UNIVERSIDAD DE EXTREMADURA

TESIS DOCTORAL

APLICACIÓN DEL MODELO ESTOCÁSTICO DE MARKOV PARA PREDECIR LA DEGRADACIÓN DE INFRAESTRUCTURAS HOSPITALARIAS

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PROGRAMA DE DOCTORADO EN MODELIZACIÓN Y EXPERIMENTACIÓN EN CIENCIA Y TECNOLOGÍA

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2022

AGRADECIMIENTOS

Me gustaría expresar mi agradecimiento a todas aquellas personas e instituciones que me han apoyado y ayudado durante el desarrollo de esta Tesis Doctoral.

En primer lugar, agradecer a mi Director de Tesis, Justo García, por animarme a iniciar mi camino hacia la investigación y por acompañarme en este proceso, con una gran motivación, esfuerzo y conocimiento. Agradecer a mi amigo y compañero Gonzalo por su gran ayuda y guía y a todos los compañeros del departamento que me han acompañado día a día y me han apoyado durante el desarrollo de este trabajo.

En segundo lugar, agradecer a mis padres por todo el apoyo durante mi formación y por su enorme esfuerzo por comprenderme y motivarme para alcanzar mis metas. Especialmente, agradecer a mi hermano por ser un gran ejemplo y por sus buenos consejos y a Marisol por su confianza y apoyo incondicional. También, agradecer a toda mi familia y amigos que me han acompañado durante esta etapa y que se alegrarán de todo lo que consiga.

Asimismo, me gustaría agradecer a la Fundación Fernando Valhondo Calaff por su apoyo a este trabajo a través de la financiación de mi contrato predoctoral y al Fondo Europeo de Desarrollo Regional por financiar las investigaciones a través del expediente GR18029 ligado al VI Plan Regional de Investigación, Desarrollo Tecnológico e Innovación de la Comunidad Autónoma de Extremadura.

Finalmente, agradecer a la Universidad de Évora y, especialmente, a los profesores Dr. Nuno de Sousa Neves y Dr. Joao Paulo de Almeida Fernandes por su acogida en la "Escola de Ciências e Tecnologia" para realizar parte de las investigaciones de esta Tesis Doctoral.

Resumen

Más de la mitad de los costes operativos de un edificio se generan durante su vida útil, incrementándose notablemente en edificios sanitarios debido a que son edificios de elevada intensidad y tienen un funcionamiento continuo durante las 24 horas del día. Los edificios sanitarios disponen de instalaciones y equipos complejos y costosos, siendo necesario un nivel de mantenimiento elevado que asegure la calidad del servicio sanitario. La crisis sanitaria de la COVID-19 ha evidenciado esta necesidad, siendo la fiabilidad de los edificios, instalaciones y equipos fundamental para garantizar la bioseguridad de sus usuarios. Por tanto, es imprescindible establecer protocolos de mantenimiento optimizados, donde se especifique las estrategias de mantenimiento más adecuadas.

El objetivo de la Tesis Doctoral es optimizar las tareas de mantenimiento realizadas sobre las partes críticas de los edificios sanitarios, instalaciones hospitalarias y equipos electromédicos, aplicando una metodología estocástica basada en las Cadenas de Markov y estableciendo operaciones de mantenimiento que permitan alargar la vida útil de los sistemas, garantizar su funcionalidad y aumentar la seguridad de los usuarios.

Las Cadenas de Markov es una técnica de predicción actualizable, que permite estimar el estado de condición de un determinado sistema simulando su proceso de degradación. De esta forma, es posible evaluar la degradación de los distintos elementos críticos de un edificio sanitario a lo largo del tiempo, tomando decisiones de mantenimiento en base a información contrastada. La metodología desarrollada en esta investigación amplía los conocimientos existentes sobre la optimización del mantenimiento, permitiendo aumentar la vida útil de los edificios, instalaciones y equipos sanitarios. Además, permite reducir los costes de mantenimiento, incrementando la sostenibilidad operativa del sistema sanitario garantizando una elevada fiabilidad.

La principal contribución de la Tesis Doctoral es la aplicación del modelo estocástico de las Cadenas de Markov para modelar la degradación y optimizar el mantenimiento de infraestructuras hospitalarias, permitiendo mejorar la toma de decisiones de los técnicos e incrementar la operatividad. A través de los modelos predictivos, se analizó la influencia del mantenimiento preventivo en el estado de condición de un sistema, obteniendo el año óptimo en el que se debe iniciar el mantenimiento para distintos escenarios y estableciendo la frecuencia con la que debe realizarse el mantenimiento de reparación o reemplazo para garantizar un valor mínimo de fiabilidad previamente definido.

La aplicación del modelo de Markov permitió determinar la frecuencia y estrategia óptima del mantenimiento de ronda de los centros de salud en función de las incidencias no urgentes mensuales, reduciendo el impacto económico y medioambiental asociado al transporte del equipo de mantenimiento. Además, se comprobó que el modelo de degradación es una herramienta adecuada para cuantificar el incremento de vida útil de un sistema y comparar diferentes soluciones constructivas en base a su fiabilidad, incrementando

el nivel de mantenibilidad de las infraestructuras hospitalarias. Por otro lado, se contrastó una metodología de análisis semiparamétrico para identificar y cuantificar la influencia de distintos factores sobre un determinado evento, mejorando la precisión del modelo de degradación de las Cadenas de Markov y el análisis de los distintos escenarios.

El conocimiento generado en la Tesis Doctoral es útil para los gestores de mantenimiento de los edificios sanitarios y los servicios de planificación y gestión de los sistemas de salud, ya que permiten establecer criterios de diseño que mejoran la infraestructura de los edificios sanitarios. Además, permiten tomar decisiones óptimas durante el funcionamiento de edificios y sus equipos, abarcando todo su ciclo de vida.

Abstract

More than half of a building's operating costs are generated during its service life. Those costs increase significantly in healthcare buildings because they are high-intensity buildings and operate continuously 24 hours a day. Healthcare buildings have complex and costly installations and equipment, and they require strong maintenance measures to ensure healthcare services quality. The recent healthcare crisis has highlighted this need, and reliabilities of buildings, facilities, and equipment have been found fundamental to ensure users biosecurity. Therefore, it is essential to establish optimised maintenance protocols by specifying the most appropriate maintenance strategies.

The objective of this Doctoral Thesis is to optimise maintenance operations carried out on the critical parts of healthcare buildings, hospital installations and electromedical equipment, applying a stochastic methodology based on Markov Chains. Consequently, maintenance operations will be established in order to extend systems service life, ensuring their functionality, and increasing the safety of the users.

Markov Chains is an updateable prediction technique, which allows estimating the condition state of a given system by simulating its degradation process. Thus, it is possible to evaluate the degradation of critical elements of a healthcare building over time, making maintenance decisions based on contrasted information. The methodology developed in this research expands the existing knowledge on maintenance optimisation, increasing the service life of buildings, facilities, and healthcare equipment. In addition, maintenance costs have been proven to be reduced by increasing the healthcare system operational sustainability and guaranteeing high reliability values.

The main contribution of this Doctoral Thesis is the application of the stochastic Markov Chain models to assess the degradation and to optimise the maintenance of hospital infrastructures, in order to improve decision-making policies by technical staff and to increase operability conditions. By using predictive models, the influence of preventive maintenance on a system condition state was analysed, and the optimal year in which maintenance should be started was obtained for different scenarios. In addition, the frequency of repairing or replacement maintenance was determined to guarantee a predefined minimum reliability value.

The application of the Markov model allowed to determine the optimal frequency and strategies for maintenance rounds in healthcare centres based on monthly non-urgent incidents, reducing the economic and environmental impact associated with maintenance staff mobility. Moreover, the degradation model was found to be a useful methodology to quantify the increase in the service life of a system. Also, different construction solutions were compared based on their reliability, in such way the level of maintainability of hospital infrastructures was increased. Furthermore, a semi-parametric analysis methodology was tested to identify and quantify the influence of different factors on a given event, so that

Markov Chain degradation models accuracy and the analysis of the different scenarios could be improved.

The knowledge generated in this Doctoral Thesis is useful for healthcare building maintenance managers and health system management services, since it allows them to establish design criteria that improve the infrastructure of healthcare buildings. In addition, it allows optimal decisions to be made during the operation of buildings and their equipment, covering their entire life cycle.

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Capítulo 1. Introducción

1.1. Preámbulo

Entre la oferta de Programas de Doctorado recogidos en el Real Decreto 99/2011, de 28 de enero, por el que se regulan las enseñanzas oficiales de doctorado, modificado por los Real Decreto 534/2013, de 12 de julio, Real Decreto 43/2015, de 2 de febrero, y Real Decreto 195/2016, de 13 de mayo; esta Tesis Doctoral se encuadra en el programa "Modelización y Experimentación en Ciencia y Tecnología", ya que incluye investigación aplicada en el campo de la Ingeniería.

La elaboración de esta Tesis Doctoral se ha llevado a cabo bajo los criterios establecidos por el artículo 33 "Tesis doctorales presentadas como compendio de publicaciones" y por el artículo 43 "Mención Internacional", de la Resolución de 14 de diciembre de 2021 (DOE de 28 de diciembre de 2021), que aprueba la Normativa de Doctorado de la Universidad de Extremadura. En dicha Resolución se exponen los requisitos necesarios para la publicación de la Tesis Doctoral por compendio de publicaciones y los requisitos para que el título de Doctor pueda incluir la mención de Doctorado Internacional.

1.2. Coherencia e importancia unitaria de la Tesis Doctoral

La presente Tesis Doctoral se compone de un total de cinco artículos científicos que tienen un objetivo general común: la optimización del mantenimiento de las infraestructuras y equipos hospitalarios para garantizar la calidad de la asistencia sanitaria. A partir de estos artículos científicos se cumplen con todos los objetivos definidos en el Capítulo 2. Estos estudios se enmarcan en una misma línea de investigación, la Ingeniería Hospitalaria; más concretamente, las publicaciones tienen una línea común: la evaluación de las estrategias y la frecuencia del mantenimiento del sistema sanitario, centrándose en la aplicación de las Cadenas de Markov para desarrollar un modelo de degradación que permita optimizar las tareas de mantenimiento. La aplicación de las Cadenas de Markov se ha realizado en distintos niveles del sistema sanitario: en centros de salud y en hospitales. Además, se validó una metodología semiparamétrica para evaluar la influencia de las variables operacionales sobre problemas complejos dentro de la Ingeniería Hospitalaria y se propuso como complemento al modelo de degradación de Markov, facilitando el proceso de desarrollo del modelo y permitiendo obtener resultados más precisos y fiables.

Todas las revistas en las que se han publicado los artículos están indexadas en la *Web of Science* (WOS) del *Institute for Scientific Information* (ISI) y dentro de los recursos de investigación del *Journal Citation Reports* (JCR), concretamente en la base de datos de *Science Citation Index* (SCI). De los cinco artículos que componen el compendio de la Tesis Doctoral, tres se encuentran en el primer cuartil y dos en el segundo cuartil. El título de los artículos que conforman el compendio se muestra en la Tabla 1.

Tabla 1. Relación de artículos científicos del compendio de publicaciones

Identificación	Título
Artículo 1	Markov model of computed tomography equipment
Artículo 2	Scheduling of preventive maintenance in healthcare buildings using Markov chain
Artículo 3	Preventive maintenance optimisation of accessible flat roof in healthcare centres using the Markov chain
Artículo 4	Condition-based maintenance of ceramic curved tiles roof in Primary Healthcare buildings using Markov chains
Artículo 5	Cox proportional hazards model used for predictive analysis of the energy consumption of healthcare buildings

La Tesis Doctoral se ha organizado en cinco Capítulos, cuyos contenidos son los siguientes:

En el Capítulo 1 se realiza un análisis exhaustivo de las principales investigaciones relacionadas con las Cadenas de Markov en edificación y en el mantenimiento de infraestructuras hospitalarias, permitiendo evaluar en profundidad sus principales necesidades y generar conocimiento útil para la comunidad científica.

En el Capítulo 2 se presenta el objetivo general de la Tesis Doctoral, los objetivos específicos planteados, los objetivos complementarios propuestos y se expone la metodología implementada en la investigación para el desarrollo de los modelos de degradación y la optimización de las operaciones de mantenimiento. Además, se muestra la herramienta complementaria al modelo de Markov que permitirá mejorar la identificación de las variables que afectan a la degradación de un sistema.

En el Capítulo 3 se presentan las cinco publicaciones que conforman el compendio de artículos de la Tesis Doctoral, mostrando los indicios de calidad de las publicaciones, un resumen de cada una y los principales resultados obtenidos.

En el Capítulo 4 se discuten los resultados obtenidos en la presente investigación, estableciendo las principales contribuciones, el alcance de los resultados y sus limitaciones.

En el Capítulo 5 se exponen las conclusiones de la Tesis Doctoral y se presentan las líneas de trabajo futuras derivadas de la investigación, destacando la utilidad del conocimiento generado para la gestión de edificios, instalaciones y equipos sanitarios y para la comunidad científica.

Los resultados desarrollados en la presente Tesis Doctoral tienen un elevado impacto en la gestión de las infraestructuras hospitalarias, ya que permite optimizar el mantenimiento de los edificios existentes y mejorar la calidad de los edificios sanitarios de nueva construcción, reduciendo los recursos destinados para su correcta operatividad.

1.3. Antecedentes y estado del arte

1.3.1. La Ingeniería Hospitalaria

La Ingeniería Hospitalaria se define como la ingeniería que interviene en todos los aspectos de la prevención, el diagnóstico, el tratamiento y la gestión de la enfermedad, así como la conservación y la preservación y mejora de la salud física y mental y el bienestar [1]. Esta disciplina se centra en la gestión, diseño, desarrollo e implementación de técnicas y tecnologías en el entorno hospitalario, desempeñando un papel importante en la mejora y el avance de la atención sanitaria. La complejidad de las infraestructuras hospitalarias y el amplio alcance de la ingeniería incrementa la necesidad de trabajar con equipos multidisciplinares para su análisis y optimización [2].

Debido a la naturaleza cambiante del sistema sanitario y a la necesidad de mejora continua de su tecnología, la Ingeniería Hospitalaria tiene como objetivo principal lograr una infraestructura sostenible que se adapte a las nuevas necesidades sociosanitarias [3], e incluye la gestión del mantenimiento de los equipos, instalaciones y elementos constructivos, garantizando a corto y largo plazo la seguridad del entorno asistencial.

La Ingeniería Hospitalaria tiene diferentes grupos de interesados: pacientes, visitantes, personal administrativo y personal sanitario [4]. La crisis sanitaria generada por la pandemia del COVID-19 ha aumentado la influencia de estos interesados sobre la sociedad, incrementando la importancia del correcto funcionamiento de los edificios sanitarios y la satisfacción de sus usuarios para garantizar la calidad de la atención sanitaria [5].

1.3.2. El edificio sanitario

Los edificios sanitarios disponen de una infraestructura compleja, que incluye equipamiento de alta tecnología para realizar una atención de calidad, estando ubicados en distintas localizaciones seleccionadas por la proximidad a los pacientes y, en consecuencia, se encuentran dispersos entre sí [6]. Estos edificios están operativos las 24 horas del día, los 365 días del año, provocando que su consumo sea muy elevado [7]. Por otro lado, debido a la criticidad de su actividad, es fundamental que el estado operativo y el mantenimiento de los edificios sea adecuado, incrementando su coste y dificultando su gestión y optimización [8]. Además, son edificios complicados de mantener, ya que están dotados de instalaciones y equipamientos complejos y costosos, cuyo correcto funcionamiento condiciona la calidad de los servicios que presta [9].

Los edificios sanitarios pueden dividirse según su actividad asistencial en hospitales y centros de salud. Por un lado, los hospitales son edificios con una infraestructura y recursos adecuados para realizar una asistencia sanitaria especializada. Más concretamente, son edificios diseñados para prevenir, diagnosticar y tratar enfermedades, dividiéndose principalmente en consultas externas, centros de especialidades, áreas de hospitalización y unidades especiales como: diálisis, unidades quirúrgicas, unidades de cuidados intensivos (UCI), urgencias, etc. [10].

Por otro lado, los centros de salud son edificios diseñados para desarrollar acciones de promoción, prevención y rehabilitación relacionadas con la atención primaria de la salud. Estos últimos se diferencian de los hospitales en que no disponen de hospitalización y no realizan intervenciones quirúrgicas [11]. En España, cada centro de salud atiende a un número determinado de pacientes, que suele oscilar entre 4.000 y 20.000 aproximadamente [12].

1.3.3. Consumo energético de los edificios sanitarios

El consumo energético de los edificios sanitarios es muy superior a otros tipos de edificios públicos, debido a su operación ininterrumpida y a sus necesidades asistenciales [13]. A pesar de que el consumo energético de los edificios está creciendo durante los últimos años, se observa cierto estancamiento debido a las acciones de eficiencia energética cada vez más extendidas [14].

Existen diferentes investigaciones que han analizado la eficiencia energética de los edificios sanitarios. Balali y Valipour [15] identificaron y jerarquizaron varias estrategias pasivas eficientes para el diseño de hospitales y centros de salud. Ede *et al.* [16] también exploraron oportunidades de mejora de la eficiencia energética de edificios sanitarios. Asimismo, la implantación de sistemas híbridos de suministro energético apoyado en energías renovables mejora enormemente el desempeño energético de las infraestructuras sanitarias [17]. Las renovaciones de equipamiento y reformas en el edificio, la implementación de tecnologías energéticas alternativas, así como la modelización de los sistemas, son las tres vías principales para mejorar la eficiencia energética de las infraestructuras sanitarias [18]. Por tanto, la optimización del consumo de energía de los edificios sanitarios es muy importante para la transición ecológica de la sociedad. Estudios previos han comprobado que el potencial de ahorro en centros de salud es de 8.60 kWh/m^2 por año, si se realiza una inversión de 1.55 €/m^2 [19].

1.3.4. Envolvente de los edificios sanitarios

Las fachadas y las cubiertas constituyen la envolvente del edificio, afectando de forma crítica al confort térmico y acústico de sus usuarios [20], al ser los elementos constructivos que más condiciona la eficiencia energética de un edificio [21]. Por lo tanto, influye de manera directa en el consumo de energía y al impacto ambiental del edificio durante su ciclo de vida [22].

Son numerosas las anomalías que afectan a la envolvente de los edificios, las cuales surgen por una gran multitud de causas y factores y repercuten en su funcionalidad [23]. Distintas investigaciones exponen la importancia de evaluar los defectos de las fachadas de los edificios, determinar sus principales causas, establecer el método de inspección o de reparación más adecuado [24–26]. Las humedades por infiltración o superficiales son unos de los defectos más frecuentes, favoreciendo la eflorescencia, crecimiento biológico, vegetal o la aparición de hongos [27], aumentando la carga microbiana de las salas y afectando significativamente a la salud de los usuarios de los edificios [28]. Este punto es crítico para los edificios sanitarios, puesto que una disminución de la calidad de aire interior incrementa el riesgo de enfermedades nosocomiales en los pacientes y trabajadores [29], generando trastornos respiratorios o enfermedades que se agrava en pacientes con patologías previas [30]. Por tanto, es fundamental asegurar la calidad ambiental interior y evitar la transmisión de enfermedades nosocomiales [31].

1.3.5. Mantenimiento en infraestructuras hospitalarias

Por definición, el mantenimiento engloba toda operación que permita que el edificio mantenga un estado de funcionalidad adecuado [32]. Según la norma UNE-EN 13306:2018 [33], el mantenimiento preventivo incluye las operaciones que reducen la degradación y el fallo de un sistema, mientras que el mantenimiento correctivo se realiza tras reconocer un fallo, e incluye las operaciones que devuelven el sistema a un estado de operatividad adecuado. Por otro lado, el mantenimiento basado en la condición es una estrategia de mantenimiento que consiste en monitorear el estado de condición de un sistema para planificar las tareas de mantenimiento [33]. Además, los centros de salud tienen un mantenimiento preventivo específico, debido a su dispersa localización, denominado mantenimiento de ronda, que consiste en que el equipo de mantenimiento realiza una visita periódica programada a cada edificio, reparando las averías no urgentes que se hayan producido entre visitas y realizando operaciones de mantenimiento preventivo planificadas con anterioridad [34].

Los edificios sanitarios están diseñados para llevar a cabo acciones de atención de la salud, siendo imprescindible disponer de personal cualificado y una infraestructura adecuada para satisfacer las necesidades de los usuarios [35]. Las operaciones de mantenimiento se realizan en base a criterios de los propios fabricantes o del departamento de mantenimiento del sistema sanitario [36]. Sin embargo, se basan en la experiencia previa y no en el estado de degradación de un determinado sistema a lo largo del tiempo. Por tanto, surge la necesidad de realizar operaciones de mantenimiento para que las instalaciones y partes críticas del edificio permanezcan en un estado de funcionamiento apropiado, garantizando la salud y la seguridad de los pacientes y trabajadores. De esta forma, los edificios sanitarios tendrían en todo momento un estado de degradación adecuado y se minimizaría el riesgo de que uno de sus elementos colapse. Por ejemplo, si las instalaciones de climatización funcionan de manera inadecuada, puede aumentar la probabilidad de trasmisión de enfermedades nosocomiales en los pacientes.

Por su parte, los equipos electromédicos también son elementos críticos de las infraestructuras hospitalarias, siendo equipos de una elevada complejidad utilizados para el diagnóstico y tratamiento de enfermedades y durante las intervenciones quirúrgicas [37]. Por tanto, es imprescindible mantener estos equipos en un estado de funcionamiento adecuado para garantizar la calidad de la asistencia [38]. En los últimos años, la calidad y complejidad de los equipos electromédicos se ha multiplicado, aumentando la preocupación de los administradores de las infraestructuras hospitalarias por el estado de condición de los equipos [39]. El mantenimiento de estos equipos debe considerarse bajo los epígrafes de seguridad, calibración y reparación [40]. Por ello, el presupuesto hospitalario destinado a las operaciones de mantenimiento de los equipos electromédicos ha aumentado, garantizando la calidad de los servicios de mantenimiento, asegurando la atención médica de los pacientes y cumpliendo con los resultados de fiabilidad esperados por el servicio sanitario [41] y con los requisitos de los usuarios [42]. Por otro lado, la información generada durante las inspecciones de mantenimiento es muy importante, ya que ayuda a detectar errores generados durante su uso [43].

Los equipos electromédicos contemplan mantenimiento preventivo [44], con el fin de realizar actividades como la actualización del sistema operativo o la calibración del equipo. Además, los protocolos de mantenimiento de los equipos electromédicos incluyen el mantenimiento correctivo, que se encarga de la reparación y sustitución de componentes cuando se detecta una avería. Este mantenimiento es tan importante, que el coste de esta actividad durante la vida de servicio de los equipos electromédicos puede llegar a superar al coste inicial invertido. Por otro lado, cuando el hospital contrata un servicio integral de mantenimiento de un equipo electromédico con el fabricante [45], éste se encarga de todo el mantenimiento necesario mediante el abono de una cuota fija anual. Este tipo de mantenimiento es muy usual y el coste es independiente de la frecuencia y la política de mantenimiento [46]. En los primeros años de funcionamiento, los equipos no presentan numerosos fallos, por lo que la cuota anual no beneficia al sistema sanitario. Sin embargo, esta situación se revierte en los últimos años de vida útil. Por tanto, es muy importante analizar los fallos a lo largo del tiempo, obteniendo información para establecer la estrategia de mantenimiento más adecuada. Este análisis permite disminuir las averías en los equipos de alta tecnología de los hospitales a través de la optimización del mantenimiento, aumentando su disponibilidad, prestando un mejor servicio sanitario [47] y mejorando la satisfacción de los pacientes [48]. Además, anticipando el mantenimiento al fallo del sistema, disminuye el tiempo en el que el equipo se encuentra fuera de uso, aumenta la calidad y se reduce el tiempo medio de amortización al incrementar el número de diagnósticos que pueden realizar [49].

La metodología predictiva desarrollada en esta investigación permitirá generar una fuente de información alternativa y objetiva que mejora la toma de decisiones y disminuye los grandes costos asociados a las operaciones de mantenimiento. En definitiva, esta investigación demuestra que es posible crear una herramienta actualizable que pueda adaptarse a los cambios que se originen en las infraestructuras hospitalarias, la tecnología o incluso situaciones de emergencia, como puede ser la crisis sanitaria ocasionada por la COVID-19.

1.3.6. Las Cadenas de Markov

Las Cadenas de Markov han sido utilizadas como técnica de simulación, toma de decisiones y predicción en ingeniería [50], siendo una metodología predictiva ampliamente utilizada para analizar diferentes problemáticas e incorporando el análisis de la degradación de un sistema entre uno de sus principales campos de aplicación [51]. Consecuentemente, es una metodología que permite predecir la degradación que sufre un determinado sistema, simulando el proceso de degradación estocástico del mismo [52]. A través del modelo generado, es posible determinar la probabilidad de que un sistema pase de un estado de condición i a un estado de condición j en un periodo de tiempo t establecido, permitiendo determinar las políticas de mantenimiento más adecuadas en función de la probabilidad de colapso [53].

Existen precedentes en la literatura científica sobre investigaciones que utilizan el modelo de Markov para evaluar la degradación de diferentes elementos constructivos y para la planificación de su mantenimiento. Por ejemplo, Ruparathna, Hewage y Sadiq [54] desarrollaron un método de gestión de activos de edificios públicos para reducir el coste asociado a su ciclo de vida y modelaron la degradación de diferentes partes críticas, estableciendo el mantenimiento más adecuado en base al riesgo. Silva *et al.* [55] analizaron la degradación de tres tipos de revestimientos con la aplicación de las Cadenas de Markov, determinando la probabilidad de fallo de los revestimientos de edificios de Lisboa (Portugal) y los factores que influyen en su degradación. Por otro lado, Ferreira *et al.* [56] modelaron la degradación de las fachadas de revestimientos cerámicos mediante la aplicación de las redes de Petri y el modelo estocástico de las Cadenas de Markov, realizando inspecciones a 195 edificios de Lisboa (Portugal).

Otros autores aplicaron el modelo de Markov sobre fachadas de paneles de hormigón para determinar su degradación, lo que les permitió realizar una comparación multiobjetivo para planificar el mantenimiento anual del edificio [57]. Grussing *et al.* [58] desarrollaron índices de condición para cuantificar la degradación de los edificios y utilizaron el modelo de Markov para predecir el valor de los índices definidos a lo largo del tiempo, obteniendo una medida del riesgo de fallo de los distintos componentes críticos de un edificio y determinando su vida útil. Coffelt, Hendrickson y Healey [59] modelaron la degradación de las cubiertas de los edificios con Cadenas de Markov, mejorando la decisión de reemplazo de este componente. Papakonstantinou y Shinozuka [60] utilizaron los procesos de decisión de Markov parcialmente observables para tomar decisiones óptimas de mantenimiento de estructuras afectadas por la corrosión. Por otro lado, Cheng *et al.* [61] realizaron un diseño óptimo de las instalaciones de agua fría de consumo humano mediante la aplicación de diferentes técnicas de predicción estadísticas, utilizando las Cadenas de Markov para obtener la distribución de probabilidad del estado de la instalación y su fiabilidad.

Sin embargo, a pesar de que las Cadenas de Markov sea considerada una metodología predictiva adecuada en el campo de la ingeniería, su aplicación no está muy extendida en el sector de la Ingeniería Hospitalaria, con pocos precedentes que desarrollen el modelo de degradación de Markov para analizar el mantenimiento. Velázquez-Martínez *et al.* [62] analizaron la cultura de seguridad de un hospital mexicano mediante Cadenas de Markov, estimando su comportamiento evolutivo a lo largo del tiempo. Gómez *et al.* [63]aplicaron las Cadenas de Markov para determinar la política de mantenimiento más adecuada para los subsistemas de distribución de gases medicinales de un hospital público. Asimismo, estos autores lo aplicaron a la energía eléctrica en centros sanitarios [64]. Carnero y Gómez [65] determinaron la política de mantenimiento más adecuada para cuatro subsistemas de diálisis de un centro de salud, mediante la aplicación de las Cadenas de Markov, apoyándose en una metodología de medición multicriterio basada en categorías. A pesar de lo anterior, no se han encontrado precedentes en la literatura científica que optimicen el mantenimiento de elementos constructivos de edificios sanitarios en base a los datos de fiabilidad generados a partir del modelo de Markov.

Por otro lado, existen precedentes de investigaciones donde se aplican el modelo de Markov para estimar la condición de equipos electromédicos y determinar su reemplazo o reparación. Por ejemplo, Pabon *et. al* [66] aplicaron el modelo de Markov para determinar el reemplazo por obsolescencia tecnológica de equipos electromédicos de radiología. Ospina *et. al* [67] diseñaron un modelo de Cadenas de Markov de tiempo continuo para modelar tres estados de los equipos de tomografía computarizada, pero sin ofrecer una estimación de la degradación porcentual de los equipos de alta tecnología en base a un histórico de datos. Tabares y Silva [68] propusieron un algoritmo probabilístico basado en las Cadenas de Markov para predecir la condición de equipos electromédicos y elaboraron un modelo para los sistemas de aspiración electromecánica. Además, las Cadenas de Markov se han utilizado para determinar la frecuencia de fallo de piezas de los equipos electromédicos, estableciendo la reserva de piezas de repuesto [69]. Asimismo, Dhillon [70] propuso, entre otras técnicas analíticas clásicas, el empleo de Cadenas de Markov para mejorar la fiabilidad y mantenimiento de los equipos electromédicos.

La literatura científica carece de investigaciones que analicen la influencia de diversos factores como la periodicidad o el año de inicio de mantenimiento sobre la vida útil de equipos, instalaciones o elementos constructivos de los edificios sanitarios. Por lo tanto, la presente Tesis Doctoral permitirá cubrir la brecha de conocimiento existente en la literatura científica para incrementar la operatividad de las infraestructuras hospitalarias.

1.4. Novedad de la Tesis Doctoral

La principal novedad de esta Tesis Doctoral es la implementación del modelo estocástico de degradación de las Cadenas de Markov para optimizar el mantenimiento de las infraestructuras y equipos sanitarios. La aplicación de esta metodología ha permitido generar información útil y actualizable para obtener la estrategia y frecuencia de mantenimiento óptima, estableciendo criterios para alargar la vida útil de las infraestructuras hospitalarias, garantizando su fiabilidad y operatividad.

A través de los análisis realizados, se ha desarrollado una fuente de conocimiento sobre los centros de salud y los hospitales, que permite mejorar el diseño de los edificios sanitarios y la gestión de la asistencia sanitaria. Concretamente, la elaboración de esta Tesis Doctoral ha desarrollado conocimiento inexistente en la literatura científica, contribuyendo en los siguientes puntos:

- Se propone un modelo de degradación de los equipos de tomografía axial computarizada. A través del análisis predictivo de la degradación se determina la vida útil de estos equipos electromédicos y la política y frecuencia del mantenimiento, minimizando el tiempo fuera de uso y aumentando su fiabilidad. La información generada permitirá reducir los altos costes de mantenimiento y contrastar las recomendaciones técnicas y protocolos de mantenimiento de los fabricantes.

- Se establece la frecuencia y la política de mantenimiento óptima de los centros de salud en función de la periodicidad de sus averías no urgentes, incrementando la fiabilidad de las infraestructuras.

- Se analiza la influencia del mantenimiento en el estado de degradación de las cubiertas de los edificios sanitarios, evaluando la influencia del número de intervenciones, del año de inicio del mantenimiento y su frecuencia (periódica o no periódica) sobre su vida útil. Los resultados obtenidos permiten estimar la vida útil en base a la fiabilidad y al mantenimiento y comparar las diferentes soluciones constructivas.

- Se propone emplear una metodología semiparamétrica para identificar las variables y cuantificar su influencia en determinados problemas complejos de la Ingeniería Hospitalaria. De esta forma, la metodología se complementa adecuadamente con las Cadenas de Markov, facilitando el desarrollo del modelo de degradación, la precisión de los resultados y el análisis de posibles escenarios.

En definitiva, la presente Tesis Doctoral propone modelos contrastados para establecer protocolos de mantenimiento de las infraestructuras y equipamientos sanitarios, optimizando la gestión del mantenimiento y las decisiones dentro de la Ingeniería Hospitalaria.

Capítulo 2. Objetivos y Metodología

2.1. Objetivos

2.1.1. Objetivo general

La presente Tesis Doctoral analiza las infraestructuras hospitalarias para aumentar su funcionalidad y fiabilidad y mejorar la calidad de la asistencia sanitaria, complementándose con las líneas de trabajo de la Ingeniería Hospitalaria ya desarrolladas. Por tanto, el objetivo general de esta investigación es la optimización de las estrategias de mantenimiento de las infraestructuras hospitalarias aplicando el modelo estocástico de degradación de las Cadenas de Markov, para determinar la frecuencia y política de mantenimiento óptima que maximiza la vida útil de las infraestructuras y garantiza su operatividad a lo largo del tiempo.

2.1.2. Objetivos específicos

El objetivo general de la Tesis Doctoral se divide en seis objetivos específicos (OE), reflejando en mayor detalle el alcance de la investigación.

Objetivo específico 1 (OE1): Optimizar la frecuencia del mantenimiento de los centros de salud, reduciendo su coste y el impacto ambiental asociado al transporte de los equipos de mantenimiento.

Objetivo específico 2 (OE2): Estimar la vida útil de las infraestructuras sanitarias, garantizando un nivel de fiabilidad elevado que asegure la calidad de la atención sanitaria y establecer la política de mantenimiento más adecuada para alargar su vida útil.

Objetivo específico 3 (OE3): Comparar diversas soluciones constructivas, estableciendo la más adecuada en términos de vida útil bajo la perspectiva de garantizar el mismo nivel de mantenimiento y fiabilidad.

Objetivo específico 4 (OE4): Analizar la influencia del mantenimiento en el estado de degradación de los sistemas estudiados, evaluando la influencia del año de inicio del mantenimiento y su periodicidad.

Objetivo específico 5 (OE5): Generar información útil para contrastar las instrucciones provistas por los fabricantes en términos de mantenimiento y vida útil, para aumentar la rentabilidad de los equipos y minimizar el tiempo en el que no se encuentran disponibles.

Objetivo específico 6 (OE6): Identificar las distintas variables que influyen significativamente en la degradación de los edificios sanitarios y equipos electromédicos, cuantificando el nivel de influencia para mejorar los modelos de degradación desarrollados y la precisión de los resultados obtenidos.

2.1.3. Objetivos complementarios

Además de los objetivos específicos, esta investigación contribuye a la consecución de los siguientes objetivos complementarios (OC):

Objetivo complementario 1 (OC1): Mejorar el análisis y el filtrado de la base de datos generada a partir del histórico de fallos de los equipos electromédicos, para incrementar la interpretación de la información obtenida y, en consecuencia, la calidad de la investigación.

Objetivo complementario 2 (OC2): Identificar las principales anomalías y fallos que afectan a la degradación de la envolvente de los edificios sanitarios, clasificándolos según su gravedad y permitiendo establecer una escala de degradación objetiva y realista.

Objetivo complementario 3 (OC3): Mejorar la predicción de los costes de mantenimiento de las infraestructuras hospitalarias, incrementando la eficiencia del sistema sanitario.

Objetivo complementario 4 (OC4): Proponer una herramienta actualizable que pueda incorporarse a los programas de gestión de activos habitualmente utilizados en los sistemas sanitarios.

2.2. Metodología

2.2.1. Descripción general

La metodología empleada en esta investigación para la optimización del mantenimiento de infraestructuras hospitalarias se basa en el modelo estocástico de las Cadenas de Markov, que permiten modelar la degradación que sufre un determinado sistema y planificar el mantenimiento en consecuencia. Más concretamente, esta metodología permite determinar la probabilidad de que un sistema cambie de un estado de degradación *i* a un estado *j* en un periodo de tiempo *t* establecido [71], cuantificando la probabilidad de que el sistema se encuentre en un estado de degradación aceptable. En la Figura 1 se muestra un esquema general de la metodología empleada.

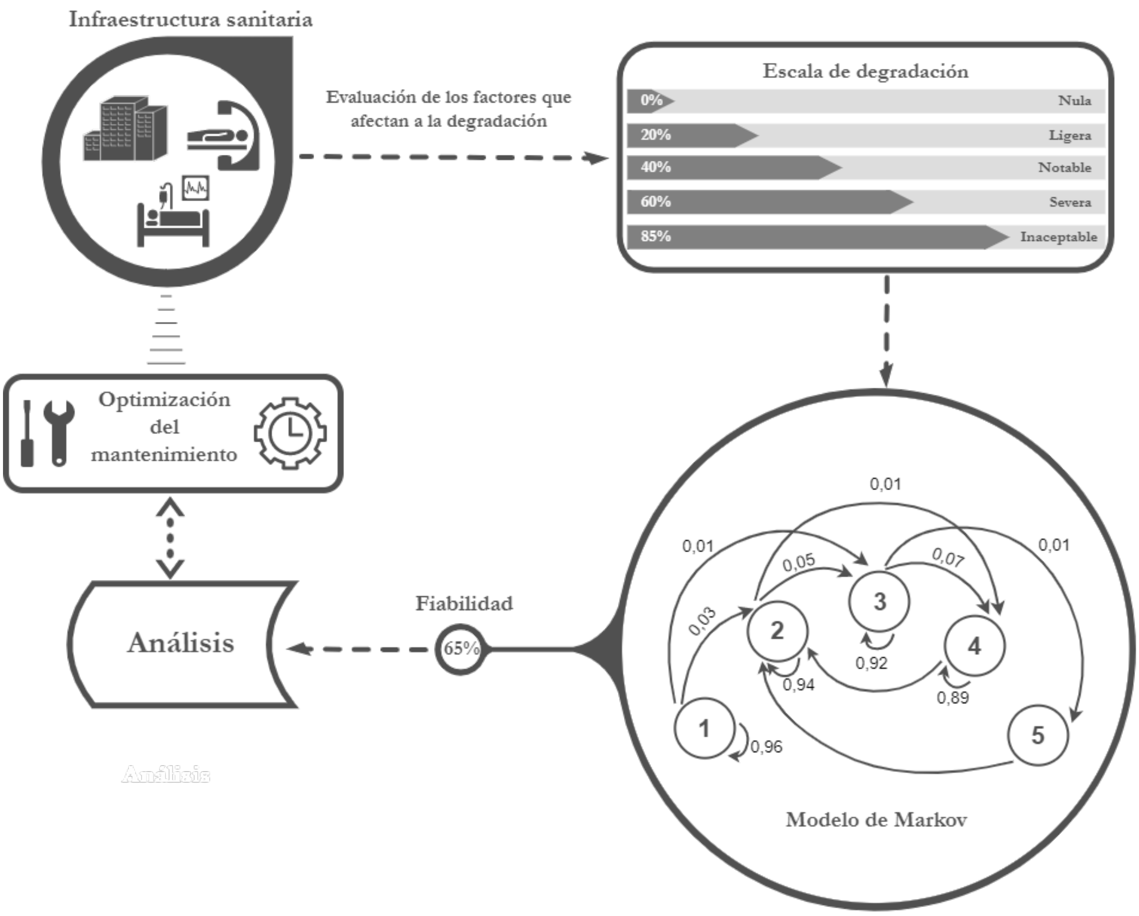


Figura 1. Esquema general de la metodología aplicada

Para poder estimar la degradación de un sistema es necesario definir su escala de degradación. Para ello, se evalúan las distintas variables y factores que afectan a su funcionalidad y fiabilidad del sistema. Además, para desarrollar el modelo de Markov es necesario construir una base de datos durante un periodo de observación establecido, permitiendo calcular la probabilidad de que un determinado sistema se encuentre en un estado de degradación tras un tiempo determinado. Este cálculo puede realizarse con distintos programas, como pueden ser Matlab ® o Microsoft Excel ®.

Para validar el modelo de degradación desarrollado se utiliza la bondad de ajuste de la prueba X^2 de Pearson [72], comprobando si la discrepancia obtenida entre los valores observados y los predichos por el modelo de Markov es admisible para un nivel de confianza del 95%.

Con el modelo de degradación de Markov es posible determinar la fiabilidad de que el sistema analizado se encuentre en un estado de degradación adecuado en cualquier instante de su vida útil. A partir de la evaluación de la fiabilidad, es posible realizar distintos análisis, como: predicción de la vida útil restante, determinación de la política de mantenimiento óptima, frecuencia del mantenimiento de reparación o reemplazo, influencia del año de inicio de las operaciones de mantenimiento o influencia de su periodicidad. Estos análisis tienen como objetivo común, la optimización del mantenimiento de las infraestructuras hospitalarias, garantizando su estado de condición y, en consecuencia, incrementando la seguridad de los usuarios y la calidad de la atención sanitaria.

2.2.2. Desarrollo del modelo de degradación de las Cadenas de Markov

El modelo de degradación de las Cadenas de Markov parte de la información obtenida durante las inspecciones de mantenimiento, en las cuales se categoriza la degradación del sistema analizado a lo largo del tiempo, para predecir su estado de condición en un instante determinado a partir de las Cadenas de Markov. De esta forma, es posible determinar el modelo de degradación que minimiza el error que se produce entre lo observado durante las inspecciones y lo predicho por el modelo de Markov [73]. En la Figura 2 se muestra el diagrama de flujo de la metodología.

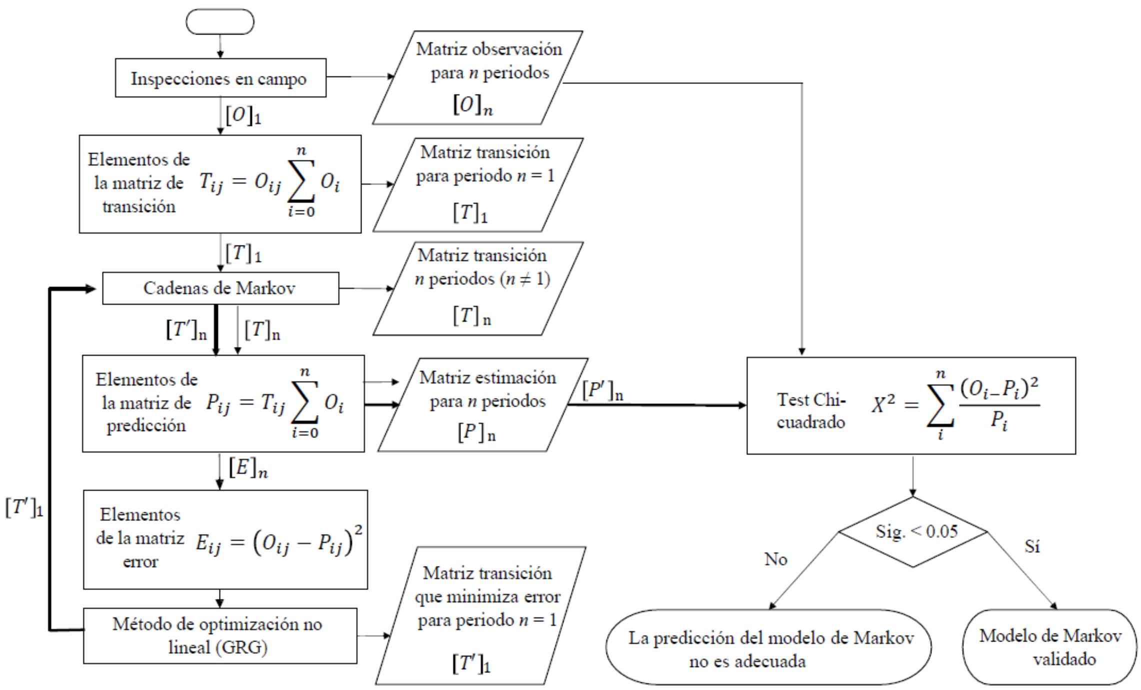


Figura 2. Diagrama de flujo de la metodología utilizada

En primer lugar, un panel de expertos en mantenimiento realiza un análisis de los distintos factores y variables que afectan al estado de condición del sistema analizado [74].

De esta forma, se establece la escala de degradación que mejor refleje el proceso de degradación que sufre el sistema bajo estudio, desde una condición de funcionamiento muy buena hasta el colapso, describiéndose detalladamente para evitar problemas de interpretación y diagnóstico durante las inspecciones. Cada nivel de degradación de la escala se representa por un estado, de manera que el componente estudiado se transforma en un sistema multiestado [75], cumpliendo con la propiedad de Markov al verificarse que el estado de degradación actual depende únicamente del último estado observado y no del pasado [76].

Una vez especificados los estados de degradación del componente, se construye la matriz de observación, la cual se obtiene a partir de la información recogida por los expertos de mantenimiento, observando la condición inicial del componente y determinando el estado final de degradación tras un periodo de tiempo. El tiempo transcurrido entre inspecciones suele variar entre un orden de magnitud de un mes y un año, estableciéndose en función de la criticidad del sistema analizado y su velocidad de degradación. En la Figura 3 se muestra la forma genérica de la matriz de observación.

$$[O] = \begin{bmatrix} O_{11} & O_{12} & \cdot & \cdot & O_{1j} \\ O_{21} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ O_{i1} & \cdot & \cdot & \cdot & O_{ij} \end{bmatrix}$$

Figura 3. Matriz de observación

La matriz de observación se elabora para cada uno de los periodos de observación realizados, n, y contabiliza el número de componentes que se encuentra en cada uno de los estados de degradación tras una inspección [77]. A partir de esta matriz, se puede obtener la matriz de transición de estados, es decir, las probabilidades de que un componente cambie de estado en un tiempo definido [78]. En la Ecuación (1) se expresa la determinación de los elementos de la matriz de transición de estados.

$$T_{ij} = O_{ij} / \sum_{x=1}^{n} O_{ix} \qquad \textbf{(1)}$$

siendo T_{ij} los elementos de la matriz de transición de estados, O_{ij} los elementos de la matriz de observación y O_{ix} los elementos de la fila correspondiente al elemento calculado.

Para obtener la matriz de transición de estados en los distintos periodos analizados, n, se aplica el modelo de Markov, calculando la probabilidad de que un componente pase de un estado i a un estado j en un periodo de tiempo específico [79]. De esta manera, se obtiene la matriz de transición en el primer periodo, $[T]_1$. En la Ecuación (2) se muestra el cálculo de la matriz de transición en un periodo n.

$$[T]_n = [T]_1^n \tag{2}$$

siendo $[T]_1$ la matriz de transición para el primer periodo y n el periodo de tiempo analizado.

A continuación, se calcula la matriz de predicción, $[P]$, para cada uno de los periodos de observación, n, permitiendo pronosticar el número de equipos que se encuentra en un estado de degradación para los distintos periodos de observación. En la Ecuación (3) se muestra el cálculo de los elementos que componen la matriz de predicción.

$$P_{ij} = T_{ij} \cdot \sum_{x=1}^{n} O_{ix} \tag{3}$$

donde P_{ij} son los elementos de la matriz de predicción, T_{ij} son los elementos de la matriz de transición y O_{ix} son los elementos de la fila correspondiente al elemento calculado, que refleja el número de componentes que se encuentran en un mismo estado inicial de degradación.

Por último, se determina la matriz error, $[E]$, que representa el error que se produce entre la matriz de observación y la matriz de predicción para un periodo n. El modelo de degradación óptimo será aquel que minimice el error generado entre ambas matrices. Los elementos de la matriz error, E_{ij}, se calculan mediante la Ecuación (4).

$$E_{ij} = (O_{ij} - P_{ij})^2 \tag{4}$$

siendo E_{ij} los elementos de la matriz error, O_{ij} los elementos de la matriz de observación y P_{ij} los elementos de predicción.

Para poder minimizar el error, previamente se deben sumar todos los elementos de la matriz error. Este proceso se repite para todos los periodos analizados, n, sumando los elementos de todas las matrices error y ponderando su resultado en función del número de componentes observados en cada periodo. La Ecuación (5) y la Ecuación (6) reflejan este proceso.

$$E_p = \sum E_{ij} \tag{5}$$

$$E_{total} = \sum_{p=1}^{n} (E_p \cdot O_p / O_T) \tag{6}$$

donde E_{total} es el error total del análisis, E_p y O_p son el error y el número de componentes observados para un periodo determinado y O_T es el número de componentes observados en todos los periodos estimados.

Empleando la herramienta de optimización *Solver* de Microsoft Excel ®, se determina la matriz de transición del primer periodo, $[T]_1$, que minimiza el error total calculado, obteniendo la matriz de transición correspondiente al primer periodo que mejor se adapta a todos los periodos observados. En la Figura 4 se muestra la matriz de transición para el primer periodo.

$$[T]_1 = \begin{bmatrix} T_{11} & T_{12} & \cdot & \cdot & T_{1j} \\ T_{21} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ T_{i1} & \cdot & \cdot & \cdot & T_{ij} \end{bmatrix}$$

Figura 4. Matriz de transición para el primer periodo

Estos elementos constituyen la matriz de transición del modelo, donde el estado de degradación de un sistema depende únicamente del último estado de degradación observado y de la probabilidad de transición de estado. Posteriormente, se procede a la validación del modelo de degradación, analizando la bondad de ajuste del modelo estadístico mediante la prueba X^2 de Pearson y determinando la discrepancia entre los valores observados y los valores obtenidos del modelo [80]. También, se verificó si la propuesta probabilística de las Cadenas de Markov es consistente con el conjunto de equipos observados. La prueba de X^2 de Pearson se muestra en la Ecuación (7).

$$X^2 = \sum_{i}^{n} \frac{(O_i - P_i)^2}{P_i} \tag{7}$$

donde n es el número de periodos analizados, O_i son los elementos de la matriz de observación y P_i son los elementos de la matriz de predicción.

2.2.3. Fiabilidad a partir de las Cadenas de Markov

Una vez validada la matriz de transición de estados y conocida la condición inicial del sistema, es posible conocer el estado del sistema para un periodo futuro. Esto se refleja en el denominado vector de estados, E_n, que representa la probabilidad que el sistema se encuentre en cada uno de los estados de degradación tras un periodo de tiempo, n [81], según la Ecuación (8).

$$E_n = E_0 \cdot [T]^n \tag{8}$$

donde E_0 es el vector de estados inicial, que representa la condición de degradación del sistema al inicio del análisis, $[T]$ es la matriz de transición de estados y n es el periodo de tiempo.

El modelo matricial de degradación de Markov permite incluir distintas políticas de mantenimiento [82], de forma que se puede determinar la mejora de condición que experimenta un sistema con la incorporación de operaciones de mantenimiento y monitorizar esta actividad. Al implementar el mantenimiento, la Ecuación (8) se transforma en la expresión mostrada en la Ecuación (9).

$$E_n = E_0 \cdot [M] \cdot [T]^n \tag{9}$$

siendo E_0 el vector de estados inicial, $[M]$ el modelo matricial del mantenimiento, $[T]$ la matriz de transición de estados y n el periodo de tiempo.

A partir del vector de estados inicial es posible evaluar la influencia del mantenimiento en la degradación del sistema para distintas condiciones de degradación iniciales, permitiendo monitorizar las actividades de mantenimiento de sistemas utilizados o nuevos. Por ello, cuando el sistema analizado se encuentra inicialmente en el primer estado, el primer elemento del vector toma el valor 1 y el resto de los estados el valor 0.

Una vez definida la política de mantenimiento y la probabilidad de que el sistema se encuentre en cada estado de degradación tras un periodo de tiempo concreto, se procede al cálculo de la fiabilidad del sistema a lo largo del tiempo, siendo la fiabilidad una variable que permite evaluar si la condición de un componente crítico de la infraestructura sanitaria es adecuada para garantizar su función.

La fiabilidad se emplea para realizar los diferentes análisis que permiten optimizar la política y la frecuencia de mantenimiento de las infraestructuras hospitalarias. Para calcular este parámetro, se define el índice de fiabilidad IF como la probabilidad de que el sistema se encuentre en uno de los estados de condición por encima del estado de colapso para un periodo n. El índice de fiabilidad se obtiene mediante la Ecuación (10).

$$IF = E_n \cdot C \tag{10}$$

donde C es el vector de colapso, el cual representa el estado límite del estudio y E_n es el vector de estados.

Los estados inferiores al estado límite del vector de colapso toman el valor 1 y los estados de degradación mayor o igual al estado de colapso toman el valor 0. De esta forma, es posible determinar la fiabilidad del sistema analizado a lo largo del tiempo y relacionar la fiabilidad en función de la política y frecuencia de mantenimiento.

Tras determinar la probabilidad de que el sistema analizado se encuentre en cada estado de degradación, es posible realizar distintos análisis que permitan determinar la influencia del mantenimiento sobre la vida útil del sistema estudiado. Con el cálculo iterativo de la fiabilidad es posible establecer la frecuencia de mantenimiento que maximiza la vida útil para un número fijo de operaciones de mantenimiento y comparar mantenimiento periódico y no periódico para establecer la mejor frecuencia en función del año de inicio del mantenimiento. Además, es posible cuantificar el incremento de vida útil en función de las operaciones de mantenimiento preventivo realizadas.

2.2.4. Análisis de supervivencia

A partir de la Ecuación (10) se determinan los valores de fiabilidad de un sistema a lo largo de su vida útil, permitiendo realizar un análisis de supervivencia del sistema analizado. En la Figura 5 se muestra un esquema de la metodología empleada para el análisis de supervivencia.

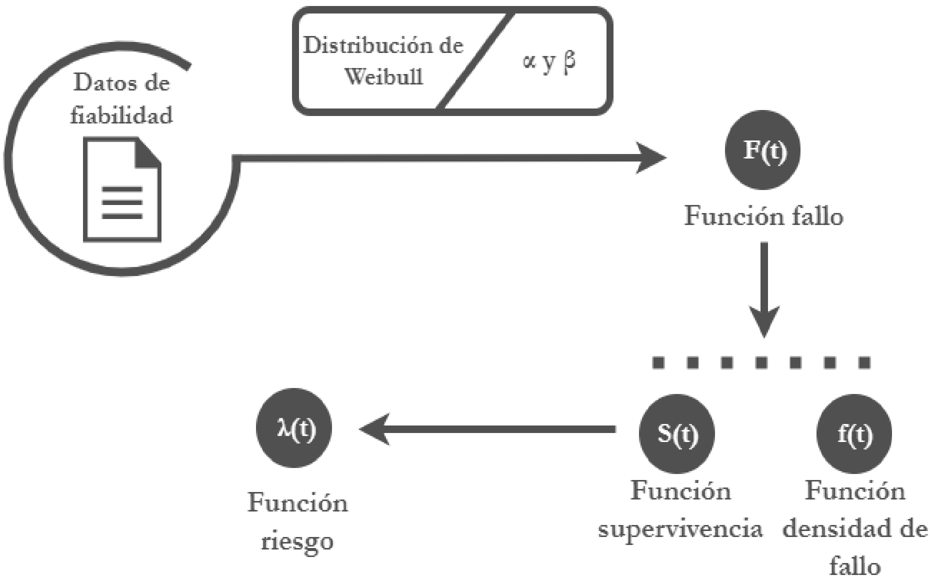


Figura 5. Esquema de la metodología empleada en el análisis de supervivencia

Se define una variable aleatoria T, que representa la vida útil del sistema analizado. Se define la función de fallo, $F(t)$, que representa la probabilidad de que un sistema falle en el tiempo t. La variable aleatoria T tiene una función $F(t)$ de distribución acumulativa definida según la Ecuación (11) [83].

$$F(t) = \mathrm{P}(T \leq t) \tag{11}$$

Para tipificar la función fallo se emplea la distribución de Weibull [84], la cual se muestra en la Ecuación (12).

$$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \tag{12}$$

donde *F* es la probabilidad de que el sistema falle en un tiempo dado t, α y β son coeficientes adimensionales que generan la forma de característica de la curva.

La función supervivencia o fiabilidad, $S(t)$, cuantifica la probabilidad de que el sistema esté operativo al final del instante t. La función supervivencia sigue una función exponencial negativa y es complementaria a la función de fallo, $F(t)$ [85]. Por lo tanto, la función supervivencia se expresa en la Ecuación (13).

$$S(t) = 1 - F(t) = e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \tag{13}$$

La función densidad de fallo se obtiene al derivar la función de fallo respecto del tiempo. Esta función se define mediante la Ecuación (14) e indica la probabilidad de fallo por unidad de tiempo.

$$f(t) = \frac{d}{dt}F(t) \tag{14}$$

A partir de la función de densidad de fallo y la función de supervivencia (fiabilidad) se obtiene la función riesgo, $\lambda(t)$. La función riesgo representa la probabilidad de que un componente falle en el siguiente instante de tiempo, considerando que no ha fallado. En la Ecuación (15) se muestra la probabilidad condicionada de que un sistema falle en un intervalo de tiempo, s, después del instante t.

$$P(t < T \leq T + s \,/\, T > t) = \frac{P(t < T \leq T + s)}{P(T > t)} = \frac{F(t+s) - F(t)}{S(t)} \tag{15}$$

Dividiendo la Ecuación (15) por el intervalo de tiempo s y realizando el límite cuando s tiende a 0, se obtiene la Ecuación (16) [86].

$$\lambda(t) = \lim_{s \to 0} \frac{1}{s} \cdot \frac{F(t+s) - F(t)}{S(t)} = \frac{f(t)}{S(t)} \tag{16}$$

siendo $\lambda(t)$ la función riesgo, $f(t)$ la función densidad de fallo, $S(t)$ la función supervivencia, $F(t)$ la función densidad de fallo y s el intervalo de tiempo.

2.2.5. Modelo de Riesgos Proporcionales de Cox

El modelo de riesgos proporcionales de Cox o regresión de Cox es un modelo predictivo útil para analizar la influencia de distintas variables sobre la ocurrencia de un evento [87]. Este modelo genera una función de supervivencia que permite predecir la probabilidad de que el determinado evento estudiado se haya producido para el instante de tiempo *t* en función de diferentes valores de variables predictoras [88]. La función supervivencia y los valores de las variables predictoras se obtienen mediante observaciones. En definitiva, el modelo de riesgos proporcionales de Cox es válido para analizar el riesgo que afecta a la supervivencia de un sistema. En la Figura 6 se muestra un esquema de la metodología empleada para desarrollar el modelo riesgos proporcionales de Cox.

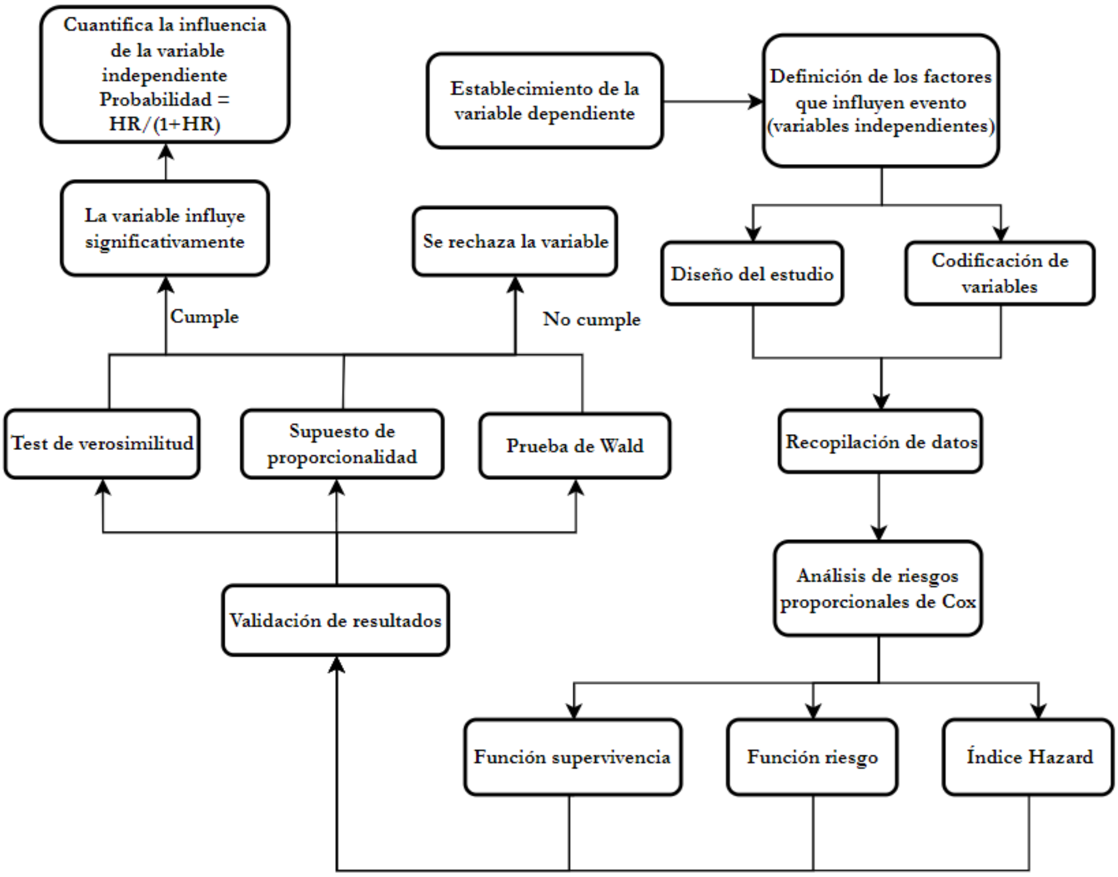


Figura 6. Esquema de la metodología para desarrollar el modelo de regresión de Cox

El modelo de riesgos proporcionales de Cox contempla dos tipos de variables: dependientes e independientes. Por un lado, la variable dependiente deberá presentar un desenlace dicotómico y dependerá del tiempo [89]. Por otro lado, las variables independientes, Z_j, no dependen del tiempo y afectan en mayor o menor medida a la variable dependiente, por lo que son adecuadas para formar el modelo de riesgos proporcionales de Cox [90].

En primer lugar, se deben identificar las variables que influyen sobre el evento analizado (variable dependiente). Posteriormente, se deben categorizar las variables independientes. Para ello, es necesario discretizarlas en rangos limitados, seleccionándose el valor de corte en base a la opinión de expertos o a un análisis realizado sobre un histórico de datos, definiéndose los valores críticos.

Además, para realizar el análisis, es necesario asignar un valor de referencia, en este caso 0 o 1. El valor de referencia no afecta a los resultados generados, pudiendo seleccionarse cualquiera de los dos valores. Sin embargo, el valor de referencia influye en la interpretación de los resultados. Por ello, se asigna el valor 1 al rango de mayor riesgo y el código 0 al de menor riesgo, de forma que el coeficiente de las variables predictoras sea siempre positivo y se mejore su interpretación.

Aunque el tiempo sea una variable continua, en el modelo riesgos proporcionales de Cox se discretiza, ya que no es posible hacer un seguimiento continuo [91]. En la práctica, se realizan observaciones donde se determinan valores discretos, de esta forma la variable tiempo se considera como un conjunto discreto de valores, t_k = [1, 2…, k], que depende de la periodicidad de las observaciones realizadas. Los periodos de observación establecidos pueden ser incompletos, generándose censuras a la izquierda y a la derecha. Por ejemplo, existe censura a la derecha si el evento analizado se da en un instante de tiempo superior al periodo de observación. De manera inversa, existe censura a la izquierda si el evento se da antes de iniciar el periodo de observación.

A continuación, se define la función riesgo del modelo de regresión de Cox, que se determina para el instante de tiempo t_k y para las variables Z_j de cada uno de los sistemas analizados, i. Esto se expresa en la Ecuación (17) [92].

$$\lambda_i(t_k, Z_j) = \lambda_0(t_k)\, exp\left(\sum_{j=1}^{p} \beta_j Z_j\right) \tag{17}$$

donde $\lambda_0(t_k)$ es el riesgo basal y β_j es el coeficiente de cada variable predictora Z_j, siendo el primer término la parte no paramétrica de la función riesgo y el segundo, la parte paramétrica.

El riesgo basal, $\lambda_0(t_k)$, sólo depende del tiempo y no se especifica paramétricamente, pudiendo ser cualquier modelo matemático [93]. Además, es idéntico para todas las unidades de observación y representa el riesgo cuando todos los factores de riesgo están ausentes, por lo que es el nivel de referencia. Para construir el modelo de riesgos proporcionales de Cox no es necesario saber cuál es el riesgo basal de las unidades de observación, ya que el posterior cálculo del índice de Hazard simplificará estos factores [94].

A partir de los datos observados y utilizando la función de verosimilitud se estima el vector β_j, que sirve de entrada al contraste de hipótesis realizado mediante el estadístico de Wald, que se muestra en la Ecuación (18).

$$W = \frac{(\beta_j - \beta_0)^2}{var(\beta_j)} \tag{18}$$

siendo β_j el parámetro obtenido al considerar que la variable independiente Z_j se encuentra incluida en el modelo de regresión de Cox, β_0 el valor hipotético de aplicar la hipótesis nula en el modelo y $var(\beta_j)$ la varianza del parámetro β_j.

La prueba de Wald es un contraste de hipótesis donde se evalúa el valor de un parámetro en un modelo previamente seleccionado y ajustado, determinando si la influencia de una variable independiente, Z_j, es significativa sobre el evento analizado al compararla con la hipótesis nula. Para un valor de significancia asociado al estadístico de Wald menor que 0,05 se rechaza la hipótesis nula y, por tanto, se considera que la variable influye significativamente en el evento planificado, debiendo formar parte de él. En caso contrario, la variable Z_j no se incluye en la regresión.

Una vez que se conocen las covariables que forman parte del modelo, se calcula el índice de Hazard mediante la Ecuación (19). El índice de Hazard es una medida de riesgo que representa la probabilidad de que los sistemas experimenten el evento analizado en un periodo de tiempo específico, comparándolo con el grupo de referencia.

$$HR = \frac{\lambda\ (t_k, Z_j)}{\lambda_0(\mathrm{t_k})} = \exp\ (\beta_j, Z_j) \tag{19}$$

donde $\lambda_0(t_k)$ es la función de riesgo basal, $\lambda\ (t_k, Z_j)$ es la función riesgo, Z_j es la variable independiente y β_j es el parámetro obtenido para cada variable independiente.

La Ecuación (19) refleja la independencia del índice de Hazard respecto al tiempo antes mencionada. La interpretación de este índice es la siguiente: un valor unitario del *HR* implica que el riesgo del sistema analizado es el mismo que el de referencia, un *HR* > 1 implica que el riesgo de que el evento suceda en el grupo de intervención es superior al grupo de referencia y, cuando *HR* < 1, significa lo contrario [95].

Para mostrar gráficamente los resultados, se establece la función de supervivencia en términos del modelo de riesgos proporcionales de Cox. Sea T_i la variable aleatoria que representa el tiempo hasta que se produce el evento para el sistema i. La función de supervivencia, $S\left(t_k, Z_j\right)$, definida en la Ecuación (20), especifica la probabilidad de que un sistema experimente el evento tras un tiempo t.

$$S\left(t_k, Z_j\right) = P(T > t_k) = S_0(t_k) exp\left(\sum_{j=1}^{p} \beta_j Z_j\right) \tag{20}$$

donde $S_0(t_k)$ es la función de supervivencia basal, que se corresponde con la supervivencia de una unidad de observación cuyas covariables están evaluadas en la referencia cero, Z_j es la variable independiente y β_j es el parámetro obtenido para cada variable independiente.

Por último, se verifica la hipótesis de riesgos proporcionales de manera gráfica mediante las curvas *Log-Log* [96]. Las curvas *Log-Log* son curvas logarítmicas obtenidas a partir de las curvas de supervivencia del modelo de riesgos proporcionales de Cox. De esta forma, se comprueba que las curvas de las funciones de supervivencia son proporcionales a lo largo del tiempo, es decir, aproximadamente paralelas, de forma que los incrementos de riesgo son constantes. Si las curvas *Log-Log* tienen una distancia vertical aproximadamente constante (son paralelas) y tienen la misma dirección, entonces se cumple la hipótesis de riesgos proporcionales.

El método gráfico de las curvas *Log-Log*, L, se basa en transformar la curva de supervivencia aplicando dos veces el logaritmo según se expresa en la Ecuación (21).

$$L = -ln(ln\ (S(t_k)) \tag{21}$$

siendo $S(t_k)$ la función supervivencia del modelo de riesgos proporcionales de Cox y L la curva *Log-Log* obtenida a partir de la curva de supervivencia analizada.

Capítulo 3. Descripción de las publicaciones

A continuación, se detallan los artículos científicos que conforman el compendio de publicaciones de la presente Tesis Doctoral, indicando los datos editoriales, los indicios de calidad, su resumen y se exponen los principales resultados obtenidos.

3.1. Markov model of computed tomography equipment

3.1.1. Datos editoriales

Título	Markov model of computed tomography equipment				
Autores	Jaime González Domínguez, Gonzalo Sánchez-Barroso, Juan Aunión-Villa y Justo García Sanz-Calcedo.				
Revista	Engineering Failure Analysis			**Año**	2021
Volumen	127	**Página**	105506	**Editorial**	Elsevier
DOI	10.1016/j.engfailanal.2021.105506			**ISSN**	1350-6307

3.1.2. Indicios de calidad

Fuente de impacto	WOS (JCR)	**Índice de impacto**	3,114
Categoría	Engineering Mechanical	**Cuartil**	Q2
Posición de la revista en la categoría	44	**Número de revistas en la categoría**	133
Citas en Web of Science	0	**Citas en Scopus**	1
Citas en Scholar	1	**Citas en Researchgate**	2

3.1.3. Resumen

Los equipos de tomografía axial computarizada (TAC) se trata de uno de los equipos de diagnóstico por imagen que más se ha desarrollado en los últimos años. Estos equipos utilizan una técnica radiológica no invasiva que permite el diagnóstico mediante la generación de imágenes. Debido a la complejidad de su tecnología, existen numerosos fallos que repercuten a su funcionalidad, generando errores de interpretación que influyen negativamente en el diagnóstico. Por lo tanto, se destinan numerosos recursos para que el estado de condición de los equipos sea adecuado y permita garantizar la calidad de la asistencia sanitaria.

El objetivo de la investigación es determinar la matriz de degradación de los TACs mediante las Cadenas de Markov, para estimar su estado de condición en función del tiempo y optimizar su mantenimiento. Para ello, se utilizó el histórico de fallos de TACs de cuatro hospitales ubicados España durante el período 2016-2020 y se definieron cinco estados de condición para estimar adecuadamente su degradación.

Los resultados validan el modelo de degradación de TACs obtenido a partir de las Cadenas de Markov, desarrollando una matriz de degradación que permite determinar la vida útil de los equipos, la política y frecuencia del mantenimiento. Estos resultados son útiles para los gestores de mantenimiento de los equipos electromédicos de cualquier hospital, ya que se puede determinar las operaciones de mantenimiento necesarias para reducir el tiempo en el que estos equipos se encuentran inactivos.

3.1.4. Resultados

Se definieron los estados de degradación en los que pueden encontrarse los TACs, desde una condición de funcionamiento muy buena hasta el colapso. En la Tabla 2 se muestra la escala de degradación de los TACs.

Tabla 2. Escala de degradación de los equipos analizados

Estado	Condición	Descripción
1	Muy bueno	No presenta ningún tipo de fallo o error
2	Buena	Presenta un fallo o error que no perjudica la funcionalidad
3	Adecuado	Presenta un fallo o error que perjudica la funcionalidad
4	Severo	Presenta varios fallos o errores que perjudican la funcionalidad
5	Inaceptable	Fallo o error que imposibilita la operatividad del equipo

Se clasificaron todos los datos obtenidos durante las inspecciones en un horizonte temporal de 12 meses, se determinaron los factores que influyeron en la degradación de los equipos y su impacto y se estableció un periodo de observación mensual. Siguiendo la metodología definida en el Capítulo 2, se obtuvo la matriz de transición de estados que minimiza el error entre lo observado durante las inspecciones de mantenimiento y lo predicho por el modelo de Markov, la cual se muestra en la Figura 7.

$$[T]_1 = \begin{bmatrix} 0{,}8993 & 0{,}0582 & 0{,}0238 & 0{,}0113 & 0{,}0059 \\ 0 & 0{,}9002 & 0{,}0590 & 0{,}0241 & 0{,}0137 \\ 0 & 0 & 0{,}9190 & 0{,}0606 & 0{,}0168 \\ 0 & 0 & 0 & 0{,}9725 & 0{,}0268 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Figura 7. Matriz de transición de los TACs

Por otro lado, en la Figura 8 se muestra una representación gráfica de las relaciones y las probabilidades de transición de los equipos.

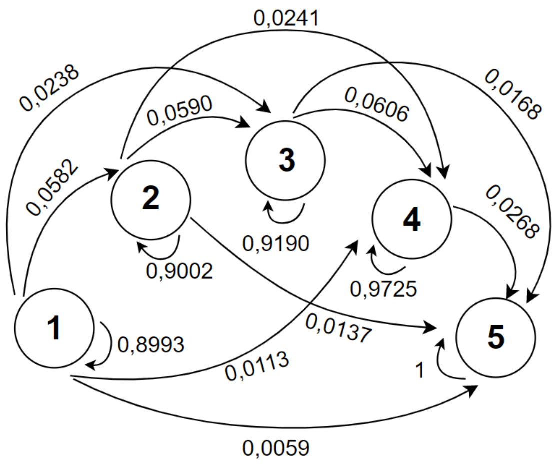


Figura 8.Grafo de transición de estados

Se observó que, para un estado de degradación inicial, la probabilidad de que se encuentre en un estado de degradación superior disminuye a medida que aumenta el estado de degradación. Por ejemplo, si un componente se encuentra en un estado inicial 1, la probabilidad de que se encuentre en el estado 5 es menor que la de que se encuentre en el estado 4. La matriz presenta una degradación gradual, es decir, a medida que el equipo se encuentra en un estado mayor, la probabilidad de que cambie de estado aumenta, reflejando que la degradación del componente incrementa la probabilidad de que cambie de estado.

Los elementos de la matriz de transición reflejan toda la información necesaria sobre la degradación de un componente. Por ejemplo, el elemento de la tercera fila y cuarta columna representa un equipo que inicialmente se encontraba en un estado de degradación 3, tiene un 6,06% de posibilidades de que se encuentre en el estado 4 tras el periodo de un mes.

Mediante la matriz de degradación se puede obtener la probabilidad de que un determinado componente esté en uno de los estados de colapso y construir las curvas que representan la probabilidad de que un equipo de TAC se encuentre en un estado de degradación en un momento dado. En la Figura 9 se muestra la evolución a lo largo del tiempo de la probabilidad que tiene un componente de encontrarse en uno de los estados.

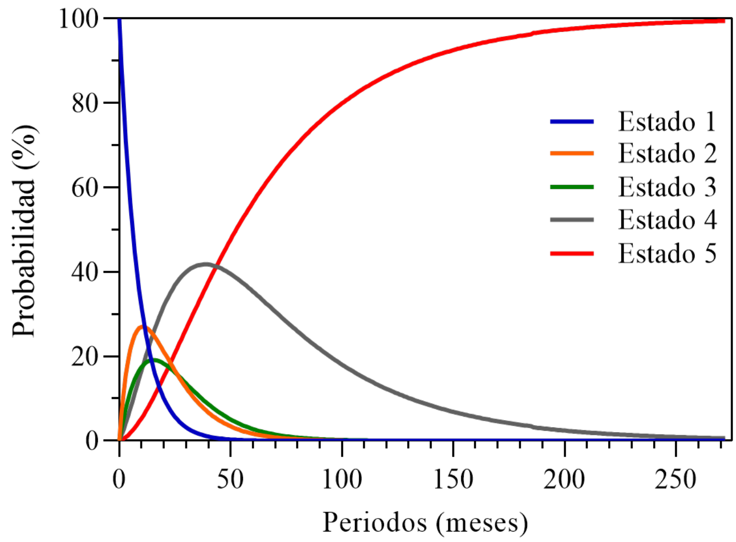


Figura 9. Curvas de probabilidad de los cinco estados de degradación

Se observó que hasta el octavo periodo la probabilidad de que el componente se encuentre en el estado de degradación 1 disminuye, mientras que aumenta la probabilidad del resto de estados. A partir de ese periodo, la probabilidad de que los componentes se encuentren en los estados 2 y 3 disminuye debido a que aumenta considerablemente la probabilidad de los estados de colapso, 4 y 5. La probabilidad del estado 2 disminuye más rápidamente que la del estado 3. Tras el paso del tiempo, la probabilidad de que los componentes se encuentren en los estados 1, 2 y 3 es nula, mientras que la probabilidad del estado 5 aumenta considerablemente.

Mediante la prueba estadística de la X^2 de Pearson se verificó que el modelo de Markov propuesto es adecuado para estimar la degradación de los equipos con un nivel de confianza del 95%, admitiendo la discrepancia entre lo observado durante las inspecciones y lo predicho por el modelo para un elevado nivel de confianza.

La utilidad de esta investigación reside en el desarrollo de un modelo que permite predecir la condición de los equipos electromédicos a lo largo de su vida útil, permitiendo planificar el mantenimiento y minimizar el riesgo de que estos equipos de diagnóstico se encuentren fuera de uso.

3.2. Scheduling of Preventive Maintenance in Healthcare Buildings Using Markov Chain

3.2.1. Datos editoriales

Título	Scheduling of Preventive Maintenance in Healthcare Buildings Using Markov Chain				
Autores	Jaime González Domínguez, Gonzalo Sánchez-Barroso y Justo García Sanz-Calcedo				
Revista	Applied Sciences			**Año**	2020
Volumen	10	**Página**	5263	**Editorial**	MDPI
DOI	10.3390/app10155263			**ISSN**	2076-3417

3.2.2. Indicios de calidad

Fuente de impacto	WOS (JCR)	**Índice de impacto**	2,679
Categoría	Engineering (Multidisciplinary)	**Cuartil**	Q2
Posición de la revista en la categoría	38	**Número de revistas en la categoría**	90
Citas en Web of Science	4	**Citas en Scopus**	7
Citas en Scholar	11	**Citas en Researchgate**	6

3.2.3. Resumen

El mantenimiento de los edificios sanitarios es una de las actividades más críticas de sistemas sanitarios, públicos o privados, ya que repercute en la seguridad y salud de sus usuarios. La optimización del mantenimiento de los edificios permite reducir los costes operativos y contribuye a aumentar la sostenibilidad del sistema sanitario. En esta investigación, se propone una herramienta para programar el mantenimiento preventivo de los centros de salud utilizando Cadenas de Markov. Para ello, los autores analizaron 25 centros sanitarios pertenecientes a tres áreas sanitarias de España, los cuales fueron construidos entre 1985 y 2005.

La aplicación de las Cadenas de Markov resultó útil para seleccionar las políticas de mantenimiento para cada edificio sanitario sin sobrepasar un límite de degradación específico, lo que permitió alcanzar una frecuencia de mantenimiento idónea y reducir el uso de recursos. Las Cadenas de Markov también fueron útiles para optimizar la periodicidad de las tareas de mantenimiento de ronda, garantizando un nivel adecuado de mantenimiento en función de la frecuencia de las averías, reduciendo el coste e impacto ambiental.

La frecuencia del mantenimiento inicial de los centros de salud analizados estaba planificada de forma quincenal, pero con la aplicación del modelo de Markov, se plantearon periodicidades de 3, 2 y 1 semana. La frecuencia del mantenimiento óptima de cada centro de salud depende de la política de mantenimiento más adecuada y del número medio de incidencias mensual. A partir de los resultados obtenidos, los centros analizados consiguieron ahorrar una media de 700 km de desplazamientos mensuales, reducir las emisiones en el conjunto de sus operaciones en 174,3 kg de CO_2eq al mes y aumentar la eficiencia global de las operaciones de mantenimiento en un 15%.

3.2.4. Resultados

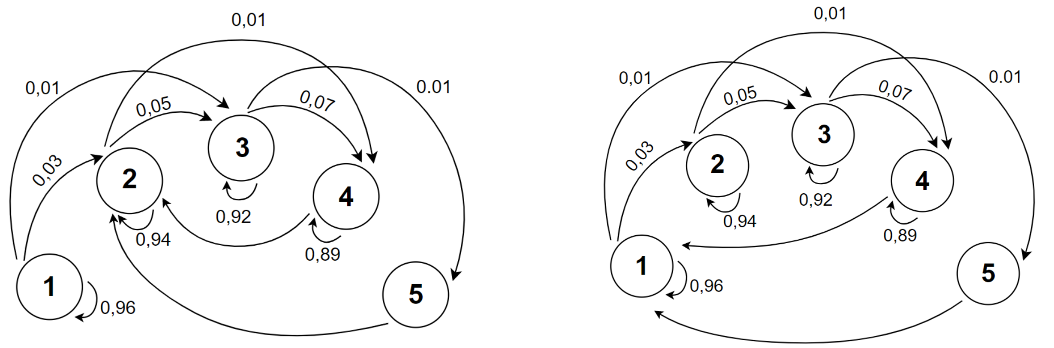
Se desarrolló un modelo de Markov de nueve estados de degradación, desde una condición excelente hasta una condición inaceptable, relacionándose cada uno de ellos con el número de incidencias mensuales y con el porcentaje de degradación. A partir del modelo generado se optimizó la política y la frecuencia de mantenimiento preventivo de los centros de salud en función de sus incidencias medias mensuales. La matriz de transición de estados empleada en esta investigación se muestra en la Figura 10.

$$P = \begin{bmatrix} 0{,}96 & 0{,}03 & 0{,}01 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0{,}94 & 0{,}05 & 0{,}01 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0{,}92 & 0{,}07 & 0{,}01 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0{,}89 & 0{,}10 & 0{,}01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0{,}85 & 0{,}11 & 0{,}03 & 0{,}01 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0{,}80 & 0{,}16 & 0{,}03 & 0{,}01 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0{,}74 & 0{,}22 & 0{,}04 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0{,}68 & 0{,}32 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Figura 10. Matriz de transición de estados del sistema

Se plantearon cinco políticas de mantenimiento distintas de forma matricial, diferenciándose en el estado de degradación máximo permisible y en el estado de condición objetivo tras las tareas de mantenimiento.

Posteriormente, se evaluaron las probabilidades de que los centros de salud se encuentren en cada uno de los estados de degradación definidos al implantar las cinco políticas de mantenimiento, de las cuales dos presentaron resultados adecuados que permitían que el sistema analizado se encontrase en todo momento en un estado de condición aceptable. En la Figura 11 se muestran los grafos de transición tras implantar las dos políticas de mantenimiento seleccionadas que presentaron mejores resultados.



a) Opción 2 **b) Opción 4**

Figura 11. Grafos de transición de las dos políticas de mantenimiento óptimas

En la opción 2 de mantenimiento el estado de degradación máximo es el estado 4 y tras el mantenimiento se regresa al estado 2. En la opción 4 de mantenimiento el estado de degradación máximo es el estado 4 y regresa al estado 1 tras el mantenimiento. No se priorizó entre las dos políticas de mantenimiento, sino que se determinó la estrategia óptima para cada centro de salud. Además, se determinó la frecuencia de mantenimiento más adecuada: 1, 2 o 3 semanas. Esta clasificación se realizó en función del número medio de incidencias mensuales de los centros de salud. En la Tabla 3 se muestra la periodicidad y la estrategia de mantenimiento en función de las incidencias medias mensuales.

Tabla 3. Incidencias medias mensuales permitidas

Frecuencia / Opción	Tres semanas	Dos semanas	Una semana
2º Opción	≤ 20 incidencias	27-30 incidencias	41-60 incidencias
4º Opción	21-26 incidencias	31-40 incidencias	61-80 incidencias

Teniendo en cuenta el número de incidencias intervenidas por cada estrategia de mantenimiento, se determinaron las incidencias máximas posibles entre visitas. El número de incidencias solucionadas tras realizar el mantenimiento especificado en la opción 2 es de 15, mientras que las incidencias corregidas con la opción 4 de mantenimiento es de 20. Por lo tanto, si un centro de salud presenta como estrategia de mantenimiento la opción 2 y una frecuencia de dos semanas, el total de incidencias máximas mensuales solucionadas tras el mantenimiento es de 30.

Analizando las incidencias medias mensuales, se agruparon los centros de salud en función de la periodicidad y la política de mantenimiento más adecuada. En la Figura 12 se muestran los resultados obtenidos.

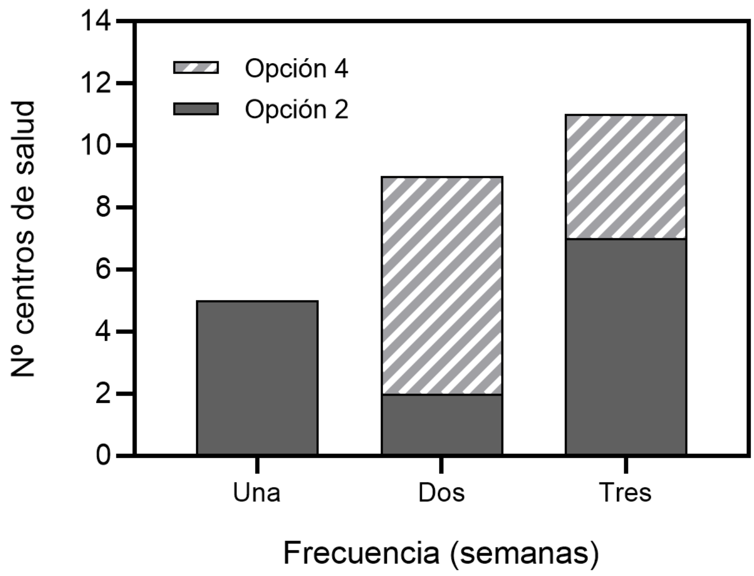


Figura 12. Centros de salud frente a la frecuencia de mantenimiento

Se obtuvo que la opción 2 es más adecuada para 14 de los 25 centros de salud analizados, de los cuales cinco tienen una frecuencia de una semana, dos cada dos semanas y siete cada tres semanas. Por otro lado, 11 centros de salud presentan la opción 4 como la más adecuada, de los cuales siete de estos centros tienen periodicidades cada 2 semanas y cuatro centros tienen una periodicidad de mantenimiento cada 3 semanas. Por lo tanto, se comprobó que combinar ambas estrategias de mantenimiento generan mejores resultados, ya que permiten que los centros de salud siempre se encuentren en todo momento en un estado de condición adecuado. Al optimizar el mantenimiento en función de las incidencias medias mensuales, se recomendó realizar una evaluación de las incidencias que se originan en los diferentes centros de salud cada 6 meses, reajustando la política y frecuencia de mantenimiento en base a esta información.

Además, en esta investigación se cuantificó la reducción de impacto ambiental asociada al transporte al optimizar la frecuencia de mantenimiento y se determinó que en los centros de salud analizados es posible ahorrar mensualmente 700 kilómetros de desplazamiento (18,5%), lo cual genera un importante ahorro de tiempo y combustible, reduciendo las emisiones en 174,3 kilogramos de CO_2eq cada mes.

Los resultados generados son útiles para la sociedad porque permite reducir el impacto ambiental asociado a las actividades de mantenimiento a través del modelo predictivo de las incidencias de un centro de salud y de la optimización de su frecuencia de mantenimiento, priorizando en todo momento la funcionalidad de estos edificios.

3.3. Preventive maintenance optimisation of accessible flat roof in healthcare centres using the Markov chain

3.3.1. Datos editoriales

Título	Preventive maintenance optimisation of accessible flat roof in healthcare centres using the Markov chain				
Autores	Jaime González Domínguez, Gonzalo Sánchez-Barroso y Justo García Sanz-Calcedo				
Revista	Journal of Building Engineering			**Año**	2020
Volumen	32	**Página**	101775	**Editorial**	Elsevier
DOI	10.1016/j.jobe.2020.101775			**ISSN**	2352-7102

3.3.2. Indicios de calidad

Fuente de impacto	WOS (JCR)	**Índice de impacto**	5,318
Categoría	Civil Engineering	**Cuartil**	Q1
Posición de la revista en la categoría	13	**Número de revistas en la categoría**	137
Citas en Web of Science	4	**Citas en Scopus**	6
Citas en Scholar	8	**Citas en Researchgate**	5

3.3.3. Resumen

La cubierta plana transitable es una de las tipologías constructivas más utilizada en hospitales, ya que permiten una adecuada ubicación y mantenimiento de instalaciones técnicas, aunque incrementan el riesgo de filtraciones que pueden alterar las condiciones normales de uso del edificio. Este tipo de cubiertas cuentan con membranas impermeables, las cuales pueden ser de diferentes materiales con diferentes propiedades.

El objetivo de este trabajo es optimizar la periodicidad de las operaciones de mantenimiento de las cubiertas planas en hospitales, para aumentar su vida útil y garantizar su fiabilidad. Se consideraron cubiertas planas transitables con tres tipos de membranas impermeables: bituminosa, policloruro de vinilo (PVC) y elastoméricas. Para contrastar el modelo de degradación, se procesó una muestra de 12 hospitales de Extremadura (España).

Los resultados muestran que es posible estimar la degradación de las cubiertas planas y determinar su mantenimiento más adecuado, teniendo en cuenta su fiabilidad. Se comprobó que, en un escenario con mantenimiento preventivo, es posible ampliar hasta 8 años la vida útil de las cubiertas con una fiabilidad elevada. En este escenario, se comprobó que la cubierta con membrana de PVC es la que tiene una menor degradación.

También se calculó la vida operativa media de las membranas, obteniéndose 28 años para las membranas de PVC, 24 años para las elastoméricas y 21 años para las bituminosas. Además, se calculó el tiempo de reemplazo de las cubiertas, de forma que es posible sistematizar las operaciones de mantenimiento, reduciendo su coste y aumentando su fiabilidad.

3.3.4. Resultados

Se definieron de forma matricial el mantenimiento de reemplazo y el mantenimiento de reparo de los elementos constructivos evaluados para establecer la mejor estrategia de mantenimiento a lo largo del tiempo. A partir del modelo de degradación de Markov de siete estados de condición, se determinó la fiabilidad de los tres tipos de cubiertas analizadas a lo largo de su vida útil y se realizó un análisis de supervivencia para compararlas. En la Figura 13 se muestra la función supervivencia de las tres membranas.

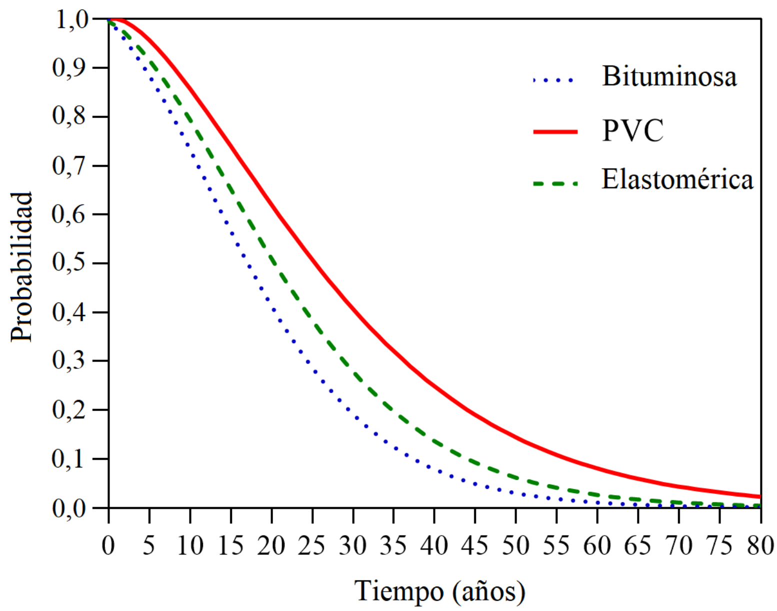


Figura 13. Función supervivencia de las tres membranas analizadas

Se observó que las membranas de PVC tienen mayor probabilidad de estar en un estado de degradación adecuado a lo largo del tiempo y que en las cubiertas bituminosas la probabilidad decrece más rápidamente.

Para calcular la vida útil de los tres tipos de cubiertas se determinó su función fallo. En la Figura 14 se muestra la función fallo de las tres membranas analizadas.

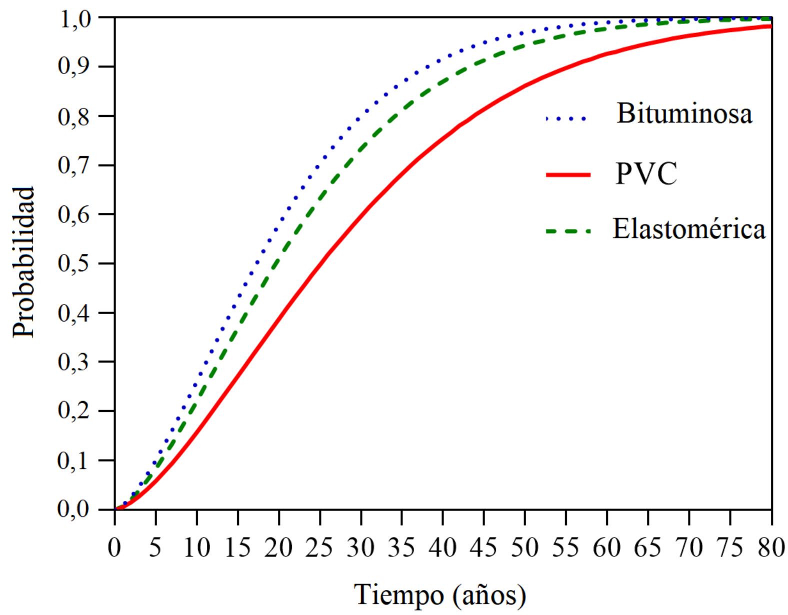


Figura 14. Función fallo de tres membranas analizadas

Se establecieron distintos valores límites de fiabilidad para analizar la evolución de la vida útil de las cubiertas, determinando su valor medio, cuyos resultados se muestran en la Tabla 4.

Tabla 4. Vida característica de las cubiertas

	Vida característica (años)		
Fiabilidad (%)	**Bituminosa**	**PVC**	**Elastoméricas**
80	8	13	10
75	10	14	11
70	11.5	16	13
65	13	18	15
63,2	13.5	19	16
60	14	20	16

En la tabla anterior se observa que para una fiabilidad mínima del 60% la vida útil es de 14, 20 y 16 años para las membranas bituminosas, PVC y elastoméricas, respectivamente.

Además, se calculó la fiabilidad de las cubiertas en función del estado de degradación inicial y de las tareas de mantenimiento preventivo, determinando la vida útil de las cubiertas para distintos escenarios. Esto es de gran utilidad para analizar el incremento de vida útil que se adquiere cuando se realiza mantenimiento preventivo. Además, este análisis es adecuado para establecer el reemplazo de las cubiertas de edificios en uso solo con la determinación del estado de degradación tras la inspección. En la Tabla 5 se muestran los resultados obtenidos.

Tabla 5. Reemplazo en función de la degradación inicial y la fiabilidad

		Escenarios				
	Estado	80%	75%	63,21%	63,21%/1M	63,21%/2M
Membrana PVC	1	13	15	20	24	28
	2	12	14	19	24	27
	3	11	13	18	23	26
	4	7	9	13	17	23
	5	7	9	12	16	23
	6	4	5	7	12	15
	7	1	1	1	1	1
Membrana bituminosa	1	8	10	14	17	21
	2	9	11	14	18	21
	3	7	9	12	16	20
	4	6	7	9	15	18
	5	4	5	8	13	17
	6	3	3	5	9	13
	7	1	1	1	1	1
Membrana elastomérica	1	10	12	16	20	24
	2	10	12	16	20	24
	3	9	10	14	19	23
	4	7	8	11	16	22
	5	5	6	9	14	19
	6	3	4	5	11	15
	7	1	1	1	1	1

Los resultados muestran que las membranas de PVC son las que menor degradación sufren, con una vida operativa de 28 años para una condición inicial excelente, siendo cuatro y siete años superior a la vida útil de las cubiertas elastoméricas y bituminosas, respectivamente. La vida útil de las cubiertas aumenta a medida que disminuye la fiabilidad mínima requerida y que se incrementa el mantenimiento preventivo. Se demostró la importancia del mantenimiento preventivo y cómo aumenta la vida operativa en un 40% para las cubiertas de PVC y en un 50% para las cubiertas bituminosas y elastoméricas. Además, se estableció el año óptimo para realizar las tareas de mantenimiento preventivo, de forma que se incremente la fiabilidad de las cubiertas analizadas. Para el escenario en el que solo se considera una operación de mantenimiento, ese debe realizarse en el año 7, 9 y 10 para las cubiertas bituminosas, elastoméricas y de PVC, respectivamente.

Estos resultados son de gran interés, puesto que permite determinar el año en el que se debe efectuar el mantenimiento de reparación y reemplazo para maximizar la vida útil de las cubiertas, garantizando en todo momento la fiabilidad de la infraestructura hospitalaria. Además, permite comparar diferentes soluciones constructivas, obteniendo resultados útiles para que los técnicos encargados de diseñar y construir los edificios sanitarios tomen decisiones que incrementen su mantenibilidad.

3.4. Condition-based maintenance of ceramic curved tiles roof in Primary Healthcare buildings using Markov chains

3.4.1. Datos editoriales

Título	Condition-based maintenance of ceramic curved tiles roof in Primary Healthcare buildings using Markov chains				
Autores	Jaime González Domínguez, Gonzalo Sánchez-Barroso, Justo García Sanz-Calcedo y Milan Sokol				
Revista	Journal of Building Engineering			**Año**	2021
Volumen	43	**Página**	102517	**Editorial**	Elsevier
DOI	10.1016/j.jobe.2021.102517			**ISSN**	2352-7102

3.4.2. Indicios de calidad

Fuente de impacto	WOS (JCR)	**Índice de impacto**	5,318
Categoría	Civil Engineering	**Cuartil**	Q1
Posición de la revista en la categoría	13	**Número de revistas en la categoría**	137
Citas en Web of Science	0	**Citas en Scopus**	0
Citas en Scholar	0	**Citas en Researchgate**	0

3.4.3. Resumen

Las cubiertas de teja cerámica son un tipo de paramento horizontal exterior comúnmente utilizado en la zona mediterránea, empleándose extendidamente en los centros de salud de Extremadura (España). Además de la impermeabilización, las cubiertas ventiladas de tejas cerámicas permiten disipar el calor solar mediante convención del aire.

El objetivo principal de esta investigación es analizar el mantenimiento basado en la condición (CBM) de las cubiertas de tejas cerámicas de los centros de salud. Se evaluó una muestra de 20 centros de salud de Extremadura (España) mediante Cadenas de Markov, la cual representa una técnica útil para analizar la influencia de la frecuencia y el año inicial de mantenimiento en el aumento de la vida útil de la cubierta.

Se determinó la frecuencia óptima de mantenimiento de las cubiertas de teja cerámicas, comprobando que la vida útil de los sistemas de cubiertas puede prolongarse utilizando un mantenimiento no periódico basado en la condición con un nivel de fiabilidad elevado. También se estimó el final de la vida útil de la cubierta, determinando que el tiempo máximo de reemplazo es de 39 años.

3.4.4. Resultados

Se analizaron las distintas anomalías que afectan al estado de condición de las cubiertas de tejas cerámicas, que depende de la gravedad de la anomalía y del área de la cubierta afectada. En esta investigación se utilizó un modelo de degradación de Markov de siete estados de condición y se representó de forma matricial el mantenimiento de reemplazo y reparo considerado.

En primer lugar, para evaluar la influencia del mantenimiento en la vida útil de la cubierta, se determinó el tiempo en el que la cubierta se encuentra en un estado de degradación adecuado sin mantenimiento, obteniendo que la cubierta analizada tiene una vida útil de 14 años. Tras este análisis inicial, se evaluó la influencia de la periodicidad del mantenimiento y del año de inicio de esta actividad, observándose que no solo influye la periodicidad de las operaciones de mantenimiento, sino que el año de inicio de estas acciones de mantenimiento es un factor muy determinante.

Se tuvieron en cuenta tres escenarios posibles: mantenimiento periódico bienal, trienal y cuatrienal y establecieron siete operaciones de mantenimiento distribuidas periódicamente a lo largo de los años para poder analizar su influencia sobre el estado de condición. Además, considerando el tiempo útil de funcionamiento de la cubierta, se estableció que el mantenimiento puede iniciarse desde el año 2 hasta el año 13. En la Tabla 6 y en la Figura 15 se muestra el año de reemplazo de la cubierta para los tres escenarios de mantenimiento y para distintos años de inicio del mantenimiento.

Tabla 6. Influencia de la periodicidad y el año de inicio del mantenimiento

Año de inicio	Reemplazo de la cubierta (años)		
	Escenario 1	Escenario 2	Escenario 3
2	26	31	35
3	27	32	36
4	28	33	36
5	28	33	37
6	29	34	37
7	30	34	38
8	30	35	38
9	30	35	38
10	31	35	38
11	31	35	31
12	31	35	28
13	31	31	21

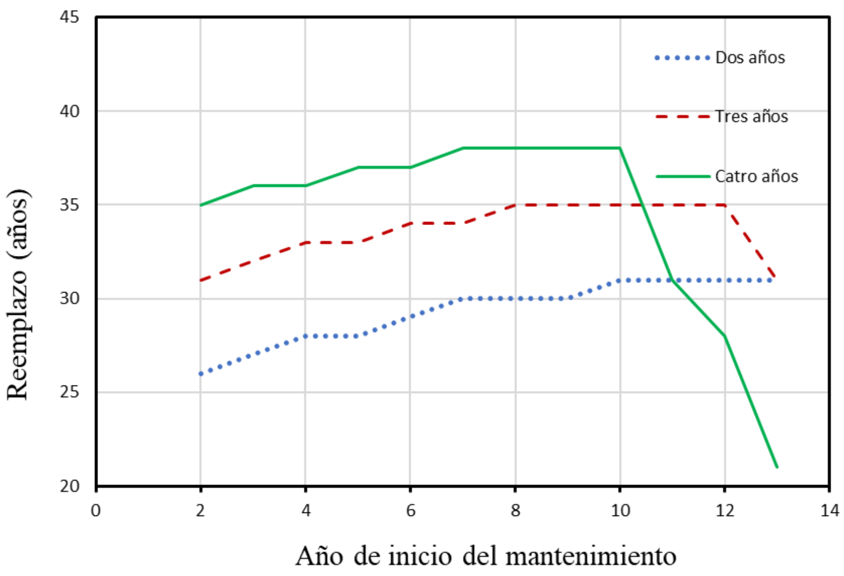


Figura 15. Influencia de la periodicidad y el año de inicio del mantenimiento

Se observó que, si el mantenimiento preventivo empieza en el segundo año tras la construcción de la cubierta cerámica, la mejor periodicidad de mantenimiento se presenta en el escenario 3, seguido del 2 y 1, reflejando la importancia de elegir adecuadamente la frecuencia con la que realizar el mantenimiento. Con el incremento del año inicial, aumentó el tiempo en el que las cubiertas se encuentran en un estado de condición adecuado. Para el escenario 3, 2 y 1 se obtiene un tiempo máximo de vida útil de 38, 35 y 31 años, respectivamente. La diferencia de 7 años entre los distintos escenarios es muy significativa, indicando la importancia de calcular cuál es la periodicidad adecuada para la cubierta de tejas cerámicas de un edificio.

Cuanto mayor es el periodo de mantenimiento, mayor es el riesgo de que el sistema colapse cuando el mantenimiento es tardío. Si en el escenario 3 el mantenimiento inicial es posterior al décimo año, se observa como decrece drásticamente la vida útil de la cubierta. Esto se debe a que la degradación es demasiado significativa como para que la frecuencia de las operaciones de mantenimiento logre aumentar suficientemente la fiabilidad de la cubierta. Este comportamiento se aprecia en menor medida en el escenario 2. Por último, se observó como el escenario 1 es el más adecuado cuando el mantenimiento se inicia en los años 11, 12 y 13.

Además, se analizó la influencia del número de operaciones de mantenimiento a lo largo de la vida útil, realizando un cálculo iterativo para determinar la frecuencia de mantenimiento óptima, que incremente la fiabilidad de la cubierta y, en consecuencia, su vida útil. En la Tabla 7 se muestra la vida útil de la cubierta tras considerar distinto número de operaciones de mantenimiento.

Tabla 7. Influencia de las operaciones de mantenimiento a lo largo de la vida útil

Mantenimiento (Uds.)	-	1	2	3	4	5	6	7
Vida útil (años)	14	19	22	26	31	34	37	39

Se observó que el mantenimiento no periódico permite que la vida útil de la cubierta sea de 39 años, demostrándose que estableciendo el año óptimo para realizar el mantenimiento genera mejores resultados que considerando actividades de mantenimiento cada 4 años. Además, se comprobó que no existe una única programación del mantenimiento que genera una vida útil de 39 años.

Los resultados de esta investigación sirven para determinar el mejor programa de mantenimiento en función del presupuesto destinado cada año a esta actividad, optimizando los recursos del sistema sanitario. Además, permite determinar la mejor frecuencia de mantenimiento tanto en los edificios sanitarios operativos o de nueva construcción, a través del análisis de la influencia de la periodicidad y del año de inicio del mantenimiento en la fiabilidad y la vida útil de las cubiertas.

3.5. Cox proportional hazards model used for predictive analysis of the energy consumption of healthcare buildings

3.5.1. Datos editoriales

Título	Cox proportional hazards model used for predictive analysis of the energy consumption of healthcare buildings				
Autores	Jaime González Domínguez, Gonzalo Sánchez-Barroso, Justo García Sanz-Calcedo y Nuno de Sousa Neves				
Revista	Energy and Buildings			**Año**	2022
Volumen	257	**Página**	111784	**Editorial**	Elsevier
DOI	10.1016/j.enbuild.2021.111784			**ISSN**	0378-7788

3.5.2. Indicios de calidad

Fuente de impacto	WOS (JCR)	**Índice de impacto**	5,879
Categoría	Civil Engineering	**Cuartil**	Q1
Posición de la revista en la categoría	9	**Número de revistas en la categoría**	137
Citas en Web of Science	1	**Citas en Scopus**	1
Citas en Scholar	1	**Citas en Researchgate**	1

3.5.3. Resumen

El consumo de energía de los edificios sanitarios es muy elevado debido a su operación continua y a la demanda proveniente de dispositivos electromédicos. El objetivo de esta investigación consiste en aplicar el modelo de riesgos proporcionales de Cox para predecir la distribución temporal de la probabilidad de exceder el consumo de energía de los edificios sanitarios. Se estableció un índice de consumo energético de referencia a partir de un análisis retrospectivo del consumo mensual de 64 edificios sanitarios durante el período comprendido entre 2015 y 2019 y se seleccionaron como parámetros funcionales del modelo de riesgos proporcionales de Cox variables constructivas, de instalaciones, demográficas y climatológicas.

En esta investigación se demostró que las variables relativas a instalaciones y a demografía influyen significativamente en el modelo semiparámetrico propuesto, se cuantificó esta influencia y se verificó gráficamente la validez del modelo. Se encontró que tener asignados más de 10.000 usuarios supone una probabilidad 124% superior de sobrepasar el consumo energético de referencia, un 97,4% más si tiene una potencia instalada mayor de 60 kW, un 94,6% más si la población donde está situado el centro de salud tiene más de 5.000 habitantes y un 69,4% superior si no usa bomba de calor para la climatización.

El modelo de riesgos proporcionales de Cox se mostró como una herramienta útil para cuantificar la influencia de diversas variables funcionales en el exceso de consumo energético de los edificios sanitarios. Los resultados de la investigación generan información objetiva para establecer, por un lado, criterios de diseño y renovación de edificios sanitarios y, por otro, estrategias de planificación asistencial, que pueden utilizarse para los edificios sanitarios existentes o de nueva construcción.

3.5.4. Resultados

El principal resultado de esta investigación es el análisis de las variables que influyen significativamente en el consumo de energía de los centros sanitarios, generando una herramienta útil para el diseño y la gestión de los edificios sanitarios. En primer lugar, se identificaron las variables que afectan al consumo de energía de los edificios sanitarios, se categorizaron las distintas variables identificadas y se determinó si su influencia era significativa a través de la prueba de Wald, cuyos resultados se muestran en la Tabla 8.

Tabla 8. Resultados de la prueba de Wald

Variable	Wald	Significancia	Afecta
Constructor	0,507	0,477	No
Año de construcción	0,953	0,329	No
Número de plantas	0,953	0,329	No
Usuarios	7,308	0,007*	Sí
Población	6,447	0,011*	Sí
Potencia instalada	5,004	0,025*	Sí
Temperatura mínima	0,001	0,975	No
Temperatura máxima	0,359	0,549	No
Temperatura media	0,283	0,673	No
Bomba de calor	4,496	0,034*	Sí

(*) estadísticamente significante

Se determinó que las variables influyentes sobre el consumo de energía son: número de usuarios, población atendida, potencia eléctrica instalada y si dispone de bomba de calor para climatización, ya que presentan un valor de significancia inferior a 0,05. Posteriormente, se cuantificó la influencia de estas variables sobre el consumo de energía mediante la determinación del índice de Hazard y se determinó el límite de control superior e inferior.

En la Tabla 9 se muestran los resultados de aplicar el modelo de riesgos proporcionales de Cox.

Tabla 9. Resultados del modelo de riesgos proporcionales de Cox

Variable	β	Exp (β)=HR	LCI (95%)	LCS (95%)
Usuarios	0,806	2,240	1,248	4,018
Población	0,666	1,946	1,164	3,253
Potencia instalada	0,680	1,974	1,088	3,581
Bomba de calor	0,527	1,694	1,041	2,758

Se estableció que los edificios sanitarios ubicados en poblaciones de más de 5.000 habitantes presentan un riesgo de exceso de consumo de energía 1,946 veces superior a los edificios que están situados en poblaciones de menos de 5.000 habitantes. Por lo tanto, en los primeros existe un 94,6% (IC-95%: 16,4%-225,3%) más de probabilidades de que se exceda el consumo de energía de referencia. Los edificios sanitarios cuya área de atención primaria supera las 10.000 personas aumentan la probabilidad de que excedan su consumo de energía un 124% más (IC-95%: 24,8%-301,8%) respecto a los edificios sanitarios cuyo número de usuarios es inferior a 10.000 personas.

Se observó que los edificios sanitarios que tienen una potencia instalada superior a 60 kW presentan un riesgo 1,974 veces superior a los edificios que tienen una potencia instalada inferior a 60 kW. Este riesgo puede variar entre 1,088 y 3,581 veces, con un nivel de confianza del 95%. Por último, cuando los edificios sanitarios no tienen bomba de calor como sistema de climatización, la probabilidad de que el centro de salud exceda su consumo de energía es 69,4% más alto que los centros sanitarios que tienen bomba de calor como sistema de climatización, variando desde un 4,1% hasta un 175,8% con un nivel de confianza del 95%.

Además, se determinaron las curvas de riesgo acumulado y de supervivencia para cada una de estas variables, determinando la probabilidad de que los edificios sanitarios excedan el consumo de energía para un tiempo establecido con la influencia de las distintas variables. A partir de las curvas de supervivencia, se determinó la probabilidad de que los edificios sanitarios no excedan el consumo de energía a lo largo del periodo de observación y se comprobó que todas las curvan son decrecientes, siendo similares para las cuatro variables.

Por último, se demostró que las cuatro variables analizadas cumplían con el supuesto de proporcionalidad del modelo de Cox, comprobando que eran proporcionales y, por lo tanto, era adecuado aplicar el modelo. En la Figura 16 se muestran las curvas Log-Log de las cuatro variables.

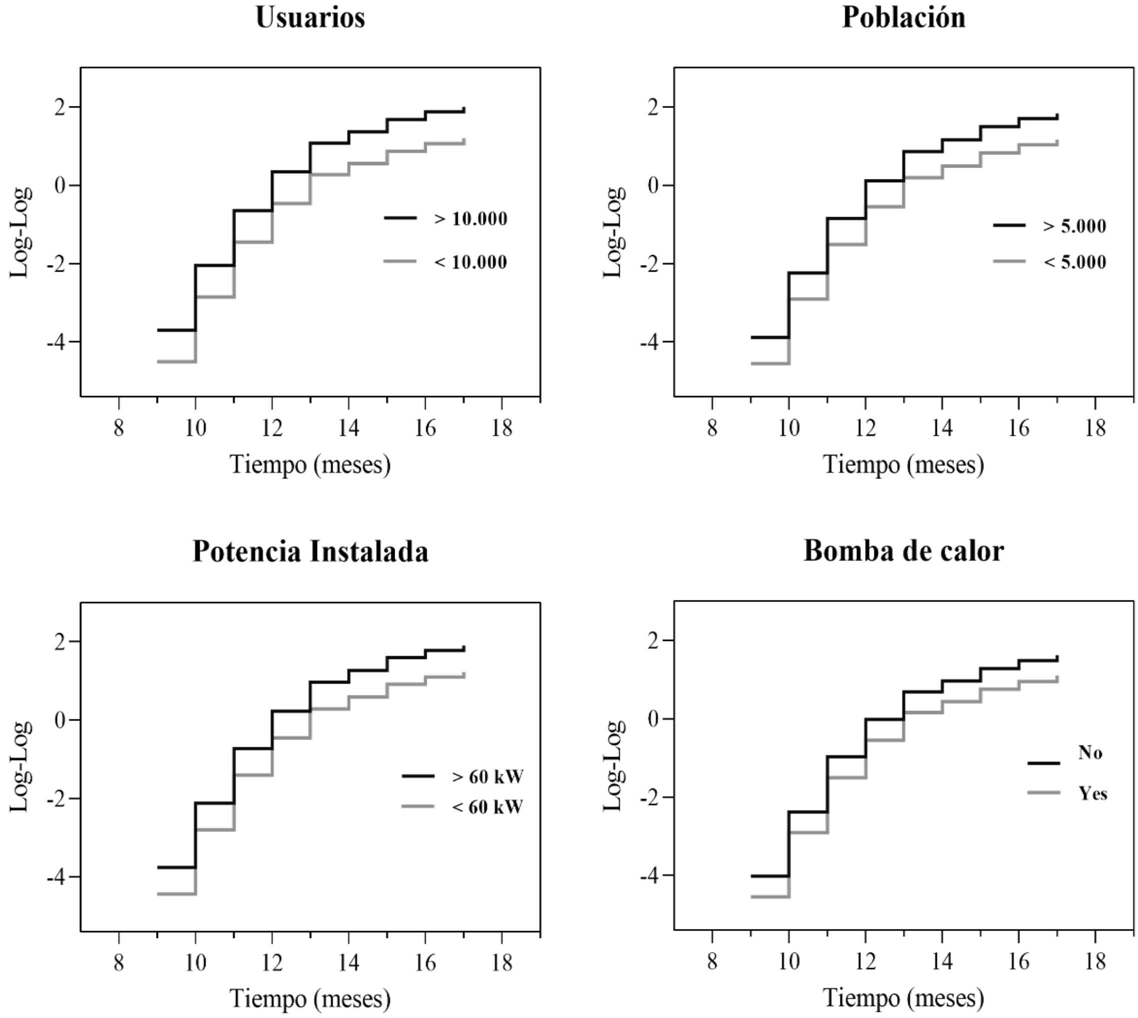


Figura 16. Curvas Log-Log de las variables que afectan al evento analizado

A partir de los resultados obtenidos se demostró la importancia de evaluar mediante herramientas estadísticas no convencionales la gestión energética de los edificios sanitarios y se contrastó que el modelo de riesgos proporcionales de Cox es una herramienta útil para identificar las variables significativamente influyentes sobre un problema multivariable dentro de la Ingeniería Hospitalaria. Además, el modelo de supervivencia de Cox permite cuantificar la influencia de las variables y obtener información útil para establecer criterios de diseño y renovación de edificios sanitarios nuevos y existentes o estrategias de planificación asistencial.

Capítulo 4. Discusión

Los edificios sanitarios tienen equipos e instalaciones singulares, más críticos y complejos que otros edificios [97]. Debido a su intensidad operativa, la degradación de estas infraestructuras es superior al resto de edificios del sector terciario, por lo que es necesario realizar un mantenimiento más intenso [98] y analizar cómo evoluciona su degradación para garantizar su operatividad, la calidad de la atención sanitaria y la salud y seguridad de sus usuarios [99].

Esta necesidad se ha incrementado durante la crisis sanitaria, ya que la infraestructura hospitalaria ha experimentado un aumento de su ocupación media, aumentando el riesgo de que los equipos electromédicos colapsen o que las instalaciones no funcionen de manera adecuada [100]. De esta forma, emplear el modelo estocástico de las Cadenas de Markov para estimar la degradación de la infraestructura sanitaria es muy útil, ya que permite optimizar la frecuencia del mantenimiento y seleccionar la estrategia más adecuada [101]. Esta metodología ha sido contrastada en la literatura existente y, actualmente, la norma UNE-EN 61703: 2021 [102], ya propone el modelo de Markov para el análisis de la fiabilidad, disponibilidad y mantenibilidad de un sistema.

El mantenimiento correctivo es el mantenimiento más frecuente en los edificios sanitarios, ya que se actúa tras la aparición del fallo [103] e incluye todas las acciones necesarias para que el sistema vuelva a adquirir una funcionalidad adecuada. Sin embargo, el mantenimiento correctivo incrementa el riesgo de que las infraestructuras hospitalarias sufran paros de emergencia o tiempos muertos, reduciendo la calidad de la asistencia sanitaria y los beneficios generados [104]. En la presente investigación se fomenta el empleo del mantenimiento preventivo frente al correctivo y se propone emplear la metodología de Markov para gestionar el mantenimiento predictivo basado en la condición futura de un sistema, reduciendo los tiempos en el que la infraestructura no esté operativa a partir de la prevención de los fallos estimados [105].

La disponibilidad presupuestaria del sistema sanitario no es ilimitada y deben priorizarse aquellas acciones que garanticen una atención sanitaria de calidad [106]. Los análisis realizados a partir del modelo de Markov generan información muy útil para realizar una buena programación del mantenimiento, gestionando adecuadamente los recursos económicos y técnicos [107]. Esta optimización de los recursos destinados al mantenimiento posibilita la inversión de los recursos económicos en la modernización de la infraestructura hospitalaria, la implementación de energías renovables o la contratación de personal asistencial.

Los equipos electromédicos son uno de los activos con mayor nivel de mantenimiento de la infraestructura hospitalaria [108], invirtiéndose numerosos recursos económicos y técnicos en mantener adecuadamente su funcionamiento [109]. Sin embargo, el tiempo en el que se encuentran fuera de uso es considerable, habitualmente debido a la necesidad de solicitar piezas de sustitución a los proveedores o fabricantes, ya que se tratan de equipos de alta tecnología con suministros limitados. La predicción obtenida a partir del modelo de degradación permite adquirir las piezas necesarias con anterioridad y disminuir los tiempos de inactividad de los equipos [110]. Esta reducción se traduce en un aumento del número de diagnósticos, incrementando la calidad de la asistencia sanitaria pública y, en el caso de la asistencia sanitaria privada, un incremento de la rentabilidad de los equipos y de los beneficios obtenidos. Además, la información generada puede ser un poder de negociación muy importante en el establecimiento de las actividades de mantenimiento subcontratadas a proveedores externos o a los propios fabricantes.

Además, la metodología estocástica del modelo de Markov permite optimizar el mantenimiento garantizando un estado de condición adecuado [111]. Esto es fundamental para los edificios y equipos sanitarios, puesto que puede fijarse un valor de fiabilidad mínimo que satisfaga las necesidades de la atención sanitaria. Por otro lado, los modelos generados por Markov son actualizables, siendo idóneos para los análisis en Ingeniería Hospitalaria, ya que es posible adaptar los modelos de degradación a los continuos cambios que sufre la infraestructura hospitalaria: ampliaciones, reordenación territorial, apertura de nuevos edificios, adquisición de nuevos equipos, mejora de las instalaciones, etc. [112]. A través de la implantación del modelo predictivo en el programa de gestión utilizado por los gestores de mantenimiento, se automatizará el proceso de decisión y se minimizarán los recursos utilizados.

A pesar de todo, el modelo de degradación de Markov presenta una serie de limitaciones debido fundamentalmente a que, para elaborar el modelo, es necesario disponer de datos de degradación observado durante inspecciones [113]. Por lo tanto, es muy complejo desarrollar modelos de degradación de equipos electromédicos nuevos de alta tecnología, ya que no se dispone de un histórico de datos consistente. Sin embargo, esta limitación no existe para equipos electromédicos como los TACs o ecógrafos, ya que son ampliamente utilizados. Por último, cuando la degradación de un sistema determinado depende de una multitud de factores, la definición de la escala de degradación es compleja. Para simplificar la evaluación de problemas multivariables en la Ingeniería Hospitalaria, la presente investigación propone emplear el modelo de riesgos proporcionales de Cox para analizar la influencia de diferentes variables sobre un evento complejo [114]. El modelo de regresión de Cox permite identificar las principales variables que afectan a un evento dependiente del tiempo [115], simplificando los análisis realizados para optimizar la infraestructura sanitaria, identificando la influencia de los distintos factores que afectan a la degradación del sistema y estableciendo los estados de degradación en consecuencia.

El modelo de riesgos proporcionales de Cox ha sido empleado con frecuencia en el análisis de las distintas variables que afectan a la supervivencia de un paciente con una determinada enfermedad o patología [116–118]. Existen algunas investigaciones que aplican este modelo en ingeniería de fiabilidad [119,120]. Sin embargo, no existen precedentes que apliquen la regresión de Cox en los problemas multivariables que se analizan en Ingeniería Hospitalaria. Por lo tanto, la aplicación de este modelo permitirá generar conocimiento inexistente útil para la optimización de las infraestructuras hospitalarias. Además, el modelo de Cox no precisa de conocer la función de riesgo del evento analizado, ya que la función de probabilidad solo depende de los coeficientes del modelo [121], permitiendo analizar eventos donde no se conoce con precisión el riesgo de fallo.

Los resultados obtenidos en esta investigación pueden aplicarse a otros países que dispongan de una infraestructura similar, incrementando la utilidad del conocimiento generado. Sin embargo, no son útiles en países donde los edificios sanitarios tengan otros elementos estructurales, la operatividad sea distinta o que se gestione de manera diferente.

Capítulo 5. Conclusiones

5.1. Conclusiones generales

La presente Tesis Doctoral se alinea con el objetivo principal de la Ingeniería Hospitalaria, ya que permite mejorar la calidad asistencial y la gestión del sistema sanitario. Concretamente, ha permitido generar un conocimiento importante e inexistente sobre la fiabilidad y mantenimiento de las infraestructuras hospitalarias, mejorando la toma de decisiones y garantizando la fiabilidad de los equipos, instalaciones y edificios sanitarios a lo largo de su vida útil.

Los resultados de la investigación reflejan la necesidad de optimizar el mantenimiento y la gestión de estas infraestructuras, reduciendo el coste operacional y aumentando su sostenibilidad. Los resultados permiten generar indicadores útiles para los responsables del área de ingeniería y mantenimiento de los sistemas de salud públicos y privados. De esta forma, se simplifica la compleja programación de las tareas de mantenimiento, disminuye el riesgo de inoperatividad de las infraestructuras, garantiza la calidad del servicio y la productividad de la organización. Además, la evaluación del mantenimiento permite establecer el presupuesto en un horizonte temporal considerable, optimizando las inversiones y el reparto del presupuesto entre los distintos servicios.

Se ha comprobado que la información generada en la investigación no solo permite gestionar adecuadamente los edificios sanitarios existentes, sino que también son útiles para diseñar nuevos centros hospitalarios. Además, ayudará a conformar las plantillas del personal encargado del mantenimiento, generando un valor añadido que ayudará al establecimiento óptimo de los recursos presentes y futuros del sistema sanitario.

En definitiva, los resultados obtenidos cumplen con los objetivos impuestos inicialmente y se alinean con la línea de investigación de Ingeniería Hospitalaria. Además, la calidad de los resultados está avalado por las cinco publicaciones científicas indexadas en *Journal Citation Reports* que componen la Tesis por compendio.

This Doctoral Thesis is in line with the main objective of Healthcare Engineering, as it enables the improvement of the quality of care and the management of the healthcare system. Specifically, it has generated important and non-existent knowledge on the reliability and maintenance of hospital infrastructures, by improving decision-making policies and by guaranteeing reliability of healthcare equipment, facilities, and buildings throughout their service life.

Research outcomes reflect the need to optimise the maintenance and management of hospital infrastructures, to reduce operational costs and to increase their sustainability. The results generate useful indicators for maintenance and engineering managers in public and private healthcare systems. Therefore, complex scheduling of maintenance operations has been reduced, as well as the risk of inoperability of infrastructures. Moreover, the quality of the service and the productivity of the organisation is consequently ensured. On the other hand, the maintenance assessment allows to establish the budget over a considerable time horizon, optimising investments, and the distribution of the budget among the different services.

It has been shown that the information generated in the research not only allows adequate management for existing healthcare buildings, but it also has been demonstrated useful for new hospital facilities. Also, it will help to optimally shape the maintenance staff layout, generating added value that will help in the optimal allocation of present and future resources within the healthcare system.

In conclusion, results meet the objectives initially set and they are aligned with the Healthcare Engineering research line. Furthermore, the quality of the results is endorsed by the five scientific publications indexed in Journal Citation Reports that conform this thesis by compendium.

5.2. Conclusiones específicas

La aplicación del modelo de Markov ha permitido evaluar la frecuencia y la estrategia de mantenimiento preventivo óptima para los centros de salud analizados en función de sus incidencias medias mensuales. De esta forma, se ha comprobado que la frecuencia actual del mantenimiento de ronda no es la más eficiente y que la frecuencia obtenida de aplicar las Cadenas de Markov permite reducir el transporte asociado a los técnicos de mantenimiento.

A partir de esta investigación se ha concluido que el modelo de degradación de Markov es adecuada para estimar la vida útil de los componentes críticos de los edificios sanitarios, ya que es posible optimizarla garantizando su fiabilidad. Por tanto, es posible comparar diferentes soluciones constructivas en base a su fiabilidad, incrementando el nivel de mantenibilidad de las infraestructuras hospitalarias.

En esta investigación se ha comprobado que es posible sistematizar las operaciones de mantenimiento en función de la degradación inicial del sistema analizado. Además, se ha evaluado la influencia del mantenimiento en la fiabilidad del sistema, cuantificando el incremento de vida útil cuando se opta por una frecuencia de mantenimiento periódico o de una frecuencia no periódica basada en el estado de condición. Se comprobó que existe más de una programación de mantenimiento no periódica que optimiza la vida útil, permitiendo seleccionar la más adecuada en función de factores técnicos, económicos, etc. También se determinó la influencia del año de inicio del mantenimiento sobre la vida útil, permitiendo programar el mantenimiento de reparación o reemplazo en consecuencia.

Otra conclusión importante de esta investigación es que se puede aplicar el modelo predictivo de Markov para el análisis de la degradación de equipos electromédicos. El funcionamiento de los equipos es complejo, pero se consiguió establecer una escala de condición apropiada y se obtuvo un modelo con una significancia adecuada. El análisis de fallos de los equipos electromédicos permite definir adecuadamente el servicio de mantenimiento necesario en caso de externalizar la actividad y permite establecer estrategias de compra a largo plazo, acuerdos con proveedores externos o seleccionar adecuadamente la tecnología.

Finalmente, se ha comprobado la eficacia del modelo de riesgos proporcionales de Cox aplicado a los análisis multivariables de problemas complejos de la Ingeniería Hospitalaria, ya que ha permitido identificar las variables más influyentes sobre el consumo de energía de los edificios sanitarios. Por lo tanto, se propone como complemento con el modelo de degradación de Markov, permitiendo identificar la influencia de los distintos factores que afectan a la degradación del sistema y estableciendo los estados de degradación en función de la información obtenida.

The application of the Markov model has made it possible to evaluate the frequency and the optimal preventive maintenance strategy for the healthcare centres analysed based on their average monthly incidents. In this way, it was found that the current frequency of maintenance rounds is not the most efficient and the application of Markov chains reduces the transport associated with maintenance technicians.

From this research it has been concluded that the Markov degradation model is very useful for estimating the service life of critical components of healthcare buildings, since it is possible to optimise it by guaranteeing its reliability. Therefore, it is possible to compare different construction solutions based on their reliability, increasing the level of maintainability of hospital infrastructures.

This research has shown that it is possible to systematise maintenance operations according to the initial degradation of the analysed system. Furthermore, the influence of maintenance on the reliability of the system has been evaluated, quantifying the increase in service life when opting for a periodic maintenance frequency or a non-periodic frequency based on the state of condition. It was found that there is more than one non-periodic maintenance schedule that optimises service life, allowing the most appropriate one to be selected based on different factors like technical or economic. The influence of maintenance initial year on service life was also determined, allowing repair or replacement maintenance to be scheduled accordingly.

Another important conclusion of this research is that the predictive Markov model can be applied to the analysis of the degradation of electro-medical equipment. The operation of the equipment is complex, but an appropriate condition scale was established and a model with adequate significance was obtained. The failure analysis of electro-medical equipment allows the maintenance service required in the event of outsourcing the activity to be properly defined and allows long-term purchasing strategies, agreements with external suppliers or the appropriate selection of technology to be established.

On the other hand, the effectiveness of the Cox proportional hazards model applied to multivariate analysis of complex problems in Healthcare Engineering has been proven, as it has allowed the identification of the most influential variables on the energy consumption of healthcare buildings. Therefore, it is proposed as a complement to the Markov degradation model, making it possible to identify the influence of the different factors that affect the degradation of the system and establishing the states of degradation based on the information obtained.

5.3. Líneas futuras de trabajo

A partir la presente Tesis Doctoral, surgen múltiples líneas futuras de investigación con un gran potencial de generar conocimiento innovador y de gran utilidad dentro de la Ingeniería Hospitalaria.

En base a la línea de investigación actual, la literatura existente y los resultados obtenidos, se plantean las siguientes líneas futuras de investigación:

- Combinar el modelo de degradación de Markov con técnicas de análisis de impacto ambiental, para obtener resultados que permitan seleccionar los elementos constructivos en función de su operatividad y a su huella de carbono durante su vida útil. De esta forma, se aumentará la sostenibilidad de la infraestructura sanitaria, reduciendo el impacto medioambiental de su actividad.

- Aplicar el modelo de riesgos proporcionales de Cox para analizar los factores que influyen significativamente en la degradación de los edificios y equipos sanitarios, utilizando los resultados obtenidos para definir y detallar los estados de degradación del sistema analizado mediante el modelo de degradación de Markov.
- Cuantificar la fiabilidad de los equipos de tomografía axial computarizada para determinar su vida útil y minimizar el tiempo en el que se encuentran fuera de uso. Además, analizar la fiabilidad de los equipos electromédicos y el coste del mantenimiento para determinar la mejor estrategia de mantenimiento posible.
- Generar un modelo predictivo de consumo de energía, agua y gases medicinales de los edificios sanitarios modelando su ocupación mediante las Cadenas de Markov. Por consiguiente, es posible estandarizar los patrones de ocupación de las áreas funcionales de los edificios sanitarios e identificar los parámetros asistenciales que afectan a la ocupación y demanda de recursos.
- Implementar técnicas de inteligencia artificial (*Machine Learning*) para generar modelos predictivos automáticos de mantenimiento de diferentes componentes relacionadas con las infraestructuras hospitalarias.
- Evaluar la resiliencia de la infraestructura sanitaria basándose en indicadores cuantitativos y actualizables que reflejen su rendimiento y operatividad, estableciendo un plan de acción donde se reflejen estrategias de diseño y de mantenimiento para incrementar su resiliencia.

Capítulo 6. Referencias

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Capítulo 7. Relación de publicaciones

En este capítulo se muestra las publicaciones derivadas directa e indirectamente de la Tesis Doctoral, reflejando el impacto de los resultados obtenidos durante el desarrollo de esta investigación. Se muestran los artículos científicos indexados en *Journal Citations Reports* que conforman el compendio de artículos, los artículos indexados en *SCImago Journal Rank* y las comunicaciones presentadas a congresos.

7.1. Artículos indexados en *Journal Citation Reports*

Anexo-I	J. González-Domínguez, G. Sánchez-Barroso, J. Aunión-Villa, J. García-Sanz-Calcedo, "Markov modelo of computed tomography equipment," *Engineering Failure analysis,* vol. 127, p.105506, 2021. DOI: 10.1016/j.engfailanal.2021.105506.
Anexo-II	J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, "Scheduling of Preventive Maintenance in Healthcare Buildings Using Markov Chain," *Applied Sciences,* vol. 10, p. 5263, 2020. DOI: 10.3390/app10155263.
Anexo-III	J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, "Preventive maintenance optimisation of accessible flat roofs in healthcare centres using the Markov chain," *Journal of Building Engineering*, vol. 32, p. 101775, 2020. DOI: 10.1016/j.jobe.2020.101775.
Anexo-IV	J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, M. Sokol, "Condition-based maintenance of ceramic curved tiles roof in Primary Healthcare buildings using Markov chains," *Journal of Building Engineering*, vol. 43, p. 102517, 2021. DOI: 10.1016/j.jobe.2021.102517.
Anexo-V	J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, N. de Sousa Neves, "Cox proportional hazards model used for predictive

analysis of the energy consumption of healthcare buildings," *Energy & Buildings*, vol. 257, p. 111784, 2022. DOI: 10.1016/j.enbuild.2021.111784.

7.2. Artículos indexados en *SCImago Journal Rank*

P. Garrido-Píriz, M. Botejara-Antúnez, G. Sánchez-Barroso, J. González-Domínguez, J. García Sanz-Calcedo, "Overview of resilience: a concept to assess healthcare infrastructure preparedness against disasters. Evaluation of existing models and applicability to HVAC systems," *IOP Conference Series: Earth and Environmental Science,* vol. 664, nº 1, p. 012052, 2021. DOI: 10.1088/1755-1315/664/1/012052.

M. Botejara-Antúnez, P. Garrido-Píriz, G. Sánchez-Barroso, J. González-Domínguez, J. García Sanz-Calcedo, "Life Cycle Assessment (LCA) in the construction of healthcare buildings. Analysis of environmental impact," *IOP Conference Series: Earth and Environmental Science,* vol. 664, nº 1, p. 012053, 2021. DOI: 10.1088/1755-1315/664/1/012053.

7.3. Comunicaciones presentadas a congresos

J. González Domínguez, G. Sánchez-Barroso, J. García Sanz-Calcedo, "Compensación en altura para tratamientos de hidrocinesiterapia en personas con dismetría mediante calzado regulable," 8º *Congreso Internacional Virtual de Enfermería Familiar y Comunitaria*. 01-19 de octubre, 2019. Cordoba (España).

J. González Domínguez, G. Sánchez-Barroso, J. García Sanz-Calcedo, "Mejora de la calidad lumínica en quirófanos portátiles mediante luminaria articulada," 8º *Congreso Internacional Virtual de Enfermería Familiar y Comunitaria.* 01-19 de octubre, 2019. Cordoba (España).

M. Botejara-Antúnez, P. Garrido-Píriz, G. Sánchez-Barroso, J. González-Domínguez, J. García Sanz-Calcedo "Life Cycle Assessment of Different Medical Devices and their Influence on the environmental Impact of Healthcare Buildings," *6th Virtual International Conference on Science, Technology and Management in Energy*. ISBN: 978-86-80616-07-0. December 14-15, 2020. Nis (Serbia).

J. González Domínguez, G. Sánchez-Barroso, J. García Sanz-Calcedo, F. Badilla-Murillo, M. Gómez-Chaparro, J. Aunión-Villa, "Applicability of statistical techniques based on Markov chains in engineering," *5th International Conference on Technological Innovation in Building.* ISBN: 978-84-182-5504-5. March 25-April 8, 2020. Madrid (Spain).

J. Aunión-Villa, J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, F. López-Rodríguez, "Assessment of the acquisition value of electro-medical equipment in relation to infrastructure, healthcare use and energy consumption in hospitals," *24th International Congress on Project Management and Engineering*. ISBN: 978-84-09-21128-9. July 7-10, 2020. Alcoy (Spain).

G. Sánchez-Barroso, J. González-Domínguez, J. Aunión-Villa, J. García-Sanz-Calcedo, F. López-Rodríguez, "Optimization of CO_2 emissions from the construction of healthcare buildings using 6D BIM technology," *24^{th} International Congress on Project Management and Engineering*. ISBN: 978-84-09-21128-9. July 7-10, 2020. Alcoy (Spain).

P. Garrido-Píriz, M. Botejara-Antúnez, F. Badilla-Murillo, G. Sánchez-Barroso, J. García Sanz-Calcedo, J. González-Domínguez, "Fundamentals of resilience applied to healthcare infrastructures in smart cities. A review," *6^{th} International Conference on Technological Innovation in Building*. ISBN: 978-84-182-5534-2. March 24-26, 2021. Madrid (Spain).

J. González-Domínguez, J. García-Sanz-Calcedo, "Applicability of Markov chains in the cost management of electro-medical equipment," *25^{th} International Congress on Project Management and Engineering*. ISBN: 978-84-09-34228-0. July 6-9, 2021. Alcoy (Spain).

G. Sánchez-Barroso, J. González-Domínguez, M. Botejara-Antúnez, P. Garrido-Píriz, B. Vargas-Vargas, J. García Sanz-Calcedo "Quantification of the influence of operation and maintenance parameters on photovoltaic plant efficiency," 7^{th} *International Conference on Technological Innovation in Building*. ISBN: 978-84-182-5541-0. March 23-25, 2022. Madrid (Spain).

A. Prieto-Fernández, A. Carmona-Baltasar, J. González-Domínguez, M. Botejara-Antúnez, G. Sánchez-Barroso, J. García Sanz-Calcedo "Applicability of Multifactor Dimensionality Reduction in Healthcare Building," 7^{th} *International Conference on Technological Innovation in Building*. ISBN: 978-84-182-5541-0. March 23-25, 2022. Madrid (Spain).

ANEXO I

Referencia

J. González-Domínguez, G. Sánchez-Barroso, J. Aunión-Villa, J. García-Sanz-Calcedo, "Markov modelo of computed tomography equipment," *Engineering Failure analysis*, vol. 127, p.105506, 2021. DOI: 10.1016/j.engfailanal.2021.105506.

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Article

Scheduling of Preventive Maintenance in Healthcare Buildings Using Markov Chain

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Received: 2 July 2020; Accepted: 28 July 2020; Published: 30 July 2020

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Abstract: The optimization of maintenance in healthcare buildings reduces operating costs and contributes towards increasing the sustainability of the healthcare system. This paper proposes a tool to schedule preventive maintenance for healthcare centers using Markov chains. To this end, the authors analyzed 25 healthcare centers belonging to the three Healthcare Districts of Spain and built between 1985 and 2005. Markov chains proved useful in choosing the most suitable maintenance policies for each healthcare building without exceeding a specific degradation boundary, which enabled achieving an ideal maintenance frequency and reduced the use of resources. Markov chains have also proven useful in optimizing the periodicity of routine maintenance tasks, ensuring a suitable level of maintenance according to the frequency of the failures and reducing the cost and carbon footprint. The healthcare centers observed during the study managed to save more than 700 km of journeys, reduce emissions in its operations as a whole by 174.3 kg of CO_2 per month and increase the overall efficiency of maintenance operations by 15%. This approach, therefore, renders it advisable to plan the maintenance of healthcare buildings.

Keywords: Markov chain; maintenance policies; healthcare center; healthcare engineering; sustainability; patrol maintenance

1. Introduction

Maintenance is one of the most critical activities in healthcare buildings since the safety of users and workers depends on its proper management [1]. It also entails considerable operating costs, mainly due to the high intensity of use of their facilities [2] and limits the productivity of an organization [3]. In addition, maintenance activities are an important source of knowledge management [4].

The Markov chain is a tool used to predict the degradation suffered by a system by simulating its stochastic degradation process [5]. The most appropriate maintenance policies for the systems studied can be determined with this tool [6]. Markov chains have been used as a simulation, decision making and engineering prediction technique [7]. However, despite being considered a suitable method for analysis, the hospital engineering sector does not appear to apply it that much [8]. Markov chains have also been useful in biomedical research in both animal and human experimentation, including but not limited to, blood pressure, the state of the patient during an illness and safety culture of health organizations [9], but have not been applied to the maintenance of healthcare buildings.

Healthcare buildings are designed to develop promotion, prevention and rehabilitation actions related to primary healthcare, and differ from hospitals in that they do not have hospital beds and do not perform surgeries [10]; they are, therefore, smaller in size. These buildings are difficult to maintain [11] given their complex and costly facilities and equipment, the correct functioning of which conditions the quality of the services it provides [12]. Another factor is their locations, selected for their proximity to the patients they serve and consequently dispersed among them [13]. The operating status of these resources depends fundamentally on a suitable design of the facilities, the quality of construction, the use of electronic equipment and the efficiency of their maintenance [14]. The different locations of the healthcare buildings mean that the maintenance is conducted through patrol maintenance. This type of maintenance consists of a team of people who make periodic scheduled visits to each building and repair non-urgent breakdowns that have occurred between visits and perform preventive maintenance previously planned operations [15].

Escobar Mejía, Holguín, and Betancourt (2007) applied the Markov chain to assess maintenance policies and reveal the best implementation method according to the outcome [16]. Velázquez-Martínez, Cruz-Suárez, and J. Santos-Reyes (2016) analyzed the safety culture of a Mexican hospital using Markov chains but did not study the impact on maintenance [17]. Lacasse, et al. (2008) adapted the Markov model to the maintenance of façades made up of concrete panels [18]. Wang and Shen (2013) also conducted a study predicting the consumption of energy of the life cycle of a residential building using the stochastic modeling based on a Markovian model, optimizing different maintenance actions according to the replacement cost of the components based on a multi-objective index [19]. Gomez and Carnero (2016) determined the most suitable maintenance policy for medicinal gas distribution subsystems for the particular case of a general public hospital. They used Markov chains with the Measuring Attractiveness by a Categorical Based Evaluation Technique [20].

Chen and Trivedi (2005) suggested a semi-Markov decision process (SMDP) for the optimization of the preventive maintenance policy based on the condition, and they presented an approach for the joint optimization of the inspection rate and maintenance policy [21]. Chen, Li, Xia, and Pan (2019) developed a hidden Markov model with auto-correlated observations for the study of the degradation of the manufacturing systems and obtained more accurate predictive values by using auto-correlated observation. They also achieved an appropriate time evolution of the degradation processes [22]. Cheng, Wang and Yan (2016) developed an optimal model of the Cold Water for Human Consumption facilities by applying different statistical predictive techniques, using the Markov chains to determine the probability distribution of equipment condition and reliability [23]. Papakonstantinou and Shinozuka (2014) used partially observable Markov decision processes to find appropriate maintenance and management policies for corroded structures [24]. On the other hand, Carnero and Gómez (2017) analyzed the ideal maintenance strategy for electricity distribution systems in organizations providing medical care through a technical assessment based on Markov chains. They proposed a model based on a combination of corrective, preventive and predictive maintenance [25]. Yang, Ye, Lee, and Peng (2019) conducted a study on a new two-phase maintenance policy to optimize revenues through performance-based contracting (PBC) [26]. However, Silva, Gaspar, Brito, and Neves (2016) used Markov chains to predict the degradation of coatings and gain further insight into how the characteristics of coatings contribute to overall degradation [27]. Ortega Madrigal et al. (2015) proposed different techniques to predict the facade and life cycles of the typical roofs, including the Markov model. They compared several construction systems to support the engineer's work in the design stages of the building [28]. Al-Momani, Al-Tahat, and Jaradat (2006) studied the performance measures for improvement of maintenance effectiveness. The results showed that despite the general increase in equipment availability, there is still a considerable mean time to repair the equipment from the registered failure day, which varies according to the type of equipment and its complexity [29].

The novelty of this work is the use of a proven tool that allows optimizing the management of buildings, ensuring an appropriate level of maintenance according to their failure frequency, thus increasing the reliability of equipment and facilities. Although Markov chains are used in all types of engineering activities, no precedents have been found in the state of the art of studies that apply this statistical model to plan and optimize the maintenance of healthcare centers. This paper, however, proposes a tool to schedule preventive maintenance for healthcare centers using Markov chains. In this way, it will be possible to optimize the periodicity of healthcare centers patrol maintenance.

2. Methods

The authors studied 25 healthcare centers belonging to three different healthcare districts in Spain, built between 1985 and 2005, from a quantitative point of view. The selection of these healthcare centers was made to be representative. They represent the same number of beds and are in the same region, so the activity generated by health care and the climate of the area is similar in the centers. When analyzing the data, statistical analysis techniques based on simple and multiple correlations were used to determine the degree of interconnection between the variables. In all cases, the standard error of the estimate and its correlation coefficient were calculated. A healthcare center is a building designed to carry out Primary Health Care Assistance actions, which has adequate staff and equipment to meet those needs. It is designed according to the World Health Organization welfare protocols to optimize the user's first contact with the Health System. It has a continuous operation 24–365, therefore the maintenance of them is critical. As the healthcare buildings studied here are isolated centers located in large urban centers, specialists should carry out routine patrol maintenance every certain period of time. The frequency with which each patrol maintenance is carried out was set in three possible alternatives: 7, 15 and 21 days. A Markov chain is split into different states. These states correspond to the states of the system analyzed [30]. For this research, a nine state Markov chain has been developed, representing the degradation of healthcare facilities. All nine states of the Markov chain are designated as the degradation scale. The probability of system degradation corresponds to the state transition probability, which is obtained based on the statistical study of maintenance incidents that occur in health centers. These probabilities constitute the transition matrix of the Markov chain, i.e., the coefficients of that matrix. These coefficients were determined through the statistical analysis of the information available in the engineering and maintenance services of the healthcare centers analyzed. This analysis is based on minimizing the error that occurs between the observations during maintenance inspections and the predictions of the Markov model [31]. Firstly, the transition matrix is obtained based on the observed data [32]. After that, the transition matrix is determined, which reduces the discrepancy between the matrix obtained from the healthcare center incidents and the matrix determined from applying the Markov model. The Solver tool of Microsoft Excel is used to minimize the error. Finally, the validation of this analysis is done through the Pearson X^2 test [33]. The incidents used in this paper are defined as nonurgent breakdowns originating in a healthcare center. These incidents may include, window insulation failure, door damage, lighting failure, humidity, damage to stretchers or noncritical equipment, among others. The percentage degradation scale as a function of the number of incidents happening in the facilities of a healthcare center is shown in Table 1, is used as a reference to illustrate the current state of the system as a function of the number of monthly incidents and the percentage of degradation. The degradation scale has a range from 1 to 9, where 1 and 9 corresponds to an excellent and unacceptable condition.

Table 1. Degradation scale of the condition according to the number of incidents.

Degree	Status Description	No of Monthly Incidents	Degradation
1	Excellent	<5	0 to 10%
2	Very good	6–10	11 to 20%
3	Good	11–15	21 to 30%
4	Acceptable	16–20	31 to 40%
5	Tolerable	21–25	41 to 50%
6	Low	26–30	51 to 60%
7	Very low	31–35	61 to 70%
8	Poor	36–40	71 to 80%
9	Unacceptable	>40	>80%

The table above shows that the number of monthly incidents that a healthcare center can have to avoid an unacceptable condition is more than forty. Preventive maintenance is implemented to prevent a health center from getting into an inadequate state of degradation. This is based on a patrol maintenance that fixes the incidents that have arisen in the healthcare centers. The following section details how to select the most appropriate maintenance policy and its respective periodicity. The variable that defines the state of the system called E_n, is defined below. This variable characterizes the state of the system in the nth observation and is a row vector that has the same number of components as system states. The compilation of all $\{E_1, E_2, E_3 \ldots E_n\}$ variables is the stochastic process. This type of study requires the future state to be independent of past states and depend only on the current state [34]. Therefore, Markov's property is fulfilled, and the probability of transition from state i to state j will be determined by Equation (1) [16]:

$$P_{ij} = P\left({}^{E_n = j}/_{E_{n-1}} = i\right) \tag{1}$$

where E_n is the vector of the observation state n and P_{ij} is the component of the transition matrix and represents the probability that the system passes from state i to j. Equation (1) reflects the probability of the system to reach state j while in state i. This Markov process is described in Equations (2) and (3):

$$E_{\mathrm{n}} = r \cdot P^n \tag{2}$$

$$Q(E) = \sum_{i=1}^{n} E_{\mathrm{n}}(i) \cdot i \tag{3}$$

where E_n is the state vector in the observation n, r is the initial state vector, P^n is the transition matrix of n steps, formed by its components ${P_{ij}}^n$, which is the probability that the system will transit from state i to j, $Q(E)$ represents the expected value of the system and $E_n(i)$ is the i-nth component of the vector and En determines the probability that the system will acquire the value i. The coefficients of the transition matrix (P_{ij}) are the result of the statistical analysis of the information obtained from 25 healthcare centers and includes the likelihood of the system moving from one state to another, plus the probability that it remains in the same state. An expert panel in the sector accepted and validated the transition matrix. The panel was formed by four hospital engineering specialists, two private institutions specialists, a technician in charge of the Technical Department of the Public Administration and a technician from the Technical Department of a private hospital. Two important aspects of the transition matrix were supervised by an expert panel. Firstly, the experts evaluated whether the structure of the matrix was correct and whether the matrix obtained showed evidence of degradation in the values. They observed that the higher the degradation state, the higher the probability that the system will change to a more adverse degradation state, and the lower the probability of remaining in the state. Secondly, they validated the coefficients of the transition matrix by verifying that the values of the system in each of the established degradation states were consistent with the existing situation in every healthcare center. Statistical evidence from the Spanish Ministry of Health and the Regional Health Service of Extremadura was also considered. The maintenance patterns were commented with the maintenance engineers of the target healthcare center, after analyzing the corresponding registers, and then assessed.

The probability of transition between states or remaining in the same one is represented in a matrix in the state transition matrix [P] shown in Figure 1.

$$[P] = \begin{bmatrix} 0.96 & 0.03 & 0.01 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.94 & 0.05 & 0.01 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.92 & 0.07 & 0.01 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.89 & 0.10 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.85 & 0.11 & 0.03 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.80 & 0.16 & 0.03 & 0.01 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.74 & 0.22 & 0.04 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.68 & 0.32 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Figure 1. Status transition matrix.

The transition graph shown in Figure 2 and representing the system's degradation state was created considering the state transition probabilities of the matrix coefficients [*P*]:

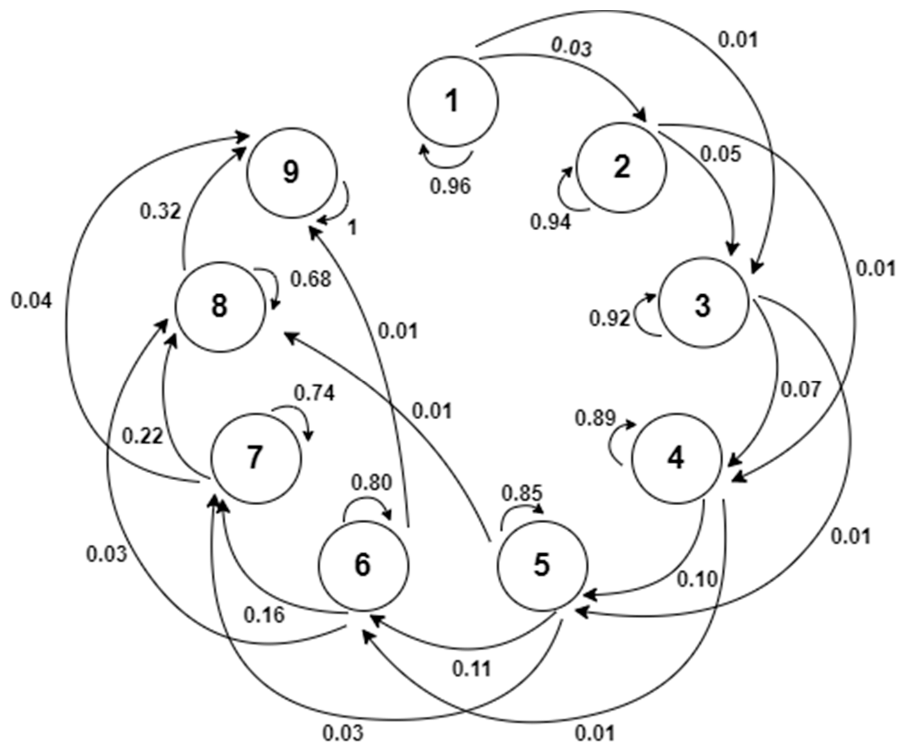


Figure 2. System transition graph.

The system presents a gradual degradation, which means that the higher the state of the system, the probability of the system remaining in that state drops and the probability of it changing state increases. There are also several consecutive changes of states, for example, from state 2 to 4. There is less likelihood of this transition happening and is caused by several factors: emergencies that cause incidents during inspections or incidents that appear simultaneously before maintenance and that cause transitions to several states.

In order to determine the most appropriate maintenance policy for healthcare centers, maintenance must be represented in a matrix form. Al-Momani et al. (2005) represented the maintenance strategy of the system in a matrix form [35]. They designed the maintenance policy for a seven-state Markov chain. So, the maximum allowed degradation state is state 4, from which the system degradation is not adequate. In addition, the selected maintenance strategy allows the system's degradation state to be improved to degradation state 2. Therefore, Equation (4) is expressed as follows:

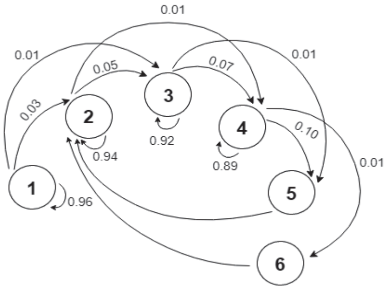
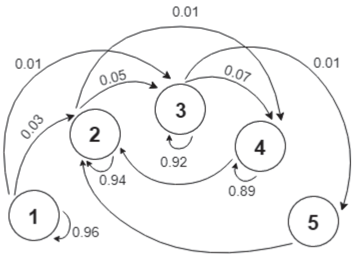
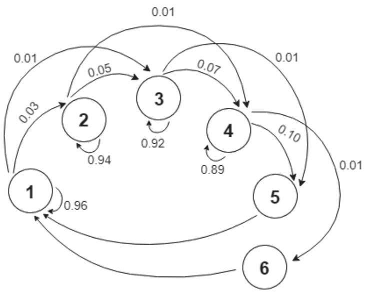
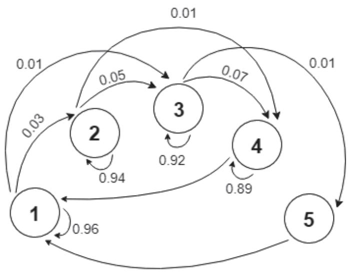
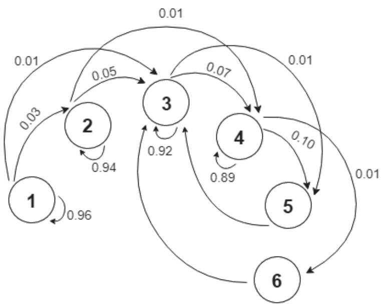
$$E_n = r \cdot (M \cdot P)^n \tag{4}$$

This model is suitable, assuming that the maintenance is carried out soon after the inspection, without letting the system change state. Moreover, if the maintenance is not conducted, the system will enter an unacceptable state (Level 9), whereas if the relevant inspections and maintenance are carried out, the system should remain operative for long periods of time.

Then, a study was conducted with Markov chains to choose the most suitable maintenance policy for each healthcare center. First, the maximum permitted degradation state was determined to reduce the array of options. For this study, a low degradation state was considered inappropriate for healthcare buildings. Therefore, the maximum state the system had to reach was 6, presenting a significant number of incidents as shown in Table 1. Healthcare centers are buildings designed to carry out Primary Health Care actions continuously 365 days a year. In this way, the state of degradation of a building should not damage the health and safety of the patients. For this reason, the maintenance policy selected must guarantee that the condition of the health centers does not reach state 6.

The selection of the optimum maintenance policy for the system is focused on choosing state i that the system can reach, and once achieved, perform the corresponding maintenance to re-establish the ideal state j. To this end, five maintenance policies were conducted, the results of which are collated in Table 2. Options 1 and 2 represent a maximum degradation state of 5 and 4, respectively, and after maintenance, the system returned to state 2. Options 3 and 4 admitted a maximum degradation state of 5 and 4 respectively, but these options returned to state 1 after maintenance. Lastly, option 5 considered the possibility of the system reaching the maximum degradation state of 5, but only returned to state 3 after maintenance.

Table 2. Results obtained from the different maintenance strategies analyzed.

Option	Transition graph	Maintenance matrix	Results
1 Maximum degradation state 5; returns to state 2 after maintenance		$\begin{bmatrix} 1&0&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0\\ 0&0&0&1&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0 \end{bmatrix}$	$\pi_1(j) = [0, 0.4447{,}0.2957, 0.2312{,}0.0261, 0.0023, 0, 0, 0]$
2 Maximum degradation state 4; returns to state 2 after maintenance		$\begin{bmatrix} 1&0&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0 \end{bmatrix}$	$\pi_2(j) = [0, 0.5785{,}0.3846, 0.0331{,}0.0038, 0, 0, 0, 0]$
3 Maximum degradation state 5; returns to state 1 after maintenance		$\begin{bmatrix} 1&0&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0\\ 0&0&0&1&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0 \end{bmatrix}$	$\pi_3(j) = [0.4245{,}0.2211, 0.1935{,}0.1432, 0.0163, 0.0014, 0, 0, 0]$
4 Maximum degradation state 4; returns to state 1 after maintenance		$\begin{bmatrix} 1&0&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0 \end{bmatrix}$	$\pi_4(j) = [0.4955{,}0.2581, 0.2258{,}0.0154, 0.0023, 0, 0, 0, 0]$
5 Maximum degradation state 5; returns to state 3 after maintenance		$\begin{bmatrix} 1&0&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0\\ 0&0&0&1&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0 \end{bmatrix}$	$\pi_5(j) = [0, 0, 0.5622, 0.3889{,}0.0450{,}0.0039, 0, 0, 0]$

3. Results

To simplify the results, the procedure for obtaining the probability that the system is in each of the states described in Table 1 for one of the five maintenance strategies is detailed. For the rest of the maintenance policies the process is the same, therefore only the results will be shown. Maintenance strategy number 2 has been chosen. The maintenance matrix *[M]* of this example is shown in Figure 3.

$$[M] = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Figure 3. Maintenance matrix.

By applying the proposed maintenance policy, the maintenance would be carried out in such a way that the system would never reach states higher than 4 and always returns to state 2, creating a regular sequence of states 2, 3 and 4, as illustrated in Figure 4.

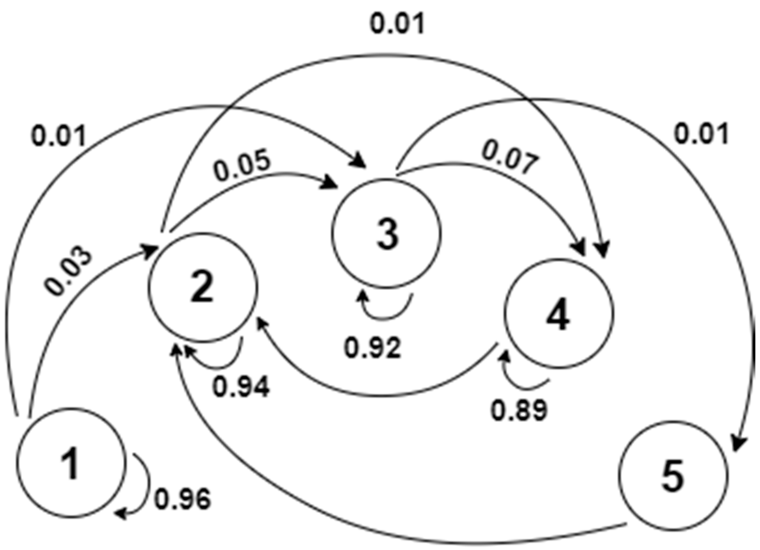


Figure 4. Maintenance strategy transition graph.

The maintenance strategy transition graph shows two parts of the process life cycle. The first goes from the initial state (1) to the first state of the periodic stage (2) and the second is a regular sequence of states 2, 3, 4 and 5. The real interest of the study lies in the analysis of this second part. The analysis of the behavior in the stationary state of the process probability distributions is one of the main problems of Markov chains. In particular, the boundary of each process probability distribution should be calculated for each state i when n tends to infinity and this boundary belongs to the distribution of probability in the space of states. If this boundary exists, it must be unique and the distribution boundary (π) must satisfy the properties shown in Equation (5) [17]:

$$\begin{gathered} \pi(i) \geq 0 \; i \; \in S \\ \sum \pi(i) = 1 \\ \pi(j) = \pi(i) \cdot P(i, j) \end{gathered} \tag{5}$$

By implementing the maintenance strategy in the form of a matrix, Equation (5) becomes Equation (6):

$$\pi(j) = \pi(i) \cdot [M(i,j) \cdot P(i,j)] \tag{6}$$

where each component of the vector $\pi(j)$ corresponds with the time in which the system remains in state j after reaching the periodic behavior. Furthermore, for the solution to correspond to a process boundary distribution, the Markov chain must have been proven irreducible and aperiodic and the chain states recurrent positive. As for the maintenance policy analysis, the state vector for 20, 40 and 80 observations are first evaluated by Equation (1), which leads to Equations (7)–(9).

$$E_{20} = [0.4420,\ 0.3478,\ 0.1919,\ 0.0164,\ 0.0018,\ 0,\ 0,\ 0,\ 0] \tag{7}$$

$$E_{40} = [0.1954,\ 0.4780,\ 0.2980,\ 0.0256,\ 0.0029,\ 0,\ 0,\ 0,\ 0] \tag{8}$$

$$E_{80} = [0.0382,\ 0.5589,\ 0.3677,\ 0.0316,\ 0.0037,\ 0,\ 0,\ 0,\ 0] \tag{9}$$

The results lead the authors to conclude that the higher the number of observations, the higher the probability of the system being in states 2 and 3, whereas the probability of the system being in state 1 is less. First element of the state vector of Equation (7) has a value of 0.442. Therefore, there is a 44.2% probability that the system is in the state of degradation 1. When the observations increase, the probability that the system is in state 1 decrease to 19.54% and 3.82% according to Equations (8) and (9) respectively. In the same way, it is proved as the value of the second and third element of the state vector increases.

Finally, the system behavior was evaluated in a stationary state, i.e., when n tends to infinity. This was determined by solving Equation (6), which translates into a system of equations made up of nine equations with nine unknowns, the results of which are:

$$\pi(j) = [0,\ 0.5785,\ 0.3846,\ 0.0331,\ 0.0038,\ 0,\ 0,\ 0,\ 0] \tag{10}$$

The authors found that the probability of the system being in a stationary state while in state 1, 6, 7, 8 or 9 was nil since they are all outside the periodic sequence. This procedure has been carried out with 5 different maintenance strategies to compare them and determine which of them is more suitable for the system. The results are shown in Table 2.

The optimal solution was obtained by comparing the results of the Markov chains and relating them to the number of incidents in the corresponding healthcare centers. Options 1 and 3 were found to be less likely to be in the first five states, i.e., the system will remain less time in states that have been deemed suitable for healthcare centers. Therefore, options 2, 4 and 5 were analyzed to select the best solution. Option 5 presents a 0.39% probability that the system is in state 6. However, despite being a very low probability, the authors considered that the system could not reach that state so the option will not be suitable. The fourth option shows a high probability that the system is in states 1, 2 and 3 with a value of 49.55%, 25.81% and 22.58%, respectively. This determines that the system will be in the first three states most of the time with this maintenance policy. The second option has a 0% chance of being in state 1 since maintenance causes the system to return to state 2. The probabilities of the system being in states 2, 3, and 5 with this maintenance policy are 57.85%, 38.46% and 3.31%, respectively. The system in the states illustrated above is suitable in both cases.

These two maintenance strategies are not prioritized, but instead there is a combination of the two, according to the average monthly incidents of each of the 25 healthcare centers to obtain a better solution. Thus, the healthcare centers that require maintenance that resolves more incidents, but with less frequency, will opt for option 4. However, centers that require more regular maintenance, but correct fewer incidents, will choose option 2. As each healthcare center is more suited to one option than the other, the use of the two maintenance strategies will increase the success of the outcome. The number of average monthly incidents that each of the healthcare centers has was recorded to determine whether the maintenance is carried out every 1, 2 or 3 weeks. These data were extracted from the historical archives available at the technical services responsible for the maintenance of the health centers, for three years. Table 3 shows the average monthly incidents, RP being the speed factor with which the first failure occurs, considering A > 2 days; B from 3–6 days; C > 6 days, N° the average monthly number of nonurgent failures and HCC is the healthcare center studied.

Table 3. Average monthly incidents of each healthcare center.

HCC	N°	RP	HCC	N°	RP	HCC	N°	RP	HCC	N°	RP	HCC	N°	RP
1	21	C	6	27	B	11	15	C	16	31	B	21	12	C
2	32	A	7	38	A	12	14	C	17	41	B	22	44	A
3	42	B	8	20	C	13	41	A	18	36	A	23	42	A
4	19	C	9	30	B	14	17	C	19	21	C	24	34	B
5	23	B	10	33	B	15	32	B	20	18	C	25	26	B

The relationship between the results shows that the maintenance frequency and policy depend on the average incidents in each of the healthcare centers every month. Table 4 shows when the maintenance is carried out according to monthly incidents and the most appropriate maintenance option.

Table 4. Maintenance frequency based on monthly incidents and maintenance policy.

Visit / Option	3 Weeks	2 Weeks	1 Week
2nd	≤20 incidents	27–30 incidents	41–60 incidents
4th	21–26 incidents	31–40 incidents	61–80 incidents

The broadest range of incidents allowed by each option was chosen, adequately managing the resources, and consequently, reducing maintenance costs. With this, the number of incidents corrected after maintenance in options 2 and 4 is 15 and 20, respectively. Therefore, this will be the maximum number of incidents allowed between maintenance visits. Table 5 shows the best maintenance option and periodicity for each of the 25 healthcare centers analyzed.

Then, the data of Table 5 were grouped by similarity of the frequency of maintenance actions of each of the centers and their respective maintenance policies. Figure 5 illustrates this grouping.

The authors found that option 2 was more convenient in 14 of the 25 healthcare centers since maintenance is carried out every week in five centers, every two weeks in two centers and every three weeks in seven centers. On the other hand, of the remaining 11 healthcare centers, seven centers have a periodicity of two weeks and four centers have a periodicity of three weeks. By optimizing the frequency of maintenance of a healthcare center, maintenance can be carried out at more appropriate times, instead of every 15 days across all the healthcare centers in the sample. This approach also reduces transport and labor costs. After conducting the study, the authors found that the healthcare centers of this study were able to save 700 km of travel per month, saving time and fuel, and reducing emissions by 174.3 kg of CO_2 each month.

Table 5. Classification of healthcare centers.

2nd Option			4th Option		
Healthcare Centers	**Incidents**	**Periodicity (Weeks)**	**Healthcare Centers**	**Incidents**	**Periodicity (Weeks)**
3	42	1	1	21	3
4	19	3	2	32	2
6	27	2	5	23	3
8	20	3	7	38	2
9	30	2	10	33	2
11	15	3	15	32	2
12	14	3	16	31	2
13	41	1	18	36	2
14	17	3	19	21	3
17	41	1	24	34	2
20	18	3	25	26	3
21	12	3			
22	44	1			
23	42	1			

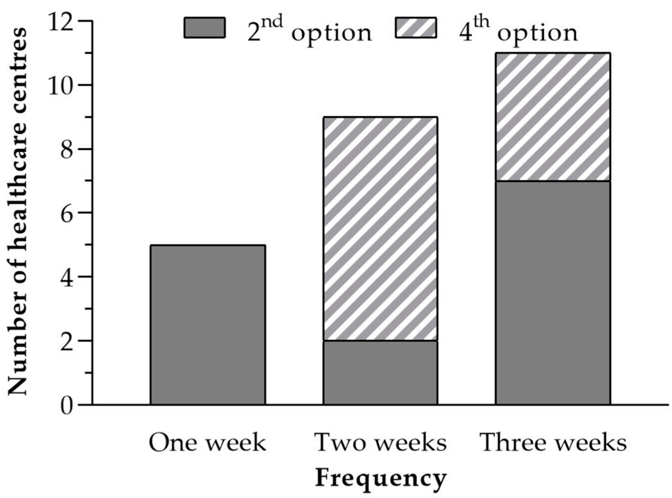


Figure 5. Bar graph of maintenance periodicity.

4. Discussion

The best maintenance strategy was determined for each of the healthcare centers analyzed based on the results of the study. This maintenance strategy should prevent the selected system from reaching a state higher than the tolerable state (5). This is of utmost importance in healthcare buildings, the facilities of which are vital for patients [36]. In many cases, making decisions in the health sector is very difficult due to its complexity and its influence on the life quality of people [37]. The authors found that the combination of two maintenance policies ensures that the system is always appropriate, and that, therefore, the joint implementation of the two policies is much better than separate implementation. For this reason, it would be convenient to conduct a study every 6 months of the average incidents found in each of the 25 healthcare centers to readjust the maintenance policy and adjust the periodicity [38].

The Markov chains have proven to be useful to determine the best maintenance strategy for healthcare buildings. With this probabilistic tool, the most appropriate maintenance policy can be determined, which prevents healthcare centers from exceeding a certain degree of degradation, thus guaranteeing the functioning of the system and the safety of the patients [39]. It also allows for planned and implemented maintenance strategies to save time and costs [40], which is one of the main objectives of hospital engineering [41].

This method was also found to allow for maintenance planning with more appropriate periods, which translates into savings in respect of travel costs and time spent on maintenance tasks. This optimizes the use of these resources and their possible use in other aspects. Also, the maintenance technician emits less CO_2 during his or her travels. The use of Markov chains for preventive maintenance planning is, therefore, part of a strategy based on circular economy [42], meeting savings and emission reduction targets. The outcome of this research is useful for planning the maintenance of healthcare centers, guaranteeing an appropriate level of maintenance according to the failures, and can be extrapolated to other buildings in the tertiary sector with similar complexity [43].

5. Conclusions

Based on the results, it can be concluded that the Markov chains are a suitable probabilistic tool to optimize the planning of preventive maintenance of healthcare centers. It allows for obtaining the maintenance strategy without the system not exceeding a certain state of degradation, and to establish the appropriate periodicity of maintenance. In this way it is possible to reduce the environmental impact of maintenance and increase the safety and health of the users of a healthcare center.

Before applying Markov's techniques, the maintenance frequency of all the health centers analyzed was 15 days. By applying this model, a periodicity of 3, 2 and 1 weeks was set according to the most appropriate maintenance policy and the average monthly number of incidents at each center. As a result, the periodicity of the patrol maintenance was optimized, preventing the system from exceeding the desired states of degradation. This resulted in a reduction in the time and distance traveled by the expert technician, thus reducing the cost of maintenance and the carbon footprint associated with the journey. Specifically, a saving of 700 km per month was achieved, which reduces 174.3 kg of CO_2 per month and an increase in overall maintenance efficiency of close to 15%.

Future work should be aimed at carrying out a comparative analysis between different healthcare centers in other countries, to analyze their behavior and deviations from the demand for corrective maintenance after applying the method proposed here. In addition, this statistical model can be applied to determine the most appropriate maintenance policy for the different elements of vital importance for the operation of sanitary buildings, such as the structure, windows, air conditioning systems, electrical energy distribution systems, water distribution system, electronic equipment, etc. In this way, the degradation of the above elements is not detrimental to the health service.

Author Contributions: Data curation, J.G.-D.; Formal analysis, G.S.-B. and J.G.-S.-C.; Investigation, J.G.-D. and J.G.-S.-C.; Methodology, J.G.-D. and J.G.-S.-C.; Resources, G.S.-B.; Software, J.G.-D. and G.S.-B.; Validation, J.G.-S.-C.; Writing—original draft, J.G.-D.; Writing—review and editing, J.G.-S.-C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by VI Regional Research, Technological Development, and Innovation Plan of the Government of Extremadura, grant number GR-18029 through European Regional Development Fund.

Acknowledgments: The authors wish to express their acknowledgement to the VI Regional Research, Technological Development and Innovation Plan of the Government of Extremadura (GR-18029), and to the European Regional Development Fund for their financial support to García-Sanz-Calcedo during his work stay at the University of Evora (Portugal).

Conflicts of Interest: The authors declare no conflict of interest.

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ANEXO II

Referencia

J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, "Scheduling of Preventive Maintenance in Healthcare Buildings Using Markov Chain," *Applied Sciences*, vol. 10, p. 5263, 2020. DOI: 10.3390/app10155263.

Derechos de autor

Engineering Failure Analysis 127 (2021) 105506

Contents lists available at ScienceDirect

Engineering Failure Analysis

journal homepage: www.elsevier.com/locate/engfailanal

Markov model of computed tomography equipment

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ARTICLE INFO

Keywords:
Markov chain
Computerised axial tomography
Healthcare centre
Sustainability
Degradation
Maintenance
Healthcare engineering

ABSTRACT

Computed tomography (CT) equipment uses a non-invasive radiology procedure to diagnose by generating images. This research aims to determine the degradation matrix and estimate the condition over time to the CT equipment to optimise their maintenance through Markov chain. The database failure history of four Spanish hospitals between 2016 and 2020 was used for this analysis. Five states of condition were used to develop the Markov degradation model, which enables the degradation of CT equipment to be properly estimated. It was found that their degradation can be modelled by Markov chains. The result is a degradation matrix with which the useful life of the equipment, the policy and the frequency of the maintenance can be established. Thus, the maintenance operations needed to reduce the equipment downtime can be determined.

1. Introduction

Computed tomography (CT) is one of the most advanced diagnostic imaging equipment around [1]. A CT scanner has X-ray tubes and detectors that rotate around the patient's body, who is positioned on a moving table. The data produced by the ionising radiation as it passes through the body is reconstructed into an image [2], which is then represented in a greyscale, which permits differentiating the structures analysed based on its density and offers significant advantages over conventional radiography procedures [3]. This fast and precise technique [4] is suitable to diagnose abdominal trauma in haemodynamically stable patients, hidden extra-thoracic metastases, congenital heart problems, bronchiectasis, tumours, mediastinal diseases, paediatric head trauma follow-up, etc. [5–9]. This equipment has increased diagnostic and therapeutic effectiveness in recent years [10], becoming an irreplaceable resource in hospitals.

However, numerous failures impair the functionality of CT [11]. Among them are artefacts, which appear frequently and can generate image interpretation errors and simulate non-existent pathologies [12]. Good coordination must be maintained among caregivers and technicians to mitigate any incidents that occur during its operation [13]. During the life of the equipment, care must be taken to ensure the quality of the electrical power supplied to the hospital's electronic equipment, as this can cause failures [14] and jeopardise patient's safety [15]. In addition, poor operator performance can lead to equipment malfunction [16]. Medical equipment used to care for patients must be safe, available and accurate [17]. Therefore, inspection and maintenance operations should be carried out to reduce the probability of system failure and improve the quality of service and patient safety [18]. These maintenance operations include preventive maintenance to avoid the equipment collapse and reduce the costs incurred by the medical centre [19]. It is

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https://doi.org/10.1016/j.engfailanal.2021.105506
Received 8 November 2020; Received in revised form 10 May 2021; Accepted 25 May 2021
Available online 29 May 2021
1350-6307/

also advisable to periodically analyse the state of obsolescence of this equipment to ensure the quality of health care provided [20]. The energy consumption of this equipment is not excessively high in the long run, since the consumption is essentially made when taking the intermittent shots. However, they do require high power for firing with peaks of 100 A.

In recent years, there has been an increase in the hospital budget for maintenance operations of high-tech medical equipment, since the quality of maintenance services is essential to ensure patients' medical care and meet the reliability results expected by the health services [21] and user requirements [22]. Typically, the expense of maintaining medical equipment over its lifetime is more significant than its initial cost [23], and the information generated during maintenance inspections can be used to detect errors caused by the use of this equipment [24].

Markov chain is a probabilistic tool used to predict the degradation suffered by a system by simulating its stochastic degradation process [25]. This model is based on the Markovian property that the future state of degradation depends only on the present state and not on the past [26]. The equipment replacement frequency can, therefore, be determined [27].

Pabon *et al.* [28] applied Markov's model to determine the replacement by obsolescence of medical radiology equipment technology. Ospina *et al.* [29] designed a continuous-time Markov chain model to model three states of CT equipment (functioning, preventive maintenance and corrective maintenance) but failed to provide an estimate of the percentage degradation of high-tech equipment based on historical data. Carnero and Gómez [30] determined the appropriate maintenance policy for four dialysis subsystems in a health centre, by applying Markov chain and the multicriteria methodology called Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH). Tabares and Silva [31] proposed a probabilistic algorithm based on Markov chains to predict the condition of medical equipment and developed the model for electromechanical, vacuum cleaner systems. Markov chain have also been used to determine the frequency of failure of medical equipment parts and establish the stock of spare parts [32]. Dhillon [33] proposed, among other classic analytical techniques, using Markov chains to improve the reliability and maintenance of medical equipment. Markov's chains were also used to analyse the safety culture of a Mexican hospital [34]. Gómez and Carnero used the Markov chain model to determine the most appropriate maintenance policy for medical gas distribution subsystems [35] and electric power [36] in health centres.

Although Markov chain have been used in much engineering activities, not much background has been found in state of the art on studies that apply them to predict the degradation and maintenance of high-tech medical equipment based on historical data. The novelty of this research is that it uses lies in using a proven tool to generate a degradation model able to predict the operating condition of the CT equipment. Thus, Markov chains could be used to increase both its reliability and availability alike.

2. Material and methods

2.1. General method

The general method followed to predict the operating life of CT equipment is shown in Fig. 1. In a first step, data from the maintenance history of CT equipment were obtained and processed to serve as input for the subsequent modelling of their degradation. Once the data were adequate, in the second step it was used to generate a Markov model.

One month was the chosen periodicity for the inspections and the subsequent development of the Markov model. Defining this time step made it possible to have an exhaustive control over the degradation of the set of equipment and, after developing its Markov model, to establish an appropriate maintenance policy.

2.2. Data collection and maintenance process of Computed tomography equipment

The failure history of eight CT scanners from four Spanish hospitals between 2016 and 2020 was analysed. This information was

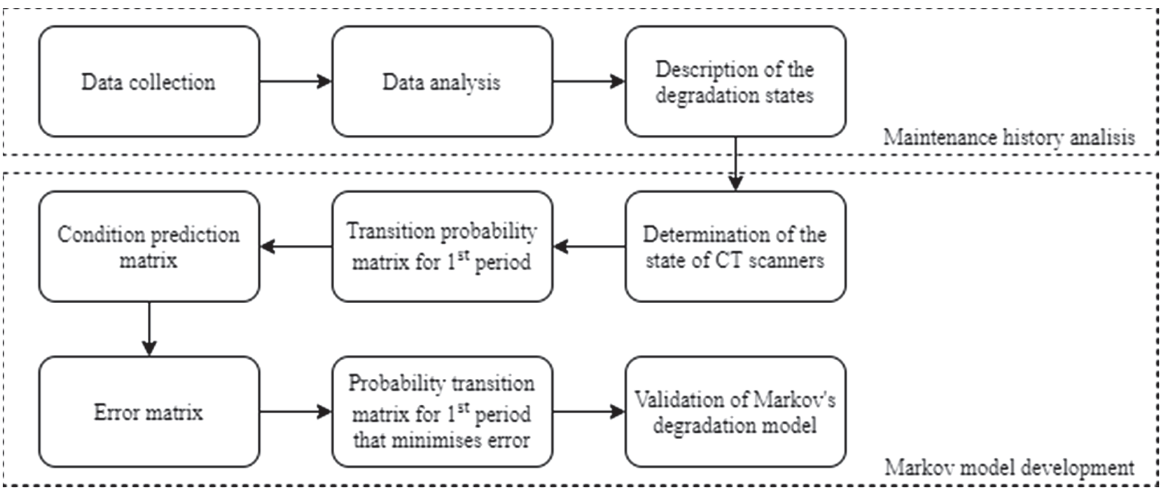

Fig. 1. Procedural steps in the research.

compiled from the regular inspections, and corrective and preventive maintenance operations carried out on this equipment. The CT scanners is between two and 13 years old, with an average of seven years old. The average unit cost was €550,000 in the range of €363,000 to €820,000.

One of the technical characteristics to be considered in CT scans is the number of image slices. Each 360-degree turn of the beam tube generates different sections of body tissue in two dimensions of thickness from 1 to 10 mm. The number of sections obtained simultaneously determines the number of image slices. The greater the number of image slices, the shorter the acquisition time and the less radiation the patient receives. This parameter is especially vital in acquiring moving tissue. The equipment studied is in the range of 16 to 160 image slices.

The manufacturer's protocol prescribes that maintenance inspections must be carried out six-monthly by their own dedicated personnel. The process starts after setting the inspection mode on CT scanners. Components inside the gantry is visual checked and the emergency bottom is operational checked. Next, the console, parts inside the gantry and oil cooler are cleaned. Operational check of the console internal fan and gantry emergency stop button are conducted. Then, power distribution, the safety circuit operation and gantry rotation speed are also verified. The X-ray system is adjusted, and the output is checked for different focal lengths. Subsequently, gantry operation panel and sensors and gantry power-supply voltage are tested. Later, maintainer checks the inside of the patient couch and the interlock mechanisms. Checking the projector projection point and interference with the covers are the latest items before a general cleaning up. Finally, the phantom is scanned to confirm that the image noises are within the standard level. Comprehensive maintenance was carried out every six months after which the manufacturer -and maintainer- certifies that equipment is in the same condition as after the first commissioning. Thus, a different device of the fault history is considered every six months. This gives a greater number of components CT scanners, which allow the degradation matrix to be estimated more accurately.

Table 1 shows the information collected in the data history.

2.3. Markov model of computed tomography equipment

Markov chains were employed to determine the degradation pattern of the CT equipment.

Since the first period hardly shows the degradation suffered by this equipment, it was eliminated. So, the second period was taken as the first one to model degradation. Thus, any error made while obtaining the transition matrix is minimised. Efforts were made to minimise the error between the degradation matrix obtained from information collected during inspections and the prediction matrix calculated using Markov chains. These matrices are obtained for a specific period (n), and the error between them is reduced using a calculation programme [37].

The degradation states that can be found in the CT equipment were defined, from a very good working condition to collapse. Each level of degradation is represented by a state so that the component studied -a CT scan- is transformed into a multi-state system [38]. The Markov property states that the degradation state of a component depends only on the last observed state [39]. Different occurrences were assigned to each degradation state to determine the condition of a CT scan during an inspection. The degradation scale used, shown in Table 2, ranges from 1 to 5, starting with a very good condition and ending with the collapse of the CT scanner.

These events were obtained in a meeting with CT scan maintenance experts at the hospitals analysed, who verified the level of degradation of each state. Thus, it was determined that the collapse of the CT scan occurs when it reaches degradation state 4 or 5 since these degradation states make it impossible to perform diagnostic tests on patients.

The observation matrix for each period n, $[O_n]_{ij}$, was constructed once the degradation states of the CT scanner were specified from the information collected by the maintenance experts. They observed the initial degradation state of the CT scanners and determining the final degradation state after a period n.

The observation matrix counted the number of CT scanners found in each of the degradation states after an inspection and it has the structure shown in Fig. 2. So, each element represented the amount of equipment from state i that transitioned to state j in period n.

The state transition probability from i to j matrix within a given period can be obtained from that information following the percentage prediction method [40].Eq. (1) expresses how to determine the elements of the transition probability matrix [41].

$$P_{ij} = O_{ij} / \sum_{x=1}^{N} O_{ix} \tag{1}$$

where P_{ij} are the elements of the state transition probability matrix, O_{ij} are the elements of the observation matrix and O_{ix} is the sum of

Table 1
Information collected in the data history.

Name	Unit	Type
Year of installation	Years	Maintenance
Days worked	Days	Working day
Days worked after hours	Days	Working day
Repaired CT scan	Unit	Maintenance
Preventive maintenance	Hours	Maintenance
Modifications on request from the factory	Hours	Maintenance
Errors that require physical intervention	Hours	Equipment failure
Errors that require remote intervention	Hours	Equipment failure

Table 2
Degradation scale.

State	Condition	Description	Example
1	Very good	It presents no kind of failure or error	The six-monthly inspection has just taken place
2	Good	Presents a fault or error that does not impair the functionality	A wireless communication problem is detected
3	Adequate	Presents a fault or error that impairs the functionality	Dirt is detected in certain non-major components
4	Severe	Presents several faults or errors that impair the functionality	Some image reconstruction problem is occurring at the same time as other functionality is not working.
5	Unacceptable	Failure or error that makes the CT scan inoperable	The X-ray tube has reached the end of its service life

$$[O] = \begin{bmatrix} O_{11} & O_{12} & \cdot & \cdot & O_{1j} \\ O_{21} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ O_{i1} & \cdot & \cdot & \cdot & O_{ij} \end{bmatrix}$$

Fig. 2. Observation matrix.

CT scanners that were initially in state i and transitioned to any state x. This is how the transition matrix was obtained in the first period, $[P]_1$.

Then discrete Markov model was implemented to obtain the state transition probability matrix in the following periods analysed. This model allowed calculating the probability of a CT scanner going from state i to state j in a specific period [42]. Eq. (2) shows the calculation of the transition matrix in periods $n \neq 1$.

$$[P]_n = [P]_1^n \tag{2}$$

The condition prediction matrix is then calculated. This matrix allows predicting the number of equipment in a state of degradation after some time n. Eq. (3) shows the calculation of the elements that make up the condition prediction matrix.

$$C_{ij} = P_{ij}\hat{A} \cdot \sum_{x=1}^{5} O_{ix} \tag{3}$$

where C_{ij} are the elements of the condition prediction matrix, P_{ij} the elements of the transition probability matrix, and O_{ix} is the sum of CT scanners that were initially in state i and transitioned to any state x.

Finally, the error between the observation matrix and the condition prediction matrix for a period n must be determined. Thus, the difference between the elements of both matrices is calculated to minimise the error later on. The elements of the error matrix E_{ij} are calculated by Eq. (4).

$$E_{ij} = (O_{ij} - C_{ij})^2 \tag{4}$$

where E_{ij} the elements of the error matrix, O_{ij} are the elements of the observation matrix, and E_{ij} are the condition prediction elements.

All the elements of the error matrix must be added together beforehand, $[E]$, to minimise the error. This is repeated for all the periods analysed. Therefore, the elements of all the error matrices should be added up, and their result weighted according to the number of CT scanners observed in the period, as reflected in Eq. (5) and Eq. (6).

$$E_p = \sum E_{ij} \tag{5}$$

$$E_{total} = \sum_{p=1}^{n} (E_p\hat{A} \cdot O_p / O_T) \tag{6}$$

being E_{total} the total error of the analysis,E_p and O_p are the error and the number of CT scanners observed for a given period and O_T is the number of CT scanners observed in all the estimated periods.

The transition matrix of the first period, $[P]_1$, is determined applying Generalized Reduced Gradient method, which minimises the total error obtained. Thus a transition matrix corresponding to the first period that best suited to all the observed periods can be achieved. Fig. 3 shows the transition probability matrix for the first period.where p_{ij} is the probability of the CT scanners changing from condition state i to condition state j in a given time.

These properties constitute the transition matrix of the Markov model. The degradation state of the equipment depends only on the last observed degradation state and the transition of state probability described in the matrix of Fig. 3 [43].

Once the transition matrix best suited to the deterioration of the CT scanners is obtained, the probability of the CT equipment being in each of the degradation states over time is obtained. First, S_0 is defined as the initial state vector of degradation. The elements of this vector represent the initial state of degradation of the CT scanners. It will, therefore, have five elements. All elements of the initial state vector have the value of 0 except the element representing the degradation of the CT scan, which takes the value of 1. Considering that the CT equipment presents the best state of condition, the initial vector is expressed in Eq. (7).

$$S_0 = [10000] \tag{7}$$

Knowing the initial degradation state of the CT scanner at a given time and its transition matrix, the probabilities of it being in each of the degradation states in Table 1 at the next inspection were determined. The degradation vector of the CT scan is set at the n^{th} observation, S_n. The degradation state vector of the CT scan can be obtained with the Chapman-Kolmogorov formula expressed in the Eq. (8).

$$S_n = S_0\hat{A} \cdot [P]_1^n \tag{8}$$

where S_0 is the initial degradation state vector and $[P]_1^n$ the transition probability matrix in period n.

The degradation model was then validated. The goodness-of-fit of the statistical model was analysed using Pearson's Chi-squared test, which determine the discrepancy between the observed values and the values obtained from the model [44]. Then, the probabilistic-based deterioration model proposal of Markov chains was found to be consistent with the set of equipment observed. Thus, χ^2 test is represented in Eq. (11).

$$\chi^2 = \sum_i^n \frac{(O_i - C_i)^2}{C_i} \tag{9}$$

where n is the number of periods analysed, O_i are the elements of the observation matrix, and C_i are the elements of the condition prediction matrix.

3. Results

The data obtained were classified over a 12-month time horizon, and the factors influencing the degradation of the equipment and its impact were determined. The state of degradation of the analysed equipment was also determined, and the number of CT scanners found in each state of degradation after a period n was obtained. Table 3 shows the observation matrix obtained for periods 2, 3, 4, 5 and 6.

The analysed equipment in the research appear to follow a degradation pattern, and as the observation period increases, more equipment is in a worse condition. Moreover, Fig. 4 shows the evolution of the number of CT scanners in each of the degradation states depending on the period analysed. As the period increases, the number of CT scanners found in the states of collapse also increased, and those in state 1 decreased. This is logical since the degradation of the observed equipment increases over time.

Fig. 5 shows the transition probability matrix of the second period, the elements of which were obtained using Eq. (2).

The elements of the transition matrix represent the probability of the equipment being in the various stages of degradation after one month. Multiplying each element by one hundred gives the probability as a percentage. In addition, all the elements corresponding to a row add up to 100%, which verifies that all the equipment studied is in one of the degradation states. The shape of the matrix is similar to that obtained in other studies [45]. The matrix in Fig. 5 has zeros under the main diagonal and state 5 is absorbing state due to the irreparability of a CT scanner when the X-ray tube breaks down. At the end of life, this part must be replaced - not repaired - with a new one. This implies a re-commissioning of the machine.

The transition probability matrix for these periods was then obtained using Eq. (2). Table 4 shows the values of the transition matrix of periods 3, 4, 5 and 6.

The probability of the equipment being in the first state of degradation decreased as the number of periods increased. This is logical due to the equipment is more degraded over time. The probability of CT scanner being in the unacceptable state, when it states 1, 2, 3 and 4 initially, is zero. This is due to the transition matrix obtained in Fig. 5 and is corrected by minimising the error.

Eq. (3) was used to obtain the condition prediction matrix, determining the number of CT scanners found in each of the degradation states as predicted by the Markovian model. Eq. (4) determines the error of the Markov model concerning the observation matrices. Table 5 shows the prediction and error matrices for the analysed periods.

The second period of the condition prediction matrix coincided with its observation matrix. Therefore, there is no error for the

$$[P]_1 = \begin{bmatrix} p_{11} & p_{12} & \cdot & \cdot & p_{1j} \\ p_{21} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_{i1} & \cdot & \cdot & \cdot & p_{ij} \end{bmatrix}$$

Fig. 3. Transition probability matrix for the first period.

Table 3
Observation matrix for the one-month interval.

$$[O]_2 = \begin{bmatrix} 29 & 4 & 2 & 1 & 0 \\ 0 & 10 & 1 & 1 & 0 \\ 0 & 0 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 3 \end{bmatrix}; \sum O_{ix} = \begin{bmatrix} 36 \\ 12 \\ 5 \\ 2 \\ 3 \end{bmatrix};$$

$$[O]_3 = \begin{bmatrix} 23 & 2 & 2 & 2 & 0 \\ 0 & 10 & 3 & 1 & 0 \\ 0 & 0 & 7 & 0 & 1 \\ 0 & 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 0 & 3 \end{bmatrix}; \sum O_{ix} = \begin{bmatrix} 29 \\ 14 \\ 8 \\ 4 \\ 3 \end{bmatrix};$$

$$[O]_4 = \begin{bmatrix} 18 & 3 & 2 & 0 & 0 \\ 0 & 9 & 2 & 1 & 0 \\ 0 & 0 & 7 & 4 & 1 \\ 0 & 0 & 0 & 6 & 0 \\ 0 & 0 & 0 & 0 & 5 \end{bmatrix}; \sum O_{ix} = \begin{bmatrix} 23 \\ 12 \\ 12 \\ 6 \\ 5 \end{bmatrix}; [O]_5 = \begin{bmatrix} 13 & 2 & 1 & 1 & 1 \\ 0 & 8 & 2 & 1 & 1 \\ 0 & 0 & 8 & 3 & 0 \\ 0 & 0 & 0 & 10 & 1 \\ 0 & 0 & 0 & 0 & 6 \end{bmatrix}; \sum O_{ix} = \begin{bmatrix} 18 \\ 12 \\ 11 \\ 11 \\ 6 \end{bmatrix};$$

$$[O]_6 = \begin{bmatrix} 8 & 4 & 0 & 0 & 1 \\ 0 & 7 & 1 & 1 & 1 \\ 0 & 0 & 9 & 1 & 1 \\ 0 & 0 & 0 & 13 & 2 \\ 0 & 0 & 0 & 0 & 9 \end{bmatrix}; \sum O_{ix} = \begin{bmatrix} 13 \\ 10 \\ 11 \\ 15 \\ 9 \end{bmatrix};$$

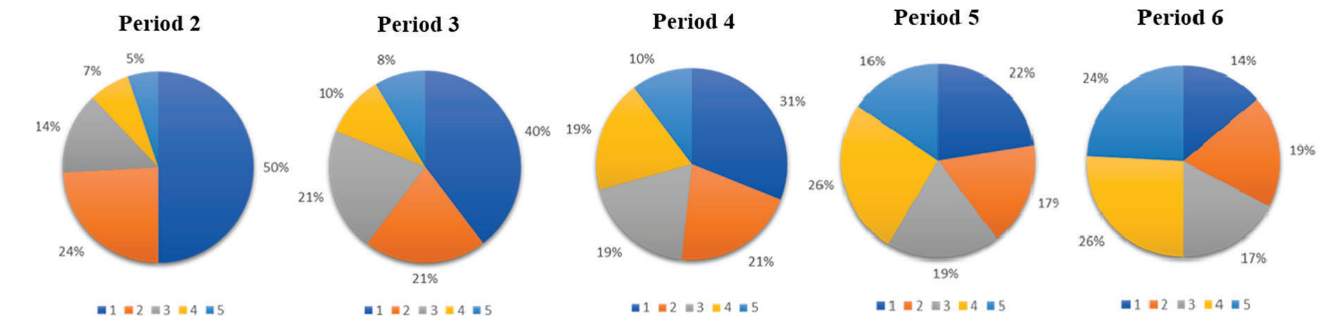

Fig. 4. Number of CT scanners in each state as compared to the periods analysed.

$$[P]_2 = \begin{bmatrix} 0.8056 & 0.1111 & 0.0556 & 0.0278 & 0 \\ 0 & 0.8333 & 0.0833 & 0.0833 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Fig. 5. Transition probability matrix for the first period analysed.

Table 4
Transition probability matrix.

$$[P]_3 = \begin{bmatrix} 0.65 & 0.18 & 0.11 & 0.06 & 0 \\ 0 & 0.69 & 0.15 & 0.15 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}; [P]_4 = \begin{bmatrix} 0.52 & 0.22 & 0.16 & 0.09 & 0 \\ 0 & 0.58 & 0.21 & 0.21 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix};$$

$$[P]_5 = \begin{bmatrix} 0.42 & 0.24 & 0.21 & 0.13 & 0 \\ 0 & 0.48 & 0.26 & 0.26 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}; [P]_6 = \begin{bmatrix} 0.34 & 0.25 & 0.25 & 0.16 & 0 \\ 0 & 0.40 & 0.30 & 0.30 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix};$$

second period analysed. All the errors in the matrices are then added up and weighted according to Eq. (6). Calculation software generates the transition matrix, which minimises the error obtained in all periods. The non-linear Generalised Reduced Gradient (GRG) optimisation method was used to determine the Markov model that best suits the degradation of the observed equipment during the inspections. Fig. 6 shows the solution that best fits the Markov model and the fault history, and Fig. 7 shows the state transition graph corresponding to its transition matrix.

This matrix reflects the degradation of the equipment studied. As the state of degradation increased the probability of the equipment being on the state is lower. For example, if a CT scan is in an initial state 1, the probability of it being in state 5 is less than that of it being in state 4. The matrix suffers a gradual degradation, so the higher the state of the system, the probability of it changing state increases. This is significant since it reflects that the degradation of the CT scan increases the probability of change of state. The

Table 5
The condition prediction matrix and error matrix obtained for each of the periods analysed.

$$[C]_2 = \begin{bmatrix} 29 & 4 & 2 & 1 & 0 \\ 0 & 10 & 1 & 1 & 0 \\ 0 & 0 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 3 \end{bmatrix}; [E]_2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$[C]_3 = \begin{bmatrix} 18.82 & 5.28 & 3.12 & 1.72 & 0 \\ 0 & 9.72 & 2.14 & 2.14 & 0 \\ 0 & 0 & 8 & 0 & 0 \\ 0 & 0 & 0 & 4 & 0 \\ 0 & 0 & 0 & 0 & 3 \end{bmatrix}; [E]_3 = \begin{bmatrix} 17.48 & 10.76 & 1.39 & 0.08 & 0 \\ 0 & 0.08 & 0.74 & 1.30 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$[C]_4 = \begin{bmatrix} 12.02 & 5.15 & 3.70 & 2.13 & 0 \\ 0 & 6.94 & 2.53 & 2.53 & 0 \\ 0 & 0 & 12 & 0 & 0 \\ 0 & 0 & 0 & 6 & 0 \\ 0 & 0 & 0 & 0 & 5 \end{bmatrix}; [E]_4 = \begin{bmatrix} 35.72 & 4.61 & 2.88 & 4.54 & 0 \\ 0 & 4.23 & 0.28 & 2.33 & 0 \\ 0 & 0 & 25 & 16 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$[C]_5 = \begin{bmatrix} 7.58 & 4.40 & 3.75 & 2.26 & 0 \\ 0 & 5.79 & 3.11 & 3.11 & 0 \\ 0 & 0 & 11 & 0 & 0 \\ 0 & 0 & 0 & 11 & 0 \\ 0 & 0 & 0 & 0 & 6 \end{bmatrix}; [E]_5 = \begin{bmatrix} 29.38 & 5.78 & 7.58 & 1.60 & 1 \\ 0 & 4.90 & 1.22 & 4.44 & 1 \\ 0 & 0 & 9 & 9 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$[C]_6 = \begin{bmatrix} 4.41 & 3.26 & 3.28 & 2.05 & 0 \\ 0 & 4.02 & 2.99 & 2.99 & 0 \\ 0 & 0 & 11 & 0 & 0 \\ 0 & 0 & 0 & 15 & 0 \\ 0 & 0 & 0 & 0 & 9 \end{bmatrix}; [E]_6 = \begin{bmatrix} 12.89 & 0.55 & 10.76 & 4.21 & 1 \\ 0 & 8.89 & 3.96 & 3.96 & 1 \\ 0 & 0 & 4 & 1 & 1 \\ 0 & 0 & 0 & 4 & 4 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$[P]_1 = \begin{bmatrix} 0.8993 & 0.0582 & 0.0238 & 0.0113 & 0.0059 \\ 0 & 0.9002 & 0.0590 & 0.0241 & 0.0137 \\ 0 & 0 & 0.9190 & 0.0606 & 0.0168 \\ 0 & 0 & 0 & 0.9725 & 0.0268 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Fig. 6. Transition matrix for the first period that minimises error.

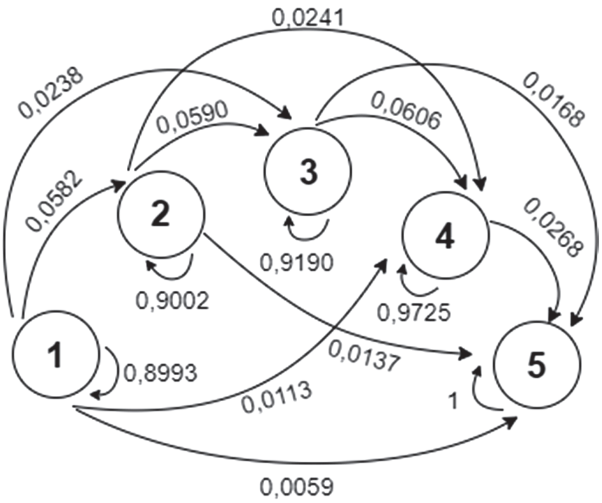

Fig. 7. Markov chain state transition diagram.

elements of the transition matrix give all the necessary information about the degradation of a CT scan. For example, the element in the third row and fourth column represents a piece of equipment initially in a state of degradation 3 and has a 6.06% chance of being in state 4 after a period of one month.

The degradation matrix allows obtaining the probability that a particular CT scanner is in one of the states of collapse and building the curves that represent the probability that a CT scan equipment is in one of the 5 states of degradation at a given time. This was based on the assumption that the initial condition of the CT equipment was very good, as certified by the manufacturer after carrying out the comprehensive six-monthly maintenance action. Fig. 8 shows the evolution over time of the CT scanners's probability of being in one of the states.

Up to the eighth period only the probability of the CT scan being in degradation state 1 decreases, while the probability of the remaining states increases. From then on, the probability of the CT scanners being in states 2 and 3 decreases because the probability of the states of collapse, 4 and 5, increases considerably. The probability of stage 2 decreases more rapidly than that of stage 3. Over time,

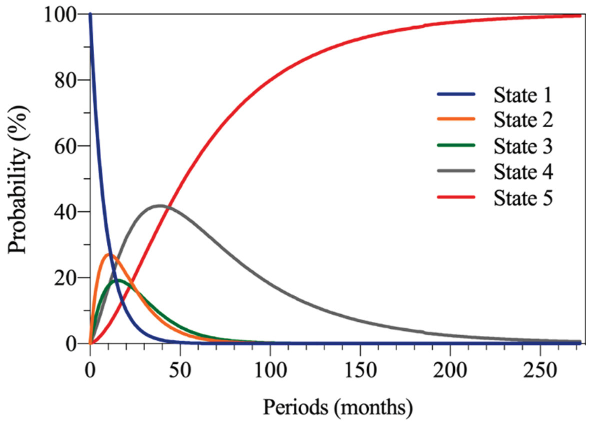

Fig. 8. Computed tomography scan state probability curves.

the probability of the CT scanners being in states 1, 2 and 3 is 0, while the probability of state 5 increases considerably. This reflects the degradation of the equipment over time and how the probability of it being in a state of collapse increases.

Finally, the number of equipment in each state of degradation was determined according to the transition matrix obtained. This allows comparing the discrepancy between the equipment observed in the inspections and those predicted by the Markov chains and applying Pearson's χ^2 test [46]. After this, Eq. (9) is applied, obtaining the values of χ^2. Table 6 predicts the number of equipment in each state of degradation in each period studied according to the Markov model and shows the χ^2 values obtained.

A 95% confidence level validated the model. Adding up all the values of χ^2 of the elements in Table 6 gives a value of 33.02. By setting a freedom value of 50, the calculated value of 33.02 was determined to be less than the value of χ^2 for a significance level of 0.05. Therefore, it was verified that the proposed Markov model is suitable to estimate the deterioration of the equipment with a 95% confidence level. So the discrepancy between what is predicted by the Markov model and what is observed during maintenance inspections is acceptable with a high level of confidence.

4. Discussion

The selection, acquisition, maintenance and life cycle of healthcare technology are essential aspects to guarantee its profitability, updating and compliance with the corporate objectives of a healthcare organisation [47]. It was found that by applying Markov chains, it is possible to properly determine the degradation matrix of CT equipment and estimate the degradation they suffer over time to then establish the most appropriate maintenance policy and frequency. Thanks to this, the equipment is kept in favourable conditions and avoids the states of collapse with the desired minimum reliability, which also reduces the downtime and increases the number of diagnoses and follow-ups that can be made on the patients [48].

In recent years, the quality and complexity of hospital equipment have multiplied, increasing the concern of hospital facility managers [49]. Maintenance of this equipment should be considered under the headings of safety, calibration and repair [50]. By

Table 6
Condition prediction matrix obtained from the final transition matrix and χ^2 values of the study.

$$[C]_2 = \begin{bmatrix} 32.38 & 2.09 & 0.86 & 0.41 & 0.21 \\ 0 & 10.80 & 0.71 & 0.29 & 0.16 \\ 0 & 0 & 4.59 & 0.30 & 0.08 \\ 0 & 0 & 0 & 1.94 & 0.05 \\ 0 & 0 & 0 & 0 & 3 \end{bmatrix}; [\chi^2]_2 = \begin{bmatrix} 0.35 & 1.73 & 1.52 & 0.86 & 0.21 \\ 0 & 0.06 & 0.12 & 1.74 & 0.16 \\ 0 & 0 & 0.04 & 0.30 & 0.08 \\ 0 & 0 & 0 & 0 & 0.05 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$[C]_3 = \begin{bmatrix} 23.46 & 3.04 & 1.36 & 0.70 & 0.37 \\ 0 & 11.34 & 1.50 & 0.68 & 0.39 \\ 0 & 0 & 6.76 & 0.92 & 0.27 \\ 0 & 0 & 0 & 3.78 & 0.21 \\ 0 & 0 & 0 & 0 & 3 \end{bmatrix}; [\chi^2]_3 = \begin{bmatrix} 0.01 & 0.35 & 0.30 & 2.44 & 0.37 \\ 0 & 0.16 & 1.49 & 0.15 & 0.39 \\ 0 & 0 & 0.01 & 0.92 & 1.97 \\ 0 & 0 & 0 & 0.16 & 2.95 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$[C]_4 = \begin{bmatrix} 16.73 & 3.25 & 1.57 & 0.87 & 0.47 \\ 0 & 8.75 & 1.76 & 0.88 & 0.50 \\ 0 & 0 & 9.31 & 1.95 & 0.61 \\ 0 & 0 & 0 & 5.52 & 0.47 \\ 0 & 0 & 0 & 0 & 5 \end{bmatrix}; [\chi^2]_4 = \begin{bmatrix} 0.10 & 0.02 & 0.12 & 0.87 & 0.47 \\ 0 & 0.01 & 0.03 & 0.02 & 0.50 \\ 0 & 0 & 0.57 & 2.15 & 0.25 \\ 0 & 0 & 0 & 0.04 & 0.47 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$[C]_5 = \begin{bmatrix} 11.77 & 3.05 & 1.59 & 0.95 & 0.52 \\ 0 & 7.88 & 2.13 & 1.17 & 0.68 \\ 0 & 0 & 7.85 & 2.26 & 0.75 \\ 0 & 0 & 0 & 9.84 & 1.13 \\ 0 & 0 & 0 & 0 & 6 \end{bmatrix}; [\chi^2]_5 = \begin{bmatrix} 0.13 & 0.36 & 0.22 & 0 & 0.45 \\ 0 & 0 & 0.01 & 0.03 & 0.15 \\ 0 & 0 & 0 & 0.24 & 0.75 \\ 0 & 0 & 0 & 0 & 0.02 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$[C]_6 = \begin{bmatrix} 7.65 & 2.48 & 1.39 & 0.88 & 0.49 \\ 0 & 5.91 & 2.02 & 1.29 & 0.71 \\ 0 & 0 & 7.21 & 2.67 & 0.94 \\ 0 & 0 & 0 & 13.05 & 1.90 \\ 0 & 0 & 0 & 0 & 9 \end{bmatrix}; [\chi^2]_6 = \begin{bmatrix} 0.02 & 0.93 & 1.39 & 0.88 & 0.53 \\ 0 & 0.20 & 0.51 & 0.04 & 0.12 \\ 0 & 0 & 0.44 & 1.05 & 0 \\ 0 & 0 & 0 & 0 & 0.01 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

identifying the condition of the inspected equipment and applying the Markov model, the maintenance to prevent the equipment from reaching a state of collapse can be designed. This maintenance is complemented by periodic preventive maintenance [51], which consist of software updates or equipment calibration.

When the hospital contracts a comprehensive service with the manufacturer, the latter takes care of all necessary maintenance for a fixed annual fee. In this case, the results of the research are very interesting for the manufacturer, since they can optimise the policy and frequency of the maintenance selected and, consequently, reduce the cost of the maintenance while the equipment is in optimal conditions [52]. This technique also allows the hospital to contrast the equipment replacement programme established by the manufacturer and replace equipment when their useful life is over [53]. In addition, when the hospital has a full-service contract [54], the model would not lead to savings in maintenance, since the amount is fixed regardless of the maintenance frequency and policy [55]. However, the collapse of the CT equipment would entail considerable loss of income and poor quality of care because patients cannot be diagnosed. Therefore, the reduction in CT equipment downtime offered by the Markov model translates into an increase in revenue and quality of care.

This degradation model has advantages over the Service Life Cycle [56], based on the replacement of the asset when it reaches the end of its useful life. The Markov model determines the most appropriate maintenance frequency and policy to optimise the time the system can operate properly. Thus, the Markov chains offer the possibility of calculating the equipment's end of life based on its reliability [57]. This is of great importance in the health sector. Thus, the reliability of the equipment is prioritised over the cost of replacement. This point interests healthcare systems, as they can establish whether the manufacturers' recommended service life is appropriate and not influenced by commercial or profitability aspects. Dose control [58] is one of the most critical factors for the renewal of equipment, but this should not be the only aspect to be weighed in, as the life of the equipment is also of great significance. Therefore, the replacement of the components of CT scanner must be established based on a combination of these factors.

The decrease in breakdowns of high-tech equipment in hospitals allows for increased availability, better health service [59] and improved patient satisfaction [60]. In addition, anticipating system failure decreases the time the equipment is out of use and increases the quality and number of diagnostics [61]. Future work should aim at calculating the degradation matrix of other high-tech equipment, determining its maintenance policy.

5. Conclusions

Five states of condition were used to develop the Markov degradation model, which enables the degradation of CT equipment to be properly estimated. The proposed degradation model was verified by analysing Pearson's χ^2. In this case, the results of the research are very interesting for the manufacturer, since they can optimise the policy and frequency of the maintenance selected and, consequently, reduce the cost of the maintenance, so the equipment is in optimal conditions. The p-value obtained was lower than the corresponding 95% confidence level, so the degradation model proposed by Markov turned out to be valid for the equipment analysed. Thus, the discrepancy between the observed equipment and that condition predicted by the Markov chains does not invalidate the problem.

The result was a degradation matrix of the computerised tomography equipment which permits determining the useful life of the equipment, the policy and the frequency of the maintenance. It was a simple and easily updatable tool that adequately estimates the degradation of equipment over time, allowing the risk of this equipment remaining out of use to be minimised.

This research is useful for predicting the operating life of CT equipment installed in hospital centres, minimising their downtime. The Markov chain is a simple model that allows obtaining the degradation of a particular system based on an existing data history; a flexible model that can easily update its data. In addition, this model could manage the maintenance actions of the CT equipment of any hospital, giving the maintenance manager a tool to estimate the life of the equipment after initially determining its state of degradation during an inspection.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors wish to acknowledge the European Regional Development Fund for the financial support provided through Research Projects GR18029 linked to the VI Regional Plan for Research, Technical Development and Innovation from the Regional Government of Extremadura (2017-2020).

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ANEXO III

Referencia

J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, "Preventive maintenance optimisation of accessible flat roofs in healthcare centres using the Markov chain," *Journal of Building Engineering*, vol. 32, p. 101775, 2020. DOI: 10.1016/j.jobe.2020.101775.

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Journal of Building Engineering 32 (2020) 101775

Contents lists available at ScienceDirect

Journal of Building Engineering

journal homepage: http://www.elsevier.com/locate/jobe

Preventive maintenance optimisation of accessible flat roofs in healthcare centres using the Markov chain

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A R T I C L E I N F O

Keywords:
Markov chain
Maintenance policies
Healthcare engineering
Flat roof
Reliability

A B S T R A C T

Technical installations can be placed on accessible flat roofs in hospitals. However, flat roofs also increase the risk of leaks and other drawbacks, which may alter the ordinary conditions of use of the building. This research aims to optimise the periodicity of flat roofs maintenance operations in hospitals to increase their useful life and guarantee their reliability. This research considered flat accessible roofs with three types of waterproofing membranes: bitumen, PVC and elastomeric. A sample of 12 hospitals in Extremadura (Spain) was processed using the Markov Chain. The results show that the degradation of flat roofs can be estimated and consequently the most appropriate maintenance plan considering reliability. The authors found that preventive maintenance contributed towards extending the lifetime of the roofs up to 8 years with reliability exceeding 63.21%. In this respect, the PVC membrane was found to suffer the least degradation. The average operating life of the membranes was calculated: 28 years for PVC, 24 years for elastomer and 21 years for bitumen. The time between replacements was also estimated, which means maintenance operations can be systematised to optimise costs and boost reliability.

1. Introduction

Flat roofs are a construction element that can be used for installations or another usage [1]. A flat inverted roof includes a layer of thermal insulation that protects the waterproofing layer [2], made of watertight membranes (bituminous, PVC or elastomeric), which protects the building from water seeping through [3]. The most common waterproofing membranes used in flat roofs are hydrocarbon (asphalt or bitumen), polymer (EPDM - ethylene propylene diene monomer) and PVC (polyvinyl chloride) [4]. There are different types of elastomeric membranes (cold, liquid, spreadable and self-adhesive), which differ in chemical composition and application [5]. Bituminous membranes are made from SBS (styrene-butadiene-styrene) or APP (atactic polypropylene) modified bitumen [6]. PVC membranes are reinforced with a fibreglass mesh and include various additives to improve their resistance to adverse weather conditions [7].

The roof is one of the building component that present the greatest number of problems [8], as the most common building pathologies are due to water infiltrations [9]. Dampness can appear due to problems in the different phases of the construction process, either in the design stage, execution or use of the building [10]. It is, therefore, necessary to systematise the maintenance processes [11]. Flat roofs allow hospitals to locate HVAC, solar thermal domestic hot water (DHW) and photovoltaic panel energy generation facilities on the outside of the building [12,13] and carry out maintenance in a safe manner without disruption. Moreover, choosing a roof with proper solar reflectance decrease the average energy consumption [14]. However, hospitals are buildings that must be operational every day of the year, and its envelope must not be compromised by water leaks, which could lead to the undesirable growth of fungi and bacteria.

Carretero-Ayuso, García-Sanz-Calcedo and Reyes Rodríguez [15] analysed 44 building projects drawn up between 2000 and 2007 to detect the common errors that designers make when designing flat roofs. They found that the projects contained many errors that would inevitably lead to future pathologies, due to dampness of the roof and lack of watertightness. They also identified the most common errors with a higher risk of producing incidents, although they did not go into detail on maintenance aspects: the installation of the membrane does not provide the minimum required height from the roof floor, minimum construction detail are not included, the membrane of critical zones are not reinforced, materials no compatible with the membranes are used, among others.

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https://doi.org/10.1016/j.jobe.2020.101775
Received 8 May 2020; Received in revised form 21 August 2020; Accepted 28 August 2020
Available online 1 September 2020

Although 65% of the operating costs of a building during its life cycle correspond to maintenance and operating expenses [16], in a hospital, operating costs are higher, mainly due to the high intensity of use, as it operates 24 h a day, 365 days a year [17]. Carretero-Ayuso and García Sanz-Calcedo [18] analysed the usual design faults in the building envelope of 17 healthcare centre projects with flat roofs in Extremadura (Spain). They detected 344 incidents, specified in 51 control parameters: specific data of drains and drainage nozzles are not provided; no construction details or data for the resolution of thermal bridges in the structure are provided; lack of semi-circular gutters, renders or primers in singularities; watertightness or air permeability is not specified; lack of prevention of moisture protection measures at the bottom of the facades, among others.

Flat roofs have advantages over other architectural solutions. For example, Marrana et al. [19] studied 472 flat roofs and found that the costs associated with their life cycle were more advantageous in economic and energy terms. In contrast, the costs of materials were the most decisive and inverted roofs with limited accessibility are cheaper. However, hospital roofs must be accessible to facilitate maintenance operations [20].

Gonçalves et al. [21] used life cycle analysis (LCA) to observe that bituminous membranes were the best option and that synthetic EPDM membranes were more expensive and had a higher environmental impact. Nevertheless, if the influence of the cost of the membranes reduces by 34% in the multi-criteria analysis, the best option would be TPO (Thermoplastic Polyolefin) membranes. The risk of failure in flat roofs is high, as numerous anomalies can affect their functionality, among others: penetration of moisture, the appearance of fungi, fracture, cracking, detachment or poor positioning of the layers, bulging, punctures or wrinkling that impairs the functionality of the roof, an inadequate slope that generates a possible pooling and poor design in the construction process [22].

Markov chains is a probabilistic tool that can be used to model the degradation suffered by a certain system, simulating its degradation process [23]. In this model, the future state of degradation only depends on the present state of deterioration and not on the past. Therefore, it is possible to predict the future condition of flat roofs, optimizing the maintenance operations required to keep the deterioration controlled and not affecting their performance. The Markov model has been used on several occasions to estimate the deterioration of the various critical components of a building [24,25]. This stochastic model allows analysing the probability of failure of a part and the likelihood of reaching a state beyond its proper functionality [26]. Although the Markov Chain is considered an adequate tool for the optimisation of maintenance, its application in healthcare centres is very scarce.

Velázquez-Martínez, Cruz-Suárez, and Santos-Reyes [27] analysed the safety culture of a Mexican hospital using Markov chains and estimated the evolutionary behaviour over time. Cheng, Wang, and Yan [28] carried out an optimal design of the Cold Water for Human Consumption (CWHC) facilities by applying different statistical prediction techniques, using the Markov chains to obtain the probability distribution of the state of the facility and its reliability. Papakonstantinou and Shinozuka [29] used partially observable Markov decision processes to find appropriate maintenance, inspection and management policies to control corrosion in structures. They combined four maintenance options and three inspection actions, demonstrating that Markov model is suitable for solving multiple degradation models.

Gómez and Carnero [30] applied the Markov chains to determine the most appropriate maintenance policy for the medical gas distribution subsystems of a public hospital.

Silva et al. [31] used the Markov chains to obtain the degradation suffered by three types of façade cladding: stone, ceramic and paint, and determined how the characteristics of the coating influenced the degradation. They also analysed the impact of the distance to the sea or humidity on degradation. Ortega Madrigal et al. [32] proposed several methods to predict façade and the most common roof life cycles, among which were the Markov model. They compared different construction systems to facilitate the technician's work in the building design phase. Edirisinghe, Zhang, and Setunge [33] modelled the deterioration of various critical construction components of community buildings, using Markov chains, obtaining models to reliably predict their decline, determining the main factors of influence. Coffelt, Hendrickson, and Healey [34] applied the Markov model to assess the deterioration of commercial roof systems and maintenance according to the condition, water leaks and cost. Ferreira et al. [35] also modelled the degradation of ceramic façade coverings, by inspecting 195 buildings in Lisbon using a Petri dish network and the stochastic model proposed by the Markov chains.

As evidenced in state of the art, there are precedents for previous work using the Markov model to estimate the degradation of various critical components in the building. However, no references from authors have applied this probabilistic model to hospital roofs, to optimise their preventive maintenance, control their reliability and reduce their operating costs and the risks of failure. Therefore, applying this methodology to hospital buildings is novel.

This research aims to optimise the periodicity of maintenance operations of flat roofs in hospitals using Markov chains as a model for monitoring condition-based maintenance. Thus, maintenance operations could be protocoled, which would reduce their cost and increase the intrinsic reliability of the roof.

2. Method

The three types of accessible flat roofs shown in Fig. 1 were analysed.

The historical data of repairs carried out on the roofs of a sample of 12 public hospitals in Extremadura (Spain) between 2002 and 2017 were analysed. The Public Healthcare Service of Extremadura provided data that were used to contrast the degradation model. They were also used to relate the different states of degradation specified in Table 1 to the different anomalies that affect the correct performance of the membranes. In addition, the data served as a base for identifying their maintenance.

Authors analysed the different degradation states i that each membrane could suffer. This state depends only on the last observed condition state. The set of deterioration states that a component can acquire forms the scale of degradation [36]. The scale reflects the deterioration of the component until its failure and has different condition values associated with each state, in a range of 0–100. This allows identifying the state of deterioration of the component in question [37]. State 7 is called the state of failure, and it is where the component is beyond repair. The degradation scale used is shown in Table 1.

According to Table 1, the degradation state changes from a faultless condition in state 1 to the collapse of the membranes in state 7. In this last state, the deterioration of the membranes is so severe that they lose their initial properties and a multitude of cracks or detachments appear. This produces water infiltrations that damage the building, affecting the health and safety of the users.

The states of degradation are not directly related to an anomaly, but to its occurrence and severity. Thus, a slight fissure can result in a condition 4 and a multitude of fissures at the singularities cause the state of deterioration to be 6. Cracks and detachments can be caused by structural movements, with internal stresses appearing on the membranes [38], detachment of the membrane with the construction elements the roofing system (drainage, vertical wall, expansion joints,...) [39], efforts generated from the transit of persons or the placement of facilities, membrane deterioration, among others [40]. On the other hand, the loss of properties can be due to ageing, chemicals generated by cleaning or maintenance, the appearance of fungi or microorganisms [41], among others. Also, it includes user claims. These are caused by the loss of the properties and result in the appearance of anomalies.

During the lifetime of a building component, planned maintenance is required to ensure its functionality [42]. This maintenance includes the

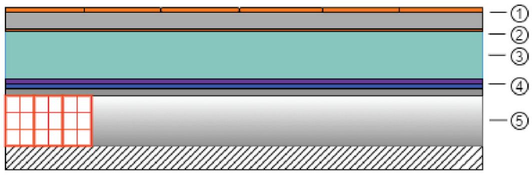
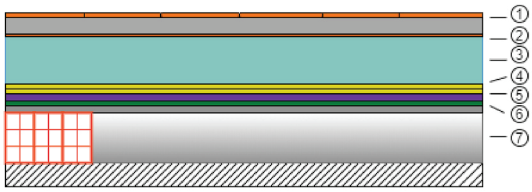
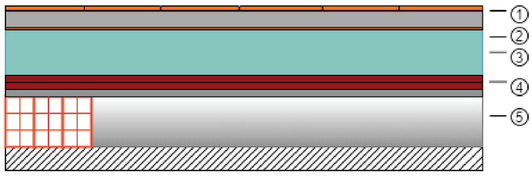
Type	Description	Sections
Bituminous membrane	Accessible inverted roof consisting of 10 cm of cellular concrete with an average thickness forming slopes, 2 cm of cement mortar base, double non-adhered layer on a sheet of plastomeric bitumen with a 50 g/m^2 glass fibre felt reinforcement, and another layer of plastomeric bitumen with a 50 g/m^2 polyethene film reinforcement, bonded to the previous one, thermal insulation of 40 mm thick extruded polystyrene and a 135 g/m^2 polypropylene vapour membrane.	 ① Tiling ② Vapour membrane ③ Extruded polystyrene ④ Double non-adhered layer ⑤ Cellular concrete - Mortar base
PVC membrane	An accessible inverted roof formed by a 10 cm layer of cellular concrete with an average thickness forming slopes, a 2 cm layer of cement mortar for regularisation and a separating layer of geotextile synthetic felt, a 1.20 mm thick waterproofing membrane with PVC and reinforced with glass fibre felt. Two layers of geotextile felt and extruded polystyrene insulation board measuring 40 mm thick and 135g/m^{2}polypropylene vapour membrane.	 ① Tiling ② Vapour membrane ③ Extruded polystyrene ④ Geotextile filter ⑤ Waterproofing membrane ⑥ Synthetic filter ⑦ Cellular concrete - Mortar base
Elastomeric membrane	An accessible inverted roof formed by a 10 cm layer of cellular concrete with an average thickness forming slopes, a 2 cm layer of cement mortar for regularisation and a double layer of elastic coating based on copolymers, applied by roller and reinforced between both layers with polypropylene fibre mesh and an insulating plate of extruded polystyrene measuring 40 mm thick with a 135g/m^{2}polypropylene vapour membrane.	 ① Tiling ② Vapour membrane ③ Extruded polystyrene ④ Two layers of elastic coating ⑤ Cellular concrete - Mortar base

Fig. 1. Description of the accessible flat roofs analysed.

performance of corrective and preventive maintenance on the roof elements and associated management, cleaning, servicing, repainting, repair and partial replacement of the membranes [43]. Therefore, maintenance operations allow the waterproofing membranes to maintain their properties by keeping moisture from penetrating into the building [44]. According to ISO 15686–1, maintenance is defined as a combination of all technical and associated administrative actions during the service life to retain a building, or its parts, in a state in which it can perform its required functions. It includes cyclical maintenance, reactive condition-based maintenance (repairs to correct defective performance) and major refurbishment [45].

Two types of maintenance were observed on the roofs analysed: corrective and preventive [46]. Corrective maintenance is carried out after the occurrence of a fault, in order to return the element to a state suitable for performing its function, while preventive maintenance aims to mitigate degradation and reduce the probability of failure [47]. The preventive maintenance involved in this study is composed in two parts. The first one is a maintenance with an established periodicity of one year, where cleaning measures of elements carried by the wind, the accumulated sediments are removed and the construction elements related to the sealing are checked. The second one concerns local repairs and replacements required to reduce membrane deterioration and minimize cracking or delamination. Corrective maintenance is based on the complete replacement of the membrane when it reaches the end of its useful life. The partial replacement of the membrane is carried out in zones where the anomalies affect its functionality. Anomalies are more frequently to appear in singular areas, such as connections with vertical walls and drains, near pipes, expansion joints, among others. Therefore, the described maintenance allows the membrane to improve its degradation state.

The probability of the component changing from condition state i to condition state j in a given time was defined, P_{ij} , to apply the Markov model [48]. These probabilities constitute the transition matrix of the Markov model. The Markov property states that the probability of a future event occurring depends only on the last observed event and not on past events. The condition of the membrane depends only on the last state of degradation observed during the maintenance technician's inspection. Therefore, the state transition probability [49] is determined by Equation (1).

$$P_{ij} = P\left(E_n = j/_{E_{n-1}} = i\right) \quad (1)$$

Where P_{ij} is the probability of the component passing from state i to

Table 1
Scale of degradation of the flat roof membrane.

Degree	Degradation	Condition Range	Description
1	Minimum	> 99	The flat roof membrane is free from defects.
2	Mild	99–92	Slight degradation of some non-critical parts of the roofing membrane that do not affect its service and reliability.
3	Minor	92–85	Minor deterioration of some non-critical parts of the flat roof membrane but may generate a slight reduction in reliability or utility.
4	Notable	85–75	The degradation of the flat roof membrane is moderate. It affects serviceability or reliability but is still adequate.
5	Significant	75–65	The performance of the flat roof membrane is affected by the deterioration of critical and non-critical parts.
6	Major	65–50	Critical parts of the flat roof membrane can be further deteriorated, resulting in a significant loss of reliability or utility.
7	Severe	≤ 50	A severe reduction in utility or reliability may arise, generating a loss of safety. Replacement of the flat roof membrane is only possible.

state j and E_n the state vector of the component in the n-th observation.

The transition matrix [P] was obtained by using a history of data collected during past observations [50]. A high amount of observed data is needed for this, as an extensive database is required for subsequent data filtering and for the resulting matrix to be close to the actual deterioration behaviour of the component. The transition matrix for n states is represented as:

$$[P] = \begin{bmatrix} P_{11} & P_{12} & \cdot & \cdot & P_{1i} \\ P_{21} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ P_{j1} & \cdot & \cdot & \cdot & P_{ij} \end{bmatrix}$$

The data needed to determine the state transition matrices of the flat roofs analysed were obtained from the study conducted by Grussing [51] in Risk-Based facility management approach for building components using a discrete Markov process - Predicting condition, reliability and remaining service life. A data set with thousands of components was collected through the U.S. Department of Defence Facility Condition Assessment Program and used to generate the degradation matrix. The components of the vector E_n are called $E_n(i)$, which represent the probability of the component being in condition i in observation n. E_0 was defined as the initial state vector of degradation. Whereas the component presents the best state of condition, the initial vector is expressed in Equation (2).

$$E_0 = [1 \;\; 0. \;\; .. \;\; 0] \tag{2}$$

Knowing the degradation state of the component at a given time and its transition matrix, the probabilities of it being in the deterioration states at the next inspection were determined using Equation (3).

$$E_n = E_0 \cdot [P]^n \tag{3}$$

The reliability and life cycle of each of the hospital's critical components or systems must also be obtained to determine the most appropriate maintenance policy for the component studied in this paper [33]. Thus, the optimal maintenance policy to be followed can be designed, so the component does not enter a state that is unsuitable and endangers patients' health, workers' safety or the functionality of the building. Hence, the reliability index, RI was defined as the probability that the degradation state of the analysed component is above the absorption state (from which there is no probability of exiting) in an established period. The absorption vector, R, was defined to obtain the index. Such a vector acquires value 1 for the states above failure and 0 when they exceed it [52], according to Equation (4):

$$RI = E_n \cdot R \tag{4}$$

Next, the condition of the three types of membranes was modelled to schedule the periodicity of condition-based maintenance. Condition-based maintenance is a monitored maintenance according to the condition of the system and includes a combination of physical condition assessment, analysis and possible further maintenance actions [47].

The maintenance of the component is thus specified for the next 20 years, and the reliability index of the system after implementing the different possible annual maintenance operations is obtained. This index will have a minimum value, which may not be exceeded, so the maintenance actions must be implemented. Subsequently, probabilistic condition-based techniques of a system were used to determine the equations that governed the model [53].

The random variable T is defined, which represents the useful life of the component to be studied. A Survival (or Reliability) function, *R(t)*, is defined, which quantifies the probability that a component is running at the end of time *t*. Also defined is the Failure function, *F(t)*, which measures the probability that a component will fail in time *t*. The first follows a negative exponential function, and both are complementary. The random variable *T* has a function *F(t)* of a cumulative distribution defined according to Equation (5):

$$F(t) = \mathrm{P}(T \leq t) \tag{5}$$

The Failure Density Function is derived from the failure function over time. It is defined by Equation (6) and indicates failure probability per time unit:

$$f(t) = \frac{d}{dt} F(t) \tag{6}$$

The hazard function *λ(t)* represents the propensity for a component to fail at the next instant, considering that up to the current one, it has not failed. A formal definition can be reached following this reasoning, which ends in Equation (8). Starting from the conditioned probability that a component fails in a time gap s after the instant t, shown in Equation (7).

$$P(t < T \leq T + s \;/\; T > t) = \frac{P(t < T \leq T + s)}{P(T > t)} = \frac{F(t+s) - F(t)}{R(t)} \tag{7}$$

By dividing this expression by the unit of time s, taking limits and establishing that s tends to zero, Equation (8) is obtained.

$$\lambda(t) = \lim_{s \to 0} \frac{1}{s} \cdot \frac{F(t+s) - F(t)}{R(t)} = \frac{f(t)}{R(t)} \tag{8}$$

The Weibull distribution was used to typify the failure functions, complementary to the reliability function, according to Equation (9).

$$R(t) = e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \tag{9}$$

Where R is the probability that the roof will be operational in a given time (t), and α and β are dimensionless coefficients that generate the characteristic shape of the curve.

3. Results

Three maintenance actions determined the most suitable maintenance policy for flat roofs: corrective, preventive and no maintenance. In this way, the preventive maintenance model developed does not include cleaning operations, elimination of sediments or revision of constructive elements that influence watertightness, since these actions are programmed and their periodicity does not have to be estimated. The periodicity of these maintenance operations is established. The frequency of preventive and corrective maintenance is obtained by the Markov model in order to ensure proper degradation of the system under analysis. If the state of degradation of the component does not impair its functionality, no maintenance operations would be carried out. corrective maintenance is defined as a full replacement of the membrane when its functionality cannot be guaranteed. Preventive maintenance includes repair and replacement measures that improve the state of deterioration and preserve the properties of the membrane. For this case, the maximum partial area that can be replaced is 5%. The most appropriate implementation period for these last two maintenance actions should optimise reliability, to reduce the probability that the component is above the state of collapse. Fig. 2 shows the corrective and preventive maintenance matrix, $[M]_{Corrective}$ y $[M]_{Preventive}$.

The corrective matrix shows how by replacing the component, it recovers to the lowest state of condition, regardless of its state. The preventive matrix reflects what this maintenance action would look like. When the component is between degradation stages 1 and 4 and is repaired, it returns to a degradation state 2. If the component is in state 5 or 6 and is repaired, it returns to a state of deterioration 3 and 4, respectively. Finally, if the component enters the state of failure (7), preventive maintenance operations do not improve the condition state and only the corrective maintenance action can be implemented.

The state transition matrix [P] estimates the probability of the roof remaining in or increasing the last observed condition state after an inspection. These probabilities depend on the roof analysed. Three matrices were used in this study, one for each type of membrane: bitumen, PVC and elastomeric, which are shown in matrix form in Figs. 3-5.

Another condition imposed is that membrane cannot return to a more favourable state of degradation without being subject to the required maintenance operations. Besides, the probability of remaining in a state is always higher than the probability of transitioning from that state. The maintenance matrix [M] will depend on the maintenance policy selected. Thus, Equation (3) is transformed into Equation (10).

$$E_n = E_0 \cdot [M] \cdot [P]^n \tag{10}$$

The model assumes that the system degrades n time intervals and that corrective and preventive maintenance is performed once in this period. In addition, the selected maintenance is carried out at the end of the n periods analysed. Therefore, solving Equation (10) gives the probability that the component is in each of the defined degradation states. In order to implement more than one maintenance operation at different intervals, first the value of the state vector E_n with maintenance in period n is calculated. Then, the value of the state vector in a higher period, E_{n+x}, where the initial state vector corresponds to the previous state vector E_n. Thus, the necessary maintenance could be implemented at the end of the $n+x$ interval.

The membrane studied were considered in the best state of condition. Five possible scenarios were assumed to establish the minimum value of the reliability index. In the first three scenarios, this parameter for each type of roof has to be higher than 80%, 75% and 63.21%,

$$[M]_{Corrective} \quad [M]_{Preventive}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Fig. 2. Corrective and preventive maintenance matrix.

$$[P]_{bituminou\ s} = \begin{bmatrix} 0.644 & 0.111 & 0.173 & 0,004 & 0,037 & 0,01 & 0,02 \\ 0 & 0.823 & 0.102 & 0.034 & 0,017 & 0,012 & 0,012 \\ 0 & 0 & 0.838 & 0.09 & 0.036 & 0,013 & 0,022 \\ 0 & 0 & 0 & 0.771 & 0.138 & 0.06 & 0,032 \\ 0 & 0 & 0 & 0 & 0.836 & 0.119 & 0.044 \\ 0 & 0 & 0 & 0 & 0 & 0.898 & 0.102 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Fig. 3. State transition matrix for accessible flat roofs covered with a bituminous membrane [51].

$$[P]_{PVC} = \begin{bmatrix} 0.679 & 0.115 & 0.141 & 0,035 & 0,018 & 0,012 & 0 \\ 0 & 0.829 & 0.089 & 0,027 & 0,035 & 0,011 & 0,01 \\ 0 & 0 & 0.896 & 0.053 & 0.03 & 0,006 & 0,015 \\ 0 & 0 & 0 & 0.846 & 0.091 & 0.034 & 0,029 \\ 0 & 0 & 0 & 0 & 0.91 & 0.063 & 0.027 \\ 0 & 0 & 0 & 0 & 0 & 0.931 & 0.069 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Fig. 4. State transition matrix for accessible flat roofs covered with a PVC membrane [51].

$$[P]_{Elastomeric} = \begin{bmatrix} 0.692 & 0.1334 & 0.114 & 0,0135 & 0,0232 & 0,0104 & 0,0135 \\ 0 & 0.8132 & 0.1104 & 0.0343 & 0,019 & 0,0126 & 0,0106 \\ 0 & 0 & 0.8576 & 0.0823 & 0.027 & 0,0138 & 0,0193 \\ 0 & 0 & 0 & 0.8304 & 0.1018 & 0.0429 & 0,0249 \\ 0 & 0 & 0 & 0 & 0.8619 & 0.1002 & 0.0379 \\ 0 & 0 & 0 & 0 & 0 & 0.9101 & 0.0899 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Fig. 5. State transition matrix for accessible flat roofs covered with an elastomeric membrane [51].

respectively, and no preventive maintenance is implemented. In the last two scenarios, reliability was assumed to be higher than 63.21% and, also, in these two scenarios, one and two preventive maintenance operations were implemented, respectively. The reliability value of 63.21% corresponds to the characteristic life of a component according to the Weibull distribution. The values of 80% and 75% were established to determine the influence of reliability on the determination of maintenance periodicity and service life. Thus, the influence of membrane reliability and preventive maintenance was determined to analyse the life of the roofs. Tables 2-4 shows the results obtained for the three types of roofs and the five possible scenarios.

On the one hand, the period of preventive maintenance was determined through an iterative process that optimizes the reliability of the system, increasing the probability that the analysed membranes do not fall into the state of collapse. On the other hand, corrective maintenance is performed when the reliability of the system is below the minimum value set for each scenario.

Implementing preventive maintenance was found to increase the reliability of the system, and the replacement of the roofing membrane can be delayed. As the scenario analysed is less reliable, the year in which the membrane is replaced increases. The minimum reliability studied is 63.21%. Above this value, there is no guarantee that the functionality of the membrane will not be affected and consequently the membrane will reach the end of its life. At the end of the service life the complete replacement of the membrane is necessary. The results show that the most appropriate scenario implements two preventive maintenance operations, and the membrane's reliability value does drop below 63.21%. The PVC membrane roof suffers the least degradation and, therefore, its replacement can be delayed.

The authors also analysed the evolution of the reliability of the three types of roofs over time to compare their deterioration. Fig. 6 shows the survival curves obtained.

PVC membrane roofs were also the most likely to be operational in a given time, whereas in bituminous roofs, the probability decreases more rapidly. The complete maintenance of the PVC membranes is carried out

Table 2
Maintenance policies for the bituminous membrane roof over 20-year horizon.

Maintenance operations of the bituminous membrane roof										
Year	R>80%		R>75%		R>63.21%		R>63.21%/1PM		R>63.21%/2PM	
	Op	R (%)	Op	R (%)	Op	R (%)	Op	R (%)	Op	R (%)
1	N	97.9	N	97.9	N	97.9	N	97.9	N	97.9
2	N	95.7	N	95.7	N	95.7	N	95.7	N	95.7
3	N	93.4	N	93.4	N	93.4	N	93.4	N	93.4
4	N	91	N	91	N	91	N	91	N	91
5	N	88.4	N	88.4	N	88.4	N	88.4	N	88.4
6	N	85.6	N	85.6	N	85.6	N	85.6	N	85.6
7	N	82.7	N	82.7	N	82.7	P	85.6	P	85.6
8	C	97.9	N	79.7	N	79.7	N	84.3	N	84.3
9	N	95.7	N	76.5	N	76.5	N	82.7	N	82.7
10	N	93.4	C	97.9	N	73.3	N	80.8	N	80.8
11	N	91	N	95.7	N	70	N	78.6	N	78.6
12	N	88.4	N	93.4	N	66.7	N	76.31	P	78.6
13	N	85.6	N	91	N	63.3	N	73.8	N	77.5
14	N	82.7	N	88.4	C	97.9	N	71.1	N	76
15	C	97.9	N	85.6	N	95.7	N	68.4	N	74.4
16	N	95.7	N	82.7	N	93.4	N	65.5	N	72.5
17	N	93.4	N	79.7	N	91	C	97.9	N	70.4
18	N	91	N	76.5	N	88.4	N	95.7	N	68.2
19	N	88.4	C	97.9	N	85.6	N	93.4	N	65.8
20	N	85.6	N	95.7	N	82.7	N	91	N	63.3

N: No maintenance operations; C: Corrective maintenance; P: Preventive maintenance; Op: Operation.
R: Reliability; 1PM: One action of preventive maintenance; 2PM: Two action of preventive maintenance.

Table 3
Maintenance policies for the PVC membrane roof over a 20-year horizon.

Maintenance operations of the PVC membrane roof										
Year	R>80%		R>75%		R>63.21%		R>63.21%/1PM		R>63.21%/2PM	
	Op	R (%)	Op	R (%)	Op	R (%)	Op	R (%)	Op	R (%)
1	N	100	N	100	N	100	N	100	N	100
2	N	99.4	N	99.4	N	99.4	N	99.4	N	99.4
3	N	98.5	N	98.5	N	98.5	N	98.5	N	98.5
4	N	97.2	N	97.2	N	97.2	N	97.2	N	97.2
5	N	95.7	N	95.7	N	95.7	N	95.7	N	95.7
6	N	93.9	N	93.9	N	93.9	N	93.9	N	93.9
7	N	92	N	92	N	92	N	92	P	93.9
8	N	90	N	90	N	90	N	90	N	92.9
9	N	87.9	N	87.9	N	87.9	N	87.9	N	91.6
10	N	85.7	N	85.7	N	85.7	P	87.9	N	90.2
11	N	83.5	N	83.5	N	83.5	N	86.4	N	88.6
12	N	81.1	N	81.1	N	81.1	N	85.5	N	86.9
13	C	100	N	78.8	N	78.8	N	84.1	N	85.1
14	N	99.4	N	76.4	N	76.4	N	82.6	N	83.2
15	N	98.5	C	100	N	74	N	80.9	N	81.2
16	N	97.2	N	99.4	N	71.6	N	79.1	N	79.1
17	N	95.7	N	98.5	N	69.2	N	77.3	N	77
18	N	93.9	N	97.2	N	66.8	N	75.4	P	77
19	N	92	N	95.7	N	64.4	N	73.4	N	76
20	N	90	N	93.9	C	100	N	71.3	N	74.8

N: No maintenance operations; C: Corrective maintenance; P: Preventive maintenance; Op: Operation.
R: Reliability; 1PM: One action of preventive maintenance; 2PM: Two action of preventive maintenance.

in a longer time interval than that of the elastomeric and bituminous membranes, as indicated in the 5 scenarios presented in Tables 2-4, . For example, in 75% reliability scenario with no preventive maintenance operations, full membrane replacement is performed in year 15, 12 and 10 for PVC, elastomeric and bituminous membranes, respectively. Based on Fig. 6, the parameters α and β of the Weibull distribution for the three types of membrane analysed (bituminous, PVC and elastomeric) were obtained and characterised in Equation (11), Equation (12) and Equation (13).

$$R(t) = e^{-\left(\frac{t}{22}\right)^{1.52}} \tag{11}$$

$$R(t) = e^{-\left(\frac{t}{32}\right)^{1.52}} \tag{12}$$

$$R(t) = e^{-\left(\frac{t}{25}\right)^{1.52}} \tag{13}$$

Where R is the probability of failure of each flat roof membrane, and t is the time to failure expressed in years. The density failure function was analysed by type of roofing membrane as a function of time. This function is defined according to Equation (6) and has been plotted in Fig. 7.

The probability of failure occurring was determined to calculate the standard life of roof membranes as a function of the likelihood they will

Table 4
Maintenance policies for the elastomeric membrane roof over a 20-year horizon.

Maintenance operations of the elastomeric membrane roof										
Year	R>80%		R>75%		R>63.21%		R>63.21%/1PM		R>63.21%/2PM	
	Op	R (%)	Op	R (%)	Op	R (%)	Op	R (%)	Op	R (%)
1	N	98.6	N	98.6	N	98.6	N	98.6	N	98.6
2	N	97.1	N	97.1	N	97.1	N	97.1	N	97.1
3	N	95.4	N	95.4	N	95.4	N	95.4	N	95.4
4	N	93.6	N	93.6	N	93.6	N	93.6	N	93.6
5	N	91.6	N	91.6	N	91.6	N	91.6	N	91.6
6	N	89.4	N	89.4	N	89.4	N	89.4	N	89.4
7	N	87	N	87	N	87	N	87	N	87
8	N	84.6	N	84.6	N	84.6	N	84.6	P	87
9	N	82	N	82	N	82	P	84.6	N	85.9
10	C	98.6	N	79.3	N	79.3	N	83.4	N	84.5
11	N	97.1	N	76.6	N	76.6	N	82	N	82.9
12	N	95.4	C	98.6	N	73.8	N	80.4	N	81.1
13	N	93.6	N	97.1	N	70.9	N	78.6	N	79.1
14	N	91.6	N	95.4	N	68	N	76.7	P	79.1
15	N	89.4	N	93.6	N	65.1	N	74.6	N	78.1
16	N	87	N	91.6	C	98.6	N	72.3	N	76.8
17	N	84.6	N	89.4	N	97.1	N	70	N	75.4
18	N	82	N	87	N	95.4	N	67.6	N	73.7
19	C	98.6	N	84.6	N	93.6	N	65.1	N	72
20	N	97.1	N	82	N	91.6	F	98.6	N	70

N: No maintenance operations; C: Corrective maintenance; P: Preventive maintenance; Op: Operation.
R: Reliability; 1PM: One action of preventive maintenance; 2PM: Two action of preventive maintenance.

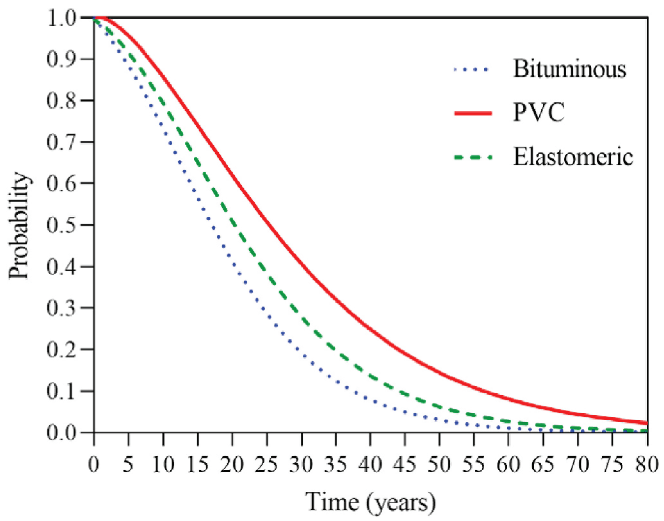


Fig. 6. Survival function of the roofing membranes over time.

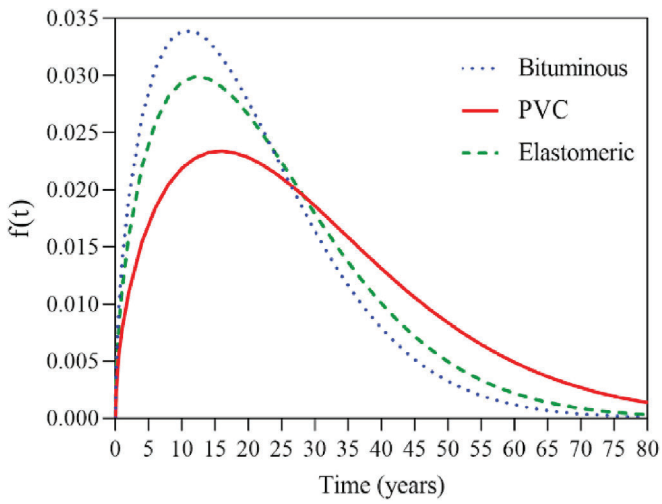


Fig. 7. The Failure Density Function of the roofs over time.

be operational in a given time, as shown in Fig. 8.

Table 5 shows the operating life of the membrane for the three types of roofs based on the failure function in Fig. 8.

The authors studied the replacement time of the waterproofing membranes while evaluating the condition of the roofs analysed in this paper. The analysis was conducted for the five scenarios defined above and allowed for planning the maintenance of the roofs already built with a simple inspection to determine the degradation of the membrane. This ensures that the roofs in use do not fail and that they perform their function with adequate reliability. Table 6 shows the replacement time of the roof depending on the initial state of degradation, the membrane and the scenario.

The authors found that if a membrane is in the state of failure (7), it must be replaced during the same year, regardless of the scenario or type of membrane. The year in which the replacement must be made is specified for the remaining stages of condition. Finally, Fig. 9 shows the failure rate for each type of membrane, calculated using equation (8), where the density function is divided by the survival function, complementary to equations (11)–(13).

The failure rate increases in all the roofs analysed. Bituminous membrane, have the steepest slope, resulting in the highest number of failures over time and the shortest operating life. Nevertheless, PVC membrane have the lowest number of failures over time and a longer life span.

4. Discussion

The increasing degree of complexity of hospitals and their facilities requires implementing an appropriate methodology for the management of the building's life cycle [54]. It was found that by applying Markov chains to plan the maintenance of the roofs, the most appropriate time for the replacement of the waterproofing membranes could be determined. Thus, maintenance operations keep the component's state of deterioration above the state of failure, with adequate reliability. Therefore, Markov chains can be useful towards efficiently planning the maintenance of the roofs, minimising the risks of component failure and

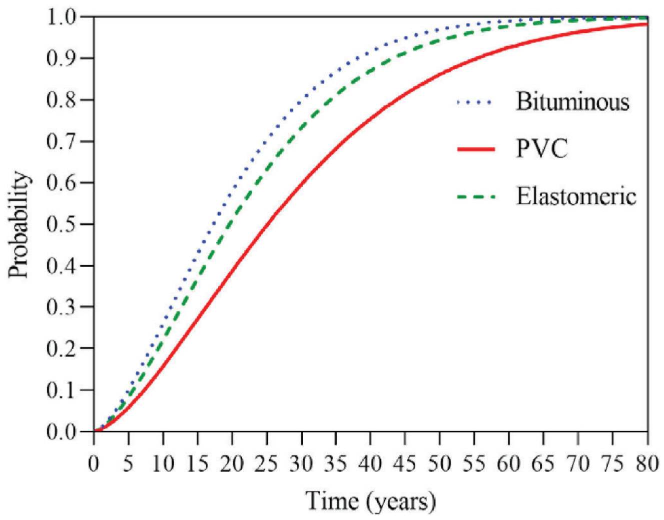


Fig. 8. Failure function of the roofing membranes over time.

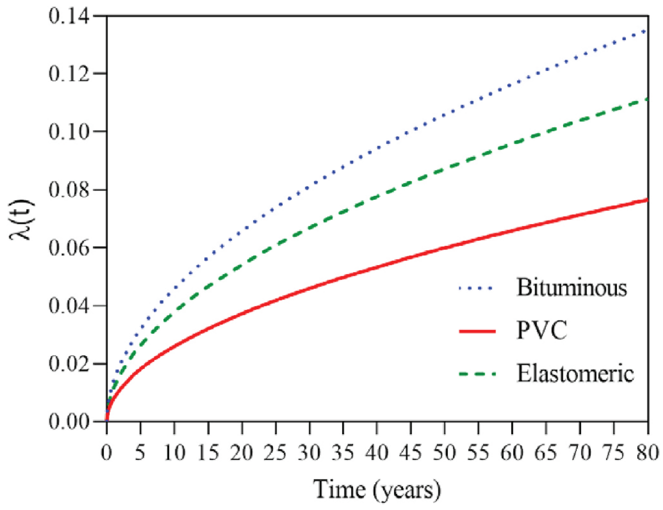


Fig. 9. Roof failure rate over time.

Table 5
Standard accessible flat roof membrane life.

Reliability (%)	Standard life (years)		
	Bituminous	PVC	Elastomeric
80	8	13	10
75	10	14	11
70	11.5	16	13
65	13	18	15
63.2	13.5	19	16
60	14	20	16

Table 6
Replacement time of the membrane according to its initial state of degradation.

	Degradation	80%	75%	63.21%	63.21%/ 1 M	63.21%/ 2 M
PVC Membrane	1	13	15	20	24	28
	2	12	14	19	24	27
	3	11	13	18	23	26
	4	7	9	13	17	23
	5	7	9	12	16	23
	6	4	5	7	12	15
	7	1	1	1	1	1
Bituminous membrane	1	8	10	14	17	21
	2	9	11	14	18	21
	3	7	9	12	16	20
	4	6	7	9	15	18
	5	4	5	8	13	17
	6	3	3	5	9	13
	7	1	1	1	1	1
Elastomeric membrane	1	10	12	16	20	24
	2	10	12	16	20	24
	3	9	10	14	19	23
	4	7	8	11	16	22
	5	5	6	9	14	19
	6	3	4	5	11	15
	7	1	1	1	1	1

controlling the cost of operations [52].

The authors found that maintenance operations could be systematised according to the initial state of degradation of the flat roof membrane, without compromising its operability. On the other hand, maintenance actions planning helps reduce the cost of this activity compared of unscheduled maintenance. Moreover, the scheduled maintenance decreases the risk of roof failure, which is essential in hospitals, since the appearance of anomalies in the roof can lead to operational malfunctions of buildings [55].

The results show that roofs with PVC membranes can stay in operation for longer, ensuring their reliability. This membrane can be replaced at least four years later than the other layers tested. Although this roof is slightly more expensive, its reliability positions it as a good alternative. However, PVC membrane emits 51% more kg of CO_2 per m^2 in its manufacture and installation than bituminous membrane [21]. Bituminous roofs have the lowest environmental impact, whereas elastomeric roofs have the highest.

Elasticity prevents the diaphragms of the flat roofs from breaking, which avoids failures [56]. Bituminous membranes have low elasticity independent of the ambient temperature. PVC membranes are highly flexible and are highly resistant to traction and breakage, as they are reinforced with a fibreglass mesh and additives to improve their resistance to the weather conditions. Preventive maintenance has also been found to be vital in reducing the degradation of flat roofs [22].

Godfried et al. [36] described the Markov model for estimating the performance and maintenance cost of a building roof and Santos et al. [57] identified problems involving the current state of the roofs, but none proposed a method for determining maintenance. In this study, a maintenance schedule was proposed that considerably increases the lifetime of the membranes.

The results obtained in Table 5 show that the useful life of the PCV, bituminous and elastomeric membranes is 20, 14 and 16 years respectively. Coffelt et al. [34] determined that the period of useful life until the roof reaches the worst state of condition is 21 years. The variation between this result and those obtained in this analysis may be due to the differences between the degradation scales and the roofs observed in the Markov model, the type of membrane and the method of obtaining the service life. In addition, the service life of this study is evaluated based on reliability, so that the membranes do not reach the state of collapse.

While other authors determine maintenance priorities based on four criteria (environmental aggressiveness, level of deterioration, extent and severity of the defect) [55] or choose maintenance activities to reduce total costs and increase performance [58], this research establishes a maintenance schedule based on the condition of the membranes. In this way, priority is given to ensuring that the condition of hospital membranes does not collapse as opposed to the cost of maintenance.

The preventive maintenance focused on repair and replacing partially of parts the membrane that were in poor condition [59]. With this in mind, maintenance and inspection operations must be logged, and the functionality of the system must be guaranteed throughout its life cycle [60]. The repair of the waterproofing must be carried out by specialized technicians [61]. However, the resources used during maintenance operations can considerably increase the environmental impact of the roofs [62].

Inspection and diagnosis have proven to be necessary to standardise and systematise procedures within a proactive maintenance strategy to prevent flat roof anomalies. For this purpose, non-destructive methods [63] and various renovation techniques are available on site to maintain and/or restore the functional properties of flat roofs [64]. Similarly, it is advisable to carry out periodic maintenance audits to determine whether the management of the assets in the building is adequate and to forecast the evolution of the demand for maintenance [65]. Most of the polymeric layers that make up a roof are incompatible with each other, so there may be interactions and incompatibilities between some of these elements [66]. Therefore, it is vital to separate them with auxiliary layers that prevent contact. The weather conditions of the area where the building is located must also be considered, for their significant influence on roof deterioration [67]. This is reflected in the system degradation matrices, and by estimating it, one can adapt and prevent the roofs from failing.

Future work should aim at studying the factors influencing the maintenance of flat roofs to obtain more indicators and determine the best maintenance policy. This methodology can also be applied to other buildings of similar characteristics and evaluate the convenience of implementing green roofs from the perspective of their maintenance [68].

This research is useful to define and protocol the maintenance operations, determining the optimal time to perform the replacement and repair operations, allowing to maintain the reliability of the system during all its service life. It also allows for more precise annual maintenance budgets.

5. Conclusions

Applying Markov chains to estimate the degradation of hospital flat roofs enables optimizing maintenance operations and increasing the reliability of the system during its service life. The authors found that with this stochastic model, maintenance of flat roofs can be planned, which minimises costs and damage from failure and breakage. Thus, the functionality of the flat roofs studied in this paper is guaranteed throughout their operational life, reducing anomalies.

The most appropriate time for the replacement of the membrane was estimated by determining their degradation status during the last inspection. This made it possible to plan the maintenance of the roofs in operation during their useful life, considering their reliability. The importance of preventive maintenance was also demonstrated along with how it increases operating life by 40% for PVC roofs and by 50% for bituminous and elastomeric roofs. The results showed that PVC membranes are the least degraded. They have an operating life of 28 years for an excellent initial condition, four and seven years longer than elastomeric and bituminous roofs, respectively. The life span of the flat roof membrane increases as the minimum reliability required decreases, and preventive maintenance increases. The authors also found that accessible flat roofs with PVC membrane need less preventive maintenance, followed by elastomeric membrane and finally, bituminous membrane.

This paper proposes a tool based on historical data that can be simply updated and can be easily extended to other roof components or building construction elements. The data set analysed does not consider factors such as the quality and execution of the construction.

Credit author statement

García-Sanz-Calcedo: Conceptualization, Methodology, Investigation, Supervision, Writing- Reviewing and Editing. **Sánchez-Barroso**: Data curation, Software, Investigation, Validation. **González-Dominguez**: Visualization, Investigation, Software, Writing- Original draft preparation.

CRediT authorship contribution statement

Jaime González-Domínguez: Visualization, Investigation, Software, Writing - original draft, preparation. **Gonzalo Sánchez-Barroso:** Data curation, Software, Investigation, Validation. **Justo García-Sanz-Calcedo:** Conceptualization, Methodology, Investigation, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors wish to acknowledge the European Regional Development Fund for the financial support provided through Research Projects GR18029 linked to the VI Regional Plan for Research, Technical Development and Innovation from the Regional Government of Extremadura (2017–2020).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jobe.2020.101775.

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ANEXO IV

Referencia

J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, M. Sokol, "Condition-based maintenance of ceramic curved tiles roof in Primary Healthcare buildings using Markov chains," *Journal of Building Engineering*, vol. 43, p. 102517, 2021. DOI: 10.1016/j.jobe.2021.102517.

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Journal of Building Engineering 43 (2021) 102517

Contents lists available at ScienceDirect

Journal of Building Engineering

journal homepage: http://www.elsevier.com/locate/jobe

Condition-based maintenance of ceramic curved tiles roof in Primary Healthcare buildings using Markov chains

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ARTICLE INFO

Keywords:
Markov chain
Ceramic curved tile roofs
Condition-based maintenance
Healthcare engineering
Reliability

ABSTRACT

Ceramic curved tile roofs (CCTR) have been used in Spain for ages. This roofing system is very common in Primary Healthcare Centers in Extremadura (Spain). The main objective of this research is to analyze the condition-based maintenance (CBM) of CCTR of Primary Healthcare buildings. Once the condition-based maintenance is analyzed, the optimal maintenance policy and frequency is obtained. A sample of 20 Primary Healthcare Centers in Extremadura (Spain) were evaluated using Markov chains, which represent a useful technique to analyze the influence of frequency and the initial year of maintenance for the increase of the CCTR service life. This study found that the service life of the CCTR can be extended by 8 years using non-periodic condition-based maintenance with a high level of reliability. The end of the service life of this system was also calculated, with a maximum estimated replacement time of about 39 years. Therefore, the maintenance program can be monitored to optimize the operation costs.

1. Introduction

Curved roof tile (CRT) is a type of covering commonly used in ventilated pitched roofs in the Mediterranean region [1], with a slope that increases runoff [2,3]. Ventilated pitched roofs are not only waterproof but also reduce solar radiation through air convention, minimizing the energy consumption of the building [4]. The ceramic roof surface can be used to place photovoltaic systems [5] and has a good solar reflectance level [6]. A ceramic tile is a constructive element designed as a gutter with parallel or convergent edges that facilitate tile joint [7]. Frequently, the roofing systems of Primary Healthcare Center in Spain are cladded with these tiles.

A Primary Healthcare Center has the necessary equipment and resources to carry out primary care actions, and is located in small and large towns that require these services [8]. Moreover, these buildings do not have enough resources to carry out surgical interventions or patient hospitalizations [9]. Since a Primary Healthcare Center operates 24 h a day, 365 days a year, it cannot afford a severe degradation [10]. In Spain, between 4000 and 20,000 patients approximately are treated yearly in each of these centers on average.

Frequently, the degradation of a building begins on the roof [11], with water infiltrations being one of the main problems. Water leaked is mainly due to errors in the design and execution stage of the project, or during the service life, that increasing the maintenance costs [12]. Generally, building degradation follows a similar trend [13], and it is easily identified by periodic inspections. The maintenance of the critical parts of a building is very important [14,15], since a building has a fairly long service life [16]. Adequate scheduling of building maintenance has been demonstrated to reduce costs and environmental impact [17].

Primary Healthcare Centers require higher maintenance costs due to its intensive activity [18]. Therefore, precise tools for maintenance scheduling should be used [19]. There are several studies in the literature regarding diagnosis of anomalies and service life of ceramic roofs, identifying the main issues that affect the degradation of the roofs and the maintenance necessary for their repair [20]. Garcez et al. [21] developed an inspection and diagnostic system to detect errors in pitched roofs related to the design stage, determining the influence of these errors on the service life of the roof and its maintenance. Ortega, Serrano and Fran [22] proposed a methodology to estimate the service life of various facades and roofs (including ceramic roofs), analyzing vulnerability using the Delphi method and identifying the diverse factors that

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https://doi.org/10.1016/j.jobe.2021.102517
Received 4 December 2020; Received in revised form 12 March 2021; Accepted 7 April 2021
Available online 22 April 2021
2352-7102/

influence a roof service life. Carretero-Ayuso and Jorge Brito [23] analyzed 65 construction projects to identify errors in the design and execution stage of the project, by evaluating the anomalies originated in the pitched roof tiles according to the roof damage.

The degradation of a system over time can be estimated using the stochastic Markov model [24]. Several studies used Markov chains as a degradation model to predict the future condition of a critical building component [25,26]. Silva et al. [27] studied the influence of sea distance, humidity and the characteristics of different cladding on the degradation of building facades using the Markov chains. Coffelt, Hendrickson, and Healey [28] used Markov model to relate the replacement of building roof systems to the degradation, service life and maintenance costs. However, maintenance was not evaluated based on its reliability. Ortega et al. [22] applied different prediction methods to determine the service life of the building envelope. Edirisinghe, Zhang, and Setunge [29] analyzed the critical components deterioration of a building and its factors, obtaining a model able to predict the future component condition. Markov chains and the ISO factor method were combined to achieve it. Papakonstantinou and Shinozuka [30] determined the most appropriate maintenance to mitigate corrosion of building structures by applying the partially observable Markov model. Rapurathna, Hewage, and Sadiq [31] modeled the degradation of HVAC systems, building envelope and lighting and electrical systems using Markov chains and applied risk-based prioritization to select the most appropriate maintenance that optimize its cost. Ferreira et al. [32] inspected 195 buildings in Lisbon and combined the Markov chains with the Petri nets, in order to predict the condition of building ceramics claddings over time. Cheng, Wang, and Yan [33] used Markov chains and Monte Carlo simulation to minimize life-cycle cost and increase the efficiency of chilled water systems designs. None of these studies used the Markov model to analyze the influence of periodicity and the initial year of maintenance on the degradation of ceramic roofs.

Furthermore, there are few studies that apply this methodology to critical construction elements in sanitary buildings [34–36]. González-Domínguez, Sánchez-Barroso, and García-Sanz-Calcedo [37] applied the Markov model to evaluate the degradation of three types of flat roofs of Healthcare Centers over time, establishing the maintenance and service life of the flat roofs based on its reliability.

Markov model is suitable for assessing the degradation of critical elements of a building over time, but it is hardly ever for healthcare infrastructures. As a novelty, this research study applies this model to establish the most appropriate time period to carry out maintenance tasks on a ceramic tile roof. Thus, the reliability of the CCTR can be ensured, minimizing failure risks. As a part of the study, maintenance is scheduled based on the condition of the ceramic roof of Primary Healthcare Buildings, ensuring their watertightness.

2. Methods

The degradation of CRT is studied in this research. A maintenance data history of 20 Primary Healthcare Centers in Extremadura (Spain), between 2008 and 2018, was analyzed in order to relate the degradation states to the anomalies of the CCTR. In addition, the database was used to contrast the degradation model and establish the most appropriate maintenance tasks. Seven possible degradation states of the ceramic tiles were identified during their service life, generating the condition scale of the ceramic curved tiles in pitched roofs [38]. The condition scale provides a classification of the ceramic tiles degradation during the inspection, starting from a very good condition until the collapse [39]. When the roof is in the last degradation state, the initial properties are lost and do not improve with maintenance. Following, the main anomalies that influence the degradation of the roof throughout time are developed. Illustrative examples of the different anomalies that damage simple ceramic tiles over time are described and shown in Table 1.

Most anomalies can cause serious problems, such as loss of watertightness of the roof, falling tiles, loss of energy from the building, reduced solar reflection, among others. These problems worsen over time. For example, surface flaking may lead to cracks on the tiles that affect the watertightness of the ceramic roof. Also, a misalignment could generate ceramic tile detachment. Other anomalies are consequence of an error in the design or execution stage of the project. Table 2 presents the scale of condition used in this research, relating the anomalies to the condition level of the CCTR.

The condition evolves from an optimum state to collapse state throughout the service life of the roof. To develop the Markov model, the collapse state must be defined. The collapse state is a degradation state that generates a loss of waterproofing, thermal and acoustic insulation and resistance to different climatological environments [47]. This can seriously damage medical facilities and equipment in Primary Healthcare Centers, decreasing the quality of sanitary assistance [48]. Moreover, indoor air quality (IAQ) is affected, encouraging the appearance of fungi [49].

The degradation states do not only depend on the emergence of an anomaly, but they are also conditioned by a set of anomalies, percentage of roof area affected and the severity of the anomalies. For example, degradation increases when the anomaly affects a critical element of the roof construction system. The same anomaly may be shown in more than one state of degradation but with different intensity. For example, biological colonization is a very common anomaly that influences the thermal insulation or solar reflectance of CCRT [50]. If this anomaly affects 2% of the area covered, the degradation state would correspond to the level 2. However, when the affected area is higher the level of state of degradation will increase.

The maximum affected roof area of each anomaly was related to those degradation states described in Table 2. In addition, the area of affected roof was defined to reach the last state of degradation. To define the percentage of affected roof for the remaining degradation states, the values of the last state were weighted. These values were quantified by experts in the subject.

In general, adverse effects through time are minimized by maintenance operations. According to the standard UNE-EN 13306:2018, *preventive maintenance* includes actions that reduce degradation and failure of an item, while *corrective maintenance* is performed after recognizing a failure, and includes actions that return the element to a state of adequate functionality [51]. *Condition-based maintenance* is a preventive procedure that monitors the state of the system and its maintenance tasks [51]. In this study, the most appropriate preventive maintenance actions were selected to improve the state of degradation of the roof, and the periodicity of *preventive maintenance* was determined based on the roof condition.

Markov chains is a stochastic model that provides the probability of the roof to change from a state of degradation i to another j in a given time t [52]. The markovian property establishes that the future degradation state of a system depends only on the current degradation state and not on the past [53]. The set of state transition probabilities constitutes the transition matrix [T]. The information obtained from previous inspections is collected to develop the transition matrix [54]. This research study used information from ceramic tile roofs analyzed by Grussing (2015) [55]. The matrix is shown in Fig. 1.

The elements of the transition matrix, T_{ij}, represent the probability in which the roof is in a specific degradation level at a given time. For example, if a roof is initially in the state of condition 3, its probability to be in degradation state 5 after one year is 0.032, and its probability of no change of state is 0.878. The transition matrix is represented graphically as a state diagram in Fig. 2.

Once the state transition matrix and the initial conditions of the roof are known, the state of the system in a future time period can be determined. This is expressed by state vector S_n, which represents the proba-

Table 1
Anomalies of simple ceramic tiles.

Code	Name	Example	Description
AN-1	**Misalignment/Displacement of ceramic tiles**		In this type of roofing, the tiles can become misaligned or displaced due to the action of the wind [40] or lack of maintenance [23], causing problems of watertightness or loosening
AN-2	**Surface dirt**		Surface dirt is a very common anomaly that influence the thermal properties of the roof [41], decreasing the reflection of solar radiation [42] and increasing its heating [43]**.** Therefore, cleaning the roof surface improves the energy efficiency of the building [44]
AN-3	**Cracks/fractures**		The environmental actions together with the mechanical ones can generate cracks and fractures, producing leaks in the roof [21]
AN-4	**Biological Colonization/Vegetation growth**		Biological colonization and vegetation growth in ceramic tiles is a very common anomaly arising from long environmental exposure and affects both the surface quality and the integrity of the material [45]
AN-5	**Flaking/spalling**		Environmental actions cause damage and even surface flaking of the roof throughout time [20]. This surface anomaly can generate cracks
AN-6	**Roof cladding deformation**		Lack of maintenance or failure of the support structure can cause serious deformation of the roof cladding, generating areas of water infiltration [46]

bility in which the ceramic roof is for each degradation state after a period of time n [56], in accordance with Equation (1).

$$S_n = S_i \cdot [T]^n \tag{1}$$

Maintenance operations are necessary to improve the degradation conditions of a system. Markov degradation matrix model allows to include different maintenance policies [57]. Consequently, the maintenance modifies Equation (1) in Equation (2).

$$S_n = S_i \cdot [M] \cdot [T]^n \tag{2}$$

Where S_i is the initial state vector, and represents the roof degradation at the beginning of the analysis. The influence of maintenance on the roof degradation is evaluated for different initial state of conditions using this vector. Therefore, maintenance activities can be monitored for both existing roofs and new ones. For that purpose, the initial state of condition takes the value of 1 and the rest of the states take 0.

Firstly, the maintenance matrix was defined, including the probability of degradation state of a ceramic roof in a specific period. And secondly, the reliability of the roof as a function of time and service life was calculated. Reliability is the capability of an element to perform a required function under given conditions and over a specified time interval [51] and it allows to assess the state of the critical building com-

Table 2
Condition scale of ceramic curved tile roof.

Level	Degradation	Description	Anomalies	Roof area affected (%)
1	Minimum	There are no anomalies on the entire surface of the roof	–	–
2	Slight	Some anomalies are observed affecting only a very low percentage of the roof area.	AN-2 AN-4	<5 <5
3	Minor	More severe anomalies appear, such as fractures, flaking, and misalignment.	AN-1 AN-2 AN-3 AN-4 AN-5	<2 5–10 <2 5–10 <2
4	Notable	Anomalies cover a larger roof area and cause higher degradation.	AN-1 AN-2 AN-3 AN-4 AN-5	2–5 10–15 2–5 <10-15 2–5
5	Significant	Anomalies cause great degradation, for example, vegetation growth can affect up to a quarter of the roof surface, reducing its insulation and solar reflectance.	AN-1 AN-2 AN-3 AN-4 AN-5	5–10 15–25 5–10 15–25 5–10
6	High	Serious anomalies affect the roof with a high level of degradation. For example, a high percentage of fractures in the tiles cause a loss of watertightness.	AN-1 AN-2 AN-3 AN-4 AN-5	10–15 25–50 10–15 25–40 10–15
7	Severe	Replacement of the roof is required due to its high degradation level.	AN-1 AN-2 AN-3 AN-4 AN-5 AN-6	>15 >50 >15 >40 >15 Non-specific area

$$[T]=\begin{bmatrix}0.722 & 0.108 & 0.109 & 0.012 & 0.009 & 0.008 & 0.032\\ 0 & 0.793 & 0.112 & 0.042 & 0.015 & 0.018 & 0.02\\ 0 & 0 & 0.878 & 0.063 & 0.032 & 0.027 & 0\\ 0 & 0 & 0 & 0.847 & 0.094 & 0.038 & 0.02\\ 0 & 0 & 0 & 0 & 0.862 & 0.076 & 0.062\\ 0 & 0 & 0 & 0 & 0 & 0.865 & 0.135\\ 0 & 0 & 0 & 0 & 0 & 0 & 1\end{bmatrix}$$

Fig. 1. State transition matrix for ceramic curve tile roofs.

ponents of a Primary Healthcare Center. Therefore, obtaining an optimal maintenance schedule to ensure the roof reliability during its service life is necessary [58]. The reliability index, *F*, was used to calculate it over time, and defined as the probability that the ceramic tile roof is in a suitable condition in a given time *n*. The reliability index was obtained using Equation (3).

$$F = S_n \cdot C \tag{3}$$

where *C* is the collapse vector, which represents the limit state of the research.

States below the limit state take the value 1 and states of degradation greater than or equal to the state of collapse take the value 0. In this way, the reliability of ceramic roofs can be calculated throughout time according to the maintenance policy and frequency, obtaining a condition-based maintenance model [37].

The optimal maintenance strategy and frequency for this type of roofing was determined based on its reliability. Therefore, a minimum reliability value was established, corresponding to the maximum value of parameter *F*. Above this value, the system reliability would not be adequate to guarantee the proper functioning of the CCTR. Thus, the roof

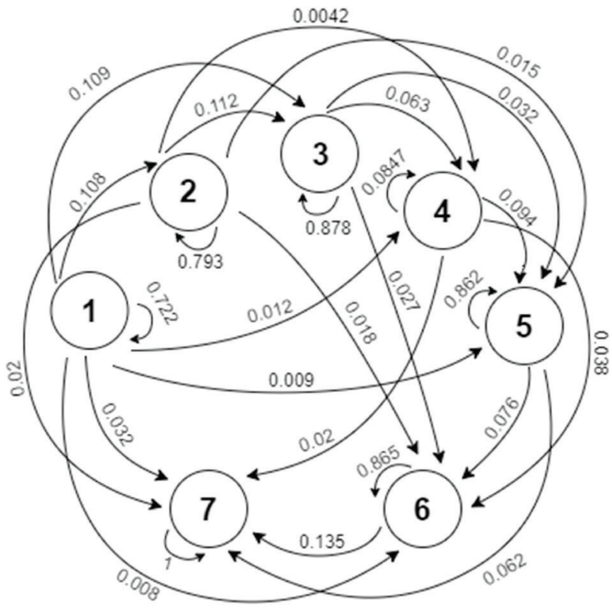


Fig. 2. Transition of state graph for ceramic curve tile roofs.

service life will end when the value of *F* exceeds the minimum reliability value (63.21%). Consequently, the corrective maintenance of the CCTR will be carried out according to its reliability. In order to maximize reliability throughout the service life of the CCTR, preventive maintenance will be analyzed and scheduled.

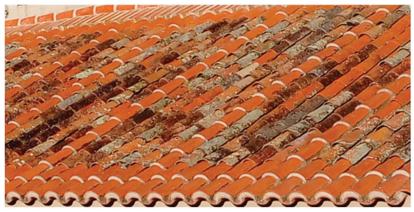
3. Results

The maintenance strategies adopted in this study are represented by two matrices, as shown in Table 3 above. The first matrix represents those preventive maintenance operations carried out during the service life of a ceramic tile roof, and the second includes corrective maintenance actions when the reliability of the system does not guarantee the watertightness. The probability of failure during the service life of the roof is minimized by preventive maintenance. This maintenance includes different tasks: cleaning of accumulated dirt, removal of biological organisms, placing of dislocated or misaligned tiles, replacing or repairing of cracked or superficially damaged tiles and replacing of tiles with superficial dirt or deteriorated pigmentation [59]. In this research, preventive maintenance replacement actions are partial and do not represent more than 10% of the total roof area. The corrective maintenance involves the total replacement of this CCTR. This maintenance is performed at the end of the service life. The above maintenance actions cost is estimated according to the technician experiences and cost simulator used [60]. The preventive maintenance budget is 18.11€/m^2 while corrective maintenance is 56,3 €/m^2.

The relationship between the maintenance and the service life of the roof was analyzed. To begin with, it takes 14 years for this type of roofs come to a collapse state when no maintenance tasks are performed. The collapse state in this methodology has been described as a degradation state, in the sense that the CCTR is unable to perform its function properly. In this research the collapse state corresponds to state 7 as described in Table 2. Primary Healthcare Centers are particularly sensitive to this degradation since its facilities are subjected to intense activity. As a result, not only the periodicity of maintenance operations, but also the initial year of maintenance are very important factor.

In this research three possible scenarios, maintenance every 2,3 and 4 years, were considered. To analyze the influence of maintenance periodicity, seven maintenance operations were taken into account in all scenarios. The maintenance costs are the same in all three scenarios, allowing the influence of periodicity on the roof reliability to be ana-

Table 3
Maintenance policy.

Maintenance	Description	Matrix	Example
Preventive	Cleaning, repair and partial replacement of the roof during its service life	$\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	
Corrective	Replacement most of the roof area at the end of the service life	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	

lyzed. Considering the maximum service time of roof operation, the maintenance was established from the second to thirteenth years. Applying the Markov degradation model, Table 4 shows the results for the three scenarios under analysis.

Depending on the initial year and the scenario considered, the maximum replacement time values of the CCTR are shown in the above table. Fig. 3 represents this results in a graph.

When preventive maintenance starts two years after the construction of the CCTR, scenario 3 presents the best maintenance periodicity, followed by scenarios 2 and 1, respectively. Therefore, it is important choose the right maintenance frequency. Moreover, the service life of the roof is longer as the preventive maintenance initial year is delayed. For scenarios 3, 2 and 1, a maximum service life of 38, 35 and 31 years was obtained, respectively. The optimal service life of the roof was calculated for the different initial year values and each scenario. The service life difference of 7 years between is very significant, showing the importance of considering the right maintenance periodicity for a given CCTR. The longer the maintenance periodicity, the greater the risk of a system failure when maintenance is delayed. If the initial maintenance is carried out after the tenth year in scenario 3, the service life of the roof is drastically reduced. Thus, maintenance does not increase the reliability of the CCTR due to its significant degradation. This behavior was observed to a lower proportion in scenario 2. Finally, scenario 1 is the most appropriate when maintenance starts in the eleventh and twelfth years, while scenarios 1 and 2 are the most suitable in the last year.

Table 4
Influence of periodicity and initial year of maintenance tasks.

Maintenance Frequency			
Initial year	Replacement		
	Scenario 1	Scenario 2	Scenario 3
2	26	31	35
3	27	32	36
4	28	33	36
5	28	33	37
6	29	34	37
7	30	34	38
8	30	35	38
9	30	35	38
10	31	35	38
11	31	35	31
12	31	35	28
13	31	31	21

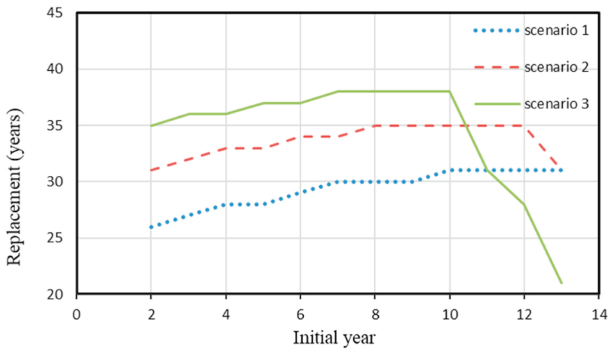


Fig. 3. Ceramic curve tile roofs replacement depending on the maintenance.

The influence of the number of maintenance actions during the roof service was determined after the analysis of the periodicity and the maintenance initial year. The optimal maintenance periodicity according to the number of maintenance actions was calculate by an iterative process. The number of maintenance operations will be determined by the maintenance budget. The iterative process aims to maximize the reliability of the roof, and consequently to increase its service life. Table 5 and Fig. 4 present the roof service life depending on the number of maintenance operations.

As shown in Fig. 4, the service life of the CCTR increases proportionally to the number of maintenance actions. However, the maintenance budget is not unlimited, therefore a good schedule is necessary. The results presented maximize the reliability of the roof.

The reliability values and the optimal years to perform the 7 maintenance actions are presented in Table 6 for two different options.

It is observed in Table 6 that a non-periodic maintenance distribution generates a service life of 39 years. The service life obtained by non-periodic maintenance is higher than the best scenario of periodic maintenance (scenario 3). Finally, no option increases the 39-year service life by modifying only the maintenance schedule.

Table 5
Influence of maintenance operations on service life.

Maintenance (uds)	–	1	2	3	4	5	6	7
Service life (years)	14	19	22	26	31	34	37	39

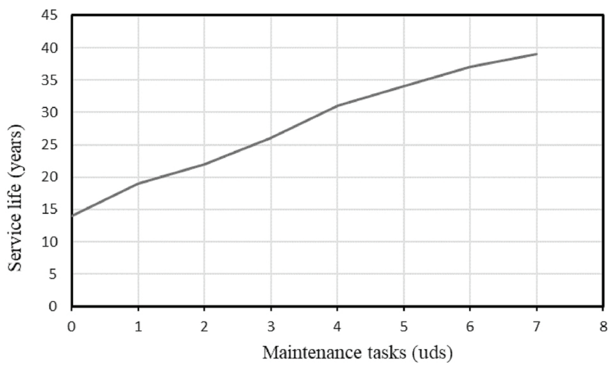


Fig. 4. Service life of the ceramic curve tile roofs against maintenance.

Table 6
Maintenance policies for the ceramic curve tile roofs.

Year	Option 1		Option 2		Year	Option 1		Option 2	
	Op	Rel (%)	Op	Rel (%)		Op	Rel (%)	Op	Rel (%)
1	N	96.8	N	968	21	P	71.5	N	74.6
2	N	94.1	N	94.1	22	N	72.9	N	73.9
3	N	91.6	N	91.6	23	N	72.2	N	72.8
4	N	89.3	N	89.3	24	N	71.1	N	71.3
5	N	87.1	N	87.1	25	N	69.7	P	69.5
6	N	84.7	P	84.7	26	P	67.9	N	71.1
7	P	82.3	N	86.2	27	N	69.5	N	70.5
8	N	84.0	N	85.0	28	N	68.8	N	69.4
9	N	82.8	N	83.4	29	N	67.8	P	67.9
10	N	81.3	N	81.5	30	P	66.3	N	69.2
11	N	79.5	P	79.4	31	N	67.7	N	68.6
12	P	77.4	N	81.1	32	N	67.1	N	67.6
13	N	79.1	N	80.1	33	N	66.0	N	66.2
14	N	78.2	N	78.8	34	P	64.7	P	64.5
15	N	76.9	N	77.1	35	N	65.9	N	66.0
16	N	75.3	P	75.0	36	N	65.4	N	65.4
17	P	73.3	N	76.8	37	N	64.5	N	64.5
18	N	75.0	N	76.0	38	N	63.3	N	63.3
19	N	74.3	N	74.8	39	R	96.8	R	96.8
20	N	73.1	P	73.2	40	N	94.1	N	94.1

N: No maintenance operations; R: Replacement; P: Preventive maintenance; Op: Operation; Rel: Reliability.

4. Discussion

The research results indicate that the low maintenance periodicity is appropriate when the maintenance is carried out close to the end of the CCTR service life. This result is quite applicable in two several situations. Firstly, it can be useful for CCTRs with a certain age and inadequate maintenance. Second, this strategy is adequate when there is no budget for maintenance in the early years. The analysis of the influence of maintenance indicates that a preventive maintenance scheduling allows managing properly the available resources. The optimum service life of each scenario is obtained for a set of initial years of the maintenance tasks. Furthermore, there is more than one periodic maintenance schedule that optimizes the life of the CCTR.

A Primary Healthcare Center is a building located in towns with more than 2500 inhabitants, which requires high maintenance due to its 24-h intense activity, 365 days a year. Markov chains allow to estimate the condition of the roof of these buildings over time. Therefore, the optimal periodicity of condition-based maintenance could be established without performing frequent inspections. Non-periodic maintenance based on the degradation condition of the roof was found to be better than maintenance on a regular basis. Also, Markov chains is a useful tool to identify different maintenance plans and select the most appropriate strategies to optimize budget assigned to maintenance actions. The maximum service time of the CCTR is 39 years for 7 maintenance tasks. Ramos et al. [61] obtained a series of degradation curves for different types of ceramic roofs estimating that the service life of the CCTR is 51 years. Nevertheless [22], refer a value of 48 years of service life, while the minimum is 10 years. Comparing the results, the difference obtained is due to the fact that both the data set analyzed, and the degradation model used are different. In addition, this difference decreases when preventive maintenance tasks are increased during its service life.

Grussing and Liu [62] used Markov chains to determine the most appropriate maintenance policy to reduce the cost of maintaining various critical elements of a building. Other authors [63] used this probabilistic tool to establish the maintenance and service life of flat roofs based on reliability. However, in this research, Markov chains were used to determine the influence of the periodicity and the initial year of the preventive maintenance on the degradation of the CCTR. Therefore, the initial year of the maintenance tasks and the optimal frequency of preventive maintenance of the roofs are established.

Also, it was found that Markov chains are an appropriate methodology for systematizing maintenance tasks, which is important for predicting the relative costs of maintaining a healthcare building [64] and contributing to the sustainability of the built environment [65]. In addition, the correct rehabilitation of the roof allows a reduction in the environmental loads [66] and the energy consumption of the building [67].

The reliability of this CCTR was prioritized over maintenance costs. Furthermore, preventive maintenance replacement was no more than 10% of the total roofing surface. This percentage of the replaced roof was considered to increase its reliability, since the implementation of an adequate preventive maintenance minimizes degradation significantly. Considering the access cost of this maintenance performance, it would be more efficient to replace a higher percentage of CCTR surface in each intervention. Thus, the risk of higher maintenance costs is assumed by setting maintenance operations and service life according mostly to reliability.

There are other types of roof that are functionally adequate for use in health care facilities. However, the ceramic tile integrates perfectly in the rural environment with a high aesthetic level [68], and it is compulsory to use in the urban frameworks of many cities with patrimonial value. In addition, the great variety of ceramic tiles allows to design different architectural styles [61] and their low environmental impact makes their use advisable compared to other typologies [69].

Ceramic tile roofs micro-ventilation using dry fixing elements is an emerging strategy, and it allows air to pass through the base as well as preventing condensation. This minimizes the energy loss through the roof and contributes to better energy efficiency of the building [70]. Hydrophobic tiles that completely prevent water absorption are also available [71]. In both cases, the results obtained in this research are applicable.

The results obtained in this research are not directly applied to other types of buildings. However, the methodology can be easily updated and adapted. Two modifications should be necessary to apply this methodology to different types of buildings. First, the maximum degradation criterion has to be established. The second modification would consist of changing the maintenance policy of those buildings to maintain reliability at high levels.

Future research should focus on planning the maintenance of different critical components of a healthcare building using Markov chains, obtaining a common maintenance schedule to reduce cost and resource collapse.

5. Conclusions

It has been determined that Markov chains are a useful probabilistic tool for monitoring maintenance operations of CCTR, obtaining the optimal policy, frequency and start of maintenance operations. This technique estimates the degradation pattern and the reliability of the CCTR as a function of maintenance, providing criteria for optimizing its service life.

The optimal maintenance initial year was determined by studying the influence of maintenance for different scenarios, where periodic maintenance is 2, 3, and 4 years. Therefore, the service life of 38, 35, and 31 years was obtained for scenarios 3, 2, and 1, respectively. The end of the service life of the CCTR was estimated to be about 39 years, considering non-periodic maintenance according to its condition. In this way, an increase from 1 to 8 years was obtained comparing periodic and non-periodic maintenance based on the condition. Markov chains were shown to be a useful methodology for determining the maintenance year, maximizing the roof service life with a high level of reliability. Therefore, the maintenance program can be monitored to optimize the cost of the operations.

The degradation model offered by Markov can be easily updated to recent data. Consequently, the Markov degradation model is very suitable for scheduling maintenance based on the condition of the CCTR. The model developed in this research is useful for Healthcare Services to determine the most adequate and sustainable maintenance of Primary Healthcare Centers. Furthermore, this methodology can be adequately applied to other type of buildings by adapting from states of degradation regardless of their activity and location.

Author statement

Conceptualization: García-Sanz-Calcedo; Data curation: Sánchez-Barroso; Formal analysis: García-Sanz-Calcedo, Sokol, González-Domínguez; Funding acquisition: García-Sanz-Calcedo; Investigation: García-Sanz-Calcedo, Sánchez-Barroso, González-Domínguez, Sokol; Methodology: García-Sanz-Calcedo, Sokol; Project administration: Sánchez-Barroso; Resources: González-Domínguez; Software: González-Domínguez, Sokol; Supervision: García-Sanz-Calcedo; Sokol; Validation: García-Sanz-Calcedo; Sokol; Visualization: González-Domínguez; Roles/Writing - original draft: González-Domínguez; Writing - review & editing: García-Sanz-Calcedo

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Part of the research was development during the authors' stays at Slovak University of Technology (Bratislava). The authors wish to acknowledge the European Regional Development Fund for the financial support provided through Research Projects GR18029 linked to the VI Regional Plan for Research, Technical Development and Innovation from the Regional Government of Extremadura (2017–2020).

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ANEXO V

Referencia

J. González-Domínguez, G. Sánchez-Barroso, J. García-Sanz-Calcedo, N. de Sousa Neves, "Cox proportional hazards model used for predictive analysis of the energy consumption of healthcare buildings," *Energy and Buildings*, vol. 257, p. 111784, 2022. DOI: 10.1016/j.enbuild.2021.111784.

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Energy & Buildings 257 (2022) 111784

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Cox proportional hazards model used for predictive analysis of the energy consumption of healthcare buildings

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ARTICLE INFO

Article history:
Received 5 September 2021
Revised 27 November 2021
Accepted 13 December 2021
Available online 16 December 2021

Keywords:
Cox proportional hazard model
Primary healthcare centre
Energy consumption
Semi-parametric model
Sustainability
Healthcare engineering

ABSTRACT

The energy consumption of healthcare buildings is very high due to their 24/7 functioning and the demand of electro-medical equipment. This excessive energy consumption cannot be attributed to a single factor. The objective of this research was to apply Cox proportional hazards model to predict the probability of energy overconsumption in healthcare buildings for different functional variables. A reference energy consumption index was established from a retrospective analysis of the monthly consumption of 64 healthcare buildings during the period 2015–2019. Functional parameters (construction, facilities, demographics, and climate) were selected as candidates for Cox proportional hazards model. The study found that the variables related to facilities and demographics significantly influence the semi-parametric model of energy consumption. Their influence was quantified, and the validity of the proposed model was verified graphically. Having more than 10,000 users was found to result in a 124% greater probability of exceeding the reference energy consumption, 97.4% greater with an installed power above 60 kW, and 94.6% greater if the town in which the healthcare building is located has more than 5000 inhabitants, and 69.4% greater if a heat pump is not used for air-conditioning. The Cox proportional hazards model was shown to be an advanced tool useful for quantifying the influence of various functional variables on the excess energy consumption of healthcare buildings. The results of the research generate objective information to establish, on the one hand, criteria for designing and renovating healthcare buildings and, on the other hand, care planning strategies.

1. Introduction

Because of their 24/7 functioning and healthcare needs, healthcare buildings consume far more energy than other types of public buildings such as schools and administrative offices [1]. Although the energy consumption of these buildings in general has increased in recent years, a certain stagnation is now being observed due to widespread energy efficiency actions being taken because of the current global health crisis [2]. Balali and Valipour [3] identified and ranked several passive efficiency strategies for designing hospitals and health centres. Ede et al. [4] also explored opportunities to improve the energy efficiency of healthcare buildings. The implementation of hybrid energy supply systems supported by renewable energies greatly improves the energy performance of health infrastructures [5]. Renovation of the equipment and reforms to the building, implementing alternative energy technologies (co-generation, tri-generation, renewable energy, hybrid systems, hydrogen-based, among others), and modeling the systems are the three main ways to improve the energy efficiency of health facilities [6]. Healthcare buildings are examples where optimization of the energy consumed can benefit society. Studies have already revealed a potential savings in health centres of 8.60 kWh/m^2 per annum with an investment of €1.55/m^2 [7].

Modeling the energy consumption of healthcare buildings regarding their functional parameters has been investigated in the literature of reference. Thus, García Sanz-Calcedo et al. [8] defined a relationship between the energy consumption of healthcare buildings with respect to the built area, but they found no correlation with regard to the building's geographical location.

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https://doi.org/10.1016/j.enbuild.2021.111784
0378-7788/

Nomenclature

AbbreviationsCPH	
	Cox proportional hazards
COP	Coefficient of performance
UCL	Upper Control Limit
LCL	Lower Control Limit
CI	Confidence interval
SDG	Sustainable Development Goals
SD	Standard deviation
24/7	Twenty-four hours a day, 7 days a week
List of notations$Z$	
	Independent variables
λ	Hazard function
λ_0	Baseline hazard function
β	Coefficient of the predictor variable
β_0	Value of β for applying the null hypothesis
HR	Hazard ratio
t	Time
T	Time until the event occurs
S	Survival function
S_0	Baseline survival function
f	Failure density function
F	Failure distribution function
Δt	Time interval
L	Graphical Log-Log
ln	Logarithm
W	Wald statistic
P	Probability
A	Cut-off value of *Minimum temperature*
B	Cut-off value of *Maximum temperature*
C	Cut-off value of *Mean temperature*
Subscripts$i$	
	Indicates each healthcare building
j	Indicates each predictor variable
k	Indicates each observation

Alshayeb et al. [9] explored the influence on energy demand of other functional variables of healthcare buildings, such as orientation, shade, and roofing material. García-Sanz-Calcedo et al. [10] also analysed the relationship between the number of users and the energy consumption of a group of healthcare buildings. Isazadeh et al. [11] identified the most appropriate measures to optimize heating, ventilation and air conditioning operations in hospitals through "continuous commissioning", reducing the facilities' energy consumption.

The amount of energy invested in the construction of a building and which remains embedded within it is substantial [12]. In this context, sustainability stands as the main necessity in the health sector, with a combination of energy efficiency actions and control of energy consumption [13–15].

The need then arises to discover which are the construction, installation, demographic, and climatological variables that influence a healthcare building's energy consumption in order to act upon them. Consequently, it is useful for a survival analysis to be carried out [16,17]. Survival analysis encompasses a set of statistical methods that aim to model the relationship between predictor variables and a specific result variable, in particular, the prediction of when a certain event will occur [18]. Many survival analysis methods need the hazard function to be known for the analysis to be carried out. Getting this information requires, however, a lot of attention on the part of the building's operators [19]. It is possible to construct a model to predict the event occurring from a retrospective analysis of historical data [20].

One of the most widely used statistical methods is Cox proportional hazards (CPH) model [21]. This model not only estimates the probability of an event occurring, but also determines the influence of different variables on that occurrence [22]. Traditionally, the CPH model has been used for reliability engineering. Tee et al. [23] used it to quantify the influence of various factors on the failure of instrument transformers. Zhao et al. [24] incorporated a continuous-time Markov chain into a CPH model of an electronic device to determine the failure distribution. Bendová et al. [25] applied the CPH model to estimate the influence of covariates on endodontic equipment failure. Cable failures have also been explored using this method [26,27]. Debon et al. [28] applied it to the study of the useful life of water supply networks. Nariswari and Pudjihastuti [29] used the CPH model to analyse the factors that affect the life of an electrical transformer. Tiwari and Roy [30] applied the CPH model to determine the cause of failure of a group of mobile phones so as to improve their reliability and extend their useful life. Liang et al. [31] used the CPH model to analyse the influence of heat stress in a workplace by quantifying the impact of humidity and temperature on safe working conditions. Thijssens and Verhagen [32] used the CPH model to analyse the impact of the operating environment on the degradation of repairable aircraft components, using historical operation and maintenance data.

This present analysis of the energy consumption of healthcare buildings considers a dichotomous event that can be seen as analogous to the outcome philosophy underlying survival analysis [33]. The accumulated excess energy consumption of healthcare buildings cannot be attributed to one specific cause, but is due to multiple factors. As the hazard function associated with cumulative energy consumption is unknown, parametric models cannot be applied. Nonetheless, the CPH model is applicable since it does not require this information about the event analysed [34].

There are no precedents in the state of the art which use the CPH model to analyse either the energy consumption of buildings or how to improve the energy efficiency of healthcare buildings. Therefore, the objective of the present research was to identify the functional variables that affect the accumulated energy consumption of a healthcare building and to quantify their influence with respect to an established reference value. In this way, it will be possible to analyse the variables that cause anomalous energy behaviour, and then plan responses to ensure the energy efficiency of the building. These results are useful when making decisions in the design phase and in controlling the building's day-to-day operation. In addition, this research contributes to increasing the importance of proper energy management of healthcare buildings with the use of advanced, unconventional, tools.

2. Material and methods

2.1. Energy consumption in healthcare buildings

A study was made of 64 public healthcare buildings in the Extremadura Region (Spain). Their construction had been commissioned by the regional and national governments between 1984 and 2005, with a mean built area of 1027 m^2 (423.5–2582.0 m^2), and a maximum of three floors. These buildings provide continuous out-patient healthcare to populations of between 1584 and 25,000 inhabitants.

The climate of the region in which the sample of buildings are located has a mean temperature of 18.5 °C (mean minimum of

10 °C and mean maximum of 28.5 °C) [35]. The air-conditioning systems installed in the healthcare buildings were of two types: (i) heat pump, or (ii) boiler for heating and air-conditioning units for summer.

A retrospective analysis was carried out of the overall energy consumption during the period 2015–2019 with data provided by the Extremadura Health Service [36]. Specifically, the overall energy consumption in terms of electrical energy was examined after adding together the electricity and thermal energy consumption, resulting in a coefficient of performance (COP) of 2.6.

In order to be able to compare the accumulated energy consumption values of the different healthcare buildings, an indicator of annual energy consumption per unit floor area of 89.13 kWh/m^2 (SD = 15.92 kWh/m^2) was established. This indicator was obtained from historical data, and represents the mean annual energy consumption of the 64 buildings. Consequently, when a building reached a cumulative energy consumption above this reference parameter, it was defined as being a failure event. The time T when each healthcare building exceeded the reference energy consumption was obtained from the monthly energy consumption data.

2.2. Cox proportional hazards model

The CPH model includes two types of variables: dependent and independent. The dependent variable must represent a dichotomous outcome [37]. In this study, the dependent variable was the accumulated energy consumption of a healthcare building. This variable makes it possible to analyse whether or not a given healthcare building surpasses a reference energy consumption at a given moment.

The independent variables evaluated in this study do not depend on time and affect the dependent variable to a greater or lesser extent. They are hence suitable to form part of the CPH regression model. As candidates for significantly influencing the buildings' energy consumption, 10 independent variables Z_j (j = 1,. . .,10) were identified.

The predictor variables *Builder* and *Heat Pump* are dichotomous. However, the rest of the independent variables are continuous, so it is necessary to discretise them into two ranges of values in order to perform CPH analysis. To dichotomise the variables, it is necessary to establish a cut-off value. The median of the range was set as the cut-off value for dichotomising the variable *Year*. The cut-off value for the variables *Population*, *Users*, *Floor*, and *Installed power* corresponds to the sample mean. However, for the variables *Minimum temperature*, *Maximum temperature,* and *Mean temperature*, the mean or median was not considered for dichotomisation because the values of these variables have a concentrated distribution around the mean values, so that a variation in the cut-off values may distort the results obtained. Consequently, multiple cut-off values have been considered to dichotomise the temperature variables, generating different scenarios that eliminate the distortion. The cut-off values for the variable *Minimum temperature* (A) are 10 °C, 11 °C and 12 °C; for *Maximum temperature* (B), 27 °C, 28 °C y 29 °C; and for *Mean temperature* (C), 17 °C, 18 °C and 19 °C.

Furthermore, to perform the analysis it was necessary to assign a reference value, in this case 0 or 1. The reference value does not affect the results generated and either value can be selected. However, the reference value influences the interpretation of the results. Therefore, code 1 was assigned to the highest risk range and code 0 to the lowest risk range, so that the coefficient of the predictor variables is always positive, and their interpretation is improved. The coding of the independent variables is shown in Table 1. The table also indicates the code that has been taken as a reference to improve the interpretation of the results.

Although *Time* is a continuous variable, it was discretised in the CPH model analysis, as continuous monitoring is not possible. In practice, observations were made where discrete values were determined. Thus, *Time* was considered as a discrete set of values that depended on the periodicity of the observations made. A 24-month period of observation of the energy consumption of the healthcare buildings – observation units – was established, conducting monthly monitoring. In this way, *Time* acquired the discrete set of values t_k, being k = [1, 2, . . .,24]. The monitoring was begun at the same time for all the observation units. At the end of each observation period, all the healthcare buildings had exceeded their cumulative reference energy consumption, and so had experienced the event under analysis. Consequently, no right-censoring was involved in constructing the CPH model [38]. Nonetheless, the beginning of the useful life of the buildings was prior to the beginning of the observation period, so left-censoring had to be considered. Statistical Package for Social Sciences software [39] was used to implement the CPH regression model of energy consumption in healthcare buildings.

For each healthcare building i, the hazard function of the CPH model was obtained for time t_k and the independent variables Z_j = (Z_1 ,. . .,Z_p) expressed as shown generically in Eq. (1) [40]:

Table 1
Candidate independent variables for Cox proportional hazards model.

Variable	Description	Coding	Reference
Builder	Entity responsible for the health building 's construction	National government – 0Regional government – 1	1
Year	Year of construction of the healthcare building	After 1995 – 0 Before 1995 – 1	0
Floor	Number of floors of the healthcare building	One floor – 0 Two or more floors – 1	1
Users	Number of users of the healthcare building	<10,000 users – 0 >10,000 users – 1	0
Population	Population of the town where the healthcare building is located	<5000 inhabitants – 0 >5000 inhabitants – 1	0
Installed power	Installed air-conditioning power in the healthcare building	<60 kW – 0 >60 kW – 1	0
Minimum temperature	Mean minimum temperature recorded in the municipality of the healthcare building	< A – 0 > A – 1	1
Maximum temperature	Mean maximum temperature recorded in the municipality of the healthcare building	< B – 0 > B – 1	1
Mean temperature	Mean temperature recorded in the municipality of the healthcare building	< C – 0 > C – 1	1
Heat pump	The healthcare building uses heat-pump air-conditioning	No – 0 Yes – 1	1

$$\lambda_i(t_k, Z_j) = \lambda_0(t_k) exp\left(\sum_{j=1}^{p} \beta_j Z_j\right) \quad (1)$$

where $\lambda_0(t_k)$ is the baseline hazard function and β_j is the coefficient of each predictor variable Z_j, the former being the non-parametric part of the hazard function and the latter the parametric part.

The baseline hazard function only depends on time. It is not specified parametrically, and can be any mathematical model [41]. It is identical for all the observation units, and represents the hazard when all the risk factors are absent, which makes it the reference level. It is not necessary to know what the baseline hazard of the observation units is in order to build a CPH model, since the subsequent calculation of the hazard ratio will simplify these factors [42].

From the monthly data of the accumulated energy consumption of each healthcare building according to the classification made on the basis of functional parameters, the vector β_j was estimated using the likelihood function. This vector served as input for the hypothesis test with the use of the Wald statistic, Eq. (2):

$$W = \frac{(\beta_j - \beta_0)^2}{var(\beta_j)} \quad (2)$$

where β_j is the parameter obtained when considering that the independent variable Z_j is included in Cox regression model, β_j is the hypothetical value of applying the null hypothesis in the model (not including it in the CPH regression model), and $var(\beta_j)$ is the variance of the parameter β_j.

The Wald test is a hypothesis test in which the value of a parameter is estimated in a previously selected and fitted model. Thus, it was evaluated whether the influence on the event analysed of an independent variable Z_j is significant, comparing it with the null hypothesis. For a significance level associated with the Wald statistic of less than 0.05, the null hypothesis was rejected, and therefore it was considered that the variable had a significant influence on the planned event and should be included in the regression analysis. Otherwise, the variable Z_j was excluded.

Once the covariates that formed part of the model were known, the hazard ratio was calculated using Eq. (3). The hazard ratio is a risk measure that represents the likelihood that the healthcare buildings experience the event analysed in a specific period of time, comparing it with the reference group.

$$HR = \frac{\lambda(t_k, Z_j)}{\lambda_0(t_k)} = \exp(\beta_j, Z_j) \quad (3)$$

Eq. (3) reflects the independence with respect to time of the aforementioned hazard ratio. The interpretation of this index is as follows: an *HR* value of unity implies that the risk of the event occurring for the healthcare building under study is the same as that of the reference, *HR* greater than 1 implies that this risk is greater, and *HR* less than 1 means the contrary.

To display the results graphically, the survival function was established in terms of the CPH model. Let T_i be a random variable that represents the time until the event occurs for the healthcare building *i*. The survival function, $S(t_k, Z_j)$, defined in Eq. (4), specifies the likelihood that a healthcare building would experience the event after a specific time:

$$S(t_k, Z_j) = P(T > t_k) = S_0(t_k) exp\left(\sum_{j=1}^{p} \beta_j Z_j\right) \quad (4)$$

where $S_0(t_k)$ is the baseline survival function, which corresponds to the survival of an observation unit –healthcare building– whose covariates are evaluated in the reference zero.

$$F(t) = P(T \leq t) = 1 - S(t) \quad (5)$$

$$f(t) = \frac{d}{dt} F(t) \quad (6)$$

At this point, the hazard function $\lambda(t)$ could be completed in accordance with Eq. (7). It represents the probability that an analysed observation unit experiences an event in a time interval Δt after the time *t:*

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} P[t \leqslant T < t + \Delta t T \geqslant t] = \lim_{\Delta t \to 0} \frac{S(t) - S(t + \Delta t)}{\Delta t \cdot S(t)} \quad (7)$$

The hazard function was expressed in terms of the survival function as in Eq. (8):

$$\lambda(t) = \frac{f(t)}{S(t)} \quad (8)$$

Finally, the proportional hazards hypothesis was verified graphically using Log-Log curves [43]. The curves of the survival functions were found to be proportional over time, i.e., approximately parallel, so that the increases in hazard are constant. Furthermore, the plots had the same direction, since there cannot be one increasing and the other decreasing or vice versa. The graphical Log-Log (L) method is based on transforming the survival curve by applying the logarithm twice as expressed in Eq. (9):

$$L = -ln(ln(S(t_k)) \quad (9)$$

where $S(t_k)$ is the survival function of the CPH model.

3. Results

Table 2 lists the Wald test results for the study's independent variables. The *Population*, *Users*, *Installed Power*, and *Heat Pump* variables were statistically significant at a level of less than 0.05. The variables *Builder*, *Floors*, and *Year* presented a significance level greater than the threshold *p*-value considered, and were therefore excluded from further analysis. In the case of temperature variables, the significance is always greater than 0.05 for the multiple cut-off values considered.

Table 3 presents the results of quantifying the influence of the independent variables on the event studied after obtaining the hazard ratio. Since appropriate references of the CPH model variable categories were taken, the β values obtained were positive, as consequently were also the hazard ratios. The CPH model not only quantifies the likelihood that the risk of a certain event occurring will increase, but also allows the confidence interval of this value to be determined [44]. Table 3 also gives these upper and lower bounds for the 95% confidence intervals.

Thus, it is found that healthcare buildings located in towns with more than 5000 inhabitants present a 1.946 times greater risk of excess energy consumption than do those in towns with fewer than 5000 inhabitants. In particular, it is 94.6% (CI-95%: 16.4%–225.3%) more likely that the reference energy consumption will be exceeded in the former. The results for the *Users* variable reflect that healthcare buildings whose primary care area exceeds 10,000 people have a 124% (CI-95%: 24.8%–301.8%) greater probability of excess energy consumption than those of areas of fewer than 10,000 users. Healthcare buildings with *Installed power* greater than 60 kW were observed to present a hazard ratio 1.974 times greater than those whose *Installed power* is less than 60 kW. This hazard ratio factor can vary between 1.088 and 3.581 times for a 95% confidence level. When healthcare buildings do not have a *Heat-pump* based air-conditioning system, the probability of the building exceeding its energy consumption is 69.4% greater than one whose air-conditioning system does use a *Heat pump.* This influence varies from 4.1% to 175.8% for a 95% confidence level.

The cumulative hazard for each of the independent variables that affect the CPH model is represented in Fig. 1. The cumulative

Table 2
Wald test.

Variable	Wald	Significance		Affects
Builder	0.507	0.477		No
Floors	0.953	0.329		No
Population	6.447	0.011	*	Yes
Users	7.308	0.007	*	Yes
Installed power	5.004	0.025	*	Yes
Minimum temperature	0.001	0.975	**	No
Maximum temperature	0.359	0.549	**	No
Mean temperature	0.283	0.673	**	No
Year	0.953	0.329		No
Heat pump	4.496	0.034	*	Yes

(*) Statistically significant.
(**) Significance value for A = 10 °C, B = 28 °C, and C = 18 °C.

hazard plots reflect the probability of healthcare buildings exceeding their energy consumption during a given time, and are therefore necessarily increasing. Consequently, the probability that the energy consumption of healthcare buildings is exceeded due to the influence of the variables increases over time. This verifies that the risk of excess energy consumption increases with the variables considered in the study.

Fig. 2 shows the survival curves of the four variables that significantly influence the CPH model of accumulated energy consumption of healthcare buildings. These decreasing plots represent the probability of healthcare buildings not exceeding their cumulative energy consumption over time. One observes that the shapes of the survival curves are similar for all four variables, but the values differ. All the survival curves are decreasing, i.e., the probability that healthcare buildings have adequate energy consumption decreases over time. In this way, there is a prediction of a 100% probability of adequate cumulative energy consumption until the end of the eighth month, and until the end of the ninth month of around 90%. The results for the end of the year may then be put into two groups. On the one hand, the category that is least likely to be below the reference consumption at the end of the year is *Users* greater than 10,000 inhabitants, with 24.4%, which is less than half of the 53.2% of *Users* less than 10,000 inhabitants. A similar situation is the case for *Installed power*. The probability that the energy consumption is not exceeded for *Installed power* greater than 60 kW is 28.2%, and 52.7% for *Installed power* less than 60 kW. A 37.4% probability of not exceeding the reference consumption is predicted for those healthcare buildings without a *Heat Pump*. However, those with a *Heat Pump* present a 56.0% success rate. Similar values are obtained for *Population*. For *Polulation* greater than 5000 inhabitans, 32.3% success is predicted, and for *Polulation* less than 5000 inhabitans, 55.9% is predicted.

To check the proportionality assumption and thus validate the requirement of the CPH model, the Log-Log plots obtained for this study are shown in Fig. 3. They check out as being parallel, and it is therefore verified that all the variables comply with the proportionality assumption necessary to apply the CPH model.

Table 3
Hazard ratios of the independent variables of Cox proportional hazards model.

Variable	β	Exp (β) = HR	LCL (95%)	UCL (95%)
Population	0.666	1.946	1.164	3.253
Users	0.806	2.240	1.248	4.018
Installed power	0.680	1.974	1.088	3.581
Heat pump	0.527	1.694	1.041	2.758

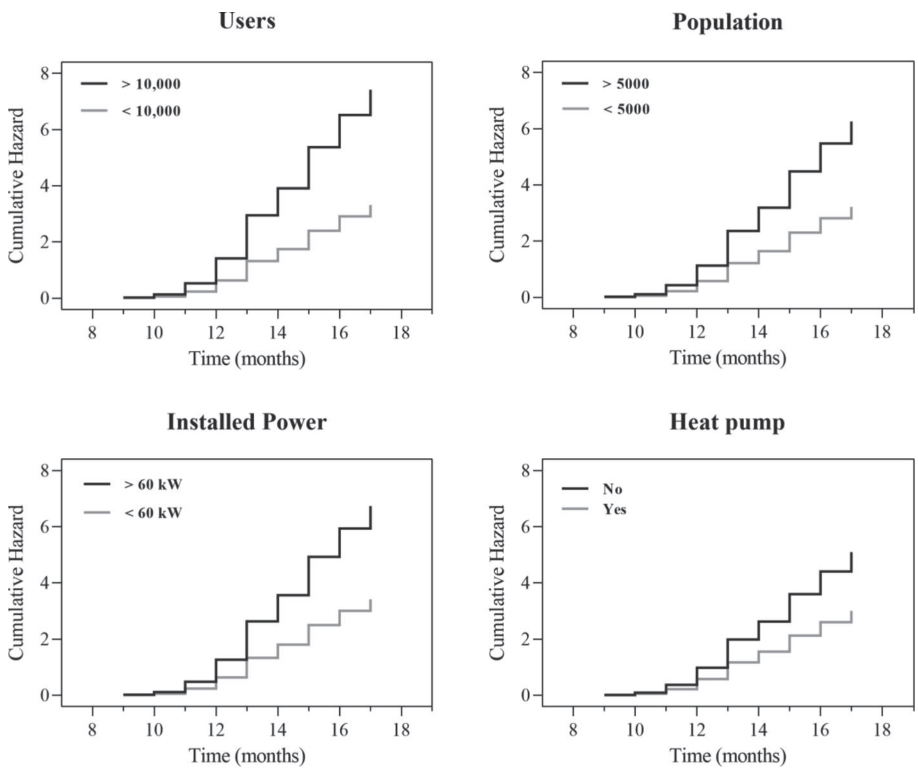

Fig. 1. Hazard plots of the variables that affect the model.

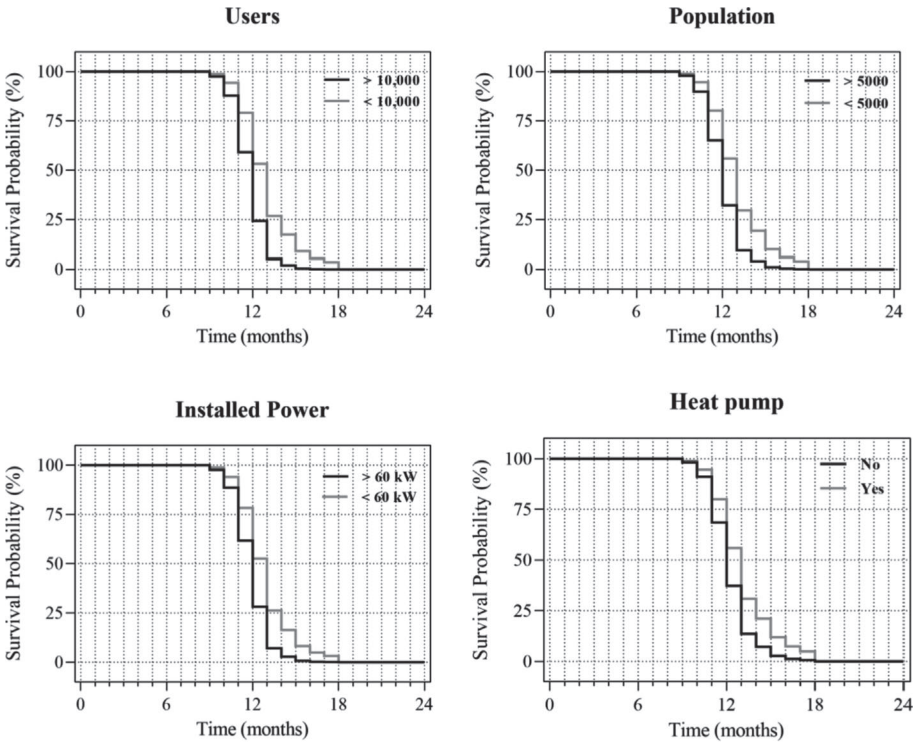

Fig. 2. Survival curves of the variables that affect the model.

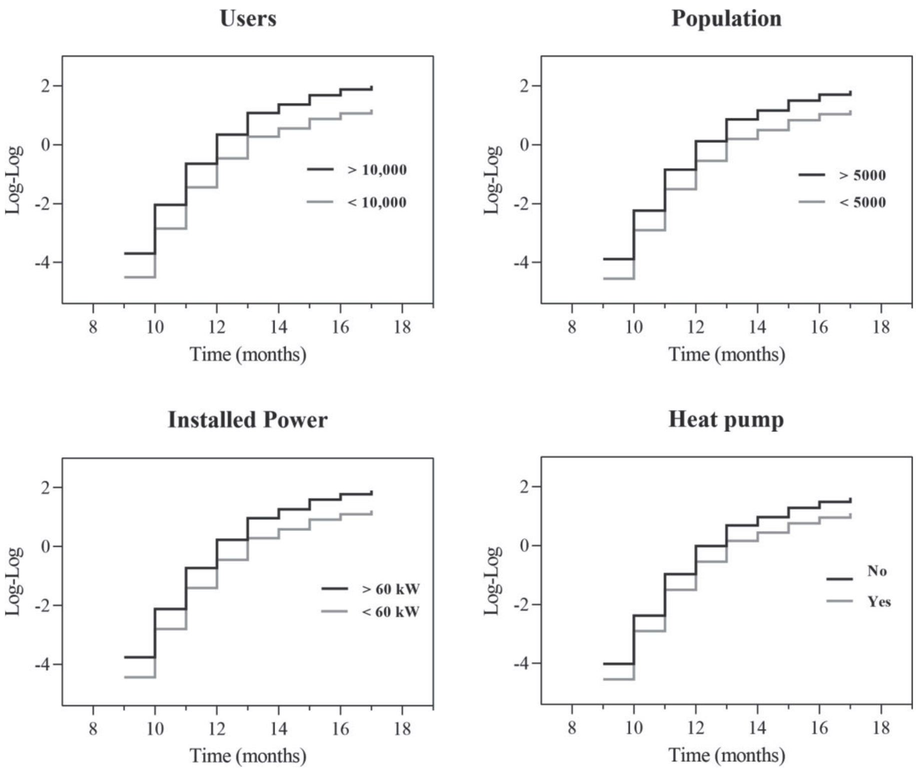

Fig. 3. Log-Log plots of the variables that affect the model.

4. Discussion

The CPH model generates a survival function to estimate the likelihood of a certain event occurring in a defined period of time according to the influence of the different identified factors [45]. The advantage of this survival analysis is that it does not need an estimate of the baseline hazard function of the event being analysed, obtaining a likelihood function that only depends on the model's coefficients [46]. Therefore, one considers it to be a very useful model to determine the effect of the covariates on the accumulated excess energy consumption of healthcare buildings. Even if several healthcare buildings exceed the reference value in the same month and duplicity in survival is generated, this does not affect the results obtained. The CPH model analyses and quantifies the factors that significantly influence the occurrence of the event under study. The importance of this model does not lie in the time in which the event occurs but in determining why it occurred. The independent variables are not duplicated, so that the risk of exceeding the energy consumption will be different.

In general, survival analyses can look at left- and right-censored data depending on the time until the event occurs and the start of the observation period, respectively [47]. Unlike other regression models such as Kaplan-Meier [48], the CPH model considers censored cases, and is moreover able to work independently of the baseline hazard function. It is thus unnecessary to know this function's form or nature. Another difference is that the CPH model allows one to study which variables increase the likelihood of a given event occurring, which is why one considers it to be appropriate when analysing the variables influencing the energy consumption of healthcare buildings. Using this method, it is possible to exclude variables that do not increase the risk of energy consumption and, at the same time, quantify the influence of those that do [49].

The inclusion of variables in the CPH model was supported by the cumulative hazard results. In addition, their inclusion followed the well-established criteria of the Wald method. Although proportional hazards were assumed in order to develop the CPH model, this hypothesis was verified after analysing the Log-Log curves.

The variables Population and Users have the same direction of influence. A healthcare building's cumulative energy consumption is more likely to exceed the reference if it is in a population larger than 5000 inhabitants and it has more than 10,000 users. It seems logical to think that the larger the healthcare building – to attend to more population – the better use will be made of the energy consumption of the building's facilities. Nonetheless, these types of healthcare buildings usually house administrative staff and other non-health services which increase their energy consumption. This statement coincides with previous studies [10]. In addition, these healthcare buildings have a larger workforce, making it more difficult to raise their awareness in terms of energy consumption. Although it is not possible to change the demographic context of existing buildings, this result allows us to establish site selection criteria for new healthcare buildings that contribute to improving the energy management of the healthcare system.

In municipalities with growing populations, it is necessary to periodically create new health zones, whose inhabitants are assigned to a specific healthcare centre. This usually involves a rearrangement of the existing ones to absorb the new demand for care. This research will help to properly plan the size and location of new healthcare centres, as well as to organise the number of users assigned to each healthcare centre.

Having more installed power in the healthcare building, usually due to its size, does not translate into more efficient consumption, and requires an increase in the importance given to preventive measures taken to maintain the efficiency of the facilities [50]. Thanks to the analysis of the independent variable *Installed power*, it was established that an installed power of healthcare buildings of less than 60 kW achieves better energy efficiency. This energy efficiency criterion conditions the design of the installations of newly constructed healthcare buildings, influencing the total installed load, limiting oversizing, and requiring more energy efficient equipment. Furthermore, this result is useful as a reference criterion for the renovation of equipment and installations in healthcare buildings already in use.

Currently, the most efficient air-conditioning technology is the heat pump [51] using aerothermal energy [52], so that the results regarding the greater risk of exceeding the cumulative reference consumption when this technology is not used are logical [53]. This result justifies the replacement of different air-conditioning technologies by aerothermal heat pumps [54,55] in existing healthcare buildings and serves as a criterion for the selection of air-conditioning technology for new buildings to be constructed. This criterion has a great impact on existing healthcare buildings, as more than 50% of the buildings analysed do not use heat pumps for air-conditioning. These buildings use duplicate systems with oil or natural gas boilers and cooling-only air conditioning equipment. At this point, other alternative solutions can also be considered for the boiler systems already installed, such as replacing them with biomass boilers which are more efficient environmentally. This change of technology would also reduce the CO_2 emissions of these buildings, whose construction already generates a high Global Warming Potential [56].

It was found that the variables *Minimum temperature*, *Maximum temperature* and *Mean temperature* do not significantly influence the excess of energy consumption of the healthcare buildings. This may be due to the fact that the healthcare buildings in the sample were all located within a similar climatological region, so that this influence was not significant. Furthermore, it was determined that this result does not change even if the cut-off value -considered to dichotomise the three temperature variables- is varied. In this way, the possible distortion that may be generated by the cut-off value used to categorise the *Mean temperature*, *Minimum temperature* and *Maximum temperature* variables was ruled out. It was also noted that neither did the year of construction of the healthcare buildings influence excess energy consumption. This may be due to the fact that the healthcare buildings studied were of old construction, and counted on no energy efficiency in their design. Older buildings have been renovating their facilities, so that the energy efficiency difference with modern buildings come from passive efficiency.

The rest of the variables studied, such as the Builder or Floors, did not significantly influence the cumulative energy consumption model of the healthcare buildings either. It could be expected that the number of floors would play a role, but this is more typical for taller buildings [53]. Healthcare buildings usually have fewer than three floors, so that they would not be typed in the category of tall buildings.

Currently, especial attention is being paid to the energy efficiency of buildings, thus generating a great change in their design and construction. According to the Energy Efficiency Directive of the European Union, buildings are essential to being able to reach the goal of reducing greenhouse gases by between 80% and 95% by 2050. This requires the renovation of state-owned buildings to improve their energy performance [57]. The basic requirement of energy saving (HE 3) of Spain's Technical Building Code establishes that buildings will have adequate lighting installations for their users which at the same time are energy efficient. In addition, according to EU Directive 2018/844, EU member countries must establish strategies for the renovation of existing buildings by transforming them into buildings with almost zero consumption [58]. In this way, in renovated buildings it will be possible to analyse the influence on their energy consumption of the different energy efficiency strategies used in the building design phase.

There are different criteria for the design, construction, and renovation of healthcare buildings in order to increase their functionality, ensure quality of care, improve their maintainability and energy efficiency [59–61]. These criteria can be complemented with those obtained in this study. With the development of this research, the functional variables that significantly affect healthcare buildings' exceeding the reference energy consumption were determined. Based on these variables, different criteria have been proposed for the design and renovation of healthcare buildings to optimise their energy consumption, developing more sustainable healthcare buildings. This will help align the design of healthcare buildings with the new sustainable development strategies and priorities established by the European Commission [62]. Furthermore, this study contributes to the attainment of the Sustainable Development Goals (SDG) of sustainable cities and communities (SDG-11) and climate action (SDG-13) described in Agenda 2030 [63].

Future research should focus on comparing healthcare buildings of different regions to determine the influence of other variables and to be able to set out measures to mitigate them. In addition, applying the CPH regression model to the energy consumption of health centres could generate useful information to establish strategies for the design of the building or its facilities to increase their sustainability and energy efficiency.

5. Conclusions

It was found that the demographic variables (*Population* and *Users*) and those related to the facilities (*Installed power* and *Heat Pump*) are adequate for the CPH model developed, and significantly influence the energy consumption of a healthcare building. Other variables concerning construction (constructing entity, number of floors in the building, and year of construction) and climate (specific to each town in which the buildings are located) showed no sufficient influence on the CPH model.

Having more than 10,000 users assigned to be building's area was found to mean a 124% greater probability of exceeding the reference energy consumption, 97.4% more if the installed power is greater than 60 kW, 94.6% more if the population where the healthcare building is located has more than 5000 inhabitants, and 69.4% more if it does not use heat-pump air-conditioning technology. For three of the four CPH model variables the quantified risk is remarkable, as they are capable of doubling the risk of excess energy consumption. Consequently, the usefulness and adequacy of using the CPH model to predict the excess cumulative energy consumption of healthcare buildings has been demonstrated.

Annually, a healthcare building that serves more than 10,000 users has a 24.4% probability of not exceeding the reference consumption compared to 53.2% for one that serves fewer than 10,000 users. In this sense, those with installed power greater than 60 kW have a 28.2% probability while for the others it is 52.7%; a probability of 37.4% is attributed to healthcare buildings that use a heat pump and 56.0% for those that use a boiler and refrigeration units; and finally, a 32.3% probability for healthcare buildings located in towns with more than 5000 inhabitants and 55.9% for those located in towns with fewer than 5000 inhabitants.

The present research has verified the importance of energy analysis of healthcare buildings using advanced non-conventional tools. In addition, the results generated are useful for establishing design criteria for new healthcare buildings, renovation criteria for existing healthcare buildings and care planning strategies, optimising the energy management of the building.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Part of the research was development during the authors' stays at University of Évora (Portugal). The authors wish to acknowledge the European Regional Development Fund for the financial support provided through Research Projects GR18029 linked to the VI Regional Plan for Research, Technical Development, and Innovation from the Regional Government of Extremadura (2017-2020).

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