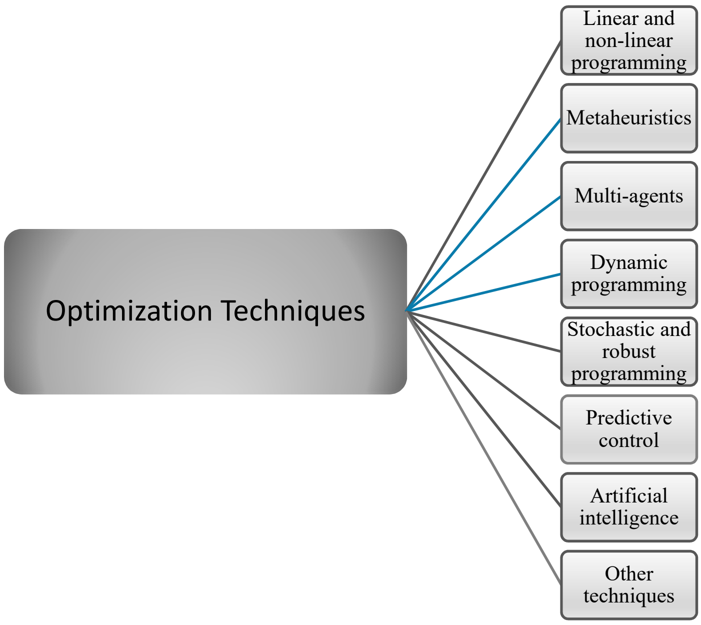

Figure 4. Optimization techniques in microgrid energy management.

Table 2. Comparative analysis of optimization mathematical models.

Optimization Mathematical Model	Advantages	Disadvantages
MILP	Linear programming (LP) is a fast way to solve the problems and the linear constraints result in a convex feasible region, being guaranteed in many cases to obtain the global optimum solution.	Reliability and economic stochastical analysis. Limited capabilities for applications with not differentiable and/or continuous objective functions.
MINLP	It uses simple operations to solve complex problems. It can obtain more than one optimal solution to choose from, which is an advantage over the MILP formulation.	High number of iterations (high computational effort).
Dynamic programming (DP)	It can split the problem into subproblems, optimizing each subproblem and therefore solving sequential problems.	Complex implementation due to high number of recursive functions.
Genetic algorithms (GA)	Population-based evolutionary algorithms that include operations such as crossover, mutation, and selection to find the optimal solution. Adequate convergence speed. Widely used in many fields.	Crossover and mutation parameters, and population and stopping criterial parameters must be set.
Particle swarm optimization (PSO)	Good performance in scattering and optimization problems.	High computational complexities.
Artificial bee colony	Robust population-based algorithm simple to implementate. Adequate convergence speed.	Complex formulation.
Artificial Fish Swarm	Few parameters, fast convergence, high accuracy, and flexibility.	Same advantages of GA but without its disadvantages (crossover and mutation).
Bacterial foraging algorithm	Size and non-linearity of the problem does not affect much. Converge to the optimal solution where analytical methods do not converge.	Large and complex search space.

Table 3. Analysis of microgrid optimization techniques.

Reference	Optimization Technique	Contributions	Constraints	Drawbacks	Single/Multi-objective
[31]	No linear and mixed integer programing	Robust optimal EMS MPC-based to obtain the optimal power scheduling for the different generators, including deferrable and dump loads.	Power balance Battery Diesel Generator Renewable Sources Load	Demand and power losses are not considered.	Multi-objective
[32]	Linear and mixed integer linear programming	Energy management strategy based on the combination of three operating strategies (continuous run mode, power sharing mode, and ON/OFF mode).	Battery Generation dispatch	Battery degradation costs in the optimization models are not considered.	Multi-objective
[35]	Mixed integer no linear programming	Reduced the overall operational costs while maintaining a secured operation of the stand-alone MG.	AC power DC power Converter power Load Distributed generators power	Battery storage systems are not considered. Emission cost of distributed generation based on biomass is not considered.	Mono-objective
[45]	Linear programming	Integration of linear programming-based with artificial intelligence techniques to sole multi-objective optimization.	Power Balance Generation limits of distributed generation	High computational complexity. Battery degradation cost is not considered.	Multi-objective
[46]	Particle swarm algorithm (PSO)	Combination of two optimal storage energy units. Less computation time than GA.	Power of the generators Power exchange with the grid Charge/Discharge of the storage units Supply and demand balance	Emission cost of the conventional generator is not considered.	Multi-objective
[48]	Particle swarm algorithm (PSO) with Gaussian mutation	PSO variant new algorithm.	Active power Voltage Current	Power losses are not considered. Emissions of distributed generation are not considered.	Mono-objective
[50]	Artificial bee colony	Two layer control model used to minimize operational cost of a microgrid.	Power balance Dispatchable resources Non-dispatchable resources Storage elements	Complex formulation. Emission cost of a dispatchable microturbine is not considered.	Mono-objective
[51]	Fuzzy logic (Grey Wolf Optimization)	Optimization of the size of the battery energy storage and of the generation plan.	Power balance Power of the generators Battery load	Battery degradation cost is not considered.	Multi-objective
[53]	Evolutionary algorithm (EA) and the particle swarm optimization (PSO) Algorithm	Application of an energy hub model for optimization of a multicarrier MG.	Power balance Voltage in the transformers	Deterministic conditions assumed are a limitation.	Mono-objective

Table 3. *Cont.*

Reference	Optimization Technique	Contributions	Constraints	Drawbacks	Single/Multi-objective
[55]	Artificial fish swarm optimization	An energy management planning of a MG including storage for a whole day is optimized, considering dynamic pricing and demand side management.	Power balance Conventional power generation Conventional power generators Energy storage Utility grid power	Battery degradation cost is not considered.	Mono-objective
[57]	Particle swarm algorithm (PSO)	Three different objectives are considered: Reliability, cost of operation, and environmental impact.	Not specified	Battery degradation cost is not considered.	Multi-objective
[58]	Bacterial foraging algorithm	Optimized the exchanging power with the grid and the generators and battery setpoints. Fast convergence.	Power balance Generation limits of distributed generators Storage limits	Power loss not considered.	Multi-objective
[60]	Mixed-integer nonlinear programming (MINLP)	Reduced dependency on forecast information. Different battery models compared.	Charge flow Dispatch of generators Generator on/off programming Charge/Discharge of batteries	Battery lifetime prediction is ignored.	Multi-objective
[61]	Dynamic Rules	MG management system uses different limits for the SOC of the batteries bank.	Battery Power balance	Battery cost and degradation are not considered.	Mono-objective
[64]	Dynamic programming	Energy management strategy for PV. Batteries to stabilize and permit PV to run at a constant and stable output power.	Charge/Discharge of batteries	Battery degradation and lifetime prediction are not considered.	Multi-objective
[70]	Multi-agents	Efficient strategy for real-time management of energy storage used to compensate power mismatch optimally.	Charge/Discharge of batteries Load Scheduling Power Balance	Prediction of battery ageing is not included.	Multi-objective
[72]	Multi-agents	Control scheme composed of several levels with coordinated control.	Charge/Discharge of batteries	High complexity control scheme.	Multi-objective
[73]	Multi-agents	Battery energy storage system, optimization problem based on distributed intelligence, and a multi-agent system.	Not specified	Battery degradation is not considered.	Multi-objective
[80]	Mixed integer programming	Dual-stage optimization. First stage determines hourly unit commitment of the generators, the second stage performs economic dispatch of the generators and batteries.	Startup costs of renewable energy and conventional generators	Power losses are not considered. Battery degradation is not considered.	Mono-objective

Table 3. *Cont.*

Reference	Optimization Technique	Contributions	Constraints	Drawbacks	Single/Multi-objective
[84]	Stochastic	A simple method to incorporate the impact of the scheduling in stand-alone mode on the grid-connected operation.	Power balance Dispatchable Distributed generation Renewable power generation Load Charge/Discharge of batteries	Battery ageing model is not considered. Emission cost of DG are not taken into consideration.	Mono-objective
[89]	Robust programming	Optimization of load management for hybrid Wind–Battery–Diesel systems.	Power Diesel Generator Power wind turbine Power battery bank	Controllable loads shifting can be non-optimal.	Mono-objective
[91]	Mixed Integer Quadratic Programming	Integrated stochastic energy management model, simultaneously considering unit commitment for generators and demand side management.	Power balance Generation Demand Reserve capacity	Computational time is higher than that of deterministic model. Emission cost of conventional generators and DG are not taken into consideration.	Mono-objective
[92]	Model predictive control	Automated load shedding of noncritical loads when foreseeable power unbalances could affect the stability of the MG.	Power distributed generators	The charging and discharging rates of the batteries were not considered. It does not consider communication delays.	Multi-objective
[97]	Model predictive control	A comprehensive mathematical formulation of the optimal EMS for stand-alone microgrids, considering power flow and unit commitment operational constraints.	Power balance Reserve Unit commitment Energy storage Grid DG	Higher computational burden and complexity. Emission cost of conventional generators is not considered.	Mono-objective
[101]	Model predictive control	The main contribution of this work is daily optimization that accounts for the degradation of the lead-acid battery by corrosion and capacity losses.	Not specified	Lithium battery model is not considered.	Multi-objective
[103]	Genetic algorithm	A novel cost function is including costs of selling and buying power, and the start-up costs of distributed resources.	Power balance Emissions Battery storage Startup and downtime of generators	Distributed sources and battery state of charge are not considered. The uncertainty in energy generation by the MGs and the uncertainty in customers are not considered.	Mono-objective
[104]	Game theory	In multiple MGs, distributed energy management schedule.	Energy exchange with the grid Generation capacity of the MG	Computational complexity is not discussed.	Multi-objective

Table 3. *Cont.*

Reference	Optimization Technique	Contributions	Constraints	Drawbacks	Single/Multi-objective
[111]	Artificial Intelligence (Fuzzy logic)	Simple implementation, improved the grid power profile quality.	Charge/Discharge of batteries	Only the battery charger/grid-connected inverter is controllable. Battery degradation is not considered.	Multi-objective
[114]	Game theory	Minimize fuel cost and trading power cost.	Power balance DG Conventional generator power Limit for the transferable power between The main grid and MG	Emission cost of conventional generators is not considered.	Multi-objective
[118]	Markov decision process	Linear model to evaluate the MG lifetime cost.	Gas turbine capacity Gas turbine emissions	Number of possible combinations of sizes is limited.	Mono-objective
[121]	Rule-based	Study on the economic projection of the hybrid system with the battery degradation costs. An optimal operating regime is developed for hybrid system, followed by a study on the levelized cost of electricity (LCOE). Accuracy of degradation costs of the energy storage.	Power balance SOC battery	Temperature not considered in the capacity fade model. Dynamic state of charge cycling conditions not considered.	Multi-objective

3.10. Microgrid Operating Modes

A considerable number of papers have been published on interconnected microgrids, while discussing various modes of microgrid operation. On the other hand, the stand-alone mode is considered by many authors as an alternative supply measure mainly in the rural areas or regions with no conventional grids [122]. Thus, both the on- and off-grid operating modes are a feasible alternative. Table 4 summarizes the above considerations.

Table 4. Microgrid operating modes.

Reference	Microgrid Mode Operation
[11,20,30,32,33,36–39,45,49,51–53,55,56,58,59,63,67–71, 74,77–81,83,85–87,91,93,94,96,99,100,103–114,117,118]	Grid-Connected
[9,31,34,40,42,44,47,48,50,54,57,60,62,65,66,72,73,75,76, 82,84,88–90,92,97,98,101,102,115,116,119,121]	Off-Grid
[8,15,19,35,43,46,61,64,95,120,122]	Grid-Connected/Off-Grid

3.11. Modelling and Simulation Tools

Table 5 presents a summary of the most popular simulation tools, wherein tools such as Matlab/Simulink (MathWorks, Natick, MA, USA) and MATPOWER have particular importance. Matlab is a numerical computing environment of 4th generation programming language, it can interface with other languages such as C, C++, C#, Java, Fortran, and Python. MATPOWER is an open-source tool that is used to simulate optimal power flows, which uses Monte Carlo to evaluate the performance of MG. Alternately, other tools such as GAMS, which is an optimization language for linear, nonlinear, and mixed programming, have been used by many authors to solve the uncertainty problem in energy management and for optimal dimensioning of the microgrid. Other tools such as CPLEX have been employed, which is an optimizer based on the C language and is compatible with other languages like C++, Java, and Python.

Table 5. Simulation software and tools used in the management of microgrids.

References	Tools	Characteristics
[61]	PSCAD/EMTDC	Simulation software power systems, power electronics, HVDC, FACTS, and control system.
[11,32,33,35,38,62,64,65, 67,70,77,93,97,104,109, 110,121]	MATLAB/Simulink MATPOWER	Matrix based programming language used by engineers in power systems, power electronics, telecommunications, and control, among others. Compatible with other programming languages (C++, Java, and fortran).
[30,76]	GAMS (GAMS Development Corp., Fairfax, VA, USA)	High level language for mathematical optimization of mixed integer linear and nonlinear.
[74]	C++	Application development environment of C++ for Windows.
[40]	TRNSYS (Thermal Energy System Specialists, LLC, Madison, WI, USA) HOMER HOGA	Simulation software to model hybrid systems of energy generation. Hybrid Optimization by Genetic Algorithms.
[75]	RSCAD (RTDS Technologies Inc., Winnipeg, MA, Canada) JADE (Jade, Christchurch, New Zealand)	Real time simulator for power systems.
[67,68,71,72]	JADE	Java environment platform for multi-agents.
[30,118,122]	HOMER	Simulation software to model hybrid systems of energy generation.
[36,83,103]	CPLEX (IBM, Armonk, NY, USA)	Optimization software compatible with C, C++, Java, and Python languages.

The simulation and modeling of microgrids has been analyzed with programs such as Simulink and PSCAD/EMTDC (Manitoba Hydro International Ltd., Winnipeg, Manitoba, Canada). Both tools are used for power control and energy management in microgrids.

Software such as HOMER (Pro Version, HOMER Energy LLC, Boulder, CO, USA), HOGA (or its updated version iHOGA) (Pro+ Version, University of Zaragoza, Zaragoza, Spain), or HYBRID2 (University of Massachusets, NREL/NWTC, Golden, CO, USA) also deserve a mention, which can be used to optimize the operation and energy management of hybrid systems with renewable energies.

4. Conclusions and Future Research

The literature review highlighted two approaches for microgrid energy management: The centralized and decentralized approaches. The first incorporates optimization using the available information in the absence of a coordination strategy between the actors in a microgrid. A computer centre transmits the optimal settings to each participant. The second approach implements optimization using partial information and a strategy for coordinating the microgrid participants; each participant evaluates its own optimal settings. Centralized management is mostly implemented in metaheuristic methods, and decentralized management is frequently implemented in methods based on multi-agents. Many publications have proposed centralized management for microgrids. However, the incursion of distributed energy resources (DER) may cause this type of management to face issues when implemented in a centralized information system because there might be a demand for high computational cost due to the large quantity of data. Distributed energy management may be an alternative solution to this problem. It solves the problem of data processing and reduces processing needs by using distributed controllers that manage the data in real time and require communication equipment that might result in additional costs (for e.g., Bluetooth, Wi-Fi, wireless networks, and IoT).

An energy management model for a microgrid includes data acquisition systems, supervised control, human machine interface (HMI), and the monitoring and data analysis of meteorological variables.

The literature review mainly presented management methods based on foresight and short-term management. The choice of centralized or decentralized management ensures that the microgrid designer and operator realize a cost–benefit balance. This enables one to determine the management model that is most convenient for the microgrid. Though decentralized management offers more flexibility, an integral analysis is necessary to ensure reliable and safe system operation.

The energy management problem or optimization control in a microgrid becomes a mono-objective management/optimization model when a single cost function is presented. This function typically corresponds to the operating cost of the microgrids. The problem becomes a multi-objective management/optimization model when it simultaneously presents a solution to the technical, economic, and environmental problems. Based on the literature, different authors have addressed the problem and provided solutions using methods such as the classic ones with linear and nonlinear programming, heuristic methods, predictive control, dynamic programming, agent-based methods, and artificial intelligence. These methods are chosen based on their practicality, reliability, and resource availability in the microgrid environment.

With regard to storage systems in microgrids, lithium batteries can be an important alternative to lead-acid batteries in the future. The advantages of Li-ion batteries compared to lead-acid batteries are a long cycle life, fast charging, high energy density, and low maintenance. Currently, lead acid batteries are economically better than Li-ion batteries when used in microgrids, but a decrease in the acquisition cost of lithium batteries is expected in the coming years that will cause them to be competitive with those of lead-acid. Thus, further research on the optimal energy management of energy systems and the management of lithium batteries is required while considering more accurate degradation models to accurately predict the battery lifetime in real operating conditions.

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Abbreviations

MG	Microgrid
AC	Alternating current line
ARMA	Auto-regressive moving average models
CSA	Crow search algorithm
DC	Direct current line
DG	Distributed generation
DER	Distributed energy resources
EEMS	Expert system for energy management
EMS	Energy management system
GAMS	General algebraic modeling system
HMI	Human machine interfaces
HOGA	Hybrid optimization by genetic algorithms
HOMER	Hybrid optimization model for multiple energy resources
iHOGA	Improved Hybrid optimization by genetic algorithms
JADE	Java platform for agent developers
MGSC	Microgrid supervisory controllers
MILP	Mixed integer linear programming
MO	Multi-objective
MPC	Model predictive control
PSO	Particle swarm optimization
PV	Photovoltaic
VPP	Virtual power plant

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Optimization of Isolated Hybrid Microgrids with Renewable Energy Based on Different Battery Models and Technologies

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Optimization of Isolated Hybrid Microgrids with Renewable Energy Based on Different Battery Models and Technologies

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Abstract: Energy supply in remote areas (mainly in developing countries such as Colombia) has become a challenge. Hybrid microgrids are local and reliable sources of energy for these areas where access to the power grid is generally limited or unavailable. These systems generally include a diesel generator, solar modules, wind turbines, and storage devices such as batteries. Battery life estimation is an essential factor in the optimization of a hybrid microgrid since it determines the system's final costs, including future battery replacements. This article presents a comparison of different technologies and battery models in a hybrid microgrid. The optimization is achieved using the iHOGA software, based on data from a real microgrid in Colombia. The simulation results allowed the comparison of prediction models for lifespan calculation for both lead–acid and lithium batteries in a hybrid microgrid, showing that the most accurate models are more realistic in predicting battery life by closely estimating real lifespans that are shorter, unlike other simplified methods that obtain much longer and unrealistic lifetimes.

Keywords: lead–acid batteries; lithium batteries; aging models; optimization; hybrid microgrids

1. Introduction

Global warming and the increase of greenhouse gases caused by fossil-fuel-based energy generation have resulted in worldwide concern about future energy supply [1]. These inconveniences have become an opportunity for the use of renewable energy such as solar, wind, tidal, geothermal, and biomass, among others. In 2018, approximately 15% of the total energy consumed worldwide was of renewable origin, and it is estimated that by 2050 this percentage may reach 28% [2]. In terms of electrical energy generated, renewable sources generated 28% of the total worldwide energy in 2018, and it is estimated that they could produce 49% by 2050 [2], reducing fossil fuel dependence and mitigating the effects caused by climate change. However, one drawback of renewable sources is their unpredictable nature and intermittency. To overcome this drawback, an attractive solution is to combine two or more energy sources in a hybrid system and include energy storage [3]. For example, photovoltaic power generation can be used during the day and wind power generation (which usually generates more energy) can be used at night, so the two sources of energy complement each other [4,5]. Furthermore, the different energy sources can be managed as a microgrid, which can solve reliability problems and provide an environmentally friendly solution [6]. In addition, increasing renewable energies can cause problems for quality; therefore, it is necessary to have a flexible and intelligent electrical network. One of the fundamental aspects to increase the electrical grid's flexibility is the use of storage systems that allow compensation for the variability of renewable energy sources. Conversely, electricity grids are designed considering energy sources that do not present variability, which happens with renewables, so electricity grids must have enough back-up capacity. Storage capacity is essential, thus making it possible to increase renewable generation while avoiding the possible problems that could be caused by its variability [3].

Hybrid microgrids are a new solution in remote areas that are difficult to access or that do not have access to conventional power grids [7]. In hybrid microgrids based on renewable energy, one of the main elements that support the energy supply due to the variable intermittency such as radiation or wind, as mentioned above, is storage technologies, and batteries in particular are the most suitable and convenient.

Batteries are the most widely used storage devices in hybrid systems due to the maturity of technologies such as lead–acid and the emergence of technologies such as lithium-based batteries. The latter represents an attractive option due to their high energy density, longer life, and better environmental sustainability [8]. In addition, lithium batteries have seen a price reduction between 8–16% annually [9].

Batteries represent a high cost within a hybrid microgrid, and their performance and duration mainly depend on the microgrid's operation. Battery life estimation is crucial since it influences the replacement costs and, therefore, the total system cost [10]. The batteries' optimal operation within a hybrid microgrid is influenced by factors such as technology, the amount of charge and discharge cycles, the current, and the operating temperature, among others [11,12]. Parameters related to aging by degradation and corrosion have been represented by authors, such as the model by Schiffer et al. [13] that used weighted cycles and applied to lead–acid batteries.

Based on this model, a comparison of lead–acid battery life prediction models was presented by Dufo-López et al. [14]. For battery life prediction, models based on equivalent cycles or "Rainflow" cycle counting models have traditionally been used [15]. As for lithium batteries, there are models (e.g., Wang et al. [16]) that include parameters such as the cycled charge (Ah) over time, charge and discharge currents, and temperature, applicable to LiFePO4/graphite (LFP) batteries. Other models for the same type of lithium batteries, such as that of Groot et al. [17], study their degradation when subjected to asymmetric charge cycles and at different temperatures. Conversely, Saxena et al. [18] considered an aging model based on state of charge (SOC) for lithium cobalt oxide LiCoO2/graphite batteries.

When batteries work in real conditions, the way they degrade and age differs from laboratory tests, so that the lifespan may be shorter than expected, as demonstrated in [19] for lead–acid batteries. When optimizing isolated hybrid systems, it is essential to consider battery aging and degradation models to estimate parameters such as net present cost (NPC) and levelized cost of energy (LCOE) [19]. In [20], the authors presented an optimization of microgrid-insulated diesel-solar-wind power charge states of lead–acid batteries. Other studies have compared aging models for lead–acid and lithium batteries used in isolated photovoltaic systems [21,22].

The optimization of isolated hybrid systems mainly depends on predicting battery life, since an erroneous or overly optimistic prediction can lead to a poor estimate of the system costs. The importance of these considerations has been highlighted in recent publications [23,24]. However, it is necessary to consider these factors in systems where the actual and climatic conditions of operation differ considerably from the datasheet and the expected life of the battery according to laboratory tests.

This article presents the optimization of an isolated hybrid microgrid considering different lead–acid and lithium battery technologies and models. The system integrates solar modules, a battery, a wind turbine, a diesel generator, an inverter, and a charge controller. In addition, this system is optimized considering different battery models and technologies. In the second section, the different battery aging models are presented. In the third section, the microgrid under consideration is shown, and the results are presented in the fourth section. Finally, the conclusions and future work are presented.

2. Materials and Methods

Battery aging models represent essential aspects such as anodic corrosion, active mass degradation, loss of adhesion to the grid, formation of lead sulfate in the active mass, loss of water, and electrolyte stratification [25]. Conversely, the models used for lithium batteries analyze capacity and power losses, impedance increase, and the effects caused by temperature [26]. The different lead–acid and lithium battery models considered in this study are described below.

2.1. Simplified Model of Equivalent Ah Cycles

This model is used by optimization programs such as HOMER [27]. In this model, battery life is supposed to be reached at the end of a finite number of charge and discharge cycles, and the number of cycles is usually shown in the battery datasheet. The IEC 60896-11: 2002 [28] establishes the number of cycles. However, this model does not consider the battery's operating status (e.g., SOC, temperature, acid stratification in the case of lead–acid batteries, current, and the amount of time the battery has not reached full charge). The number of complete cycles (Z_n) is calculated by Equation (1):

$$Z_n(t+\Delta t) = Z_n(t) + \frac{\left|I_{dischbat}(t)\right| \times \Delta t}{C_n}, \quad (1)$$

where $\left|I_{dischbat}(t)\right|$ (A) is the absolute value of the discharge current. C_n is the nominal capacity of the battery (Ah).

If $Z_n(t) = Z_{\mathrm{IEC}}$ (when the number of cycles performed from the beginning of life until time t (h) is the same as the IEC number of cycles provided by the manufacturer), then the end of the battery life is reached.

2.2. Cycle Counting or Rainflow Model

The cycle-counting model, also known as "Rainflow," is based on the Dowing algorithm [29]. This model is based on the Z_i cycle count, corresponding to each Depth of Discharge (DOD) range (%), which is divided into m intervals for 1 year (an average year or the whole life). For each interval, there are several cycles until failure (CF_i). The battery life is calculated by Equation (2):

$$Life_{bat} = \frac{1}{\sum_{i=1}^{m} \frac{Z_i}{CF_i}}, \quad (2)$$

This model takes into consideration the depth of discharge of the cycles; however, it does not take into account the batteries' operating conditions, such as acid stratification, current, and temperature.

2.3. Schiffer et al.'s (2007) Model

The Schiffer model is a weighted charge model (Ah) proposed by Schiffer et al. [13] specifically for lead–acid batteries. The actual cycled charge in Ah is multiplied continuously by a weight factor that fully represents the battery's actual operating conditions, considering the SOC (e.g., temperature, acid stratification, current, and the time it takes without reaching full charge) during the battery lifetime. The end of the battery's lifetime is reached when its remaining capacity corresponds to 80% of the nominal capacity. Users can adapt this model to different battery types using the lifetime and flotation datasheet. Complex calculations to calculate the final loss of battery capacity due to continuous corrosion and degradation are made using Equation (3):

$$C_{rest}(t) = C_d(0) - C_{corr}(t) - C_{deg}(t), \quad (3)$$

where C_{corr} is loss of corrosion capacity, C_{deg} is degradation capacity losses, and $C_d(0)$ is initial normalized battery capacity.

This model allows us to model the charge controller and configure the protections against overloads and other parameters.

2.4. Wang et al.'s (2011) Model

Wang et al.'s (2011) model provides a life cycle model for LiFePO4/graphite lithium–ferrophosphate batteries considering parameters such as accelerated charge/discharge tests under different temperature conditions and discharges depths [30]. At low charge rates, the results indicate that the loss of capacity is significantly affected by time and temperature, whereas the effect is less important in the depth of discharge. This model underestimates the loss of capacity at 60 °C and overestimates it at 45 °C. The authors obtained a percentage of capacity loss given by Equation (4):

$$Q_{loss}(\%) = 30,330 \times exp\frac{-31,500}{8.314 \times T}\, A_h^{0.552}, \tag{4}$$

where T is the absolute temperature in kelvins and A_h is the amount of charge (Ah) involved in the charging process since the start of battery operation.

This equation is valid for charge rates equivalent to C/2; that is, 2-h full charge and discharge times. Charging rates are evaluated from this value up to 10C; that is, the battery will be fully charged in one-tenth of an hour. In our paper, we use this equation during the average year or the whole life.

2.5. Groot et al.'s (2015) Model

Groot et al. [17] obtained an empirical equation for lithium batteries of 2.3 Ah. It is shown that the life cycle of LiFePO4/graphite lithium–ferrophosphate batteries not only depends on the rates of charge and discharge (current), temperature, and depth of discharge, but is also affected by the pauses between charge and discharge times and those dependencies are highly nonlinear. To model the above, they proposed an empirical relationship given by Equation (5):

$$Q_{EOL} = \left(a \times e^{b \times I} \times T^{(C \times I^2 + d \times I + e)}\right) + f, \tag{5}$$

where Q_{EOL} is the charge that the battery can deliver in its lifetime (kAh), I is the charge rate, T is the temperature in °C, and a, b, C, d, e, and f are adjustment constants. In our paper, we use this equation during the average year or the whole life.

2.6. Saxena et al.'s (2016) Model

Saxena et al.'s (2016) model [18] quantifies the life cycle for lithium oxide cobalt LiCoO2/graphite batteries subjected to charge states between 0–60%. It develops a model that estimates the batteries' loss of capacity and the influence of the SOC and the rate of charge. Percentage of capacity loss is modeled by Equation (6):

$$Q_{loss}(\%) = K1 \times \mathrm{SOC}_{mean} \times (1 + K2 \times \Delta\mathrm{SOC} + K3 \times \Delta\mathrm{SOC}^2 \times \left(\frac{EFC}{100}\right)^{0.453}, \tag{6}$$

where SOC_{mean} is the average SOC (30–50%), ΔSOC is variation of the SOC (100–60%), EFC is equivalent full cycles, and $K1$, $K2$, $K3$ = 3.25, 3.25, and 2.25, respectively. In our paper, we use this equation during the average year or the whole life.

2.7. Aging by Calendar Model

This model considers two options for determining age, the first proposed by Petit et al. [30], which takes into account the loss of battery capacity due to two factors: current and temperature. Equation (7) describes this model:

$$Q_{loss}^{cyc}(\%) = B_{cyc} \times exp\left(\frac{-Ea_{cyc} + \gamma \times |I|}{R \times T}\right) Ah^{Z_{cyc}}, \tag{7}$$

where B_{cyc} is an exponential factor in Ah^{1-Zcyc}, which depends on the current, Ea_{cyc} is the activation energy expressed in J mol^{-1}, γ is a coefficient to determine the acceleration in aging due to the current J mol^{-1} A^{-1}, $|I|$ (A) is the absolute value of the current, R is the gas constant (8.314 J·mol^{-1}·K^{-1}), T is the absolute temperature (K), and Z_{cyc} is a constant with a value close to 0.5.

Swierczynski et al. [31] presented the other model that considers the storage temperature, the number of cycles, and depth described using Equation (8):

$$Q_{loss}(\%) = \left(0.019 \times \mathrm{SOC}_{st}^{0.823} + 0.5195\right) \times \left(3.258 \times 10^{-9} \times T^{5.087} + 0.295\right)\right) \times t_m^{0.8}, \tag{8}$$

where t_m is the storage time in months, T is the temperature in °C, and SOC_{st} is the SOC at which the battery is stored (%).

The iHOGA (improved hybrid optimization by genetic algorithms) [15] software version 2.5 allows selecting any of the two models. The value of the current is limited in such a way that when the current is below $\mathrm{C}_{\mathrm{times}}$, the nominal capacity of the batteries' (0.2 by default) calendar aging model is used, and when it is higher, a cyclic aging model is used. In our paper, we use these equations during the average year or the whole life.

2.8. Economic Calculations

iHOGA software performs the simulation of different combinations of components (photovoltaic (PV) generator, wind turbine/s, battery bank, diesel generator, etc.) during a whole year, in hourly steps, except for the cases where the Schiffer et al. [13] model for the battery is selected. In these cases, the simulation is also performed in hourly steps during the number of years of the battery lifetime (a priori it is not known, but it becomes known when the battery's remaining capacity has dropped to 80%).

For each combination of components and control strategies of the system, NPC and LCOE must be calculated so that the genetic algorithm [32] used by iHOGA can calculate the fitness of each combination and finally, after several generations, achieve the optimal system (the optimal combination of components and control strategy).

The NPC (€) of a combination of components i and control strategy k ($\mathrm{NPC}_{i,k}$) is obtained considering the acquisition cost of all the components, the installation and replacement costs of the components, the operating and maintenance (O&M) cost, and the fuel cost during the system lifetime, $Life_{system}$ (years). All the cash flows are converted to the initial moment of the system (hour 0, year 1), considering inflation and interest rates [23]:

$$\begin{aligned}\mathrm{NPC}_{ik} = \textstyle\sum_j \Bigg[Cost_j + \mathrm{NPC}_{repj} \textstyle\sum_{t_y=1}^{Life_{system}} \left(Cost_{O\&M_j} \times \frac{(1+Inf_{general})^{t_y}}{(1+I)^{t_y}}\right)\Bigg] + \\ \textstyle\sum_{t_y=1}^{Life_{system}} \left(Cost_{fuel} \times \frac{(1+Inf_{fuel})^{t_y}}{(1+I)^{t_y}}\right) + Cost_{INST},\end{aligned} \tag{9}$$

where j is the different components, t_y is one year of the system lifetime, $Cost_j$ is the acquisition cost of component j, NPC_{repj} is the sum of the replacement costs of component j during the system lifetime minus the residual cost of component j at the end of the system lifetime, $Cost_{O\&Mj}$ is the annual O&M cost of component j, $Inf_{general}$ is the general annual expected inflation, I is the annual interest rate,

$Cost_{fuel}$ is the annual cost of the fuel used by the diesel generator, Inf_{fuel} is the annual expected diesel fuel inflation, and $Cost_{INST}$ is the installation cost.

The LCOE (€/kWh) of a combination of components *i* and control strategy *k* ($\text{LCOE}_{i,k}$) is calculated as follows:

$$\text{LCOE}_{i,k} = \frac{\text{NPC}_{i,k}}{E_{load} \times Life_{system}}, \tag{10}$$

where E_{load} (kWh/yr) is the annual expected load of the system.

2.9. Case Study

The microgrid considered for this study is located in the community of Nazareth (Department of La Guajira, Colombia), and its coordinates are latitude 12° 20′ 52.14″ N, longitude −71°16′8.80″ W. This place belongs to Colombia's non-interconnected area (the Spanish acronym ZNI is used for these areas); however, it is located in a geographical place with a high potential for solar and wind resources, where proposals for microgrids have been made [33,34]. In addition, this area is characterized by not having 100% energy supply coverage. Figure 1 shows the microgrid.

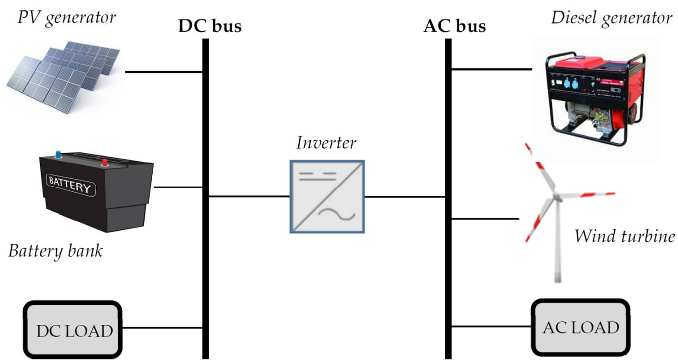

Figure 1. Nazareth microgrid [35].

The load profile is obtained according to the Energy Solutions data for the non-interconnected areas of Colombia IPSE (the government branch that plans and promotes these energy systems) [36], with an average temperature of 27 °C [37]. Table 1 shows the irradiation and wind data of the system installation site obtained from [38]. It can be seen that variation in irradiation and wind throughout the year is not very high. This situation is typical at latitudes close to the equator [39,40]. This small variability in wind and photovoltaic resources throughout the year allows for better use of renewable sources than at other latitudes [6]. The average daily electricity consumption is 30 kWh/day. The consumption is for households and street lighting. As it is an isolated microgrid, not interconnected with an electricity system, consumers of the microgrid cannot participate in the Colombian electricity market as self-consumers. The high number of areas not connected to the electricity grid is one of the most significant obstacles for renewable energy sources to participate in the Colombian electricity market [41].

Table 1. Irradiation and wind speed at the microgrid location.

Month	Irradiation (kWh/m^2/day)	Wind Speed (m/s)
January	5.86	7.04
February	6.51	7.24
March	7.02	7.1
April	6.92	6.93
May	6.72	6.86
June	7	7.64
July	7.13	7.39
August	7.17	6.62
September	6.66	5.7
October	5.99	5.25
November	5.57	5.75
December	5.39	6.7

Figures 2 and 3 show the wind speed and solar radiation values for 1 year at the simulated microgrid's location. Figure 4 shows the load profile during a typical day.

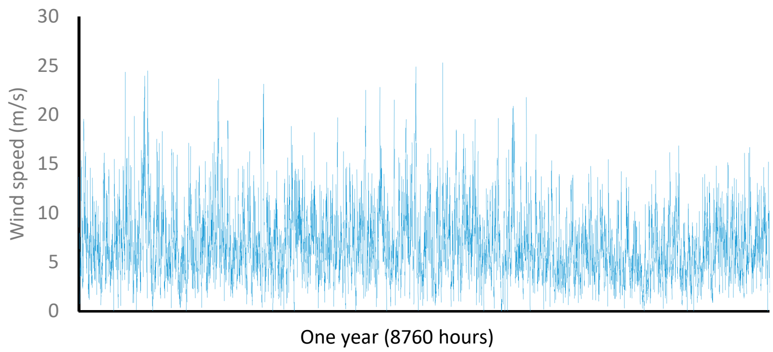

Figure 2. Wind speed (in an average year) at the microgrid location.

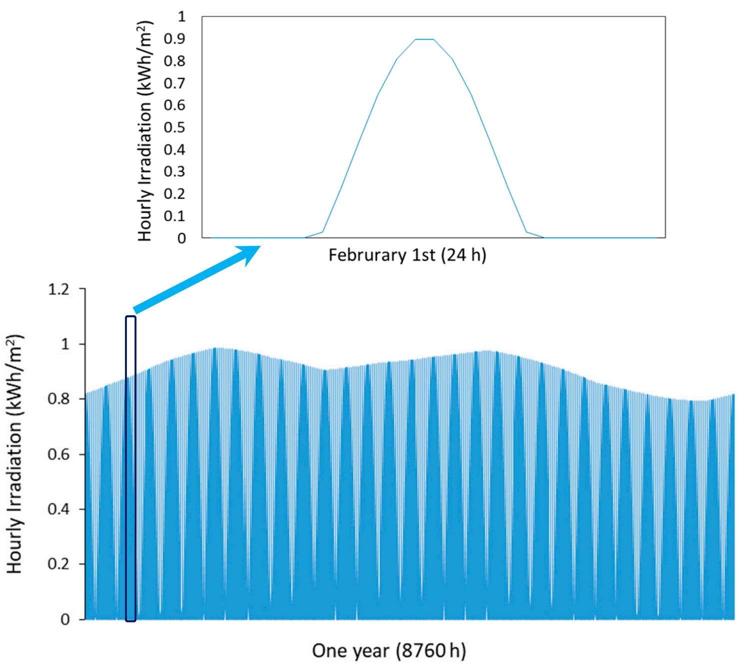

Figure 3. Hourly solar irradiation (in an average year) and detail for a specific day at the grid location.

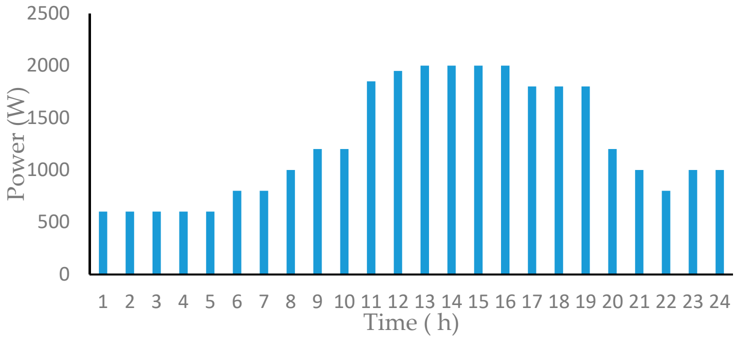

Figure 4. Typical daily load profile for the case study at the grid location.

The voltages in the microgrid are 48/220 V (CD/AC), the wind turbine power is 600 W, the inverter charger is 500 VA/48 V/70 A, the charge controller is PWM/48V/40A, and the diesel generator power is 1.6 kW. The other system data are summarized in Tables 2 and 3.

The system's lifetime is considered the same as a PV generator's expected lifetime (the most common PV lifetime considered by researchers all around the world is 25 years). The economic data used to calculate the NPC of the actual system are shown in Table 4, obtaining the results of Section 3.1.

Table 2. Photovoltaic (PV) data of the simulated microgrid.

PV Module Type	Monocrystalline
PV module power (Wp)	380
Number of PV modules in serial/Parallel	2/22
PV module short current I_{sc} (A)	10.11
PV module open-circuit voltage V_{oc}(V)	24
PV module temperature coefficient (%/°C)	−0.37
NOCT (°C)	48°
PV module slope	15°
PV module azimuth	0°

Table 3. Batteries data.

Battery Type	OPZS
Number of batteries in serial/parallel	24/1
Battery voltage (*V*)	2
Battery capacity C_{10} (Ah)	3360
Battery float life at 20 °C (years)	15
Battery equivalent full cycles	1500

Table 4. Economic data for net present cost (NPC) calculation.

Parameters	Economic Data
Battery bank acquisition cost	30,960 €
PV generator acquisition cost	9680 €
PV generator expected lifetime	25 years
Diesel generator acquisition	800 €
Diesel generator expected lifetime	10,000 h
Inverter acquisition cost	2915 €
Wind turbine acquisition cost	4255 €
Wind turbine generator expected lifetime	15 years
Controller acquisition cost	2215 €
Expected controlled and inverter lifetime	10 year
The lifetime of the system	25 years
Average annual interest rate/inflation rate	4%/4%
Installation cost	500 €

In this work, electricity supply optimization has been carried out for this case, considering various possibilities for the PV generator size, as well as for the wind turbine, diesel generator, and lead–acid batteries. In addition, various lithium battery sizes have been considered.

Tables 5–9 show, in detail, the parameters used in the optimization for each of the system components.

Table 5. PV modules considered in the optimization.

Parameters	Data
Nominal Power	380 Wp
I_{sc}	10.11 A
NOCT	47°
α	−0.37%/°C
Acquisition cost	220 €
Lifespan	25 years
Nominal voltage (2 in serial)	24 V
Maximum number allowed	2 in serial/50 in parallel

Table 6. Wind turbines used in optimization.

Parameters	Model 1: WT600	Model 2: WT3000
Maximum power	660 W	3471 W
Hub height	13 m	15 m
Acquisition cost	4255 €	7555 €
Lifespan	15 years	15 years
O&M cost	85 €/year	50 €/year
Maximum number allowed in parallel	3	3

Table 7. Batteries used in the optimization.

Parameters	Lead–Acid 1	Lead–Acid 2	Lithium 1	Lithium 2
	OPZS	OPZS	BYD B-Box 5.0	LG Chem
Capacity	1865 Ah	3360 Ah	106.6 Ah	63 Ah
Acquisition cost	820 €	1010 €	3390 €	3400 €
O&M cost (one cell)	8.2 €/year	10.1 €/year	20 €/year	30 €/year
O&M cost (whole bank) *	50 €/year	50 €/year	50 €/year	50 €/year
Nominal voltage	2 V	2 V	48 V	48 V
Float life at 20 °C	20 years	18 years	10 years	10 years
Equivalent full cycles	1500	1600	6000	3200
SOC_{min}	20%	20%	20%	20%
Self-discharge	3%/month	3%/month	2%/month	2%/month
Number of series batteries	24	24	1	1
Maximum number in parallel	6	6	6	6

* Cost of the maintenance technician's journey.

Table 8. Diesel generator considered in the optimization.

Parameters	Data
Nominal Power	1.9 kVA
Minimal power	30%
Acquisition cost	800 €
Lifespan	10,000 h
O&M cost	0.14 €/h
Diesel fuel cost (including transportation)	1.13 €/l
Maximum number allowed in parallel	2

Table 9. Inverter/charger considered in the optimization.

Nominal Power	5 kVA
Efficiency	90%

Optimization means also looking for the optimal control strategy between the two preselected options by the iHOGA software [42]. The two global strategies are as follow:

- Demand monitoring: Based on systems that include batteries and either diesel or gasoline generators, when the energy from renewable sources is not enough to meet the demand, the batteries will provide the rest of the energy. If the batteries cannot cover all of the demand, then the generator will work to meet the rest of the demand.
- Cyclic charging: If the generator is required to provide power, then it will only work at its nominal power not only to meet the demand but also to charge the batteries only during that hour. This strategy may have a variation called a cyclic strategy up to the setpoint, which means that the diesel generator will continue to operate at its nominal power until the battery bank reaches a specific value of SOC charge status, which is at 95% by default.

3. Results

3.1. Actual System

Table 10 shows the simulation results of the current system obtained from the data summarized in Section 2, considering different battery-aging models.

Table 10. Simulation results for the current system, using the three lead–acid battery-aging models and an average ambient temperature of 27°.

Battery-Aging Model	Lifespan (years)	NPC (€)	LCOE (€/kWh)
Rainflow cycle counting	9.23	98,891	0.36
Average full equivalent cycles	9.23	99,061	0.36
Schiffer	7.05	119,458	0.49

It is observed that the battery life is shorter with the Schiffer model (the most realistic model), and therefore more replacements are necessary throughout the system's lifetime (25 years), so that NPC and LCOE are higher than using the other less realistic models.

3.2. System Optimization

Various optimizations have been made considering the different component options detailed in Section 2 (Tables 5–9). For each battery life model, two optimizations have been made, one for a hypothetical case of an average temperature of 20 °C and another for the real average temperature of the system's location, which is 27 °C.

Table 11 shows the results for the microgrid optimization considering the three aging models for lead–acid batteries (equivalent cycle model, Rainflow, and Schiffer et al.). Classic models such as equivalent cycles and Rainflow present similar results, both in the expected lifetime as well as factors such as NPC and LCOE. These costs are higher when considering Schiffer's aging model, which is more realistic, since decreasing the batteries' lifetime would require more replacements during the project lifetime and therefore increase the total system cost.

It is also observed that using the equivalent cycle and Rainflow models, the battery lifetime is that of the floating lifetime since few cycles are performed per year. There is a reduction in the batteries' lifetimes due to a 39.2% temperature increase using the real average temperature (27° at the installation site) compared to the case of 20 °C (the reduction is of the order of 50% for every 8.3 °C increase [43]). This reduction is much lower when using the Schiffer model since it considers many more parameters in addition to the temperature and cycles.

Considering the most realistic model (Schiffer) at the real average temperature (27 °C), the best system would be composed of the following: PV with 31.9 kWp capacity, diesel with 1.9 kVA capacity, wind with 660 W capacity, batteries with a 89.520 kWh energy storage capacity, inverter of 5 kVA capacity, with demand monitoring as the optimal control strategy, a battery life of 5.52 years, a NPC of €104,690, and an LCOE of €0.36/kWh. Compared to the result of the current system, considering the Schiffer model (Table 4), where the NPV is €119,458 and the LCOE is €0.49/kWh, it is observed that the current system is not optimal.

The results for one of the optimal cases obtained are shown in Figure 5 (with lead–acid batteries, Schiffer aging model, and at a temperature of 27 °C). The mono-objective optimization consists of obtaining the lowest NPC. The results show a minimum NPC of €104690 and an equivalent level of total CO_2 emissions during the year of 1824 kg/year.

In Figure 5, the horizontal axis shows the generations of the evolutionary algorithm used by the iHOGA optimization software. An evolutionary algorithm generation is similar to an iteration [32].

Table 11. Results of the system optimizations in the case of lead–acid batteries, using the three battery life models and with two different values of average ambient temperature (20 °C or 27 °C).

Battery Aging Model [1]	Ambient Temp.	Optimal System Configuration [2] (In all cases: Diesel Generator Power = 1.9 kVA, Battery Bank Capacity = 89.52 kWh, and Inverter Power = 5 kVA)	Control Strategy [3]	Lifetime (Years)	NPC (€)	LCOE (€/kWh)
AFEC	20°	12.16 kWp/0 kW	LF	20	52,544	0.19
AFEC	27°	12.16 kWp/0 kW	LF	12.31	59,413	0.21
RCC	20°	34.2 kWp/0 kW	LF	20	52,013	0.19
RCC	27°	33.4 kWp/0 kW	LF	12.31	59,413	0.21
Schiffer	20°	32.68 kWp/0 kW	LF	7.73	91,573	0.32
Schiffer	20°	32.68 kWp/0 kW	CC	7.59	92,195	0.32
Schiffer#	20°	32.44 kWp/0 kW	CC	7.36	92,650	0.32
Schiffer	27°	31.9 kWp/660 kW	LF	5.52	104,690	0.36
Schiffer	27º	29.64 kWp/660 kW	CC	5.67	104,730	0.36
Schiffer#	27º	29.64 kWp/660 kW	CC	5.63	105,307	0.36

[1] AFEC = average full equivalent cycles. RCC = rainflow cycle counting. Schiffer# = Schiffer without continuing up to SOC setpoint.; [2] PV power (kWp)/Wind turbine power (kW).; [3] LF = load following. CC = cycle charging.

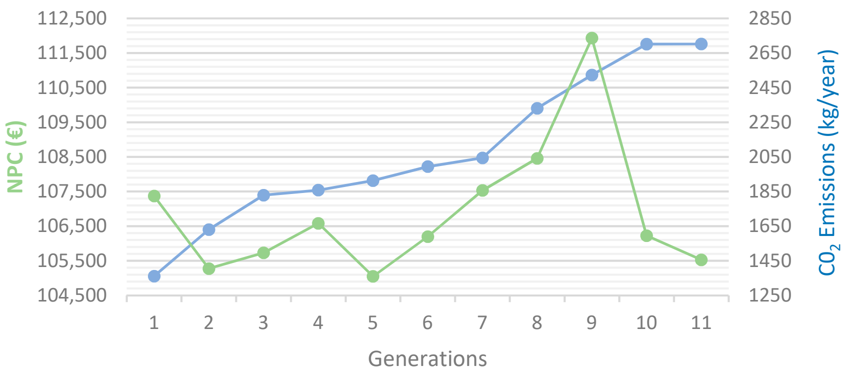

Figure 5. Results for NPC and CO_2 emissions for every generation.

Figure 6 shows the annual distribution of energy generated in this case by the system for a year. The percentage of energy generated by renewables is 96.81%. Of this, 9703 kWh/year is supplied by the photovoltaic generator and 6705 kWh/year by wind turbines, while a smaller contribution is made by the 541 kWh/year diesel generator. The excess energy is 3496 kWh/year, which could be used to charge electric vehicles or to generate hydrogen, which could later be used in fuel-cell-powered electric vehicles [44].

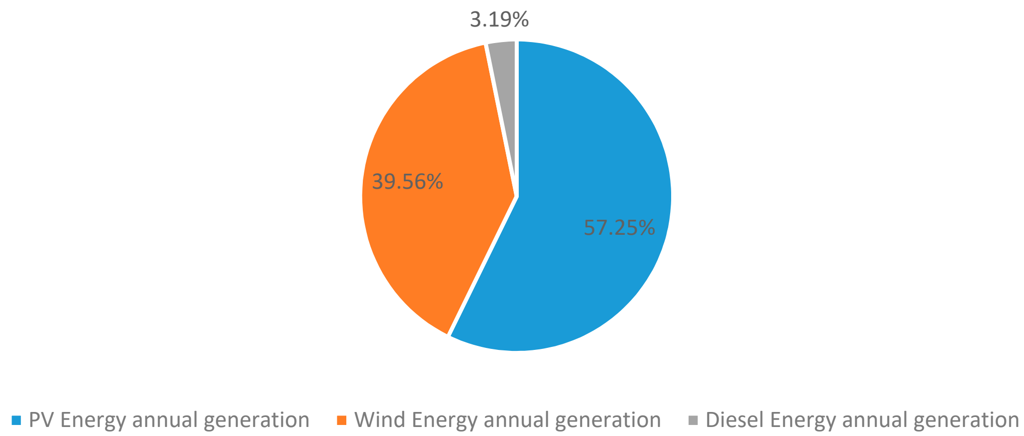

Figure 6. Annual energy distribution.

The optimization results considering lithium batteries instead of lead–acid batteries are shown in Table 12. It is considered that the lithium batteries used can be LiFePO4/graphite or LiCoO2/graphite. Wang et al.'s model proved the most optimistic even when compared to the Groot model when the temperature rises, whereas Saxena's model showed similar results for different temperatures because it is based on the SOC.

Table 12. Results of the optimizations for the case of lithium batteries, using the three models of battery life and with two different average ambient temperature values (20 °C or 27 °C).

Battery Aging Model [1]	Ambient Temp.	Optimal System Configuration [2] (In all Cases, Inverter Power = 5 kVA)	Control Strategy [3]	Lifetime (Years)	NPC (€)	LCOE (€/kWh)
Wang	20°	14.44 kWp/1.9 kVA/0 kW/15.35 kWh	LF	10	47,889	0.17
Wang	20°	15.2 kWp/1.9 kVA/0 kW/20.46 kWh	CC	10	52,657	0.18
Wang	27°	14.44 kWp/1.9 kVA/1.66 kW/15.35 kWh	LF	6.15	56,204	0.20
Wang	27°	13.68 kWp/1.9 kVA/1.66 kW/15.35 kWh	CC	6.12	64,796	0.23
Groot	20°	14.44 kWp/1.9 kVA/0 kW/15.35 kWh	LF	10	47,934	0.17
Groot	20°	PV 15.2 kWp/1.9 kVA/0 kW/20.4 kWh	CC	10	52,657	0.19
Groot	27°	14.44 kWp/1.9 kVA/0 kW/15.35 kWh	LF	6.15	56,204	0.20
Groot	27°	15.2 kWp/1.9 kVA/0 kW/20.4 kWh	CC	6.15	63,747	0.23
Saxena	20°	13.68 kWp/1.9 kVA/0 kW/15.35 kWh	LF	3	78,427	0.29
Saxena	27°	19 kWp/1.9 kVA/3.32 kW/15.35 kWh	LF	3.03	84,742	0.22
AFEC	20°	20.52 kWp/1.9 kVA/1.66 kW/10.2 kWh	LF	10	54,216	0.19
AFEC	27°	13.68 kWp/3.8 kVA/3.32 kW/5.1 kWh	LF	6.15.	58,216	0.2
AFEC	27°	15.2 kWp/1.9 kVA/0 kW/20.4 kWh	CC	6.15.	63,747	0.23
RCC	20°	14.44 kWp/1.9 kVA/0 kW/15.3 kWh	LF	9.88	48,455	0.18
RCC	20°	15.2 kWp/1.9 kVA/0 kW/20.4 kWh	CC	9.88	53,461	0.19
RCC	27°	14.44 kWp/3.8 kVA/3.32 kW/5.1 kWh	LF	6.15	57,162	0.2

[1] AFEC = average full equivalent cycles. RCC = rainflow cycle counting.; [2] PV power (kWp)/Diesel generator power (kVA)/Wind turbine power (kW)/Battery bank capacity (kWh); [3] LF = load following. CC = cycle charging.

It is observed in the results of Table 7 that even with the most pessimistic model, the NPC and LCOE are much lower than those of lead–acid battery optimizations using the realistic Schiffer model (Table 6), leading to the conclusion that lithium batteries are suitable for this case.

4. Discussion

In this work, different models and battery technologies have been compared in the optimization of a hybrid microgrid. The classic lead–acid battery aging models used by various researchers, such as the equivalent cycle model and the Rainflow cycle counting model, generally tend to overestimate the battery's lifespan up to three times its actual duration. However, Schiffer et al.'s [13] weighted model has shown better results since their predictions are closer to the real ones. The results from the different optimizations show that lower net current costs (NPC) and lower LCOE are obtained for both lead–acid and lithium battery models; therefore, it is concluded that the current system is not optimized.

As for LiFePO4/graphite lithium–ferrophosphate batteries, Groot et al.'s [17] model presents more realistic results than Wang et al.'s [16] model, mainly due to temperature increases. Conversely, Saxena et al.'s [18] model showed the same results despite the variation in temperature, since the model is based on the SOC. Finally, comparing the two technologies (lead–acid vs. lithium), the results show lower NPC and LCOE costs for the case of lithium (compared to the realistic Schiffer model for lead–acid), which allows more optimistic insight into the exploration of new aging models for emerging technologies such as lithium batteries, as they represent an alternative storage technology for hybrid microgrids.

5. Conclusions

The most relevant conclusions of this work are as follows:

1. Optimal dimensioning and management of the elements that make up a microgrid give rise to significant energy and economic benefits.
2. Classic models for estimating battery life provide results that are too optimistic, so it is advisable to use models that are more realistic.
3. The effect of temperature in the estimation of battery life can be significant, so models that consider this parameter should be used.
4. Lithium-ion batteries are suitable as storage systems in a microgrid since they give rise to a lower cost throughout the life of the installation due to a longer lifespan than lead–acid batteries and a lower maintenance cost.

These conclusions allow us to state that it is necessary optimize the designs of microgrids not connected to the electricity grid since the economic benefits can be significant. An adequate design will allow for better use of renewable generation, and even take advantage of the surplus energy that can be used in electric vehicles, or in the case of islands, for water desalination. Furthermore, it is necessary to be open-minded and use other storage technologies, in addition to lead–acid batteries, since a lower initial cost does not imply that the total cost, throughout the life of the installation, will be low. Therefore, the use of other generation technologies, such as lithium-ion batteries, should be considered in the design, although their initial cost may be higher.

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Nomenclature and Abbreviations

a, b, C, d, e, f	adjustment constants
AFEC	Average Full Equivalent Cycles
A_h	amount of charge involved in the charging process since the start of battery operation (Ah)
B_{cyc}	exponential factor
CC	Cycle Charging
C_{corr}	final loss of battery capacity due to continuous corrosion and degradation
C_{corr}	loss of corrosion capacity
C_d (0)	initial normalized battery capacity
C_{deg}	degradation capacity losses
CF_i	cycles until failure for interval *i*
$Cost_{fuel}$	annual cost of the fuel used by the diesel generator (€)
$Cost_{INST}$	installation cost (€)
$Cost_j$	acquisition cost of component *j* (€)
$Cost_{O\&Mj}$	annual O&M cost of component *j* (€)
C_n	nominal capacity of a battery (Ah)
DOD	Depth of Discharge (%)
Ea_{cyc}	activation energy expressed in J mol^{-1}
EFC	Equivalent Full Cycles
E_{load}	annual expected load of the system (kWh/yr)
iHOGA	improved Hybrid optimization by genetic algorithms
HOMER	Hybrid optimization model for multiple energy resources
I	charge rate (A)
IEC	International Electrotechnical Commission
Inf_{fuel}	annual expected diesel fuel inflation (€)
$Inf_{general}$	general annual expected inflation (%)
IPSE	Instituto de Planificación y Promoción de Soluciones Energéticas para las Zonas No Interconectadas
I_r	annual interest rate (%)
I_{sc}	PV module short current (A)
LCOE	Levelized Cost of Energy
$\mathrm{LCOE}_{i,k}$	LCOE (€/kWh) of a combination of components *i* and control strategy *k*
LF	Load Following
$Life_{bat}$	battery life (h)
NOCT	Nominal operation cell temperature (°C)
NPC	Net Present Cost (€)
$\mathrm{NPC}_{i,k}$	NPC (€) of a combination of components *i* and control strategy *k*
NPC_{repj}	sum of the replacement costs of component j during the system lifetime minus the residual cost of component *j* at the end of the system lifetime (€)
O&M	operating and maintenance costs
PV	Photovoltaic
Q_{EOL}	charge that the battery can deliver in its lifetime (kAh)
Q_{loss}	percentage of capacity loss (%)
Q_{loss}^{cyc}	percentage of capacity loss (%)
R	gas constant (8.314 J·mol^{-1}·K^{-1})
RCC	Rainflow Cycle Counting
Schiffer#	Schiffer without continuing up to SOC setpoint
SOC	State of Charge (%)
SOC_{mean}	average SOC (30%–50%)
$\mathrm{SOC}_{\min}$	minimum SOC allowed
$\mathrm{SOC}_{\mathrm{st}}$	SOC at which the battery is stored (%)
t	elapsed time, in hours
T	temperature (K, °C)

t_m	storage time, in months
t_y	one year of the system lifetime
V_{oc}	PV module open-circuit voltage (V)
Z_{cyc}	constant with a value close to 0.5
Z_i	cycle count
Z_{IEC}	number of cycles provided by the manufacturer to reach the end of the battery life.
$Z_n(t)$	number of complete cycles
γ	coefficient to determine the acceleration in aging due to the current (J mol^{-1} A^{-1})
α	PV module temperature coefficient (%/°C)
ΔSOC	variation of the SOC (100%–60%)
$\lvert I_{dischbat}(t)\rvert$	absolute value of the discharge current (A)

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Optimization and Feasibility of Standalone Hybrid Diésel-PV-Battery Microgrid Considering Battery Technologies

Optimization and Feasibility of Standalone Hybrid Diesel-PV-Battery Microgrid Considering Battery Technologies

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***Abstract*—Isolated microgrids with renewable energy are an alternative to provide energy service in remote areas or islands. To obtain a viable solution from the economic and environmental point of view it is important to consider the costs and technology of the batteries, since these are one of the main component in an isolated microgrid because they act as a backup to manage the intermittence of solar radiation. In this article the optimization of a hybrid microgrid for the Múcura island in Colombia is analyzed. The optimization model includes battery types and technologies, component cost and fuel cost. The results show the viability of the optimization under different scenarios where a reduction of system costs is obtained.**

***Keywords*—Standalone Microgrid, optimization, Lead-acid batteries, Lithium batteries, Load Shifting, iHOGA**

I. Introduction

Access to electricity has been one of the most relevant issues for sustainable development [1]. In many developing countries it is a challenge to supply electricity to rural areas. In Colombia, nearly 52% of the territory is located within a zone called ZNI (Zona No Interconectada in Spanish), which is an area where the electric system is not connected to the country main grid [2]. This zone has a poor energy service and it is based mainly of diesel generators, solar panels and small hydroelectric plants [3]. In some rural areas located in these territories, the average daily energy supply is about 6 hours [4]. The integration of these resources through isolated hybrid microgrids constitutes a challenge for the energy supply in these areas [5]–[7]. Usually a hybrid microgrid is made up of diesel generators, photovoltaic generators, wind turbines, biomass, fuel cells or some other renewable source.

Due to the renewable resources intermittency present in solar energy and wind power, isolated hybrid microgrids use battery-based storage systems [8]. This makes the optimal dimensioning of these systems a special challenge [9]. There are many studies that analyze the technical, economic and environmental feasibility for different hybrid microgrids [10]–[12]. Optimization aims to obtain the most suitable configuration at the lowest cost and many of these studies use software tools such as HOMER [13], [14]. Some studies such as [15] shows that a considerable cost reduction is achievable with an optimized hybrid microgrid design. A paper presented in [16] shows that a hybrid diesel/solar/battery system presents higher costs during the winter month due to the increase of energy consumption and low levels of radiation. Many researchers in recent years have worked on electrification of remote areas using hybrid systems [17]–[19].

A recent work based on the combination of heuristic and stochastic methods for a hybrid diesel/solar/wind/battery system is presented in [20], highlights the inclusion of battery aging models and control variables. In [21] the authors use the HOGA software to optimize a hybrid diesel/PV/wind/battery system and the results show a considerable reduction in costs and emissions.

Some recent works refer to electrification using hybrid microgrids in island areas [22]. However, few publications compare the viability of emerging lithium battery-based storage technologies with mature technologies such as lead-acid. Therefore, more studies are needed to analyse the feasibility of battery use from a technical, economic and environmental point of view.

This article discusses the optimization of an isolated microgrid with renewable energies analyzing the technical, ecologic and environmental feasibility considering the life span of lead-acid and lithium batteries. Particularly, based on an existing non-optimized energy generation system in Múcura Island, some improvements are proposed in terms of: bigger solar PV installation, improved battery technologies, a generation control strategy and a load shifting method. Those improvements are optimized in terms of cost. In Section II the methodology is proposed, in Section III the results and discussion are presented and finally some conclusions are given in Section IV.

II. Methodology

The system is modeled and optimized using the software iHOGA 2.5 [23]. Model is built with the software help, first the location is selected, then the real consumption profile is analyzed, then the availability of renewable resources

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and finally the different optimizations of the system are obtained:

A. Geographical location and climate

The Múcura island belongs to the municipality of Cartagena, Department of Bolivar, and is classified as a population center located in the ZNI zone, as an island territory of Colombia. Table I describes geographic and climatic information of the Múcura island.

TABLE I
GEOGRAPHIC AND CLIMATE INFORMATION IN MÚCURA ISLAND

Geographic coordinates	Altitude (m)	Precipitation (mm/year)	Avg. annual temperature (°C)
9.73° N, -75.71° W	6	916	27.5

B. Population and consumption profile

The inhabitants of Múcura island have problems with access to drinking water and energy supply. Their main economic activities are fishing and tourism [24], although they currently have a hybrid diesel/PV/battery system [25] Table II summarizes the data for this system.

TABLE II
CURRENT STATUS OF POWER GENERATION SYSTEMS

Average electricity consumption kWh/day	Power factor	Installed Capacity	Average daily electricity service (h)
322	0.91	Diesel 116 kW, PV 30 kW, Batteries 480 kWh[1]	13.45

[1]96 Batteries 2500 Ah/2 V

The consumption profile is based on [26] and is shown in Figure 1. There is a consumption peak at midday and a sustained consumption in night hours. This is explained because the island has high tourism activities and resorts, and there are many night activities.

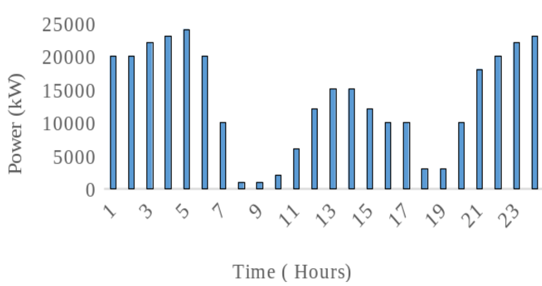

Fig. 1. Daily profile load in Múcura island

C. Renewable resources

The town of Múcura island is located in an insular region where the annual daily-average horizontal solar irradiation is between 5.5 and 6 kWh/m^2 according to the solar irradiaton map from IDEAM [27].

Figure 2 show hourly irradiation data over a year [28]. The average wind speed data is less than 3 m/s so it is not feasible to consider wind turbines for this location.

According to UPME, plant factor for PV is estimated in 20%, which is equivalent to the system working for 4.8 hours per day with a standard irradiance of 1 kW/m^2 [29], [30].

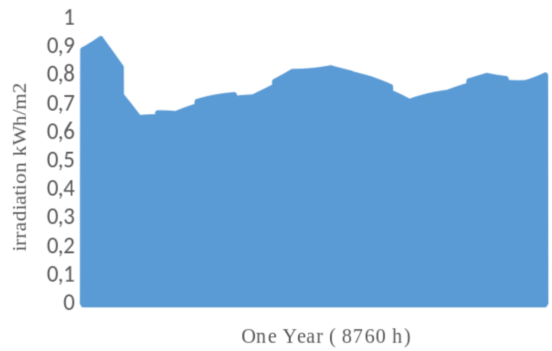

Fig. 2. Global horizontal solar irradiation for Múcura island

D. Data used in the optimization

Tables III to VII describe the parameters used in microgrid optimization. The life time of the system is the same as that of the photovoltaic generator (25 years). The models used for the estimation of the life of the batteries are the one of Schiffer [31] which is a model of weighted charge for lead-acid batteries and the model of Wang et al [32] which is a model that considers different depths of discharge for various temperature conditions in LiFePO4/Lithium Graphite Phosphate batteries [33]. For the inflation rate, the Colombian rate of 4% was used [34] and an interest rate of 7%.

TABLE III
PV MODULES

Parameters	Data
Nominal Power	380 Wp
I_{SC}	10.11 A
NOCT	47°
α	0.37%/°C
Acquisition cost	220
Lifespan	25 years
Nominal voltage	24 V
Slope	10°
Minimum/maximum number of modules in serial	2/13

The optimization will also seek the optimal control strategy, between the two pre-selected by the software iHOGA 2.5, there are two global strategies:

- Load Following (LF): In this strategy, in systems that include batteries and generator either diesel or gasoline, when the energy from renewable sources

$$\mathrm{NPC}_{i,k} = \sum_{j}\left[\mathrm{Cost}_j + \mathrm{NPC}_{\mathrm{rep}_j} + \sum_{t_y=1}^{\mathrm{Life_{sys}}}\left(\mathrm{Cost}_{O\&M_j}\frac{(1+\mathrm{Inf_{Gen}})^{t_y}}{(1+I)^{t_y}}\right)\right] + \sum_{t_y=1}^{\mathrm{Life_{sys}}}\left(\mathrm{Cost_{fuel}}\frac{(1+\mathrm{Inf_{fuel}})^{t_y}}{(1+I)^{t_y}}\right) + \mathrm{Cost_{Inst}} \quad (1)$$

TABLE IV
Batteries

Parameters	Lead–Acid 1	Lead–Acid 2	Lithium 1	Lithium 2
Model	OPZS	OPZS	BYD B-Box 5.0	BYD B-Box 7.5
Capacity	546 Ah	3500 Ah	106.6 Ah	160 Ah
Acquisition cost	216 €	1457 €	3390 €	4700 €
O&M cost (one cell)	2.16 €/year	14.57 €/year	20 €/year	20 €/year
Nominal voltage	2 V		48 V	
Float life at 20 °C	15 years		10 years	
Equivalent full cycles	1600		6000	
SOCmin	20 %		10 %	
Self-discharge	2%/month			
N° Batteríes in serial	150		7	

TABLE V
Diesel generators

Parameters	Data	
Nominal Power	82 kVA	150kVA
Minimal power	30%	30%
Acquisition cost	14000 €	18000 €
Lifespan	30,000 h	30,000 h
O&M cost	0.42 €/h	0.52 €/h
Diesel fuel cost (including transportation)	0.8 €/l	0.8 €/l
Maximum number allowed in parallel	2	2

TABLE VI
Inverter/Charger

Parameters	Data	
Nominal Power	30 KVA	50 kVA
Efficiency	90%	90%
Acquisition cost	38240 €	42940 €
Lifespan	10 years	10 years

TABLE VII
Minimum/maximum number of components in parallel

DC Voltage	Batteries		PV	Diesel Generator
	Lead–Acid (OPZS)	Lithium (BYD)		
300	1/3	1/51	0/45	1/1

is not sufficient to cover the demand, the rest of the energy will be covered by the batteries. If the batteries cannot cover all the demand, the generator will operate to cover the rest of the demand.

- Cyclic Charging (CC): The difference from the previous strategy is that in case the generator is required to operate, it will run at its nominal power not only to meet the demand but also to charge the batteries only during that hour. This strategy can have a variation called cyclic strategy up to the "set-point" which means that the diesel generator will continue to operate at its nominal power until the battery bank reaches a specific value of state of charge SOC which by default is 95%.

E. Economic calculations

For each combination of components and control strategies of the system, NPC (Net Present Cost) and LCOE (Levelized Cost of Energy) must be calculated so that the genetic algorithm used by iHOGA can calculate the fitness of each combination and finally, after several generations, achieve the optimal system (the optimal combination of components and control strategy).

The LCOE is a method used to compare different energy generation technologies, which takes account the NPC of energy generated over its lifetime. This method is widely used to evaluate the feasibility of energy generation systems, in contrast with other methods like the IRR (which is not commonly used) [35].

The NPC of a combination of components i and control strategy k ($\mathrm{NPC}_{i,k}$), shown in the Equation 1, is calculated taking account of the acquisition cost of all the components, the installation and replacement costs of the components, the operating and maintenance (O&M) cost, and the fuel cost during the system lifetime (in years) [36]. All the cash flows are converted to the initial moment of the system (hour 0, year 1), considering inflation and interest rates [37].

In Equation 1, j is the different components, t_y is one year of the system lifetime, Cost_j is the acquisition cost of component j, $\mathrm{NPC}_{\mathrm{rep}_j}$ is the sum of the replacement costs of component j during the system lifetime minus the residual cost of component j at the end of the system lifetime, $\mathrm{Cost}_{O\&M_j}$ is the annual O&M cost of component j, $\mathrm{Inf_{Gen}}$ is the general annual expected inflation, I is the annual interest rate, $\mathrm{Cost_{fuel}}$ is the annual cost of the fuel used by the diesel generator, $\mathrm{Inf_{fuel}}$ is the annual expected diesel fuel inflation, and $\mathrm{Cost_{Inst}}$ is the installation cost.

The LCOE of a combination of components i and control strategy k ($LCOE_{i,k}$) is calculated in the equation 2, where E_{load} (kWh/yr) is the annual expected load of the system.

$$LCOE_{i,k} = \frac{\text{NPC}_{i,k}}{E_{\text{load}} \times \text{Life}_{\text{sys}}} \quad (2)$$

Optimization can be mono-objective (minimum system costs) or multi-objective when other variables such as equivalent emissions or unserved energy are simultaneously minimized.

TABLE VIII
SIMULATION RESULTS FOR THE CURRENT SYSTEM, USING THE LEAD–ACID BATTERY-AGING MODEL

Battery-Aging Model	Lifespan (years)	NPC (€)	LCOE (€/kWh)
Schiffer	0.8	3407944	1.16

III. SIMULATION AND RESULTS

A. Simulation of the current system

The optimized microgrid is shown in Figure 3. The simulation of the current system is presented in table VIII. A high net present value (NPV) is shown considering the small contribution of the PV generator in the energy supply under current operating conditions.

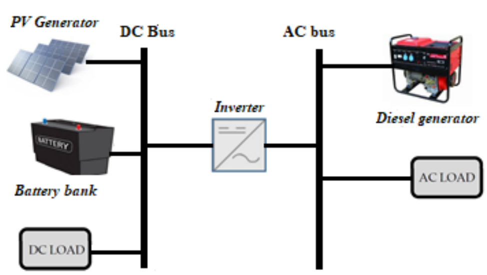

Fig. 3. Múcura island microgrid

In Table IX the results of the optimization using lead-acid batteries are presented, resulting in a longer battery life in the case of selecting cyclic load (DC) as a control strategy. Table X shows the results for lithium batteries. All the optimizations were made keeping the real average temperature of the location 27.5° and with an angle of inclination 10° for the PV modules.

B. Load shifting

Load shifting is a demand management technique that seeks to reduce the operating costs of the microgrid by shifting consumption to hours of maximum irradiation and reducing the contribution of diesel generators in the energy generation, thereby reducing costs and fuel [38].

Figure 4 shows the load shifting for the town of Múcura island. This allows to use the potential of solar energy in daylight hours in order to reduce costs for the use of diesel generators.

Tables XI and XII present the results for optimizations with lead-acid and lithium batteries respectively.

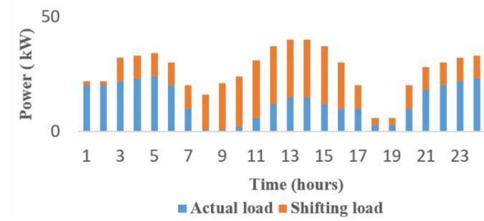

Fig. 4. Load shift for Múcura island

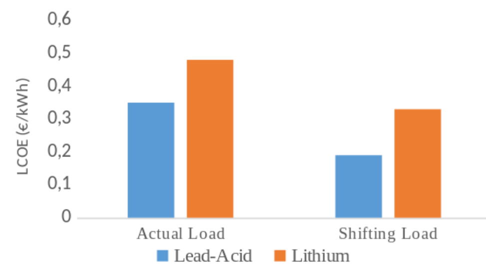

Fig. 5. Comparative LCOE for Lead-Acid vs Lithium Batteries

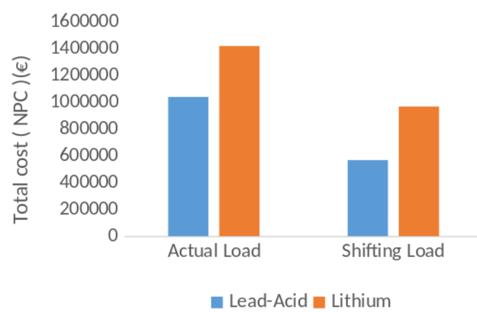

Fig. 6. Comparative NPC for Lead-Acid vs Lithium Batteries.

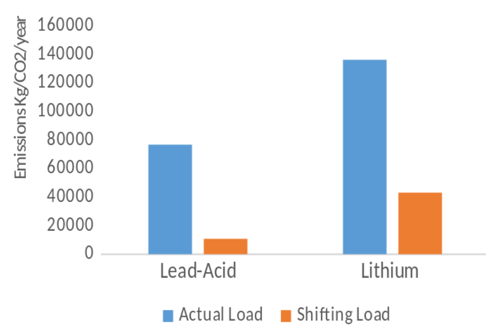

Fig. 7. Comparative emissions for Lead-Acid vs Lithium Batteries.

In figure 5 a comparison is made for the lowest costs obtained in each case. An important decrease in the LCOE is observed in the optimization of the microgrid when load shifting is performed.

In figure 6 a cost reduction is achieved when moving loads is applied for both types of batteries. This decrease is close to 46% in the case of lead-acid batteries and 32% in lithium batteries.

Figure 7 shows the emission levels of the two charge profiles, which show a significant decrease in emissions

TABLE IX

Results of the system optimizations in the case of lead–acid batteries (actual load)

Optimization type	Control Strategy [1]	Diesel Generator (kW)	Inverter (kW)	PV (Power kWp)	Batt. Bank Capacity (kWh)	Battery Lifetime (Years)	Emissions (Kg CO_2 /year)	NPC (€)	LCOE (€/kWh)
Mono-objective	LF	82	30	192.66	327.6	4.51	76778	1041148	0.35
	CC	82	30	281.58	1008	7.57	63831	1242545	0.42
Multi-objective	LF	82	30	192	327.6	4.52	76742	1041148	0.35
	CC	82	30	291.46	1008	7.55	63264	1414566	0.42

TABLE X

Results of the system optimizations in the case of Lithium batteries (actual load)

Optimization type	Control Strategy [1]	Diesel Generator (kW)	Inverter (kW)	PV (Power kWp)	Batt. Bank Capacity (kWh)	Battery Lifetime (Years)	Emissions (Kg CO_2 /year)	NPC (€)	LCOE (€/kWh)
Mono-objective	LF	82	30	79.04	96	5.56	136315	1421978	0.48
	CC	82	30	83.98	96	4.75	131625	1403436	0.48
Multi-objective	LF	82	30	79.04	96	5.72	136016	1426620	0.49
	CC	82	30	79.04	96	4.89	130449	1399265	0.48

TABLE XI

Results of the system optimizations in the case of lead–acid batteries (shifting load)

Optimization type	Control Strategy [1]	Diesel Generator (kW)	Inverter (kW)	PV (Power kWp)	Batt. Bank Capacity (kWh)	Battery Lifetime (Years)	Emissions (Kg CO_2 /year)	NPC (€)	LCOE (€/kWh)
Mono-objective	LF	82	50	187.7	327.6	4.23	11102	563168	0.19
	CC	82	50	192.6	327.6	4.2	11016	565880	0.19
Multi-objective	LF	82	50	187.7	327.6	4.26	11126	561228	0.19
	CC	82	50	187.7	327.6	4.26	11543	564297	0.19

TABLE XII

Results of the system optimizations in the case of lithium batteries (shifting load)

Optimization type	Control Strategy [1]	Diesel Generator (kW)	Inverter (kW)	PV (Power kWp)	Batt. Bank Capacity (kWh)	Battery Lifetime (Years)	Emissions (Kg CO_2 /year)	NPC (€)	LCOE (€/kWh)
Mono-objective	LF	82	50	202.54	192	6.08	43182	969041	0.33
	CC	82	50	202.54	63.9	5.02	91925	1105344	0.38
Multi-objective	LF	82	50	128.4	144	5.73	57269	1003063	0,39
	CC	82	50	128.4	144	5.77	88857	1193716	0.41

[1]LF = load following, CC = cycle charging

when the modified charge profile is used.

IV. Conclusions

In this article an optimization of an insulated microgrid based on diesel-solar-batteries for the Múcura island in Colombia was presented. The main contribution of this work is that the feasibility of this system has been studied taking into account real consumption data, renewable resources and the costs of all components during the project life. The results of the simulation show that it is possible to reduce the operating costs of a microgrid by reducing the use of diesel fuel, making optimal use of local renewable energies and guaranteeing energy supply throughout the year. Lead-acid and lithium-based battery technologies have been compared and the viability of the latter is demonstrated due to their longer life and lower maintenance cost.

Due to the high potential of solar energy in the geographic zone, applying load shifting is a viable technique to lower both costs and the average emissions. The results of the simulation presents an average reduction of 40% in the LCOE, 35% in the NPC and 80% in the emissions for either battery technologies.

Future work includes the inclusion of tidal power in the optimization analysis, since the Múcura island has a potential for such energy source. Another area is to explore and include other sources of energy for the integration in the microgrid design and analysis.

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Techno-Economic Feasibility Analysis through Optimization Strategies and Load Shifting in Isolated Hybrid Microgrids with Renewable Energy for the Non-Interconnected Zone (NIZ) of Colombia

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Article

Techno-Economic Feasibility Analysis through Optimization Strategies and Load Shifting in Isolated Hybrid Microgrids with Renewable Energy for the Non-Interconnected Zone (NIZ) of Colombia

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Abstract: In developing countries, electrification in remote areas, where access to energy is limited or null, has been one of the biggest challenges in recent years. Isolated microgrids with renewable generation are an efficient alternative for the energy supply in these areas. The objective of this work was to analyse the techno-economic viability of 6 isolated microgrids in different locations in the non-interconnected zone of Colombia, considering different climatic conditions, the availability of renewable resources, the current consumption profile, and a modified profile applying demand-side management. Modelling and simulation were performed considering storage systems based on lithium and lead-acid batteries. The resulting simulations provide the optimal system cost, emissions levels, electricity cost and battery lifetime. This study demonstrates that isolated hybrid microgrids with renewable energy are a feasible alternative to solve access to energy problems, reducing the need for diesel generators and optimizing the use of renewable energies and battery-based storage systems.

Keywords: lead–acid batteries; lithium batteries; load shifting; optimization; hybrid microgrids

1. Introduction

A modern and reliable electricity supply is crucial for human well-being and for the economic development of a country. Access to energy is vital and allows the provision of drinking water, lighting, heating, food, transportation, and telecommunications [1]. However, approximately 1 billion people still do not have access to electricity and live in areas without connection to the electricity grid [2].

In Colombia, as in the rest of the countries of Latin America, access to electricity in remote areas is very limited due to the lack of infrastructure necessary to bring electricity to these places [3] and due to the precarious economic conditions of potential users, so it is not profitable for electricity companies to invest in these areas. In the so-called non-interconnected zone (NIZ), which corresponds to 52% of the territory of Colombia, approximately 92% of the electrical energy is generated by thermal plants with diesel generators, and the rest is generated by small hydroelectric plants. In these areas, the population lives in places with difficult access, which increases the price of fuel (diesel) in thermal plants, which emit polluting gases and generate noise pollution [4], so this generation system is not the most recommended [5]. In addition to this insufficient and limited electricity supply, autonomous energy resources have not been improved or used [6], which has led to poor social and economic development of the population of these areas.

The Government of Colombia, through Law 697 of 2001, established that the rational use of energy was a matter of social character and of national interest. Law 1715 of 2014 [7] advocated the use of nonconventional sources for energy generation. Programmes such as PROURE [8] (Rational and Efficient Energy Use Programme and unconventional energy sources) promoted the financing of energy generation projects in the NIZ. All these initiatives can foster distributed generation and microgrids since they allow electricity to be generated and supplied near the places where it is consumed. A microgrid can be defined as a system that includes generation sources, loads and small-scale energy storage devices [9]. They are called hybrid microgrids when they combine two or more energy sources, such as diesel generators, renewable energies, fuel cells, etc. [10]. Hybrid microgrids can be an alternative energy supply in remote areas and they have already been used in several countries for the electrification of rural areas or islands [11–20].

The use of more than one source of electric power generation, of storage systems, and the intermittent nature of solar and wind irradiation complicate the design of hybrid microgrids, since it is necessary to find the optimal design from an economic, technical and environmental point of view [21]. Several studies have attempted to determine the best design, maximizing the use of renewable energies and minimizing the use of fossil fuels [22–27]. In [28] the authors performed a technical and economic assessment, using HOMER, of a hybrid PV-wind-diesel system in a village located in a remote area. Kaabeche et al. [29] presented an iterative method for the optimization of an isolated PV-wind-diesel hybrid system. Ocon et al. [30] studied the behavior of 215 microgrids with a 20% reduction in energy costs. Bekel and Bjorn [31] presented a study on a hybrid system that supplied energy to 200 families in an isolated community. In another work [20], Gebrehiwot et al. performed a sensitivity analysis to determine the effect of variations in solar radiation, wind and diesel price in a hybrid system.

The optimization of isolated microgrids depends mainly on the cost and lifetime of the batteries, and there are several studies focusing on the technical and economic analysis of systems that use lead-acid batteries [32], since this is the most commonly used technology in these systems. Other studies focus on the techno-economic analysis of microgrids in rural areas, such as the one carried out by López-González et al. [33] where 13 microgrids were proposed for remote areas in Venezuela, including PV-wind generation systems with lead-acid batteries. Other authors, such as Dhundara et al. [34] have carried out a techno-economic analysis of a microgrid considering the state of charge of lead-acid and lithium batteries, taking into account consumption data, resources and current prices. A recent study conducted a techno-economic analysis of photovoltaic systems [35] for a locality of the NIZ of Colombia. In another study, Guacaneme et al. [36] presented several solutions using microgrids for rural areas of Colombia.

Considering all these previous works, it can be affirmed that it is necessary to carry out more studies to determine the characteristics that isolated microgrids must have in developing countries [37,38]. It will thus be possible to study their behavior from a technical, economic and environmental point of view in current climate conditions and in situations in which changes in consumption occur, determining the net present cost (NPC) of the system, the levelized cost of energy (LCOE) and the level of emissions [39–41].

This article presents a techno-economic analysis for 6 isolated microgrids with renewable energy generation located in the NIZ of Colombia. Section 2 describes the methodology used, considering factors such as geographical location, climate, the profile of current and managed demand, and the availability of renewable resources in the 6 localities. Section 3 shows the results of the microgrid optimizations. In Section 4, the discussion is presented, and finally, the conclusions of this work are presented.

2. Materials and Methods

The models of the 6 generation systems were simulated using iHOGA 2.5 software [42]. iHOGA (improved Hybrid Optimization by Genetic Algorithms) is a software developed in C++ by researchers of the University of Zaragoza (Spain) for the simulation and optimization of hybrid stand-alone and also grid-connected electric power generation systems based on renewable energies. It includes advanced optimization models (genetic algorithms), which implies the possibility of obtaining the optimum system using very low computational times. iHOGA uses advanced models to accurately estimate the lifetime of the batteries, which are generally the most expensive components, with high requirements for costly replacements.

As a first criterion for the selection of microgrids, the availability of renewable resources was taken into account. The input data for the optimization correspond to irradiation and wind speed data for each location [43], as well as the actual daily load profiles, the modified profiles applying demand-side management, and financial data, such as the inflation rate and the interest rate of money. As a result of the optimizations, the sizes of each of the components were obtained, which corresponded to the solution with the lowest LCOE. In addition to the economic results, the total CO_2 emissions of the life cycle and the useful life of the batteries were obtained.

2.1. Geographic Location and Climate

The locations selected for this study are located within the NIZ. However, they have very different climatic conditions and renewable resources. The 6 selected locations have an altitude of less than 300 metres. The first three locations are found in tropical forests, Guacamayas is in the tropical savanna, Providencia has a dry tropical climate, and Puerto Estrella has an arid desert climate [44,45]. Figure 1 shows the map locations, and the Table 1 shows the geographic and climate information of the selected locations:

Figure 1. Geographical location of the isolated hybrid microgrids.

Table 1. Geographic and climate information [45].

Location	Geographic Coordinates	Altitude (m)	Precipitation (mm/Year)	Average Annual Temperature (°C)
Titumate	8.31 N, −77.08 W	16	2392	27
Tarapacá	−2.86 S, −69.73 W	62	2853	27
Santa Rosa	1.68 N, −78.59 W	56	2292	26
Guacamayas	2.21 N, −74.72 W	280	2145	25.5
Puerto Estrella	12.21 N, −71.18 W	69	100	30
Providencia	13.35 N, −81.36 W	72	2108	27.5

2.2. Population

The population density of these localities is very low, classified as populated centers according to the classification of the National Administrative Department of Statistics (DANE) [46]. These communities have the particularity that they belong to rural areas with accessibility problems and they lack access to the electricity networks belonging to the National Interconnected System (NIS). Table 2 shows the number of households in each locality.

Table 2. Number of households for each location.

Department	Location	Number of Households
Chocó	Titumate	138
Amazon	Tarapacá	205
Nariño	Santa Rosa	173
Guaviare	Guacamayas	205
Guajira	Puerto Estrella	20
San Andres	Providence	1

2.3. Energy Demand and Current Generation Sources

Most of the energy demand of these communities corresponds to lighting, small appliances and refrigeration equipment. The demand for energy during daylight hours is low because the main activities in these communities are agriculture and fishing, which naturally take place outside of the home. For the preparation of meals, mainly firewood is used, and in some cases liquid propane gas (LPG) [47]. Table 3 shows the current situation of energy demand and generation systems of the 6 locations. In the case of Providencia, the average consumption for an isolated house was selected, and in the case of Puerto Estrella, the consumption for 20 houses was considered, and wind generation was not considered because the wind turbines currently installed were not in service [48]. Figure 2 shows 2 of the systems considered in this work; they are currently operating as hybrid systems in Titumate and Puerto Estrella.

Table 3. Current status of the power generation systems [49].

Location	Average Electricity Consumption (kWh/Day)	Power Factor	Generation Source	Installed Capacity (kW)	Average Daily Electricity Service (h)
Titumate	245	0.92	Diesel/PV	250	6.2
Tarapacá	890	0.93	Diesel	280	10.3
Santa Rosa	105	0.97	Diesel	175	1.5
Guacamayas	394	0.89	Diesel/SHP	150	20.2
Puerto Estrella [1]	52	0.90	Diesel/PV/Batteries	425	7.3
Providence [2]	6	0.95	Diesel	4300	24

[1] Average electricity for 20 households. [2] Average electricity for 1 household.

Figure 2. Current status of microgrids: (**a**) Titumate, and (**b**) Puerto Estrella.

The annual profiles of the daily demand for the 6 locations were prepared using data provided by the national monitoring center of the Institute of Planning and Promotion of Energetic Solutions (IPSE) in the Non Interconnected Zones [50]. Figures 3 and 4 show the average daily demand curves for one year, as well as the daily demand profile for the 6 locations. It is important to note that most of the energy demand is produced at night, except in the case of Providencia, where consumption is similar during all hours of the day. In some of the simulations, a modified demand curve was used applying demand-side management [51,52].

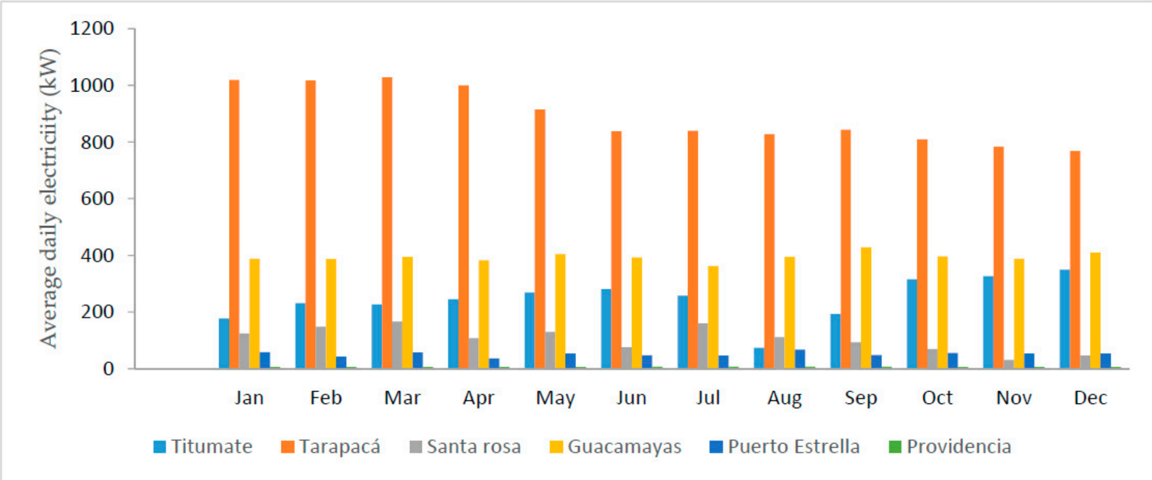

Figure 3. Average electricity consumption for each location.

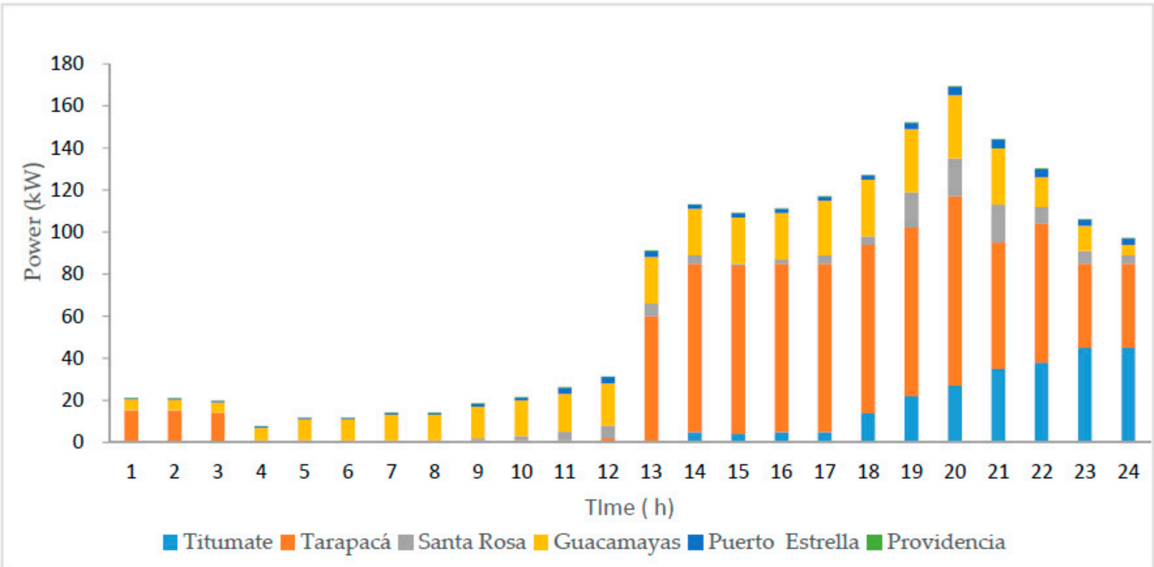

Figure 4. Typical daily load profile for each location.

2.4. *Availability of Renewable Resources*

The 6 locations selected for this study have average daily irradiation values of 4.5 kWh/m^2/day, exceeding the global average value [53]. On the other hand, only in Puerto Estrella and Providencia is generation by wind resource viable, with both having an average wind speed greater than 8 m/s [54]. Figures 5 and 6 show the hourly irradiation and wind speeds over a whole year. Puerto Estrella is located in an area with the highest average wind speeds in South America, making wind power generation viable [55].

Figure 5. Global horizontal solar irradiation (in an average year) for the six locations [43].

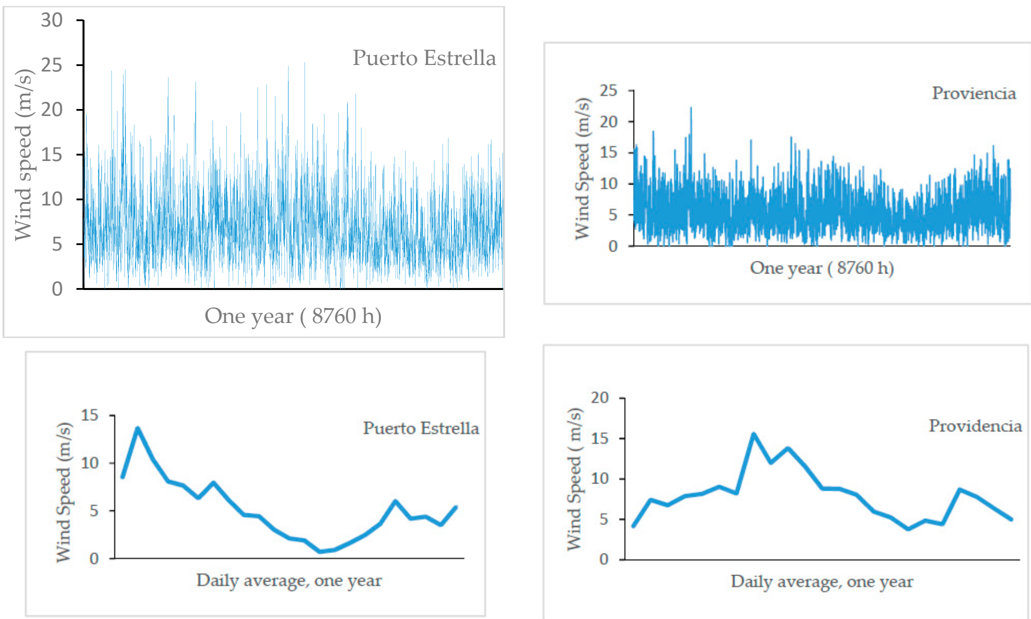

Figure 6. Wind speed (in an average year, hourly and daily values, for two locations) [43].

2.5. Parameters Used in the Optimization

Tables 4–9 show the parameters used in the optimization of the microgrids in the 6 locations. Commercial PV modules, wind turbines, batteries, diesel generators and inverter/chargers were selected. The minimum/maximum number of components in parallel shown in Table 9 were obtained with the pre-sizing calculations of iHOGA, these were needed to limit the search space in the optimization. In all cases, it has been considered that the lifespan of the system coincides with that of the photovoltaic generator (25 years). The models used to estimate battery lifetime were those of Schiffer et al. [56] for lead-acid, and the model by Wang et al. [57] for LiFePO4/graphite lithium iron phosphate batteries. For the diesel generators and the wind and hydraulic turbines, the mathematical models are found in [58]. The calculations of life cycle emissions were based on previous work [59]. The inflation rate of Colombia was applied, which is currently 4% [60], and an interest rate of 7% was used. With these parameters, the iHOGA software was able to obtain the optimal solutions (generation of system configurations for each microgrid) using evolutionary algorithms [61].

Table 4. PV modules considered in the optimization.

Parameters	Data
Nominal Power	380 Wp
Short-circuit current (Isc)	10.11 A
Nominal operation cell temperature (NOCT)	47°
Temperature coefficient of power (α)	−0.37%/°C
Acquisition cost	220 €
Lifespan	25 years
Nominal voltage	24 V
Minimum/maximum number of modules in serial	2/13

Table 5. Wind turbines used in optimization.

Parameters	Model 1: WT600	Model 2: WT1500	Model 3: WT3000
Maximum power	660 W	1660 W	3471 W
Hub height	13 m	13 m	15 m
Acquisition cost	4255 €	4875 €	7555 €
Lifespan	15 years	15 years	15 years
O&M cost	85 €/year	98 €/year	150 €/year

Table 6. Batteries used in the optimization.

Parameters	Lead–Acid 1	Lead–Acid 2	Lead–Acid 3	Lithium 1	Lithium 2	Lithium 3
	OPZS	OPZS	OPZS	BYD B-Box 5.0	BYD B-Box 7.5	BYD B-Box 10
Capacity	162 Ah	546 Ah	3500 Ah	106.6 Ah	160 Ah	213 Ah
Acquisition cost	110 €	216 €	1457 €	3390 €	4700 €	6400 €
O&M cost (one cell)	1.1 €/year	2.16 €/year	14.57 €/year	20 €/year	20 €/year	40 €/year
Nominal voltage	2 V	2 V	2 V	48 V	48 V	48 V
Float life at 20 °C	15 years	15 years	15 years	10 years	10 years	10 years
Equivalent full cycles	1600	1600	1600	6000	6000	6000
SOCmin	20%	20%	20%	10%	10%	10%
Self-discharge	2%/month	2%/month	2%/month	2%/month	2%/month	2%/month
No. batteries in serial for 300 V DC voltage	150	150	150	7	7	7
No. batteries in serial for 48 V DC voltage	24	24	24	1	1	1

Table 7. Diesel generator considered in the optimization.

Parameters	Data				
Nominal Power	1.9 kVA	3 kVA	31 kVA	82 kVA	150 kVA
Minimal power	30%	30%	30%	30%	30%
Acquisition cost	800 €	1050 €	8850 €	14,000 €	18,000 €
Lifespan	10,000 h	10,000 h	20,000 h	30,000 h	30,000 h
O&M cost	0.14 €/h	0.17 €/h	0.35 €/h	0.42 €/h	0.52 €/h
Diesel fuel cost (including transportation)	0.8 €/l	0.8 €/l	0.8 €/l	0.8 €/l	0.8 €/l
Maximum number allowed in parallel	2	2	2	2	2

Table 8. Inverter/charger considered in the optimization.

Nominal Power	0.9 kVA	8 kVA	50 kVA	100 kVA	150 kVA
Efficiency	90%	90%	90%	90%	90%
Acquisition cost	800 €	3840 €	38,000 €	55,000 €	65,000 €
Lifespan	10 years	10 years	10 years	10 years	10 years

Table 9. Minimum/maximum number of components in parallel.

Location	DC Voltage	Batteries		PV	Diesel Generator	Wind Turbine
		Lead–Acid (OPZS)	Lithium (BYD)			
Titumate	300	1/3	1/36	0/31	1/1	-
Tarapacá	300	1/10	1/137	0/115	1/1	-
Santa Rosa	300	1/2	1/16	0/13	1/1	-
Guacamayas	300	1/5	1/63	0/52	1/1	-
Puerto Estrella	48	1/61	1/82	0/30	0/1	0/3
Providencia	48	1/1	1/6	0/5	1/1	1/1

In addition to the optimal configurations of the generation systems, iHOGA determined the most appropriate control strategy between the two that were considered. These two strategies are as follows:

- Load following (LF): In systems that include batteries and a diesel or gasoline generator, when the energy from renewable sources is not sufficient to satisfy the demand, the batteries are responsible for supplying this deficit. In the case that the batteries are not able to supply all the energy demanded, it is the generator that must provide it.
- Cycle charging (CC): Differs from the previous strategy in that in the event that the generator is required to operate, it will operate at its nominal power to satisfy the demand and, in addition, to charge the batteries only during that hour. There is a variant of this cycle charging strategy, called the setpoint strategy, in which the diesel generator continues to operate at its nominal power until the battery bank reaches a specific value of state of charge, which by default is 95%.

3. Simulation and Results

3.1. Simulation of the Current System

For the 6 locations, the current systems were simulated. In the six cases, taking into account that the generation of energy is carried out basically by diesel generators, high generation costs could be expected. However, a very low LCOE was obtained in the town of Guacamayas because in this case, in addition to diesel generation, there is a small hydroelectric plant. Table 10 shows a summary of the simulation results.

Table 10. Simulation of current status of power generation systems.

Location	Total Net Present Cost (NPC) (€)	Emissions kgCO_2/yr	Levelized Cost of Energy (LCOE) (€/kWh)
Titumate	2,963,765	414,571	1.32
Tarapacá	5,542,385	564,205	0.68
Santa Rosa	1,409,383	121,216	1.46
Guacamayas	106,506	9098	0.03
Puerto Estrella	361,235	3,3741	0.77
Providencia	156,015	9491	2.85

The most adequate isolated microgrid for the energy demand of the population of Titumate corresponded to a combination of PV-diesel-battery. Figure 7 shows the daily load curve for this location considering the current load and the modified load with demand-side management. The modified load was obtained by changing the timing of some of the consumptions, to coincide with hours of high irradiation. In many cases it is difficult to change the hours of electricity consumption, since it implies a change in the population's habits. However, in this work we want to see the implication of this change in the cost of the optimal system.

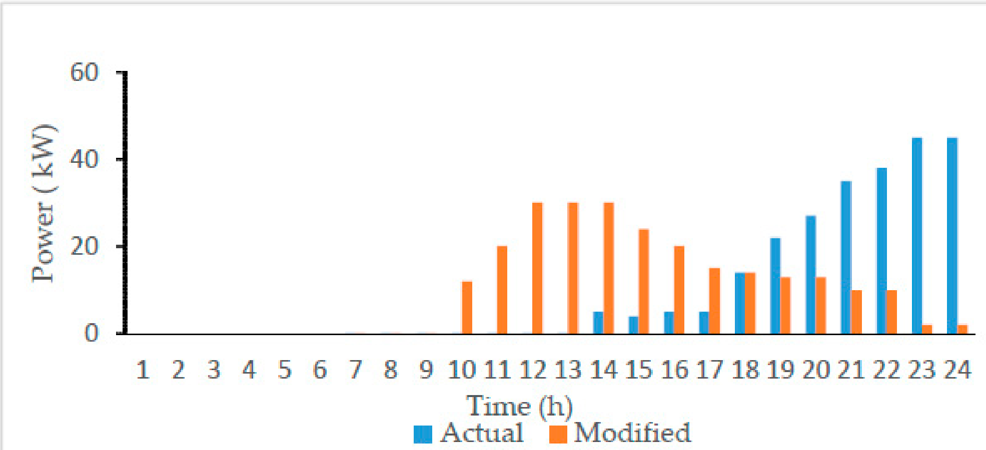

Figure 7. Daily load profile for Titumate.

The results are shown in Table 11, where a considerable reduction of the NPC is observed in systems with lead-acid batteries (52%) and in systems that use lithium batteries (56%). Similarly, the production cost of each kWh is reduced by 75–90% compared to the current system.

Table 11. Optimization for Titumate (average ambient temperature of 27 °C).

In All Cases: Diesel Generator Power = 31 kVA									
Load Profile [1]	Control Strategy	PV (Power kWp)	Battery Type	Battery Bank Capacity (kWh)	Inverter (kVA)	Lifetime (Years)	NPC (€)	Emissions (kgCO_2/yr)	LCOE (€/kWh)
Actual	LF	153	Lead–Acid	491	100	3.38	792,873	20,713	0.35
	CC	133.4	Lead–Acid	491.4	100	4.1	861,882	30,244	0.39
	LF	143.2	Lithium	288	100	6.08	830,833	7187	0.37
	CC	143.2	Lithium	288	100	6.08	830,833	7574	0.37
Modified	LF	138.32	Lead–Acid	163.8	50	4.3	357,241	8015	0.16
	CC	138.32	Lead–Acid	163.8	50	4.25	367,657	9783	0.16
	LF	138.2	Lithium	63.39	50	6.08	361,712	6761	0.16
	CC	138.32	Lithium	96	50	6.08	403,540	5058	0.18

[1] LF = load following. CC = cycle charging.

Figure 8 shows the results of the optimization for the first 4 days of the year in the town of Titumate considering the cases of the current load and of the modified load with the best NPCs. It is observed how the SOC of the battery bank increases when using the modified load profile, remaining practically above 60%. This can extend the useful life of the batteries and simultaneously reduce the operation time of the diesel generator.

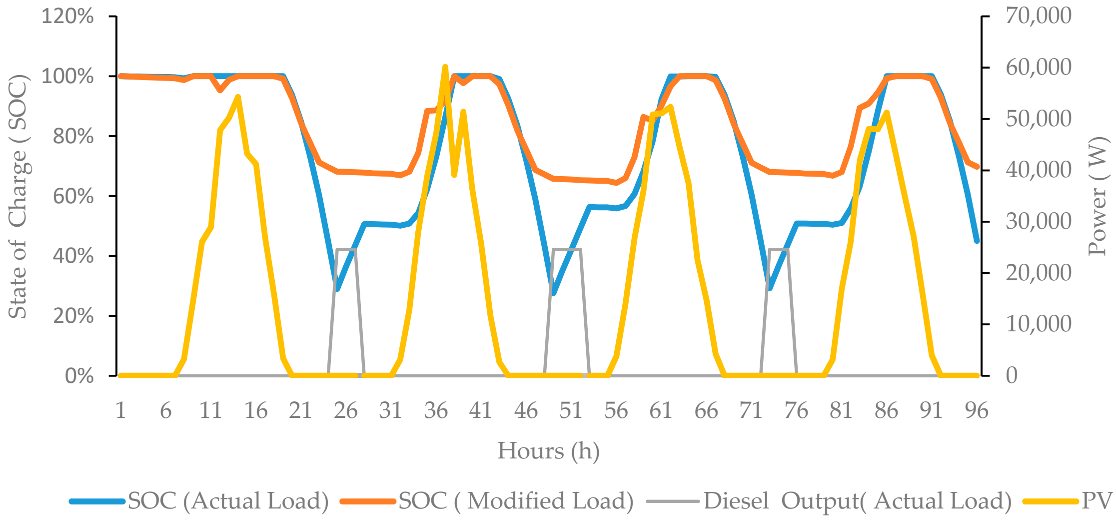

Figure 8. Comparative state of charge of the battery bank for 4 days (Titumate).

3.2. *Tarapacá*

Figure 9 and Table 12 show, respectively, the load profile and the results for the optimal system configuration. The lowest NPC value is obtained with the modified load profile (1,125,231 €), with an LCOE of 0.14 €/kWh and an emission level of 36,049 kgCO_2/year, with a useful life of batteries of 4.83 years.

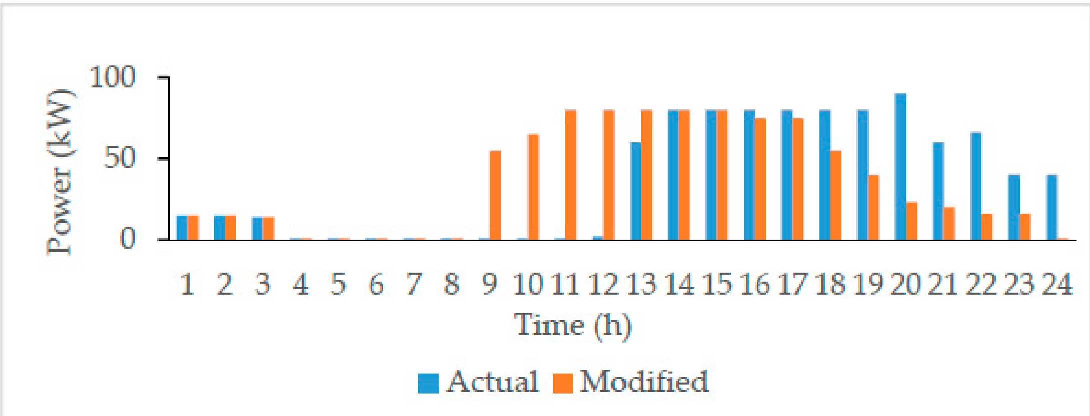

Figure 9. Daily load profile for Tarapacá.

Table 12. Optimization for Tarapacá (average ambient temperature of 27 °C).

In All Cases: Diesel Generator Power = 31 kVA									
Load Profile [1]	**Control Strategy [1]**	**PV (Power kWp)**	**Battery Type**	**Battery Bank Capacity (kWh)**	**Inverter (kVA)**	**Lifetime (Years)**	**NPC (€)**	**Emissions ($kgCO_2$/yr)**	**LCOE (€/kWh)**
Actual	LF	582.92	Lead–Acid	819	150	3.76	1,365,502	35,401	0.17
	CC	582.92	Lead–Acid	840	150	3.87	1,365,502	35,401	0.16
	LF	518.7	Lithium	528	150	5.91	1,762,981	36,974	0.22
	CC	577.98	Lithium	576	150	5.91	1,821,317	26,183	0.22
Modified	LF	1007.7	Lead–Acid	327.6	100	4.83	1,125,662	36,084	0.14
	CC	1022.5	Lead–Acid	327.6	100	5	1,125,231	36,049	0.14
	LF	548.34	Lithium	240	100	5.91	1,136,681	24,931	0.14
	CC	568.1	Lithium	255.9	100	5.91	1,152,948	21,894	0.14

[1] LF = load following. CC = cycle charging.

3.3. *Santa Rosa*

Figure 10 and Table 13 show, respectively, the load profile and the optimization results for the Santa Rosa locality. The optimization of the hybrid PV-diesel system reduces the NPC by 41% using lead-acid batteries and the current load curve and 34% with lithium batteries if the consumption is concentrated during daylight hours. Similarly, the LCOE is reduced from 1.46 €/kWh (see Table 3) to 0.24 €/kWh when lithium batteries are used and consumption is displaced. These results present a great improvement with respect to the current situation.

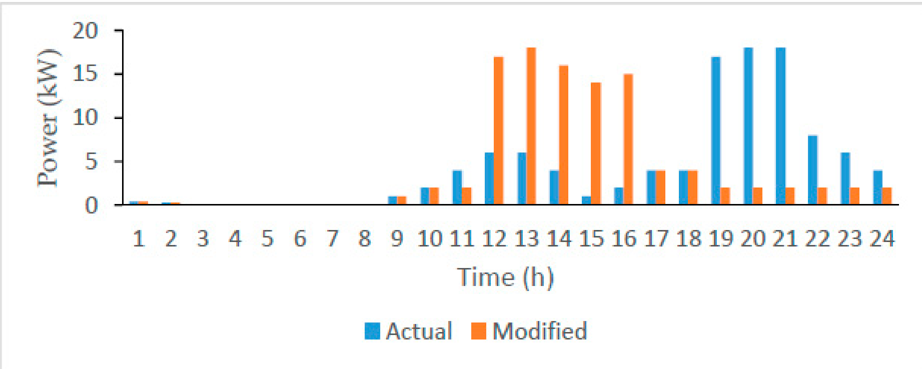

Figure 10. Daily load profile for Santa Rosa.

Table 13. Optimization for Santa Rosa (average ambient temperature of 26 °C).

In All Cases: Diesel Generator Power = 82 kVA									
Load Profile	**Control Strategy [1]**	**PV (Power kWp)**	**Battery Type**	**Battery Bank Capacity (kWh)**	**Inverter (kVA)**	**Lifetime (Years)**	**NPC (€)**	**Emissions ($kgCO_2$/yr)**	**LCOE (€/kWh)**
Actual	LF	59.28	Lead–Acid	163.8	50	4.18	361,764	10,900	0.38
	CC	59.28	Lead–Acid	327.6	50	4.87	394,403	5770	0.40
	LF	59.28	Lithium	96	50	6.48	345,806	2711	0.36
	CC	59.28	Lithium	96	50	6.48	345,086	2711	0.36
Modified	LF	59.28	Lead–Acid	48.6	50	4.28	232,190	3032	0.24
	CC	59.28	Lead–Acid	48.6	100	4.28	232,879	3107	0.24
	LF	59.28	Lithium	31.9	50	6.48	228,281	2168	0.24
	CC	59.28	Lithium	31.9	50	6.48	228,281	2168	0.24

[1] LF = load following. CC = cycle charging.

3.4. *Guacamayas*

For this location, the results are shown in Figure 11 and Table 14. The optimal system has an NPC of € 273,133 and an LCOE of € 0.08/kWh, corresponding to a PV-diesel-hydro system with lead-acid batteries and diesel-hydro with lithium batteries, under the same load profile. Having battery storage increases the reliability of the system, mainly against phenomena such as El Niño, in which the level of the rivers drops considerably [62].

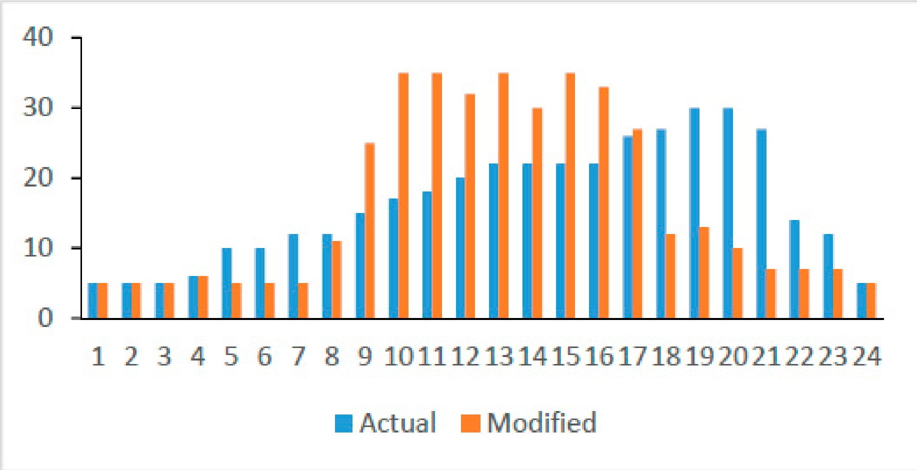

Figure 11. Daily load profile for Guacamayas.

Table 14. Optimization for Guacamayas (average ambient temperature of 25.5 °C).

In All Cases: Diesel Generator Power = 31 kVA										
Load Profile	Control Strategy [1]	Hydropower (kW)	PV (Power kWp)	Battery Type	Battery Bank Capacity (kWh)	Inverter (kVA)	Lifetime (Years)	NPC (€)	Emissions ($kgCO_2$/yr)	LCOE (€/kWh)
Actual	LF	20	34.58	Lead–Acid	252	50	9.89	301,270	3143	0.08
	CC	20	34.58	Lead–Acid	252	50	9.89	301,270	3143	0.08
	LF	50	-	Lithium	31.9	50	6.59	273,133	9364	0.08
	CC	50	-	Lithium	31.9	50	6.59	273,133	9364	0.08
Modified	LF	20	34.58	Lead–Acid	252	50	9.74	316,132	3797	0.09
	CC	20	34.58	Lead–Acid	252	50	9.74	316,132	3797	0.09
	LF	50	-	Lithium	31.9	50	6.59	273,133	9364	0.08
	CC	50	-	Lithium	144	50	6.59	273,133	9364	0.08

[1] LF = load following. CC = cycle charging.

It can be seen that the modified profile, with the lead-acid battery optimal system, cost is slightly higher than the actual profile optimal system cost. It happens because the battery lifetime is slightly lower in the modified case. The advanced lead-acid battery lifetime model used [56] considers many variables to determine the battery degradation, including, for each time step: current (charge and discharge rates), charge throughput, time between full charge, time at low SOC, partial cycling, temperature . . . A small difference in the load profile can imply low changes in these variables and therefore a small change in the battery lifetime estimation. In this case the modified load profile implies a slightly lower battery lifetime.

3.5. Puerto Estrella

Figure 12 shows the load curve, and Table 15 shows the optimization results. The high average wind speed and irradiation values confirm that the optimal hybrid system is PV-wind-diesel. The NPC decreases when considering the modified load profile, 45.3% when using lead-acid batteries and 32.8% when using lithium batteries. A shorter longevity of the useful life of the batteries is observed because the ambient temperature of the locality is 30°.

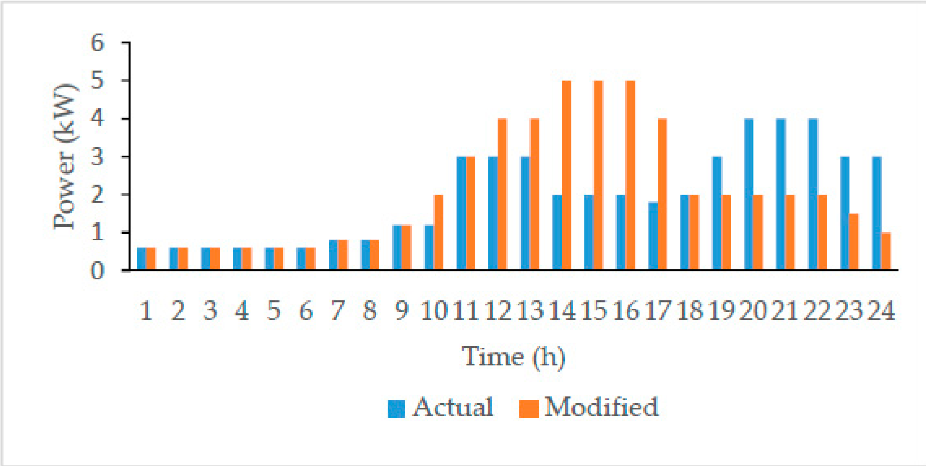

Figure 12. Daily load profile for Puerto Estrella.

Table 15. Optimization for Puerto Estrella (average ambient temperature of 30 °C).

In All Cases: Diesel Generator Power = 3 kVA										
Load Profile	**Control Strategy [1]**	**PV (Power kWp)**	**Battery Type**	**Battery Bank Capacity (kWh)**	**Inverter (kVA)**	**Wind(kW)**	**Lifetime (Years)**	**NPC (€)**	**Emissions ($kgCO_2$/yr)**	**LCOE (€/kWh)**
Actual	LF	15.96	Lead–Acid	100,8	8	3.47	5.92	110,319	2211	0.23
	CC	18.24	Lead–Acid	100,8	8	3.47	5.53	110,342	2156	0.23
	LF	36.48	Lithium	30,7	8	3.47	4.78	126,822	1708	0.27
	CC	43.32	Lithium	27,6	8	3.47	4.68	119,772	1867	0.25
Modified	LF	23.56	Lead–Acid	37,4	8	0	4.78	61,448	1253	0.13
	CC	23.56	Lead–Acid	26,2	8	0	4.69	52,437	1195	0.13
	LF	27.36	Lithium	17,9	8	3.47	4.55	85,176	1091	0.18
	CC	28.88	Lithium	12,7	8	3.47	4.7	84,349	1193	0.18

[1] LF = load following. CC = cycle charging.

Figure 13 shows the simulation for the first 4 days of the year for the town of Puerto Estrella. With the modified load, the output power of the wind turbine is better used in hours of low radiation, which leads to an increase in the SOC of the battery bank.

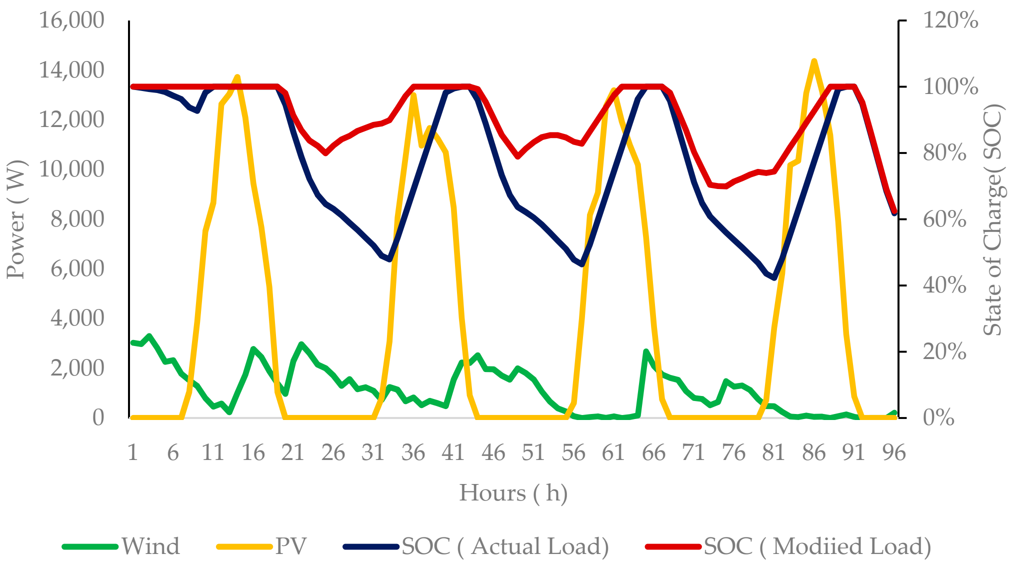

Figure 13. Comparative state of charge of the battery bank for 4 days (Puerto Estrella).

3.6. Providence

For this location, the optimal generation system is PV-wind-diesel, which has an LCOE up to 83% lower than the current system, based only on diesel generators. It also presents a considerable reduction in NPC and LCOE when the modified load profile is considered. Figure 14 and Table 16 show, respectively, the load profile and the optimization results for this location.

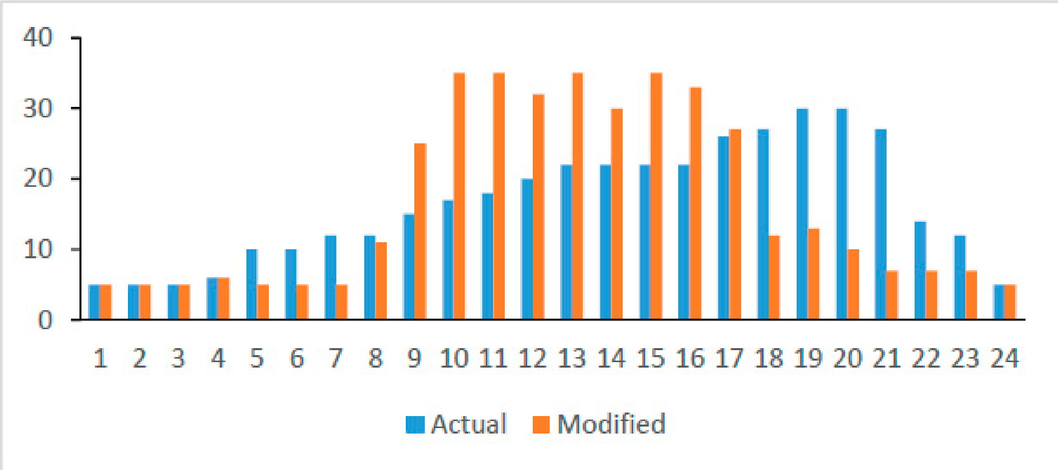

Figure 14. Daily load profile for Providencia.

Table 16. Optimization for Providencia (average ambient temperature of 27.5 °C).

In All Cases: Diesel Generator Power = 1.9 kVA										
Load Profile	**Control Strategy** [1]	**PV (Power kWp)**	**Battery Type**	**Battery Bank Capacity (kWh)**	**Inverter (kVA)**	**Wind (kW)**	**Lifetime (Years)**	**NPC (€)**	**Emissions ($kgCO_2$/yr)**	**LCOE (€/kWh)**
Actual	LF	3.04	Lead–Acid	7.7	0.9	0.66	4.55	31,447	285	0.57
	CC	3.04	Lead–Acid	7.7	0.9	0.66	4.51	31,626	304	0.58
	LF	2.28	Lithium	2.5	0.9	0.66	5.98	29,523	365	0.54
	CC	2.28	Lithium	5.1	0.9	0.66	5.98	30,878	195	0.56
Modified	LF	2.28	Lead–Acid	7.7	0.9	0.66	3.29	32,817	256	0.48
	CC	2.28	Lead–Acid	7.7	0.9	0.66	8.97	26,543	170	0.48
	LF	2.28	Lithium	2.5	0.9	0.66	5.98	26,696	169	0.48
	CC	2.28	Lithium	2.5	0.9	0.66	5.98	26,781	179	0.48

[1] LF = load following. CC = cycle charging.

4. Discussion

Figure 15 shows the different energy costs obtained with the current and modified load profiles for the 6 microgrids using lead-acid batteries and the load following strategy. A lower energy price is observed in 5 of the locations using a modified load profile. Figure 16 shows the NPCs of the 6 locations for optimization using lithium batteries and with the load following strategy, observing a decrease in costs in 5 of the 6 microgrids using modified load profiles. In three locations (Titumate, Santa Rosa and Puerto Estrella) the cost reduction is around 50% with the modified load profile.

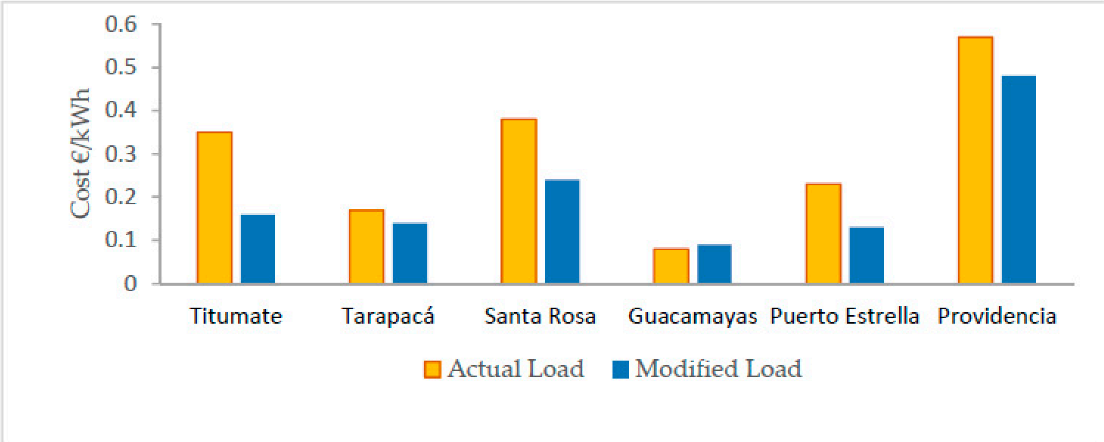

Figure 15. Cost of energy for different optimal systems.

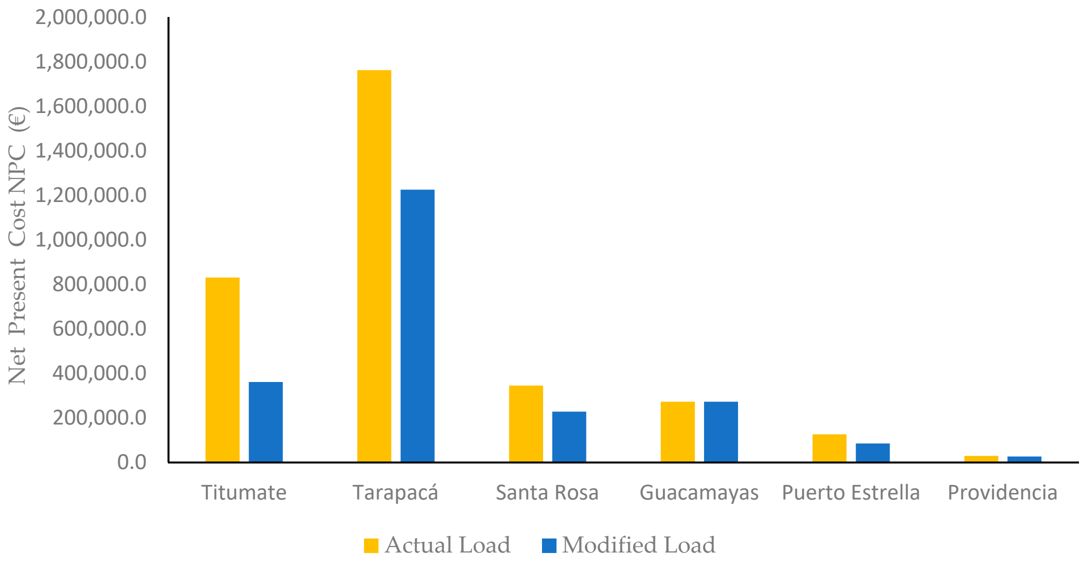

Figure 16. Total net present cost (NPC) for different optimal systems.

The level of emissions also decreases in 5 locations, as seen in Figure 17, where the results of the optimizations using lithium batteries with the cycle charging control strategy are presented.

The results obtained in the simulation model of the microgrid is performed during several years (usually 20–25 years), the performance is repeated considering all years the same, considering the load to be constant. This is a limitation, as load can change during the years.

Further research should be done for the accurate estimation of the diesel price, considering that diesel cost in the NIZ of Colombia is highly variable due to its drawbacks associated with the transportation in areas of difficult access. Further research could also include sensitivity analysis considering factors such as: load variation, the price of fuel, renewable energy subsidies, interest rates and acquisition cost of components of the system. In addition, the simulations were performed using mono-objective optimization (minimization of NPC), however future studies can address the use of multi-objective optimization including equivalent CO_2 emissions, human development index (HDI) and job creation. All of these features are available in the iHOGA software.

From a technical and economical point of view, this study opens the possibilities for exploring isolated hybrid microgrids in developing countries like Colombia, considering future technological improvements and cost reductions in batteries and PV modules.

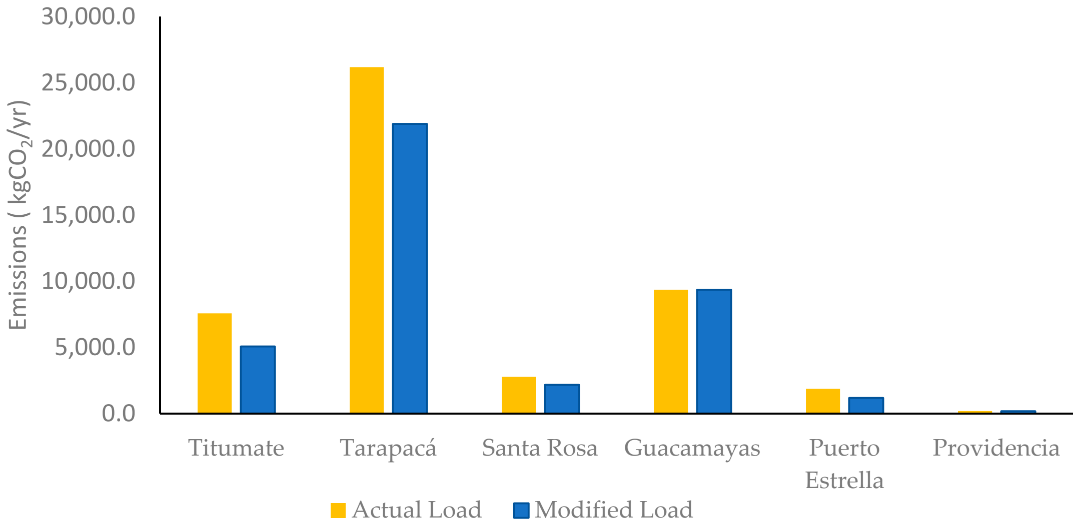

Figure 17. Total CO_2 emissions for different optimal systems.

5. Conclusions

This article presents a techno-economic study of isolated microgrids of the NIZ of Colombia. Optimal generation hybrid systems have been obtained for 6 locations, considering the possibility of using diesel generators, solar panels, hydraulic turbines, wind turbines and batteries. The results show that NPC values lower than the current ones (powered mainly with diesel) can be achieved in almost all scenarios thanks to the reduction in the number of operating hours of the diesel generators and the use of demand-side management. However, this demand-side management is limited, to a large extent, by the difficulty of changing the consumption habits of users. The results have also shown that lithium batteries can be a good alternative to lead-acid batteries, considering the useful life and costs of the system.

It is important to note that optimization strategies could include a demand side management program that can reduce operation cost. In addition, the development of microgrids with renewable energies in rural areas also will help to meet the challenge of energy supply of remote zones and will reduce the dependence on fossil fuels. The study findings provide a basis to explore optimization of microgrids with other technologies such as fuel cells and biomass. Nevertheless, the Colombian government will have to play a crucial role for the development of the isolated hybrid microgrids in remote areas.

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Nomenclature and Abbreviations

iHOGA	Improved Hybrid Optimization by Genetic Algorithms
HOMER	Hybrid Optimization Model for multiple Energy Resources
NPC	Net Present Cost
LCOE	Levelised Cost of Energy
NIS	National Interconnected System
NIZ	Non-Interconnected Zones
SHP	Small Hydroelectric Plant
SOC	State of Charge (%)
NOCT	Nominal operation cell temperature (∘C)
IPSE	Institute of Planning and Promotion of Energetic Solutions

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Apéndice: Factor de Impacto de las revistas y áreas temáticas

Applied Sciences

- Factor de impacto: 2.474
- Promedio de los últimos 5 años: 2.458

Clasificación en el área de ingeniería: (Fuente: SCIMAGO)

Engineering (miscellaneous)	2016	Q2
Engineering (miscellaneous)	2017	Q2
Engineering (miscellaneous)	2018	Q1
Engineering (miscellaneous)	2019	Q1

Energies

- Factor de impacto: 2.702

Clasificación en el área de ingeniería (Fuente: SCIMAGO)

Año	Electrical and Electronic Engineering	Energy Engineering and Power Technology	Energy (miscellaneous)	Renewable Energy, Sustainability, and the Environment
2016	Q1	Q2	Q2	Q2
2017	Q1	Q2	Q2	Q2
2018	Q1	Q2	Q2	Q2
2019	Q2	Q2	Q2	Q2

Contribuciones del Doctorando en las publicaciones

	Energy Management in Microgrids with Renewable Energy Sources: A Literature Review	Optimization of Isolated Hybrid Microgrids with Renewable Energy Based on Different Battery Models and Technologies	Optimization and Feasibility of Standalone Hybrid Diésel-PV-Battery Microgrid Considering Battery Technologies	Techno-Economic Feasibility Analysis through Optimization Strategies and Load Shifting in Isolated Hybrid Microgrids with Renewable Energy for the Non-Interconnected Zone (NIZ) of Colombia
Conceptuallización	Sí	Sí	Sí	Sí
Metodología	Sí	Sí	Sí	Sí
Software	Si	Sí	Si	Si
Análisis formal	Sí	Sí	Sí	Sí
Investigación	Sí	Sí	Sí	Sí
Recursos	Si	Sí	Sí	Sí
Gestión de datos	Sí	Sí	Sí	Sí
Escritura- Borrador original	Sí	Sí	Sí	Sí
Escritura- Revisión edición				
Visualización	Sí	Sí	Sí	Si
Supervisión			Sí	
Admnistración del proyecto			Sí	
Adquisición de fondos			Sí	