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MEJORA DE LA EFICIENCIA ENERGÉTICA DE CIUDADES INTELIGENTES APLICANDO TÉCNICAS DE "SOFT COMPUTING"

Tesis Doctoral presentada por

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“Non nobis, Domine, non nobis,

sed nomini tuo da Gloriam”

(Salmo 115, 1)

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Resumen

La presente Tesis es fruto de un trabajo de investigación para mejorar el aprovechamiento energético mediante la aplicación de técnicas de *soft computing* en sistemas de alto consumo de una ciudad. Los conceptos de ciudad inteligente (*smart city*), edificio inteligente (*smart building*) y alumbrado inteligente (*intelligent street ligthing* o *smart street lighting*) utilizan las Tecnologías de la Información y las Comunicaciones (TIC) para mejorar la eficiencia energética, incrementando la calidad de los servicios en cuanto al bienestar y confort de las personas de forma sostenible. El estudio se focaliza en dos sistemas urbanos de alto consumo: la climatización de edificios y el alumbrado público, dotando de "inteligencia" a la gestión y "robustez" al control.

Se presentan 3 artículos realizados por el autor que han sido publicados en revistas de alto impacto internacional en los que se pone a prueba la investigación de esta Tesis. En ellos se abordan problemas de eficiencia energética en entornos urbanos a los que se aplican arquitecturas de gestión autónoma, sistemas de lógica borrosa y modelos de redes neuronales, incluidos en el conjunto de técnicas aproximativas de Inteligencia Artificial, conocidas como *'soft computing'*. Los resultados obtenidos se prueban en casos de estudio de interés por su actualidad y novedad. Así, el primer artículo explica una nueva arquitectura de agentes inteligentes denominada ACODAT (*Autonomous Cycle of Data Analysis Tasks*) que permite la gestión autónoma de la climatización de edificios y prueba su idoneidad. El segundo artículo propone un controlador avanzado basado en lógica borrosa denominado LAMDA (*Learning Algorithm for Multivariate Data Analysis*), que mejora la respuesta a perturbaciones y cambios de contexto de un controlador capaz de trabajar con sistemas no lineales. El tercer artículo analiza el rendimiento de distintas arquitecturas de una red neuronal tipo perceptrón (MLP) que se usará como función de ajuste de simulaciones rápidas de alumbrado para optimizar varios objetivos simultáneamente.

Abstract

This Dissertation is a research with the aim to improve the energy efficiency with soft computing techniques applied on highly consuming systems deployed in cities. 'Smart city', 'Smart building' and 'Smart street lighting' are convenient concepts for the energy efficiency improvement and sustainability research, by using the Information and Communications Technologies (ICT), procuring better living conditions for citizens. This study focuses on building's Heating, Ventilation and Air Conditioning (HVAC) systems and public street lighting, providing artificial intelligence to systems' management and robustness to control.

This work is made of three scientific articles written by the Author, published in international journals with high impact indexation proving the research interest of this Dissertation. They address energy efficiency problems in cities with autonomic management, fuzzy logic control systems and artificial neural networks models, all considered under the Artificial Intelligence' soft computing techniques. The achieved results are of noticeable scientific and technical interest. Thus, the first article describes the new autonomic management architecture of building's HVAC system with Autonomous Cycle of Data Analysis Tasks (ACODAT) and proves its suitability. The second article proposes an advanced fuzzy control method: Learning Algorithm for Multivariate Data Analysis (LAMDA), that improves the response to uncertainty and context changes of nonlinear HVAC systems. The third article analyzes the performance of different MLP's architectures to work as the fitness function for fast street lighting simulations with multiple optimization objectives.

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Sigla	Significado en inglés	Significado en español
5G	5th Generation Mobile Communications Standardd	5ª generación del estándar de comunicaciones móviles
6LowPAN	IPv6 over Low -Power Wireless Personal Area Networks	Red inalámbrica de área personal de bajo consumo sobre IPv6
ACO	Ant Colony Algorithm	Algoritmo de colonia de hormigas
ACODAT	Autonomic Cycle of Data Analysis Task	Tareas de Ciclo Autónomo de Datos
AMR	Automatic Meter Reading	Lectura automática de contador
ANN	Artificial Neural Network	Red Neuronal
API	Application Program Interace	Interfaz programa de aplicación
ART	Adaptive Resonance Theory	Teoria de resonancia adaptativa
ATM	Asynchronous Transfer Mode	Modo asíncrono de transferencia
BACnet	Building Automation & Control Network	Red de automatización y control de edificios
BAS	Building Automation System	Sistema de automatización de edificios
BI	Business Intelligence	Inteligencia de negocio
BIoT	Building Internet of Things	Internet de las Cosas para Edificios
BLE	Bluetooth Low Energy	Bluetooth de bajo consumo
BMS	Building Management System	Sistema de Gestión de Edificios
CATV	Cable TV	TV por cable
CMS	Circuit Monitoring System	Sistema de monitorización de circuitos
CNN	Convolutional Neural Network	Red neuronal convolucional
COP	Coefficient of Performance	Coeficiente de rendimiento (Calorífica)
CPU	Central Processign Unit	Unidad central de procesamiento

Sigla	Significado en inglés	Significado en español
CRM	Customer Relationship Management	Gestión de las relaciones con clientes
CTRL	Control	Control
DL	Deep Learning	Aprendizaje Profundo
DOI	Digital Object Identifier	Identificador de objeto digital (Artículos)
EC	Evolutionary Computing	Computación evolutiva
EER	Energy Efficiency Rate	Coeficiente de eficiencia energética (Frigorífica)
ERP	Enterprise Resource Planning (ISA 95 & IEC 62264)	Planificación de los Recursos de Empresa
FL	Fuzzy Logic	Lógica Borrosa
FTTB	Fiber to the Business	Fibra hasta el trabajo
FTTH	Fiber to the Home	Fibra hasta el hogar
Fuzzy-PI	Proportional Integrative Controller with FL	Controlador PI con Lógica Borrosa
GA	Genetic Algorithm	Algoritmo genético
GAN	Generative Adversarial Network	Red generativa antagónica
GPU	Graphical Processing Unit	Unidad de procesamiento gráfico
HVAC	Heat, Ventilation and Air Conditioning	Climatización de edificios
IA	Artificial Intelligence (AI)	Inteligencia Artificial
IaaS	Infrastructure as a Service	Infraestructura como servicio - Procesamiento, memoria
IEA	International Energy Association	Asociación Internacional de la Energía
IEC	International Electrotechnical Commission	Comisión Internacional de Electrotecnia
IEEE	Institute of Electrical and Electronics Engineers	Instituto de Ingenieros en Electricidad y Electrónica
IoT	Internet of Things	Internet de las Cosas
IP	Internet Protocol	Protocolo Internet
ISA	International Standards on Auditing	Estándares internacionales de Auditoría
ISDN	Integrated Services Digital Network	Red digital de servicios integrados

Sigla	Significado en inglés	Significado en español
ISSN	International Standard Serial Number	Número Serie Estándar Internacional (Publicación)
JCR	Journal Citation Report (Clarivate Analytics)	Informe de Citas a Artículos Científicos
KNX	ISO/IEC 14543, OSI-based Protocol	Protocolo de comunicaciones OSI, ISO/IEC 14543
LAMDA	Learning Algorithm for Multivariate Data Analysis	Algoritmo de Aprendizaje por Análisis Multivariante de Datos
LAN	Local Area Network	Red de área local
LED	Ligth-emitting Diode	Lámparas que funcionan con LEDs
MAN	Metropolitan Area Network	Red de datos metropolitana
ML	Machine Learning	Aprendizaje Automático
MLP	Multilayer Perceptron	Perceptrón Multicapa
MPC	Model Predictive Control	Control por Modelos Predictivos
MSE	Mean Squared Error	Error Cuadrático Medio
OPT	Optimization	Optimización
PaaS	Platform as a Service	Plataforma como Servicio - Desarrollo
PC	Personal Computer	Ordenador personal
PI	Proportional Integrative Controller	Controlador PI
PIB	GDP, Gross Domestic Product	Producto Interior Bruto
PR	Probabilistic Reasoning	Razonamiento probabilístico
PSO	Particle Swarm Optimization	Optimización con enjambre de partículas
RBF	Radial Basis Function	Función de base radial
RNN	Recurrent Neural Network	Red Neuronal Recurrente
SA	Simulated Annealing	Calentamiento simulado
SaaS	Software as a Service	Software como servicio - Usuario
SC	Soft Computing	Computación aproximativa
SDH	Synchronous Digital Hierarchy	Jerarquía Digital Síncrona

Sigla	Significado en inglés	Significado en español
SIP	Session Initiation Protocol	Protocolo de iniciación de sesión
SJR	SCimago Journal Rank	Ranking de Publicaciones Científicas (SCimago)
SOM	Self-organizing Map	Mapa autoorganizativo
TIC	Information Technologies (IT)	Tecnologías de la Información y las Comuicaciones
TV	Television	Televisión
UMTS	Universal Mobile Telecommunications Service	Servicio de telecomunicaciones móviles universal
VLSI	Very Large Scale Integration	Integración de componentes electrónicos a gran escala
WDM	Wavelength Division Multiplexing	Multiplexación por longitud de onda
xDSL	Any Digital Subscriber Line	Cualquier técnica de acceso por el bucle de telefonía de abonado
ZigBee	IEEE 802.15.4 Specification	Especificación IEEE 802.15.4
Z-wave	Zensys' Wireless Communications Protocol	Protocolo propietario desarrollado por Zensys

1 Introducción

Los artículos que componen esta Tesis proponen el uso de tecnologías de *soft computing* para mejorar la eficiencia energética en ciudades inteligentes, *smart cities* aplicándolos a casos de instalaciones de climatización de edificios y alumbrado público, caracterizados por su alto consumo eléctrico. Además de la eficiencia eléctrica, las mejoras se extienden a los objetivos primarios de diseño como el bienestar, confort o la seguridad, a la vez que permiten añadir otros nuevos como la estética o la durabilidad. La investigación ha considerado tanto la fase de explotación de los sistemas como la fase de diseño de las instalaciones.

La costumbre y los malos hábitos en la explotación de grandes sistemas hacen que los equipos puedan estar trabajando por debajo de su rendimiento óptimo o bien malgastando energía. Así, en el caso de los sistemas de climatización de edificios, los operarios actúan sobre los sistemas de acuerdo con unas pautas históricas que normalmente no se han revisado [1] o siguen planes automáticos de puesta en marcha y parada preestablecidos que no tienen en cuenta las particularidades del entorno o del momento [2]. A esto se une el que todo sistema real se ve sometido a perturbaciones imprevistas que lo sacan de sus objetivos de funcionamiento óptimo y cuya recuperación será lenta y costosa [3].

Los sistemas de control se automatizan, pero no se les saca el máximo rendimiento posible, ya que son complejos y diferentes unos de otros, por los que los ingenieros y operadores trabajan con procedimientos preestablecidos desde hace tiempo y el cambio a una nueva tecnología no es fácil. Además, los datos de funcionamiento registrados, que podrían permitir estrategias de eficiencia a medio plazo, no se someten a procesos de revisión sistemáticos que lleven a introducir mejoras. En este sentido, evaluar la información de comportamientos no lineales viene siendo costosa y difícil de adaptar en un contexto dinámico e imprevisible.

A las ineficiencias operativas se añaden las propias del diseño. Cuando se proyecta un sistema, como la climatización o el alumbrado, normalmente se realiza siguiendo una normativa determinada, lo que lleva a proyectar sistemas ‘conservadores’, pero con rigidices que impiden desarrollar soluciones intermedias de mejor rendimiento. A nivel de diseño también, es necesario tener en cuenta las tolerancias de los valores señalados en los manuales de los equipos, lo que generalmente lleva a ‘sobredimensionarlos’. Por si no fuera bastante, los sistemas, ya en fase de operación, comienzan un proceso de degradación difícil de detectar y que compromete progresivamente los objetivos al sistema de forma imperceptible. Por último, los proyectistas que realizan replanteos previos considerando el entorno de la instalación pueden echar en falta información del contexto real o de los requerimientos particulares del diseño, que, de conocerse o estimarse adecuadamente en esta etapa, lo mejorarían significativamente.

Para solventar estas ineficiencias esta Tesis propone el uso de técnicas de *soft computing* (SC) para automatizar, optimizar, controlar y modelar. Se propone una gestión autónoma de climatización de edificios que se rige por criterios de optimización que continuamente se adaptan a las situaciones cambiantes. La automatización consigue reducir los costes de mantenimiento y la supervisión inteligente, alargar los ciclos de vida de los equipos. Se propone también un método de control avanzado por lógica borrosa que da robustez frente a perturbaciones imprevistas del contexto para equipos de climatización, caracterizados por su no linealidad. Finalmente se analizan modelos neuronales que aprenden con el contexto en tiempo real, detectando cambios imperceptibles y prediciendo comportamientos que apoyan la toma de decisiones a medio y largo plazo. Los modelos propuestos, por su naturaleza aproximativa, permiten evaluar problemas con información incompleta y considerar situaciones no previstas.

1.1 Hipótesis

La Hipótesis se formula en los siguientes términos:

> *“El consumo de energía en las ciudades es creciente y su generación produce un impacto no deseado en el medioambiente. El diseño y la explotación de instalaciones urbanas de gran consumo -normalmente complejas y con comportamientos no lineales- pueden mejorar significativamente su eficiencia energética con la utilización de técnicas de Soft Computing al permitir resultados aproximativos factibles.”*

En los siguientes subcapítulos se explican los contenidos de la Hipótesis, justificando su necesidad y estableciendo las bases de la investigación realizada.

1.1.1 Efectos de la producción energética

Actualmente, la población mundial es de 7.800 millones de personas. Viene creciendo desde 1950 a un ritmo del 1,6%, aunque también se ve que va reduciéndose en los últimos años. La Figura 1 muestra la evolución y la tasa de crecimiento.

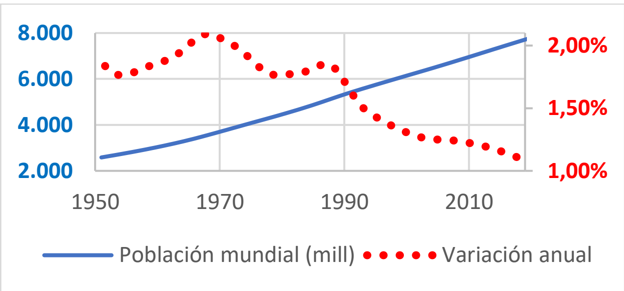


Figura 1. *Evolución de la población mundial (millones de personas) y de su tasa de crecimiento (%). Elaboración propia con información de worldometer.info (Mayo 2020).*

Además, la producción de recursos para satisfacer la demanda de la sociedad se basa en un crecimiento sostenido, basado en principios tales como la “sociedad de consumo”, el “progreso” o la “sociedad del bienestar y de las libertades”, que tienen un origen común en una cultura que busca “… sacar el mayor placer posible de una realidad cuya dimensión material se concibe prácticamente como la única existente” [4]. Se puede visualizar en la Figura 2 cómo la tasa de crecimiento actual, 1,8%, y la proyectada, 4,7%, superan el crecimiento de la población anteriormente indicado.

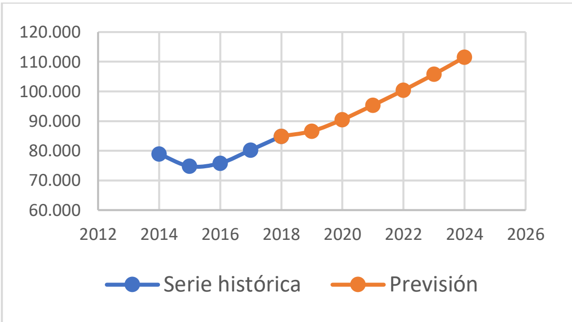
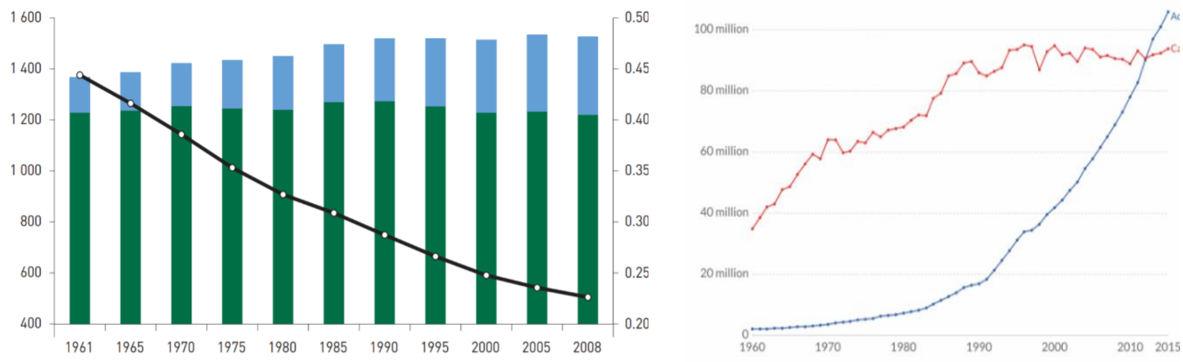


Figura 2. *Evolución del PIB mundial en miles de millones de dólares a 2018 [5].*

Consecuentemente, este aumento de la población y de sus necesidades conlleva un incremento en el consumo de recursos naturales que, por otra parte, son limitados, llegando a producir desequilibrios en su regeneración natural y su sostenibilidad. Así, se modifican mayores extensiones de la superficie terrestre para la producción agropecuaria [6] o se extraen más recursos marítimos para alimentación y otras industrias [7], como muestra la Figura 3.



(a) (b)

Figura 3. *(a) Extensión mundial (Ha) de tierras cultivables. En verde los cultivos de secano y en azul, los de regadío. La línea negra muestra la dedicación de la tierra per cápita [6]. (b) Producción pesquera mundial en millones de toneladas, según FAO. La línea roja indica las capturas en el mar y la línea azul, piscicultura [7].*

El abastecimiento de estas necesidades crecientes de la sociedad conlleva un mayor consumo de energía [5], como puede verse en la Figura 4.

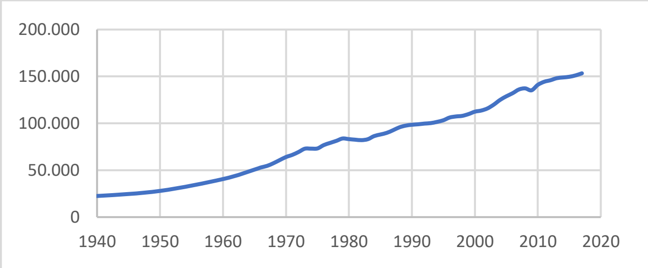


Figura 4. *Evolución del consumo anual de energía en TW.h desde 1940 [5].*

La necesidad creciente de energía no se abastece de forma natural, como podría ser mediante generación hidráulica, que apenas supone el 2,7% de la producción, o con fuentes renovables, como la termosolar, la fotovoltaica o la eólica, que suponen solo el 4,2% del total [8]. Por otro lado, la producción por fisión nuclear, que no produce emisiones contaminantes a la atmósfera, tiene una oposición frontal de la sociedad por la dificultad de gestionar sus residuos y el temor a la magnitud de sus accidentes, por lo que no crece y aporta el 1,7% de la producción total. Por consiguiente, la producción energética predominante es predominantemente de combustión fósil o biomasa, extrayéndose del petróleo, el 34,5%, del carbón, el 27,9%, del gas natural, el 24,5% y de la biomasa, el 7,1%. En la Figura 5 se visualiza intuitivamente el origen de la producción energética.

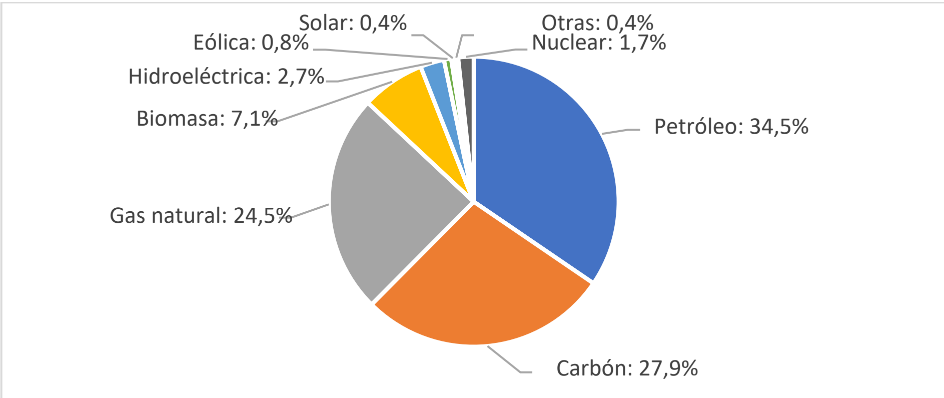


Figura 5. *Fuentes de producción energética mundial (2018) [8].*

La predominancia de la combustión trae consigo emisiones y residuos que polucionan el ambiente y afectan directamente a la salud, aumentando la prevalencia de patologías como la obstrucción pulmonar, los cánceres de pulmón, las enfermedades coronarias y apoplejías [9]. Además de la salud, las emisiones y residuos también pueden causar efectos no deseados en el entorno natural que requieren atención, ya que degradan paulatinamente las condiciones de habitabilidad. Algunos de estos problemas emergentes, cuya relación causal con las emisiones es motivo de controversia, son el aumento de la temperatura media de la superficie terrestre [10], el aumento del nivel de las aguas marinas [11], la problemática de la gestión de residuos [12] y el aumento de la intensidad de fenómenos atmosféricos en ciertas zonas [13]. La Figura 6 muestra los resultados de diversos estudios hechos al respecto.

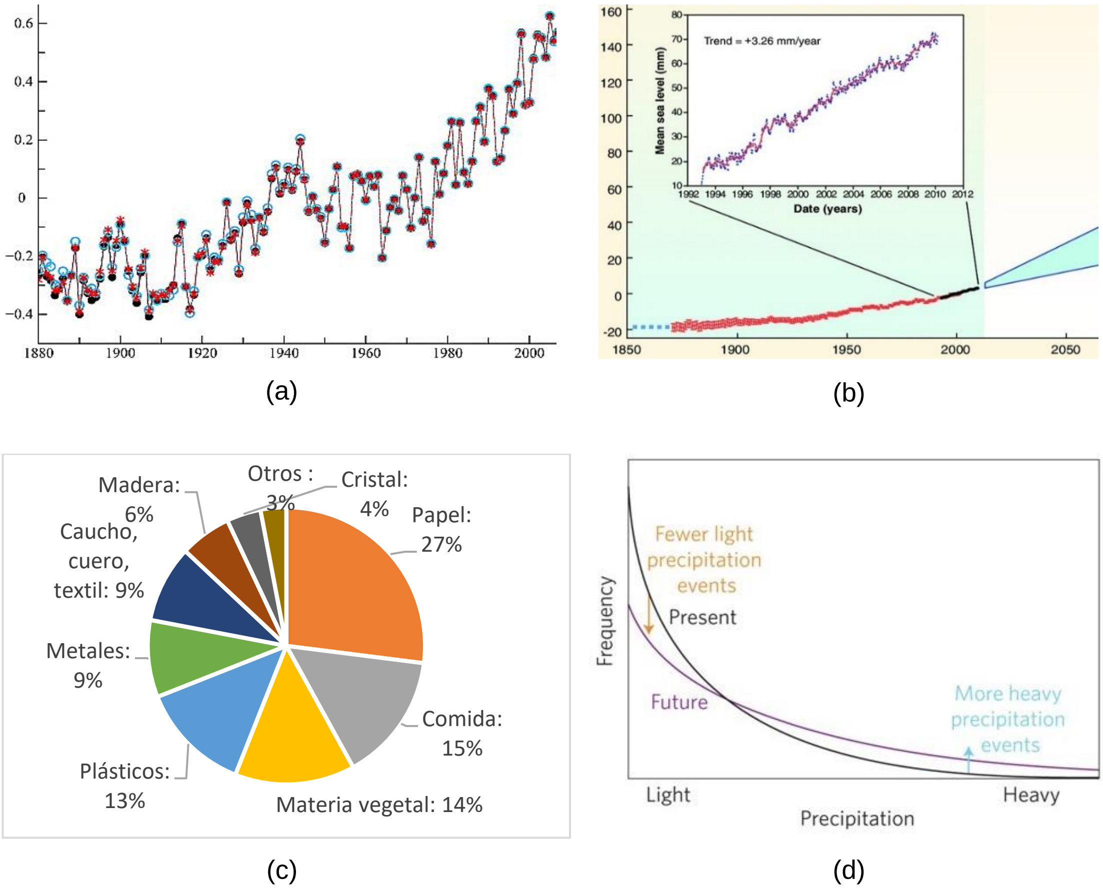


Figura 6. *(a) Temperatura media continental y oceánica [10]. (b) Variaciones medias del nivel del mar en cm, según la observación histórica de las mareas, lecturas satelitales y proyección de la tendencia en el siglo XXI [11]. (c) Tipos de residuos que se generan en Estados Unidos (2013) [12]. (d) Representación de la frecuencia de precipitaciones y de su intensidad [13].*

1.1.2 Eficiencia energética

La eficiencia energética es la relación entre la cantidad de energía utilizada en una actividad y la prevista para su realización. La energía producida o consumida se compara con las unidades que mide esa actividad con la que se relaciona, como pueden ser kilómetros en el transporte o unidades fabricadas en la producción industrial. La eficiencia también se puede segmentar para diferenciar sectores industriales, su valor en el mercado o el peso relativo de los productos. Se pueden desglosar los costes de cada una de sus fuentes de generación, según la eficiencia de cada tecnología, las inversiones o de la mano de obra que emplean.

La eficiencia energética puede medirse con indicadores termodinámicos, que, o bien comparan la variación de entalpia a la entrada del sistema con la salida, o bien relacionan el valor real con un valor ideal teórico [14]. Normalmente los indicadores termodinámicos se emplean para medir la eficiencia de equipos y dispositivos. Un segundo tipo de indicadores son los termo-físicos que comparan unidades energéticas con unidades de producción físicas, como kilómetros o unidades de producto. Y un tercer grupo de indicadores son los termo-económicos, que comparan magnitudes económicas con la producción, como la comparación del PIB con la generación eléctrica. Estos son más conocidos al emplearse en la toma de decisiones políticas. Finalmente están los indicadores que se miden en unidades monetarias. La Figura 7 muestra la necesidad de información para cada tipo de indicador según la propuesta de la IEA [14].

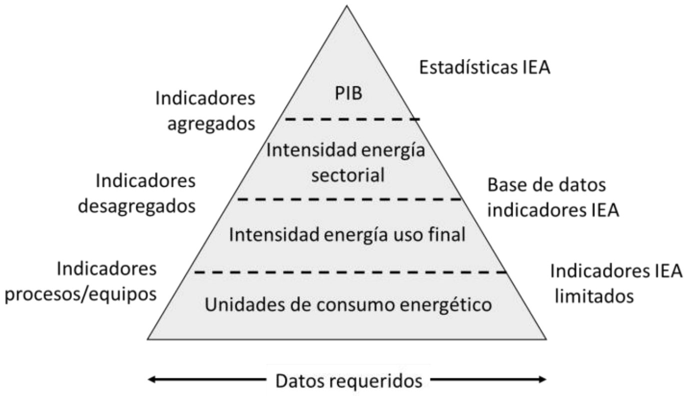


Figura 7. *Pirámide de indicadores de la eficiencia energética de la Agencia Internacional de la Energía, EIA según su grado de agregación [14].*

Se representan a continuación cómo se calculan los indicadores de eficiencia energética de una instalación de climatización de un edificio y de una instalación de alumbrado público que se van a emplear en esta Tesis.

Para evaluar la eficiencia energética en una instalación de climatización se evaluará el consumo de energía anual y se comparará con el que resulte después de aplicar las técnicas propuestas:

$$E_{cons} = \frac{\int_0^{365x24} P(t)\, dt}{1000}$$

Donde E_{cons} es la energía anual consumida en un año en $\left[\frac{MW.h}{año}\right]$ y $P(t)$ es la potencia consumida en el instante t en $[KW.h]$. También se empleará el indicador del coste de la energía anual:

$$Coste = \int_0^{365x24} P(t)\, T(t)\, dt$$

Donde $Coste$ es el precio de la energía anual consumida [€/año], $P(t)$ es la potencia consumida en el instante t en $[KW.h]$ y $T(t)$ es la tarifa aplicable en el tramo en el que transcurre t en $\left[\frac{€}{KW.h}\right]$. También se propone un indicador del rendimiento, similar al de las máquinas de refrigeración, que viene dado por el efecto de la potencia a la salida debido a la potencia a la entrada para todo el sistema:

$$COP_{Inst} = \frac{W_{tot}(t)}{P_{tot}(t)}$$

Donde COP_{Inst} es el rendimiento de toda la instalación, que no debe confundirse con el COP o EER de cada máquina, y es adimensional; $W_{tot}(t)$ es la potencia térmica entregada a toda la instalación y $P_{tot}(t)$ es la potencia total consumida en la instalación.

Respecto del alumbrado público, el indicador de eficiencia se empleará el que se establece en los manuales [15]:

$$\varepsilon = \frac{S\,E_m}{P}$$

Donde ε es la eficiencia energética de una instalación de alumbrado público medida en $\left[\frac{m^2 .\, lux}{W}\right]$, S es la superficie iluminada por la iluminancia media en servicio de la instalación en m^2, E_m es la iluminancia media en servicio de la instalación en lux y P es la potencia activa total instalada en W.

1.1.3 Avances Tecnológicos

La sociedad, en el momento que se hace consciente de los problemas que genera la producción energética, busca soluciones para reducir el consumo o mejorar su eficiencia. Normalmente, el enfoque político-económico busca reducir el consumo restringiendo la movilidad, reduciendo servicios públicos, estableciendo horarios, penalizando el uso de determinados materiales, limitando permisos, o regulando con medidas fiscales a las empresas, como la tasa por emisiones de carbono [16]. También puede actuar favoreciendo una educación en el ahorro, el respeto al medioambiente, reclamando la responsabilidad individual o realizando inversiones en el desarrollo de energías renovables, normalmente ligadas a la tecnología. La cuota de producción con renovables ha experimentado un crecimiento medio anual en los últimos 10 años de 5.8%, frente al 1,2% de las de combustión. La Figura 8 muestra la evolución del gasto gubernamental en I+D+i a nivel mundial en este sector.

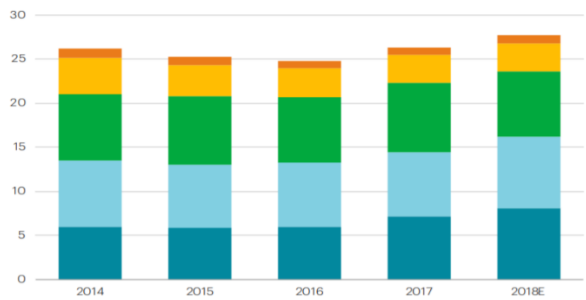


Figura 8. *Evolución del gasto gubernamental en I+D+i en energía en miles de millones de dólares. En azul oscuro, China, en azul claro, Norteamérica, en verde, Europa, en amarillo Japón, Corea y Oceanía y en naranja, el resto [17].*

El enfoque tecnológico va más allá de la reducción del consumo, permitiendo abordar la mejora de la eficiencia energética. La digitalización y las Tecnologías de la Información y las Comunicaciones (TIC) han supuesto un factor de construcción social, apoyado al máximo nivel por las economías occidentales [18-20]. Haciendo un breve trayecto en su evolución, la electrónica de dispositivos viene miniaturizándose en la integración a gran escala (VLSI) manteniendo el ritmo que vaticinara Moore en 1965, aumentando capacidad de los dispositivos, como CPU o GPU, y abaratándolos. Se han implementado técnicas de computación paralela y organizado los recursos de forma ubicua, *pervasive computing*. La forma de trabajar jerárquica y centralizada, representada tiempo atrás por los *mainframes* dio paso al uso del ordenador personal (PC), con su propia capacidad de procesamiento local para aplicaciones ofimáticas y de programación. Más adelante se convertiría en una terminal de usuario en arquitecturas cliente-servidor, montadas en flexibles granjas de servidores que aligeran el lado del usuario, *thin client*, potenciando la independencia del usuario respecto del dispositivo.

La infraestructura de comunicaciones aumentó el ancho de banda en el acceso, aprovechando el bucle de abonado con xDSL, el despliegue de coaxial de las cadenas de CATV y, más adelante, instalando fibra óptica (FTTH o FTTB). La red móvil también aumentaría su capacidad (UMTS o 5G) y se fusionaría con la red de datos, que, a su vez, se conectaría con la red telefónica (ISDN, SIP). Las redes de datos locales (LAN, MAN) también se asimilarían gracias al protocolo IP, al tiempo que se vienen desarrollado las redes inalámbricas (WiFi y WiMax) proporcionando una gran flexibilidad de conexión. La red troncal, o *backbone*, también incrementaría su capacidad con la multiplexación síncrona (SDH), asíncrona (ATM) y la división de longitud onda (WDM).

Los recursos de computación han podido virtualizarse y ofrecerse bajo demanda como hardware (IaaS), como aplicaciones de software (SaaS) o como plataformas de desarrollo de aplicaciones (PaaS) en la llamada Nube o *Cloud Computing*. Aplicaciones básicas como el e-Mail o los motores de búsqueda se ven enriquecidas con el reconocimiento biométrico del material multimedia, la interoperación con las redes sociales, la realidad aumentada o con el despliegue de redes de sensores para Internet de las cosas (IoT) e inteligencia ambiental. Las TIC han alcanzado los negocios y administraciones en la denominada transformación digital, mejorando los sistemas ofimáticos, los sistemas (ERP, CRM), proporcionando colaboración, comunicación y herramientas de inteligencia de negocio (BI). La analítica de datos se ha visto potenciada con la capacidad de manejar grandes cantidades de información en profundidad, visibilidad, velocidad y confiabilidad mediante *Big Data*, los algoritmos de aprendizaje automático (ML) y *deep learning* (DL).

Conviene destacar el esfuerzo conjunto de la sociedad en la estandarización internacional, el aseguramiento de la portabilidad, la regulación de la competencia de los servicios, la oferta de datos abiertos, *open data*, la “democratización” de los recursos y servicios de red, la universalización del acceso a las TIC, o la libre disposición de software abierto [21]. En síntesis, la digitalización ha creado grandes sinergias entre áreas que continuamente se ven sometidas a investigación por la literatura científica y adoptadas en el sector empresarial.

1.1.4 Smart city

La aplicación de la tecnología al control y la automatización de dispositivos y sistemas da lugar al concepto de inteligencia [artificial], a veces recibiendo el sobrenombre de *intelligent* o *smart*. Por ejemplo, se consideraba “inteligente” al dispositivo o sistema al que se le incorporaba electrónica o programación de instrucciones, como las tarjetas inteligentes, *smart cards* en los 70 o cuando los terminales telefónicos incorporaban aplicaciones interactivas a finales de los 90, *smartphones*. La automatización y la capacidad integradora de diferentes áreas de conocimiento y sus avances han sido la base para el desarrollo de sistemas inteligentes más avanzados capaces de una mayor adaptación a entornos cambiantes e imprevistos, actuando sobre procesos complejos en sistemas físicos como en ingeniería o economía.

El interés científico de ciudad inteligente, *smart city*, se expande en la primera década del 2000, aunque ya había comenzado con una primera denominación de *ciudad digital*. Este primer término hacía recaer el peso en el aspecto tecnológico para mejorar los servicios públicos de alta calidad y proximidad, como la seguridad, productividad, competitividad, innovación, emprendimiento, participación, formación y capacitación [22]. El interés de utilizar el término *smart city* en esta investigación es el de delimitar un ámbito con un sentido de utilidad humana y social a la tecnología, en el que destacan el conseguir un desarrollo económico-ambiental duradero, la gobernanza participativa, la gestión prudente y reflexiva de los recursos naturales, o el buen aprovechamiento del tiempo de los ciudadanos. Como se ha visto, las necesidades de mejora se agudizan con el crecimiento de la población y de su rápido desplazamiento hacia las ciudades, obligando a tomar medidas sostenibles, como las *eco-friendly best practices*, que la Unión Europea recomienda para obtener su etiqueta ecológica. Por tanto, en la ciudad inteligente confluyen dos tendencias de investigación diferentes, como muestra la Figura 9. Por un lado, aquella en que predomina la economía y la política ambientales y, por otro, aquella en la que predominan las TIC y que algunos autores de esta tendencia consideran que la *smart city* forma incluso parte de la IoT [23, 24].

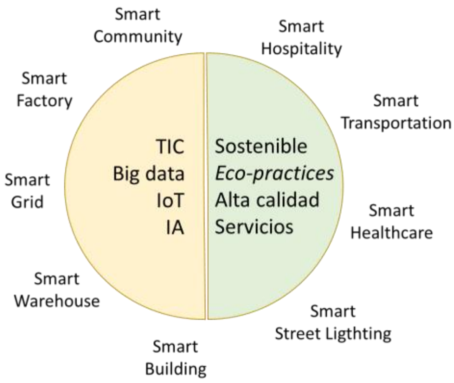


Figura 9. *Conceptos en torno a las smart cities sostenibles [24].*

Dentro de los bloques funcionales de una *smart city*, que se han ido deduciendo o agregando a lo largo de su evolución, se encuentra el edificio inteligente, o *smart building*. Se trata de una convergencia de varias ideas, cuyo origen es incluso anterior al de *smart city* [25]. La primera de ellas viene de la domótica, *smart home* o *home automation*, que desarrollaba dispositivos para el hogar programables y controlables remotamente para mejorar el confort y la comodidad en los 70. La segunda idea se centraba en la supervisión de edificios para incrementar el ahorro energético, con el concepto de *Energy Management System* también en los 70 [26]. Y la tercera idea fue la automatización de los sistemas comunes de los edificios (climatización, iluminación, elevadores, sistema antincendios) con una plataforma informática, *Building Automation System* (BAS), para optimizar la explotación, ahorrar energía, abaratar costes y mantener el confort [17].

La integración de los distintos sistemas y la incorporación de nuevas funciones de supervisión llevó a cambiar su denominación por la de *Building Management System* (BMS) [27], dejando a un lado la simple idea de automatización de BAS. Sería lógico pensar que actualmente se viene dando una integración de los distintos sistemas del edificio debido a la conectividad de las redes y a la funcionalidad común, pero esto no es lo habitual, sino que cada sistema funciona con su propia gestión, generalmente del fabricante. La gestión separada es ineficiente ya que almacena información en "silos" independientes, con estructuras y protocolos de comunicación diferentes, lo que lleva a tener que duplicar elementos, como los sensores, dificulta la reutilización y limita el conocimiento del sistema. No obstante, el protocolo IP ha venido a reducir la separación entre redes y las comunicaciones inalámbricas de corto alcance y bajo consumo como ZigBee, Z-Wave, 6LowPAN o BLE muestran sus ventajas en el despliegue de redes de sensores en edificios, *Building Internet of Things* (BIoT), ofreciendo una gran flexibilidad y capacidad de control frente a redes de control más clásicas, como KNX o BACnet que requieren cablear el edificio.

En cuanto al nivel de supervisión, se desarrollan módulos que ofrecen una funcionalidad común a los distintos sistemas, bien de forma independiente al BMS o como una "extensión" de éste, para no incurrir en costes de renovación y formación [28]. La monitorización de circuitos, *Circuit monitoring System* (CMS), o el sistema de lectura automática de contadores, AMR, *Automatic Meter Reading* son dos ejemplos. La Figura 10 representa este concepto de modularidad en el que se permite la interacción entre los distintos bloques que representan aplicaciones o utilidades para formar capacidades funcionales superiores, como diagnosticar con más precisión al relacionar anomalías o simples eventos en distintos orígenes.

Figura 10. *Arquitectura modular de la gestión de servicios de un edificio [28].*

Este nuevo paradigma de gestión requiere una investigación más profunda en las áreas de seguridad y privacidad de las comunicaciones, de modo que inspire confianza a los agentes implicados y les permita mejorar sus funciones tácticas y estratégicas [17].

Hay otro bloque funcional de una *smart city* de interés que es el alumbrado público inteligente, o *smart street lighting*. Es un concepto que aparece por primera vez registrado como patente de sistemas de control inteligente de alumbrado exterior en 1999 [29]. Consiste en la regulación automática de las condiciones de alumbrado exterior de modo que el servicio se adapte automáticamente al contexto, como el tipo de usuario que transita por la zona iluminada, la intensidad de tráfico o las condiciones meteorológicas. Su asociación como bloque funcional a la *smart city* será posterior [30].

1.1.5 Instalaciones urbanas con alto consumo

El 55,3% de la humanidad habita en ciudades y la previsión de la ONU es que en 2030 sea el 60% [31], lo que hace razonable el esfuerzo investigador en el ámbito urbano. Mauro en su artículo de 2015 [32] retoma un informe de la IEA de 2011 [33] en el que se estima que las instalaciones de edificios consumen a nivel mundial el 32% del consumo eléctrico de las ciudades y en la Unión Europea el 40%. Por otro lado, Bajer en 2018 [28] retoma el desglose del consumo que hizo Bertoldi [34] en ciudades de la Unión Europea (UE-27) [28] y presenta el gráfico de la Figura 11, en la que se ve cómo la climatización absorbe la mitad del consumo y la iluminación, la cuarta parte.

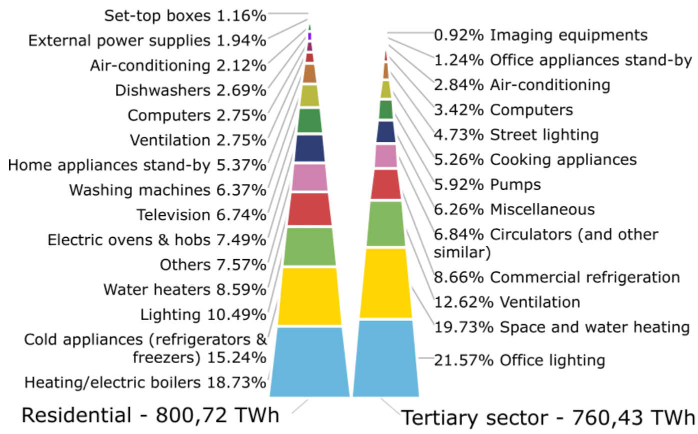


Figura 11. *Consumo eléctrico doméstico y el sector terciario desglosado para la UE-27 en 2007 [28].*

El trabajo de Minoli de 2017 [35] actualiza los datos anteriores indicando que, en Estados Unidos, la climatización consume en media el 32,7%, la iluminación, el 17,1% y los equipos de oficina, el 13,6%. En edificios públicos, como oficinas, centros comerciales, hospitales u hoteles, el consumo por climatización puede llegar al 40,3% del total.

El alumbrado público no tiene un consumo tan significativo en la ciudad como la climatización, ya que apenas supone el 5%, aunque investigar sus características en común puede conllevar ciertos avances. El alumbrado hace más seguras las vías, reduciendo los delitos en un 20% y el número de accidentes en un 35%, además de fomentar el comercio y proporcionar entornos de valor estético. Es necesario recordar que la sustitución de las lámparas de mercurio y balastos por sistemas LED está suponiendo ahorros de consumo energético sustanciales, estimándose entre el 31% y el 60% [36]. Un estudio de Northeast Group, prevé que el cambio a LED puede alcanzar el 84% de las instalaciones y que el 37% de las instalaciones pueden incorporar tecnología *smart street lighting* para 2025 [37]. Pero la contaminación lumínica sigue indicando que se emiten cantidades de luz innecesarias [38] y la tecnología puede ayudar con ajustes "inteligentes".

1.1.6 Técnicas de *soft computing*

Algunos sistemas de cierta complejidad o sometidos a situaciones con incertidumbre, son difíciles -o imposibles- de modelar con métodos físicos y matemáticos exactos, haciendo necesario acudir a métodos imprecisos. *Soft Computing* (SC), o informática aproximativa, es un conjunto de técnicas tolerantes a la imprecisión e incertidumbre, capaces de trabajar con información incompleta, *partial truth*. Así se consigue que el problema se vuelva manejable, la solución sea más robusta y los costes computacionales se reduzcan [39]. El contenido del SC se ha ido construyendo con aportaciones científicas sucesivas en la que juega un papel destacable el trabajo de Zadeh sobre conjuntos borrosos, *fuzzy sets*, en 1965 [40], así como su estudio de los procesos de decisión en sistemas complejos de 1973 [41] y el informe de 1979 sobre la teoría de la posibilidad y análisis aproximativo de datos. La incorporación al SC de las redes neuronales y otras técnicas, que incluso habían aparecido con anterioridad, se produciría más adelante. Actualmente el SC se aplica en gran cantidad de áreas, como la economía, ingeniería, tratamiento masivo de datos, *data mining*, diagnósticos médicos avanzados, etc.

Formalmente, el SC se engloba dentro de la Inteligencia Artificial (IA), lo que permite flexibilizar la adquisición de conocimiento y enriquecer sus representaciones. Desde que MacCarthy propusiera en 1956 el concepto de IA [42], ésta ha adoptado distintos enfoques como el cibernético, desarrollado anteriormente por Wiener [43], la representación simbólica o la sub-simbólica, en la que principalmente se engloba el SC.

Las componentes fundamentales del SC son la lógica borrosa, *fuzzy logic* (FL), las redes neuronales (ANN) y la computación evolutiva (EC). Más tarde se añaden la teoría del caos y otras teorías del aprendizaje. Los modelos neuronales se ampliaron después con los modelos de aprendizaje profundo, *Deep Learning* (DL), entre los que figuran las redes neuronales recurrentes (RNN), las redes convolucionales (CNN), las redes generativas antagónicas (GAN) o las máquinas de Boltzman. En la Figura 12 se muestra una clasificación de algunas de estas técnicas.

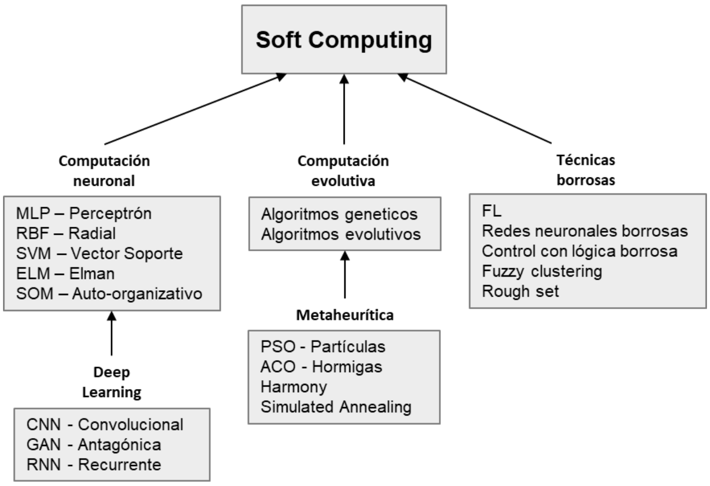


Figura 12. *Algunas técnicas empleadas en soft computing [44]*

SC emplea redes neuronales (ANN) para construir modelos que predicen o clasifican. Las arquitecturas más sencillas de las que se utilizan son el perceptrón (MLP), en el que el número de neuronas y capas es configurable, y la de función radial (RBF), con una capa intermedia de funciones de transferencia no lineales. RBF se entrena más rápidamente que el primero, pero su rendimiento es inferior, ya que necesita un conjunto de datos mayor [45].

Los algoritmos evolutivos y otras técnicas de búsqueda metaheurísticas se utilizan para optimizar los parámetros de los modelos, siendo los más comunes en SC los algoritmos genéticos (GA), *Simulated Annealing* (SA), *Ant Colony Optimization* (ACO), para resolver problemas de gran envergadura, y *Particle Swarm Optimization* (PSO). Son muy utilizados para resolver problemas con múltiples objetivos contrapuestos entre sí, para los que obtienen soluciones globales en tiempos razonables.

La lógica borrosa se emplea desde hace décadas para resolver diferentes tipos de problemas relacionados con la toma de decisiones aproximadas, trabajando con entradas imprecisas y definiendo intervalos de tolerancia (*fuzzy numbers*). También pueden transformar información en términos lingüísticos comprensibles que alimenten una máquina de inferencias con un conjunto de reglas predefinido, cuya salida obtendrá los datos numéricos requeridos [46].

Las técnicas de SC pueden combinarse entre sí para mejorar su rendimiento y extender sus resultados. Así, por ejemplo, se ha estudiado la utilización conjunta de un MLP con una red RBF, manteniendo la precisión del aprendizaje con un conjunto de datos más reducido. También se han combinado algoritmos de optimización a los métodos de aprendizaje de modelos neuronales, como aplicar GA en *backpropagation* [46]. En la Figura 13 puede verse una representación más intuitiva de estas combinaciones [47].

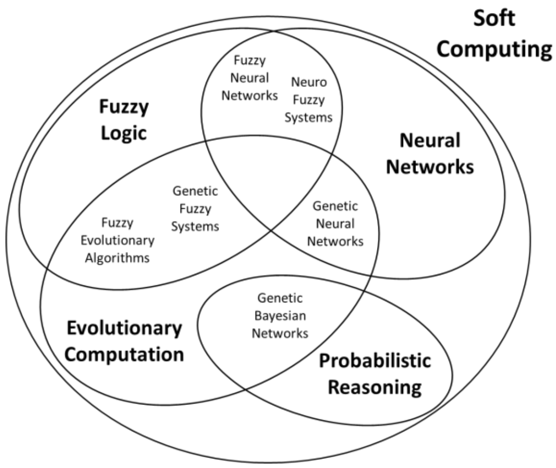


Figura 13. *Combinación de técnicas en SC [47].*

Se han empleado también programación genética (GP), GA y PSO mejorando la resolución de las membresías de redes neuronales borrosas. GA también se ha probado en optimización multiobjetivo con valores reales (no binarios) usando programación cuadrática secuencial dando soluciones óptimas de Pareto muy eficientes. Se puede conseguir una eficiencia mayor con enjambre de partículas (PSO), al reducir el entrenamiento un 50% comparado con GA, además de lo simple de su implementación. SA puede hibridarse con GA (GSA) para la optimización de parámetros en el aprendizaje de una ANN.

La aplicación de técnicas de SC, ANN y GA, al optimizar el funcionamiento de un BMS pueden conseguir ahorros del 27% [48]. Otros estudios consiguen mejoras del 19,7% del coste de la energía al aplicarse un optimizador al control del ambiente [49]. Hay investigaciones que muestran un ahorro del 10% en días cálidos y del 30 % en días fríos al acoplar un MPC con modelos de ML [50]. Con respecto al alumbrado público, cuando se aplica optimización al diseño y al replanteo pueden conseguirse un ahorro de energía entre el 50% y el 70% [51].

1.2 Objetivos

El objetivo general es la presentación de varias técnicas de *soft computing* que, al aplicarlas a instalaciones urbanas de gran consumo eléctrico, mejoran la eficiencia energética sin perjudicar la calidad de los servicios.

1.2.1 Objetivos Específicos

El objetivo principal se desglosa en objetivos específicos que se desarrollan en los artículos científicos publicados, constituyendo la aportación novedosa de esta Tesis.

1. Definir una arquitectura de gestión autónoma flexible que actúe sobre cualquier sistema de climatización a través de un modelo propio, bajando el consumo eléctrico, manteniendo el confort y reduciendo los costes operativos, empleando técnicas de optimización de múltiples objetivos y modelos híbridos de predicción.
2. Analizar un novedoso sistema de control avanzado de equipos de climatización que haga más robusto su funcionamiento y permita mejorar múltiples objetivos en tiempo real.
3. Realizar un análisis sistemático del rendimiento de arquitecturas MLP en su aprendizaje y bondad de ajuste para simular un sistema de alumbrado público.

1.2.2 Plan de trabajo

El trabajo investigador lo ha desarrollado el Autor gracias a su vinculación al Departamento de Ciencias de la Computación de la Universidad de Alcalá de Henares, manteniendo una fluida colaboración con miembros investigadores de otras universidades:

- Universidad Francisco de Vitoria (Madrid, España)
- Universidad de los Andes, Bogotá (Bogotá, Colombia)
- Universidad Tecnológica de Panamá (Panamá)
- Escuela Politécnica Nacional (Quito, Ecuador)
- Universidade de Coimbra (Portugal)

La Tabla 1 recoge las actividades realizadas por el autor, describiéndolas, indicando las dependencias de cada una, la documentación o herramientas necesarias para realizarlas (Entrada) y los resultados de las mismas (Entregables).

Tabla 1. *Actividades de la investigación llevadas a cabo por el Autor*

PT	Nombre	Dep.	Entrada	Entregables
1	Estudio dominio climatización y herramientas	no	Documentación y asesoramiento técnico	Informe sobre la investigación relacionada
2	Identificación modelo general de climatización	1	Base datos extraída del BMS Teatro Real	Modelo multi-HVAC
3	Elaborar concepto arquitectura de gestión autónoma climatización	2	Documentación ciclos autónomos de datos (ACODAT)	Descripción ACODAT para climatización
4	Propuesta calibración in-service con modelo de datos	no		Descripción hibridación modelos caja blanca y negra
5	Investigación eficiencia algoritmos optimización multiobj.	no		Informe sobre la investigación relacionada
6	Adaptación de optimización multiobjetivo climatización	5		Optimización confort, energía, coste y rendimiento
7	Descripción de la monitorización de la degradación del COP	no		Propuesta de ciclo de datos para monitorización del COP
8	Investigación sobre méodos de control avanzanzados	no		Informe sobre la investigación relacionada
9	Diseño método control avanzado para climatización	8	Estudio sobre el algoritmo LAMDA	Descripción del algoritmo
10	Comparación de LAMDA con otros de uso común	9	Matlab, Simulink	Estudio comparativo
11	Estudio específico alumbrado público y herramientas	no		Informe sobre la investigación relacionada
12	Estudio sobre modelos de redes neuronales	no		Informe sobre la investigación relacionada
13	Evaluación aprendizaje y recursos MLP	11, 12	DIALUX	Rendimiento y consumo de recursos
14	Estudios relacionados con soft computing	no		Informe sobre la investigación relacionada
15	Preparación y defensa del Artículo 1	1, 2, 3, 4, 5, 6, 7		Publicado en agosto 2019
16	Preparación y defensa del Artículo 2	8, 9, 10		Publicado en enero 2020
17	Preparación y defensa del Artículo 3	11, 12, 13		Publicado en julio 2019
18	Contribución Congreso IENER 2019	3		Publicado en Junio 2019
19	Elaboración de un modelo físico de climatización	2		
20	Contribución Congreso IESTEC 2019	13, 17		Publicado en octubre 2019
21	Estudio efecto configuración neutro en hospitales	no		
22	Publicación en RISTI efectos neutro en hospitales	19		Publicado en octubre 2019

1.2.3 Estructura de la Tesis

Esta Tesis tiene la modalidad de “Tesis por compendio” debidamente regulada en la normativa de la Universidad. El Artículo 5.1 del Reglamento [52] establece que:

> *“Si la Comisión Académica del Programa lo autoriza, la Tesis Doctoral podrá realizarse mediante el compendio de artículos del doctorando en publicaciones de reconocido prestigio. El número mínimo de artículos será de tres. La Tesis deberá incluir, además de los artículos, un resumen amplio que dé coherencia al conjunto de la investigación, en el que se muestre la línea argumental de la misma, así como un capítulo de conclusiones. Se entenderá por publicaciones de reconocido prestigio las utilizadas para la obtención de complementos de investigación (sexenios) en el ámbito en el que se desarrolle la investigación.”*

Los tres artículos han sido publicados en una revista, cuyo ranking internacional de citas se sitúa en el primer cuartil (Q1), tanto para el Journal Citation Report (JCR) de Clarivate Analytics, como para el SCimago Journal Record (SJR) de SCimago, como puede verse en la Tabla 2.

Tabla 2. *Indice de impacto y ranking por categorías en 2018 de la publicación según JCR y SJR*

Categoría	JCR	SJR
Indice de impacto	4,098	0,609
Computer science - IS	Q1	Q1
Engineering, Electrical & Electronics	Q1	Q1 (Engineering)
Telecommunications	Q1	N/A

La Tesis presenta tres artículos en los que el Autor ha tenido un destacado rol investigador, organizativo y de defensa y que se referencian a continuación:

1. Aguilar, J., **Garces-Jimenez, A.**, Gallego-Salvador, N., De Mesa, J. A. G., Gomez-Pulido, J. M., & Garcìa-Tejedor, À. J. (2019). *Autonomic Management Architecture for Multi-HVAC Systems in Smart Buildings*. IEEE Access, 7, 123402-123415.
2. Morales Escobar, L. A., Aguilar, J., **Garcés-Jiménez, A.**, Gutierrez de Mesa, J. A., & Gomez-Pulido, J. M. (2020). *Advanced Fuzzy-Logic-Based Context-Driven Control for HVAC Management Systems in Buildings*. IEEE Access, 8, 16111-16126.
3. **Garces-Jimenez, A.**, Castillo-Sequera, J. L., Del Corte-Valiente, A., Gómez-Pulido, J. M., & González-Seco, E. P. D. (2019). *Analysis of artificial neural network architectures for modeling smart lighting systems for energy savings*. IEEE Access, 7, 119881-119891.

Siguiendo las directrices de la normativa al respecto de la modalidad de compendio, la Tesis sigue la estructura que se presenta a continuación:

I. La Sección 1 es la Introducción donde se presenta la Hipótesis, su justificación y los objetivos. Al final se presenta la estructura de la Tesis y se formaliza la modalidad de compendio de artículos.

II. La Sección 2 presenta cada artículo haciendo un resumen previo de su contenido y señalando los detalles de su publicación.

III. La Sección 3 presenta otros méritos conseguidos hasta la fecha relacionados con la investigación.

IV. La Sección 4 presenta una Memoria en la que se hace un resumen amplio de la Tesis, describe las aportaciones del autor, valora su interés científico, extrae las conclusiones e indica el trabajo futuro.

2 Artículos

En esta sección se describen y exponen los 3 artículos principales que forman el compendio de esta Tesis, identificando el artículo por su título, el resto de los autores del artículo y su registro internacional en el DOI.

También se identifica la editorial, la fecha de publicación y los indicios de calidad acreditados para continuar con la traducción del resumen de cada artículo al español.

2.1 Artículo 1

2.1.1 Identificación del artículo

Título (original):	**Autonomic Management Architecture for Multi-HVAC Systems in Smart Buildings.**
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2.1.3 Resumen del artículo

El artículo propone una arquitectura autónoma de un sistema múltiple de climatización de edificios, representado por un modelo denominado multi-HVAC basado en la arquitectura de “Ciclos Autónomos de Datos”. Un sistema multi-HVAC consiste básicamente en un conjunto de subsistemas compuestos de bombas de calor, grupos de frío, torres de refrigeración y calderas, entre otros. El enfoque de la investigación radica en optimizar el consumo energético, manteniendo el confort interior y maximizando el rendimiento de los equipos, mediante la selección del modo operacional óptimo del sistema. Los modos operacionales son combinaciones de las capacidades de producción de las distintas máquinas. La arquitectura se implementa mediante tareas de análisis de datos (DAT) que responden a la información que proporciona el propio sistema y su contexto, constituyendo un sistema de gestión autónomo. Algunas DATs analizan la información para calcular el modo operacional óptimo en un momento dado, otras controlan los subsistemas de climatización. El sistema se modela matemáticamente y se calibra durante el funcionamiento con la información recogida por los sensores de ambiente. El artículo aplica el concepto a dos casos de estudio de dos edificios en los que las instalaciones de climatización son en uno homogénea y en otro heterogénea demostrando la capacidad de generalización de la arquitectura propuesta,

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Autonomic Management Architecture for Multi-HVAC Systems in Smart Buildings

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ABSTRACT This article proposes a self-managing architecture for multi-HVAC systems in buildings, based on the "Autonomous Cycle of Data Analysis Tasks" concept. A multi-HVAC system can be plainly seen as a set of HVAC subsystems, made up of heat pumps, chillers, cooling towers or boilers, among others. Our approach is used for improving the energy consumption, as well as to maintain the indoor comfort, and maximize the equipment performance, by means of identifying and selecting of a possible multi-HVAC system operational mode. The multi-HVAC system operational modes are the different combinations of the HVAC subsystems. The proposed architecture relies on a set of data analysis tasks that exploit the data gathered from the system and the environment to autonomously manage the multi-HVAC system. Some of these tasks analyze the data to obtain the optimal operational mode in a given moment, while others control the active HVAC subsystems. The proposed model is based on standard standard HVAC mathematical models, that are adapted on the fly to the contextual data sensed from the environment. Finally, two case studies, one with heterogeneous and another with homogeneous HVAC equipment, show the generality of the proposed autonomous management architecture for multi-HVAC systems.

INDEX TERMS HVAC system, autonomic computing, data analysis, smart building, multi-objective optimization, multi-chiller, building management systems.

NOMENCLATURE

ANFIS	Adaptive Network based Fuzzy Inference System
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ACODAT	Autonomic Cycle of Data Analysis Tasks
ARIMA	Autoregression Integrated Moving Average
ARMAX	Autoregression Moving Average eXogenous
ARX	Auto Regression eXogenous
BAS	Building Automation System
BCS	Building Control System
BD	Big Data
BEMS	Building Energy Management System
BMS	Building Management System
COP	Coefficient Of Performance
CVaR	Conditional Value at Risk
DAT	Data Analysis Tasks
DL	Deep Learning
DMC	Dynamic Matrix Control
EA	Evolutionary Algorithm
EEV	Electronic Expansion Valve
EER	Energy Efficiency Ratio
ETL	Extraction Transformation and Load process
FBC	Feedback Control
FFW	Feedforward Control
FPGA	Field-programmable Gate Arrays
FAN	Fuzzy Adaptive Network
GA	Genetic Algorithm
GPC	Generalized Model Control
HVAC	Heating, Ventilation and Air-Conditioning
IAQ	Indoor Air Quality
IEC	International Electrotechnical Commission
IoT	Internet of Things
ISO	International Organization for Standardization
JIT	Just in Time

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LQ	Linear Quadratic
LQG	Linear Quadratic Gaussian
MPC	Model (Based) Predictive Control
MOGA	Multi-objective Genetic Algorithm
MPSO	Multi-Objective Particle Swarm Optimization
NZEB	Nearly Zero Energy Buildings
NSGA	Non Dominated Sorting Genetic Algorithm
PID	Proportional, Integral and Derivative modules
PDF	Probability Density Function Approximation
PLC	Programmable Logic Controllers
RC	Resistive Capacitive
SARIMA	Seasonal Autoregressive Integrated Moving Average
SQP	Sequential Quadratic Programming
SPEA	Strength Pareto Evolutionary Algorithm
4SID	Sub-Space State Space Identification
SVM	Support Vector Machines
TCBM	Topological Case Base Modeling

I. INTRODUCTION

The need for saving energy to improve the sustainability of the Planet is increasingly worrying society and requires to put significant research on it. Based on recent studies [1], it is observable that buildings contribute to the 40% of the world energy consumption, being the HVAC systems the most demanding. Nations are also acting to mitigate the impact of an excessive energy consumption, like Europe, where the Community takes directives about the design of NZEB, namely 2010/31/EU and 2012/27/EU [10]. Several strategies address this challenge by retrofitting building architecture and facilities [11], automating control operations control [12], or predicting building behavior with advanced AI and EA techniques [13]–[15]. Working on efficient energy management solutions in buildings, especially for HVAC systems, leads to significant economic, social, and environmental improvements [6], [10].

It is far more sustainable and cost effective to improve the management systems to achieve higher efficiency than replacing HVAC systems with more efficient modern technologies [5], [10]. Recent articles emphasize the use of advanced control algorithms [2]–[4], [6] and the optimization of the HVAC system parameters [8], [18], [19], for improving the energy efficiency in buildings, as an inefficient operation of HVAC systems can result in excessive energy consumption.

Therefore, it is fundamental to improve the efficiency of the existing HVAC systems, in order to decrease energy usage. The HVAC energy demand is directly related to the indoor temperature setpoints, the type of building and the regional climate, among other parameters. Particularly, in this work are analyzed buildings with multi-HVAC systems. In this context, it is required the determination of the optimal functional mode of the multi-HVAC systems for a given situation, in order to improve their energy consumption, equipment performance and thermal comfort.

This research describes a new concept that relies on three fields of study. The first is about the modeling techniques of HVAC systems. The second is about multi-objective optimization for obtaining the optimal configurations of HVAC subsystems for saving energy consumption and cost, maximizing the comfort and the equipment performance. Finally, the last one is about self-management architecture for multi-HVAC systems.

A multi-HVAC system assumes that the system is split it up in several HVAC subsystems, such as chillers, heat pumps or boilers, with their associated mechanisms. Each HVAC subsystem can be turned on or off or regulated, contributing to generate different operational modes for the multi-HVAC system. The optimization identifies possible operational modes and which one best fits the set of objectives. The proposed architecture is based on the Autonomous Cycle of Data Analysis Tasks (ACODAT) [34], [35] paradigm, that defines a set of Data Analysis Tasks (DATs) [35] that autonomously interact providing intelligent supervision for achieving the pursued strategic goals. Some DATs monitor the selected variables (e.g., energy cost, CO_2 emissions) and make decisions that deliver to other DATs; other DATs extract knowledge to predict potential system behaviors; others identify relations between variables; there are DATs that search for the optimal multi-HVAC system operational mode, and others supervise the system performance. A particular feature of DATs is that they can extract information from both the system physics formulation or the available historical system data records.

The proposed solution is general for any building, although requires to be customized for each context. This work analyzes buildings with heterogeneous multi-HVAC systems (different heat pumps, chillers, etc.) for testing the versatility of the paradigm ACODAT to deliver the optimal functional mode of the multi-HVAC system for any given situation.

The main contributions of this article are: i) A proposal of a general autonomous architecture based on ACODAT paradigm to manage multi-HVAC systems in buildings, optimizing multiple goals, according to the changing contextual information; ii) An extension of domain-based models with data-driven knowledge models, to predict on the fly multi-HVAC systems context-driven behaviors.

This paper is organized as follows: Section II presents the related works. Section III describes the proposed autonomous management architecture, based on the key aspects of multi-HVAC systems and ACODAT paradigm. Section IV illustrates the generality of this approach, applying it to 2 different case studies. Section V gives the result analysis and compares with other works and, finally, conclusions and further works are described in Section VI.

II. RELATED WORK

Energy consumed in HVAC systems has been widely discussed in the literature. This research extends the scope by addressing different fields while proposing a new paradigm. It starts presenting the progress in modeling HVAC systems, because this is determinant for the proposed architecture. This article outlines some of the recent works on modeling, centered on mathematical models, data-driven models or simulated models. Then, some works introduce strategies for Building Management Systems, being this the appropriate context for the proposed autonomic architecture. Another related area is the implementation of advanced control algorithms and the improvement of the design of HVAC systems to reach the highest possible level of thermal comfort for the occupants, minimizing the energy consumption. This section concludes presenting the ACODAT paradigm and its utilization in different domains. The revision of literature shows that ACODAT-based autonomic management architecture has not been used in HVAC systems yet and that there are not approaches for obtaining an efficient context-based operation of multi-HVAC systems.

A. HVAC SYSTEMS

Modeling HVAC systems deals with complex structures, including chillers, heat pumps, heating/cooling coils, boilers, air-handling units, thermal storage systems and liquid/air distribution systems. Sensors and actuators allow the regulation of the controllable plant variables, such as the ambient temperature in the occupied zones, the static pressure in the pipes, the chilled flowing water temperature or the air fans speed. At this low level, the HVAC system is difficult to manage, as its physical behavior is dynamic and nonlinear, such as its high thermal-inertia. The generation of an accurate and effective model for these systems is still challenging.

There is a comprehensive work of Afram and Janabi-Sharifi [22], updated by Afroz *et al.* [6], in which the known modeling techniques are evaluated and classified in three kinds: physics-based -also known as white-box, mathematical or forward-; data-driven -or black-box-; and a combination of them, known as hybrid -or grey-box-. Physics-based approaches use governing laws of Physics, such as the flow balance, the heat transference or the energy-mass balance to define a set of mathematical equations that describe the HVAC system. Data-driven approaches collect data from the system and the context under normal or abnormal utilization, identifying the relations between the input and output variables with AI techniques. The grey-box approaches define the basic model with physics-based methods, and adjust their parameters with AI-based algorithms. The physics-based model is normally applied to HVAC system components. This is illustrated with an example. A chiller is one of the main HVAC system components, which removes heat from a fluid in a vapor compression cycle or an absorption cooling cycle and consumes almost half of the total energy. It has four modules: a compressor, an evaporator, a condenser, and an EEV, that is normally modeled separately with the following design assumptions [7]:

- The refrigerant properties of each component are homogeneous.
- The refrigerant mass flow rate goes through the compressor and is considered constant throughout the system.
- The expansion process through the EEV/orifice plate is isenthalpic.
- The temperature of the walls does not vary through the cross-section, or across the ducts.

Supposing that the refrigerant is in a quasi-steady state, using the energy balance equations proposed in [6], the heat transfer rate of the evaporator (Q_e) and the mass flow rate of the refrigerant ($\dot{m}_r$) can be obtained with:

$$\dot{Q}_e = \alpha_{ei}A_{ei}(T_{wo} - T_{we}) \quad (1)$$

$$\dot{m}_r(h_1 - h_6) = \alpha_{eo}A_{eo}(T_{we} - T_e) \quad (2)$$

where, h_1 is the enthalpy of the refrigerant at the evaporator outlet-compressor inlet (kJ/kg), h_6 is the enthalpy of the refrigerant expansion valve exit/evaporator inlet (kJ/kg), A_{ei} is the area of the evaporator inlet (m^2), A_{eo} is the area of the evaporator outlet (m^2). T_{wo} is the return water temperature (°C), T_{we} is the temperature of the evaporator wall (°C), T_e is the temperature of the refrigerant at the evaporator inlet (°C), α_{ei} is the heat transfer coefficient of refrigerant entering the evaporator (W/m^2 K) and α_{eo} is the heat transfer coefficient of the refrigerant leaving the evaporator (W/m^2 K). In a similar way, the heat transfer rate of the condenser (Q_c) and the other parameters of the HVAC system, like the dynamic temperature of the heating/cooling coil, can be obtained applying the energy balance in the air–water heat exchanger [6].

Given the case that the dynamics of the HVAC system could be simulated with their differential equations, the actual behavior would differ from the theoretical construction due to several factors, like the design assumptions made to simplify the equations, or the natural equipment feature degradation.

Besides, when considering an HVAC system, which is already installed in a building, for generating its model formulation, the scarce and unstructured documentation and the hidden acquired habits by the engineers and operators, make the data-driven modeling approach interesting to perfect the mathematical approach. Physics-based systems provide a good generalization capability, but are not accurate, because of the significant number of parameters and assumptions that are defined to work with them and their dynamical characteristics.

Data-driven models collect HVAC system data under different conditions: normal and abnormal situations. A relation is also defined between the input and output variables using Statistics or AI techniques, such as ANNs [16], or, in some cases, with DL techniques [17]. Examples of black-box models are: TCBM, 4SID, PDF, JIT, several ANN architectures, SVM, FAN, Takagi-Sukeno Fuzzy, ANFIS, Linear and Polynomial Time Series regression, ARX, ARMAX, and ARIMA.

Some authors have recently proposed the utilization of BD-based techniques to improve the operations of existing buildings [19]. Several studies addressed the type of buildings differentiating their use, like residential, commercial, office buildings or education facilities [21], limiting the generalization capabilities of these methods. Old buildings with their special requirements [20] have been treated by retrofitting the HVAC systems, but very few have addressed the control system for improving their performance and efficiency, like the case of a museum that requires an environment for the pictures conservation as an unavoidable physical constraint [18]. Other proposals bring useful metaphors for treating the model behavior, like considering an HVAC system as a cyber-physical system [20] because of its ''integration of computation and physical processes''.

Finally, grey-box models show better generalization capability than data-driven models. The main strength is that are capable to capture any unmodelled effect left out of the equation and adapt to dynamic changes. Some examples in the literature are RC Equivalent Circuit, based on genetic algorithms that discover the resistance and capacitance parameters; Simulated Zone Model RC whose parameters are identified by SQP; or Physics-based ARMAX to predict room temperature.

This research requires to compare the special case of multi-HVAC architectures, mostly treated in literature as homogeneous multi-chiller systems, although not fully comparable to multi-HVAC systems. Literature discusses about the modification of the ''thermal load'' variable in commercial buildings [7], the optimization of the cooling load sharing of a multi-chiller system using a probability density distribution profile [4], the optimization of multi-chillers with multiphase genetic algorithms [23]. the use of data for evaluating the performance of a multi-chiller system [24], the use of a general algebraic method for modelling multi-chiller systems [25], or a sequencing of multi-chillers [26]. In any case, the term of multi-HVAC used in this article as an alternative to multi-chiller includes the heterogeneous characteristics of the HVAC sub-systems.

B. BUILDING MANAGEMENT SYSTEM

As the complexity of HVAC systems has been growing, a management system is increasingly required. BMS is the generic name, but there are also in the literature other different names that express slightly different approaches. For example, BAS synthesizes the building automation technologies, like ISO/IEC 14543-3 or ISO/IEC-14908. Another example is BEMS that networks the setpoints, device controllers, system logic, timers, trend logs, alarms coming from the different building facilities, or simple controllers, providing a friendly interface to manage them [5]. The three main objectives of BEMS are: a) to provide a healthy and pleasant indoor climate; b) to ensure the safety of users and owners; and c) to ensure cost-effective operations with respect to both energy and personnel. The common functionalities are:

- Energy remote monitoring.
- Optimization and control of energized building facilities.
- Equipment operations according to forecast.
- Energy management information reporting.

The minimal components of a BEMS are: the central station, connected with remote outstations -also called controllers-. The central station has an interface with the remote outstations enabling some control functions on them, depending on the client's requirements (for instance, energy savings, security, etc.). It is yet unclear how much an optimal use of BEMS can reduce energy usage and at what costs. Estimations about the energy savings differ considerably with building uses and other considerations. Some authors estimate energy savings up to 27% with BEMS [8], while others estimate energy savings up to 20% with optimal control of space heating. Others reduce the benefits up to 10% in lighting and ventilation [9].

A BMS is a computer-based control system that controls and manages building's mechanical, electrical and electromechanical equipment, such as lighting, HVAC systems, fire systems, elevators or security systems. The BMS is capable to improve the energy efficiency, the environmental conditions, or the building operations and manageability [15]. Finally, BCS is another name that focuses on simple control models.

Foreseen evolution directs towards smart buildings with hyper-connected environments, managed with intelligent IoT based BMSs, making use of advanced AI analytics. ACODAT tackles present challenges and its architecture is prepared for managing these new paradigms.

C. HVAC CONTROL SYSTEMS

HVAC control systems make use of conventional and advanced methods. It is interesting to know the evolution as most of them are still in use and object of ongoing research. The first automation was implemented in preprogrammed sequences of instructions in PLCs and FPGAs actuating on the controlled components. Then, PID FBC and FFW modules provide regulation, minimizing the difference between the controlled signal and the setpoint and its time-domain characteristics. PID is still present in 9% of the publications about HVAC control. Self-tuning techniques, like gain scheduling (in 9% of publications), decoupler, state-space representation and transfer functions, have improved the robustness and adaptation capability of HVAC control. Most recent advances in control make use of optimization schemas, like LQ or LQG. Model-based prediction is becoming popular with MPC [3], and its variants, DMC and GPC, today found in 15% of publications. It is also important to note the growing multiagent architectures, so useful for large systems, which are in 14% of publications, and fuzzy logic control systems to optimize the model and control parameters, which are in 13% of the studies.

An interesting case of two-stage energy management strategy for a commercial building, has tried incorporating the uncertainty of electricity prices in a model predictive control (MPC) for the energy management optimization [39]. In this case, they carry out a power balance between the power supply and the load on the building, while the operational costs are minimized. The predicted values for load demand, wind power, and electricity price are forecasted with SARIMA model. In addition, the CVaR value is used to assess the uncertainty in the electricity prices.

D. MULTI-OBJECTIVE OPTIMIZATION IN HVAC SYSTEMS

The HVAC system operations can be managed to get optimal performance. The optimization problem seeks to identify the best system configurations and schedules to save energy, maximize the comfort and reduce the operating costs [3]. Some authors consider thermal comfort as a constraint and others, another objective to maximize, preferring the later in this proposal, adding a degree of freedom to the optimization problem. Some works also consider indoor humidity, subjective IAQ index, retrofit costs, lighting consumption, plug loads, or visual comfort level [27]. Very few authors include the equipment performance in the equations, such as the maximization of the COP for heating, or the EER for cooling, and their seasonal variations in multi-chiller systems [28].

For making practicable this multi-objective optimization process in real-time management, recent literature commonly assesses different EAs. Most popular techniques considered for optimization are based on GAs [3], and its multi-objective variations, such as MOGA, NSGA or SPEA [29]. Other considered techniques are MPSO [30], ANN-based models, Newton-Raphson method or Interior Point method [3]. Some authors also research on non-supervised data mining techniques to discover hidden patterns that could eventually improve the energy efficiency in HVAC systems [31].

E. AUTONOMIC CYCLE OF DATA ANALYSIS

Literature interest focuses on HVAC systems control improvement with optimization techniques, mainly based on predicting models [2], grouping the operating elements in higher layers or orchestrating their control agents to supervise the whole system [15], or just for automating operations [10], but none of them deals with a comprehensive autonomic management architecture for HVAC systems.

ACODAT is a computing paradigm that includes a set of data-driven tasks, DATs to pursue a common goal for the managed process [6]. DATs exploit the data collected from the system to build knowledge models that describe, optimize and predict its behavior. DATs co-operate among them and interact with the system according to their specific roles [35], [36]:

- System inspection: These DATs extract information monitoring the system behavior and its context. This requires systematic ETL processes. DATs generate an image about the current conditions. Data could be predicted or estimated with different contextual information.
- System analysis: These DATs interpret, understand, and diagnose the current state of the system. They build knowledge models with the prepared information from the inspecting DATs considering the system dynamics.
- Decision making: These DATs impact on the system dynamics because their decisions are translated into physical orders for the actuators to activate or regulate the equipment to reach the desired objectives of comfort or deactivate them to save energy.

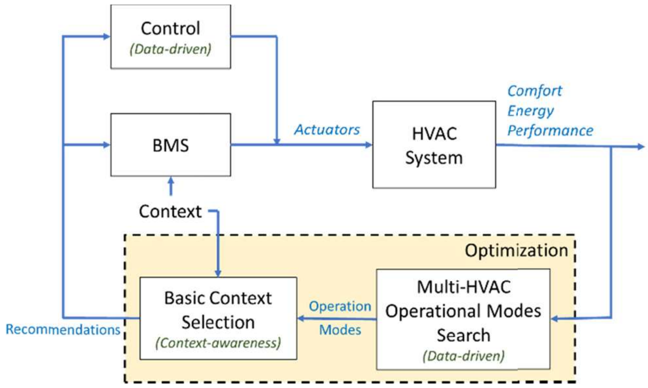

FIGURE 1. Autonomic multi-HVAC management.

ACODAT paradigm requires the following elements to work [36]:

- Multidimensional data model to store the data collected from different sources that characterize the system behavior for the DATs.
- Platform to host the tools for DATs to use data mining, semantic mining or linked data.
- Multi-adaptive and polyvalent mechanisms to respond in real time to new inputs and conditions (e.g., outdoor changes, climate change, new uses, new rules, etc.)

ACODAT-based architectures are prepared to use data mining or semantic mining techniques and allow advanced types of knowledge representations, like ontologies or cognitive maps. Particularly, when data comes in streaming, it is necessary to use ETL combined with data mining mechanisms. When ACODAT reads data from offline sources, like Web repositories, then uses data collection and curation processes with semantic mining and linked data tools.

III. AUTONOMOUS ARCHITECTURE

A. GENERAL MODEL

The first goals of ACODAT paradigm for the management of building's multi-HVAC systems is to identify its optimal operation point, done with the Optimization Module, and adapt the multi-HVAC system to accomplish this optimal operation, done with the BMS and Control modules. This is shown in Figure 1. The first module explores different combinations of HVAC sub-systems and selects the best one for the current conditions. The second module then translates the decision made into specific orders to the Control and BMS Modules. The proposed architecture works perfectly with different AI techniques to solve this problem.

B. DETERMINATION OF MULTI-HVAC OPERATIONAL MODES

1) EXPLORING POSSIBLE MULTI-HVAC OPERATIONAL MODES

The Optimization Module identifies the best operational mode of the multi-HVAC system to minimize the energy consumption and cost, and maximize the ambient comfort and the equipment performance. The problem is defined as a multi-objective optimization. This section sets out the objective cost functions and shows how the knowledge models based on AI exploit the data of the context. These knowledge models will be used in a future ACODAT architecture functionality for supervision, detection and diagnosis of multi-HVAC systems.

a: DEFINITION OF THE MULTIOBJECTIVE OPTIMIZATION PROBLEM

As seen in previous sections, buildings' multi-HVAC system have several combinable HVAC subsystems for heating or cooling generation. The optimization model requires to define those possible operational modes and identify the optimal one that maximizes energy savings with the highest possible indoor comfort, leading to resolve a multi-objective optimization problem with conflict among the objectives. Thus, the proposed approach is to search of non-dominated-Pareto optimal- solutions [18].

The main decision variable is the $\mathrm{HVAC_{mode}}$, that defines the optimal combination of multi-HVAC subsystems to be used in a given time, t. The multi-objective optimization problem is formulated as follows:

$$\begin{aligned} &Min_{HVAC_{mode},t}(P_{\mathrm{consumed}}(\mathrm{HVAC_{mode}},t),\\ &\quad Cost_e(\mathrm{HVAC_{mode}},t), COP_{global}(\mathrm{HVAC_{mode}},t),\\ &\quad \mathrm{Comfort}(\mathrm{HVAC_{mode}},t)) \end{aligned} \tag{3}$$

where, the cost functions to be optimized are:

- $P_{\mathrm{consumed}}(\mathrm{HVAC_{mode}},t)$ is the total power required by the current mode of the multi-HVAC system, defined as [7]:

$$\begin{aligned} &P_{\mathrm{consumed}}(\mathrm{HVAC_{mode}},t)\\ &\quad = \sum P_{\mathrm{chiller}}(j,t) + P_{\mathrm{CT}}(j)\\ &\qquad + P_{\mathrm{cwp}}(j) + P_{\mathrm{wpp}}(j), \quad \forall j \in HVAC_{mode} \end{aligned} \tag{4}$$

where, $P_{\mathrm{chiller}}(\mathrm{j,t})$ is the power required by $\mathrm{j^{th}}$ chiller, $P_{\mathrm{CT}}(j)$ is the power required by $\mathrm{j^{th}}$ cooling tower, $P_{\mathrm{cwp}}(j)$ is the power required by $\mathrm{j^{th}}$ cooling water pump, and $P_{\mathrm{wpp}}(j)$ is the power required by $\mathrm{j^{th}}$ primary circuit chilled water pump. Typical fluids in HVAC subsystems are water and gas, condensing water or air [32]. The variables of Equation (4) are specific for water and when the fluid is air, the variables P_{cwp} and P_{CT} are not applicable - equals 0 in this model-. $P_{\mathrm{CT}}(j)$ is obtained from the cooling tower manufacturer's technical specifications, while $P_{\mathrm{cwp}}(j)$ and $P_{\mathrm{wpp}}(j)$ are defined in the design of the HVAC system. $P_{\mathrm{chiller}}(\mathrm{j,t})$ is:

$$P_{\mathrm{chiller}}(\mathrm{j,t}) = CC(j,t)/COP_{maker}(j)$$

$$\mathrm{CC(j,t)} = \begin{cases} Q_{fluid}(j,t) * Heat_{fluid}(\mathrm{j}) * \rho_{fluid}(\mathrm{j}) \\ \quad *\Delta T_{HVAC}(j,t), & \text{if } < \mathrm{CAP(j)} \\ CAP(j), & \text{otherwise} \end{cases}$$

$COP_{maker}(\mathrm{j})$ is the coefficient of performance of the $\mathrm{j^{th}}$ chiller, CAP(j) is the capacity of the $\mathrm{j^{th}}$ chiller, both obtained from the manufacturer's technical specifications, $Q_{fluid}(j,t)$ is the flow rate of the $\mathrm{j^{th}}$ chiller, $Heat_{fluid}(j)$ is the specific heat capacity of the fluid in the $\mathrm{j^{th}}$ HVAC subsystem, $\rho_{fluid}(\mathrm{j})$ is the density of the fluid in the $\mathrm{j^{th}}$ HVAC subsystem, $\Delta T_{HVAC}(j,t)$ is the difference between the input and the output temperatures of the $\mathrm{j^{th}}$ HVAC subsystem.

- $\mathrm{Cost_e(HVAC_{mode},t)}$ is the cost of the energy, and it is obtained with:

$$\begin{aligned} &Cost_e(\mathrm{HVAC_{mode}},\mathrm{t})\\ &\quad = P_{consumed}(\mathrm{HVAC_{mode}},\mathrm{t}) * TE_i, \quad \textit{for } t \in i \end{aligned} \tag{5}$$

where, TE_i is the tariff rate applied to the energy consumed in Period i corresponding to moment t.

- $\mathrm{Comfort(HVAC_{mode},t)}$ is the comfort perceived in the different building zones (offices, halls, etc.) and grows as the difference between the setpoints and the current room temperatures in each zone ($\overrightarrow{\Delta T}_{comfort}(zones,t)$) gets smaller. The optimization problem seeks to minimize this difference. The equation transforms comfort to demanded power ($P_{demanded}(\mathrm{t})$) in t to the HVAC system to reach the thermal comfort in each zone:

$$\begin{aligned} P_{demanded}(t) &= Heat_{air} * \rho_{air} * \sum_{z=1}^{Z}\\ &\quad \times (Q_{air}(\mathrm{z,t}) * \Delta T_{comfort}(z,t) \end{aligned} \tag{6.a}$$

where Z is the number of zones in the building. The minimization of $\mathrm{P_{demanded}(t)}$ implies the maximization of $\mathrm{Comfort(HVAC_{mode},t)}$, hence allowing to replace the later with $\mathrm{P_{demanded}(t)}$ in Eq. (3).

Comfort $\mathrm{(HVAC_{mode},t)}$ can also be redefined considering that the multi HVAC system has a maximum power $P_{max}(\mathrm{HVAC_{mode}}) = \sum_{j \in HVAC_{mode}} \mathrm{CAP}(j)$, delimiting the maximum temperature change ($T_{max}(\mathrm{HVAC_{mode}})$, which can be obtained from the manufacturers' specifications. This idea allows to determining $\Delta T_{off}(\mathrm{HVAC_{mode}})$ as the difference between the global temperature setpoint and the maximum temperature that the current $\mathrm{HVAC_{mode}}$ can supply. Some authors call the global setpoint as *social setpoint,* and has different ways to be obtained [37]. The demanded thermal power to the current $\mathrm{HVAC_{mode}}$ ($P_{thermic}(\mathrm{HVAC_{mode}},t)$) for the thermal comfort is:

$$\begin{aligned} &P_{thermic}(\mathrm{HVAC_{mode}},t)\\ &\quad = (\Delta T_{comfort}(\mathrm{HVAC_{mode}},t) *\\ &\qquad \times \sum_{j \in HVAC_{mode}} \mathrm{CAP}(j))/\Delta T_{\mathrm{off}}(\mathrm{HVAC_{mode}}) \end{aligned} \tag{6.b}$$

where ($\Delta T_{comfort}$ ($\mathrm{HVAC_{mode}}, t$) is the global temperature desired in the building (social setpoint) at time t. In this case, the minimization of $\mathrm{P_{thermic}}(\mathrm{HVAC_{mode}}, \mathrm{t})$ implies the minimization of $\Delta T_{comfort}$, hence the maximization of Comfort($\mathrm{HVAC_{mode}}$, t), so that it can be replaced by $\mathrm{P_{thermic}}(\mathrm{HVAC_{mode}}, \mathrm{t})$ in Eq. (3).

- COP_{global} (HVACmode, t) is the current coefficient of performance of the multi-HVAC system for the selected operational mode, which is the ratio between the supplied thermal power ($P_{demanded}(t)$) or $P_{thermic}$ ($\mathrm{HVAC_{mode}}, t$)), and the electrical power that the multi-HVAC system consumes (P_{consumed} ($\mathrm{HVAC_{mode}}, t$):

$$COP_{global}(\mathrm{HVAC_{mode}}, \mathrm{t}) = \frac{P_{demanded}\ (\mathrm{t})}{P_{\mathrm{consumed}}\ (\mathrm{HVAC_{mode}}, t)} \tag{7.a}$$

or

$$COP_{global}\ (\mathrm{HVAC_{mode}}, \mathrm{t}) = \frac{P_{thermic}\ (\mathrm{HVAC_{mode}}, t)}{P_{\mathrm{consumed}}\ (\mathrm{HVAC_{mode}}, t)} \tag{7.b}$$

With this set of equations (4, 5, 6, and 7) the multi-objective optimization problem is defined generating a Pareto front, i.e. a set of optimal solutions, for each possible $\mathrm{HVAC_{mode}}$.

b: DATA-DRIVEN APPROACHES IN THE DEFINITION OF THE OPTIMIZATION PROBLEM

The previous objective functions are defined according to specific mathematical models. In this section, the mathematical expressions are complemented using data-driven models that identify the actual conditions from the data captured from the multi-HVAC system.

- Data model for Equation (4). Historical records have the P_{consumed} ($\mathrm{HVAC_{mode}}, t$) simultaneously with other variables, which it could depend on. To incorporate these possible relations, the equation is redefined as

$$P_{\mathrm{consumed}}\ (\mathrm{HVAC_{mode}}, t) = V1\ (j) \tag{8}$$

where, $V1\ (j)$ is a *predictive model* based on the historical data of the j$^{\mathrm{th}}$ HVAC subsystem. It is of significant interest to note that this hybrid approach, not only refine the results of the pure mathematical model, but also allows the inspection of the performance degradation throughout the lifecycle of the j$^{\mathrm{th}}$ HVAC subsystem, impossible to obtain otherwise (see equation (4)).

- Data model for Equation (5). This equation can be improved in different ways. In some countries, the pricing period could be contracted in real time auctions. In this case, the historical price evolution and the climatic conditions could be used to predict the optimal tariff rate periods to hire energy, modifying Equation (5):

$$\begin{aligned} &Cost_e\ (\mathrm{HVAC_{mode}}, \mathrm{Hire_{mode}}, t) \\ &\quad = P_{Max,i} * TP_i\ (\mathrm{Hire_{mode}}) \\ &\qquad + P_{consumed}\ (\mathrm{HVAC_{mode}}, t) * TE_i(\mathrm{Hire_{mode}}), \quad for\ t \in \boldsymbol{i} \end{aligned} \tag{9}$$

where, $\mathrm{Hire_{mode}}$ indicates if tariff rates are fixed or auctioned, and $TP_i(auction)$ and TE_i(auction) are predictive models based on historical data from the auctions and climatic conditions. This model optimizes the energy contractual cost and can be automated the auction process.

The other possible extension of the mathematical model is to obtain the optimal moments to activate the HVAC subsystems according to the tariff period i, which will be studied in next works.

- Data model for Equations (7.a) and (7.b). Global COP, COP_{global} ($\mathrm{HVAC_{mode}}$, t), is also registered or easily obtained from historical records coming associated with variables, which it could depend on. This allows building a model of this variable using these variables to predict future COP values. The expression can be redefined as:

$$COP_{global}(\mathrm{HVAC_{mode}}, \mathrm{t}) = \mathrm{V2(j)} \tag{10}$$

where $V2\ (j)$ is a *predictive model* based on the historical data from each HVAC subsystem. $COP_{global}(\mathrm{HVAC_{mode}}, \mathrm{t})$ can be redefined as an unknown function F(j) between the variables defined in Eq. 7.a or 7.b. In this case, it is necessary to define this function F(j), which is an *identification model* based on the historical data of $COP_{global}(\mathrm{HVAC_{mode}}, \mathrm{t})$, and these variables. Again, this model is also capable to capture the performance degradation of the j$^{\mathrm{th}}$ HVAC subsystem according to the current behavior of these variables, which is not done with just the mathematical definition.

The enhancement of the mathematical optimization problem with these data-driven models improves predicting capabilities, in order to bring new functionality and capabilities, such as the analyses of the subsystem's degradation or the automation of power tariff contracting.

2) SELECTION OF THE MULTI-HVAC OPERATIONAL MODE TO IMPLEMENT

The previous phase identified a set of solutions for each operational mode -individuals on Pareto front- obtained with any of the possible multi-objective optimization techniques. Now, the optimization problem must consider multiple Pareto fronts to select the optimal operational mode. An individual in a Pareto front represents an optimal solution for a given operational mode, where some of the objective functions are weighted to get optimal nondominated solutions. For example, one of the solutions could only minimize the $COP_{global}(\mathrm{HVAC_{mode}}, \mathrm{t})$. Several solutions are therefore possible for this problem. One particular Pareto Front could be obtained from the intersection of the different Pareto Fronts of the different operational modes, considered together to build a single Pareto Front from them that can be seen as a convex hull. This case is solved using classical multi-objective optimization techniques. Another solution analyzes the behavior of each Pareto Front of each HVAC mode with respect to the high level optimization requirements and then select one of them. This section explores these alternatives.

a: DETERMINATION OF ONE GENERAL PARETO FRONT

In Equation (3), the multi-objective problem is defined for only one Pareto Front, analyzing different HVAC modes that could be used in the current multi-HVAC system, where each HVAC mode represents the combination of HVAC subsystems used in Equations (4), (5), (6.a) or (6.b), and (7.a) or (7.b). Thus, Equation (3) is general, evaluates the HVAC modes and uses a general Pareto Front to analyze them.

b: ANALYSIS OF EACH PARETO FRONT

This section proposes an intelligent decision system based on the results of the previous phase and some other relevant information to select the HVAC mode. The general structure of the intelligent decision system is:

$$\text{If(decision\_condition) then (individual}_\text{i})$$

where *decision_condition* is a set of weights that defines the importance of each objective function, and $individual_i$ is the selected solution from the proposed Pareto Front with the multi-objective optimization technique. Each weight is set in real-time according to the relevance of each objective function for the current context and are defined as fuzzy variables as follows:

- *W1(P)* defines the importance of the minimization of P_{consumed}. It is a fuzzy variable that depends on the current values of $\Delta T^f_{HVAC}(\text{j}, \text{t})'s$ of the j^{th} chiller in the current HVAC mode. With this information, *W1(* P) is defined as:

$$\text{If } \Delta T^f_{HVAC}(1,\text{t}) \text{ and } \ldots \Delta T^f_{HVAC}(\text{j},\text{t}) \text{ then W1(P)}, \quad \forall j \in HVAC_{mode}$$

where $\Delta T^f_{HVAC}(j,t)$ is a fuzzy variable with values {high, average, low}, and so does *W1(P).*

- *W2(Cos$_{te}$)* defines the importance of the minimization of *Cost* e, and it is a fuzzy variable that depends on the current values of TE^f_i and $\Delta T^f_{HVAC}(\text{j}, \text{t})'s$. With this information, *W2(Cost$_e$)* is defined as

$$\text{If } TE^f_i \text{ and } (\Delta T^f_{HVAC}(1,\text{t}) \text{ and } \ldots \Delta T^f_{HVAC}(\text{j},\text{t})) \text{ then } W2(Cost_e)$$

where *W2(Cost$_e$)* can be {high, average, low} and TE^f_i values are{coming in, in, going out}.

- *W3(COP)* defines the relevance for maximizing the *COP*. It is a fuzzy variable that depends on the current values of $\text{P}^f_{demanded}(t)$ or $\text{P}^f_{thermic}(\text{HVAC}_{\text{mode}}, t)$ and $\Delta T^f_{HVAC}(\text{j}, \text{t})' s$. With this information, *W3(COP)* is defined as

$$\text{If } (\text{P}^f_{demanded}(t) \text{ or } \text{P}^f_{thermic}(\text{HVAC}_{\text{mode}}, t))) \text{ and } \Delta T^f_{HVAC}(1,\text{t}) \text{ and } \ldots \Delta T^f_{HVAC}(\text{j},\text{t})) \text{ then } W3(COP)$$

where $\text{P}^f_{demanded}(t)$ or $\text{P}^f_{thermic}(\text{HVAC}_{\text{mode}}, t))$ are fuzzy variables with the values {high, average, low}; and *W3(COP)* with {high, average, low}.

- *W4(Comfort)* defines the importance for maximizing the comfort. It is a fuzzy variable that depends on the current restrictions of $\overrightarrow{\Delta T}^f_{comfort}(zones, t)$, which can be {high, not}. This information defines W4(Comfort):

$$\text{If } \overrightarrow{\Delta T}^f_{comfort}(zones, t) \text{ then } W4(Comfort)$$

where $\overrightarrow{\Delta T}^f_{comfort}(zones, t)$ is a set of fuzzy variables with values {very strict, strict, normal, not strict}; and *W4(Comfort)* can be {high, average, low}. *W4(Comfort)* can also be calculated considering $\Delta T_{comfort}(\text{HVAC}_{\text{mode}}, t)$ as a fuzzy variable defining the *social setpoint* of the building at time *t* [37].

C. TRANSLATION OF SELECTED OPERATIONAL MODE TO THE MULTI-HVAC SYSTEM

This module translates the operational mode obtained in the previous module to a set of control signals to operate the multi-HVAC system. Chillers generally work with discrete ON/OFF or PID controllers. They could perform at their level improvements for energy efficiency, as shown in the previous section. Particularly, RC model is quite popular method for modeling thermal dynamics based on MPC. The first order RC modeling HVAC dynamics is formulated as:

$$C_i \dot{T}_{i,t} = \frac{T_{o,t} - T_{i,t}}{R_i} + \sum_{j \in N(i)} \frac{T_{j,t} - T_{i,t}}{R_{ij}} + P_{i,t}$$

where N(i) are neighboring zones of zone i, C_i and T_i are the thermal capacitance and room temperature of zone i, T_o is the outside dry bulb temperature, $P_{i,t}$ is the energy consumption at time t, and R_i and R_ij are the thermal resistance for zone i against the outside and the neighboring zone j. Once calculated C_i, R_i, R_ij for every zone, there is a 1st order system that models the thermal dynamics.

At time t, the building's running profile is $\text{X}_\text{t} := [\text{X}^{\text{uc}}_{,\text{t}}; \text{X}^{\text{c}}_{,\text{t}}; \text{X}^{\text{phy}}_{,\text{t}}]^\text{T}$, where T is the rolling horizon; $\text{X}^{\text{uc}}_{,\text{t}}$ denotes a collection of uncontrollable measurements, such as zone temperature, lighting schedule, in-room appliances schedule or room occupancies; $\text{X}^{\text{c}}_{,\text{t}}$ denotes a collection of controllable measurements, such as zone temperature setpoints or appliances working schedule; $\text{X}^{\text{phy}}_{,\text{t}}$ denotes the set of physical measurements or forecast values, such as dry bulb temperature, humidity and radiation level. Since $\text{T}_\text{i} \in \text{X}^{\text{uc}}$ and $\text{T}_\text{o} \in \text{X}^{\text{phy}}$, equation (10) can be reformulated by summing the P_i for all zones to get the overall building thermal dynamics:

$$P_\text{t} = f_{RC}(X_{t-T}; \ldots; X_t) \tag{11}$$

Equation (12) is further used in the optimal control problem:

$$minimize_{X^c_t \ldots X^c_{t+T}} \sum_{\tau=0}^{T} P^2_{t+\tau} \tag{12}$$

where T denotes the rolling horizon of the predictive model. $\text{X}^{\text{uc}}_{,\text{t}}$ and $\text{X}^{\text{c}}_{,\text{t}}$ have constraints.

This research considers an intelligent controller based on AI techniques that automatically makes changes according to weather parameters, and will be developed in future works. The data driven control method replaces the traditional MPC controller, building the dynamic model as it takes data from the multi-HVAC system.

IV. CASE STUDIES

A. HETHEROGENEOUS MULTI-HVAC SYSTEM IN OLD BUILDINGS

1) BACKGROUND

This case study is the HVAC system in Madrid Opera, known as Teatro Real, in Madrid City, Spain. The floor size is 65,000m^2 (700,000ft^2), the theatre occupancy is 1,746 seats. The stage area is 1,430m^2 (15,400ft^2) operated with an advanced rigging system that fully changes scene resources. The building has 11 lounges for events, 4 rehearsal rooms, 7 studios, a surrounding office area, warehouses and technical areas.

Madrid climate is predominantly dry with cold winters, with day average 0°C (32°F) in January, and hot summers with temperatures above 35°C (95°F).

The building is used from September to July and recently opens for specific events in August, requiring heating and cooling. The multi-HVAC system has two water-air heat pumps with 195kW of nominal thermal power each for heating and cooling, and two water-water chillers with 350kW each for extra cooling. Each HVAC machine could be seen as a HVAC subsystem. The multi-HVAC system is supervised and operated with a BMS that collects the temperatures from sensors located all over the zones and writes the instructions on the actuators regulating the water or air flow rates and fluid temperature. The BMS supervises 1,824 digital and analog variables.

The diversity of uses of the theater, rehearsal rooms and lounges in different seasons and hours of the day make the HVAC operation complex and require routines established beforehand for the field operators. They receive an order sheet with the schedule, setpoints and the HVAC subsystems to activate for the events. The engineering department takes the schedule of activities, labor hours and weather forecast to prepare the order sheet, which is a set of basic start/stop instructions that, once they are grouped in the different subsystems, can be mapped into an operational mode of the multi-HVAC system.

Figure 2 depicts the existing working scenario in which the field operator executes the instructions of the order sheet. BMS are generally versatile and can be programmed according to the timetable or optimization policies, however, in practice, this is so complicated that only a little functionality is used.

The BMS saves records with 169 variables, like outdoor temperature, room temperatures, electrical supplied power, thermal energy generated by each subsystem and their current COP, sampling every 15 minutes, in a persistent database. The BMS also stores 45 additional temperatures read from different zones of the building, sampled every hour in another table of the database. Another table keeps other variables read from subsystem components only during the theater shows and rehearsals from another 69 sensors every 10 minutes.

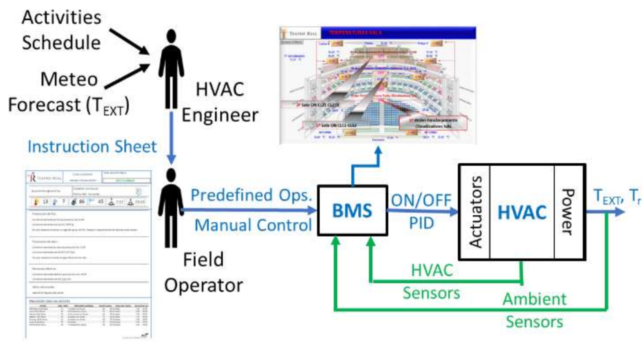

FIGURE 2. Existing multi-HAVC system operation.

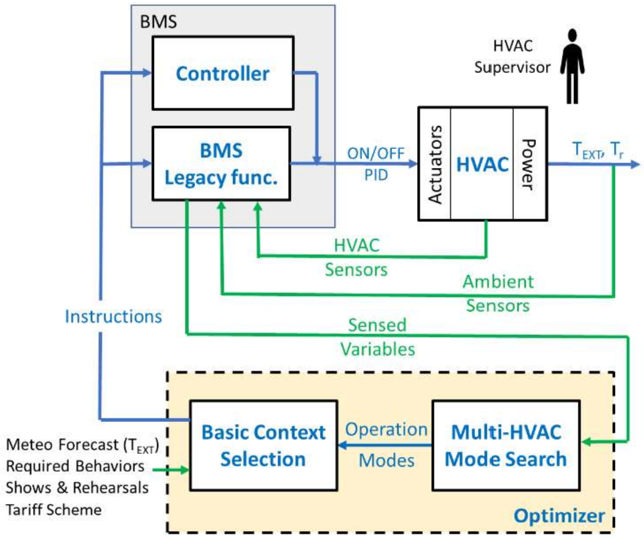

FIGURE 3. Instantiation of ACODAT in opera building.

2) INTRODUCTION OF ACODAT IN EXISTING HVAC INSTALLATION

Figure 3 shows the instantiation of ACODAT in the Opera HVAC. In this case, the different components of the optimization module are incorporated into the multi-HVAC system, except the Control Module that resides in the BMS. The selection of the multi-HVAC operational mode is essential and uses the strategies and equations defined in Section III.B. The Optimization Module can use the historical data stored in the BMS for data models.

a: EXPLORATION OF POSSIBLE MULTI-HVAC OPERATIONAL MODES

The first activity is to define the existing HVAC subsystems in the Opera building to identify then the possible operational modes of the multi-HVAC system. This requires the definition of the next variables for each HVAC subsystem:

TABLE 1. Some characteristics of the chillers obtained from manuals.

$Heat_{Water}(j)$	4.186 J/g°C
$\rho_{Water}(j)$	1 Kg/l
CAP(Chiller)	350 KW

TABLE 2. Tariff periods (TE) of the power.

Tariff price	Period 1	Period 2	Period 3		Period 4	Period 5	Period 6
€/KW	39,1394 27	19,5866 54	14,3341 78		14,3341 78	14,3341 78	6,5401 77

TABLE 3. Utilization of the TEs during the year.

Rate Periods																								
Months	Hours																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
JANUARY				P6					P2			P1				P2				P1			P2	
FEBRUARY				P6					P2			P1				P2				P1			P2	
MARCH				P6								P4								P3			P4	
APRIL				P6												P5								
MAY				P6												P5								
JUNE (1-15)				P6					P4			P3								P4				
JUNE (15-30)				P6						P2					P1						P2			
JULY				P6						P2					P1						P2			
AUGUST												P6												
SEPTEMBER				P6					P4			P3								P4				
OCTOBER				P6												P5								
NOVEMBER				P6								P4								P3			P4	
DECEMBER				P6					P2			P1				P2				P1			P2	

- Specific heat capacity of the fluid in Subsystem j, $Heat_{fluid}$ (j)
- Density of the cooling fluid in Subsystem j, ρ_{fluid} (j)
- Maximum electrical power consumed in Subsystem j, P_{max}(j)
- Maximum temperature provided with Subsystem j, T_{max} (j)
- Thermal capacity of Subsystem j, *CAP(j)*

These values are normally available in manufacturers' specifications. ACODAT also requires tariff rates in period i, TE_i, to calculate the energy cost. The tariff scheme varies throughout the year (see Tables 2 and 3).

The Opera HVAC system has two similar heat pumps and two similar water-water chillers. Some of the characteristics of the chillers are given in Table 1.

The model also requires the zone's size -lounges, rehearsal rooms, studios, offices, theater- to specify the demanded thermal power.

Data driven models use the historical data in the BMS database (see Section IV.A.1) to predict behaviors and identify deviations of the different components of the multi-HVAC system. The management is not only reduced to immediate operations, but also allows mid- and long-term functionality, such as monitoring the performance degradation of the equipment, which will be developed in next works.

b: SELECTION OF THE MULTI-HVAC OPERATIONAL MODE TO BE LAUNCHED

In this case study, the selection of the operational mode also depends on contextual variables, like weather forecasts, events schedule, which naturally suppose different weights for the cost objectives. A fuzzy intelligent decision system, as proposed in Section III.B, will select the convenient mode for each situation.

The event scheduling portraits information about the date, hour, duration of the required temperature setpoints for each zone. With this table and weather forecasts, fuzzy variables that weight the importance of each objective cost are defined:

- *W1(P)* is defined with the values of variables P_{consumed} and $\Delta T^{f}_{HVAC}(\text{j, t})'s$.
- *W2($Cost_{te}$)* is defined with the values of variables TEi and $\Delta T^{f}_{HVAC}(\text{j, t})'s$.
- *W3(COP)* is defined with the values of variables $\text{P}^{f}_{demanded}(t)$ or $\text{P}^{f}_{thermic}(\text{HVAC}_{\text{mode}}, t)$ and $\Delta T^{f}_{HVAC}(\text{j, t})'s$.
- *W4(Comfort)* is defined with the importance of the restrictions ($\overrightarrow{\Delta T}^{f}_{comfort}(zones, t)$).

Thus, this system is context-aware, capable to change the weights based on contextual information (events, working hours...) and sensed variables, to evaluate different states of the system. The Fuzzy Intelligent Decision Module can autonomously select the optimal multi-HVAC mode for each state. The system selects one non-dominated individual, according to the real scenario and changes the system behavior accordingly.

c: TRANSLATING THE SELECTED OPERATIONAL MODE FOR THE MULTI-HVAC SYSTEM

At the end of the process, the output of the fuzzy intelligent decision module directly feeds the BMS at the right time, with the necessary instructions to activate the optimal multi-HVAC mode, closing the control loop with the low-level instructions to operate each multi-HVAC subsystem. This requires that the recommended optimal multi-HVAC mode obtained in the Fuzzy Intelligent Decision Module to be translated in a set of values necessary for the BMS to accomplish the mode by activating, deactivating or regulating the addressed elements of the multi-HVAC system.

B. HOMOGENOUS MULTI-HVAC SYSTEM IN A NEW BUILDING

1) BACKGROUND

This second case study introduces ACODAT for San Pedro Hospital HVAC at Logroñ o City, Spain. The HVAC system is composed of 4 chillers, three with 3.5MW of thermal power and another with 1MW and 5.8 EER and, again, ACODAT determines the optimal operational mode. Figure 4 depicts the HVAC system functional diagram.

The Logroñ o's climate is warm and temperate, with significant precipitations. Temperatures are higher on average in July, 21°C (70°F), and lower in January with temperatures averaging 5°C (41°F).

Hospital zones include patients' rooms with 630 hospital beds, 12 examination rooms, 30 operating rooms, 18 recovery posts, 21 monitoring boxes, 16 emergency boxes, 4 resuscitation beds, radiology and scanning areas, kitchen, café, pharmacy, assembly hall with 200 seats, chapel room, administrative offices. The total floor size is 126,057m^2 (1,356.866ft^2).

2) INTRODUCTION OF ACODAT IN EXISTING HVAC INSTALLATION

The ACODAT can be also used to determine the multi-HVAC operational mode to be deployed, as it was explained in Section III. In addition, the data driven approaches allow exploiting the prediction models previously defined for this system, to make the optimization model more robust.

a: EXPLORATION OF THE POSSIBLE MULTI-HVAC OPERATIONAL MODES

Again, the first activity is to define the different HVAC subsystems in the Hospital, considering the similarities of three of the chillers. Thus, it is necessary the definition of the different variables as of Section III in this context. Particularly, the next variables must be defined for each HVAC subsystem: $Heat_{fluid}$ (j), ρ_{fluid} (j), T_{max} (j) and $CAP(j)$. It is necessary to define the foreseen hospital zones, such as operating rooms, patient rooms, etc. The Hospital tariff scheme has a single rate.

On the other hand, data driven models built for predicting energy consumption of the Multi-HVAC system can be used, with the data driven approach defined in Section III, to solve the optimization problem. Equal to the first case study, these models can be used for determining the degradation of the equipment.

b: SELECTION OF THE MULTI-HVAC OPERATIONAL MODE TO BE LAUNCHED

The hospital has only one type of HVAC subsystem, water-water chillers, 3 of them with the same capacity. The objective reduces to determine the number of chillers to use. Thus, it is necessary a general Pareto Front, resolvable with classical multi-objective optimization techniques, using the equations defined in Section III.B.2.

3) TRANSLATING THE SELECTED OPERATIONAL MODE FOR THE MULTI-HVAC SYSTEM

The multi-objective optimization technique identifies the operating mode of the multi-HVAC system. This information provides the control commands to execute the optimal multi-HVAC mode in the Hospital. The previous module determines the optimal multi-HVAC mode in the current context, which is then translated in the setpoints and control signals that govern the control system and equipment.

V. DISCUSSION AND COMPARISON WITH PREVIOUS WORKS

This section presents a comparison of the proposed approach with previous works, based on the next questions (see Table 4):

A. Do the articles propose an autonomic process of management for HVAC systems?

TABLE 4. Comparison with other works.

Works vs. Criteria	A	B	C	D
[5], [11], [13], [14]			x	
[17], [20], [25], [26]			x	
[27], [29]				x
[3], [10]		x		
[4]	x			
[18]			x	x
[15]		x	x	
This proposal	x	x	x	x

B. What is the scope of the proposal when considering other tasks beyond control and optimization (supervision, maintenance, etc.)?
C. Is it possible to exploit data from HVAC systems to build knowledge models (classification, state recognition, prediction)?
D. Is it possible to expand the study to different contexts (smart buildings, malls, museums)

The selected references have the closest topics to the proposed HVAC concept, including multi-objective optimization, control systems, energy optimization, multi-chiller systems, BMS and data-driven predicting models.

This research and [4] are the only ones that propose an autonomic management for HVAC systems. In this proposal, the analytical tasks can be shared with other autonomic cycles with different goals, such as the HVAC system supervisor or the self-configurator for mitigating faults and degradations throughout the lifecycle. Most works are very context specific and, therefore, not generalizable as the proposed solution.

This approach can use any possible AI method during the instantiation of the paradigm and is adaptable to multi-HVAC or single-HVAC systems, either centralized or distributed. It also defines self-improving scenarios, steadily monitors the equipment performance degradation, provides correction measures to reconfigure the operations autonomously or reports recommendations to the system administrator. This is based on an ongoing learning from the gathered data that minimizes the impact of initial bad operations habits, and provides a wider view of tactic and strategic functionalities, reducing the cost of operations. In conclusion, ACODAT management does not only control, but also forecasts, plans, organizes or commands. This approach does no need to invest in retrofitting the existing HVAC installations, changing facilities or redesigning the building.

The proposed approach is also the only work that combines a mathematical formulation of the optimization problem with data-driven models of prediction, which can be used to solve performance degradation problems, get better tariffs, etc. while the architecture searches for the best multi-HVAC configuration.

Finally, this work includes the maximization of the COP for heating or the EER for cooling, which have been rarely considered for multi-chillers in the literature [28]. This information about these coefficients, not only improves the optimization, but also detects the degradation of the

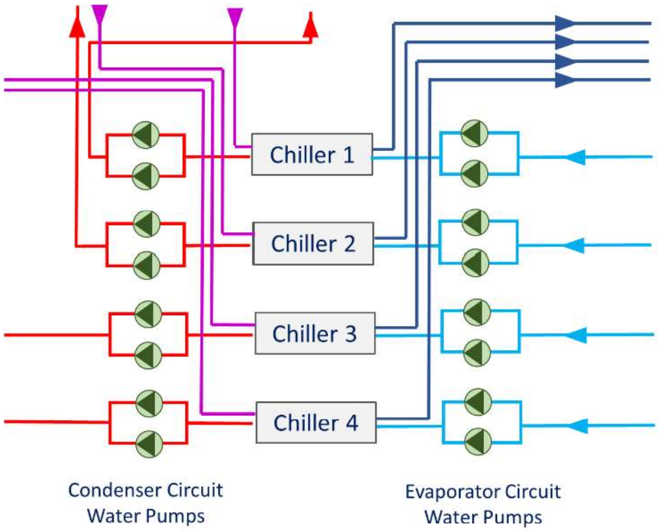

FIGURE 4. **HVAC system of the Granada hospital.**

HVAC system components throughout the time, becoming an original contribution of this article.

In general, ACODAT paradigm improves the energy consumption, the indoor comfort and the equipment performance. It allows the determination and selection of the optimal operational mode of the multi-HVAC system, i.e. the optimal combination of HVAC subsystems for a given context. It is the only work that considers multi-HVAC systems and proposes the full management of the closed loop (optimization and control phases). There are many approaches for controlling HVAC systems for improving energy efficiency depending on the building uses -commercial, residential-, such as the predominant nonlinear adaptive controls or MPC [2]. Others just focus on comfort control in the energy optimization strategy [5], assuming normal occupancy conditions [3], or applying deep learning to predict complex user behaviors [17].

At this moment, as far as we know, there is not any other architecture in the literature of self-management for multi-HVAC systems in a building, preventing from comparing the outcomes of the proposed model with previous models. It is observable that previous works are: 1) normally HVAC system centered [2], [6], [13]; 2) Some of them are focused on delimited problems, like control or optimization problems in HVAC systems [3], [10], [13], [14], [18], [27], not considering their integration in an autonomic architecture; 3) with datasets of specific HVAC systems, and normally not for buildings with multi-HVAC systems [4], [25]. Thus, the proposed autonomic management architecture for multi-HVAC systems is a novelty that integrates autonomous tasks that not only solve the brought up problems so far, but also improves itself and is ready for effectively incorporate new functionality at any level to improve its efficiency. Section IV details how to use this architecture in different building types with heterogeneous or homogeneous multi-HVAC systems, showing with 2 case studies the versatility of the proposed approach.

VI. CONCLUSION

This paper proposes an autonomous management architecture for multi-HVAC systems for buildings, based on the ACODAT concept. This architecture determines the optimal operational mode of the multi-HVAC systems, this is the set of HVAC subsystems to be activated, deactivated or regulated in a given context, in real time.

Specifically, ACODAT allows self-optimizing multi-HVAC systems. The optimization problem has multiple objectives to explore each feasible multi-HVAC operational mode (combination of HVAC subsystems), to maintain the comfort and improve the energy efficiency in a given context. The architecture is then complemented with data-driven models for prediction, to inspect performance degradation or to work with better tariff rates when the architecture searches for the possible multi-HVAC modes. This brings up another interesting problem: the selection of the best individual from the set of Pareto Fronts obtained for each possible operational mode. This work proposes two alternatives to solve this problem, either the utilization of fuzzy decision systems to select the best individual from the Pareto Fronts weighting fuzzy variables according to current contextual policies, or the utilization of a global Pareto Front as a consequence of joining the different sets of Pareto Fronts.

ACODAT uses/develops different models of knowledge, such as predictive, identification or optimization models. These data-based knowledge models can be also used in other contexts, for example, with supervisory tasks, or inspecting tasks that determine the performance degradation of multi-HVAC system components. ACODAT can be extended furthermore to incorporate more goals, even for improving itself like self-healing or self-security.

Next works will focus on the development of data-driven knowledge models (predictive and identification models) and the implementation of multi-HVAC system optimization strategies, particularly, the fuzzy decision system to select the best individual from the set of Pareto Fronts. Other case studies will also be considered to test the scalability and versatility of the architecture. It is also in consideration to evaluate how it works in distributed multi-HVAC system, where maybe some ideas about multiagent systems orchestration could be used [33], [38]. The modularity of ACODAT will also make possible to adapt and test it in IoT, smart building, big data scenarios. Finally, this research foresees future study on the necessary inclusion of indoor humidity and the subjective IAQ index, the retrofit costs, lighting consumption, or the visual comfort.

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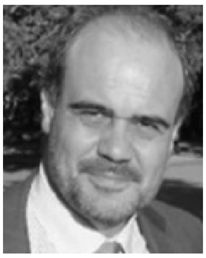

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2.2 Artículo 2

2.2.1 Identificación del artículo

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2.2.3 Resumen del artículo

El control de los sistemas de climatización para edificios y su modelado no son problemas triviales debido a la complejidad de su comportamiento dinámico y su respuesta no lineal. El modelado matemático es complicado al ser sistemas que consisten en varios elementos, como bombas de calor, grupos de frío, calderas, unidades de intercambio de aire, ventiladores, sistemas de distribución y de almacenamiento térmico. Este artículo propone la aplicación del método LAMDA para el control avanzado de sistemas de climatización de edificios. LAMDA utiliza una metodología de clasificación por lógica borrosa y no precisa de un modelo matemático a priori que evalúe el comportamiento del sistema. El método calcula primero el grado de adecuación del sistema para cada clase y luego determina el grado de similitud. Así se identifica el estado funcional del sistema, también denominado 'clase'. Luego LAMDA emplea un método nuevo de inferencia que calcula la acción de control necesaria para llevar al sistema al estado de error nulo. LAMDA se aplica a la regulación de un sistema de climatización de un edificio y se analiza su rendimiento comparándolo con otros métodos similares. El rendimiento de LAMDA muestra un resultado superior, llevando a que pueda convertirse en un método que mejore los sistemas de gestión de edificios (BMS). LAMDA tiene un excelente comportamiento ante perturbaciones repentinas, actuando sobre el control de forma suave y superando a los otros métodos.

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Advanced Fuzzy-Logic-Based Context-Driven Control for HVAC Management Systems in Buildings

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ABSTRACT Control in HVAC (heating, ventilation and air-conditioning) systems of buildings is not trivial, and its design is considered challenging due to the complexity in the analysis of the dynamics of its nonlinear characteristics for the identification of its mathematical model. HVAC systems are complex since they consist of several elements, such as heat pumps, chillers, valves, heating/cooling coils, boilers, air-handling units, fans, liquid/air distribution systems, and thermal storage systems. This article proposes the application of LAMDA (learning algorithm for multivariable data analysis) for advanced control in HVAC systems for buildings. LAMDA addresses the control problem using a fuzzy classification approach without requiring a mathematical model of the plant/system. The method determines the degree of adequacy of a system for every class and subsequently determines its similarity degree, and it is used to identify the functional state or class of the system. Then, based on a novel inference method that has been added to LAMDA, a control action is computed that brings the system to a zero-error state. The LAMDA controller performance is analyzed via evaluation on a regulation problem of an HVAC system of a building, and it is compared with other similar approaches. According to the results, our method performs impressively in these systems, thereby leading to a trustable model for the implementation of improved building management systems. The LAMDA control performs very well for disturbances by proposing control actions that are not abrupt, and it outperforms the compared approaches.

INDEX TERMS HVAC control, control engineering, fuzzy logic, artificial intelligence, LAMDA.

I. NOMENCLATURE

4SID	Subspace-based State-Space System Identification
ACODAT	Autonomous Cycle of Data Analysis Tasks
AI	Artificial Intelligence
ANFIS	Adaptive-Network-based Fuzzy Inference System
ANN	Artificial Neural Networks
ARIMA	Autoregression Integrated Moving Average
ARMAX	Autoregression Moving Average eXogenous
ARX	Auto Regression eXogenous
BMS	Building Management System
CVaR	Conditional Value at Risk
DAT	Data Analysis Tasks
DMC	Dynamic Matrix Control
EEV	Electronic Expansion Valve
EHAC	Extended Horizon Adaptive Control
EPSAC	Extended Predictive Self-Adaptive Control
FAN	Fuzzy Adaptive Network
FBC	Feedback Controllers
FDI	Fault Detection and Isolation
FFBP	Feed-Forward Back-Propagation
FPGA	Field-Programmable Gate Arrays
FL	Fuzzy Logic
GA	Genetic Algorithms

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GAD	Global Adequacy Degree
GPC	Generalized Model Control
HAD	Higher Adequacy Degree
HVAC	Heating, Ventilation and Air-Conditioning
IT	Information Technology
LAMDA	Learning Algorithm for Multivariate Data Analysis
JIT	Just in Time
LAMDA	Learning Algorithm for Multivariable Data Analysis
LQ	Linear Quadratic
LQG	Linear Quadratic Gaussian
ML	Machine Learning
MAC	Model Algorithmic Control
MAD	Marginal Adequacy Degree
MIMO	Multiple-input and Multiple-output
MLP	Multilayer Perceptron
MPC	Model Predictive Control
NNARX	Neural Network Auto Regression eXogenous
PDF	Probability Density Function Approximation
PFC	Predictive Functional Control
PID	Proportional, Integral and Derivative
PLC	Programmable Logic Controller
RBF	Radial Basis Function
RD	Robust Distance
RGA	Relative Gain Array
RNN	Recurrent Neural Networks
SARIMA	Seasonal Autoregressive Integrated Moving Average
SISO	Single Input and Single Output
SP	Set Point
SVM	Support Vector Machines
TCBM	Topological Case Base Modeling
T-S	Takagi-Sugeno
WLAC	Weighted Locally Adaptive Clustering

II. INTRODUCTION

Buildings require most of the total supplied energy, with breakdowns of 40% to 42% in Western countries [1]–[4]. This energy feeds the elevators, plugged-in IT equipment, electronic devices, and lights, along with the HVAC system and the security and fire systems. Above all, the HVAC facility consumes most of the energy that is supplied to the building. As energy production remains contaminating and expensive and has substantial negative impacts on the environment and finances, the optimization of building energy with a focus on HVAC systems is necessary. The energy saving problem can be addressed by retrofitting the building architecture, renovating old installations or adding intelligence to the BMS, thereby leading to a savings of up to 30%. It is far more sustainable and cost-effective to improve the control algorithms to realize higher efficiency than to renovate the HVAC equipment with more efficient modern technologies [1], [2], [4], [5].

System automation enables operation with autonomous optimization principles that maintain comfort and reduce the amount of consumed energy. Automatic control is essential for coping with unforeseen user activities in smart buildings. IT achievements and industrial engineering breakthroughs enable the envisioning of smart buildings with self-adapting facades, shapes and autonomous behaviors, for maximizing the comfort of the occupants in changing contexts with nearly zero carbon emissions. Therefore, the objective that is pursued with the automation of HVAC control is to maximize the thermal comfort while minimizing the energy consumption. The operational efficiency of an HVAC system strongly depends on its control system and optimization parameters.

The construction of an accurate and effective model of an HVAC system is challenging. Modeling its characteristics, nonlinearities, dynamics and highly constrained parameters complicates the design and operation. Advanced control system engineering provides several approaches for improving control systems and reducing the energy consumption while ensuring the indoor thermal comfort with satisfactory robustness and stability. Solving the problem requires the following steps, among others: focusing on the control problem; solving the multiobjective optimization problem; synthesizing the system management at the supervisory level; and proposing new predictive or adaptive models that mimic the system behavior.

There are interesting reviews that address the strengths, weaknesses and performances of HVAC control models and their applicability in practical contexts [4], [5], [7]–[11]. Each proposed control model in HVAC systems requires assumptions regarding the system properties and the environment, to balance its simplicity with its accuracy.

According to current research, online feedback-based data analytics for smart building diagnosis and management require software-intensive solutions. FL can be used in control engineering; it ignores an HVAC system's nonlinearities and does not require parameter tuning, in contrast to other conventional methods. Fuzzy logic controllers show lower performance while adapting to signal variations with respect to MPC techniques [12] and, additionally, prove their robustness in real-time operations since they do not require learning processes, in contrast to ANN models. FL defines a set of control rules and obtains the control output with a fuzzy inference from the current input. The use of fuzzy sets in complex industrial system control is well documented in the literature [11], [13]–[15] and yields superior results to those of classical controllers; however, a key limitation originates from the elucidation with heuristic control rules [14], [15]. To overcome this limitation, various studies propose learning mechanisms for fuzzy controller rules, although their performances are not yet satisfactory.

On the other hand, LAMDA [16] operates on online contextual data and discovers the GAD of a class for each individual with fuzzy clustering. The GAD is a numerical array with values that range from 0 to 1; these values quantify the membership degree of any object/individual to the system classes. Thus, LAMDA assigns an individual to the most suitable class. LAMDA, by detecting the operational system states, becomes a powerful tool for classification and clustering [16]–[18]. LAMDA has been used in FDI to detect the operational states—either normal or abnormal—by identifying faults with the data that are gathered from sensors [19]–[23]. The classification performance of LAMDA has been improved with LAMDA-FAR [24] and LAMDA-HAD [25], [26] and clustering with LAMDA-RD [27] and the LAMDA triple π operator (LAMDA-TP) [28], [29]. More recently, LAMDA has been proven to provide a satisfactory model for control systems by driving the process from its current functional state to the required state with an inference method that assigns a numerical value to the controller output [30].

This article proposes an advanced LAMDA-based control method that provides robustness and intelligence in HVAC systems. LAMDA modeling overcomes the process complexity by designing the controller from currently available data and by avoiding other considerations, such as nonlinearities, operating constraints, time delays and uncertainties. This study proves that LAMDA satisfies the demanding HVAC control requirements due to the following characteristics [26], [27]:

- LAMDA operates in both supervised and unsupervised learning scenarios.
- LAMDA enables the definition of clear control rules (classes) because its structure is known.

Thus, the main contribution of this work is the design of a new type of intelligent controller that is based on LAMDA and applied to regulation of an HVAC system. The main advantages of our method are that it does not require a mathematical model of the system and it requires few variables to be parameterized. HVAC systems are an excellent case study for evaluating our proposed controller since their dynamics are complex due to the many elements that are involved. For the controller design, it is necessary to establish classes (operational states) of the system and their rules. Then, an inference method based on [30] is defined. For the validation of the proposed method, a comparative analysis of the behavior of the LAMDA controller is performed by comparing it against other well-known methods and evaluating its performance and robustness when disturbances are added to the system. Excellent results have been obtained with the LAMDA controller in various scenarios.

This article presents a review of the various control methods that are used in HVAC systems in Section II. Section III introduces the process of HVAC systems and the basic formulation of LAMDA. Section IV describes how the LAMDA control capabilities operate in HVAC systems. Section V evaluates our control approach in a real context and analyzes its performance in comparison with other conventional control models. Finally, Section VI presents the conclusions of the paper.

III. RELATED WORKS

HVAC control modeling can be approached using physics or deduced from the input and output data. HVAC control systems use conventional and advanced methods. Among the conventional methods, the PID controller is still considered in 9% of the literature on HVAC control, which represents a significant interest. Other self-tuning techniques, such as gain scheduling, are also considered in the 9% portion. Decoupling, state-space representation and transfer functions are also considered. Advanced control methods implement techniques to predict the system behavior, optimize several objectives and adapt to it. The LQ and LQG optimization schemas provide higher robustness and stability. With the exponential progress of IT, MPC and its variants attract the attention of researchers in 15% of HVAC-related articles, followed by multiagent architectures, which are studied in 14% of the articles. Fuzzy logic control also provides interesting results and is considered in 13% of studies [1], [9].

A. GENERAL CONTROL MODELS

White box—or forward—models are built with mathematical formulations. They model the mass balance, heat transfer, thermal momentum or flow rates with differential equations. They require knowledge of the physical and/or chemical laws of the system. The key advantage is that they provide an easy analysis with a simple algebraic formulation and robust generalization. These mathematical models are typically used in HVAC system design. They are typically applied in simpler systems, such as SISO and steady-state or quasi-steady-state systems without high-frequency disturbances, e.g., temperature and relative humidity changes in HVAC. In any case, they inherently incur high computational expenses. They outperform black box models when the feedback system information is scarce or incomplete [9].

Black box—or inverse—models approach the problem empirically by collecting system performance data and using these data to establish a relation between the inputs and outputs via ML, statistical or AI methods. Current research considers AI for plant modeling, controller design, system performance improvement, calibration and parameterization. One of the key advantages is that once AI models have been learned, they are very fast and require few computational resources, especially those that are based on neural networks [31]. Other data-driven models of interest in the literature are frequency-domain, data mining, state-space, geometric, case-based reasoning, stochastic and instantaneous methods [9]. ANN have been used in simulations of heat pump operation [32] and models to optimize simultaneously the building energy and comfort [33]. A particular case of neural networks is the modeling of the system dynamics with RNN [34]. RNN can be simulated with evolutionary algorithms [35]. However, studies on ANN models have not been widely conducted in the HVAC industry yet "due to uncertainty, long training periods, and complexity in setting up and maintaining the system" [36]. Other black box approaches utilize statistics and rely on identifying the best sample of a population. Statistical approaches use linear or polynomial time series regression models in control design to fit the system trajectories. Examples include the nonlinear ARX model, the ARMAX model and the ARIMA model [1]. Some of these methods do not consider the system output, whereas others do not consider the inputs [7]. Statistical models cannot simulate nonlinear behaviors standalone and require the support of other methods, such as ANN, as discussed in articles on HVAC control, such as NNARX, FFBP and RBF methods [9].

FL modeling is showing satisfactory performance in control and can interact with ANN models and GA algorithms to provide hybrid models with the best characteristics of black box and white box models [14], [15]. FL uses simple mathematics for nonlinear and complex systems, which are sufficient for HVAC [11]. The FAN and NFIS improve the prediction accuracy, and the T-S fuzzy model can be applied to online models [13]. In [6], an HVAC system for a motor vehicle is proposed and includes a climate control circuit that is coupled to onboard sensors, a human-machine interface, and climate actuators. The control system receives crowd data and at least one weight, which indicates the confidence level that is associated with the crowd data. It generates command parameters using a set of fuzzy rules in response to the crowd data and the weights. It shows high precision and rapid operation; however, for higher accuracy, FL requires more grading, which increases the number of rules exponentially, and more grading is not always available for some components. Other drawbacks of bare FL are its lower speed compared with other models, the lack of a real-time response, and learning from feedback.

Several studies propose optimizing the performance by implementing clustering techniques that are based on a clustering ensemble, such as WLAC [37]; by setting the weights for the fine-tuning of the fuzzy algorithm [38]; or via an iterative fusion of the base clusters [39], which yields visible improvements. Additionally, in [40], a clustering approach is proposed with the objective of minimizing the effect of the differences in the quality and diversity of the base clusters [40]. The contextual information, such as seasonal periods or scheduled activities, and the knowledge of the system's behavior are translated into fuzzy rules that shorten the model training process. FL does not require a mathematical formulation for representing the physics of the system nor mechanisms for overcoming the nonlinearities [11].

Finally, hybrid models combine black box and white box models to balance their drawbacks. Hybrid models use optimization to obtain the system parameters, such as least squares, gradient descent and genetic algorithms (GAs) [1]. For example, a two-stage energy management strategy has been developed for commercial buildings with these models [41]. One of the interesting contributions of that study is the inclusion of uncertainties in electricity prices in the MPC logic for optimizing the energy consumption. They propose balancing the power supply and the building load while minimizing the operational costs. The load demand, wind power and electricity price are forecasted with a SARIMA model and a CVaR is added to consider the price uncertainties. In [12], an HVAC system has been modeled using MATLAB, which uses a fuzzy controlling system and an RBF to define a predictive control system.

B. HVAC CONTROL METHODS

Kozák *et al.* [42] utilize a classical automation of control by looping back the output to the SP input to obtain the difference, or error signal, the amplitude of which regulates the actuators. These FBC stabilize unstable processes and reduce the sensitivity to parameter variations. Performance is guaranteed even when there are uncertainties that do not match exactly the real process. SP, which is typically the thermal expectation in HVAC, may be complemented with other information sources such as timers for regular activity, event scheduling, or weather forecasting for predicting outdoor conditions. In [43], PID controllers for the HVAC industry are described. In the case of HVAC systems, plain PID controllers do not perform well due to the nonlinearities of the system. Installations are designed to work at a full load, but the equipment typically works at a partial load, which is inefficient and requires autotuning techniques such as relay-autotuning or open-loop step tests. Classical methods for tuning the gains of PID controllers include the Ziegler-Nichols method and the Cohen-Coon method [44]. FL realizes higher performance in tuning PID control today. These basic control methods are widely implemented in PLCs and in FPGAs as they have simple control laws that are used in multipurpose applications [36].

In advanced strategies, one of the problems is to work with multiple variables, with techniques that split a MIMO system into SISO subsystems, such as the RGA [42], or that split the decentralizing PID controllers into a number of controllers that equals the number of inputs. These methods encounter challenges when finding Lyapunov functions and proving their stability, are complex and sensitive to parameter variations, have a limited operating range, or require the measurement of all state variables.

The new principles in control [9], [34], [36] , [45] are optimally, robustness and intelligence. In HVAC, the robustness principle aims at addressing the design problem of partial loads attenuating the effects of disturbances and at stabilizing operations to improve the performance. An HVAC control prediction strategy uses models to anticipate the system dynamics, such as MPC, and typically simulates the system dynamic behavior by solving linear or quadratic problems, such as Euler-Lagrange equations. MPC controllers optimize the control for a future time horizon by analyzing possible state trajectories, but the results are applicable only for the current timeslot, and the optimization must be recalculated for the next horizon in the next timeslot. MPC is gaining support in complex systems [1], [7], [8], [33], [46], [47],

TABLE 1. Classification of scientific references according to the addressed problem.

Approach	References
Model-specific	[1, 7, 9, 33]
Classical Control	[11, 36, 42, 43, 49, 50]
Hard Control	[11, 33, 42, 43, 48, 51]
Soft Control	[1, 5, 6, 9, 14, 15, 31, 33, 43, 45, 48, 51]
AI Control	[1, 8, 9, 32, 34, 35, 36, 42, 43, 46, 53, 54]
Supervisory Control	[33, 36, 42, 43, 48, 55, 56]

namely, systems that have high-order dynamics or long delays, while nonpredictive PID controllers are still preferred for simpler systems [43]. Examples of the studied MPC approaches for buildings are DMC, MAC, PFC, EPSAC, EHAC and GPC [47]. MPC can realize robustness against disturbances by predicting possible extreme disturbances, e.g., in min-max MPC; by surpassing the constraints, e.g., in constraint tightening MPC; by using FBC to converge to the nominal model, e.g., in tube MPC; or by collecting several samples online for modeling spaces that are generated by disturbances, e.g., in multistage MPC. When the HVAC control strategy is an optimization strategy, there are multiple aspects to address: the objectives, constraints, disturbances, modeling techniques and receding horizon [33]. Control optimization, which is model-free and is also known as an expert system, is conducted online with incomplete datasets and penalizes the accuracy. A simplified model of central chiller components that uses genetic optimization algorithms realizes 0.73% to 2.55% accuracy [48].

Finally, due to the complexity of HVAC control, it has been approached from various angles. Table 1 presents a classification of the bibliography according to the main field that is addressed in each article. The first approach is for the problem of simulating the system behavior, namely, the modeling problem. The second, third and fourth approaches hardly discuss the problem of control with classical, hard or soft methods. The fifth approach is the introduction of artificial intelligence in the control model. The last approach seeks energy savings from the complete system supervision.

The scientific literature on FL methods in HVAC control looks promising because simple mathematics are used for nonlinear and dynamic systems. However, FL requires more rules for the realization of higher accuracy; this requirement reduces the speed, and such rules are not always available. Real-time response HVAC control with FL has not been studied so far. This limitation is one of the problems the proposed method aims at addressing, by using contextual information or real-time feedback.

IV. AUTONOMOUS ARCHITECTURE

A. HVAC SYSTEMS

HVAC system direct modeling mimics complex structures, such as chillers, heat pumps, heating/cooling coils, boilers, air-handling units, thermal storage systems and liquid/air distribution systems. Sensors and actuators enable the regulation of the controllable plant variables, such as the ambient temperature in the occupied zones, the static pressure in the pipes, the chilled flowing water temperature and the air fan speed. An HVAC system is difficult not only to simulate but also to manage due to the nonlinearities and dynamics of its physical behavior. This difficulty is demonstrated with the following example: A chiller removes heat from a fluid in a vapor compression cycle or an absorption cooling cycle, which consumes almost half the energy. It has a compressor, an evaporator, a condenser, and an EEV, which are typically designed separately under the following assumptions [1], [2]:

- The refrigerant properties are homogeneous in each component.
- The refrigerant flow rate through the compressor is constant throughout the system.
- The expansion process through the EEV/orifice plate is isenthalpic.
- The temperature of the walls does not vary through the cross-section or across the ducts.

If the refrigerant is in quasi-steady state, using the energy balance equations that are proposed in [1], the heat transfer rate in the evaporator (Q_e) and the refrigerant mass flow rate ($\dot{m}_r$) are obtained via Eqs. (1) and (2):

$$\dot{Q}_e = \alpha_{ei} A_{ei} \left(T_{wo} - T_{we}\right) \tag{1}$$

$$\dot{m}_r \left(h_1 - h_6\right) = \alpha_{eo} A_{eo} \left(T_{we} - T_e\right) \tag{2}$$

where h_1 is the enthalpy of the refrigerant at the evaporator outlet-compressor inlet (kJ/kg), h_6 is the enthalpy of the refrigerant expansion valve exit/evaporator inlet (kJ/kg), A_{ei} is the area of the evaporator inlet (m^2), and A_{eo} is the area of the evaporator outlet (m^2). T_{wo} is the return water temperature ($°C$), T_{we} is the temperature of the evaporator wall ($°C$), T_e is the temperature of the refrigerant at the evaporator inlet ($°C$), α_{ei} is the heat transfer coefficient of the refrigerant that is entering the evaporator (W/m^2K) and α_{eo} is the heat transfer coefficient of the refrigerant that is leaving the evaporator (W/m^2K). Via a similar approach, the heat transfer rate of the condenser (Q_c) and the other parameters of the HVAC system, such as the dynamic temperature of the heating/cooling coil, can be obtained by applying the energy balance in the air–water heat exchanger [1].

The mathematical formulation is even more complicated when applied to the case of an existing building HVAC system due to the scarce and unstructured available documentation and because the hidden habits that have been acquired by the engineers and operators hinder the modeling of an identical system.

In contrast, data models are simple to build, but quality data are required for building trustable models. Typically, some of the essential data are not always available or sensors generate interferences. Filtering, sensor networks, detection algorithms, and virtual sensors improve the model, but are insufficient for practitioners. The previous section presented

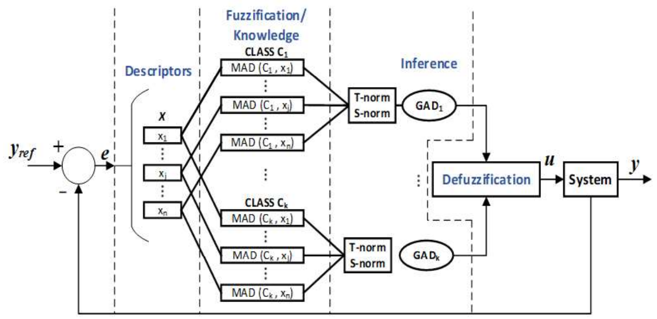

FIGURE 1. Functional blocks of a LAMDA controller.

another approach for overcoming modeling issues by perfecting the mathematical simulation with data models, collecting HVAC system data in normal or abnormal conditions, and using statistics, AI [46] or DL [34]. The studied models include TCBM, 4SID, PDF, JIT, MLP, SVM, FAN, T-S fuzzy, ANFIS, linear and polynomial time series regression, ARX, ARMAX, and ARIMA.

B. LAMDA CONTROLLER

LAMDA is a clustering algorithm that uses the degree of adequacy to classify each individual. The analysis of the similarity compares the features of any object $X = \left[x_1; ...;x_j; ...;x_n\right]$, with those of the existing classes $C = \{C_1;C_2; ...;C_k; ...;C_m\}$ [26]. LAMDA is a noniterative algorithm, and it was intended for use in system supervisory tasks and in the identification of functional states. This study extends its applicability to control systems by identifying the current system operational state and driving it to the target state, which is defined by its variables [30]. The main strategy is to set rules, namely, classes in LAMDA terminology, based upon the knowledge of the system behavior and the context information, as in other conventional fuzzy controllers. Figure 1 illustrates the structure of a LAMDA controller.

The features of the objects are normalized to [0, 1] to improve the performance via the following formula:

$$\bar{x}_j = \frac{x_j - x_{jmin}}{x_{jmax} - x_{jmin}} \tag{3}$$

where x_{jmin} is the minimum value of feature x_j, x_{jmax} is the maximum value of feature x_j and $\bar{x}_j$ is the normalized feature.

With normalized values, LAMDA calculates the marginal adequacy degree (MAD), which describes the similarity of any feature with the corresponding feature of the class. MADs are calculated with probability density functions, such as that of the normal distribution:

$$MAD_{k,j}\left(\bar{x}_j \mid \rho_{k,j}\right) = e^{-\frac{1}{2}\left(\frac{\bar{x}_j-\rho_{k,j}}{\sigma_{k,j}}\right)^2} \tag{4}$$

where $\rho_{k,j}$ is the mean of the jth feature in the kth class and $\sigma_{k,j}$ is the standard deviation of the jth descriptor in the kth class.

After obtaining the MADs, LAMDA calculates the GADs using aggregation functions T-norm (Eq. (5)) and S-norm (Eq. (6)) and the parameter $\alpha \in [0, 1]$, which represents the level of exactitude. As α increases, the classification becomes more selective [27]. When two or more features are considered, the GADs are computed recurrently.

$$T(a, b) = \frac{1}{1 + \sqrt[p]{\left(\frac{1-a}{a}\right)^p + \left(\frac{1-b}{b}\right)^p}} \tag{5}$$

$$S(a, b) = 1 - \frac{1}{1 + \sqrt[p]{\left(\frac{a}{1-a}\right)^p + \left(\frac{b}{1-b}\right)^p}} \tag{6}$$

Parameter p modifies the sensibility and is typically set to $p = 1$. The GADs are computed for every class. The GAD of the kth class is obtained via Eq. (7):

$$\begin{aligned} &GAD_{k,\bar{X}}\left(MAD_{k,1}, \ldots MAD_{k,n}\right) \\ &\quad = \alpha T\left(MAD_{k,1}, \ldots, MAD_{k,n}\right) + (1-\alpha) \\ &\qquad \times S\left(MAD_{k,1}, \ldots, MAD_{k,n}\right) \end{aligned} \tag{7}$$

In classification tasks, the normalized object $\bar{X}$ is assigned to the class with the maximum GAD, as expressed in Eq. (8), where the index is the identifier of the selected class.

$$index = \max\left(GAD_{1,\bar{X}}, GAD_{k,\bar{X}}, \ldots, GAD_{m,\bar{X}}\right) \tag{8}$$

The previous steps describe how LAMDA identifies the current operational state of the system. However, in the case of a LAMDA controller, it is not sufficient to identify the functional state in which the system is operating; therefore, the control requires an inference method for driving the system to the desired state. This method is realized by defining the known rules that govern the plant, similar to conventional fuzzy controllers. The following expression defines the generic inference mechanism for LAMDA:

$$R^{(l)}: \quad IF\left\{\bar{x}_1\ is\ F_1^i\ and \ldots,\ and\ \bar{x}_n\ is\ F_n^k\right\}\ THEN\ \left\{y_l\ is\ G^l\right\} \tag{9}$$

where $\bar{x}_j$ takes values from the universe of discourse U_j. The linguistic output variable y_j is defined in the universe of discourse V_j. F_j^l and G^j are fuzzy sets in U_j and V_j, respectively, $(j = 1, ...,n)$, $(l = 1, ...,m)$, where n is the number of features and m is the number of rules, which are also known as LAMDA classes.

In this case, LAMDA operates with the GADs using the first-order T-S inference method, where $G^j = q^j$. Eq. (10) expresses how to obtain a crisp output:

$$u = \beta \sum_{k=1}^{n} q^k GAD_{k,\bar{X}} \tag{10}$$

where u is the controller output, q^k is the weight that is applied in the kth class, and β is the parameter for moderating u,

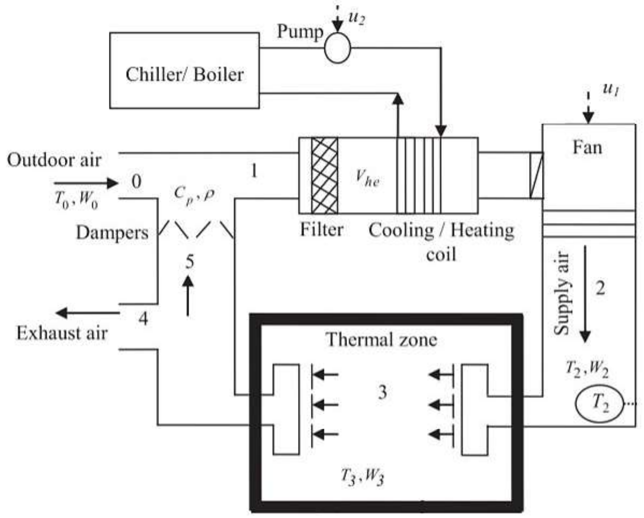

FIGURE 2. Block diagram of a simple HVAC system [53].

thereby limiting the controller's output to the class boundaries. It is calculated in the training phase via Eq. (11):

$$\beta = \frac{\max\left(q^k\right)}{\sum_{k=1}^{n} q^k GAD_{k,\max(\bar{X})}} \tag{11}$$

V. LAMDA CONTROLLER IN HVAC SYSTEMS

As discussed in the previous sections, HVAC systems are nonlinear and dynamic and require complex control methods. Controllable variables in the thermal zone are coupled and interact with each other.

This section tests LAMDA with the HVAC system that was defined by Arguello-Serrano and Velez-Reyes [51], in which the objective is to regulate the temperature ($T_3[°F]$) and relative humidity (W_3 $[lb/lb]$) parameters in a thermal space, namely, Zone 3, as illustrated in Figure 2.

Outdoor air (fresh air) flows into the system, 25% of which mixes with 75% of the returning air, and the remainder is expelled. The mixed air passes through a filter to the heat exchanger, where it is conditioned by following the SP reference. The conditioned air is propelled to the thermal zone with a fan. The system must control variables T_3 and W_3 simultaneously, based on thermal loads by varying the fan speed, u_1, to regulate the air flow rate and the cold-water pumping rate, u_2, from the chiller to the heat exchanger.

The HVAC system differential equations of energy and mass balances from the conventional mathematical model are:

$$\dot{T}_3 = \frac{f}{V_s}(T_2 - T_3) - \frac{h_{fg}}{C_p V_s}(W_s - W_3) + \frac{1}{0.25 C_p V_s}\left(Q_0 - h_{fg} M_0\right) \tag{12}$$

$$\dot{W}_3 = \frac{f}{V_s}(W_s - W_3) + \frac{M_0}{\rho V_s} \tag{13}$$

TABLE 2. Numerical values for system parameters.

$\rho = 0.0074\ [lb/ft^3]$	$C_p = 0.24\ [Btu/lb°F]$
$T_{ref} = 55\ [°F]$	$T_{3ref} = 71\ [°F]$
$W_{3ref} = 0.0088\ [lb/lb]$	$V_{he} = 60.75\ [ft^3]$
$f_{ref} = 17{,}000\ [ft^3/min]$	$V_s = 58{,}464\ [ft^3]$
$W_s = 0.007\ [lb/lb]$	

$$\dot{T}_2 = \frac{f}{V_{he}}(T_3 - T_2) - \frac{0.25f}{V_{he}}(T_0 - T_3) - \frac{f h_w}{C_p V_{he}}(0.25 W_0 + 0.75 W_3 - W_s) - 6000\frac{gpm}{\rho C_p V_{he}} \tag{14}$$

where h_w is the enthalpy of liquid water, W_0 is the humidity ratio of outdoor air, h_{fg} is the enthalpy of water vapor, V_{he} is the volume of the heat exchanger, W_s is the humidity ratio of the supply air, W_3 is the humidity ratio of Zone 3, C_p is the specific heat of air, T_0 is the temperature of outdoor air, M_0 is the moisture load, Q_0 is the sensible heat load, T_2 is the temperature of the supply air, T_3 is the temperature of Zone 3, V_s is the volume of Zone 3, ρ is the air mass density, f is the volumetric flow rate of air (ft^3/min), and gpm is the flow rate of chilled water (gal/min). The assumptions that are made in the derivation of this mathematical model are also detailed in the study of Arguello-Serrano and Velez-Reyes [51].

Representing the system in state-space notation for the design of the control system, let $u_1 = f$, $u_2 = gpm$, $x_1 = T_3$, $x_2 = W_3$, $x_3 = T_2$, $y_1 = T_3$, and $y_2 = W_3$. The following parameters are defined to complete the model: $\alpha_1 = 1/V_s$, $\alpha_2 = h_{fg}/C_p V_s$, $\alpha_3 = 1/\rho C_p V_s$, $\alpha_4 = 1/\rho V_s$, $\beta_1 = 1/V_{he}$, $\beta_2 = 1/\rho C_p V_{he}$, and $\beta_3 = h_w/C_p V_{he}$. The mathematical model of (10), (11) and (12) can be reformulated as:

$$\dot{x}_1 = u_1\alpha_1 60(x_3 - x_1) - u_1\alpha_2 60(W_s - x_2) + \alpha_3\left(Q_0 - h_{fg}M_0\right) \tag{15}$$

$$\dot{x}_2 = u_1\alpha_1 60(W_s - x_2) + \alpha_4 M_0 \tag{16}$$

$$\dot{x}_3 = u_1\beta_1 60(x_1 - x_3) + u_1\beta_1 15(T_0 - x_1) - u_1\beta_3 60(0.25W_0 + 0.75x_2 - W_s) - 6000u_2\beta_2 \tag{17}$$

$$y_1 = x_1 \tag{18}$$

$$y_2 = x_2 \tag{19}$$

Table 2 and Table 3 list the numerical values that were chosen for the simulation and the system parameters at the operating point, respectively.

f (u_1) and gpm (u_2) are the control actions that modify the target variables T_3 (x_1) and $W_3(x_2)$. Figure 3 illustrates the mutual interactions among these parameters within the differential equations, thereby rendering a MIMO control problem.

In the figure, $G_1(\cdot)$, $G_2(\cdot)$, and $G_3(\cdot)$ are expressions (15), (16) and (17), respectively.

TABLE 3. Numerical values for system parameters at the operating point.

$x_1^0 = 71\ [°F]$	$x_2^0 = 0.0092\ [lb/lb]$
$x_3^0 = 55\ [°F]$	$T_0^0 = 85\ [°F]$
$W_0^0 = 0.0018\ [lb/lb]$	$M_0^0 = 166.06\ [lb/hr]$
$u_1^0 = 17{,}000\ [ft^3/min]$	$u_2^0 = 58\ [gpm]$
$Q_0^0 = 289{,}897.52$	$W_s^0 = 0.007\ [lb/lb]$

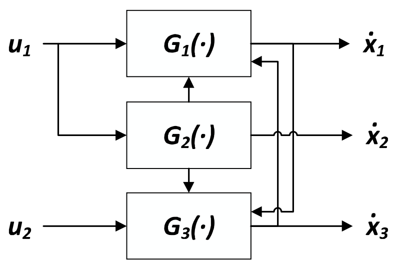

FIGURE 3. Block diagram of the HVAC model (MIMO system).

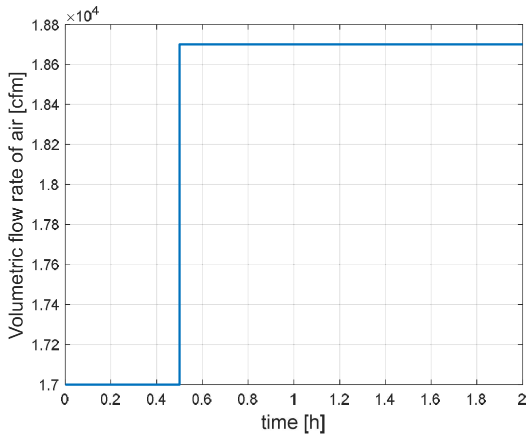

FIGURE 4. Step change of 10% is applied to u_1.

The proposed controller analyzes the data to discover possible relations between inputs and outputs by implementing two LAMDA controllers, one for each of the two output zone variables, namely, x_1 and x_2. To validate this implementation, it is necessary to determine whether the outputs are coupled, in which case a decoupling stage is required.

The method starts applying a step at one of the inputs and monitoring the response at the outputs to obtain the numerical values in the convenient FOPDT (first-order plus dead time) form:

$$\frac{X(s)}{U(s)} = \frac{Ke^{-t_0 s}}{\tau s + 1} \tag{20}$$

In the experiment, a step change of 10% is applied in the HVAC system operating point to u_1, as plotted in Figure 4, to monitor the controllers' responses at outputs x_1 and x_2, while u_2 remains unchanged.

Figure 5 plots the response of x_1 to the step change of u_1.

An approximate model of the transfer function g_{11} is obtained via the reaction curve method. In this case, t_1 is the time for the curve to reach 28% of the total change, and t_2 is the time to reach 63.6%. These parameters are obtained via

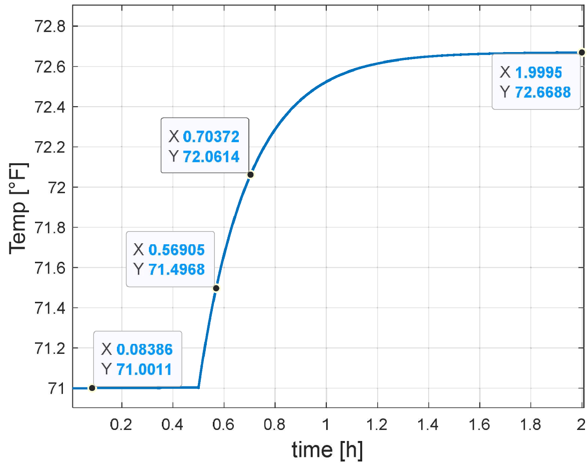

FIGURE 5. Response of x_1 to the 10% step change of u_1.

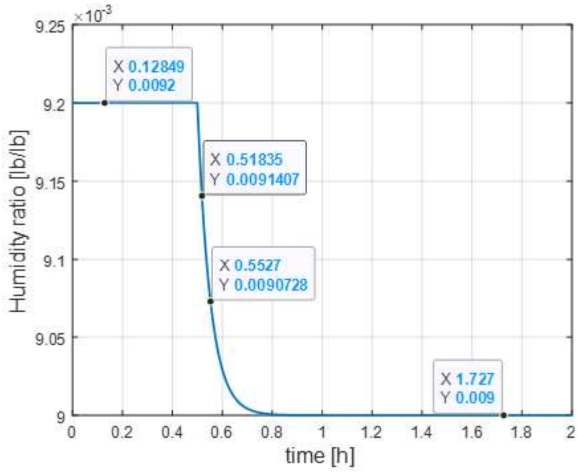

FIGURE 6. Response of x_2 to the 10% step change of u_1.

Eqs. (21) - (24).

$$\begin{aligned} t_1 &= 0.5690 - 0.5 = 0.0690\text{ h};\\ t_2 &= 0.7037 - 0.5 = 0.2037 \end{aligned} \tag{21}$$

$$\tau_D = \frac{3}{2}(t_2 - t_1) = \frac{3}{2}(0.2037 - 0.0690) = 0.2021\text{h} \tag{22}$$

$$K_D = \frac{\Delta x_1}{\Delta u_1} = \frac{72.6688 - 71}{18700 - 17000} = 9.8164 \times 10^{-4} \tag{23}$$

$$\begin{aligned} t_D &= t_2 - \tau_D = 0.2037 - 0.2021 = 0.0016\text{h} \Longrightarrow \\ g_{11} &= \frac{9.8164 \times 10^{-4} e^{-0.0016}}{0.2137s + 1} \end{aligned} \tag{24}$$

Figure 6 plots the response of x_2 to the step change of u_1. An approximate model of the transfer function g_{21} is obtained via the reaction curve method. The parameters are obtained via Eqs. (25) - (28).

$$\begin{aligned} t_1 &= 0.5183 - 0.5 = 0.0183\text{ h};\\ t_2 &= 0.5527 - 0.5 = 0.0527\text{h} \end{aligned} \tag{25}$$

$$\tau_D = \frac{3}{2}(t_2 - t_1) = \frac{3}{2}(0.0527 - 0.0183) = 0.0516\text{h} \tag{26}$$

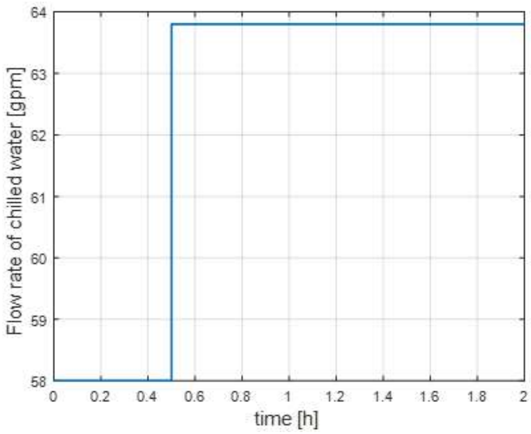

FIGURE 7. Step change of 10% is applied to u_1.

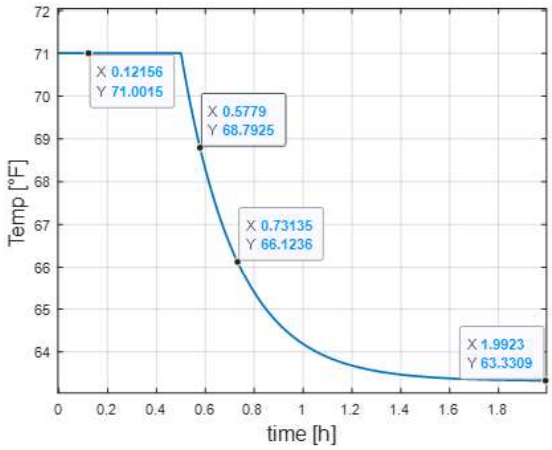

FIGURE 8. Response of x_1 to a 10% step change of u_2.

$$K_D = \frac{\Delta x_2}{\Delta u_1} = \frac{0.009 - 0.0092}{18700 - 17000} = -1.1764 \times 10^{-7} \quad (27)$$

$$t_D = t_2 - \tau_D = 0.0527 - 0.0516 = 0.0011\text{h} \Longrightarrow$$

$$g_{21} = \frac{-1.1764{\times}10^{-7}e^{-0.0011s}}{0.0527s + 1} \quad (28)$$

The next action in the experiment is to apply a step change of 10% in the HVAC system operating point at u_2, as plotted in Figure 7, while u_1 remains unchanged.

Figure 8 plots the response of x_1 to the step change of u_2. An approximate model of the transfer function g_{12} is obtained via the reaction curve method. These parameters are obtained via Eqs. (29) - (32).

$$t_1 = 0.5779 - 0.5 = 0.0779\text{h};$$

$$t_2 = 0.7313 - 0.5 = 0.2313\text{h} \quad (29)$$

$$\tau_D = \frac{3}{2}(t_2 - t_1) = \frac{3}{2}(0.2313 - 0.0779) = 0.2301\text{h} \quad (30)$$

$$K_D = \frac{\Delta x_1}{\Delta u_2} = \frac{63.3306 - 71}{63.8 - 58} = -1.3223 \quad (31)$$

$$t_D = t_2 - \tau_D = 0.2313 - 0.2301 = 0.0012\text{h} \Longrightarrow$$

$$g_{12} = \frac{-1.3223e^{-0.0012s}}{0.2301s + 1} \quad (32)$$

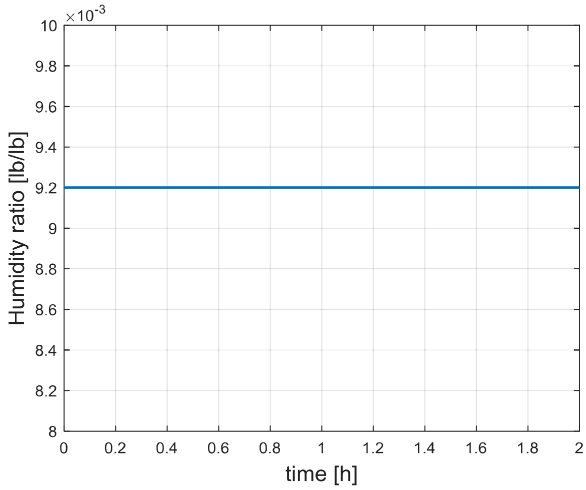

FIGURE 9. Response of x_2 to a 10% step change of u_2.

Figure 9 plots the response of x_2 to the step change of u_2. An approximate model of the transfer function g_{22} is obtained via the reaction curve method. These parameters are obtained via Eq. (33).

According to Figure 9, x_2 remains unchanged with a step change of u_2. Thus:

$$g_{22} = 0 \quad (33)$$

Based on the obtained transfer functions, the linearized model can be represented by matrix $G(s)$:

$$X(s) = G(s)\,U(s) \quad (34)$$

where:

$$G(s) = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \quad (35)$$

Substituting Eqs. (24), (28), (32) and (33) into Eq. (35) yields:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \dfrac{9.8164 \times 10^{-4}e^{-0.0016}}{0.2137s + 1} & \dfrac{-1.3223e^{-0.0012s}}{0.2301s + 1} \\ \dfrac{-1.1764 \times 10^{-7}e^{-0.0011s}}{0.0527s + 1} & 0 \end{bmatrix} \times \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad (36)$$

From $G(s)$, the gains of each element are obtained to yield gain matrix K.

$$K = \begin{bmatrix} 9.8164 \times 10^{-4} & -1.3223 \\ -1.1764 \times 10^{-7} & 0 \end{bmatrix} \quad (37)$$

The RGA [57] is a matrix (Bristol's matrix) that is used to measure the interaction between the inputs and outputs in a multivariate process control. It is defined as:

$$RGA(K) = \Lambda(K)\,K \times \left(K^{-1}\right)^T \quad (38)$$

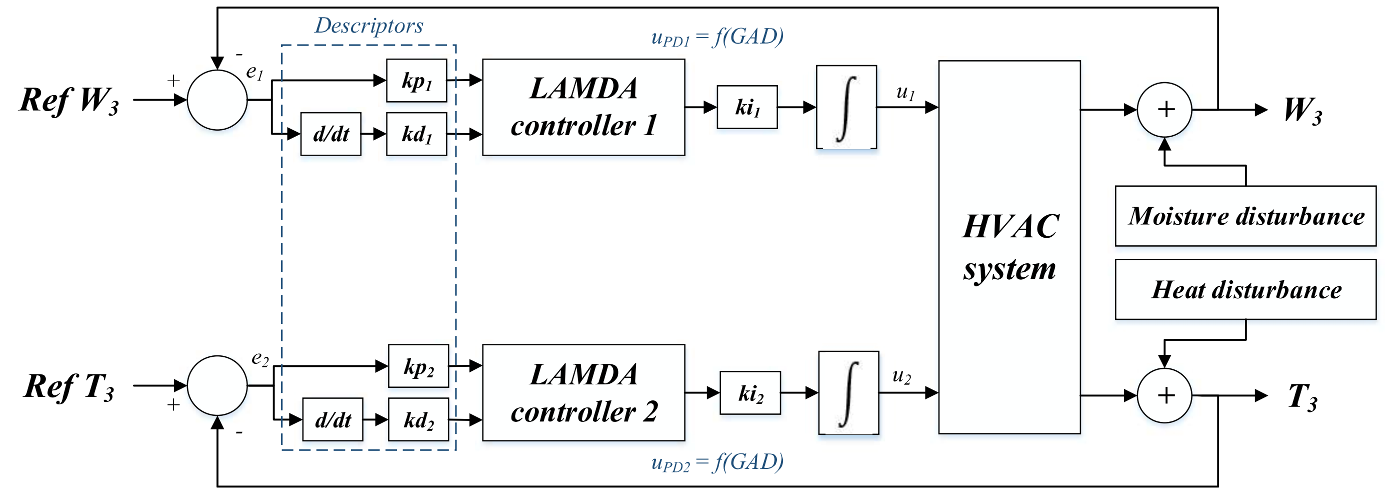

FIGURE 10. HVAC system two-closed-loop LAMDA control scheme (decoupled).

where the operator $\times$ denotes element-by-element multiplication:

$$\Lambda(K) = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

The parameters of $\Lambda(K)$ describe the dependence between the inputs and outputs (Eq. (37)), thereby leading to the conclusion that the decoupling stage is not necessary for this control. Due to the HVAC system characteristics and the resulting parameters of $\Lambda(K)$, the control design with two independent LAMDA controllers, namely, one for the temperature x_1 and another for the relative humidity x_2, is feasible.

$$u_2 \rightarrow x_1 \quad \text{and } u_1 \rightarrow x_2 \tag{39}$$

Figure 10 illustrates the operational scheme of the proposed control system with two separated control loops, each of which is dedicated to maintaining one of the two variables that are associated with the thermal zone comfort.

This model could be approached as an FOPDT system; however, the transformation uncertainties and the nonlinear effects would degrade its performance. This degradation motivates the design of LAMDA-PI controllers for maintaining the steady-state error as close to zero as possible since the control target is to maintain the temperature at $71[°F]$ and the relative humidity at $0.0092[lb/lb]$. Figure 10 illustrates the LAMDA-PD controllers at the input stage, the signals of which are integrated to obtain the LAMDA-PI controllers [30]. The added blocks have scaling gains of kp_1, kd_1, ki_1, kp_2, kd_2 and ki_2 for tuning the responses of the controllers.

The controllers' inputs are e and $\dot{e}$, where e is the error that is obtained via the subtraction of the SP reference and the current system output and $\dot{e}$ is its derivative. These variables are used to drive the system to the desired zero state, in which the error and its derivative are equal to zero, and to maintain it at zero.

The centers of fuzzy classes C_k and their respective parameters in the consequent q^k are presented in Figure 11; they are the training data for LAMDA operation. Twenty-five classes

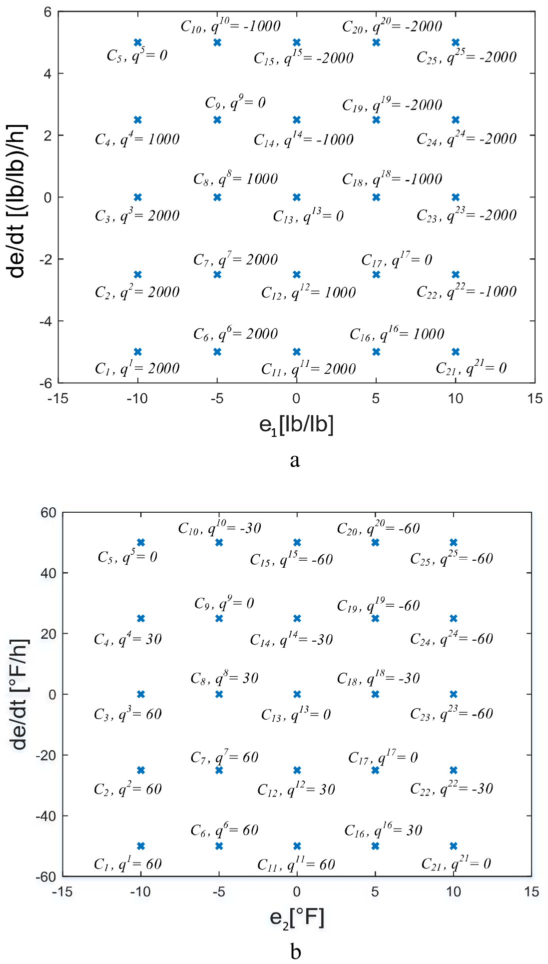

FIGURE 11. Defined classes and outputs for: a) the relative humidity LAMDA controller and b) the temperature LAMDA controller.

are defined for each controller, and the centers are set as a combination of the following sets:

$$e_1 = [-1, -0.5, 0, 0.5, 1]\, 10^{-4} \left[\frac{lb}{lb}\right] \text{ and}$$

$$\dot{e}_1 = [-0.5, -0.25, 0, 0.25, 0.5]\, 10^{-5} \left[\frac{lb/lb}{h}\right] \tag{40}$$

TABLE 4. Numerical values for system parameters at the operating point.

Controller	Gains
PI controller 1	$kp_1 = -103132, ki_1 = -40626460$
PI controller 2	$kp_2 = -1.8, ki_2 = -6.29$
Fuzzy-PI controller 1	$kp_1 = 0.02, kd_1 = 0.0005, ki_1 = 200$
Fuzzy-PI controller 2	$kp_1 = 1, kd_1 = 0.05, ki_1 = 10$
LAMDA-PI controller 1	$kp_1 = 0.02, kd_1 = 0.0005, ki_1 = 200$
LAMDA-PI controller 2	$kp_1 = 1, kd_1 = 0.05, ki_1 = 10$

$$e_2 = [-10, -5, 0, 5, 10]\left[{}^{\circ}F\right] \text{ and}$$
$$\dot{e}_2 = [-5, -2.5, 0, 2.5, 5]\left[\frac{{}^{\circ}F}{h}\right] \tag{41}$$

VI. SIMULATIONS AND RESULTS

In this section, our method is compared against two additional controllers, namely, PI and conventional Fuzzy-PI [59], to evaluate their behaviors in the regulation tasks and to analyze their performances and responses to disturbances. The main criteria for the evaluation of the approaches is the IAE (integral absolute error, see Eq. (42)), which is an index that measures the performances of the controllers. The IAE reflects the cumulative error, namely, how far the response is from the applied reference. Therefore, the controller that realizes the minimum index value performs the best.

$$IAE = \int_0^{\infty} |e(t)|\, dt \tag{42}$$

As discussed above, disturbances that simulate thermal loads in the system are added for evaluating the robustness of the closed-loop system.

The PI controllers are calibrated at the beginning via the Smith and Corripio method [58] to realize the best performance based on the IAE minimization. The Fuzzy-PI controllers have been designed by considering Gaussian membership functions with their maximum values at the center points of the LAMDA classes for the same rules for a fair comparison with the LAMDA-PI controller. The sample time in this experiment is set to 0.01 hours, which is equivalent to 36 seconds, and the gains of the Fuzzy-PI and LAMDA-PI controllers have been empirically calibrated to perform their control actions in the same ranges as the PI controllers. The gains of the studied controllers are presented in Table 4.

The objective of the studied HVAC system is to maintain the temperature T_3 at 71 $[{}^{\circ}F]$ and the relative humidity at 0.0092 $[lb/lb]$; namely, this maintenance is a problem of regulation in the field of automatic control. The experiment begins with the application of a moisture disturbance in Zone 3, as is illustrated in Figure 10. The moisture disturbance signal for robustness consideration that is applied to the system is plotted in Figure 12.

The control actions and system responses of the PI and LAMDA-PI controllers are presented in Figure 13 for comparison.

The resulting IAEs after the application of the moisture disturbance to the HVAC system are presented in Table 5.

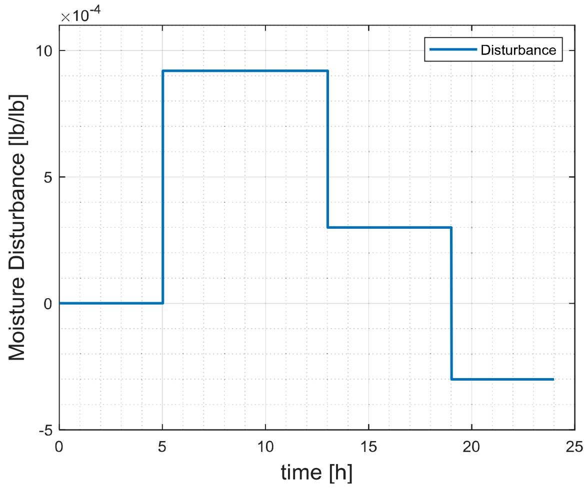

FIGURE 12. Moisture disturbance signal for testing the controller's robustness feature.

Additionally, Table 5 presents the differences and the relative percentages of variation $\Delta\%$ (Eq. (43)) with respect to the best IAE value "IAE_B" (the value that is marked in bold text):

$$\Delta\% = \frac{|IAE_X - IAE_B|}{\frac{(IAE_X + IAE_B)}{2}} \tag{43}$$

where IAE_X is the index of the controller that does not perform the best.

The results in Figure 13 and Table 5 demonstrate that the LAMDA controller realizes the best IAE performance when a moisture disturbance is applied in the thermal zone. The applied disturbance affects both the W_3 and T_3 outputs, of which the latter is more affected. However, the LAMDA-PI controller corrects the disturbance faster, thereby leading to lower overshoots in the response. This outcome also implies an energy savings when driving the system to the desired state. This smoother or less abrupt behavior is shown in the magnified frames in Figure 13, thereby proving the improvement both graphically and numerically. In the case of temperature, the improvement over the PI controller is 142%, and that over the Fuzzy-PI is 32%; for humidity, the improvement over the PI controller is 3.5%, and that over the Fuzzy-PI is 13%. The smoother control signal enables faster regulation of the output variables, thereby demonstrating the robustness of the proposed controller.

In the next test, a temperature (heat) disturbance is applied in Zone 3, as plotted in Figure 10. The heat disturbance signal for robustness analysis is presented in Figure 14.

The controllers react to the changes and the responses are plotted in Figure 15, in which the performances of PI and LAMDA-PI are compared.

The resulting IAEs after the application of the temperature disturbance to the system are presented in Table 6. Additionally, Table 6 presents the differences and the relative percentages of variation $\Delta\%$ with respect to the best IAE (the value that is marked in bold text).

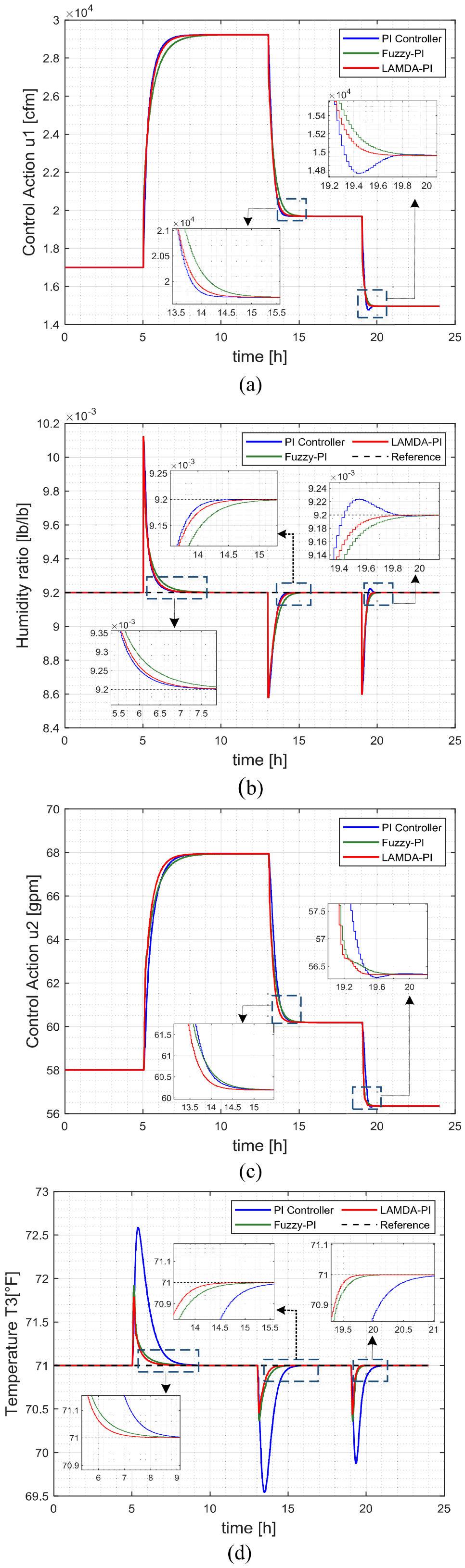

FIGURE 13. Comparative results with a moisture disturbance: (a) control action u_1, (b) humidity ratio W_3, (c) control action u_2, and (d) temperature T_3.

The results in Figure 15 and Table 6 demonstrate again that the LAMDA controller realizes the best IAE performance when a temperature disturbance is applied in the

TABLE 5. IAE comparison with the application of a moisture disturbance to the HVAC system.

Controller	IAE	Difference	Δ%
PI controller 1	6.62×10^{-4}	0.24×10^{-4}	3.582
Fuzzy-PI controller 1	7.30×10^{-4}	0.92×10^{-4}	13.33
LAMDA-PI controller 1	$\mathbf{6.38 \times 10^{-4}}$	-	-
PI controller 2	3.42	2.85	142.7
Fuzzy-PI controller 2	0.79	0.22	32.13
LAMDA-PI controller 2	**0.57**	-	-

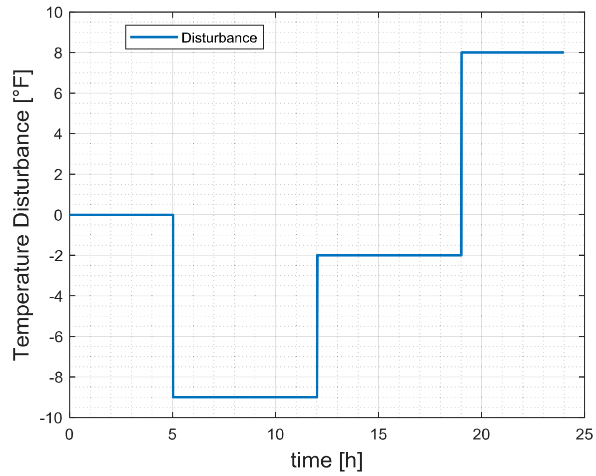

FIGURE 14. Temperature disturbance signal for robustness analysis.

thermal zone. The applied disturbance affects only the T_3 output. Again, the LAMDA-PI controller yields the best results for this test. Our approach shows improvements in the case of temperature over the PI controller of 5% and over Fuzzy-PI of 148%, and for humidity, it shows improvements over the PI controller of 6% and over the Fuzzy-PI of 2.4%. The Fuzzy-PI controller presents a more abrupt control action than that of the LAMDA-PI controller, and the PI controller has a smoother but slower response, which causes the system to take longer to reach the reference values (see the magnified frames in Figure 15), thereby increasing the energy consumption of the actuators (fan and chiller) for maintaining the system at the desired reference values.

A. DISCUSSION OF THE RESULTS

In the studied HVAC system for buildings, two types of disturbances have been applied separately: temperature (heat) and moisture.

It has been shown that the moisture disturbance that is applied to the thermal zone most affects the behavior of the system and is the most critical for the control system since it causes the two controllers to begin regulating the variables T_3 and W_3.

All the tested controllers realize the control objective of stabilizing the system at the desired reference values, namely, $71°F$ and 0.0092 lb/lb. However, it is important to analyze the ways in which the approaches stabilize the system, along with their respective performances. In all the tests that were conducted, LAMDA-PI yields the lowest IAE values,

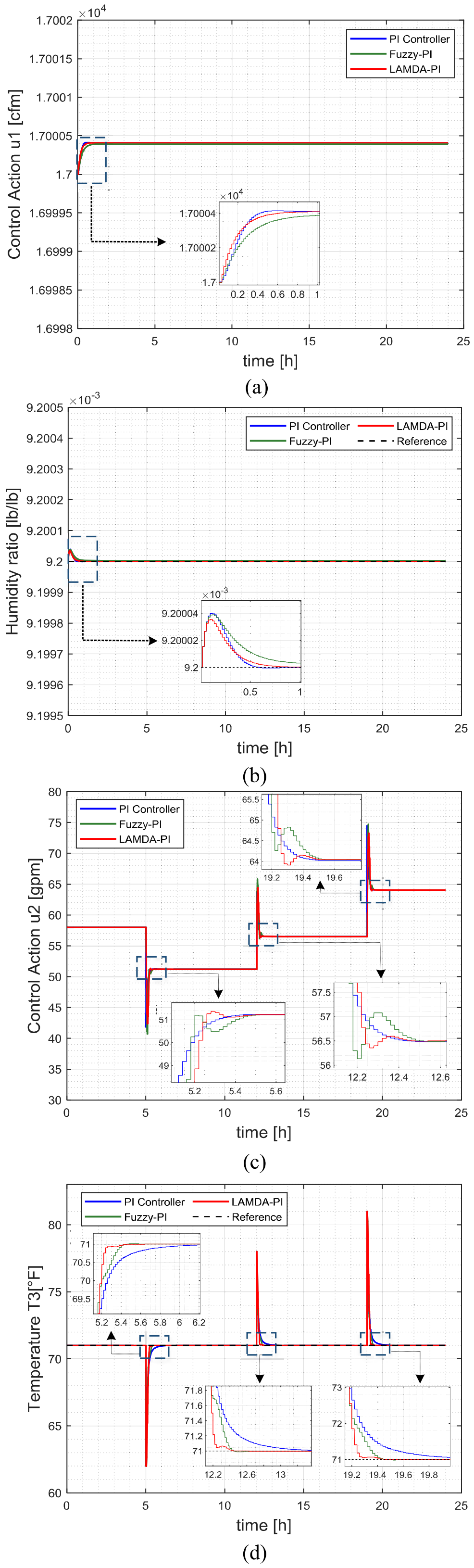

FIGURE 15. Comparative results with a temperature disturbance: (a) control action u_1, (b) humidity ratio W_3, (c) control action u_2, and (d) temperature T_3.

demonstrating that in the presence of significant step-type disturbances (±10% of the reference values), the controller takes the system quickly to the reference without failing or becoming unstable. In the case of humidity (see Figure 13b), it performs without overshoot and faster than the Fuzzy-PI controller, where LAMDA realizes higher performance with values that exceed 30%. In the case of temperature disturbances (see Figure 15c and 15d), the response is the fastest without producing considerable oscillations, such as those observed in Fuzzy-PI, or a very slow response, as in the case of the PI, which results in high energy consumption that must be reduced in systems of this type. The control actions that are produced by the LAMDA-PI controller are not abrupt and can be physically implemented in the studied system.

TABLE 6. IAE comparison with the application of a temperature disturbance to the HVAC system.

Controller	IAE	Difference	Δ%
PI controller 1	1.03×10^{-8}	0.51×10^{-9}	5.11
Fuzzy-PI controller 1	6.65×10^{-8}	67.1×10^{-9}	148
LAMDA-PI controller 1	$\mathbf{9.79 \times 10^{-9}}$	-	-
PI controller 2	3.12	0.19	6.07
Fuzzy-PI controller 2	3.01	0.08	2.45
LAMDA-PI controller 2	**2.93**	-	-

The implementation of the proposed controller shows advantages in terms of both the performance and the response to disturbances, and its design is simple since no mathematical model of the HVAC system is required and it is only necessary to define the centers of the classes and the rules based on the knowledge of the HVAC system. Our proposed approach also improves the results with respect to Fuzzy-PI, which presents a similar design methodology, but requires the definition of additional parameters for the Gaussian, triangular or trapezoidal membership functions.

With respect to the depreciation of the overall control system, it has been shown that the controller exhibits a satisfactory response to changes in the dynamics of the HVAC system; namely, the system remains stable even though the conditions of the HVAC system to be controlled are modified, demonstrating the excellent features of our method. With respect to controlling system failures, future studies will analyze this problem in the context of a supervision system.

VII. CONCLUSION

Advanced building HVAC control is a necessity in our society for ensuring the comfort of the occupants and saving energy. The soft control or AI methods that are based on ANN, FL and evolutionary algorithms are yielding interesting results in terms of accuracy and computational optimization performance. This paper proposes an HVAC control that is based on the LAMDA, which is a fuzzy logic clustering approach for smart buildings. The proposed model outperforms other conventional controllers.

LAMDA control is a powerful technique for knowledge extraction because it supports both the identification of the most relevant system features and control decision-making. This is a singular characteristic from the modeling perspective. Mathematical models are difficult to implement, require assumptions that reduce the accuracy of the simulation, and are unable to support online solutions due to their complexities. Empirical approaches typically suffer from lack of quality data or sufficient information for building reliable models.

Due to the need to save energy, maintain comfort and add objectives to the HVAC control system, a general approach is required that results in a complex and multifaceted problem because multidimensional data are required that are not possible to analyze via simple techniques. The proposed approach enables the definition of the main domain-based features of the studied phenomena, and this definition is used to implement useful strategies for driving the controller from its current state to the desired target state.

The implementation of a LAMDA-based controller drives the HVAC system to the target state by calculating the adequacy with respect to the class (GADs). The versatility of the algorithm has been demonstrated by comparing LAMDA-PI with the conventional PI and Fuzzy-PI controllers. The main advantage of working with LAMDA is that it is only necessary to define the centers of the fuzzy logic classes and the weights for the outputs, and no additional parameters are required, such as in conventional fuzzy controllers.

This article has demonstrated the utilization of contextual information in real time in a LAMDA controller. The proposed approach includes the contextual data in the error input as real-time feedback information with a manageable number of rules. The results of the experiments for evaluating the robustness have proven that higher precision and faster operation of LAMDA-PI are achieved compared with available conventional controllers and that LAMDA-PI provides energy savings, as it manages the actuators using a softer approach. In addition, the proposed controller can be trained with an online learning mechanism for real-time calibration. In future work, the ability to self-adjust the classes for the algorithm without requiring the human expertise of the designer will be extended by using the gradient descent algorithm.

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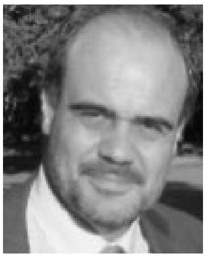

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2.3 Artículo 3

2.3.1 Identificación del artículo

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DOI:	10.1109/ACCESS.2019.2932055
Coautores:	Dr. José Luis Castillo Sequera Dr. Antonio del Corte Valiente Dr. José Manuel Gómez Pulido

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2.3.3 Resumen del artículo

La población mundial continúa creciendo y tiene la tendencia a concentrarse en grandes ciudades, lo que aumenta la demanda de iluminación de los espacios públicos, para preservar la seguridad, permitir la orientación visual, conseguir efectos estéticos y aumentar la calidad de vida. Esto conlleva el incremento del consumo energético y de la polución lumínica. Las herramientas comúnmente usadas para el diseño de la iluminación de los espacios públicos no incluyen otros objetivos de optimización, como el de la energía y sus parámetros de diseño vienen predefinidos por el ingeniero, por lo que no son optimizables. Las técnicas de optimización multiobjetivo evolutivas podrían tener un enorme potencial de aplicación en el diseño y replanteo de estos sistemas, por su buen comportamiento en modelos con comportamientos no lineales, así como la disponibilidad de las mismas. Este estudio investiga un modelo de "caja negra" que calcula las funciones objetivo para de este tipo de optimizadores, basado en diferentes arquitecturas de redes neuronales que simulan el funcionamiento de un sistema de alumbrado público. La comparativa se establece midiendo el rendimiento del modelo, la velocidad de entrenamiento, la bondad de ajuste con un conjunto de datos generados en condiciones diferentes. Se emplean perceptrones multicapa (MLPs) variando el número de capas y el número de neuronas en cada capa, analizando cuál es el mejor modelo que emula el comportamiento de un sistema de alumbrado. El aprendizaje es supervisado mediante los resultados obtenidos con la conocida herramienta de diseño de software abierto, DIALux. El experimento se ha repetido varias veces de modo que se pudiese estabilizar el rendimiento de cada arquitectura. En este sentido también se ha podido determinar el número necesario de intentos para conseguir unos valores confiables. Los resultados muestran que el algoritmo de entrenamiento Levenberg-Marquardt es el mejor comportamiento tiene en los distintos aspectos analizados, resultando que las redes neuronales no mejoran al aumentar el número de neuronas en sus capas internas.

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Analysis of Artificial Neural Network Architectures for Modeling Smart Lighting Systems for Energy Savings

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ABSTRACT Currently, population growth is global and tends to concentrate in large cities, which increases the demand for illuminating public spaces for safety, visual orientation, aesthetic considerations, and quality of life. The undesirable side effects are increase in energy consumption and light pollution. The current tools used for designing public lighting systems are not suitable for optimizing multiple objectives in addition to energy savings, and these solutions could provide for a more sustainable environment. The application of evolutionary optimization techniques seems to be growing rapidly because of the nonlinearity of the model behavior and the nonproprietary nature of the algorithms, which are considered as *black box systems*. This paper develops a data model for these types of optimizers, analyzing the ability of different artificial neural network (ANN) architectures to simulate a simple public lighting design by measuring the performance with respect to the fitness function, training speed, and goodness of fit with a dataset generated with different conditions. The architectures selected in this paper are those with multilayer perceptrons (MLPs) with different hidden layer configurations using different numbers of neurons in each layer, which have been analyzed to determine the configuration that best fits the purpose of this work. The data for training the ANNs were generated with a recognized open-software platform, DIALux. The experiments were repeated and analyzed to determine the variance of the results obtained. In this way, it was possible to identify the most appropriate number of iterations required. The results show that better precision is obtained when using the Levenberg–Marquardt training algorithm, especially when the ANN architecture has fewer neurons in the hidden layer.

INDEX TERMS Public lighting design, artificial neural networks, multilayer perceptron, data modeling, energy efficiency, uniformity ratio of luminance, sustainable cities.

I. INTRODUCTION

The urban population maintains a growth rate that evolves and is expected to reach two-thirds of the overall population by 2050 [1]. This requires wider illumination of public areas, and the undesired effects are an increase in energy consumption and light pollution. Greenhouse gas emissions and global warming, partially caused by the production of energy, put pressure on the private and public sectors to find more sustainable solutions. Public lighting consumes 19% of the global electricity production [2]. Security and aesthetic concerns [3] are unavoidable constraints for saving energy, leading researchers to consider multiple objectives in the optimization approaches. Design optimization is expected to achieve significant energy savings, approximately 35% with adaptive methods [4] or 45% by using optimal elements [5].

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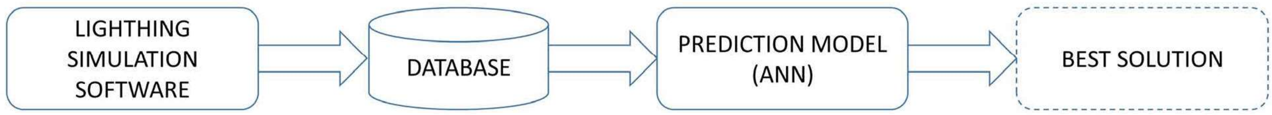

FIGURE 1. Process to build the best data-driven model that will simulate the behavior of a lighting system. The selected architecture will support an evolutionary optimizer with energy consumption as the cost function.

The European Union, under the European Standardization Framework, is regulating both the functional requirements and indicators of energy performance within Standard EN13201.

This article follows the Guidelines from Part 2 of the Standard –EN13201-2:2016, regarding the selection of more appropriate lighting types, according to given situations and their required performance. It also follows Part 3 –EN13201-3:2016-, using the accepted mathematical procedures and conventions, such as the photometric performance in road lighting with its specific parameters. Moreover, it uses Part 5 –EN13201-5:2016- for the performance indicators for compliance. It is necessary to note that the final decision to illuminate a road is left to each country and its cities, according to the standard from the International Commission on Illumination governing the lighting of roads for motor and pedestrian traffic, CIE115:2010, which is taken as a reference.

These guidelines aim to maximize the visualization, orientation and security levels for pedestrians and vehicles [6]–[9]. An appropriate illumination of streets, roads and parks helps to reduce the crime rates and vandalism that transform cities into unsafe places to live [10], [11]. The lamp types, pole features, street dimensions and surrounding requirements are the inputs for designing any lighting project. The design tools compute them and indicate which results are compliant, such as the minimum overall uniformity ratio of luminance, the road surface illuminance in dry conditions, disturbing brightness (discomfort glare) or the surroundings conditions [12]–[16].

However, most common design tools lack the option for optimizing the energy consumption together with other cost objectives. The AGi32 [17], DIALux [18], DL-Light [19], FocusTrack [20], TracePro [21], LD Assistant [22], Vectorworks Spotlight [23], systems compute the energy usage according to the normative standard but do not suggest alternative designs for saving energy.

The fundamental contribution of this article is to determine the most efficient multilayer ANN architecture with conventional training functions and demonstrate its capabilities in a set of simplified public lighting scenarios [24]–[28]. The justification of this research about ANNs over other algorithms is the potential brought for engineers who are designing new public light installations or re-designing existing ones in the field, being able to optimize multiple objectives others than the standard ones, such as energy, cost, maintenance, aesthetics or durability. The machine learning capability in the ANN provides, not only those discrete values set by the Normative, but also continuous values obtained from standard features and from new unforeseen variables, like observed nearby reflective materials, unavoidable shapes, unexpected shadows, nonstandard climate conditions, singular spacing or color combinations. Other simpler algorithms, like white box or formulae-based ones, possibly give more accurate results, but are rigid and cannot adapt to these new scenarios because required to be previously obtained. In addition, the Mean Squared Error (MSE) analysis, the number of epochs and the time consumed obtained from the tried algorithms show that the learning process speed is affordable. Computational speed issues will be anyhow matter of future discussions.

The simulator generates two separated datasets with the lighting simulation software: one for training, the Training Dataset (TDS), and another for proofing the obtained models, the Proof Dataset (PDS), prepared with different lamps and design parameters than those chosen for the TDS. The neural learning starts randomly dividing the TDS into 3 sets for training, testing and validating. PDS does not train any ANN, but proves the models obtained with the TDS. The best performance in terms of MSE and coefficient of determination (R^2) allows the comparison of the ANN architectures. Other parameters have been recorded to observe the learning process, but they are not required in the comparison. The PDS is then tried in the models and its performance is expected to confirm the comparison (Fig. 1).

The rest of the paper is organized as follows: In Section 2, the concept of an ANN-based model, the ANN architectures and the training algorithms are presented. Section 3 describes the experimental results and introduces the discussions. Then, Section 4 presents the conclusions and suggests future work.

II. MATERIALS AND METHODS

This research selects the best ANN architecture to produce fast lighting simulations [29] that will provide the data for an optimizer with the objective function of minimizing the energy consumption while maintaining the uniformity ratio of luminance (U_0) within the normative standard [30]. The first step is to obtain reliable data for training and testing the potential models. The data are generated with DIALux Public Lighting Design Tool [31], [32] and configured with two predefined solution spaces, giving two datasets, TDS and PDS. Then, ten multilayer feed forward ANNs are built and trained with the TDS. The ANN architectures are then tested with the second PDS.

The process is repeated several times until the selected performance parameters suffer less variance. The maximum number of iterations is predetermined with a simple

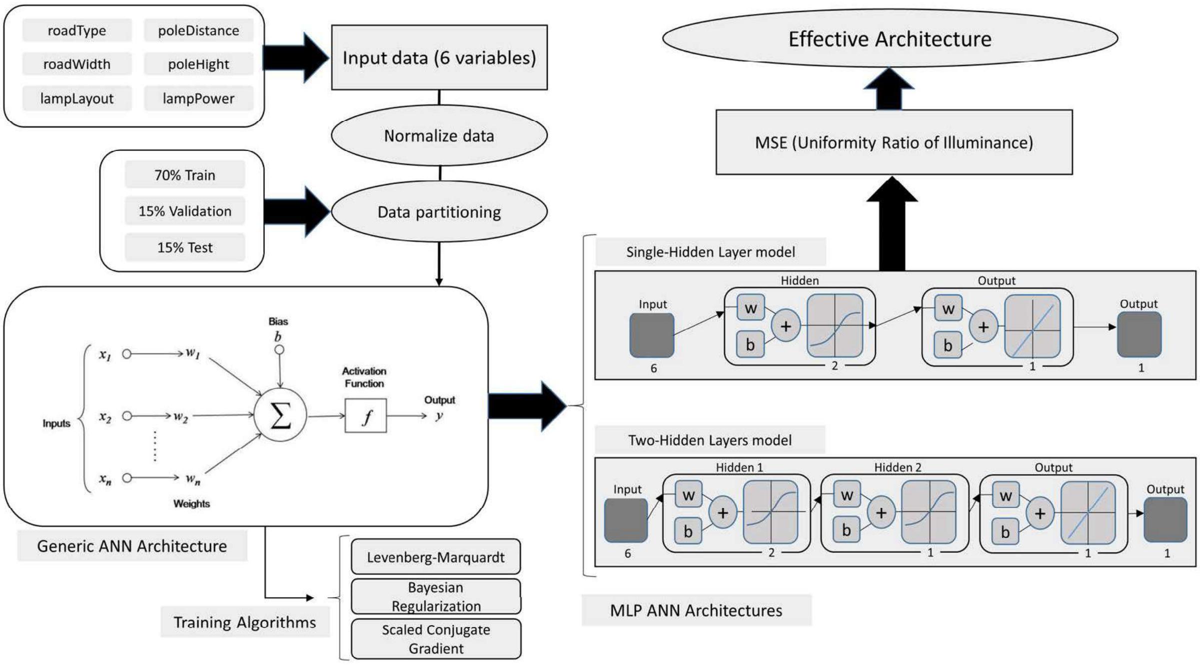

FIGURE 2. **The ANN analysis models the dataset by training the ten ANN architectures with the three back-propagation algorithms.**

graphical approach. The best architecture is the fastest and most accurate lighting simulator.

A. PUBLIC LIGHT DESIGN

The design of public road lighting follows the above mentioned normative approach. The key objective is to appropriately light roads for car traffic security, visibility and orientation. The goals of road lighting design are as follows:

1) obtain a sufficient average luminance (L_m) [33],
2) minimize the uniformity ratios of luminance (U_0 and U_L),
3) limit glare to avoid blinding,
4) consider surrounding lighting (edge factor), and
5) ensure optical orientation.

To simplify the analysis with the aim to include the remaining parameters in subsequent research, several simplifications have been applied to the road conditions. The datasets are generated for the ME1 and ME2 road lighting recommendations, since the generalization to other types is simple. The difference between ME1 and ME2 is that the average luminance is 2cd/m^2 for the former and 1.5cd/m^2 for the latter. The threshold increment of 10% and surrounding rate of 0.50 are the same for both. The model only considers the overall uniformity ratio of luminance [34], being extendable to the global uniformity or surround ratio afterwards.

The model requires the selection of lamps and ballasts, but the large number of brands, models and types makes its implementation time consuming. The common types of lamps are made of sodium-vapor, mercury-vapor, metal-halide or LED [9]. This research only considers LED-type lamps because they are becoming the predominant type used among designers due to their low energy consumption compared with other types of lamps.

B. MULTILAYER PERCEPTRON ANN

The ANNs are capable of incorporating nonlinear effects and interactions among the variables of the data model as a black box. The intrinsic machine learning ability automatically extracts the hidden patterns from the data and detects trends, offering an alternative way to evaluate complex relationships. However, the ANN parameters are difficult to interpret and explain due to the wide empirical process of construction and training. For this reason, our research shows the best ANN model, taking as a reference the comparison of the results obtained (Fig. 2).

Data-driven optimization methods work with data generated by system simulators, which holds true for energy consumption simulation.

For some problems, the ANN is basically designed by trial and error, selecting the best configuration by analyzing the results. This is the case in this research, which obtains the best MLP architecture by varying the number of hidden layers and neurons and testing various back-propagation algorithms [35].

The number of hidden layers and neurons in each layer affect the capacity of the model for generalization, i.e., the accuracy in computing new examples. Some authors demonstrate that the number of hidden layers is normally between the size of the input layer and the output layer, or slightly higher [36]. The generally accepted convention is the *universal approximation theorem* [37], which simplifies the problem by stating that two-hidden layers or in most cases, one-hidden layer, are sufficient to achieve the best results. Lippmann adds that single hidden layer ANNs are able to solve arbitrarily complex problems, given that the hidden layer includes at least three times the number of input nodes [38].

Hecht-Nielsen extends the Kolmogorov theorem [39] to demonstrate that single hidden layer ANNs with 2N+1 neurons and continuous, nonlinear monotonically increasing transfer functions are sufficient to compute any continuous function of N input variables [40]. However, the estimation of the number of hidden neurons in each layer is done with empirical rules and is therefore difficult to justify. The *rule of the geometric pyramid* assumes that the number of neurons in the hidden layer must be less than the total number of input variables but higher than the number of output variables [41]. In addition, the number of neurons in each layer follows a geometrically decreasing progression from the input to the output. The number of intermediate neurons must be close to $\sqrt{M.N}$ where N is the number of input variables and M is the number of output neurons. On the other hand, according to the *rule of the hidden layer*, the number of hidden neurons is proportional to the number of input neurons [42]. Typically, the number of hidden neurons should not be more than twice the number of input variables.

C. BACKPROPAGATION TRAINING

The supervised training of an MLP normally obtains its configuration by comparing the outputs after using the dataset to model the expected outputs in an iterated trial-and-error process, seeking to minimize the error with the backpropagation algorithms that conveniently tune the weights and biases. These algorithms require that the MLP structure or topology, i.e., the MLP architecture, and the number of neurons and hidden layers, are set before the training starts, making the selection of the architecture a guessing procedure. The number of forward and backward operations is large, requiring nonnegligible computational resources, although once the MLP is trained and the system is modeled, the computation is fast.

Any training algorithm modifies the weights according to the following expression:

$$W_{ji}\,(n+1) = W_{ji}\,(n) + \Delta W_{ji}(n) \tag{1}$$

where W_{ji} is obtained via the training algorithm rule and n is n^{th} iteration. If $E\,(n)$ is the output error after the nth training iteration, there are two possible ways to test the performance:

$$E\,(n) = \frac{1}{2N} \sum\nolimits_{z} \sum\nolimits_{j} (e_j^z(n))^2 \tag{2}$$

$$E\,(n) = \frac{1}{2} \sum_{j=1}^{M} e_j(n)^2 \tag{3}$$

where N is the total number of input/output pairs, z is the zth input/output pair of the TDS, j is the jth output layer neuron, and M is number of output neurons.

The first expression defines the ANN global error, while the second is the immediate MSE that approximates the former with less computational effort. In both cases, e_j is the error between the prediction and real value.

MLPs can be compared to logistic regression classifiers where the inputs are first transformed with a nonlinear transformation, θ, in the hidden layer that makes the data linearly separable:

$$h\,(x) = \theta\,(x) = S(b_{(1)} + W_{(1)} \tag{4}$$

Vector $h\,(x)$ is the hidden layer. The sub index in parenthesis represents the particular layer. The machine learning process seeks to minimize the error function and adjusts the weight matrix. Specifically, for a one-hidden layer, the function F(x) is:

$$F\,(x) = G(b_{(2)} + W_{(2)}S\left(b_{(1)} + W_{(1)}\right)) \tag{5}$$

where $b_{(1)}$ and $b_{(2)}$ are the bias vectors; $W_{(1)}$, $W_{(2)}$ are the weight matrices, and G and S are the activation functions. The $W_{(1)}$ columns are the weights from the input units to the i^{th}-hidden layer unit.

For computation, we use the multipurpose numeral-computing tool MATLAB, developed by Mathworks, which has three default choices for the backpropagation algorithm, represented by S(we have taken the default Matlab values):

1) Levenberg-Marquardt [43]–[46]: This algorithm iteratively locates the minimum of a multivariate function, expressed as the sum of squares of nonlinear real-valued functions. MATLAB recommends it for most problems as it trains the MLP faster but requires more memory.
2) Bayesian Regularization: This algorithm updates weights and biases in the same way as the Levenberg-Marquardt algorithm but minimizes a combination of squared errors and weights. The resulting model also generalizes well and obtains better solutions for many practical problems but is slower.
3) Scaled Conjugate Gradient: This is the simplest algorithm and is used for stable training. It updates the weights and biases towards the negative gradient of the performance function [47]. It is recommended for large problems as it works with first-order gradients and not with the second-order Jacobian, being more memory efficient. The weights are initialized with small values around the origin so that the activation function can operate in its linear zone, where the gradients are larger.

The Levenberg-Marquardt training algorithm computes the expression defined by:

$$(J^t * J + \lambda * I) * \delta = J^t * E \tag{6}$$

where J is the Jacobian matrix for the system, λ is the damping factor, I is the identity matrix, δ is the weight update vector that we want to obtain, and E is the error vector containing the output errors for each input vector used in training the network. Figure 3 shows a diagram of the Levenberg-Marquardt

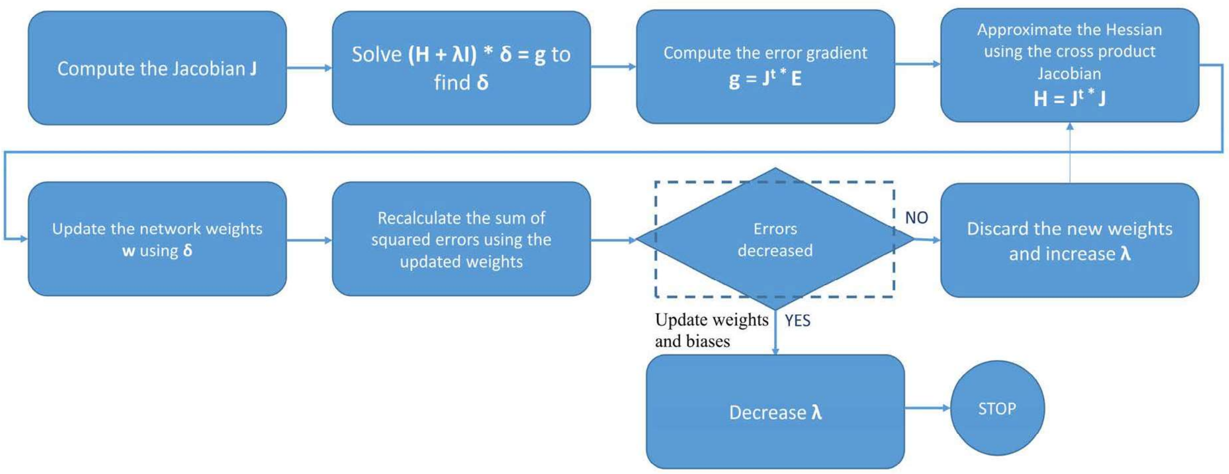

FIGURE 3. Flow diagram of the Levenberg-Marquardt training algorithm.

training algorithm. Only the method of updating the weights and biases differs in each algorithm.

The MLP architecture has some drawbacks [48], [49]. The main limitation is that it cannot guarantee a global minimum during training and the network may converge to a local minimum. Training the network several times by using a different random starting positions each time and then obtaining the model that results in the best RMS error will mitigate this issue. In any case, finding the global minima in deep networks appears to be unnecessary because local minima are approximately as good as global minima [50].

Another limitation is that the number of hidden neurons must be set manually. Setting this value too low may result in underfitting, while setting this value too high may result in overfitting. By training a regular multilayer neural network in classification tasks using a training dataset and starting from randomly initialized weights, the stochastic gradient descent algorithm can attain 100% accuracy [51].

D. TRANSFER FUNCTION

The MLP architecture also defines the transfer/output functions for the network topology. To ensure that the learning process obtains a result, these functions must be continuous and differentiable at all points. The most common functions are the sigmoid function for the hidden layers and the linear function for the output layer. The sigmoid function is defined as

$$Sc\,(x) = \frac{1}{1 + e^{-cx}} \tag{7}$$

where c is the steepness of the curve.

E. PROPOSED MULTILAYER FEED FORWARD ARCHITECTURES

Designing an ANN is mostly an empirical process that balances the accuracy and the ANN generalization capability. Adding more hidden layers to the architecture normally worsens its performance and generalization capability.

The *rule of the single layer* [52] suggests building the first hidden layer of this experiment with up to six neurons, one for each input variable from the input layer. The experiment will also try one and two-hidden layer architectures, anticipating possible discontinuities in the data behavior. For the studied models with two-hidden layers, the *rule of the geometric pyramid* is applied [53]. The rule says that the size of every hidden layer decreases in geometric order related to the previous layer from the input to the output.

The activation function for hidden layers is the sigmoid and the linear function is for the output layer. Following these considerations, the experiment builds the following ten architectures (Fig. 4):

1) One-hidden layer with two neurons: "2"
2) One-hidden layer with three neurons: "3"
3) One-hidden layer with four neurons: "4"
4) One-hidden layer with five neurons: "5"
5) One-hidden layer with six neurons: "6"
6) Two-hidden layers with two and one neurons: "2-1"
7) Two -hidden layers with three and one neurons: "3-1"
8) Two -hidden layers with four and two neurons: "4-2"
9) Two -hidden layers with six and two neurons: "6-2"
10) Two-hidden layers with six and three neurons: "6-3"

Only the number of neurons, number of layers, and learning algorithms are changed. The *learning rate* and other parameters remain unchanged for all the architectures. Once selected the ANN topologies and the appropriate activation functions, the model can be trained with the training algorithms to obtain a simulation of the results. Each of these analyzed architectures represents different configurations, with one or two hidden layers, and with different numbers of hidden neurons to determine the configuration that best suits the purpose of the work.

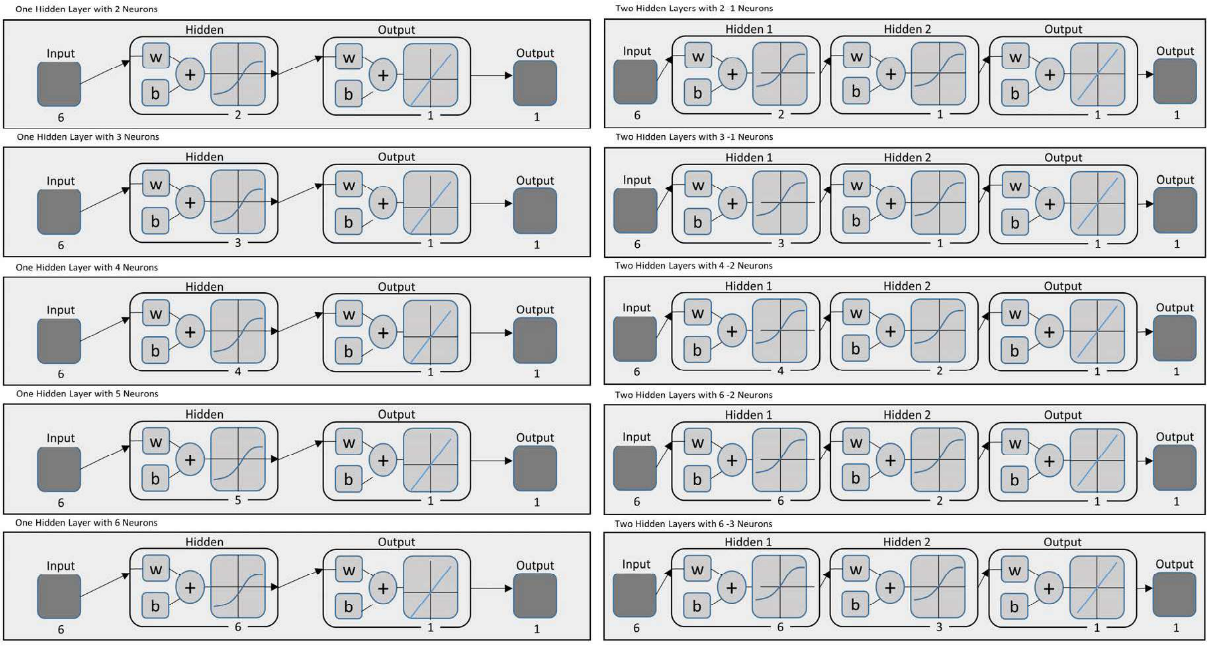

FIGURE 4. **Proposed MLP architectures for the analysis: (left) One HL; (right) Two HLs.**

F. MEASURED PERFORMANCE STABILITY

The performance measured at the end of the process is variable, as the standard process takes three random datasets for modeling: training, testing and validating. In this case, 70% of the TDS is used to train and 15% each to test and validate. The results are biased and prevent a reliable comparison. The algorithm takes examples randomly.

The solution proposed in this research is the repetition of the experiment, assuming some natural trend that is verifiable at the end of the repetitions, until the performance values become stable. The results of every repetition are grouped into 15 sets containing 5 to 75 elements in increments of 5. These groups are then parsed through a boxplot graphical analysis to identify the group with fewer repetitions that first reaches the stable parameters for every performance indicator. The minimum number of tries allows for the reliable performance measurement of the ten architectures for comparison.

G. TRAINING DATASET (TDS)

The models corresponding to each MLP architecture are trained with the TDS generated with the DIALux software tool and are made up of 648 different design conditions given by these variables (Table 1):

1) Road lighting classes, according to EN13201: ME1 or ME2 restrictions for heavy traffic.
2) Road width: 7 m, 9 m or 12.5 m.
3) Lamp layout: only one-side of the road, two-sides of the road or alternating-one-right-next-left.
4) Separation between poles: 10 m, 25 m or 50 m
5) Pole height (3): 4 m, 8 m or 12 m
6) LED lamp power (4): 30 W, 91 W, 174 W or 276 W

TABLE 1. **Training data set.**

Variables	Values	Description
RoadType	ME1, ME2	Road lighting classes
RoadWidth	7, 9, 12.5	Width of the road [m]
LampLayout	One side, two sides, alternating	Position of lamps in the road
PoleDistance	10, 25, 50	Separation between poles [m]
PoleHeight	4, 8, 12	Height of the pole [m]
LampPower	30, 91, 174, 276	Power of the LED lamp [W]

The software tool simulates these configurations and yields the average luminance (L_m), global and longitudinal uniformity (U_0 and U_L), threshold increment (TI) and surround ratio (SR). For this research, the single output is U_0, the dependent variable of the fitness function, for simplicity purposes [54], leaving the other variables for coming research.

To obtain a more representative dataset, we used the actual nominal value of the lamp power, which was checked with the manufacturer.

H. PROOF DATASET (PDS)

To test that the selected model better approaches any other design condition, the DIALux software generates a second dataset, the PDS, with 64 examples interpolating and extrapolating values different to those of the TDS (Table 2):

1) Road lighting requirements according to EN13201: ME1 or ME2
2) Road width: 8 m or 15 m

TABLE 2. Proof data set.

Variable	Values	Description
RoadType	ME1, ME2	Road lighting requirements
RoadWidth	8, 15	Width of the road [m]
LampLayout	One side, two sides	Position of lamps in the road
PoleDistance	15, 35	Separation between poles [m]
Pole height	10, 15	Height of the pole [m]
LampPower	105, 182	Power of the LED lamp [W]

3) Lamp layout: only one-side of the road or two-sides of the road
4) Separation between poles: 15 m or 35 m
5) Pole height: 10 m or 15 m
6) LED Lamps Power: 105 W or 182 W

III. EXPERIMENTAL RESULTS AND DISCUSSION

The ANN training process randomly splits the TDS into three subgroups: training (70%), validation (15%) and testing (15%). The training subset of the TDS is used to adjust the weights and biases of the network. The validation subset is used to measure the network generalization. The test subset analyzes the network performance after the training. At the end of this stage, the trained topologies are trialed with different design conditions from the PDS to measure their accuracy.

The discussion addresses the MSE performance with the TDS, total time consumed, required number of epochs and MSE performance with the PDS. The process is repeated to obtain reliable values.

Taking the 1-sample mean or median of the TDS or PDS MSE, it is observable that the experiment requires more than one repetition to obtain stable values; otherwise, it would be impossible to evaluate the behaviors.

To quantify the required number of samples, we have assumed as a first approach the study of [55]. We assume that the population is large as it is derived from combining 648 examples using sets of 75, which are the times to train every architecture with every single learning algorithm.

We use the formula of the mentioned study to estimate the number of samples necessary to obtain enough confidence to ensure the MSE achieved by the TDS and PDS:

$$n_o = \frac{Z^2 * s^2}{e^2} \tag{8}$$

where n_o is the sample size, Z is the abscissa of the normal curve that cuts off an area of α at the tails (1 - α equals the desired confidence level), e is the desired level of precision (in the same unit of measure as the variance) and s^2 is the variance of an attribute in the population.

Assuming a confidence level of 99%, an acceptable error of the MSE value of approximately 6% and the obtained standard deviation with the 75 repetitions, we observe that it is necessary to repeat the experiment at least 39 times for the TDS. In addition, we can visualize these figures in boxplots to depict the variations of the average performance (MSE) for the TDS (Fig. 5) and PDS (Fig. 6) with the sample size used for training.

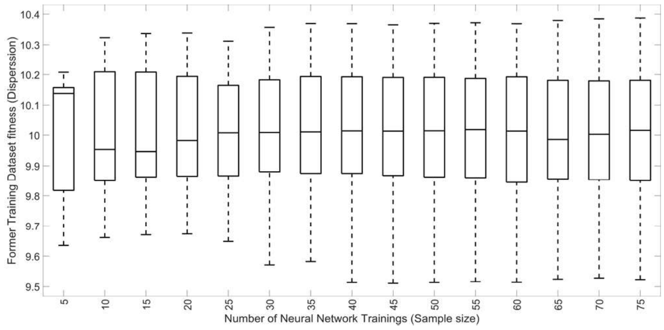

FIGURE 5. Variation of the average performance (MSE) for the TDS with the sample size used for training.

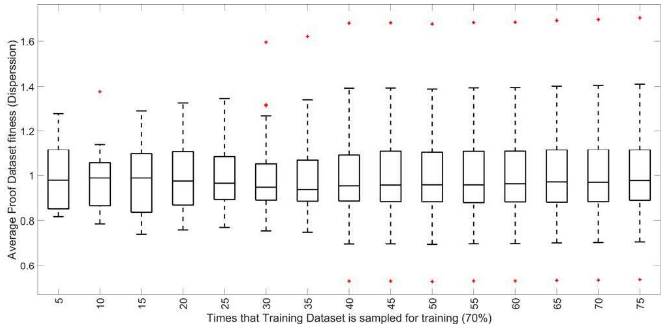

FIGURE 6. Variation of the average performance (MSE) of the PDS with the sample size used for training.

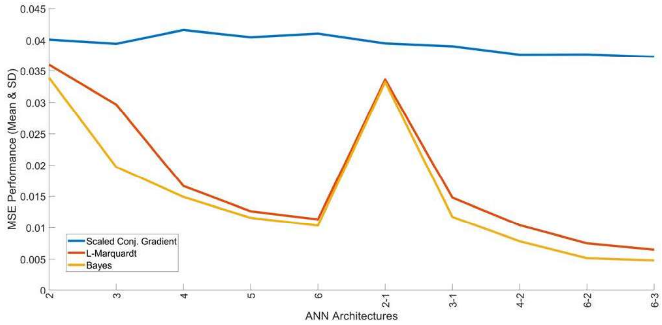

FIGURE 7. Performance (MSE) versus ANN architectures for different training algorithms.

Figure 7 shows the ANN topology performance, with the median MSE and Standard Deviation (SD) for each of the ten topologies applying the three proposed back propagation algorithms: Levenberg-Marquardt, Bayesian regulation and scaled conjugate gradient.

Figure 8 shows the MSE performance of the PDS for each MLP architecture.

Figures 9 and 10 depict similar results for the number of epochs and the time consumed by each algorithm.

The Levenberg-Marquardt achieves results very similar to the best value but at the expense of a shorter time, so comparing it with the other algorithms, it is the chosen algorithm in this experiment. However, the Bayesian algorithm shows the worst characteristics due to the additional calculation needed to refine the optimization. The number of neurons and hidden layers increases the computational resources required.

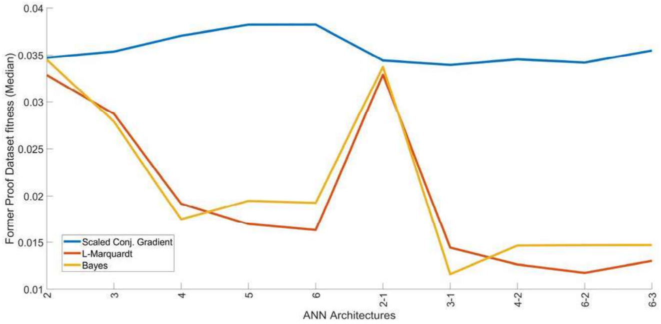

FIGURE 8. Architecture fitness for each architecture and training algorithm.

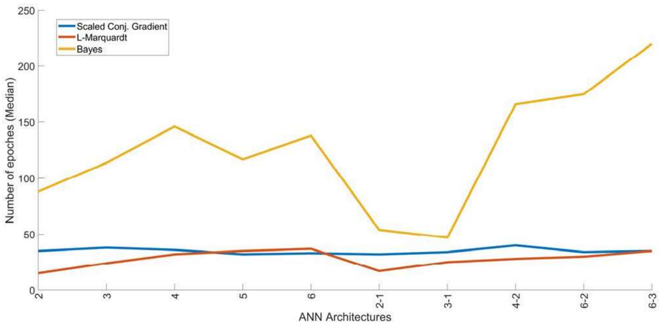

FIGURE 9. Number of Epochs required for each architecture and training algorithm.

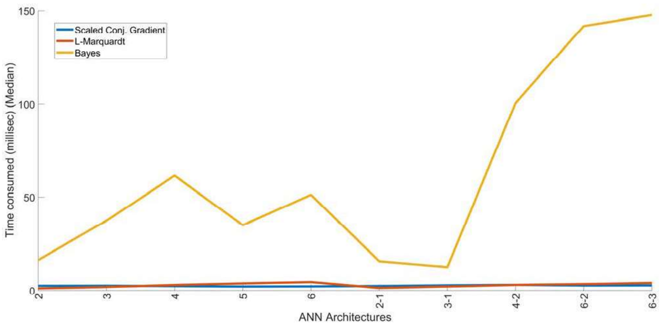

FIGURE 10. Time consumed for each architecture and training algorithm.

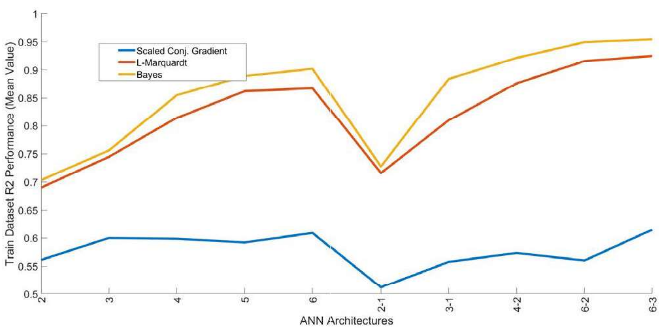

FIGURE 11. Coefficient of determination (R2) of the TDS versus ANN architectures for different training algorithms.

Additionally, Figures 11 and 12 plots the coefficient of determination (R^2) as performance indicators since it considers the intrinsic variance of the training/test data.

The R^2 analysis confirms our initial conclusions, improving the visibility of their variance. Negative values obtained

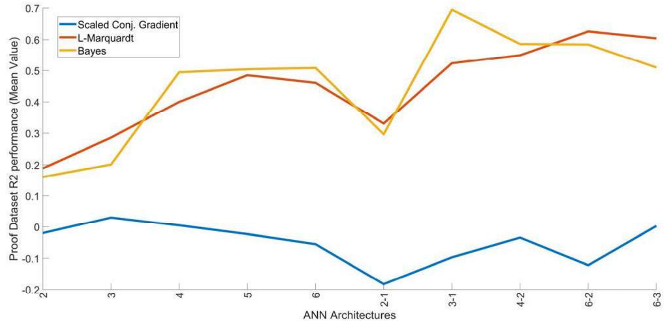

FIGURE 12. Coefficient of determination (R2) of the PDS versus ANN architectures for different training algorithms.

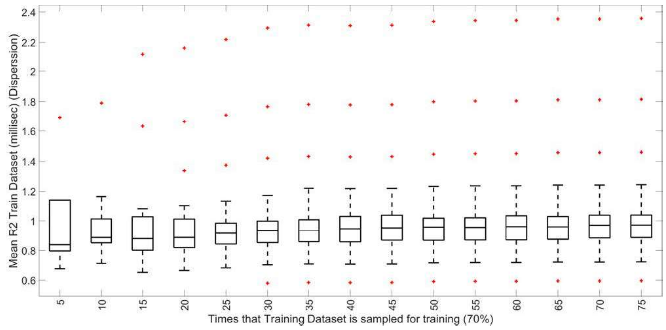

FIGURE 13. Variation of the coefficient of determination (R2) for the TDS with the sample size used for training.

for certain ANN architectures are possible and mean that the goodness of these models are even worse than the horizontal mean [56]. The parametrical contrast of the normalized values of TDS and PDS for R^2 performance concludes that both datasets have the same probability distribution with SCG and LM learning algorithms.

Figure 13 visualize a boxplot to depict the variations of the R^2 for the TDS with the sample size used for training, observing similar stabilization with the sample size to that of the MSE.

We observed that the different architectures showed very different performances with the proof dataset when compared to the TDS. The median and mean TDS MSE performance improve with ANN complexity. The median and mean PDS MSE performance also improved with the same ANN complexity. Both TDS and PDS have similar MSE performance levels even when the PDS is different from the TDS.

Now, the best performance in terms of the MSE is achieved by the Bayesian learning algorithm, and the worst is achieved by the scaled conjugate gradient. However, the worst time consumer is the Bayesian algorithm, and we observe that the Levenberg-Marquardt algorithm performance is slightly worse than that of the Bayesian algorithm, but it is faster; as it is a good trade-off between the two the Levenberg-Marquardt algorithm is the favorite in this experiment.

IV. CONCLUSION AND FUTURE WORK

As the number of neurons increases, the MLP architecture performance improves. The performance with a two-layer architecture also increases with the number of neurons.

The best performance value is for the MLP with six neurons in the input layer and two or three neurons in the output layer.

It is important to note that with only 648 samples of lamps in the dataset with certain conditions, it is possible to train an MLP that provides a good model for another dataset of different lamps in other environmental conditions. This promising result will be extended by research in the near future. The best performance of the MLPs used in the experiment with the second dataset is again a 6-2 architecture, giving a similar order of magnitude compared with the original dataset.

The Bayesian training algorithm achieved the best performance, while the scaled conjugate gradient method achieved the worst. However, the time consumed by the Bayesian training algorithm is nearly 10 times higher for the 6-2 architecture. The time consumed seems to be proportional to the number of epochs that each algorithm repeats in the simulation. Bayesian training takes 270 epochs to model the 6-2 architecture, while the SCG and Levenberg Marquardt algorithms only require approximately 50 epochs. It is noticeable that for the two latter methods, the time consumption and the epochs are quite steady.

The Levenberg-Marquardt performance is similar to that of the Bayesian algorithm, and the resource consumption, which is similar to that of the scaled conjugate gradient method, also works, making it the best option as a training algorithm.

The simulation process is repeated to obtain more reliable values, as it is impossible to establish a model with only one sample. The sample size has been roughly calculated for a given confidence level and average MSE. Both the median and mean values are similar, and their boxplot figures confirm the analysis

This research proposes a new methodology to analyze the best ANN architecture to simulate the behavior of a lighting system. ANNs have the advantage of learning and modeling complex relationships in nonlinear systems. After the learning process, ANNs can generalize and infer unseen relationships on unseen data, making the model generalizable and predictive. Because ANNs do not impose any restrictions on the input variables, they can better model highly volatile data with nonconstant variance. Unlike many other prediction techniques, ANNs have parallel processing capability and high-speed response [57].

The empirical nature of this paradigm requires methodical studies on different architectures to widen the initial scope. Future research aims to extend the analysis as follows:

1) To include multiple outputs for designer work.
2) The study of the influence of each input variable explaining the outputs.
3) To include the rest of variables normally considered by road lighting simulators, analyzing their predominance with a previous feature analysis.
4) To study the online learning mechanisms for unexpected variables, like climate, human behavior, aesthetics considerations or nearby obstacles.
5) The use of signal processing to transform the lamp variables into ANN readable values (new types of lamps, such as solar-powered lamps, could be easily included in the model [58], [59]).
6) Analysis of the ANN architectures behavior with different activation functions.
7) Analysis of new ANN architectures that could bring more efficiency in the optimization and adaptation to context information, such as weather variability [60], [61].
8) Analysis of evolutionary optimization algorithms to for energy savings and other requirements from public lighting designers and site surveys.

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3 Otros méritos relacionados con la investigación

En el ámbito de la investigación realizada para esta Tesis, se presentan otros resultados que avalan el interés de la misma, como contribuciones a distintos congresos con artículos publicados, premios y ayudas a la investigación.

3.1 II Congreso IENER '19

Título del Artículo:	**Arquitectura de gestión autónoma para la gestión de edificios inteligentes**
Congreso:	iENER'19 II Congreso Internacional de Ingeniería Energética
Lugar:	Madrid, España
Fechas:	26 junio 2019 27 junio 2019
Organizador:	Association of Energy Engineers. Spain Chapter
Referencia para citas:	Gallego-Salvador, N., Aguilar, J., Garces-Jimenez, A., Gutierrez de Mesa, J. A., Gomez-Pulido, J., Garcia-Tejedor, A. (2019). A multi-HVAC system autonomic management architecture for smart buildings. IENER 2019 II Congreso de Ingeniería Energética.

3.2 VI Congreso IESTEC 2019

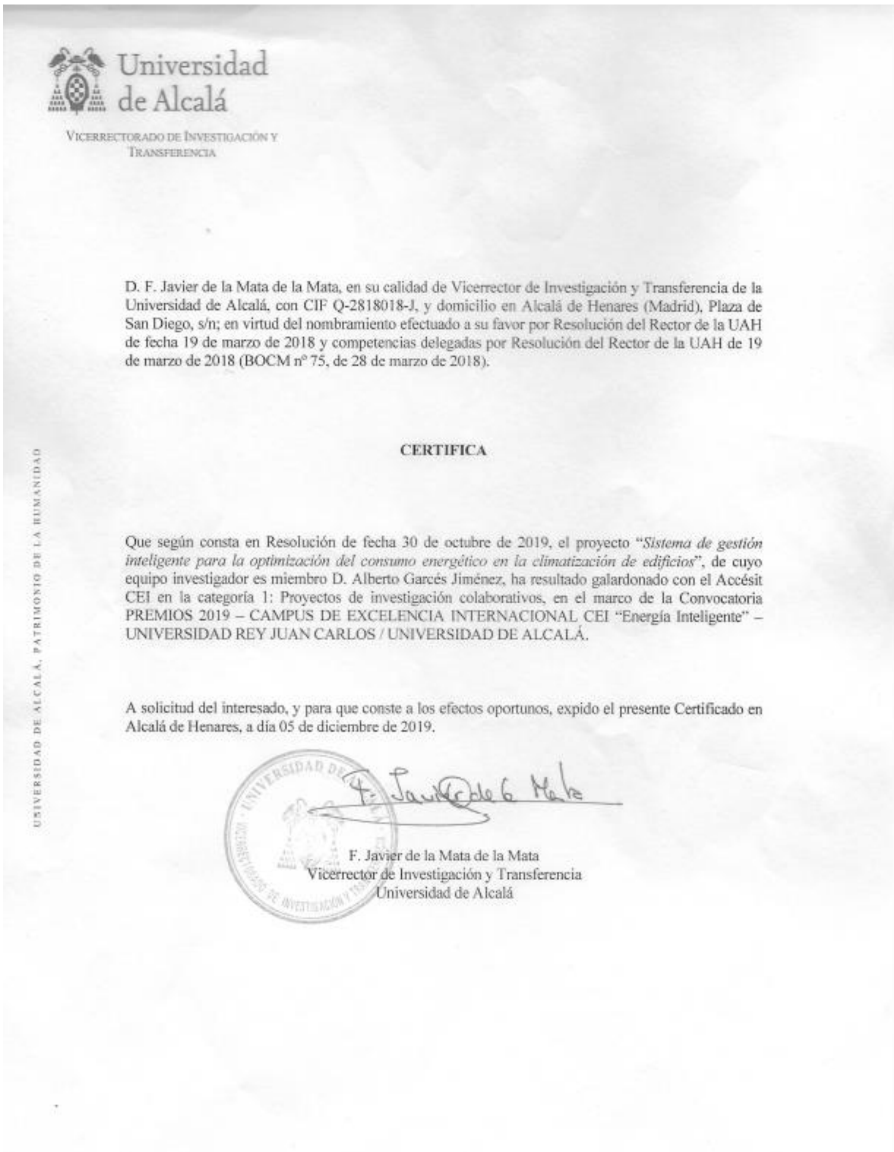
Título del Artículo:	**Propuesta de un modelo físico para sistemas de climatización múltiple de edificios para optimizar su eficiencia energética.**
Congreso:	VII Congreso Internacional de Ingeniería, Ciencias y Tecnología
Lugar:	Panamá City, Panamá
Fechas:	9 octubre 2019 11 octubre 2019
Organizador:	Universidad Tecnológica de Panamá
Referencia para citas:	Mendoza-Piti, L., Garces-Jimenez, A., Aguilar-Castro, J., Gomez-Pulido, J.M., Vargas-Lombardo, M. (2019). Proposal of Physical Models of Multi-HVAC Systems for Energy Efficiency in Smart Buildings. IESTEC 2019 VII International Engineering Sciences and Technology Conference. 9 to 11 October, Panama. DOI: 10.1109/IESTEC46403.2019.00120.

3.3 Revista RISTI

Título del Artículo:	**Influencia del régimen del neutro en la toma de tierra en la compatibilidad electromagnética para hospitales.**
Revista:	risti
Organizador:	Associação Ibérica de Sistemas e Tecnologias de Informação
ISSN:	1646-9895
Ranking:	SJR (2018): 0.217 Ranking SJR (2018): Q3
Referencia para citas:	Dominguez-Gonzalez-Seco, E.P., Gómez-Pulido, J.-M., Garces-Jimenez, A., Gomez-Gomez, D. (2019). Influence of the Electromagnetic Compatibility of the Configuration of the Neutral in Grounding Systems for Hospital. Revista Ibérica de Tecnologías de la Información N. E23, pp. 417-429

3.4 Premios

El 30 de octubre de 2019, los rectores de las Universidad de Alcalá de Henares y de la Universidad Rey Juan Carlos otorgaron un Accésit al proyecto "Sistema de gestión inteligente para la optimización del consumo energético en la climatización de edificios" en la Convocatoria de Premios 2019 - Campus de Excelencia Internacional "Energía Inteligente" en la categoría de Proyectos de Investigación Colaborativos. La cuantía del premio es de 4.000€. La línea de investigación plantea la mejora del modelo de datos empleando series temporales sobre el conjunto de eventos registrados del sistema. Este modelo contribuirá a la arquitectura en el aprendizaje en la detección de fallos y en el mantenimiento preventivo. La Figura 14 corresponde al certificado de la participación del Autor firmado por el Vicerrector de Investigación y Transferencia.



Universidad de Alcalá

VICERRECTORADO DE INVESTIGACIÓN Y TRANSFERENCIA

D. F. Javier de la Mata de la Mata, en su calidad de Vicerrector de Investigación y Transferencia de la Universidad de Alcalá, con CIF Q-2818018-J, y domicilio en Alcalá de Henares (Madrid), Plaza de San Diego, s/n; en virtud del nombramiento efectuado a su favor por Resolución del Rector de la UAH de fecha 19 de marzo de 2018 y competencias delegadas por Resolución del Rector de la UAH de 19 de marzo de 2018 (BOCM nº 75, de 28 de marzo de 2018).

CERTIFICA

Que según consta en Resolución de fecha 30 de octubre de 2019, el proyecto "*Sistema de gestión inteligente para la optimización del consumo energético en la climatización de edificios*", de cuyo equipo investigador es miembro D. Alberto Garcés Jiménez, ha resultado galardonado con el Accésit CEI en la categoría 1: Proyectos de investigación colaborativos, en el marco de la Convocatoria PREMIOS 2019 – CAMPUS DE EXCELENCIA INTERNACIONAL CEI "Energía Inteligente" – UNIVERSIDAD REY JUAN CARLOS / UNIVERSIDAD DE ALCALÁ.

A solicitud del interesado, y para que conste a los efectos oportunos, expido el presente Certificado en Alcalá de Henares, a día 05 de diciembre de 2019.

F. Javier de la Mata de la Mata
Vicerrector de Investigación y Transferencia
Universidad de Alcalá

UNIVERSIDAD DE ALCALÁ, PATRIMONIO DE LA HUMANIDAD

Figura 14. *Certificado de obtención de Accesit por investigación en Energía Inteligente de la Universidad de Alcalá y la Universidad Rey Juan Carlos de 2019*

3.5 Ayudas a la investigación

El 1 de abril de 2020, el Vicerrector de Investigación de la Universidad Francisco de Vitoria concedió una beca al Centro de Innovación Experimental del Conocimiento (CEIEC) donde colabora el Autor al Proyecto denominado “MOGA-TR: Optimización multiobjetivo para el control autónomo del sistema de climatización del Teatro Real” por valor de 6.168€.

La línea de investigación plantea resolver el problema de optimización mediante el empleo de técnicas de optimización multialgoritmo.

4 Memoria

Esta sección consta de cuatro partes en las que se explica la investigación desarrollada por el autor en cada artículo. Después se analiza la frecuencia en la que aparecen los contenidos trabajados en la literatura científica y, finalmente, se exponen las conclusiones de la Tesis con las líneas abiertas de investigación.

4.1 Aportaciones del autor

4.1.1 Primer Artículo

El primer artículo presenta una novedosa arquitectura de gestión autónoma de sistemas de climatización denominada ACODAT (*Autonomic Cycle of Data Tasks*) [53] que aprende en tiempo real del contexto con tareas de análisis de ciclos autónomos de datos. Esto da lugar a un sistema que puede automatizar decisiones estratégicas, como anticiparse al reemplazo de elementos o trabajar con los que estén en su régimen óptimo [54]. Además, al aprender del contexto en tiempo real, mejoran su precisión y adaptan sus objetivos. Los ciclos autónomos forman una arquitectura modular que, entre otras prestaciones, permiten su introducción en los sistemas de gestión reales (BMS) de forma gradual. Del mismo modo, la gestión permite ser abordada en un entorno multiagente pudiendo adaptarse a requerimientos de gestión jerárquicas que se coordinan en una ciudad inteligente [55]. La Figura 15 muestra la interacción de los distintos elementos del sistema con la inteligencia ACODAT.

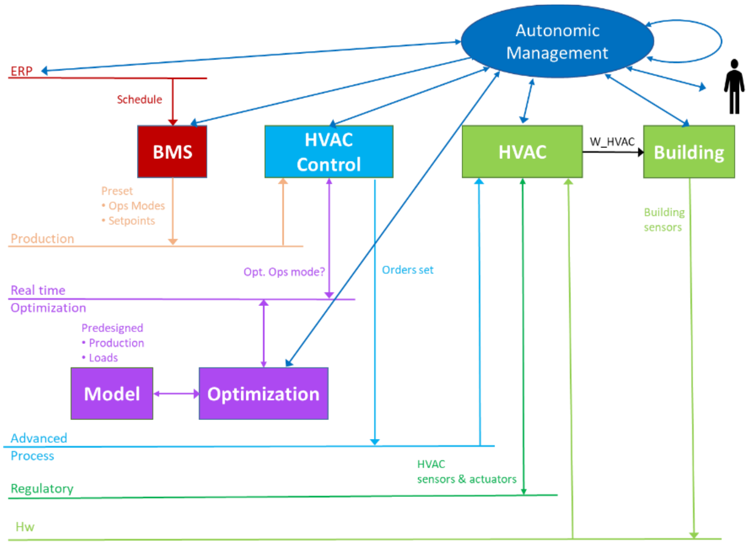


Figura 15. *La gestión es autónoma y accede a todos los elementos de la climatización del edificio.*

La gestión trabaja con un modelo predictivo, llamado multi-HVAC, que evalúa los objetivos a partir de la capacidad de las máquinas climatizadoras y la información de contexto para optimizar la energía, el confort y el coste y, además, incluye el objetivo de maximizar el rendimiento de las máquinas, apenas tratado en la literatura. La optimización multiobjetivo se realiza con GA, pero permite implementar un banco de optimizadores diferentes que aumenten la eficacia de la toma de decisiones de control y gestión. El sistema propuesto puede recibir y procesar la información de contexto, como la previsión meteorológica o realizar la contratación de la energía online directamente en subasta eléctrica, prediciendo el comportamiento mejor, con el consiguiente ahorro. Otro ciclo autónomo de datos puede calibrar las salidas de un modelo de “caja blanca”, mejorando su precisión en tiempo real [56]. Otro ciclo autónomo puede dedicarse a comprobar la degradación del rendimiento de los equipos en el tiempo [57], proporcionando ventajas de mantenimiento preventivo considerables. Esta arquitectura no solo supervisa el sistema, sino también puede incluir otro ciclo autónomo que permita su propia supervisión, regulando sus funciones básicas de autoconfiguración, auto-cuidado, auto-seguridad y auto-optimización, como indica la Figura 16.

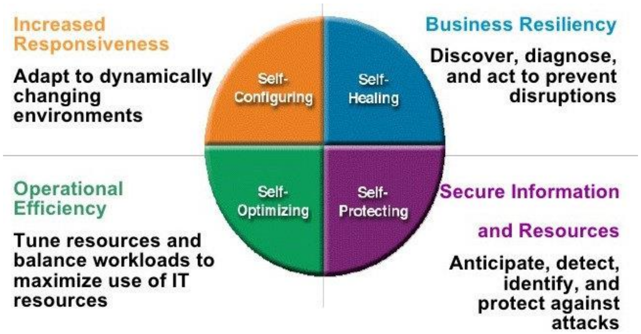


Figura 16. *Dimensiones de la autosupervisión del sistema de gestión según el modelo “Autonomic Computing”: Auto-optimización, Autoprotección, Cuidado propio, Autoconfiguración [58].*

El concepto se prueba con los datos de dos instalaciones de climatización muy diferentes, una heterogénea, compuesto de sistemas que han ido desplegándose a lo largo del tiempo en el Teatro Real de Madrid -edificio del siglo XIX- y otra homogénea con máquinas idénticas y balanceadas en el nuevo Hospital de San Pedro en Logroño mostrando su capacidad de generalización.

4.1.2 Segundo Articulo

El segundo artículo presenta un método de control avanzado, denominado LAMDA (*Learning Algorithm for Multivariate Data Analysis*) [59], basado en lógica borrosa que dota a los equipos de climatización de un edificio de mayor robustez frente a perturbaciones imprevistas, guiando rápidamente el funcionamiento del sistema a su mejor estado posible en condiciones multivariantes y descubriendo sus posibles nuevos estados sin supervisión. La Figura 17 presenta un diagrama de bloques de su funcionamiento.

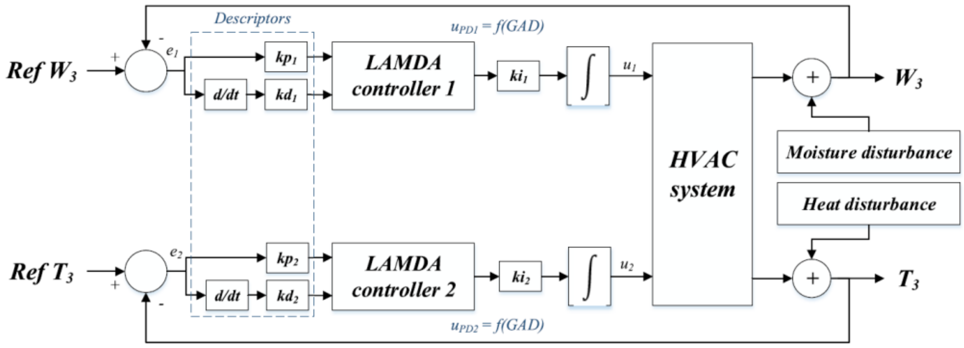


Figura 17. *Diagrama de bloques de funcionamiento del mecanismo de control avanzado LAMDA en seguimiento de dos variables W3 y T3, humedad y temperatura respectivamente.*

LAMDA es un controlador que guía al sistema hacia sus condiciones ideales, reaccionando con rapidez a cualquier tipo de perturbación y con independencia de que las no linealidades de su comportamiento. Primero averigua los estados adecuados (clases) por *clustering*, empleando lógica borrosa y aplicando las órdenes necesarias para llevarlo al mejor de ellos. El artículo lo compara con otros métodos similares observándose unos resultados en su régimen transitorio sensiblemente superiores en cuanto a la estabilidad y robustez en sistemas de climatización.

Es la primera vez que se observan los resultados con este método en su régimen transitorio ante un cambio brusco e imprevisto de contexto (variables controladas) en un subsistema de climatización de edificios. El controlador evalúa primero la adecuación de los estados (clases) de forma no supervisada y luego optimiza la regulación basándose en la similitud de los posibles estados con el más adecuado. Al comparar su comportamiento con sistemas comúnmente empleados (PI y Fuzzy-PI), se obtiene una respuesta significativamente mejor en la velocidad de adaptación y estabilidad, tal y como se muestra en la Figura 18.

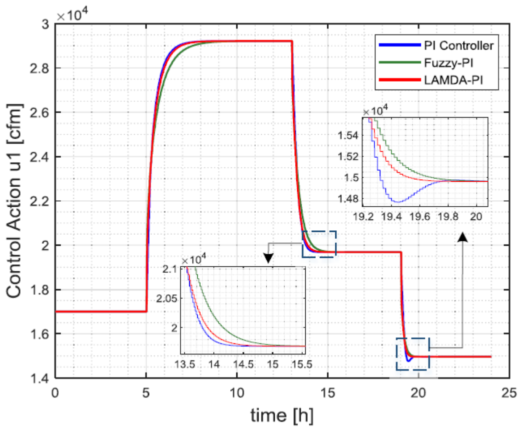


Figura 18. *Respuesta a una perturbación de un pulso de temperatura de los controladores LAMDA-PI, Fuzzy-PI y PI.*

La prueba muestra la capacidad resolutiva de *soft computing* en este caso de control multivariante en tiempo real, ahorrando un importante consumo de recursos.

4.1.3 Tercer Artículo

El tercer artículo genera modelos de datos con redes neuronales MLP para simular el comportamiento de una instalación de alumbrado público cuyas salidas serán las funciones de ajuste de la optimización del sistema. A los objetivos propios de diseño como la luminancia o la uniformidad, se podrá añadir el de ahorro energético. El modelo permite obtener resultados en el campo continuo, evitando las restricciones normativas de los programas de diseño. Se emplean diferentes perceptrones variando el número de capas, el número de neuronas y el método de aprendizaje por *backpropagation*, que se analizan atendiendo a su bondad de ajuste y a los recursos consumidos.

Como el rendimiento de cada configuración sale diferente cada vez que se realiza una partición aleatoria, se repite el experimento hasta que el resultado se estabiliza en torno a un valor medio. Es la primera vez que se realiza un análisis gráfico y analítico del aprendizaje del perceptrón. La Figura 19 proporciona el resultado gráfico de uno de los análisis a modo de ejemplo.

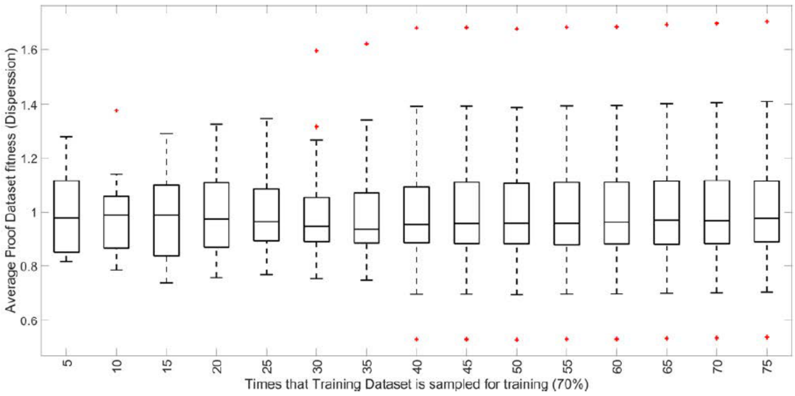


Figura 19. *Variabilidad de la degradación de la precisión de cálculo de un MLP en términos de error cuadrático medio (MSE) en función del número de repeticiones al calcular un conjunto de datos no relacionado con el de entrenamiento.*

Además del análisis de repeticiones para evaluar el aprendizaje, la investigación enriquece las técnicas de *soft computing* al evaluar por primera vez el nivel de degradación del modelo al trabajar con conjuntos de datos no relacionados con el conjunto de entrenamiento. La Figura 20 muestra el comportamiento de distintos perceptrones ante un conjunto de datos independiente del de entrenamiento.

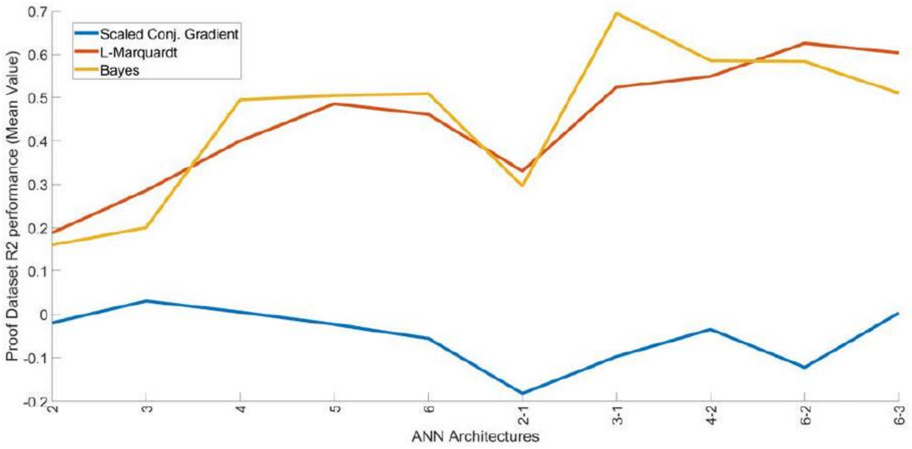


Figura 20. *Coeficiente de determinación (R2) de la precision del aprendizaje en función de los algoritmos de backpropagation empleados.*

El empleo de redes neuronales permite la adaptación a las particularidades del terreno o del momento en que opera la instalación, incluir consideraciones estéticas o elaborar propuestas con datos de entrada incompletos. La Figura 21 muestra el procedimiento que ha seguido el experimento.

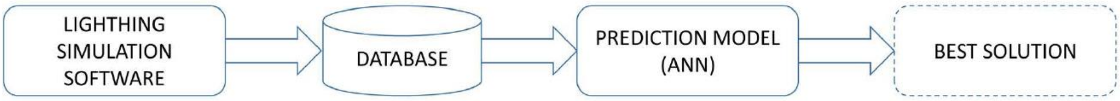


Figura 21. *Preparación del experimento que permite la evaluación de las distintas configuraciones de un MLP para simular una instalación de alumbrado público.*

4.2 Interés científico

Las técnicas de *soft computing* (SC) ofrecen un entorno de resolución de problemas complejos muy novedoso, aunque se han venido desarrollando desde hace décadas. Los avances tecnológicos han permitido volver a retomarlas y conviene observar la evolución de los conceptos clave de esta Tesis en la literatura científica, para ubicarla con perspectiva. Para ello se realiza un sencillo análisis sobre el número de publicaciones con uno de los motores de búsqueda más utilizados en el ámbito científico, Scopus, para obtener información simple, inmediata, pero suficiente para el objetivo planteado. Para ello se empieza identificando los conceptos clave de la Tesis, así como algunas combinaciones de interés documental y se obtienen sus frecuencias de publicación anuales, así como sus categorías. La Tabla 3 recoge el número total de títulos de cada concepto clave y el año de la primera publicación.

Tabla 3. Número de publicaciones y año del primer artículo con los conceptos clave de la Tesis encontrados con el motor de búsqueda de Scopus.

Concepto clave	Español	Número de artículos	Primer artículo
"HVAC"	Climatización	14.770	1969
"HVAC", "BMS"	Climatización, Gestión	1.627	1974
"HVAC", "Control"	Climatización, Control	7.445	1972
"Street Lighting"	Alumbrado Público	839	1970
"Soft Computing"	Soft Computing	23.363	1983
"Artificial Intelligence"	Inteligencia Artificial	343.151	1954
"Smart City"	Ciudad Inteligente	22.441	1983
"Smart Building"	Edificio Inteligente	3.163	1983
"Intelligent Street Light"	Alumbrado Público Inteligente	17	2011

El número de artículos sobre IA es comparativamente muy alto, 343.151 respecto de los otros conceptos. Esto es normal ya que bajo "Inteligencia Artificial" se aglutinan aplicaciones y enfoques diversos, que se han ido incorporando a lo largo de más de 6 décadas. "Climatización", "*Soft Computing*" y "Ciudad Inteligente" son también términos con un elevado número de artículos, mientras que el número de artículos de "Alumbrado Público" es escaso, 839 desde 1970 y tan solo 17 de "Alumbrado Público Inteligente" desde 2011.

A continuación, se representa en la Figura 22 la evolución temporal de los conceptos más significativos.

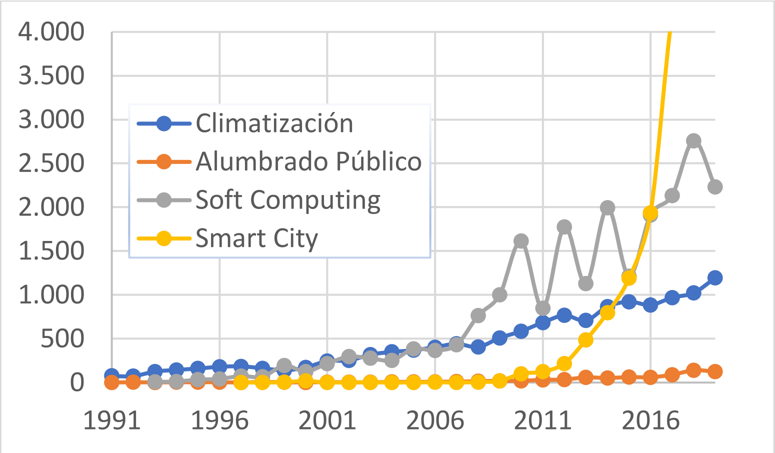


***Figura 22.** Evolución de la frecuencia de publicación de artículos encontrados con los conceptos clave de la Tesis por el motor de búsqueda de Scopus.*

Todas las frecuencias crecen, pero a diferente ritmo. Es llamativa la investigación en "*Smart City*", que se dispara de forma brusca a partir de 2010, año en que se publicaban 100 artículos, hasta los 5,000 anuales de media de los últimos 3 años. "*Soft Computing*" también incrementa la frecuencia, mostrando altibajos muy acusados. Por su parte, la frecuencia de artículos sobre “Climatización” tiene un crecimiento sostenido más discreto y lo lleva haciendo desde finales de los 90.

En la Tabla 4 se presentan el número de artículos y el año de la primera publicación para las combinaciones de conceptos de interés.

Tabla 4. *Número de publicaciones y año de aparición del primer artículo con combinaciones de conceptos relevantes de esta Tesis con el motor de búsqueda de Scopus.*

Combinaciones conceptos	Español	Número de artículos	Primer artículo
“HVAC”, “BMS”, “AI”	Climatización, Gestión, IA	65	1987
“HVAC”, “Control”, “AI”	Climatización, Control, IA	118	1987
“Street Light.”, “Optimization”	Alumbrado Público, Optimización	645	1973
“Street Light.”, “Optimization”, “AI”	Alumbrado Público, Optimización, IA	3	2017
“Smart City”, “Smart Building”	Ciudad Inteligente, Edificio Inteligente	3.050	1984
“Smart City”, “Smart Street L.”	Ciudad Inteligente, Alumbrado Inteligente	245	2012
“HVAC”, “Street Lighting”	Climatización, Alumbrado Público	3	2011
“Smart City”, “Smart Building”, “Smart Street L.”	Ciudad Inteligente, Edificio Inteligente, Alumbrado Inteligente	27	2012

Es llamativo que no aparezcan estudios con “Ciudad Inteligente”, “Edificio Inteligente” y “Alumbrado Público Inteligente”, como se combinan en esta Tesis. También destaca la escasez de artículos de “Alumbrado Público” que tratan de “IA” y “Optimización”, sólo 3, y los artículos que tratan de forma simultánea “Alumbrado Público” con “Climatización”, 3, abriendo un campo de investigación por explorar. El tratamiento de “IA” con “Gestión [de Edificios]”, aunque lleva desde 1987 apareciendo en publicaciones, tiene también un número bajo, 65 publicaciones, lo que puede suponer una oportunidad de investigación. “Alumbrado Público” y “Optimización” tienen 645 artículos publicados desde 1973, que son pocos comparativamente, pero aún menos, sólo 3 artículos desde 2017, que además contengan “IA”. La investigación en estos últimos propone prototipos que ajustan automáticamente la iluminación en cada punto en función del usuario (peatón, ciclista o conductor de automóvil) [60], a través de comunicaciones inalámbricas entre puntos, y que permiten también rastrear el consumo.

Esta Tesis propone un concepto nuevo, **Smart BMS** (*Smart Building Management System*), que consistiría en la aplicación de técnicas de IA a la supervisión inteligente de los sistemas de edificios. El término se diferencia del concepto original de BMS en que emplea principalmente IA en el análisis de la información, en la toma de decisiones autónoma, en la interacción con el usuario, se adapta al entorno, pudiendo coordinarse con otros agentes o gestionar sistemas heterogéneos, proporcionando una funcionalidad de calidad al usuario.

La Figura 23 muestra la evolución de la frecuencia de anual de publicaciones de los principales conceptos combinados.

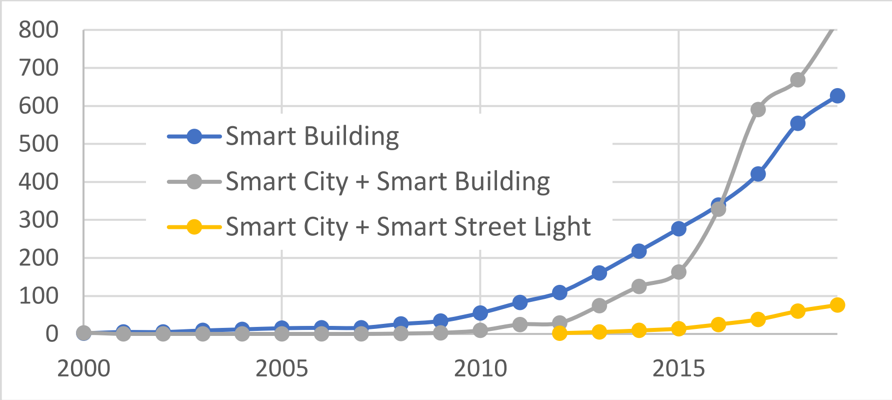


Figura 23. *Evolución de la frecuencia de publicación de artículos relacionados con las tecnologías smart que se tratan en esta Tesis obtenidos con el motor de búsqueda de Scopus.*

La frecuencia de "Alumbrado Público Inteligente" crece al combinarse con "Ciudad Inteligente" y deja ver una tendencia de convertirse en uno de sus bloques funcionales [61]. De la misma manera la frecuencia de artículos con "Edificio Inteligente" se ven potenciados al combinarse con "Ciudad Inteligente".

Por otro lado, Scopus informa de una serie de categorías asociadas con cada artículo, como "Energía", Matemáticas" o "Economía". Por ejemplo, la búsqueda de "HVAC" y "*Control*" ha encontrado 7.445 artículos para los cuales se identifican estas categorías:

- Energía: 1.471 artículos
- Medioambiente: 1.029 artículos
- Informática: 1.247 artículos
- Ingeniería: 5.631 artículos
- Matemáticas: 646 artículos
- Ciencias de la Decisión: 66 artículos

La suma de estos artículos es 10.090, que es mayor que el número de artículos encontrados, 7.445, ya que algunos de ellos se ven incluidos en 2 o más categorías. Se relacionan entonces las categorías entre sí considerando todas las búsquedas de conceptos relacionados con la Tesis y de sus combinaciones por si pudiese observarse algún aspecto de interés. Para ello, se relativizan antes las frecuencias con el número total de cada búsqueda. Siguiendo con el ejemplo anterior, la incidencia normalizada de la categoría "Energía" en los artículos encontrados con los conceptos "*Control*" y "HVAC" es:

$$Inciedencia_{Energia} = \frac{Articulos_{Energia}}{Articulos} = \frac{1471}{10090} = 0{,}146 \; para \; '\mathrm{Control}' \; y \; '\mathrm{HVAC}'$$

Tras normalizar se correlacionan las categorías entre sí obteniéndose la Tabla 5.

Tabla 5. *Matriz de correlaciones entre las categorías de los artículos encontrados con los conceptos de esta Tesis. Cuanto más verde más relación positiva y cuanto más rojo, más negativa (Heat map).*

Correlación	Energía	Medioambiente	Informática	Ingeniería	Matemáticas	Decisión
Energía	1,000	-0,023	-0,458	0,446	-0,504	-0,408
Medioambiente	-0,023	1,000	-0,784	0,722	-0,743	-0,376
Informática	-0,458	-0,784	1,000	-0,968	0,790	0,597
Ingeniería	0,446	0,722	-0,968	1,000	-0,770	-0,718
Matemáticas	-0,504	-0,743	0,790	-0,770	1,000	0,368
Decisión	-0,408	-0,376	0,597	-0,718	0,368	1,000

Los valores más próximos a 1 indican coincidencia de las categorías en los mismos artículos, mientras que los próximos a -1 indican que las coincidencias en un mismo artículo son escasas. Observando el *heatmap* se pueden extraer las correlaciones más relevantes, tanto positivas (+) como negativas (-), que se representan ordenadas en la Tabla 6.

Tabla 6. *Correlaciones más altas entre categorías de artículos relacionados con conceptos que se tratan en la Tesis. En rojo se representan las negativas (-).*

corr(Informática, Matemáticas)	0,790
corr(Medioambiente, Ingeniería)	0,722
corr(Informática, Decisión)	0,597
corr(Informática, Ingeniería)	-0,968
corr(Medioambiente, Informática)	-0,784
corr(Ingeniería, Matemáticas)	-0,770
corr(Medioambiente, Matemáticas)	-0,743
corr(Ingeniería, Decisión)	-0,718

La mayor relación en términos absolutos se da entre las categorías “Informática” e “Ingeniería”, -0,968. Al ser negativa, indica que raramente aparecen ambas en los mismos artículos. “Informática” aparece razonablemente relacionada con “Matemáticas” y con “Ciencias de la Decisión”, 0,790 y 0,597 respectivamente. Por su parte, resulta llamativa la relación entre “Ingeniería” y “Medio Ambiente” con una correlación de 0,722, debido a que la temática de la Ingeniería es más técnica (Mecánica, Aeronáutica, Construcción, Civil, Bioingeniería, Ingeniería Química o Industrial) y la de las Ciencias del Medio Ambiente, más social (Desarrollo Sostenible, Paisajismo, Protección de la tierra, Impactos Medioambientales de las Inversiones, Hidrología o Ecología).

Aun tomando las precauciones necesarias de la categorización semiautomática de Scopus, puede pensarse en un nuevo término, derivado de la innovación de esta Tesis, con potencial investigador, denominado **"Ingeniería Inteligente" ("Smart Engineering"),** que puede definirse como la mejora de la calidad en la construcción y explotación de los sistemas de ingeniería mediante la IA para mejorar las condiciones de vida de la sociedad y el respeto al entorno.

4.3 Conclusiones y trabajo futuro

La presente Tesis propone nuevas aplicaciones de SC sobre instalaciones de alto consumo de acuerdo con los principios de una *Smart City*. Podría parecer redundante combinar el enfoque de una "*Smart City*" y sus bloques "*Smart Building*" y "*Smart Street Lighting*" con las técnicas de "*Soft Computing*" al estar tan caracterizadas por el uso de tecnologías de IA, pero la intención investigadora de esta Tesis necesita mantener ambas aproximaciones. La ciudad inteligente tiene objetivos sociales transcendentes, como la sostenibilidad y la calidad de los servicios, mediante la aplicación de la tecnología para conseguir mejorar la eficiencia energética. El edificio inteligente concreta más este objetivo centrándose en la gestión avanzada de sus sistemas, mediante el control, la automatización, la optimización y la supervisión. El alumbrado público inteligente, centra sus avances en la adaptación automática del servicio al usuario. Por su parte, SC emplea cálculos y razonamientos aproximativos para resolver en tiempos razonables problemas complejos, dinámicos, no lineales y que requieren adaptación a contextos inciertos.

Habiendo encontrado en la revisión bibliográfica escasos artículos, como el de Hobby et al. [61], que aborden la mejora de la eficiencia energética desde este enfoque combinado, se ha propuesto la definición por primera vez del término INGENIERÍA INTELIGENTE, o *Smart Engineering*, en el que quedan contenidos aquellos ámbitos de la ingeniería inspirada en la sostenibilidad y la calidad del servicio que son susceptibles de mejora con tecnologías de IA.

Con esta visión, el recorrido conclusivo por los artículos expuestos comienza con la nueva arquitectura de gestión autónoma, ACODAT concebida para mejorar la eficiencia energética. Sus ciclos autónomos emplean SC para optimización multiobjetivo del control con modelos de predicción de caja blanca y caja negra basados en el nuevo concepto de hibridación multi-HVAC. El sistema mantiene y mejora la calidad del servicio, maximizando el confort de los usuarios, ahorrando costes gracias al menor consumo energético, a la mejora de los ciclos de vida del equipamiento y a su propio funcionamiento autónomo. Además, monitoriza degradaciones imperceptibles de los equipos lo que permite anticipar soluciones y reducir significativamente los costes de las averías. La mejora de la calidad del servicio, el ahorro y la sostenibilidad son características propias de la ciudad y edificios inteligentes.

El control avanzado LAMDA combina de forma novedosa técnicas SC en equipos de climatización superando la robustez de otros controladores comúnmente utilizados. El controlador se adapta a las no linealidades del sistema, proporcionando una reacción más rápida que otros métodos similares. A diferencia de otros mecanismos de lógica borrosa, su aprendizaje no supervisado permite la adaptación en tiempo real a cualquier perturbación sin aumentar exponencialmente la complejidad de computación. La aplicación de LAMDA se desarrolla en el enfoque de edificio inteligente, al regular el sistema hacia el confort con mayor celeridad y consumir menos recursos.

Finalmente, se analiza de forma sistemática el rendimiento de múltiples configuraciones de una red neuronal MLP consiguiendo indicadores estables que permiten seleccionar la mejor opción para modelar un sistema de alumbrado público en cuanto a la precisión y al consumo de recursos computacionales. Así, se catalogan los métodos de aprendizaje por *backpropagation*, el número de neuronas y el de capas. Los resultados permiten plantear la adaptación permanente del modelo al terreno y al momento con aprendizajes en tiempo real. Las redes neuronales mejoran su eficacia cuanto más cubre el conjunto de entrenamiento los casos posibles. Por eso, se presenta como primicia una evaluación cuantitativa de cómo se degrada la predicción al aplicar al modelo casos alternativos fuera del espacio de soluciones del conjunto de entrenamiento. Con ello se cumple el doble objetivo de estimar el grado de precisión ante entornos nuevos y de conocer la capacidad del sistema para recalibrarse. El alumbrado público inteligente ha estado muy centrado en adaptarse al tipo de usuario (peatón, motorista, conductor o ciclista), mientras que esta investigación, gracias a las sinergias con edificios inteligentes, inspira nuevos enfoques en Ingeniería Inteligente.

A continuación, se presenta un resumen de las conclusiones expuestas en la Tabla 7.

Tabla 7. *Resumen de conclusiones.*

Técnicas y objetivos	**Objetivos Smart City**	**Técnicas Soft Computing**	**Resultado**
Artículo 1	**Smart Building**: reduce la energía consumida, ahorra costes de energía y de mantenimiento y maximiza el confort de los usuarios.	**Agentes computacionales**: aprenden en tiempo real, autogestionados y con capacidad de integrar entornos más amplios en estrucutra multiagente. **Modelos predictivos de datos**: que permiten una adaptación inmediata al emplear recursos computacionales reducidos y detectar cambios sutiles en el rendimiento a lo largo de la vida útil. **Algoritmo genético de optimización multiobjetivo**: que establece mediante una decisión apriorística la ponderación de cada objetivo en función de las situaciones y usos del edificio.	**ACODAT:** arquitectura de gestión de sistemas de climatización de edificios. **multi-HVAC**: modelo de climatización de edificios general.
Artículo 2	**Smart Building**: acelera la transición al confort y ahorra recursos computacionales.	**Clustering**: que permite una rápida adaptación de los estados potenciales del sistema para afrontar las perturbaciones imprevistas. **Lógica borrosa:** que permite decisión más rápidas hacia las mejores condiciones de funcionamiento, manteniendo razonablemente bajos los recusos computacionales.	**LAMDA:** control avanzado de sistemas de climatización de edificios.
Artículo 3	**Smart Street Lighting**: mejora la eficiencia energética, permite plantear nuevos objetivos más humanos y obtener soluciones con requerimientos incompletos.	**Redes neuronales**: que proporcionan una función de ajuste para algoritmos de optimización que se adapta al terreno y al momento evaluando la degradación respecto de la extrapolación de nuevos casos.	**Análisis MLP:** rendimiento de simulación de sistemas de alumbrado.

En cuanto al futuro es interesante considerar la aplicación del enfoque aproximativo de SC a la mejora de la eficiencia energética a las fases de explotación y diseño de forma conjunta y desarrollar mecanismos automáticos de intercambio de experiencia o aprendizaje entre ambas. Básicamente, se implementarán nuevas funcionalidades de IA mediante ciclos autónomos de datos en un entorno de gestión autónoma con capacidad de coordinación multi-agente con otros sistemas bien en su ámbito (el propio edificio o la sección de alumbrado), bien en un ámbito de cooperación (otros edificios, secciones de alumbrado o sistemas de la ciudad), mejorando en tiempo real su rendimiento y proporcionando apoyo a la decisión a medio y largo plazo. Su concepción modular permite empaquetar las funcionalidades de servicio y las internas del sistema en componentes diferenciadas que luego se incorporarán o retirarán gradualmente.

La Figura 24 ofrece el ámbito de la investigación en forma de itinerario en la que se muestran los paquetes de trabajo y sus dependencias sobre los planos de explotación y de diseño.

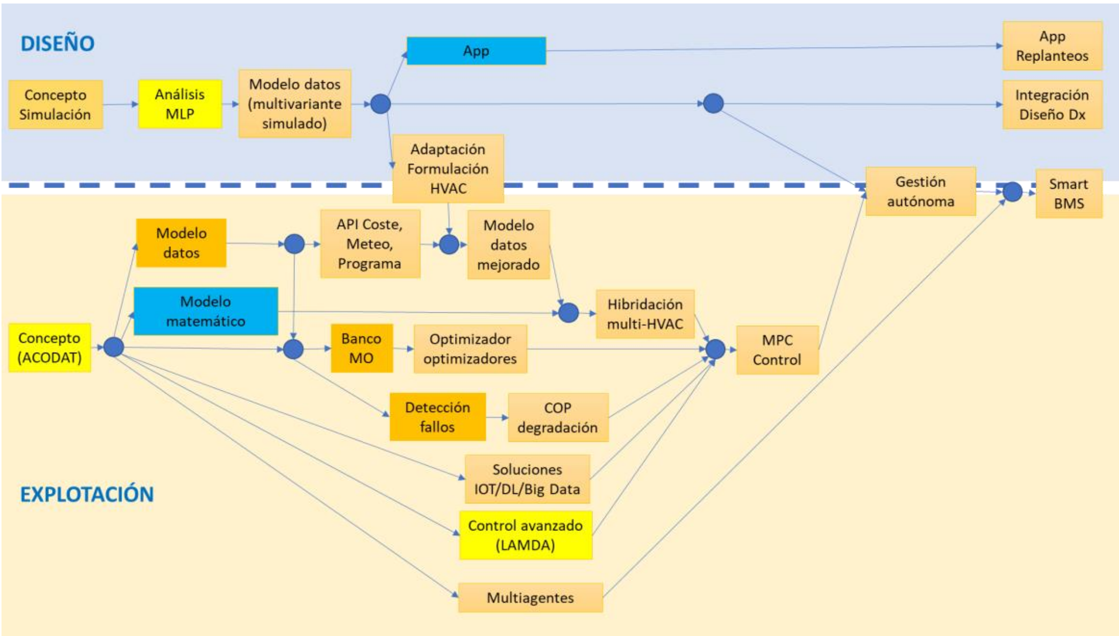


Figura 24. *Secuencia de paquetes de investigación del proyecto de Ingeniería Inteligente en el que se enmarca esta Tesis. Los bloques en amarillo son los artículos presentados*

Cada bloque constituye un paquete de trabajo con un resultado investigador. Las flechas indican una precedencia orientativa de unas investigaciones frente a otras. Los bloques amarillos son los resultados ya alcanzados con los artículos publicados, mientras que los colores anaranjados más oscuros indican un grado de madurez superior en la investigación. Los bloques de color azul son trabajos que de alguna forma ya se han realizado por parte de otros grupos investigadores.

Se está investigando un sistema de detección de fallos con varios ciclos de aprendizaje supervisado y no supervisado que monitorice el deterioro gradual de los equipos y permita asociaciones no predefinidas de eventos para el diagnóstico avanzado de averías y la gestión estratégica (a medio y largo plazo). Se plantea el análisis de ciclos autónomos que trabajen coordinados con los existentes pero dedicados a la auto-supervisión del sistema, de modo que pueda configurarse o protegerse. También se implementarán ciclos autónomos de comunicación, colaboración y orquestación para trabajar en entornos cooperativos multi-agente.

En cuanto a los modelos predictivos, también se analizarán las mejoras que aporte la cooperación con modelos de series temporales y redes neuronales recurrentes (RNN). También se trabaja en automatizar la lectura de información de contexto exterior al sistema mediante API inteligentes que negocien las tarifas eléctricas en subasta *online* o recojan automáticamente la predicción meteorológica.

A nivel de control, se probará un banco de optimizadores con algoritmos metaheurísticos que trabajen en paralelo generando múltiples frentes de Pareto para aproximar más rápidamente a la solución ideal. Podrán programarse políticas de decisión que primen unos objetivos sobre otros según la información contextual. Además, se está completando la investigación sobre la estabilidad del control avanzado LAMDA aplicada a los sistemas de climatización.

En el ámbito de la iluminación se ampliará el análisis sistemático a modelos neuronales con múltiples salidas. A semejanza de la climatización, se van a probar algoritmos evolutivos de optimización que permitan diseños más eficientes con datos incompletos. Se desarrollará una aplicación para dispositivos móviles con interfaz mejorada para realizar replanteos. Se investigarán los requerimientos para que una API permita la comunicación automática con los simuladores de diseño actuales.

La intención del Autor es la de haber contribuido con su trabajo, consciente de las limitaciones de los avances propuestos, a presentar un panorama de gran potencial investigador para el beneficio de la sociedad y el respeto a su entorno.

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