UNIVERSIDAD DE EXTREMADURA

TESIS DOCTORAL

ESTUDIO, ANÁLISIS Y DESARROLLO DE ESTRATEGIAS DE MANTENIMIENTO EN MAQUINARIA Y SISTEMAS INDUSTRIALES. EVALUACIÓN DE RIESGOS, FIABILIDAD, DISPONIBILIDAD.

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PROGRAMA DE DOCTORADO EN INGENIERÍAS INDUSTRIALES

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2022

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Juan Álvarez Domínguez

AGRADECIMIENTOS

Resulta meridianamente complejo acertar y no olvidar todos los agradecimientos que se derivan de la obtención de un mérito distinguido. En este sentido, ruego en primer lugar disculpas a todas aquellas personas que me rodean, han apoyado el desarrollo de este trabajo y no he nombrado por causas puramente de olvido humano.

En mi opinión, para poder optar al alcance de este mérito, resulta imprescindible la implicación personal, la determinación en las decisiones y llevarlas a cabo sin cesar. Encontrar un tema de tesis resulta muy complejo y es una de las primeras decisiones que se deben tomar. En este sentido, la constante búsqueda bibliográfica en las plataformas conocidas y lectura de numerosos artículos ha supuesto la inversión de una gran cantidad de tiempo. Añadido y de vital importancia, conocer las "palabras clave" adecuadas para que los motores de búsqueda ofrecieran resultados esperados. Todo ello ha supuesto el descubrimiento de un tema relevante sobre el que hay mucho que decir y que continuar investigando, tras la lectura (D.M.) de este trabajo de tesis. Quiero agradecer al director de Tesis, David Rodriguez Salgado su constante apoyo y claridad en los enfoques, decisiones que debían ser tomadas. Sin un buen tutor con mucha experiencia, resultaría muy difícil alcanzar este reto. De igual forma, quiero agradecer a todos mis compañeros del área de Ingeniería de los Procesos de Fabricación y de nuestra área afín de Ingeniería Mecánica Francisco Javier y Paco, sus apoyos puntuales que tengo en alta consideración.

Para finalizar, quiero agradecer a mi Mujer, mi familia, padres y hermanos, la constante confianza siempre depositada en Mí, para conseguir alcanzar este objetivo académico.

ÍNDICE GENERAL

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Introducción

INTRODUCCIÓN GENERAL

El desarrollo del entorno industrial en la fabricación requiere cada vez mas el empleo de procesos de fabricación más automatizados, confiables y disponibles. De este modo, siempre será posible responder a la demanda estable o estacional con una producción repetitiva y niveles de calidad estables. El sector agroalimentario es un buen ejemplo en el que esta realidad, está cada vez más presente. Las máquinas que desarrollan una sola operación (single-stage machines) están siendo reemplazadas por otras máquinas que desarrollan varias operaciones (multi-stage machines)

En el caso de una utilización de máquinas de una sola etapa, la composición del sistema productivo se realiza con la asociación serie de todas las máquinas que sean necesarias para alcanzar las transformaciones necesarias. Si por criterios de capacidad, es requerido, se puede disponer de sistemas paralelos en una misma etapa que permitan alcanzar la producción requerida (work in process) por el mercado en el tiempo que la requiere (time takt) evitando la aparición de cuellos de botella.

Cuando se utilizan máquinas multietapa, desde la entrada hasta la salida de la máquina, todas las operaciones que se realizan en ella están completamente eslabonadas. Este hecho es de gran importancia, ya que para que la etapa n+1 funcione correctamente, la etapa n debe hacer realizado su trabajo correctamente. Normalmente este tipo de máquinas trabajan con grandes series de producciones ya que su capacidad de producción no es fácilmente modificable, como si ocurre en el caso de utilización de máquinas de una sola etapa.

Si en ambos escenarios de utilización de máquinas se analiza la fiabilidad (1) y disponibilidad (2), se debe estudiar:

$$Fiabilidad, R(t) = \frac{Nº\ items\ manufacturados\ con\ éxito\ en\ t}{Nº\ total\ items\ manufacturados\ en\ t} \qquad (1)$$

$$Disponibilidad\ , A = \frac{MTBF}{MTBF+MTTR} \qquad (2)$$

Donde MTBF es el tiempo medio entre fallos y MTTR es el tiempo medio de reparación:

$$MTBF = MTTF + MTTR \qquad (3)$$

Aplicando estos conceptos los sistemas de fabricación compuestos por máquinas de una etapa o máquinas multietapa, el objetivo de la fabricación es mantener el mayor nivel de fiabilidad y disponibilidad posible durante el tiempo de producción.

En este sentido, la aparición de fallos inesperados por causas conocidas o desconocidas, en primer lugar, interrumpe la fabricación que impide la respuesta en tiempo a la demanda. En segundo lugar, provoca la pérdida de la producción en curso, con los costes de oportunidad asociados.

Tanto en el caso de utilización de máquinas de una etapa como en el caso de máquinas multietapa, el estudio de la fiabilidad, se centra en estudiar:

- Máquinas de una etapa: La fiabilidad de cada etapa y posteriormente presentar un sistema serie para el estudio de la fiabilidad del proceso completo.
- Máquinas multi etapa: La fiabilidad de cada componente, ya que como todas las etapas están eslabonadas, le fallo en un componente supone el fallo de la máquina. Esta tesis doctoral se centrará en este tipo de máquinas.

Centrando el foco de atención en las máquinas multietapa, si se desarrollase el concepto de fiabilidad, como la calidad extendida en el tiempo, sería preciso recurrir a modelos estadísticos, como el Lognormal, Poissón, exponenencial, Weibul, otros. De este modo, se podría estudiar la fiabilidad de todos los componentes, que no es más que intentar modelizar sus individuales leyes de degradación que provocan el fin de su vida útil por funcionamiento. Lo cierto es que los componentes utilizados en los sistemas de producción industrial, no ofrecen información sobre la fiabilidad de los equipos en el tiempo (ejemplos de casos clásicos como, número de horas de funcionamiento de bombillas led o endurancia mecánica-eléctrica en contactores para el accionamiento de motores) Añadido a lo anterior, aún sin ese dato proporcionado, también se requeriría información sobre las condiciones de operación, adecuada selección del componente para tipo de trabajo que deberá realizar con altos niveles de repetitividad. Es evidente que quien mejor puede desarrollar el estudio de la degradación de un producto y proporcionar una ecuación (1) para un componente, es quien lo pretende fabricar.

En definitiva, sería deseable que todos los componentes de la máquina pudieran disponer de un valor real de su MTTF, relacionado con unas condiciones de operación estables ambientales, eléctricas y/o mecánicas. Para que el valor de la disponibilidad (2) fuera el mejor posible, el valor de MTTR debería ser el menos posible, nunca pudiendo ser cero. Para conseguir este valor bajo de MTTR es imprescindible tener presente este concepto en el diseño y fabricación de la máquina y por tanto, a utilización de conceptos como DFMA (desing for Manufactuting and Assembly) y si fuera preciso un análisis de FMEA (Failure Mode and Effect Analysis)

El desarrollo de esta tesis se centra en el estudio de la selección de estrategias de mantenimiento preventivo y predictivo para las maquinas multietapa en el sector agroalimentario. Para ello se ha desarrollado un trabajo experimental basado en una máquina multietapa termo formadora de terrinas.

ANTECEDENTES

La figura (1) muestra la maquina objeto de evaluación que ha sido estudiada en dos artículos publicados y un tercero actualmente en fase "*minor revisión*". Este tipo de maquinas se suelen utilizar para generar terrinas llenas de aceite o vinagre. En el caso de necesitar un relleno de mayor densidad, se debe modificar el sistema de dosificación.

Figura (1). Máquina Termoformadora de terrinas, multietapa.

Esta máquina está compuesta por las siguientes etapas:

- ETAPA 1. Dispensador del polímero para el termoformado del molde de la terrina.
- ETAPA 2. Precalentamiento del polímero de la terrina.
- ETAPA 3. Termoformado por compresión y vacío del molde de la terrina. En el caso de esta máquina el molde del termoformado es para conformar 6 moldes idénticos de terrinas. Esta cantidad permite definir las siguientes etapas.
- ETAPA 4. Dosificación de los 6 moldes termoformados por bombas peristálticas, controladas por servoaccionadores que controlan principalmente la posición.
- ETAPA 5. Dispensador del polímero de la tapa de la terrina. Alineación y control por sensor de mácula.
- ETAPA 6. Adhesión del polímero de la tapa al molde termoformado tras la dosificación.
- ETAPA 7. Corte de las terrinas conforme a la geometría acordada.

La figura (2) muestra la imagen de la máquina en estudio con las etapas definidas.

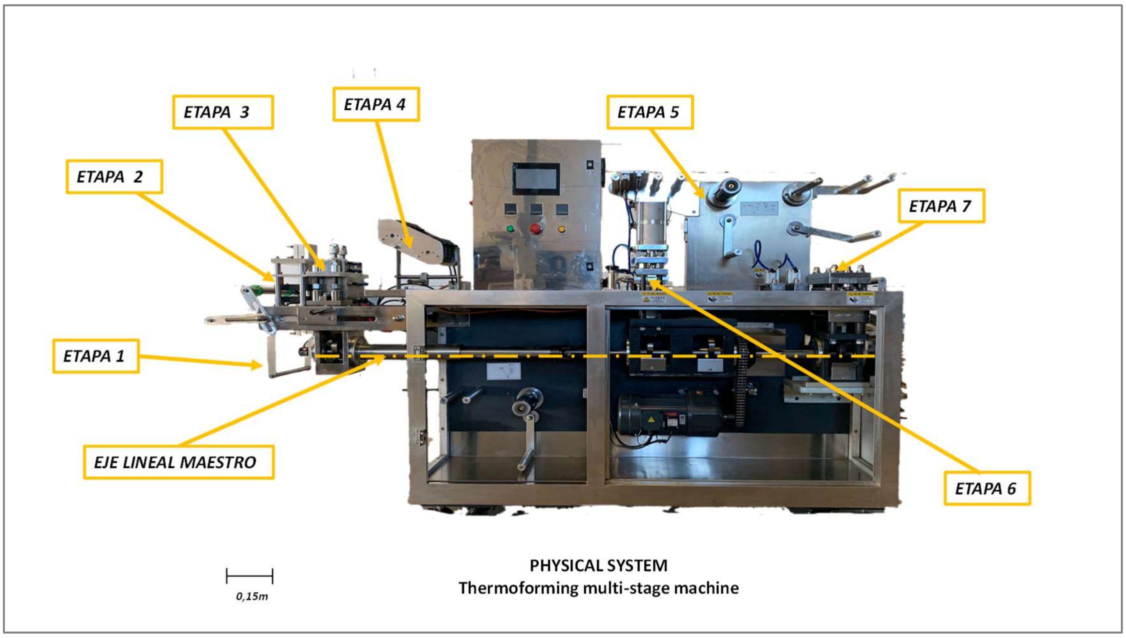

Figura (2). Etapas en la máquina termoformadora de terrinas.

En la parte inferior de la máquina se encuentra un eje maestro que tiene en su extremo izquierdo un codificador que envía la posición de 0 a 1000 en cada ciclo completo de trabajo, constantemente al autómata que controla el funcionamiento de esta máquina. La existencia de este eje maestro y el codificador permiten el desarrollo de estrategias de mantenimiento predictivo.

Para este tipo de máquina el tiempo de ciclo, esto es el tiempo invertido entre dos salidas consecutivas de "un conjunto de 6 terrinas" por la última etapa, es 4 segundos. Para coordinar los tiempos de trabajo necesarios en cada etapa, están previsto motores de avance y distancias que permiten el normal funcionamiento de la máquina de forma coordinada, resolviendo el problema de cuellos de botella.

El producto final que se obtiene es mostrado en la figura (3)

Figura (3). Terrina fabricada por la termoformadora.

En resumen, el funcionamiento de esta máquina como ejemplo de máquinas multietapas industriales, refleja las siguientes características:

- Exige constante coordinación entre todas las etapas.
- Siempre trabaja de la misma forma.
- Normalmente son máquinas fabricadas a medida para una producción determinada, con un grado de customización alto. Por tanto, no son máquinas que se fabriquen en serie.
- El alto grado de customización hace que no existan estrategias de mantenimiento ya que son específicas para cada tipo de maquina en función de su customización.
- Trabajan con grandes lotes de producción, solo empleando tiempos intermedios para aprovisionamiento de consumibles.
- Tiempo de ciclo muy bajo.
- Diversidad de componentes de diferente naturaleza, eléctricos, electrónicos, mecánicos y neumáticos.

Para el normal funcionamiento de estas máquinas, por tanto, hay que evitar:

- La aparición de fallos inesperados durante el encargo de un lote de producción.
- La inadecuada selección de componentes.
- La inadecuada ubicación o estudio de las condiciones de funcionamiento del componente.

- El desconocimiento de una estrategia o estrategias de mantenimiento que permitan mantener el apropiado nivel de disponibilidad en la máquina para atender "sin fallos inesperados" la producción encargada.

En consecuencia, es necesario plantearse los siguientes objetivos para conseguir el normal funcionamiento de la máquina:

- Disponer de estrategias de mantenimiento confiables, rápidas que permitan planificar actuaciones preventivas de mantenimiento y posibiliten avisos de potenciales fallos mediante estrategias predictivas.
- Disponer de una metodología para el análisis de la condición general de operación de los componentes, así como indicadores basados en los tiempos de reparación (Mean Time to Repair MTTR) de todos los componentes.
- Disponer de una estrategia para conocer el nivel de confianza de los componentes, basado en sus tiempos hasta el fallo (Mena Time To Failure MTTF)
- Disponer de una metodología global y dinámica para establecer una estrategia de mantenimiento para cada componente en función de su comportamiento y MTTR.

Para alcanzar los objetivos planteados se proponen los siguientes artículos, mostrados en la tabla (1)

OBJETIVO	TRABAJO
Disponer de estrategias de mantenimiento confiables, rápidas que permitan planificar actuaciones preventivas de mantenimiento y posibiliten avisos de potenciales fallos mediante estrategias predictivas.	**Paper -I**: Maintenance Strategies for Industrial Multi-Stage Machines: The Study of a Thermoforming Machine.
Disponer de una metodología para el análisis de la condición general de operación de los componentes, así como indicadores basados en los tiempos de reparación (Mean Time to Repair MTTR) de todos los componentes.	**Paper -II**: Analysis of the Influence of Component Type and Operating Condition on the Selection of Preventive Maintenance Strategy in Multistage Industrial Machines: A Case Study
Disponer de una estrategia para conocer el nivel de confianza de los componentes, basado en sus tiempos hasta el fallo (Mena Time To Failure MTTF) Disponer de una metodología global y dinámica para establecer una estrategia de mantenimiento para cada componente en función de su comportamiento y MTTR.	**Paper -III**: An approach for predictive maintenance decisions for components of an industrial multistage machine that fail before their MTTF. A case Study.

Tabla (1). Síntesis de objetivos y artículos realizados para alcanzarlos.

La norma UNE-EN 13306 estudia la terminología del mantenimiento. En ella se definen las estrategias de mantenimiento preventivo, predictivo, y correctivo. Así mismo, la norma UNE-EN 15341 estudia el mantenimiento e indicadores clave de rendimiento del mantenimiento. Estas normas han sido consultadas para que los trabajos realizados estén en línea con ambas. Ante divergencia o novedad, los trabajos han remarcado la causa de la divergencia o dicha novedad.

El desarrollo e implantación de una metodología para la toma de decisiones sobre las estrategias de mantenimiento en máquinas multietapa, es una temática que no está desarrollada en estas máquinas, aunque si es estudiada para otro tipo de máquinas o entornos.

La presencia de este tipo de máquinas en la industria de la manufactura y de la alimentación es cada vez mayor. El grado de customización para conseguir máquinas *"ad hoc"*, que se ajusten perfectamente a las necesidades de cada usuario, es alcanzable en la producción de este tipo de máquinas. Debido a esto, la inexistencia de estrategias y metodologías de mantenimiento que pueden ser utilizadas en este tipo de máquinas, representa un avance para la manufactura, caracterizada por ausencia de fallos inesperados y alta repetitividad, esto es, que los productos fabricados sean iguales. El objeto de esta tesis y los artículos realizados es ofrecer una respuesta a esta necesidad.

PRESENTACIÓN TEMÁTICA DE LOS ARTÍCULOS.

Paper -I: Maintenance Strategies for Industrial Multi-Stage Machines: The Study of a Thermoforming Machine.

Antecedentes y conceptualización.

Este primer artículo presenta la problemática descrita en la máquina estudiada, centrando la atención en desarrollar alternativas de mantenimiento preventivo y predictivo en una máquina termoformadoras de terrinas, que es un tipo de máquina multietapa. Para ello, evalúa dos estrategias de mantenimiento preventivo programado: Preventive Programing Maintenance (PPM) e Improve Preventive Programing Maintenance (IPPM), comparando los resultados que ofrecen ambas estrategias de mantenimiento en términos de disponibilidad y eficiencia de los componentes.

PPM se basa en el conocimiento individual de todos los tiempos que requiere un componente en ser reemplazado desde que presenta un fallo con independencia de la naturaleza del fallo.

IPPM se basa en la estrategia PPM, destacando que se considera cero el tiempo TTPR como residual, esto es, lo tiene el usuario de la m´quian en su propio stock de seguridad. Como es normal, en función de cómo afecte en el MTTR el valor de TTPR esta estrategia ofrece mejoras en los resultados de eficiencia y disponibilidad, pero más allá de eso, es una herramienta que permite detectar qué componentes que pueden ocasionar una parada larga en el funcionamiento de la máquina. En este trabajo, solo se advierte la diferencia, no se indica cómo seleccionar una u otra estrategia PPM o IPPM.

Dado que las estrategias de mantenimiento preventivo solo se pueden basar en el conocimiento previo de tiempos individuales de mantenimiento de los componentes, estas estrategias no son capaces de avisar con antelación de un fallo inesperado que puede afectar a toda la producción en curso. Debido a eso, se desarrollan dos estrategias de mantenimiento predictivo: Algorithm Life Optimization Programing (ALOP) y Digital Behaviour Twin (DBT). Ambos algoritmos son desarrollados siendo sus características principales:

ALOP es un algoritmo estadístico, que compara valores muestreados de sensores específicamente distribuidos por la máquina y establece unas desviaciones. Utiliza como escala de medida el tiempo igual a 100 ciclos. Calcula el MTTF de cada componente en tiempo real. Así mismo, proporciona avisos sobre valores de sensores que exceden los límites admisibles o tolerables por la máquina y que no tendiendo porque provocar un fallo, pueden afectar a la "repetitividad" de su trabajo. La escala sobre la cual se referencian todos los cálculos es la temporal, cada 100 ciclos. El algoritmo paso a paso está desarrollado en el artículo.

DBT es un algoritmo no estadístico, que basa su funcionamiento en el conocimiento del patrón normal y repetitivo de funcionamiento de la máquina. Utiliza también las medidas de los mismos sensores que ALOP, pero añade una más, el valor del codificador que tiene el eje maestro. De este modo, en toda posición (desde 0 a 1000) todos los sensores deben proporcionar unos valores considerados como normales, así como los actuadores que controlan los motores o la neumática den están activados o desactivados. Una vez conocido el patrón, el funcionamiento se basa en hacer lecturas cada 10 posiciones del encoder y comprobar que los estados de los actuadores son los correctos, así como las medidas de los sensores son normales.

La sección dos del artículo describe la metodología utilizada, que se basa en la aplicación de los siguientes pasos:

- Conceptualización de la máquina. En esta sección se seleccionaron los componentes más importantes, cuya confiabilidad, eficiencia y disponibilidad se iban a estudiar.
- Análisis de las causas y consecuencias de un fallo en los componentes seleccionados.
- Propuesta de tiempos de mantenimiento individuales por componente, así como ecuaciones para el cálculo de confiabilidad, eficiencia y disponibilidad.
- Proposición y ubicación de sensores adecuados cuyos valores estén asociados al buen funcionamiento de los componentes.
- Proposición y desarrollo de algoritmos para estrategias ALOP y DBT.

- Ubicación de un eje lineal maestro para el caso de DBT, mediante el cual se relaciona el estudio con la posición del encoder y posteriormente se convierte a unidades de tiempo.
- Configuración de la función de registrador de datos del controlador lógico programable (PLC) y registro de todos los valores relevantes en cada estrategia.
- Registro de los fallos y errores detectados en ALOP y DBT.
- Evaluación de los resultados obtenidos.

Aportaciones del artículo.

- Las estrategias de mantenimiento preventivo PPM e IPPM basadas en los tiempos individuales de mantenimiento de los componentes, permiten modelizar la disponibilidad y eficiencia de la máquina y en caso de IPPM detectar componentes cuyo fallo puede ocasionar un alto valor de TLP (time lost production) y por tanto un tiempo de inoperatividad de la máquina alto.
- El algoritmo de mantenimiento predictivo ALOP puede proporcionar el valor en tiempo real de MTTF de cada componente, así como avisos de inminentes fallos. No obstante, dado que el cálculo está referenciado al tiempo, es posible que se produzcan desviaciones que puedan ocasionar “falsos avisos” dado que algunos sensores pueden proporcionar valores muy distintos si solo se toma la escala temporal, para establecer medidas. Si es válido si la medida del sensor debe está siempre en el mismo valor y no sufre cambios bruscos en sus valores.
- El algoritmo de mantenimiento predictivo DBT, permite conocer el comportamiento normal de la máquina y referenciarlo a la escala de la posición de un encoder. De este modo, se puede monitorizar con mucha precisión, el funcionamiento de los actuadores y sensores y, por tanto, detectar con mucha rapidez cualquier fallo en un sensor, componente o actuador que no cumpla con el patrón de funcionamiento normal. Es un procedimiento sencillo que solo es posible utilizarlo en máquinas con un encoder.
- Los algoritmos ALOP y DBT detectan posibles fallos antes de que ocurran, pudiendo establecerse estrategias de parada antes de que afecte a un lote de producción en curso.

- El algoritmo DBT puede proporcionar cuantos ciclos de producción van a ser atendidos dentro de los márgenes admisibles para garantizar repetitividad en la producción. Esta información es muy útil antes de lanzar una orden de producción en dicha máquina.

Paper -II: Analysis of the Influence of Component Type and Operating Condition on the Selection of Preventive Maintenance Strategy in Multistage Industrial Machines: A Case Study.

Antecedentes y conceptualización.

Una vez conocidas las posibles estrategias de mantenimiento para este tipo de máquinas, el objeto de este artículo es proporcionar decisiones sobre qué tipo de mantenimiento preventivo debe tener cada componente. Para ello, se realiza un análisis por tipo de componente y se define una condición global de operación (GOC) basado en la temperatura, humedad (IP, IEC-62262) y grado de protección contra golpes mecánicos (IK, IEC-62262) para cada componente. Así mismo en función de los valores de MTTR, TLP y TTPR de cada componente se establecen dos indicadores de desempeño (KPI´s) que permiten modelizar una matriz para la toma de decisiones sobre qué estrategia de mantenimiento es más adecuada para cada componente.

La sección dos del artículo describe la metodología utilizada, que se basa en la aplicación de los siguientes pasos:

- En primer lugar, se selecciona el MSTM como caso de estudio. Luego se caracteriza la máquina de termoformado multietapas y posteriormente se identifican todos los componentes y se clasifican por tipo de componente.
- Definición del concepto Condición Global de Operación (GOCi) como parámetro de interés para proponer una estrategia de mantenimiento.
- Definición de tiempos de mantenimiento para cada componente y definición de eficiencia y disponibilidad.
- Estudio y registro de los tiempos de mantenimiento individuales de cada componente en el MSTM. Evaluación de los resultados de aplicar las estrategias PPM e IPPM en una misma máquina en términos de MTTR, TLP, eficiencia y disponibilidad. Evaluación para cada tipo de componente.
- Definición de Indicadores Clave de Desempeño (KPIs) como resultado de las expresiones propuestas en base a los tiempos de mantenimiento definidos y estudiados en el paso cuatro.

- Propuesta de matriz multidimensional para evaluar la estrategia de mantenimiento sugerida para cada componente en un mismo MSTM como combinación de una Condición Global de Operación (GOCi), indicadores clave de desempeño y tipo de componente.
- Evaluación de los resultados obtenidos.

Aportaciones del artículo.

- La definición de una condición global de operación e indicadores de desempeño basados en los tiempos individuales de mantenimiento de cada componentes permite desarrollar un procedimiento para la toma de decisiones sobre la mejor estrategia de mantenimiento.
- La aplicación de la matriz propuesta para la toma de decisiones sobre le mantenimiento de cada componente, refleja unos niveles de eficiencia y disponibilidad muy parecidos a los que se obtendrían con la única aplicación de la estrategia IPPM.
- Existen ciertas indefiniciones en la propuesta para algunos componentes, esto es, la decisión de la estrategia que propone la matriz de decisiones está entre PPM o IPPM. Para estos casos se evalúa el impacto de la cantidad de componentes que pasarías a ser PPM o IPPM en el caso de que la decisión se declinara por PPM o IPPM. UN estudio complementario de costes facilitaría la decisión más objetiva posible, sin olvidar, en ningún caso el valor real de TLP de cada componente.
- El estudio de la localización de un componente en una MSTM y su condición global de operación influye notablemente en la estrategia de mantenimiento que precisa.

Paper -III: An approach for predictive maintenance decisions for components of an industrial multistage machine that fail before their MTTF. A case Study.

Antecedentes y conceptualización.

Este trabajo centra la atención en proponer un procedimiento para la utilización de una estrategia de mantenimiento predictivo en una máquina multietapa. El mantenimiento predictivo no es una estrategia que pueda utilizarse como única estrategia de mantenimiento en una MSTM. Siempre es imprescindible tener un control de los tiempos hasta el fallo MTTF de cada componente, así como unos tiempos de reparación MTTR. El objeto de este artículo es desarrollar una metodología general para que, partiendo de la aplicación de la estrategia PPM para todos los componentes de una MSTM que empieza a operar, existan diferentes posibilidades de cambio de estrategia en función de, si el componente falló antes de su MTTF fijado inicialmente, si el fallo es debido a causas conocidas o desconocidas y a los valores de los indicadores de desempeño. Este artículo también define el concepto nivel de confianza del componente para que se pueda evaluar si el comportamiento previsible del componente coincide con el real y por tanto, sus valores de MTTF son confiables y permiten establecer estrategias de mantenimiento preventivo.

La sección dos del artículo describe la metodología utilizada, que se basa en la aplicación de los siguientes pasos:

- La máquina de termoformada multietapa es seleccionada como caso de estudio. Esta máquina fue caracterizada, identificando todos los componentes y clasificándolos por tipo.
- Definición de tiempos de mantenimiento confiables para cada componente. Muy importante un MTTF adecuado para cada componente.
- Definición de posibles estrategias de Mantenimiento Preventivo y estrategias de Mantenimiento Predictivo adoptadas.
- Se estudiaron los componentes que presentaron fallos ante su MTTF tras un año de funcionamiento.

- Todos los componentes con avisos de fallo son mostrados. Se utiliza el algoritmo predictivo DBT para identificar fallos antes de que ocurran de manera inesperada. El aviso del algoritmo no implica un cambio de estrategia de mantenimiento. El único propósito es el registro de datos para posterior comparación.
- Propuesta de un procedimiento para tomar decisiones para posibles cambios en la estrategia de mantenimiento en los componentes estudiados buscando la causa del fallo y luego evaluando dos indicadores clave de desempeño (KPI)
- Evaluación de los resultados obtenidos.

Aportaciones del artículo.

- Proporcionar una metodología para utilizar y dejar de utilizar el mantenimiento predictivo.
- La aplicación de la metodología propuesta proporciona una herramienta completa para gestionar el mantenimiento de una maquina multietapa, teniendo cada componente su propia estrategia de mantenimiento.
- Disponer de una metodología dinámica que se adapte a las circunstancias variables que puedan producirse durante el funcionamiento de una máquina, permite poder tomar decisiones en función de los acontecimientos, con el grado de conocimiento o desconocimiento que sea en cada caso.
- La aplicación continua de este método sobre una misma máquina en el tiempo puede proporcionar un gran control sobre los fallos y por tanto de la disponibilidad de la máquina.
- La definición y utilización del nivel de confianza de los componentes, permite conocer, comparar y optimizar la confiabilidad del valor del MTTF de los componentes, permitiendo la certera aplicación de estrategias de mantenimiento preventivo en la máquina.
- La utilización del mantenimiento predictivo para conocer la causa de los fallos de los componentes permite el restablecimiento de la estrategia de mantenimiento preventivo en el componente y el descubrimiento de posibles fallos de diseño de la máquina.

2

Resultados, discusión y conclusiones

RESULTADOS, DISCUSIONES Y CONCLUSIONES DEL TRABAJO COMPLETO DE LA TESIS

En este capítulo se evalúan los resultados, su discusión y las conclusiones obtenidas tras el desarrollo y explicación de los tres artículos.

Este análisis es global y no tiene por qué coincidir con las conclusiones individuales de cada trabajo. Los objetivos que motivaron esta tesis han sido tratados en los tres artículos.

Los resultados obtenidos en los trabajos son:

- Obtención de dos estrategias de mantenimiento preventivo (PPM e IPPM) y dos estrategias de mantenimiento predictivo (ALOP y DBT) para la máquina en estudio. Todas las estrategias requieren caracterización de la maquina y ajuste de parámetros.
- Obtención de una matriz para la toma de decisiones sobre el tipo de mantenimiento preventivo, basado en el tipo de componente, su condición global de operación e indicadores clave de desempeño basados en sus tiempos individuales de mantenimiento.
- Obtención de un procedimiento general para gestionar el mantenimiento de cada componente de la maquina en estudio, proponiendo decisiones como adoptar o no mantenimiento predictivo cuando sea necesario, analizando los valores prefijados de MTTF que permiten frente a la realidad, evaluar la confiabilidad o nivel de confianza de los componentes y, de este modo, poder plantear de una forma segura la aplicación de estrategias de mantenimiento preventivo PPM e IPPM.

Sobre los resultados obtenidos hay que hacer las siguientes consideraciones:

La máquina en estudio es un tipo de máquina multietapa. Por tanto, los resultados obtenidos en los tres trabajos deben intentar replicarse en otras máquinas para conocer su reproducibilidad en un entorno más amplia de máquinas multietapa industriales. Las metodologías proporcionadas lo permiten, pero su efectividad sin su aplicación es una incógnita.

En relación con las estrategias de mantenimiento preventivas, no siempre es fácil acceder a valores confiables de todos los tiempos individuales de mantenimiento. Sin estos valores la aplicación de las estrategias propuestas PPM e IPPM no sería posible. La adopción de valores erróneos supondría un resultado erróneo en la estrategia de mantenimiento.

En relación con los algoritmos ALOP y DBT, su utilización requiere la utilización de sensores específicos en la máquina. La posible aplicación de estos algoritmos en otras máquinas multietapa, supondría la definición y utilización de nuevos sensores cuyos valores podrían aportar información sobre el estado de los componentes. Así mismos ambos requieren la utilización de procesadore de datos y generadores de tablas de valores, así como entornos HMI (Human Inferface Machine) que permiten al operador ajustar su funcionamiento y visualizar los avisos en casa caso.

Además, la utilización de ambos algoritmos va muy ligada al programa de control de proceso de la máquina que normalmente gestiona un autómata programable. En este caso, la utilización puede suponer la necesidad de un segundo autómata si la potencia de cálculo no es amplia para procesar el control del proceso y el control del mantenimiento.

Sobre el estudio y definición de las condiciones de operación, junto a los indicadores clave de desempeño para definir la matriz de toma de decisiones sobre estrategias de mantenimiento preventivo PPM e IPPM: Sería muy interesante poder evaluar al "sensibilidad" de este método frente a cambios suaves o abruptos en los valores de TTPR (tiempo de aprovisionamiento del componente) De este modo, puede evaluarse si el método sigue ofreciendo una respuesta confiable en estas circunstancias.

En el caso de las indefiniciones obtenidas por la matriz de toma de decisiones, lo adecuado sería poder realizar una evaluación del coste de los componentes y del tiempo de pérdida de producción requerido para la sustitución del componente averiado.

La posibilidad de definir cuando utilizar el mantenimiento predictivo para descubrir la causa de un fallo inesperado, es una ventaja para el usuario de la máquina. Pero el simple hecho de poder recurrir a dicho mantenimiento predictivo requiere su utilización un coste asociado, por tanto. Sería interesante conocer el coste requerido para implementar el mantenimiento predictivo basado en sensores y determinar si la estrategia de mantenimiento predictivo basado en a la sensorización es la más adecuada y menos costosa para este tipo de máquinas.

La confiabilidad de un producto es un concepto fácil de definir, entender y muy difícil de calcular. Tal y como se indicó en la introducción, existen muchos modelos para calcular la confiabilidad de los componentes. En un entorno conservador, la mejor forma de aproximar su valor sería evaluando el tiempo de operación disponible del componente en la zona II de la curva de la bañera, renunciando a la zona III donde la tasa de fallos sube rápidamente. Si esto se hiciera así, el modelo exponencial sería muy utilizable, dado que la tasa de fallos seria constante, λ, pero dado que λ es la inversa de MTBF, al final dependería de la suma de MTTF y MTTR.

La relación con lo anterior, poder disponer de un valor acertado de MTTF supondría le conocimiento necesario para establecer un valor de fiabilidad límite para programar la sustitución de un componente. Dado que los fabricantes de los componentes, en general, no aportan información clara sobre estos valores, no queda otra posibilidad que recurrir a la experiencia acumulada y posteriormente tras la aplicación del método propuesto en el tercer trabajo, alcanzar un valor real por aproximaciones sucesivas.

Las conclusiones que se extraen de este trabajo, una vez discutidos los resultados obtenidos son:

La primera conclusión que se debe obtener es que el trabajo realizado está basado en un tipo de máquina multietapa. Sería realmente interesante poder realizar estas pruebas en otras máquinas multietapa lo cual requeriría, la caracterización de cada máquina, evaluación de tiempos individuales y selección del algoritmo para el mantenimiento predictivo. Por tanto, todos los resultados obtenidos son para un caso y con lo experimentado solo se puede concluir con que sería interesante poder aplicarlo en otras máquinas multietapa.

La segunda conclusión que puede obtenerse es que basar las estrategias de mantenimiento preventivo sobre los tiempos individuales de mantenimiento de cada componente, permite poder evaluar los tiempos de reparación MTTR y cómo afecta el tiempo de aprovisionamiento TTPR en dicho MTTR. Todas las máquinas multietapa pueden ser caracterizadas en este sentido y por tanto el mantenimiento preventivo propuesta puede ser utilizado en otras máquinas multietapa.

Si se pretende evaluar el mantenimiento preventivo de una máquina multietapa y se quiere minimizar la aparición de fallos debidos al desgaste debido al funcionamiento normal de los componentes, es preciso recurrir a la ley exponencial y obtener los valores de MTTF y MTTR de cada componente.

En relación con la alternativa de mantenimiento preventivo IPPM presentada, sería correcto indicar que los análisis del coste del componente y del impacto económico del TLP, aportarían información relevante para una toma de decisiones más medida, esto es, que antes de tomarla, se evaluase económicamente su adopción.

Sobre las estrategias de mantenimiento predictivo, es importante remarcar que se han basado en el análisis de los valores de sensores asociados a componentes, cuyos valores evaluados en el tiempo, proporcionan información sobre el estado de los componentes. La utilización de los llamados gemelos digitales (digital twin) aportaría muy buena información y gestión del mantenimiento de estas máquinas, pero para ellos habría que modelizar el comportamiento físico de cada máquina. Debido a que estás máquinas son productos "ad hoc", utilizar el modelo digital sería enormemente costoso. Con seguridad, la adopción de una estrategia IPPM sería más rentable. El concepto desarrollado del algoritmo DBT, proporciona un patrón de comportamiento normal, que no requiere aprendizaje y permite una evaluación rápida y precisa, más aún si se referencia a la posición de un encoder. El algoritmo ALOP, dado que basa su medición en la escala temporal, solo debe ser utilizado para sensores cuyas medidas sean constantemente iguales. En caso de amplias divergencias entre los valores posibles del sensor, el algoritmo ALOP puede proporcionar "falsos avisos".

El estudio de las condiciones de operación de los componentes es ventajoso al aportar información sobre el tipo de mantenimiento que debe llevar y los riesgos inevitables de fallos que tiene debido a su localización en la máquina y por tanto los riesgos de que se produzcan fallos inesperados por tener una condición de operación desfavorable o muy desfavorable.

La aplicación sucesiva en el tiempo de la metodología propuesta en el tercer trabajo permite, por aproximaciones sucesivas, localizar posibles fallos de diseño, obtener valores confiables de MTTF en cada componente y en consecuencia programar actuaciones de mantenimiento coordinadas con los tiempos de producción.

La evaluación del nivel de confianza en los componentes también puede permitir, ante fallos repetitivos en los mismos componentes, si los trabajos de mantenimiento se están efectuando correctamente.

3

PAPER -I: MAINTENANCE STRATEGIES FOR INDUSTRIAL MULTI-STAGE MACHINES: THE STUDY OF A THERMOFORMING MACHINE.

Autores:	García, F.J.Á., Salgado, D.R.
Revista:	Sensors ISSN 1424-8220.
Número:	2021, Volume 21 Issue 20, 6809.
Temática especial:	Multistage Manufacturing Processes in the Industry 4.0 for Zero-Defect Products.
Fecha publicación:	13 octubre 2021.
DOI:	https://doi.org/10.3390/s21206809

sensors

Article

Maintenance Strategies for Industrial Multi-Stage Machines: The Study of a Thermoforming Machine

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Abstract: The study of reliability, availability and control of industrial manufacturing machines is a constant challenge in the industrial environment. This paper compares the results offered by several maintenance strategies for multi-stage industrial manufacturing machines by analysing a real case of a multi-stage thermoforming machine. Specifically, two strategies based on preventive maintenance, Preventive Programming Maintenance (PPM) and Improve Preventive Programming Maintenance (IPPM) are compared with two new strategies based on predictive maintenance, namely Algorithm Life Optimisation Programming (ALOP) and Digital Behaviour Twin (DBT). The condition of machine components can be assessed with the latter two proposals (ALOP and DBT) using sensors and algorithms, thus providing a warning value for early decision-making before unexpected faults occur. The study shows that the ALOP and DBT models detect unexpected failures early enough, while the PPM and IPPM strategies warn of scheduled component replacement at the end of their life cycle. The ALOP and DBT strategies algorithms can also be valid for managing the maintenance of other multi-stage industrial manufacturing machines. The authors consider that the combination of preventive and predictive maintenance strategies may be an ideal approach because operating conditions affect the mechanical, electrical, electronic and pneumatic components of multi-stage industrial manufacturing machines differently.

Keywords: maintenance; sensors; multi-stage machine; maintenance algorithm; thermoforming

Citation: García, F.J.Á.; Salgado, D.R. Maintenance Strategies for Industrial Multi-Stage Machines: The Study of a Thermoforming Machine. *Sensors* **2021**, *21*, 6809. https://doi.org/10.3390/s21206809

Academic Editors: Jose Vicente Abellan-Nebot and Ignacio Peñarrocha-Alós

Received: 13 September 2021
Accepted: 12 October 2021
Published: 13 October 2021

1. Introduction

The industrial production environment is becoming increasingly competitive, reliable and optimised. Industrial environments comprise several coordinated production lines and supplementary services that work towards achieving their production objectives.

Production processes are usually made up of several operation steps. Depending on the design of the production system, a common solution proposes using the same single-stage machines for each operation step. These days, there is another increasingly popular alternative based on multi-stage machines, in which the same machine carries out all the production phases.

From a maintenance viewpoint, in case of using single stage machines for different operation steps, any failure in one of the machines in a phase does not necessarily imply a production stoppage, although it may mean a temporary loss of the line's production capacity. However, in industrial production systems based on multi-stage machines, a multi-stage machine is a machine that performs different consecutive operations within a production process. In this case, a failure in any machine component means a complete stoppage of the production line. As a result, the study of component reliability and availability is critical in this type of machine.

Multi-stage machines are used in many industrial processes such as ultrasonic cleaning machines, terrine thermoforming machines, transfer solutions in packaging, fruit sorters, control solutions at logistic warehouse inputs and outputs.

Maintenance and availability monitoring strategies have evolved with time and changes in machine manufacturing technology. Preventive maintenance strategies are currently known to be the most popular [1]. In industrial machines, besides maintenance strategies based on predictive maintenance [2,3], statistical studies have also been carried out for prescriptive maintenance [3], conceptualisation based on Cyber-Physical Systems, artificial intelligence, Big Data [4] or even Digital Twin (DT) modelling [5].

1.1. Preventive Programming Maintenance (PPM)

This is the most popular maintenance strategy in the industrial environment. Taghipour, S. [6] studied this strategy by monitoring the degradation of components in production lines, using an exponential model to obtain the best maintenance strategy. Duffuaa, S. [7], however, related the study of PPM to monitoring and process decisions on a single-stage machine.

The study of the reliability of multi-stage machines provides interesting information for decision-making and PPM strategies. This strategy has already been used in studies by Panagiotis, H. [8] and Ahmadi, A. [9], which showed a model of machine reliability monitoring in which decisions on preventive or corrective maintenance were made based on observed reliability, although they did not consider the cost of maintenance. Zhen Hu [10] uses the health index to assess the remaining component lifetime on manufacturing lines.

David, J. [11] suggested PPM modelling based on knowledge of all the times involved in the repair and commissioning of the machine. Each component has its own Mean Time To Repair (MTTR) depending on its availability, installation difficulty and configuration (see Equation (1)). This analysis may reflect critical values that may affect the maintenance strategy for each component.

Liberopoulos, G. [12] analysed the reliability and availability of a process based on the reliability and availability of each component susceptible to failure or wear and tear.

1.2. Improvement Preventive Programming Maintenance (IPPM)

This is based on the PPM strategy. This maintenance strategy minimises component replacement times and increases component safety stock, resulting in a minimum MTTR value and increasing component availability. Gharbia, A. [13] analysed the relationship between stock cost and scheduled preventive maintenance time. This maintenance strategy is widely used on intensively operated multi-stage machines. A shutdown due to an unexpected failure entails high opportunity costs. IPPM is used for all components or for components with a high replenishment time.

1.3. Algorithm Life Optimisation Programming (ALOP)

This is a proposed maintenance strategy that aims to improve the maintenance of the machines by making decisions based on analysing sensor signals and a predictive algorithm of the state of the most relevant components.

Knowledge of the wear and tear of components is a difficult task to model. Studies by A Molina and G Weichhart used information from specific sensors at strategic locations on machines or systems, which provided information related to production status, such as Desing S^3-RF (sustainable, smart, sensing, reference framework) [14,15]. Decisions were made by computing the data obtained. As a complement, Molina, A. [16] developed the Sensing, Smart and Sustainable studies, where he introduced the environmental factor in the monitoring and managing of Cyber-Physical Systems (CPS).

Satish T S Bukkapatnam suggested the use of specific sensors for anomaly–fault detection in processes [17]. P Ponce proposed studies using sensors and artificial intelligence [18] for the agri-food industry. Ponce, P., Miranda, J. and Molina, A. [19] proposed using sensors, the interrelation of their measurements with the machine components and a data computation system as a strategy to learn about the real state of the machine components.

1.4. Digital Behaviour Twin (DBT)

Introducing Industry 4.0 in production processes paves the way for Smart Manufacturing [20,21] in the industry. In manufacturing multi-stage machines, DBT allows the study of new strategies based on collecting and processing data and defining standard behaviour patterns, which are then compared with real behaviours. This strategy provides essential information for decision-making based on the analysis of current behaviour and comparison of sensor readings.

Using smart devices, cloud computing [22], the study of Machine to Machine (M2M) strategies [23], while maintaining a high level of security and data quality based on international standards [24,25] is indispensable to achieve the full potential of Industry 4.0. Alsharif, M. and Rawat, D.B. [26] propose cloud-base service architecture form managing machine learning models that best fit different Internet of Things (IoT) device operational configurations for security. The necessary traceability in the value chain is possible with the application of the so-called Industry 4.0 [27–29].

Moreover, the conception of Cyber-Physical Systems (CPS) [30–32], Mixed-Criticality Systems (MCS) [33] or Industrial Cyber-Physical Systems (ICPS) [34] have prompted a change in the definition of systems, their monitoring and study to obtain the best information and interaction in real-time between a physical system and the monitoring, data computation, communication and interrelation with other systems [35]. K Meng's paper, called Smart Recovery Decision-Making (SRDM) [36], uses data computation for end-of-life prediction of products.

Decision-making based on accumulated knowledge by the design and assessment of behavioural models is possible thanks to Behavioural Design Encapsulations defined by Stary, C. [37]. They are based on the reconfiguration of patterns with the accumulated knowledge of experience.

The emergence of the DT concept has made it possible to know and digitally simulate the behaviour of the physical model, and therefore improve control over the reliability and availability of equipment, as JdA Bertazzi [38] points out. However, for its application in multi-stage machines, a study and precise modeling of the physical behavior is required, in addition to subsequent adjustments and, finally, the verification that the model responds in the same way as the real model to external changes, boundary conditions or production [39–42].

Some studies define Evolutionary Digital Twin (EDT) as a parallel and complementary digital approach to DT and the real model [43]. Thus, knowledge of reality is also used as a source of learning for the system. This study allows the response of the model to be more flexible and adaptive to changes through supervised learning.

In a study by Wright, L. and Davison, S. [44], a DT is defined as an executable virtual model of a physical part or system. The digital model must then include the equations of the physical system and sensors that provide feedback on the real behaviour. Therefore, a DT can report on the correct or incorrect performance, decision-making or even prediction of the machine's lifetime. The study also indicates that to achieve a behavioural model with DT, it must have sensors, be accurate in its calculations and be quick to suggest decisions.

Studies by Chakraborty, S. and Adhikari, S. [45] propose the modelling of a DT through the parallel study of response prediction and reality learning. A DT is used to simulate the behaviour of machines [46]. The study by Ritou, M. [47] defines the concept of "digital shadow" as a model that extracts information from the physical system, computes the values and proposes decisions on the state of the machines.

Few references dedicated to maintenance management in industrial manufacturing multi-stage machines have been found during the search for references.

1.5. Methodology of the Case Studied

This paper, however, studies a real case of a multi-stage thermoforming machine with a capacity of six terrines per cycle and a cycle time of 4 s. Four maintenance strategies were studied for one year: two usual preventive maintenance strategies (PPM and IPPM) and two predictive maintenance proposals (ALOP and DBT), adapted to Multi-Stage Machines technology.

The work carried out in this research is based on the use of four different maintenance strategies whose operation was observed for one year. The thermoforming multi-stage machine was working continuously 8 h a day, Monday to Friday, for a year. To carry out the work, the following steps were followed in order:

1. Conceptualisation of the machine. In this section, the most important components, whose reliability, efficiency and availability were to be studied, were selected;
2. Analysis of the causes and consequences of a failure in the selected components. (See Table 1);
3. Proposition of individual maintenance times per component, as well as equations for calculating reliability, efficiency and availability;
4. Proposition and location of appropriate sensors whose values are associated with the proper functioning of the components;
5. Proposition and development of algorithms for ALOP and DBT strategies;
6. Location of a master linear axis for the case of DBT, by means of which the study is related to the position of the encoder and subsequently converted to units of time;
7. Configuration of the Programmable Logic Controller (PLC) datalogger function and record all the relevant values in each strategy;
8. Recording of the failures and errors detected in ALOP and DBT;
9. Evaluation of the results obtained.

Table 1. Basic decomposition of components and faults in a multi-stage thermoforming machine.

Item	Component	Type	Fault Source	Consequence of Failure
1	Master power switch	Power Machine/Static	Ambient condition, Power supplier event	Stop
2	PLC	Control/Static	Ambient condition, Power supplier event	Stop
3	HMI	Control/Static	Ambient condition, Power supplier event, Crash	Stop
4	Chromatic sensor	Sensor/Static	Ambient condition, Power supplier event, Crash	Malfunction
5	Plug-in relay	Control device/Static	Ambient condition, Power supplier event	Stop
6	Command and signalling	Control	Ambient condition, Power supplier event, Crash	Stop
7	Safety limit switch	Security/Static	Ambient condition, Power supplier event	Stop
8	Safety relay	Security/Static	Ambient condition, Power supplier event	Stop
9	Safety button	Security/Static	Ambient condition, Power supplier event, Crash	Stop
10	Temperature controller	Control/Static	Ambient condition, Power supplier event	Stop
11	Solid state relay	Actuator/Static	Ambient condition, Power supplier event	Malfunction
12	Thermal resistance	Actuator/Dynamic	Global fatigue	Malfunction
13	Thermocouple sensor	Control/Dynamic	Global fatigue	Malfunction
14	Tape drive	Actuator/Static	Ambient condition, Power supplier event	Stop
15	Tape Motor	Motor/Dynamic	Global fatigue	Malfunction
16	Bronze cap	Mechanism/Dynamic	Global fatigue	Malfunction
17	Linear axis	Mechanism/Dynamic	Global fatigue	Malfunction
18	Lineal bearing	Mechanism/Dynamic	Global fatigue	Malfunction
19	Pneumatic valve	Actuator/Dynamic	Pressure failure, Failure valve	Malfunction
20	Pneumatic cylinder	Actuator/Dynamic	Pressure failure, Cylinder failure	Malfunction
21	Pressure sensor	Control/Static	Ambient condition, Power supplier event	Stop
22	Servo drive peristaltic pump	Actuator/Dynamic	Ambient condition, Power supplier event	Stop
23	Peristaltic pump	Actuator/Dynamic	Global fatigue	Malfunction
24	Terrine cutter	Mechanism/Dynamic	Global fatigue, Mechanical hit	Malfunction
25	Absolute encoder	Control/Dynamic	Ambient condition, Power supplier event. Mechanical hit	Stop

The objectives proposed in this study are:

1. Obtain a systematic approach to managing the maintenance of multi-stage machines, so that it can allow their use not only in the case studied;
2. Evaluate and compare the results that are obtained with the different of maintenance strategies;
3. Propose a maintenance strategy for the detection of unexpected failures that cause manufacturing without expected quality or production stoppage.

2. Case Studied

Production in small packages, known as single use, is increasingly present in the industrial environment. Commonly used products such as oil, vinegar, etc., are already marketed on a large scale by many industries that produce them in large production batches. Figure 1 shows an image of the multi-stage thermoforming machine studied in this article.

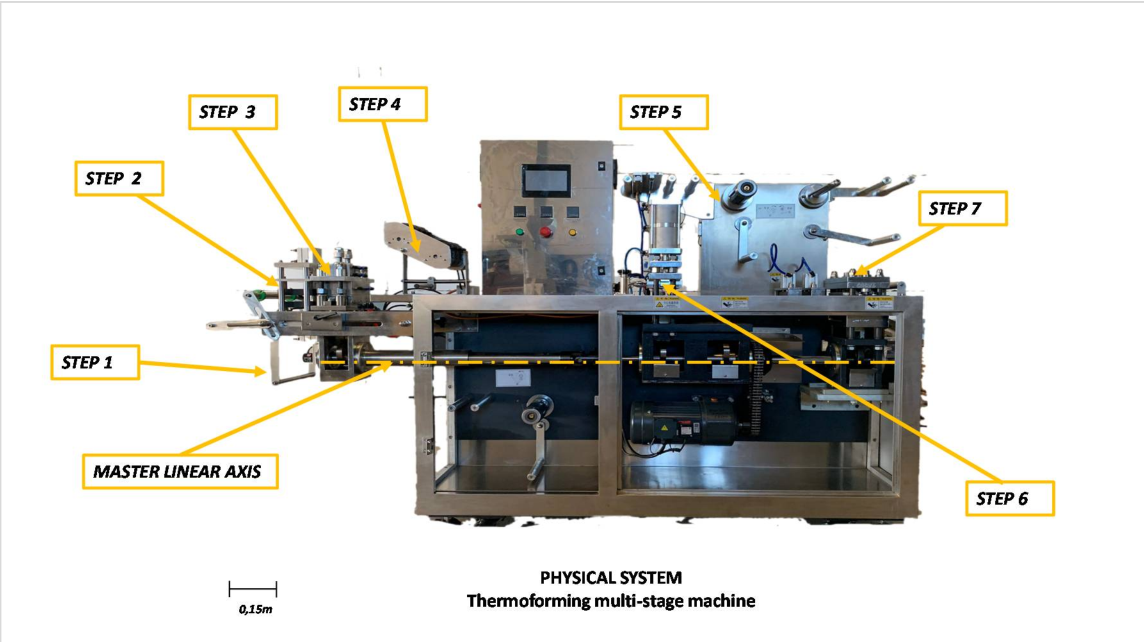

Figure 1. A thermoforming multi-stage machine of 6 terrines per cycle.

This multi-stage thermoforming machine consists of:

- A structural, fixed part, usually not subject to wear and tear but must be adequately protected against corrosion and meet health and food standards;
- Electronic components, power actuators, servo drives, motors, gearboxes, variable speed drives, electrical and electronic devices, including the HMI operator terminal, which are usually 4.3, 7 and 10 inch touch screens;
- Mechanical components subject to movement, such as bearings, shafts, belts and cams. They are generally designed with fatigue-resistant materials but may be damaged by wear and tear and environmental conditions;
- The peristaltic and pneumatic drive system, with which the filling of the terrines and the upward and downward movements of sets of cylinders for adhesion, sealing, glueing and cutting of the terrines are produced, respectively. These systems have bronze bushings, which often suffer from wear and tear;
- A polymer roll dosing system for the top and bottom of the tray. The movement of these rollers is carried out as required at any given moment.

Improvements in process monitoring and technology have made this type of machine controllable by PLC that receive status signals from the field and act on the power actuators for the coordinated execution of all movements. The same technology can be used to manage the availability of the machine or its components.

Table 1 shows a basic decomposition of the components of the machine subject to failure in this paper. A distinction is made between static or moving elements, the possible fault source and the consequence of its failure.

Multi-stage thermoforming machines are one of many multi-stage machines in industrial manufacturing processes. These machines comprise several sub-processes ranging from the management of the polymer film to the container and lid, including the dosage and final cut. Figure 2 shows the steps of this machine ordered sequentially.

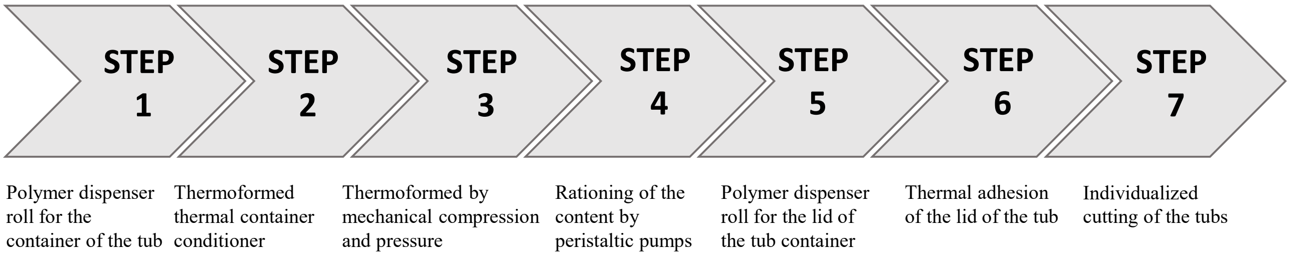

Figure 2. Sub-process in thermoforming and terrine filling machines.

Production capacity can vary from 6 to 12 terrines in the last step, depending on whether the machine is designed for manufacturing 3, 6, 9 or up to 12 tubs simultaneously. Normally, production is carried out with thermoforming moulds of 2, 4, 6 and 12 tubs, composed of one or two rows according to the design of the multi-stage thermoforming machine, then in one cycle, up to 12 tubs can be manufactured simultaneously. This affects the size, the mould of the thermoformer, the number of peristaltic pumps, the rails for the row passage, the lid's thermal bonder and the tub cutter's size. Here, the thermoforming mould used is for six tubs, and the cycle time is 4 s.

Figure 3 shows the terrine used. It is possible to see the lid and the tub. When the lid is added by Step six, terrine is obtained.

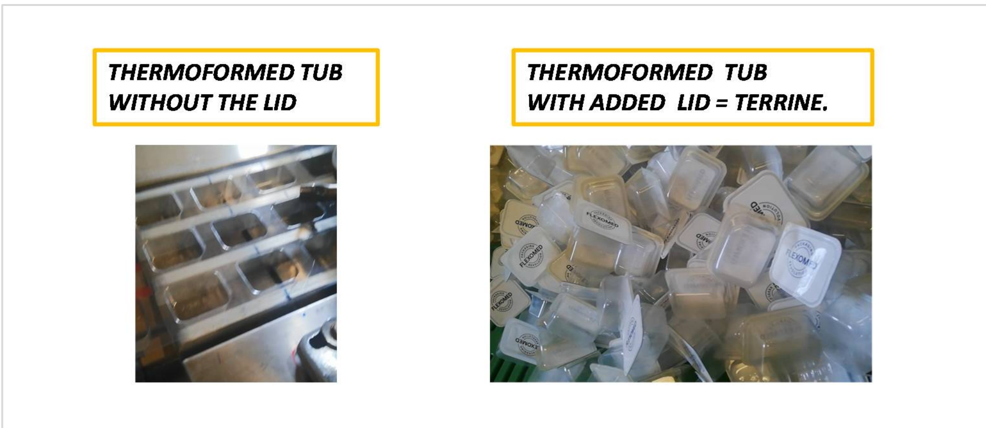

Figure 3. Example of terrine obtained in the thermoforming multi-stage machine studied.

Standard operation requires the constant coordination of all sub-processes since a failure in one of them means production stoppage. There is a master linear axis (see Figure 1) in the lower part of the machine that runs from the thermal conditioner of the polymer for the thermoformer container to the cutter for finished tubs, which permits coordinated movements with cams in synchronised positions to ensure the process is controlled at a constant speed.

It can be understood that a critical component failure can lead to a failure of the whole machine either because it works without the necessary quality or because it cannot continue with the commissioned work.

The times involved in the study of the failures [11,12], are:

- TTRP: Time to replace a component;
- TTC: Time to configure;
- TTMA: Time to mechanical adjustment;
- TTPR: Time to provisioning;
- MTTR: Mean time to repair;
- MTTF: Mean time to failure;
- MTBF: Mean time between failure;
- TTLR: Line restart time, defined by expert knowledge;
- TLP: Time lost production.

$$\mathrm{MTTR} = \mathrm{TTRP} + \mathrm{TTC} + \mathrm{TTMA} + \mathrm{TTPR} \tag{1}$$

$$\mathrm{TLP} = \mathrm{MTTR} + \mathrm{TTLR} \tag{2}$$

$$\mathrm{MTBF} = \mathrm{MTTR} + \mathrm{MTTF} \tag{3}$$

with these times, two concepts are used: efficiency (4) and availability (5). Both concepts will be used as indicators of success in the preventive control of machine failures.

$$\mathrm{Efficiency} = 1 - \frac{\mathrm{TLP}}{\mathrm{MTTR} + \mathrm{MTTF}} \tag{4}$$

$$\mathrm{Availability} = \frac{\mathrm{MTBF}}{\mathrm{MTBF} + \mathrm{MTTR}} \tag{5}$$

3. Maintenance Strategies for the Multi-Stage Thermoforming Machine

The maintenances assessed in an initial phase on this multi-stage thermoforming machine have been PPM and IPPM. High levels of availability and efficiency are achieved. ALOP and DBT strategies have been assessed, and failures were detected before the static value of MTTF (see Table 2) determined by PPM and IPPM.

3.1. PPM: Preventive Programming Maintenance

This strategy is based on using existing data from the usage of the machine. With the information gained from the usage of the machine, each component has its own time values (TTRP, TTC, TTMA, TTPR, MTTR, MTTF, MTBF, TTLP, TLP), and an individual value for availability and efficiency.

The results of setting the line restart time, TTLR, at 14.400 s and using stable market values (values obtained from manufacturers and experience) for the times in this machine are shown in Table 2:

Using the exponential function given by expression 6, the reliability of all the components is calculated in a time equal to MTTF. Figure 4 shows the results.

$$\mathrm{R}_{(\mathrm{t})} = \mathrm{e}^{-\lambda \mathrm{t}} \tag{6}$$

where λ factor is the inverse value of MTBF [48] if we consider the constant fatigue of components.

Table 2. Thermoforming components times in seconds. Efficiency and availability in %.

Component	MTTR	TTRP	TTC	TTMA	TTPR	MTTF	TLP	Efficiency	MTBF	Availability
Master power switch	14,400	3600	0	0	10,800	9,999,999	28,800	99.71%	10,014,399	99.86%
PLC	435,600	3600	86,400	0	345,600	9,999,999	450,000	95.69%	10,4435,599	95.99%
HMI	435,600	3600	86,400	0	345,600	9,999,999	450,000	95.69%	10,435,599	95.99%
Chromatic sensor	176,520	3600	120	0	172,800	5,000,000	190,920	96.31%	5,176,520	96.70%
Plug-in relay	14,400	3600	0	0	10,800	5,000,000	28,800	99.43%	5,014,400	99.71%
Command and signalling	14,400	3600	0	0	10,800	5,000,000	28,800	99.43%	5,014,400	99.71%
Safety limit switch	14,400	3600	0	0	10,800	9,999,999	28,800	99.71%	10,014,399	99.86%
Safety relay	14,400	3600	0	0	10,800	9,999,999	28,800	99.71%	10,014,399	99.86%
Safety button	14,400	3600	0	0	10,800	9,999,999	28,800	99.71%	10,014,399	99.86%
Temperature controller	435,600	3600	86,400	0	345,600	9,999,999	450,000	95.69%	10,435,599	95.99%
Solid state relay	176,400	3600	0	0	172,800	5,000,000	190,800	96.31%	5,176,400	96.70%
Thermal resistance	25,500	14,400	0	300	10,800	3,700,800	39,900	98.93%	3,726,300	99.32%
Thermocouple sensor	14,700	3600	0	300	10,800	3,700,800	29,100	99.22%	3,715,500	99.61%
Tape drive	435,600	3600	86,400	0	345,600	9,999,999	450,000	95.69%	10,435,599	95.99%
Tape motor	187,200	14,400	0	0	172,800	5,000,000	201,600	96.11%	5,187,200	96.52%
Bronze cap	288,000	28,800	0	86,400	172,800	7,750,000	302,400	96.24%	8,038,000	96.54%
Linear axis	288,000	28,800	0	86,400	172,800	7,625,000	302,400	96.18%	7,913,000	96.49%
Lineal bearing	288,000	28,800	0	86,400	172,800	7,500,000	302,400	96.12%	7,788,000	96.43%
Pneumatic valve	176,400	3600	0	0	172,800	9,999,999	190,800	98.13%	10,176,399	98.30%
Pneumatic cylinder	176,400	3600	0	0	172,800	9,999,999	190,800	98.13%	10,176,399	98.30%
Pressure sensor	176,700	3600	300	0	172,800	5,000,000	191,100	96.31%	5,176,700	96.70%
Servo drive peristaltic pump	435,600	3600	86,400	0	345,600	9,999,999	450,000	95.69%	10,435,599	95.99%
Peristaltic pump	547,200	14,400	0	14,400	518,400	5,000,000	561,600	89.88%	5,547,200	91.02%
Terrine cutter	288,000	28,800	0	86,400	172,800	9,999,999	302,400	97.06%	10,287,999	97.28%
Absolute encoder	360,000	14,400	86,400	86,400	172,800	5,000,000	374,400	93.01%	5,360,000	93.71%

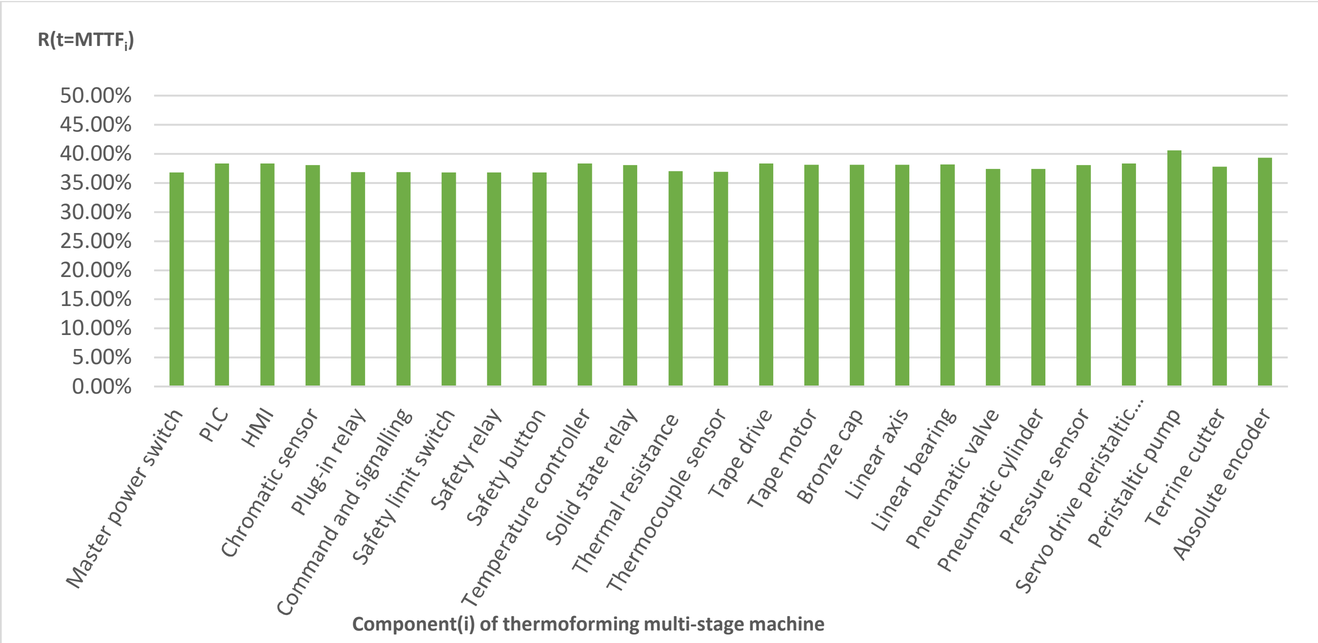

Figure 4. Reliability calculated at MTTF with the exponential function (6) in the PPM strategy.

3.2. IPPM: Improvement Preventive Programming Maintenance

Table 2 shows the TTPR value for all items. It is a significant value when calculating the MTTR value (see Equation (2)).

The IPPM strategy is based on the TTPR of components that would considerably reduce the value of MTTR, and consequently, in the efficiency and availability values. Table 3 shows the results of substituting the TTPR for a residual search time in own stock. Then if the component fails and needs to be replaced, the TTPR value affects the MTTR very little and therefore increases the availability and efficiency of the machine (see Equations (4) and (5)).

The results obtained reveal very high efficiency and availability values for PPM (see Table 2) and IPPM. Components with a high TTPR value improve their efficiency and availability values. Comparison of the results between the two provides a maximum increase in efficiency in 9.26% and availability by 8.4%. Figure 5 shows a comparison of these results.

In other components such as 2, 3, 10, 11, 14, 15, 21 and 22 there has also been an increase in efficiency and availability above 3%.

The results obtained reveal that availability and efficiency improve with the implementation of the IPPM strategy.

The results show that electronic components such as the PLC, HMI, temperature controller, solid state relay, pressure sensor, servo drive form peristaltic pump, peristaltic pump and absolute encoder improve their availability with this strategy, while mechanical components such as the bronze cap, linear axis, linear bearing, pneumatic valve, pneumatic cylinder and terrine cutter partially improve their availability. Consideration of market conditions, transport problems, supply problems or health scares can increase the value of TTPR. These events do not affect the IPPM strategy because it is based on having the components in stock. To avoid affecting the PPM strategy, the TTPR value should be changed by frequently consulting the market for this time in all components. The availability and efficiency of the machine can be maintained in this case and do not decrease due to external causes if a failure occurs.

Table 3. Comparison of efficiency and availability between PPM and IPPM.

Item	Component	PPM		IPPM		Difference IPPM-PPM	
		Efficiency	Availability	Efficiency	Availability	Efficiency	Availability
1	Master power switch	99.71%	99.86%	99.82%	99.96%	0.10%	0.10%
2	PLC	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
3	HMI	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
4	Chromatic sensor	96.31%	96.70%	99.63%	99.92%	3.32%	3.22%
5	Plug-in relay	99.43%	99.71%	99.63%	99.92%	0.21%	0.21%
6	Command and signalling	99.43%	99.71%	99.63%	99.92%	0.21%	0.21%
7	Safety limit switch	99.71%	99.86%	99.82%	99.96%	0.10%	0.10%
8	Safety relay	99.71%	99.86%	99.82%	99.96%	0.10%	0.10%
9	Safety button	99.71%	99.86%	99.82%	99.96%	0.10%	0.10%
10	Temperature controller	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
11	Solid state relay	96.31%	96.70%	99.63%	99.92%	3.32%	3.22%
12	Thermal resistance	98.93%	99.32%	99.21%	99.60%	0.28%	0.28%
13	Thermocouple sensor	99.22%	99.61%	99.50%	99.89%	0.28%	0.28%
14	Tape drive	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
15	Tape Motor	96.11%	96.52%	99.42%	99.71%	3.31%	3.19%
16	Bronze cap	96.24%	96.54%	98.35%	98.55%	2.11%	2.01%
17	Linear axis	96.18%	96.49%	98.32%	98.53%	2.14%	2.04%
18	Linear bearing	96.12%	96.43%	98.29%	98.51%	2.18%	2.07%
19	Pneumatic valve	98.13%	98.30%	99.82%	99.96%	1.69%	1.66%
20	Pneumatic cylinder	98.13%	98.30%	99.82%	99.96%	1.69%	1.66%
21	Pressure sensor	96.31%	96.70%	99.63%	99.92%	3.32%	3.22%
22	Servo drive peristaltic pump	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
23	**Peristaltic pump**	**89.88%**	**91.02%**	**99.14%**	**99.42%**	**9.26%**	**8.40%**
24	Terrine cutter	97.06%	97.28%	98.72%	98.87%	1.66%	1.59%
25	Absolute encoder	96.12%	96.43%	98.29%	98.51%	2.18%	2.07%

3.3. ALOP: Algorithm Life Optimisation Programming

The MTTF of each component can be changed with this strategy by analysing the behaviour of measurements from various sensors. This strategy would enable optimising the useful life of each component. This strategy is compatible with maintenance decisions, and conclusions of the previous strategy can be applied by the algorithm.

Figure 6 shows this model, in which the PLC that manages the process is the same equipment that manages the ALOP algorithm. It consists of sensors in specific parts of the multi-stage thermoforming machine. The real-time processing of the values measured by the sensors allows to know the status of the components and calculate the MTTF in real time. This quality allows a failure to be detected before it occurs. Compared to the PPM and IPPM strategies that keep the MTTF at a fixed value, this strategy detects failures before a static time (remember static MTTF in the PPM and IPPM strategies). The possibility of detecting failures before the fixed MTTF value proposed in PPM or IPPM causes the lower efficiency and availability values of this strategy compared to the two previous strategies (see Equations (4) and (5)).

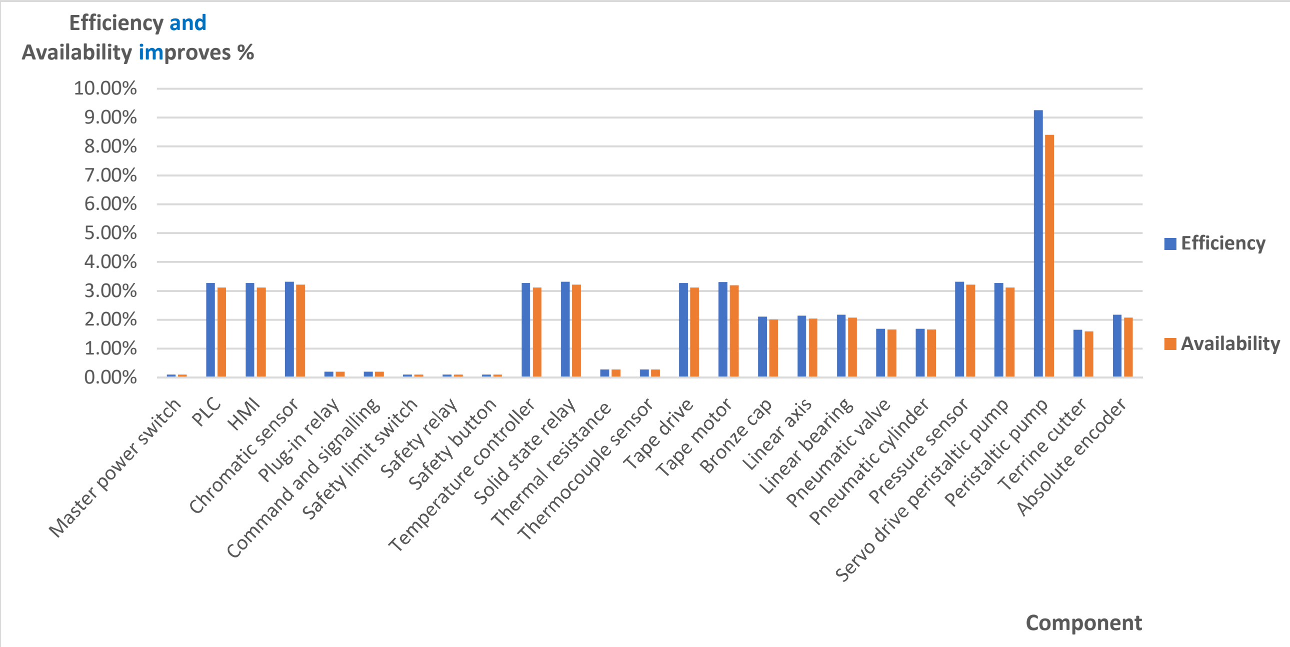

Figure 5. Percentage of improvement in efficiency and availability using IPPM strategy in terms of PPM.

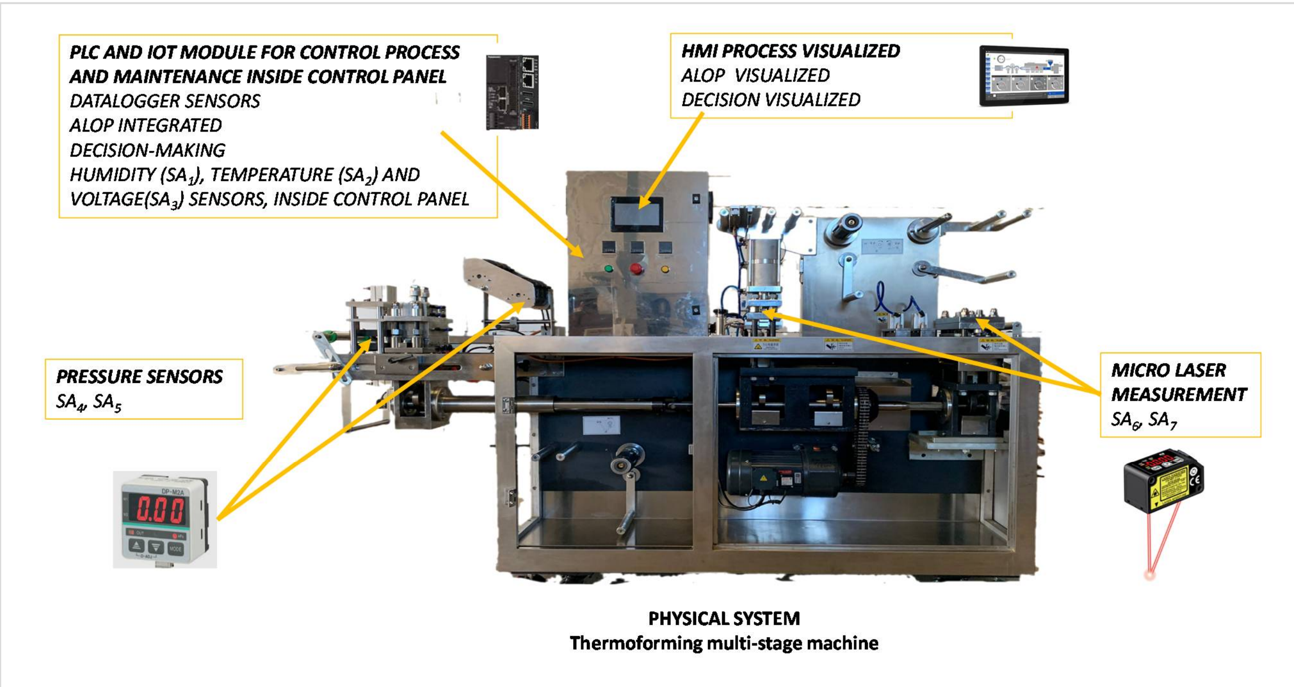

Figure 6. The setup of ALOP strategy.

Table 4 contains the sensors used in the multi-stage thermoforming machine and the component group they affect.

All sensors provide an analogue output signal. A datalogger oversees monitoring, recording and treating the signals in real-time.

Table 4. Sensors and components used for the ALOP model.

Sensor	Description	Items Affected
SA_1	% humidity inside the control panel	1, 2, 3, 4, 5, 8, 10, 11, 14, 22, 24, 25
SA_2	C^a temperature inside control panel	1, 2, 3, 4, 5, 8, 10, 11, 14, 22, 24, 25
SA_3	Voltage RMS in IGBT	1, 2, 3, 4, 5, 8, 10, 12, 14, 15, 19, 20, 21, 22, 23, 25
SA_4	Pressure sensor for thermoformer tub MODEL DPM2A of PANASONIC	10, 12, 13, 16, 18, 19, 20, 21
SA_5	Pressure sensor for peristaltic pumps MODEL DPM2A of PANASONIC	22, 23
SA_6	Micro laser measurement, side front MODEL HGC of PANASONIC	14, 15, 16, 17, 18
SA_7	Micro laser measurement, side rear MODEL HGC of PANASONIC	14, 15, 16, 17, 18

Mathematical Model of the Algorithm

The adoption of this model is based on the accumulated experience in the usage of the PPM and IPPM strategies in the multi-stage thermoforming machine. ALOP was implemented when specific components with available lifetimes according to their proposed MTTF in PPM or IPPM were experiencing unexpected failures. Poor knowledge of the causes of such failures and the impossibility of solving this problem with PPM or IPPM led to the creation of ALOP in an attempt to correct the MTTF value according to the reality measured by sensors reporting to the process control PLC.

This algorithm proposes the calculation of reliability parameters such as MTTF by using the values of distributed sensors that provide information on physical magnitudes whose normality values are recorded. The aim is to compare and adjust the times before failure to then adjust the MTTF value for each component and calculate the component's reliability using the exponential model. As a complement to the algorithm, a warning factor (WF) indicating an unacceptable value of a sensor will be proposed.

The application of this ALOP model focuses on components not kept in stock that cause machine downtime and whose failure causes a considerable TLP value (see Equation (2)). Components such as command and signalling (buttons, switches), a master power switch, plug-in relay and safety components do not apply to this model due to being components of very low cost and high availability of stock.

Equations (7) and (8) are proposed for the calculation of $\mathrm{MMTF_i(t)}$. A step-by-step algorithm will then be proposed to enable decision-making:

$$\mathrm{MTTF_i(t) = [MTBF_{i,0} - (t - t_0)]fc_{(i)} - MTTR_i} \tag{7}$$

where $\mathrm{MTBF_i}$ is the mean time between failures of component "i". This value is shown in Table 2, which results from adding the MTTF and MTTR values for each component proposed in the PPM and IPPM strategies. $\mathrm{MTTR_i}$ is the mean time to repair a failure of equipment "i". $\mathrm{fc_{(i)}}$ is a correction factor for component "i" that depends on the measurements of its associated sensors and is calculated every 100 machine cycles (Since the cycle time is 4 s (see the beginning of Section 2) and therefore 100 cycles correspond to 400 s, it is considered a reasonable time to take measurements on the sensors) and corresponds to the following equation:

$$\mathrm{fc_{(i)}} = \prod_{\mathrm{j=1}}^{\mathrm{n}} \frac{\sigma_{\mathrm{(t)j,i}}}{\sigma_{\mathrm{(t+100)j,i}}} \tag{8}$$

where $\sigma_{\mathrm{(t)i,j}}$ is the standard deviation at time "t" of the measurement of sensor "j" whose evolution can provide information on the reliability and availability status of component "i". $\sigma_{\mathrm{(t+100)j,i}}$ is the standard deviation at time "t + 100" of the measurement of sensor "j", the evolution of which can provide information on the reliability and availability status of component "i".

The risk function described in D M Frangopol's study [49] is then used for each component:

$$\mathrm{fr_{(t,i)} = (1 - R_{(t,i)})\, Cf_i} \tag{9}$$

where $fr_{(t,i)}$ is the risk in economic terms based on the reliability of component "i" at time "t" and $R_{(t,i)}$ is the reliability of component "i" at time "t", which is calculated using the exponential model $R_{(t,i)} = e^{\frac{-\lambda}{t}}$, where λ coincides with $\frac{1}{MTBF_{i-LC}}$ where $MTBF_{i-LC}$ is the mean time between failures of the previous assessment time of component "i". Cf_i is considered constant and is the cost in economic terms of the TLP due to a failure to be repaired in component "i".

The risk factor $fr_{(t,i)}$ is used to advance sourcing decisions for component "i" even if the algorithm has not yet suggested it. It is essential to define risk margins for each component so the value of $fr_{(t,i)}$ must be within the margins set by the user. The lower the reliability of a component $R_{(t,i)}$, the higher its failure function $F_{(t,i)} = 1 - R_{(t,i)}$. Therefore, the product between $F_{(t,i)}$ and the constant value Cf_i will become larger and larger until it reaches $Cf_i(R_{(t,i)} = 0)$. Here, the component fails, and the value of $fr_{(t,i)}$ is maximum (see Equation (9)). The comparison between $fr_{(t,i)}$ is used as an indicator for the acquisition of component "i".

The warning level or technical alarm WF is an inadmissible value for each sensor, set as a technical warning threshold indicating which components may be affected by the warning. This warning may lead to a decision to procure the component or replace it if it is in stock. A Gaussian distribution criterion based on the confidence level of the sample of values is used for verification. The following equation is used:

$$WF > \overline{SA_j} \pm c_i \times \sigma_j \tag{10}$$

where c_i expresses the confidence level or permissiveness of accepting or not accepting deviations from the mean measured value of each sensor. Following the Gaussian Normal distribution criterion, the smallest value of "c" is 0.67 [50], corresponding to a confidence level of 50% of the measured values. Each sensor can have a different value of c_i depending of the dispersion of its measurements. In this study, $c_i = 0.67$ was used for all "j" sensors, because it is a restrictive criterion in the Gaussian distribution, so that the algorithm will be more sensitive to variations that are far from the mean value of the sensor measurement.

Proposed ALOP algorithm:

STEP 1. The time for evaluation and recalculation of values is set as t = 1000 s.
STEP 2. From t = 0, values are taken from the "j" sensors measurements, SA_j. every 10 s.
STEP 3. $\overline{SA_j}$ And σ_j is calculated every 100 s.
STEP 4. At t = 1000 s, $fc_{(i)}$ is calculated for each component "i".
STEP 5. The values $MTBF_{i,1000}$ and $MTTF_{i,1000}$, $R_{i,1000}$, $Eff_{i,1000}$, $AV_{i,1000}$ are calculated.
STEP 6. The value of $MTTF_{i,1000}$ is compared with $MTTR_i$ and subsequently with $TTPR_i$.
STEP 7. The risk factor $fr_{(1000,i)}$ of component "i" is calculated. It is compared to the cost of component "i":

$$\text{IF } fr_{(1000,i)} > \text{Component } \cos t_i \rightarrow \text{Component supply } {''}I{''} \\ \rightarrow \text{ Component supply } {''}I{''} \tag{11}$$

$$\text{IF } fr_{(1000,i)} < \text{Component } \cos t_i \rightarrow \text{No decisions} \tag{12}$$

STEP 8. If $MTTF_{i,1000} < MTTR_i$, the notification for acquiring component "i" is initiated.
STEP 9. If there are no warnings in Steps 7 and 8, compliance with the following is verified:

$$\text{IF } WF_j < \overline{SA_{j,1000}} \pm c \text{ x } \sigma_{j,1000} \rightarrow \text{No decisions} \tag{13}$$

$$\text{IF } WF_j > \overline{SA_{j,1000}} \pm c \text{ x } \sigma_{j,1000} \rightarrow \text{Technical warning} \tag{14}$$

STEP 10. At t = 1000 s, $MTBF_0$ values are updated to $MTBF_{1000}$ since the 1000 s that has elapsed is to be deducted from the mean time to failure of component "j".
STEP 11. Start the algorithm again at Step 2.

This algorithm was adjusted successively over 1 year. In the conclusions, the results of ALOP will be compared with DBT and the effectiveness of their respective algorithms.

3.4. DBT: Digital Behaviour Twin

This strategy proposes using a real-time model that maps the outputs to actuators of the process control (PLC). The monitoring of these variables reports the real operating status of the machine in the order to know which commands are being executed, which field signals are being measured and their values. This strategy uses the position of the absolute encoder, which measures the position of the main shaft of this multi-stage machine. Depending on the position in each cycle, the commands representing the expected behaviour of the process are activated in a coordinated order.

Figure 7 shows the schematic of the DBT model setup for this strategy. It uses the same sensors as ALOP (see Table 4). In this strategy, the activations and deactivations of the actuators are monitored, and the sensor values and the position of the absolute encoder are compared with a so-called normal behaviour pattern. An essential difference to the ALOP strategy is the use of a different measurement scale. ALOP assesses the sensor measurements according to the time algorithm, whereas DBT uses the assessment of the sensor measurements in terms of the position taken by the absolute encoder (see item 25, Table 2).

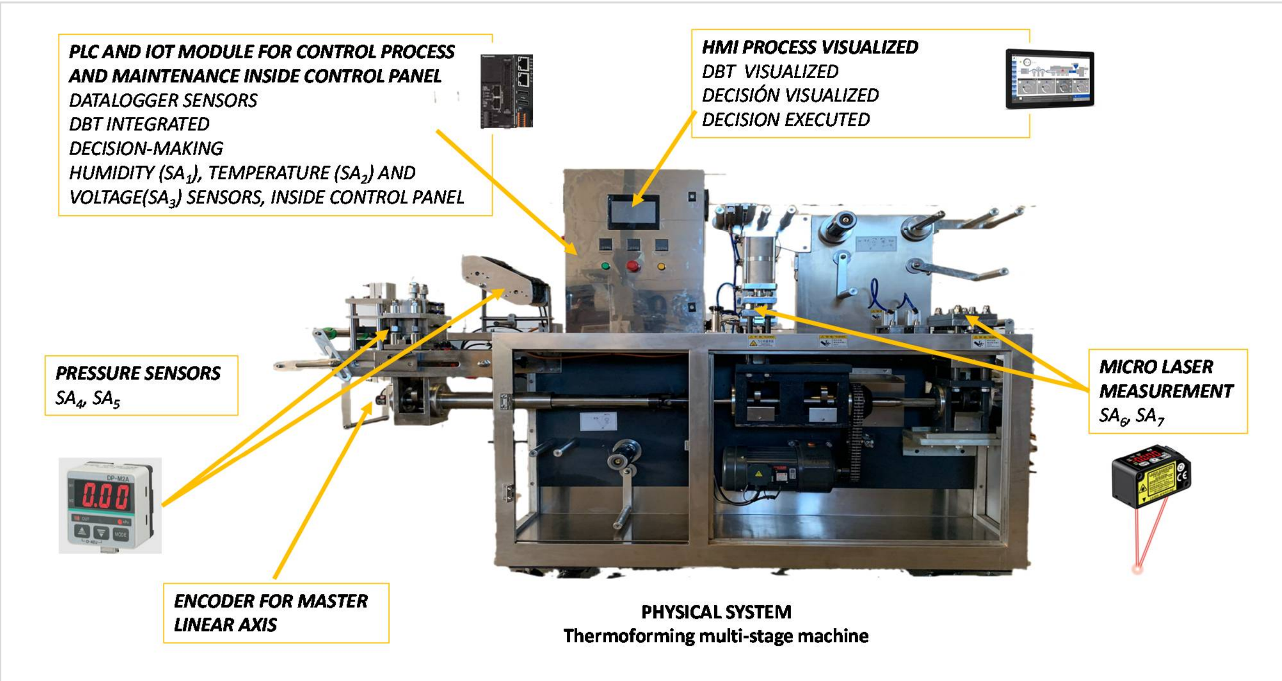

Figure 7. The setup of the DBT maintenance strategy.

The DBT strategy proved to be efficient in this paper and can, therefore, be considered appropriate for developing maintenance strategies for other industrial multi-stage machines. The position of the main shaft of the machine is known through the encoder. The decision-making provided by the proposed DBT algorithm is performed on the time scale by converting the encoder position to time.

In this machine, a work cycle starts at position 0 and ends at position 999 of the absolute encoder. All sensor measurements are linked to machine actuators. They are then recorded and stored according to the encoder position. As a result, a behavioural pattern is obtained with sensor measurement values within the maximum and minimum thresholds and is considered the standard behavioural reference for the multi-stage thermoforming machine. During the normal operation of the machine, the real values are compared with the standard to determine whether the machine is working correctly. The strategy also studies the trend of sensor values and whether they show a potential risk to component lifetime or manufacturing quality.

If the encoder position indicates it and a "z" Actuator (AC_Z) is activated, this input is represented with value one or zero if not activated. The SA_i sensors in Table 4 provide measurements throughout the cycle regardless of activations or non-activations of the AC_Z actuators. All SA_i sensors have a nominal, minimum and maximum value. The decision to assess or replace the component is made based on the analysis of the measurement trend of its associated SA_i sensors and the maximum and minimum values allowed for these measurements.

Table 5 shows the pattern of behaviour of the machine from encoder position 0 to 999. The study has evaluated both the state of the actuators and the value of the sensors every 10 incremental positions of the encoder.

Table 5. Normal pattern of behaviour of multi-stage thermoforming machine.

EP (Encoder Position)	**0**	**10**	**100**	**200**	**300**	**400**	**450**	**500**	**600**	**700**	**800**	**900**	**970**	**980**	**990**	**999**
AC_1: Cam bottom dead centre	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1
AC_2: Drag start point	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AC_3: Blown Time	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
AC_4: Start of heater operation	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0
AC_5: Dosing point	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
AC_6: Top point cams	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0
AC_7: Home pushers	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0
AC_8: Start blowing	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
SA_1: Humidity % inside Control Panel	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60
SA_2: Temperature inside Control Panel	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
SA_3: Voltage supplier inside Control Panel	230	230	230	230	230	230	230	230	230	230	230	230	230	230	230	230
SA_4: Pressure sensor Thermoforming step (bar)	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
SA_5: Pressure sensor after Peristaltic Pump (bar)	0	0	0	0	0.2	0	0	0	0	0	0	0	0	0	0	0
SA_6: Laser measure hp heat seal front (Data in mm)	0	0	0	0	5.0	5.0	5.0	5.0	0.0	0	0	0	0	0	0	0
SA_7: Laser measure hp heat seal rear (Data in mm)	0	0	0	0	5.0	5.0	5.0	5.0	0.0	0	0	0	0	0	0	0

The relevance of sensor measurements can be recognised by using the encoder position.

Therefore, this strategy allows maintenance to be managed by adjusting the operating time of components at the end of their useful life or when they may be damaged by external causes and need to be replaced.

DBT Mathematical Model

Since the normal behaviour pattern and the nominal, maximum and minimum values of the sensors at all encoder positions are known, Artificial Intelligence procedures are not necessary. This feature is considered an advantage of this strategy.

Proposed DBT algorithm:

STEP 1. The assessment procedure starts every 10 encoder positions (EP_{10} to EP_{1000}).

STEP 2. An assessment is carried out every 10 positions:

- Actuator values AC_z (binary value zero or one);
- Values of SA_i sensors (analogue signals)

STEP 3. Pattern checks:

- The AC_z activations reading for the Encoder Position (EP) 10 value should coincide with the valid pattern (see Table 5) If not → PLC or encoder fault.
- The SA_i sensor reading for the EP10 value should coincide with the valid standard (see Table 5) If not → Step 4.

- The AC_z activations reading for the SA_i value should coincide with the valid pattern (see Table 6) If not → Step 4.

STEP 4. Checking deviations of SA_i sensors:

$$\text{If } SA_{i,} \in (SA_{i,VN} - |d_{min}|, SA_{i,VN} + |d_{max}|) \rightarrow \text{No decisions.} \quad (15)$$

$$\text{If } SA_{i,} \notin (SA_{i,VN} - |d_{min}|, SA_{i,VN} + |d_{max}|) \rightarrow \text{Assessment of components associated with } SA_i \text{ sensor} \rightarrow \text{Step 5} \quad (16)$$

where d_{max} and d_{min} are the maximum and minimum deviations allowed in the measurements of the "i" sensors.

STEP 5. The trend is assessed by analysing the mean and standard deviation of the last 1000 cumulative measurements of the SA_i value of sensor "i", whose value is other than zero.

$$\overline{SA}_{i(10-1000)} = \sum_{EP=10}^{EP=1000} \frac{SA_{i-EP}}{1000} \quad (17)$$

Table 6. Comparison of unexpected failures detected for ALOP and DBT.

Item	Component	ALOP True	ALOP False	DBT True
1	Master power switch			
2	PLC			
3	HMI			
4	Chromatic sensor	1		1
5	Plug-in relay	1	1	1
6	Command and signalling			
7	Safety limit switch			
8	Safety relay			
9	Safety button			
10	Temperature controller	1	1	1
11	Solid state relay	1		1
12	Thermal resistance	1	1	1
13	Thermocouple sensor	1	1	1
14	Tape drive			
15	Tape Motor			
16	Bronze cap			1
17	Linear axis			
18	Linear bearing			1
19	Pneumatic valve			
20	Pneumatic cylinder			
21	Pressure sensor	1		1
22	Servo drive peristaltic pump			
23	Peristaltic pump	1		1
25	Absolute encoder			1

For this calculation, the SA_i values that must have a defined value is different from than zero according to the behavioural pattern will be considered.

$$\sigma_{SA_i}^{EP=1000} = \frac{\sum_{10}^{1000}\left(SA_{i-EP} - \overline{SA}_{i\ (10-1000)}\right)^2}{1000-1} \quad (18)$$

Based on the above values and assuming a Gaussian probability distribution, it is evaluated if the value is included in a statistical limit based on the previous measures.

$$(SA_{i,VN} - |d_{min}|,\ SA_{i,VN} + |d_{max}|) \in \left(\overline{SA}_{i(10-1000)} \pm 3 \times \sigma_{SA_i}^{EP=1000}\right) \quad (19)$$

If the trend is maintained, the algorithm calculates the time remaining before the SA_i sensor measurement can indicate a failure and/or an undesired shutdown.

The result is studied on the encoder scale. Therefore, the result is obtained in the number of cycles missing for the measurement of a sensor to go beyond its limits. $NCTF_{SAi}$ is the number of cycles to failure indicated by the SA_i sensor.

STEP 6. Decision taking.

Once the study of the trend of the SA_i sensor values in the encoder position has been completed, the relationship between the encoder position scale and the time is defined. In this case (see beginning of Section 2):

$$1\ \textit{work cycle} \equiv 1.000 \text{ encoder positions from 0 to 999} = 4 \text{ s}$$

$$MTTF_{SAi} = NCTF_{SAi} \times TC \quad (20)$$

Expression (20) can calculate the number of cycles that can be performed with the sensor values within their maximum and minimum thresholds.

The DBT strategy and the encoder assessment scale in the maintenance management of the multi-stage thermoforming machine makes it possible to ascertain:

- Deviations in the measurements of the "j" sensors, whose relationship is established with the "i" items by Table 4;
- Whether the evolution of any of the "z" actuator activation/deactivation commands is correctly coordinated and is proceeding according to the normal pattern;
- If any of the measurements of the "j" sensors conform to the encoder position;
- If any of the measurements of the "j" sensors conform to the activation pattern of the "z" actuators at each encoder position;
- Whether the absolute encoder is providing the shaft position information correctly;
- Whether the process control, PLC, is executing the commands correctly according to the encoder position.

It also makes it possible to:

- Take early decisions on machine components and prevent unwanted faults by assessing the measurements of each sensor and observing the measurement trend;
- Know the planned production that can be performed without a failure;
- Adjust the d_{max} and d_{min} values for each SA_i sensor, allowing the establishment of a confidence margin where the output meets industry quality standards;
- Very precise control of deviations from nominal measurements of the "j" sensors by being assessed only when indicated by the position of the encoder and the "z" actuators and the sensor shows a value other than zero (see Step 5 of the DBT algorithm).

4. Results and Conclusions

The ALOP and DBT strategies have been tested on the multi-stage thermoforming machine working continuously 8 h a day, Monday to Friday, for a year. Table 6 shows the number of unexpected failures, with information on the warnings of each algorithm and which have warned of a real failure, and which have not.

Unexpected failures can be detected with ALOP and DBT algorithms. However, the ALOP algorithm has shown false warnings. The authors consider this may be due to ALOP taking measurements from each sensor every 10 s, whereby the nominal measurement value of the sensor or zero value may be recorded. As a result, the dispersion of measurements may be excessive. Increasing this dispersion may cause false warnings (see expression 8). For the DBT model, the trend of the measurements is only assessed on the measured value, which will always be very close to the nominal value unless the sensor fails.

As a follow-up, the DBT algorithm has detected unexpected failures in mechanical items 16 and 18. Failures in affected components are detected if the deviations in the SA_6 and SA_7 sensors are greater than 0.5 mm. The detection of possible failures in mobile mechanical equipment requires a maintenance strategy in which the assessment of deviations is as accurate as possible, with DBT being the best alternative.

Item 25 (encoder) suffered an accidental mechanical shock. From that moment on, its operation was not correct as the commands executed to the actuators started to be carried out without the expected coordination. Step 3 of the DBT algorithm warned very quickly, in less than one cycle. ALOP did not detect it because it uses the SA_1, SA_2 and SA_3 sensors for that component, and none of the three sensors noticed an anomaly in the measurements. As a consequence, the machine was stopped by an operator.

As both algorithms detected failures in some components, the MTTF was reduced. To manage the maintenance of this alteration, the MTTF value of components triggered component replacement decisions as the mean time to failure was reduced and, therefore, the component's lifetime ended. Their Efficiency and Availability values changed (see Equations (4) and (5)).

Figures 8 and 9 show the comparison of Efficiency and Availability in percentage values of the components that presented unexpected failures detected by ALOP and DBT, and their values obtained in PPM and IPPM (see Table 3).

The detection of failures before the MTTF stated in the PPM and IPPM strategies is the consequence of the decrease in the efficiency and availability values of the affected components. However, the relevance of the decrease in the values can be compared to the advantages of detecting a failure before an unexpected stoppage and the opportunity costs it may entail (proposed for future research).

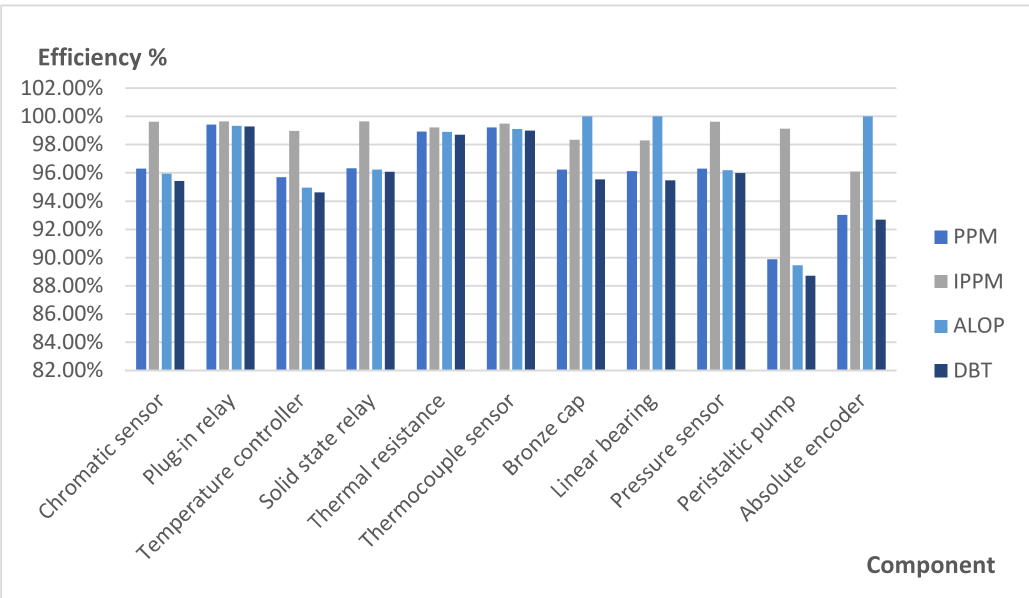

Figure 8. Comparison of efficiency values in affected components.

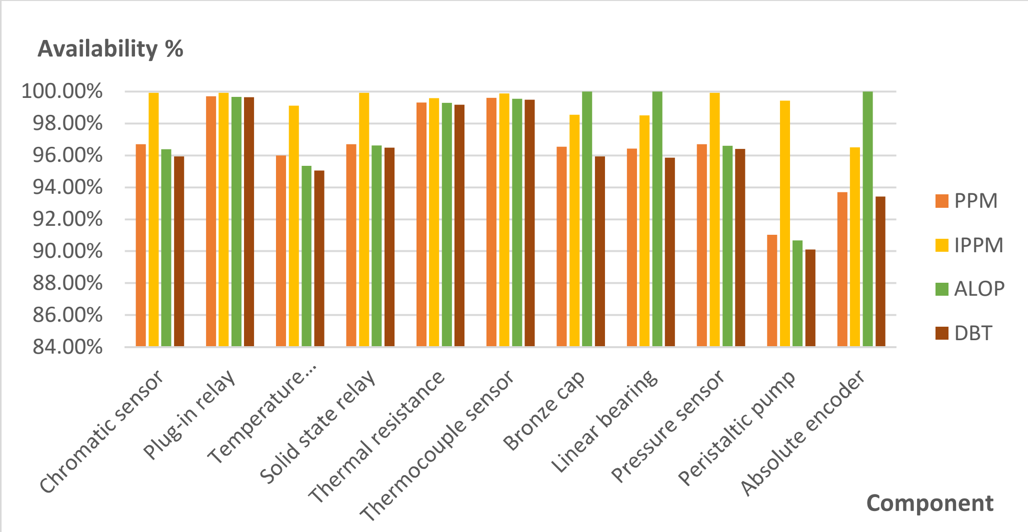

Figure 9. Comparison of availability values in affected components.

The study of maintenance strategies for multi-stage machines can be an avenue for future research. Through the results obtained, a solution is offered for unexpected failure detection, which for this type of machine is of great importance. With the results obtained, these conclusions can be drawn:

- The algorithms proposed for the ALOP and DBT strategies show favorable results, and their use can be proposed for managing the maintenance of other multi-stage machines;
- Because multi-stage machines require better maintenance control to detect unexpected failures, ALOP and DBT can be proposed as suitable strategies for this type of machine;
- Unexpected failures can be detected with ALOP and DBT strategies. The authors consider that both strategies complement PPM or IPPM, and their combined study could be an avenue for future research;
- The accuracy of the measurement evaluation procedure of the DBT strategy allows the detection of faults in moving mechanical components with very low deviations from nominal values;
- Knowledge of a normal operating pattern of machines is a very reliable source of knowledge for maintenance management. It allows the best assessment of component lifetime by setting limit deviations (d_{max} and d_{min}) (See Step 4 in the DBT algorithm) on sensor-measured values, based on the quality standards of each industry;
- The detection of unexpected mechanical or electronic components failures may be due to alterations of environmental operating conditions and non-recommended voltage values;
- The knowledge of the production that can be performed without failures is only achieved with the DBT model;
- The IPPM application offers improvements of efficiency and availability and minimises MTTR, but stock costs can grow;
- Improvements in the efficiency and availability of the electronic components (see components 2, 3, 4, 10, 11, 14, 15, 21 and 22 in Figure 5) and partially the mechanical components (see components 10, 16, 17, 18, 19 and 23 in Figure 5) are noticeable. As with PPM, this strategy also fails to detect unexpected failures;
- Applying PM techniques based on the time scale is interesting if the SA_i sensor values provide constant and similar measurements throughout the process. Otherwise, the dispersion in values may not correctly reflect reality. On multi-stage thermoforming machines, it is very beneficial to evaluate the measurements on the scale of the encoder positions and then decide on the time scale.

The authors consider the following avenues for future research:

- Comparative study between the decrease in efficiency and availability by applying ALOP and DBT strategies, and the benefits of detecting unexpected failures compared with static value of MMTF provided by the PPM and IPPM strategies;
- Study of the application of different maintenance strategies for each kind of component in the same multi-stage machine;
- Study of the cost of the different maintenance strategies in a multi-stage machine.

Author Contributions: Conceptualisation, F.J.Á.G.; methodology, F.J.Á.G.; validation, F.J.Á.G. and D.R.S.; formal analysis, F.J.Á.G.; investigation, F.J.Á.G. and D.R.S.; resources, F.J.Á.G.; writing—original draft preparation, F.J.Á.G.; writing—review and editing, F.J.Á.G. and D.R.S.; visualisation, F.J.Á.G.; supervision, F.J.Á.G.; funding acquisition, F.J.Á.G. and D.R.S. All authors have read and agreed to the published version of the manuscript.

Funding: This study has been carried out through the Research Project GR-18029 linked to the VI Regional Research and Innovation Plan of the Regional Government of Extremadura.

Acknowledgments: The authors wish to thank the European Regional Development Fund "Una manera de hacer Europa" for their support towards this research. This study has been carried out through the Research Project GR-18029 linked to the VI Regional Research and Innovation Plan of the Regional Government of Extremadura.

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

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4

PAPER -II: ANALYSIS OF THE INFLUENCE OF COMPONENT TYPE AND OPERATING CONDITION ON THE SELECTION OF PREVENTIVE MAINTENANCE STRATEGY IN MULTISTAGE INDUSTRIAL MACHINES: A CASE STUDY

Autores:	García, F.J.Á., Salgado, D.R.
Revista:	Sensors ISSN 2075-1702.
Datos edición:	2022, Volume 10, Issue 5, 385.
Temática especial:	Reliability of Mechatronic Systems and Machine Elements: Testing and validation.
Fecha publicación:	17 mayo 2022.
DOI:	https://doi.org/10.3390/machines10050385

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Analysis of the Influence of Component Type and Operating Condition on the Selection of Preventive Maintenance Strategy in Multistage Industrial Machines: A Case Study

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Abstract: The study of industrial multistage component's reliability, availability and efficiency poses a constant challenge for the manufacturing industry. Components that suffer wear and tear must be replaced according to the times recommended by the manufacturers and users of the machines. This paper studies the influence of the individual maintenance values of Main Time To Repair (MTTR), Time To Provisioning (TTPR) and Time Lost Production (TLP) of each component, including the type of component and operation conditions as variables that can influence deciding on the best preventive maintenance strategy for each component. The comparison between different preventive maintenance strategies, Preventive Programming Maintenance (PPM) and Improve Preventive Programming Maintenance (IPPM) provide very interesting efficiency and availability results in the components. A case study is evaluated using PPM and IPPM strategies checking the improvement in availability and efficiency of the components. However, the improvement of stock cost of components by adopting IPPM strategy supposes the search of another more optimal solution. This paper concludes with the creation of a multidimensional matrix, for that purpose, to select the best preventive maintenance strategy (PPM, IPPM or interval between PPM and IPPM) for each component of the multistage machine based on its operating conditions, type of component and individual maintenance times. The authors consider this matrix can be used by other industrial manufacturing multistage machines to decide on the best maintenance strategy for their components.

Keywords: maintenance strategies; preventive maintenance; operation condition; type of component; global operation condition; multistage industrial machine; thermoforming

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Citation: García, F.J.Á.; Salgado, D.R. Analysis of the Influence of Component Type and Operating Condition on the Selection of Preventive Maintenance Strategy in Multistage Industrial Machines: A Case Study. *Machines* **2022**, *10*, 385. https://doi.org/10.3390/machines10050385

Academic Editors: Sven Matthiesen and Thomas Gwosch

Received: 3 March 2022
Accepted: 16 May 2022
Published: 17 May 2022

1. Introduction

The study of the reliability, availability and efficiency of industrial multistage components poses a constant challenge for the manufacturing industry.

Manufacturing processes can be studied by adopting combinations of different machines that work in a coordinated way, either in series or parallel. The machines can be single stage machines, i.e., machines in charge of one phase of production, or multistage machines, which develop several phases of the production process.

Maintenance strategies must be different for each type of process and machine used. With processes based on a series-parallel combination of single stage machines, an unexpected stoppage caused by the failure of a component does not necessarily stop production altogether, but it may decrease the value of production capacity. With processes based on multistage machines, except for redundancy of these multistage machines, a stop caused by a component failure can cause the entire production process to stop.

Because of this condition in multistage machines, the components, their operating condition and their reliability for the performance of the work they must carry out must be carefully studied. The preventive maintenance strategy [1] is one of the most popular strategies in the industry. According to Colledani [2], equipment availability, product quality and system productivity are strongly related. Moreover, Colledani stated that preventive maintenance policies significantly affect the completion time of a batch [3].

Cheng-Hung [4] proposed a Dynamic Dispatch and Preventive Maintenance model (DDPM) that considers dispatching-dependent deterioration and machine health-dependent production rates for C, a dynamic decision model. Colledoni [5,6] cited in his works that opportunistic maintenance affected the performance in multistage manufacturing systems. Similarly, Xiaojun [7] proposed opportunistic preventive maintenance for Serial-Parallel Multistage Manufacturing Systems (SP-MMSs).

Recent works of Azimpoor [8] reveal that a machine's lifetime is divided into two stages in a failure process, showing defect arrival and then failure arrival. So, the maintenance schedule can be a combination of orders to repair and inspect machines. In this way, Ruiz Hernández [9] believed that poor maintenance could not reinstate the machine to an "as-new" status and this had to be considered when designing maintenance policies. Additionally, Guanghan [10] cited four degradations stages of multistage machines: normal stage, slow degradation, fast degradations and fail.

An effective maintenance policy typically seeks high-quality mechanical reliability, and the minimum possible maintenance cost [11–15]. Xiaojun [16] studied the Condition-Based Maintenance (CBM) policy in multistage manufacturing systems and the positive effects on the quality of the machine work with the most appropriate preventive maintenance decisions. Qipeng [17] proposed using Multistage Stochastic Mixed-Integer Programming (MSMIP) to seek optimal operations regarding maintenance outage scheduling of the machine.

Yingsai [18] studied preventive maintenance based on a policy to improve operation efficiency by modelling an algorithm to obtain the optimal parameters to ascertain the frequencies of inspections and maintenance. Similarly, Grossmann [19] concluded that a Markov decision-making process model is an interesting framework for modelling the stochastic dynamic decision-making process of condition-based maintenance.

Qing [20] proposed preventive maintenance based on quality rework loops for detecting random machine failures. Qiuhua [21] proposed using a constraint to a two-stage assembly flow shop against a fixed preventive maintenance time, using the Weibull probability distribution to calculate the optimal maintenance interval. This ensures the production flow is continuous and ensures the reliability of the machine.

1.1. Preventive Programming Maintenance

Preventive programming maintenance is used in most manufacturing industries. The work of Jun-Hee [22] proportionated preventive maintenance scheduling to minimise the risk of failure in a single-process machine. Other studies by Taghipour [23] and Duffuaa [24] developed models based on integrating the maintenance schedule into the production to improve the machine's quality and performance.

The study of the availability to show the performance level of a multistage system was developed by Arvanitoyannis [25]. Ahmadi [26] used Reliability-Centred Maintenance (RCM) based on condition-based maintenance to decide which maintenance action must be undertaken. Zhen [27] studied the health index to obtain and measure the reliability of a complex production process to reflect the in-time operation state of the production process.

Jiři [28] studied the losses in production and analysed the priority in the corrective and preventive maintenance as the fastest return to the normal activity of the machine. He also used the main time between failure and main time to failure and other delayed times to minimise the cost and improve the availability of the machine. Liberopoulos [29] analysed all the times involved in main time to repair in a single-parallel multistage machine. He also proposed the use of time lost for production as an indicator of the availability of the process.

1.2. Improved Preventive Programming Maintenance

The improved preventive programming is based on the PPM strategy. This strategy minimises the TTPR of all the components by improving the safety of own stocks to reduce the MTTR and improve efficiency and availability ratios. Ren [30] analysed the product-service system (PSS) as an important challenge to providers to perform preventive maintenance based on historical data combined with real-time operational data.

Gharbi [31,32] analysed the effects of joint production and preventive maintenance controls for manufacturing systems, using a make-to-stock strategy and age-based on preventive maintenance, minimising the inventory cost according to unreliable manufacturing periods.

Hongbing [33] studied the optimisation of preventive maintenance by a joinder of maintenance and production considering the maintenance costs, processing costs and completion rewards using the Markov model to form a decision process.

García and Salgado [34] studied the modelling of a multistage machine and preventive maintenance strategies to improve the machine's efficiency and availability.

Ferreira [35] introduced the reactive and proactive concepts to evaluate the components obsolescence and then a new Key Performance Indicators (KPI_S) for a matrix decision for industrial maintenance evaluation.

This paper studies a real case based on a MultiStage Thermoforming Machine (MSTM).

The objective is focused on the selection of the most appropriate preventive maintenance strategy for the components of the studied machine. For that purpose, the preventive maintenance strategies PPM and IPPM are studied, and their results compared. Initially the machine works with PPM strategy. Looking for the improvement of efficiency and availability, IPPM strategy is proposed for use. Results show that a combination of different maintenance strategies is more interesting from a cost point of view. In the aim to reach the objective, the authors propose a methodology for selecting PPM or IPPM strategy for the components depending on the location of the component and new indicators, defined in Step 5 in Section 2. This research proposes a n dimensional matrix for that purpose.

2. Materials and Methods

The work carried out in this article is based on the analysis of one year working of the MSTM. The results obtained with PPM and IPPM strategies are different, so a multicriteria decision method is studied for selecting the appropriate preventive maintenance strategy for different components in the same machine. The result of this multicriteria analysis is the multidimensional matrix proposed and adopted for the machine.

The methodology used in this research and its ordered executed steps, is as follow:

- Step One: First, the MSTM is selected as case study. Then the thermoforming multistage machine is characterised and subsequently all the components are identified and classified by component type. See Section 3.1;
- Step Two: Definition of the concept Global Operation Condition (GOC_i) as an interesting parameter to propose a maintenance strategy. See Section 3.2;
- Step Three: Definition of maintenance times for each component an efficiency and availability definition. See Section 3.3;
- Step Four: Study and collection the individual maintenance times for each component in the MSTM. Evaluation of the results of applying the PPM and IPPM strategies in the same machine in MTTR, TLP, efficiency and availability terms. Evaluation for each component type. See Sections 3.4 and 3.4.1 for PMM strategy and 3.4.2 for IPPM strategy. The results provided by the Section 3.4 are not part for the results of this research, due to the fact that the objective of this research is the selection of the appropriate preventive maintenance strategy for each component and the results of this section are the efficiency and availability values for both strategies;
- Step Five: Definition of Key Performance Indicators (KPIs) as the result of proposed expressions based on maintenance times defined and studied in step four. See Section 3.5.1;

- Step Six: Proposal of a multidimensional matrix for evaluating the maintenance strategy suggested for each component in the same MSTM as a combination of a Global Operation Condition (GOCi), key performance indicators and type of component. See Section 3.5.2;

  Results, discussion, conclusions, and futures research are shown in Sections 4–6. This paper is organised following the outlined steps.

Other Considerations

If the analysed machine will present a lot of unexpected failures in different types of components, the authors suggest using FMECA analysis to achieve a better design and manufacture of the multistage machine.

The definition of the maintenance strategies is lined up to EN 13306:2001. Also, the new KPIs proposed are not the same that technical groups in EN 15341:2007 but allow new and interesting results.

3. Case Studied

3.1. Definition of A Multistage Thermoforming Machine and List of Studied Components

Thermoforming and tub-filling machines are one case among the many that exist. This study covers this type of machine. Figure 1 shows the MSTM and the components' placement.

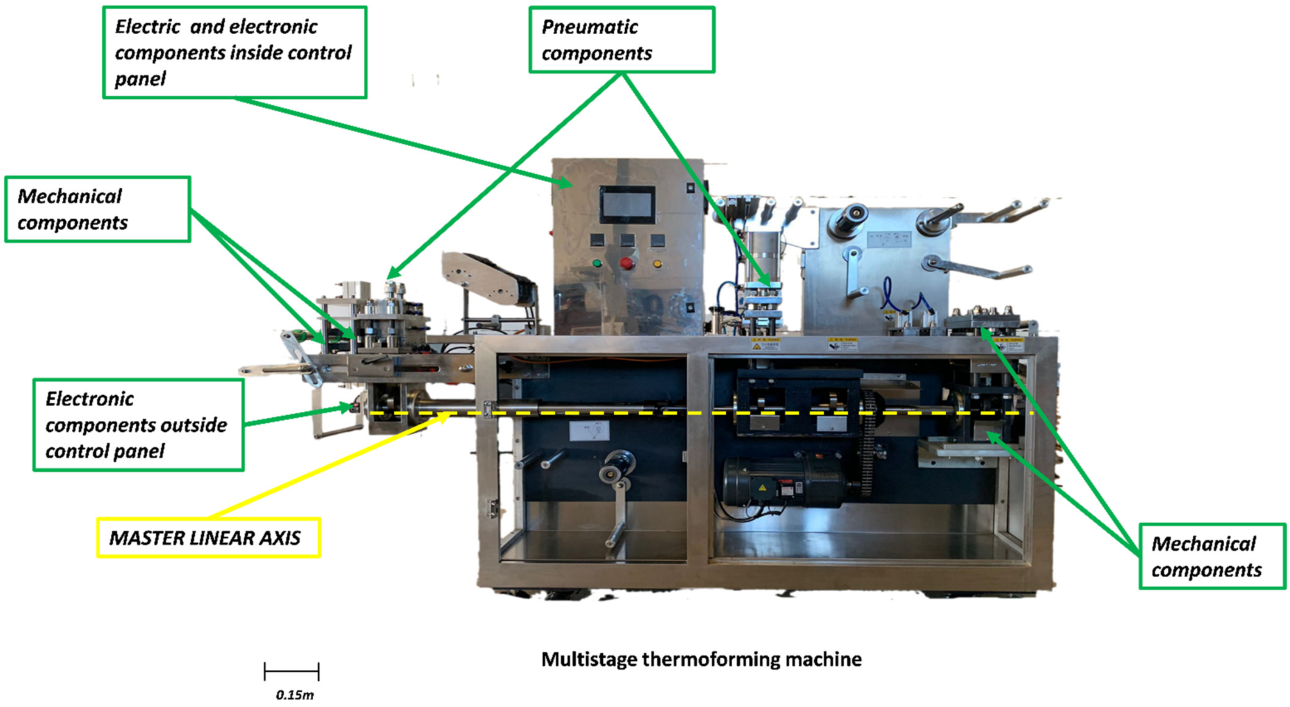

Figure 1. A multistage thermoforming machine of 6 terrines per cycle and its type of components.

These machines comprise several steps, from managing the polymer film, the container and the lid to the dosage and final cut.

The cycle time in this machine is 4 s, during which six terrines are manufactured. Standard operation requires the constant coordination of all steps since a failure in one of them means the global failure and loss of the ongoing production.

There is a master linear axis in the lower part of the machine from the thermal conditioner of the polymer for the container thermoformer to the cutter for finished tubs, which ensures the coordinated operation of the entire machine (see Figure 1).

A structural, fixed part is usually not subject to wear and tear but must be protected against corrosion and meet health and food operation conditions. This multistage machine has many component types. The classification of the components is as follows:

- Electrical components;
- Electronic components;
- Mechanical components;
- Pneumatic components.

The assignment of the type of component has been made by applying the following criteria:

- Electrical components are all those that works in alternating voltage and current;
- Electronic components are all those that need analog signals of voltage or current to work. Those components that use electronic control cards and power electronics equipment in their operating principle, such as thyristors or insulated gate bipolar transistors, are also included;
- Mechanical components are all those that move or are actuated abruptly. The peristaltic pump is included in this group since its drive is carried out by a servomotor that controls the proper dosage. Additionally, the thermocouple sensor is considered as a mechanical component due to its location is inside of the mechanical base for thermoforming creating tub (see step 3 in Figure 2) and inside of the mechanical base for the thermal adhesion (see step 6 in Figure 2). Both mechanical bases are in constant movement;
- Pneumatic components are all those that require pressurised air for their operation.

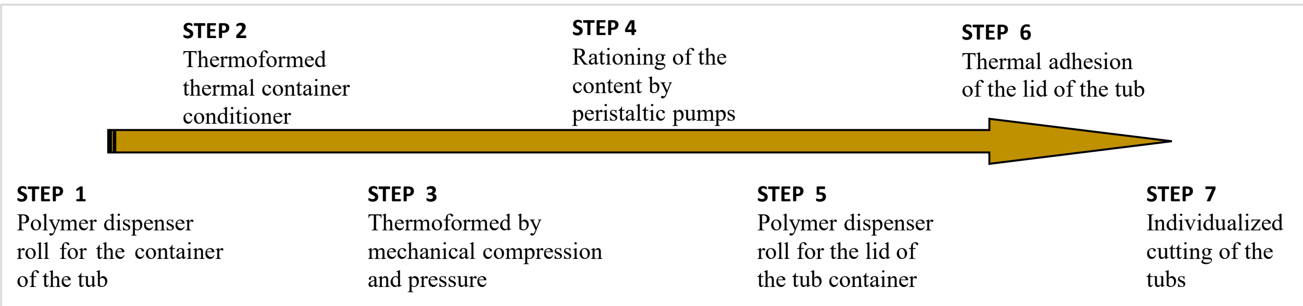

Figure 2. Subprocess in the studied MSTM.

3.1.1. Electrical Components

They are usually inside the control panel, but those that entail human-machine interface (HMI) are on the outer face of the door control panel. Table 1 shows the list of electrical components in this MSTM, with the failure source and event.

Table 1. Electrical components in the studied MSTM with failure source and event.

Component	Failure Source	Failure Event
Master power switch	Ambient condition, Power supplier event	Stop
Plug-in relay	Ambient condition, Power supplier event, Unexpected hit	Malfunction
Command and signalling	Ambient condition, Power supplier event	Stop
Safety limit switch	Ambient condition, Power supplier event, Unexpected hit	Stop

3.1.2. Electronic Components

Electrical components are usually inside the control panel, e.g., the programming logic controller (PLC) and solid-state relays, but some components can be on the outer face of the control panel, as with the electrical components that have human-machine interactions. Sensors are typically distributed around the machine and are subject to degrading and unexpected hits. Table 2 shows the list of electronic components in this MSTM, with the failure source and event.

Table 2. Electronic components in the studied MSTM with failure source and event.

Component	Failure Source	Failure Event
PLC	Ambient condition, Power supplier event	Stop
HMI	Ambient condition, Power supplier event	Stop
Chromatic sensor	Ambient condition, Power supplier event	Stop
Safety relay	Ambient condition, Power supplier event	Stop
Temperature controller	Ambient condition, Power supplier event, Unexpected hit	Stop
Solid-state relay	Ambient condition, Power supplier event	Stop
Frecuency inverter	Ambient condition, Power supplier event	Malfunction
Pressure sensor	Pressure failure, Global fatigue	Malfunction
Servo drive peristaltic pump	Ambient condition, Power supplier event	Stop
Absolute encoder	Ambient condition, Power supplier event, Unexpected hit	Malfunction

3.1.3. Mechanical Components

Some are subject to movement, degrading and unexpected hits. They are selected with fatigue-resistant materials but may be damaged by wear, environmental conditions, and unexpected hits. Table 3 shows the list of mechanical components in this MSTM, with the failure source and event.

Table 3. Mechanical components in the studied MSTM with failure source and event.

Component	Failure Source	Failure Event
Safety button	Ambient condition, Power supplier event	Stop
Thermal resistance	Ambient condition, Power supplier event	Malfunction
Thermocouple sensor	Global fatigue	Malfunction
Motor belt	Ambient condition, Power supplier event	Stop
Bronze cap	Global fatigue	Malfunction
Linear axis	Global fatigue	Malfunction
Linear bearing	Global fatigue	Malfunction
Peristaltic pump	Ambient condition, Power supplier event	Stop
Terrine cutter	Global fatigue	Malfunction

3.1.4. Pneumatic Components

These components are distributed all over the machine and are subject to degrading and unexpected hits. Table 4 shows the list of pneumatic components in this MSTM, with the failure source and event.

Table 4. Pneumatic components in the studied MSTM with failure source and event.

Component	Failure Source	Failure Event
Pneumatic valve	Ambient condition, Power supplier event, Global fatigue, Pressure failure	Malfunction
Pneumatic cylinder	Ambient condition, Power supplier event, Global fatigue, Pressure failure, Failure pneumatic valve	Malfunction

3.2. Operation Conditions

Operation conditions are different depending on the situation and type de component selected. In this study, the operation conditions assessed are:

- Work temperature;
- Work Humidity, studied by Ingress Protection rating (IP) according to IEC 62262 [36];
- Impact Protection rating (IK) according to IEC 62262 [36].

Table 5 shows the classification of operation conditions and three operation stages defined in this study.

Table 5. Type of operation conditions for temperature, humidity and IK.

Type of Operation Condition	Temperature	Humidity	IK Rating
A	Outdoor and ventilated situation	Indoor with appropriate IP	Indoor and mechanically protected
B	Indoor and ventilated situation	Outdoor with appropriate IP	Outdoor and protected against mechanical shock
C	Indoor and non-ventilated situation	Outdoor with not appropriate IP	Outdoor and not protected against mechanical shock

The authors propose a definition of Global Operation Condition (GOC_i) for each component as a decisive variable to select the appropriate preventive maintenance strategy for the "i" component. This GOC_i is defined by a sequence of three letters (A, B or C) that mention the three operation conditions studied in Step 3 in Section 2 (see Table 5). In general, the structure of a GOC_i is expressed at it follows:

- First letter: Temperature condition (A, B or C);
- Second letter: Humidity condition (A, B or C);
- Third letter: IK rating condition (A, B or C).

So, if we consider, for example, a component with a BAA value of GOC_i, it means the following:

- First letter B: Indoor and ventilated situation;
- Second letter A: Indoor with appropriate IP;
- Third letter A: Indoor and mechanically protected.

3.3. Expressions Proposed for the Preventive Maintenance Study

As stated in Section 1, a failure of most components should lead to a global failure in this type of machine. So, if the critical scenario is studied, the MSTM will present a global failure if a component fails.

The times studied for the failures [28,29] are:

- TTRP: Time to replace a component;
- TTC: Time to configure;
- TTMA: Time to mechanical adjustment;
- TTPR: Time to provisioning;
- MTTR: Mean time to repair;
- MTTF: Mean time to failure;
- MTBF: Mean time between failure;
- TTLR: Line restart time, defined by expert knowledge;
- TLP: Time lost production.

MTTR (1), TLP (2), MTBF (3), efficiency (4) and availability (5) can be calculated with these equations. Efficiency and availability are used as indicators of success in preventive maintenance.

$$\mathrm{MTTR} = \mathrm{TTRP} + \mathrm{TTC} + \mathrm{TTMA} + \mathrm{TTPR} \tag{1}$$

$$\mathrm{TLP} = \mathrm{MTTR} + \mathrm{TTLR} \tag{2}$$

$$\mathrm{MTBF} = \mathrm{MTTR} + \mathrm{MTTF} \tag{3}$$

$$\text{Efficiency} = 1 - \frac{\mathrm{TLP}}{\mathrm{MTTR} + \mathrm{MTTF}} \tag{4}$$

$$\text{Availability} = \frac{\mathrm{MTBF}}{\mathrm{MTBF} + \mathrm{MTTR}} \tag{5}$$

3.4. Preventive Maintenance Strategies for Multistage Thermoforming Machines

The maintenance strategies studied for this MSTM are PPM and IPPM. The efficiency and availability results improve by applying the IPPM strategy. However, applying the IPPM strategy for all the components is not the best scenario for the end user because the stock costs increase. The value of TTLR for both strategies is set at 14,400 s given by the user experience of the machine.

3.4.1. Preventive Programming Maintenance

This strategy uses its own times per component (TTPR, TTC, TTMA, TTRP). All the times are obtained for the usage of the machine. The results are shown in a different table for each type of component.

Table 6 shows the electrical components times and the value of efficiency and availability calculated with Equations (4) and (5).

Table 6. Electrical components times in seconds. Efficiency and availability calculated in % with PPM strategy.

Component	MTTR	TTPR	MTTF	TLP	Efficiency	Availability
Master power switch	14,400	10,800	9,999,999	28,800	99.71%	99.86%
Plug-in relay	14,400	10,800	4,999,999.5	28,800	99.43%	99.71%
Command and signalling	14,400	10,800	4,999,999.5	28,800	99.43%	99.71%
Safety limit switch	14,400	10,800	9,999,999	28,800	99.71%	99.86%

Table 7 shows the electronic components times and the value of efficiency and availability calculated with Equations (4) and (5).

Table 7. Electronic components times in seconds. Efficiency and availability calculated in % with PPM strategy.

Component	MTTR	TTPR	MTTF	TLP	Efficiency	Availability
PLC	435,600	345,600	9,999,999	450,000	95.69%	95.99%
HMI	435,600	345,600	9,999,999	450,000	95.69%	95.99%
Chromatic sensor	176,520	172,800	4,999,999.5	190,920	96.31%	96.70%
Safety relay	14,400	10,800	9,999,999	28,800	99.71%	99.86%
Temperature controller	435,600	345,600	9,999,999	450,000	95.69%	95.99%
Solid-state relay	176,400	172,800	4,999,999.5	190,800	96.31%	96.70%
Frecuency inverter	435,600	345,600	9,999,999	450,000	95.69%	95.99%
Pressure sensor	176,700	172,800	4,999,999.5	191,100	96.31%	96.70%
Servo drive peristaltic pump	435,600	345,600	9,999,999	450,000	95.69%	95.99%
Absolute encoder	360,000	172,800	4,999,999.5	374,400	93.01%	93.71%

Table 8 shows the mechanical components times and the value of efficiency and availability calculated with Equations (4) and (5).

Table 8. Mechanical components times in seconds. Efficiency and availability calculated in % with PPM strategy.

Component	MTTR	TTPR	MTTF	TLP	Efficiency	Availability
Safety button	14,400	10,800	9,999,999	28,800	99.71%	99.86%
Thermal resistance	25,500	10,800	3,700,800	39,900	98.93%	99.32%
Thermocouple sensor	14,700	10,800	3,700,800	29,100	99.22%	99.61%
Motor belt	187,200	172,800	4,999,999.5	201,600	96.11%	96.52%
Bronze cap	288,000	172,800	7,750,000	302,400	96.24%	96.54%
Linear axis	288,000	172,800	7,625,000	302,400	96.18%	96.49%
Linear bearing	288,000	172,800	7,500,000	302,400	96.12%	96.43%
Peristaltic pump	547,200	518,400	4,999,999.5	561,600	89.88%	91.02%
Terrine cutter	288,000	172,800	9,999,999	302,400	97.06%	97.28%

Finally, Table 9 shows the pneumatic components times and the efficiency and availability value calculated with Equations (4) and (5).

Table 9. Pneumatic components times in seconds. Efficiency and availability calculated in % with PPM strategy.

Component	MTTR	TTPR	MTTF	TLP	Efficiency	Availability
Pneumatic valve	176,400	172,800	9,999,999	190,800	98.13%	98.30%
Pneumatic cylinder	176,400	172,800	9,999,999	190,800	98.13%	98.30%

Figure 3 shows a comparative average ratio for efficiency and availability in the PPM strategy by component type.

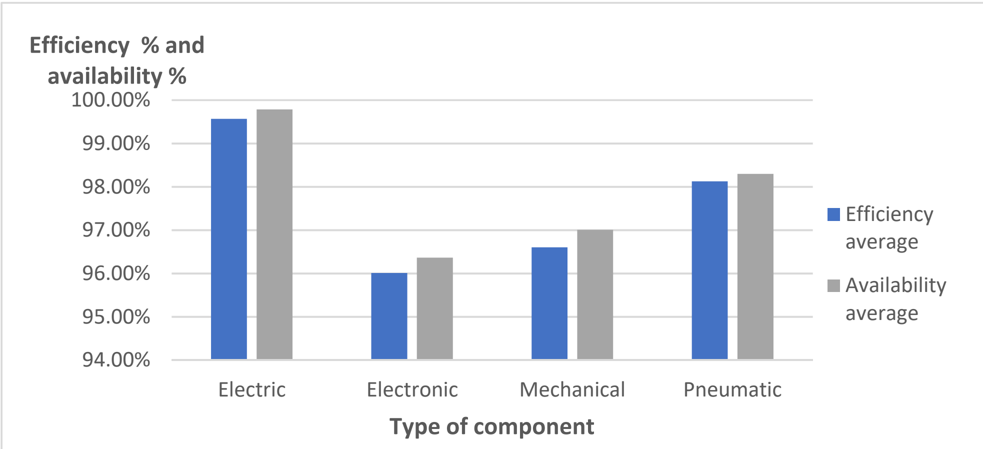

Figure 3. Average efficiency and availability values in % by type of component with the PPM strategy.

Electrical components have the higher average values of efficiency and availability, with a maximum value of 99.71% in efficiency and availability.

Figure 4 also shows the maximum and minimum values for each type of component. Here, the minimum efficiency and availability values of electronic and mechanical components suggest using another maintenance strategy. The machine efficiency and availability levels depend on the efficiency and availability of all the components. So, the objective of the maintenance strategy is to achieve higher efficiency and availability for all the components and not for just many components.

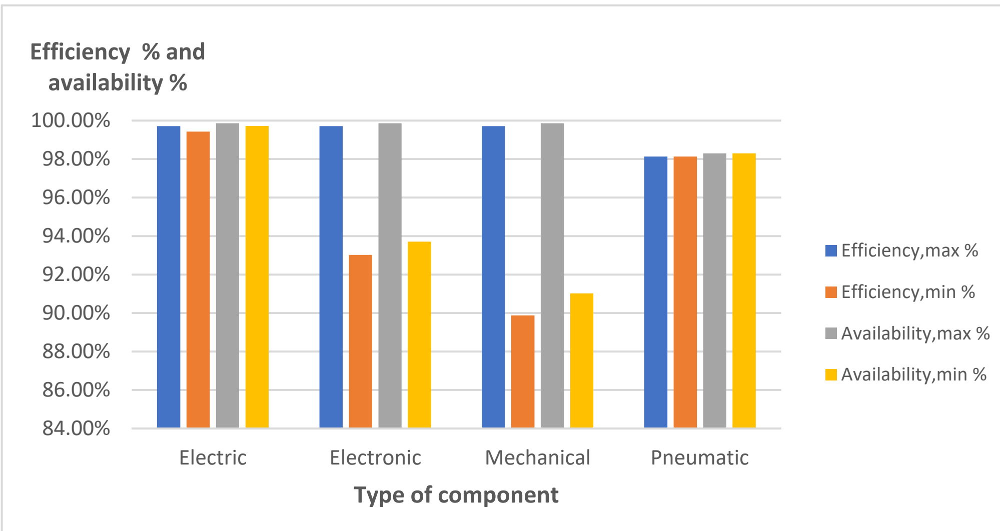

Figure 4. Maximum and minimum efficiency and availability values in % by type of component with the PPM strategy.

3.4.2. Improve Preventive Programming Maintenance

The IPPM strategy is based on reducing the TTPR time for all the components by increasing the security stocks for the components. The TTPR value in this strategy is a residual value consisting in the transport and picking time to machine of the component waiting for in the safety stock.

Table 10 shows the electrical components times and the efficiency and availability values calculated with Equations (4) and (5).

Table 10. Electrical component times in seconds. Efficiency and availability calculated in % with the IPPM strategy.

Component	MTTR	TTPR	MTTF	TLP	Efficiency	Availability
Master power switch	3900	300	9,999,999	18,300	99.82%	99.96%
Plug-in relay	3900	300	4,999,999.5	18,300	99.63%	99.92%
Command and signalling	3900	300	4,999,999.5	18,300	99.63%	99.92%
Safety limit switch	3900	300	9,999,999	18,300	99.82%	99.96%

Table 11 shows the electronic components times and the efficiency and availability values calculated with Equations (4) and (5).

Table 11. Electronic component times in seconds. Efficiency and availability calculated in % with IPPM strategy.

Component	MTTR	TTPR	MTTF	TLP	Efficiency	Availability
PLC	90,300	300	9,999,999	104,700	98.96%	99.11%
HMI	90,300	300	9,999,999	104,700	98.96%	99.11%
Chromatic sensor	4020	300	4,999,999.5	18,420	99.63%	99.92%
Safety relay	3900	300	9,999,999	18,300	99.82%	99.96%
Temperature controller	90,300	300	9,999,999	104,700	98.96%	99.11%
Solid-state relay	3900	300	4,999,999.5	18,300	99.63%	99.92%
Frecuency inverter	90,300	300	9,999,999	104,700	98.96%	99.11%
Pressure sensor	4200	300	4,999,999.5	18,600	99.63%	99.92%
Servo drive peristaltic pump	90,300	300	9,999,999	104,700	98.96%	99.11%
Absolute encoder	187,500	300	4,999,999.5	201,900	96.11%	96.51%

Table 12 shows the mechanical components times and the efficiency and availability values calculated with Equations (4) and (5).

Table 12. Mechanical component times in seconds. Efficiency and availability calculated in % with the IPPM strategy.

Component	MTTR	TTPR	MTTF	TLP	Efficiency	Availability
Safety button	3900	300	9,999,999	18,300	99.82%	99.96%
Thermal resistance	15,000	300	3,700,800	29,400	99.21%	99.60%
Thermocouple sensor	4200	300	3,700,800	18,600	99.50%	99.89%
Motor belt	14,700	300	4,999,999.5	29,100	99.42%	99.71%
Bronze cap	115,500	300	7,750,000	129,900	98.35%	98.55%
Linear axis	115,500	300	7,625,000	129,000	98.32%	98.53%
Linear bearing	115,500	300	7,500,000	129,900	98.29%	98.51%
Peristaltic pump	29,100	300	4,999,999.5	43,500	99.14%	99.42%
Terrine cutter	115,500	300	9,999,999	129,900	98.72%	98.87%

Finally, Table 13 shows the pneumatic components times and the efficiency and availability values calculated with Equations (4) and (5).

Table 13. Pneumatic component times in seconds. Efficiency and availability calculated in % with the IPPM strategy.

Component	MTTR	TTPR	MTTF	TLP	Efficiency	Availability
Pneumatic valve	3900	300	9,999,999	18,300	99.82%	99.96%
Pneumatic cylinder	3900	300	9,999,999	18,300	99.82%	99.96%

As with Figures 3 and 5 shows a comparative average ratio for efficiency and availability in the IPPM strategy by component type.

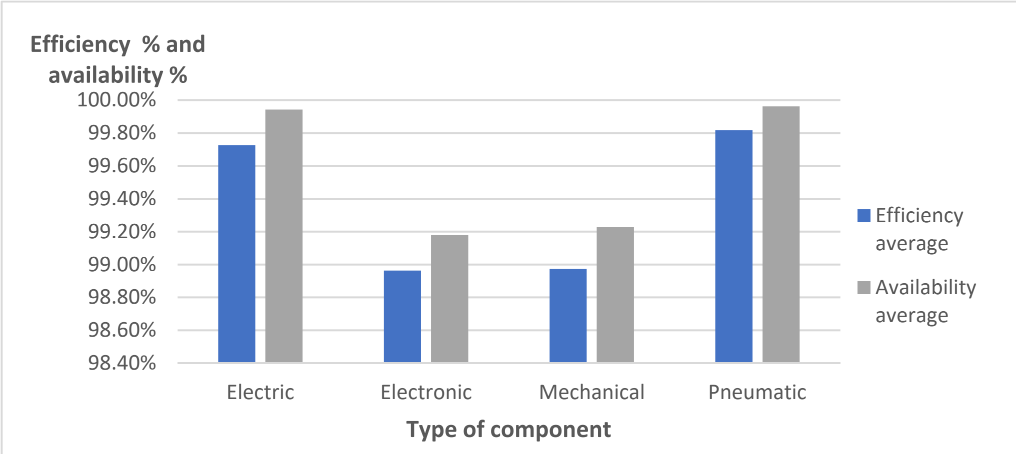

Figure 5. Average efficiency and availability values in % by component type with the IPPM strategy.

When comparing Figures 3 and 5, the efficiency and availability increase their values in all components, especially in pneumatic components. Electronic and mechanical components also increase their values. Figure 6 show the minimum and maximum new efficiency and availability values when applying the IPPM strategy.

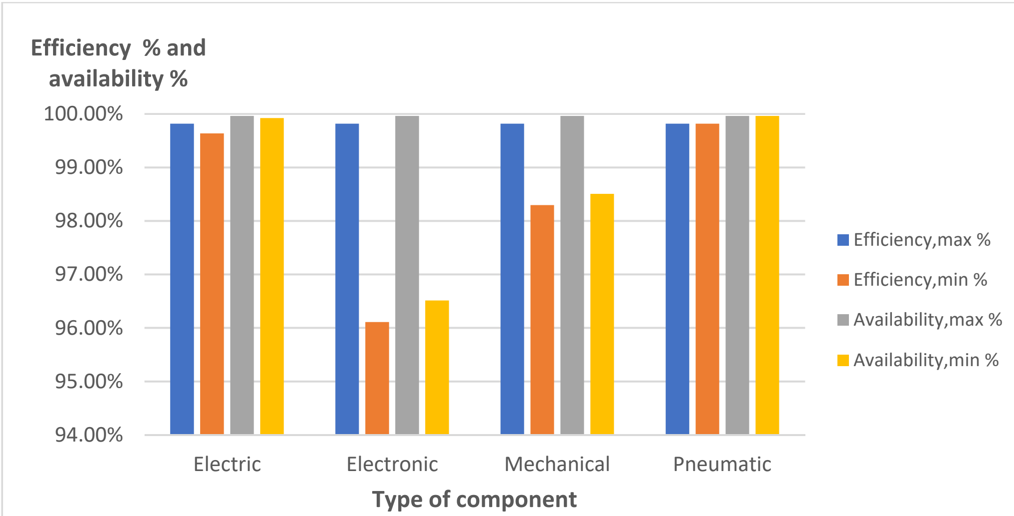

Figure 6. Maximum and minimum efficiency and availability values in % by component type with the IPPM strategy.

A simple comparison between Figures 4 and 6 show the increase obtained in pneumatic components by applying the IPPM strategy. Their efficiency and availability levels improve to above 99.82% values. Electronic and mechanical components also improve their minimum efficiency and availability values by 3.09% and 2.81% for electronic components and 8.42% and 7.48% for mechanical components. Increasing the components' minimum efficiency and availability values allows for improving MSTM efficiency and availability globally.

3.5. Selection of Preventive Maintenance Strategies

The results obtained by applying the PPM and IPPM strategies show very interesting efficiency and availability values, but in the same machine, as is well-known, all the components do not have to use the same maintenance strategy. In this section, the authors propose a singular study that allows for selecting the best strategy for each component. This selection depends on parameters such as type of component, operation condition and own time values of all the components.

3.5.1. Parameter for the Selection under Study

An analysis of the results obtained when applying PPM and IPPM shows that component type is an important parameter for deciding on preventive maintenance strategy. For example, applying IPPM in electrical components does not show a remarkable increase, so the conclusion could be not applying IPPM in electrical components.

The operation conditions in Table 5 denote the relevance of the adequate operation conditions for all the components by selecting the appropriate tolerance to temperature and an appropriate value of IP and IK ratings. A high-quality component working in inadequate operation conditions, compared with their datasheet, could entail unexpected failures and a decrease in efficiency and availability of the MSTM. Each component may have an individual condition, shown by three letters A, B or C for this study.

Attending to the definition of each operation condition, it is easy to understand that many combinations of operation conditions cannot exist simultaneously. For example, a component cannot be located indoors and outdoors, so combinations such as AAA are impossible.

Individual maintenance times of all the components allow for knowing the influence of the MMTR and TLP times in the efficiency and availability of the MSTM, so for this study, these KPIs are used:

$$KPI_1 = (MTTR - TTPR)/MTTR \tag{6}$$

$$KPI_2 = TTPR/TLP \tag{7}$$

Equation (6) states the influence of the TTPR in MTTR. For this KPI_1 singular value is used at 25% result.

Equation (7) also shows the influence of the TTPR in the TLP (see Equation (2)). A Higher value of TTPR greater than TLR could entail a considerable stop time in the MSTM and the assumption of undesirable opportunity costs. In this $KPI_{2,}$ the singular value used is 70% result.

3.5.2. N-Dimensional Matrix for Preventive Maintenance Selection

Using the three parameters explained in the previous subsection, an n-dimensional matrix is proposed to select the appropriate maintenance strategy for the component, where *n* is set in five dimensions:

- Operation condition;
- Type of component;
- Value of Equation (6);
- Value of Equation (7);
- Combination of Equations (6) and (7) values.

To understand and use this 5-dimension matrix, the authors propose a plane conversion in which the operation condition is the column, and the rest of the conditions are fixed in mixed lines, as shown in Table 14.

Table 14. N-dimensional matrix for preventive maintenance selection in MSTM.

Type of Component	KPI	Operation Condition					
		ABB	ABC	ACB	ACC	BAA	CAA
Electrical	$KPI_1 > 25\%$ $KPI_2 < 70\%$	II	III	II	III	II	II
	$KPI_1 < 25\%$	I	II	II	II	I	II
	$KPI_2 > 70\%$	III	III	III	III	III	III
Electronic	$KPI_1 > 25\%$ $KPI_2 < 70\%$	II	III	III	III	II	III
	$KPI_1 < 25\%$	II	III	II	III	II	III
	$KPI_2 > 70\%$	III	III	III	III	III	III

Table 14. *Cont*.

Type of Component	KPI	Operation Condition					
		ABB	ABC	ACB	ACC	BAA	CAA
Mechanical	$KPI_1 > 25\%$ $KPI_2 < 70\%$	II	III	II	III	II	III
	$KPI_1 < 25\%$	I	III	I	III	I	III
	$KPI_2 > 70\%$	III	III	III	III	III	III
Pneumatic	$KPI_1 > 25\%$ $KPI_2 < 70\%$	II	III	III	III	III	III
	$KPI_1 < 25\%$	II	III	II	III	III	III
	$KPI_2 > 70\%$	III	III	III	III	III	III

Selection I indicates PPM strategy; selection III indicates IPPM strategy, and; selection II shows an intermediate situation between PPM and IPPM strategies, where there is a special consideration of the necessary constant for analysing the TTPR of each component. Selection II is called "Interval PPM to IPPM strategy" in this paper.

4. Results

Applying the n-dimensional matrix for the preventive maintenance strategy in the components of a multistage thermoforming machine allows for improving efficiency and availability. Table 15 shows the application of the n-matrix in this study.

Table 15. Results and comparison of the application of n-dimensional matrix for maintenance strategy decision.

	PPM Strategy		IPPM Strategy		N-MATRIX PROPOSAL		
Component	Efficiency	Availability	Efficiency	Availability	Efficiency	Availability	Maintenance Strategy
Master power switch	99.71%	99.86%	99.82%	99.96%	99.71%	99.86%	PPM
PLC	95.69%	95.99%	98.96%	99.11%	98.96%	99.11%	IPPM
HMI	95.69%	95.99%	98.96%	99.11%	98.96%	99.11%	IPPM
Chromatic sensor	96.31%	96.70%	99.63%	99.92%	99.63%	99.92%	IPPM
Plug-in relay	99.43%	99.71%	99.63%	99.92%	99.43%	99.71%	PPM
Command and signalling	99.43%	99.71%	99.63%	99.92%	99.43%	99.71%	PPM
Safety limit switch	99.71%	99.86%	99.82%	99.96%	99.71%	99.86%	PPM
Safety relay	99.71%	99.86%	99.82%	99.96%	99.71%	99.86%	PPM
Safety button	99.71%	99.86%	99.82%	99.96%	99.71%	99.86%	PPM
Temperature controller	95.69%	95.99%	98.96%	99.11%	98.96%	99.11%	IPPM
Solid-state relay	96.31%	96.70%	99.63%	99.92%	99.63%	99.92%	IPPM
Thermal resistance	98.93%	99.32%	99.21%	99.60%	98.93%	99.32%	Interval PPM to IPPM
Thermocouple sensor	99.22%	99.61%	99.50%	99.89%	99.22%	99.61%	Interval PPM to IPPM
Frequency inverter	95.69%	95.99%	98.96%	99.11%	98.96%	99.11%	IPPM
Motor belt	96.11%	96.52%	99.42%	99.71%	99.42%	99.71%	IPPM
Bronze cap	96.24%	96.54%	98.35%	98.55%	96.24%	96.54%	PPM to IPPM Interval
Linear axis	96.18%	96.49%	98.32%	98.53%	96.18%	96.49%	PPM to PPM Interval
Linear bearing	96.12%	96.43%	98.29%	98.51%	96.12%	96.43%	PPM to PPM Interval
Pneumatic valve	98.13%	98.30%	99.82%	99.96%	99.82%	99.96%	IPPM
Pneumatic cylinder	98.13%	98.30%	99.82%	99.96%	99.82%	99.96%	IPPM
Pressure sensor	96.31%	96.70%	99.63%	99.92%	99.63%	99.92%	IPPM
Servo drive peristaltic pump	95.69%	95.99%	98.96%	99.11%	98.96%	99.11%	IPPM
Peristaltic pump	89.88%	91.02%	99.14%	99.42%	99.14%	99.42%	IPPM
Terrine cutter	97.06%	97.28%	98.72%	98.87%	97.06%	97.28%	PPM to IPPM Interval
Absolute encoder	93.01%	93.71%	96.11%	96.51%	93.01%	93.71%	PPM to IPPM Interval

The comparison of combined average values for all the components by efficiency and availability is shown in Figure 7.

The average values show that a mixed preventive maintenance strategy for the components in a machine is an efficient solution to reach reasonable values of efficiency and availability. The IPPM strategy provides better results for all the components but can increase the maintenance cost for the whole machine, due to PPM strategy does not need stock of components and IPPM strategy that needs stock for all the components (see the beginning of the Section 3.4.2.).

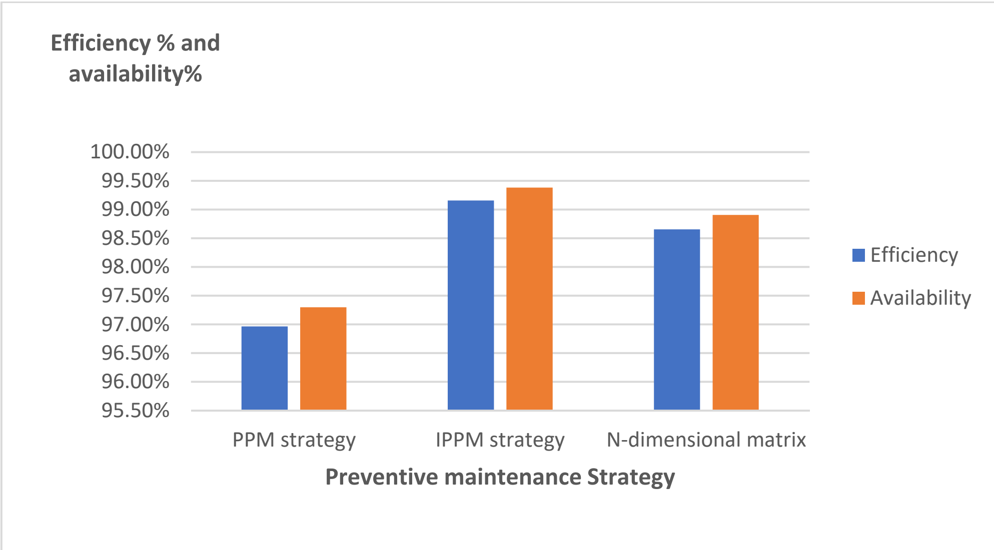

Figure 7. Comparison of mixed average values in applying the PPM strategy, the IPPM strategy and the n-dimensional matrix preventive maintenance proposal.

5. Results Discussion

The results obtained showed an optimisation procedure to select the appropriate maintenance strategy for different components in a multistage machine. Table 16 shows the efficiency and availability improvements comparing PPM and IPPM strategies for type of component.

Table 16. Efficiency and availability improvements comparing PPM and IPPM strategies for type of component.

Type of Component	Efficiency Maximum %	Efficiency Minimum %	Availability Maximum %	Availability Minimum %	Efficiency Average	Availability Average
Electrical	0.10%	0.21%	0.10%	0.21%	0.16%	0.16%
Electronic	0.10%	3.09%	0.10%	2.81%	2.95%	2.82%
Mechanical	0.10%	8.42%	0.10%	7.48%	2.37%	2.22%
Pneumatic	1.69%	1.69%	1.66%	1.66%	1.69%	1.66%

For Electrical components, the possibility to not use IPPM strategy selected for a component that only needs PPM strategy is an improve of the global maintenance strategy for the machine. See maximum, minimum and average compared values of efficiency and availability in electrical components.

In the case of Electronic and Mechanical components, the IPPM application improves the efficiency and availability values; this is also demonstrated in Pneumatic components, with minor improvement values in efficiency.

The application of *n* dimensional matrix can reduce maintenance costs. In this machine, the application of different strategies for each component supposes a change in the number of components that require stock due to their strategy adopted. Table 15 shows the maintenance strategy proposed for n-matrix. Table 17 shows the number of each component used in the MSTM and then compares the number of those that need stock depending on their maintenance strategy adopted, PPM, IPPM and n-matrix. In the outlined comparison data, the authors use two scenarios with n-matrix:

- Scenario one. The denominated "PPM to IPPM Interval" used in Table 15 is declined to PPM strategy, so the components do not need stock;
- Scenario two. The denominated "PPM to IPPM Interval" used in Table 15 is declined to IPPM strategy, so the components need stock.

Table 17. Comparing the number of type of components that require stock due to the maintenance strategy adopted.

Number of Type Component	Component	Number of Components Who Require Stock due to Their Maintenance Strategy Adopted			
		PPM Strategy	IPPM Strategy	N-Matrix (Scenario One)	N-Matrix (Scenario Two)
1	Master power switch	0	1	0	0
1	PLC	0	1	1	1
1	HMI	0	1	1	1
1	Chromatic sensor	0	1	1	1
3	Plug-in relay	0	3	0	0
1	Command and signalling	0	1	0	0
1	Safety limit switch	0	1	0	0
1	Safety relay	0	1	0	0
1	Safety button	0	1	0	0
4	Temperature controller	0	4	4	4
4	Solid state relay	0	4	4	4
4	Thermal resistance	0	4	0	4
4	Thermocouple sensor	0	4	0	4
2	Frequency inverter	0	2	2	2
2	Motor Belt	0	2	2	2
8	Bronze cap	0	8	0	8
1	Linear axis	0	1	0	1
8	Linear bearing	0	8	0	8
4	Pneumatic valve	0	4	4	4
6	Pneumatic cylinder	0	6	6	6
2	Pressure sensor	0	2	2	2
1	Servo drive peristaltic pump	0	1	1	1
3	Peristaltic pump	0	3	3	3
1	Terrine cutter	0	1	0	1
1	Absolute encoder	0	1	0	1

The application of n-matrix supposes a decrease in number of components that required stock due to the maintenance strategy adopted. According to Table 17, Figure 8 shows the global number of components that require stock due to their maintenance strategy.

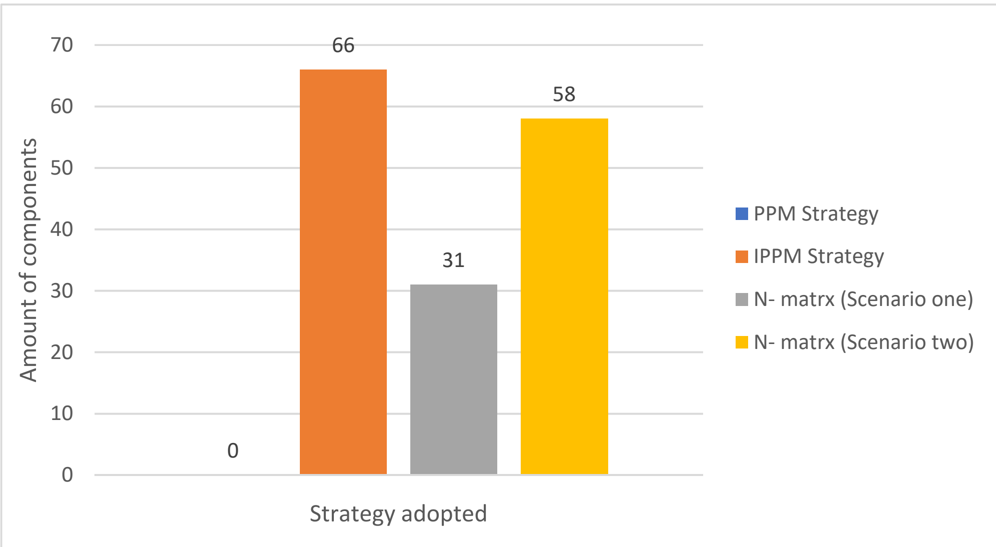

Figure 8. Comparison of the global number of components that require stock due to the maintenance strategy adopted.

Depending on the scenario adopted with n-matrix, the decrease in the number of components that require stock is between 12.12% and 53.03%. It is easy to understand that this decrease will mean decreases in maintenance costs.

Additionally, as Figure 7 shows, the efficiency and availability ratios are maintained in higher values. For more understanding, the authors consider relevant the analysis of efficiency and availability values with the application of PPM, IPPM and n-dimensional matrix strategies as follows:

- The comparison of PPM and n-dimensional matrix strategies, shown in Figure 7, indicates an improve of 1.65% in efficiency and 1.6% in availability.
- The comparison of IPPM and n-dimensional matrix strategies indicates a decrease of 0.51% in efficiency and 0.48% in availability.
- The comparison of PPM and IPPM shows the higher average values, situated at 2.16% in efficiency and 2.08% in availability.

So, the decrease in values of efficiency and availability caused by the application of n-matrix compared with IPPM strategies allows for applying the n-dimensional matrix for the optimal strategy for each component.

The authors consider that the results shown in Table 14 indicate that the KPI_1 and KPI_2, defined in Section 3.5.1, suggest a precise cost study for the best decision making. This study can offer the negative impact of a component failure due to its main time to repair and line restart time, as a new dimension for the proposed matrix.

Table 15 shows a Maintenance Strategy called *PPM to IPPM Interval*. For real case, a strategy PPM or IPPM must be selected for this component, so the authors consider important the cost analysis for this decision.

6. Conclusions

The preventive maintenance strategy for all the components of a multistage machine depends on the individual maintenance times and depends on the operation condition of each type of component. In this way, the definition of the Global Operation Condition (GOCi.) for each component allows for the study of the optimal preventive maintenance strategy used, PPM or IPPM.

The authors consider the application of the methodology used in this research relevant, step by step, for other industrial multistage or single machines, due to the fact that multistage and single machines need an appropriate preventive maintenance strategy for all their components.

Obtaining an n-dimensional matrix to select the best preventive maintenance strategy by type of component allows for maintaining a higher values of efficiency and availability for type of components. A minor decrease compared with IPPM strategy (see Table 16) is offset by the decrease on stock cost. The end users of the industrial multistage or single machines always need information and procedures to applying the appropriate maintenance strategy, so this contribution allows them to fulfill that need.

The location of a component in the machine allows for knowing the Global Operation Condition (GOCi) depending on the individual maintenance times and makes it possible to find the same type of components with different preventive maintenance strategies proposed by the n-dimensional matrix. In this way, the results shown and discussed in this research can be interesting for the industrial machinery manufacturer, by the preliminary study of the optimal operation condition for each component of the machine.

For the preventive maintenance strategy, it is necessary to study the individual maintenance times as it shown in Section 3.3. Additionally, the analysis of the individual values of TTPR, TLP, MTTR for each component allows for calculating the KPI's used by the n-dimensional matrix. These KPIs are different, as shown in EN 15341:2007, but allow new results.

For a more precise decision with the *PPM to IPPM Interval* maintenance strategy proposed by the n-dimensional matrix (see Table 15), it will be interesting to study the cost of all the components as a new dimension of the matrix.

The authors consider the following future research:

With the applied methodology of this research and given the recent increase in materials costs, it is suggested to study the analysis of the impact and variation in the cost of the components to decide the best preventive maintenance strategy, using a new dimension n-dimensional matrix.

Selective study of the suitability of components with high TTPR in multistage machines significantly influences the efficiency and availability of the industrial multistage machine. This study can determinate the maximum TTPR to maintain the adequate preventive maintenance strategy and then suggest the possible change of the component for another with minor TTPR.

Application of n-dimensional matrix in other multistage industrial machines. Results and comparison of the same used methodology in this research.

Adding predictive maintenance strategy in n-dimensional matrix for undefined interval PPM and IPPM maintenance strategies.

Author Contributions: Conceptualisation, F.J.Á.G. and D.R.S.; methodology, F.J.Á.G.; validation, F.J.Á.G. and D.R.S.; formal analysis, F.J.Á.G.; investigation, F.J.Á.G. and D.R.S.; resources, F.J.Á.G.; writing-original draft preparation, F.J.Á.G.; writing-review and editing, F.J.Á.G. and D.R.S.; visualisation, F.J.Á.G.; supervision F.J.Á.G.; project administration, F.J.Á.G. and D.R.S.; funding acquisition, F.J.Á.G. and D.R.S. All authors have read and agreed to the published version of the manuscript.

Funding: This study has been carried out through the Research Project GR-18029 linked to the VI Regional Research and Innovation Plan of the Regional Government of Extremadura.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors wish to thank the European Regional Development Fund "Una manera de hacer Europa" for their support towards this research. This study has been carried out through the Research Project GR-21098 linked to the VI Regional Research and Innovation Plan of the Regional Government of Extremadura.

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

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5

PAPER -III: AN APPROACH FOR PREDICTIVE MAINTENANCE DECISIONS FOR COMPONENTS OF AN INDUSTRIAL MULTISTAGE MACHINE THAT FAIL BEFORE THEIR MTTF. A CASE STUDY.

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Revista: Systems ISSN 2079-8954.

Datos edición: 2022, Volume 10, Issue 5, 174.

Temática especial: Data Driven Decision-making for Complex Production Systems.

Fecha publicación: *29 Septiembre 2022*

DOI: https://doi.org/10.3390/systems10050175 systems

Article

An Approach for Predictive Maintenance Decisions for Components of an Industrial Multistage Machine That Fail before Their MTTF: A Case Study

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Abstract: Making the correct maintenance strategy decision for industrial multistage machines (MSTM) is a constant challenge for industrial manufacturers. Preventive maintenance strategies are the most popular and provide interesting results but cannot prevent unexpected failures and consequences, such as time lost production (TLP). In these cases, a predictive maintenance strategy should be used to maintain the appropriate level of operation time. This research aims to present a model to identify the component that failed before its mean time to failure (MTTF) and, depending on whether the cause of the failure is known, propose the use of a predictive maintenance strategy and further decision-making to ensure the highest possible value from operating time. Also, it is necessary to check the reliable value of MTTF before taking certain decisions. For this research, a real case study of a MSTM was characterized component by component, setting the individual maintenance times. The initial maintenance strategy used for all the components is the preventive programming maintenance (PPM). If a component presents an unexpected failure, a method is proposed to decide whether the maintenance strategy should be changed, adding a predictive maintenance strategy to monitor said component. The research also provides a trust level to evaluate the reliable value of MTTF of each component. The authors consider this approach very useful for machine manufacturers and end users.

Keywords: predictive maintenance; multistage machine; sensorisation; decision-making; mean time to failure; algorithm; system

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Citation: García, F.J.Á.; Salgado, D.R. An Approach for Predictive Maintenance Decisions for Components of an Industrial Multistage Machine That Fail before Their MTTF: A Case Study. *Systems* **2022**, *10*, 175. https://doi.org/10.3390/systems10050175

Academic Editor: Ed Pohl

Received: 17 July 2022
Accepted: 26 September 2022
Published: 29 September 2022

1. Introduction

Multistage machines (MSTM) are quite common in the manufacturing processes industry. These machines are more complex than single-stage machines. The diversity of components and coordinated steps or successive transformations they perform entails the need to establish an adequate maintenance strategy for each component.

It is very important to bear in mind that a failure in one of the components of a multistage industrial machine can lead to a failure in the whole machine. Due to this condition, the best maintenance policy must combine the most suitable strategies for each component. Different components of the same multistage machine may well have different maintenance strategies depending on their maintenance parameters that affect their mean time to repair (MTTR). Once the component has been repaired or substituted, the machine must return to its normal work rhythm and needs time to restart the line (TTLR).

The success in the use of these machines is to meet high demands without unexpected failures that involve the loss of production in progress and a high operation recovery time. Due to this, it is very important that the components of the machine are reliable. If these components have an individual MTTF, this time must be reliable to establish maintenance policies that allow for optimizing the stop-operation time; it is necessary to have the right components, and reliable MTTF. Also it is very important that the main devices and location components used in the MSTM are correct, in order to eliminate avoidable failures. If the MTTF is reliable, it is therefore possible to program the preventive maintenance, so it is necessary to establish the adequate time to maintenance that does not affect the scheduled production.

Preventive maintenance is the most popular strategy in industrial manufacturing systems. Therefore, there must be an adequate level of stocks of components based on a mathematical model proposed in the decision-making strategy. The optimal decision process for setting time to production and time to maintenance programming is studied by A. Gharbi [1], namely, how to develop a mathematical model based on the cost for optimal decision making. A. Gharbi's [2] research also found the most appropriate production rate and preventive maintenance schedule that minimizes the total cost of maintenance and inventory/backlog in periodic preventive maintenance.

As already known, for established scheduled preventive times, is important to define what to do in these times. MTTR considers time to provisioning, time to replacement or removal of component, time to configuration or setting and time to mechanical adjustments. H. Jun-Hee [3] proposed in his research that periodic machine maintenance for single machines and flow-shop scheduling models should be based on an algorithm, minimizing the total weighted completion time. His work defines two principal maintenance actions, setup operations and removal operations, in a production system based on a sequence of single-stage machines. If a removal or setting time is required, a lateness time must be considered. As an in-line process needs to be functioning with stage coordination, is very important to measure the operation times and make the maintenance decisions. If the functioning of the MSTM requires setting maintenance operations during the times of normal operations, this can affect the cycle operation time of the whole machine, and some lateness times must be studied before the maintenance of the machine begins. Other studies have proposed how to realize the appropriate preventive maintenance with imperfect actions, while continuing the normal operation condition, as J. Zuhua [4] showed how to create function blocs in a Programming Logic Controller (PLC) with a previous data acquisition system.

But the important question for preventive maintenance is how to accomplish it, and what might be the appropriate procedure, depending on the system's definition and its complexity. Hernández, D.R. [5] modeled a discrete-time infinite horizon Markov Decision Problem, and F. Chiacchio [6] a stochastic-hybrid reliability model. Other studies, such as M. Fujishima [7], have calculated the optimal time to start preventive maintenance before an unexpected failure. A recent study by A. Irfan [8] modelled a series-parallel system, proposing a reliability model using a Lagrangian optimization method to guarantee MTTF values and avoid unexpected failures. Also, when an unexpected failure occurs, some essential information should be known. For example, the cause of the failure is important, whether the cause stems from a poor design of the machine or an incorrect location of the component, or whether the cause can be eliminated altogether to restore the machine's functioning with a higher level of availability and security. Also, it is important to determine whether the cause is a normal or an occasional (infrequent) situation.

All the components of a machine are always subject, at least, to the laws of degradation. Therefore, even working in its ideal operating conditions, the component will end up failing. In this sense, it would be appropriate to be able to calculate the reliability, as in D.M. Frangopol [9], of the component in the whole machine. However, this study is very complex and normally the manufacturer of the components only defines normal working conditions and sometimes the operating time. Therefore, it is necessary to study models that evaluate whether the component is suitable for the machine and if it is, whether it is so in the normal operation of the machine. G. Silva [10] proposes a model to decide on the most suitable maintenance strategy for the obsolescence of electronic components by creating a decision-making tool, and analyzing the risks, the obsolescence of the components and the consequences of a failure. Recent research by Garcia, F.J.Á. and Salgado, D.R. [11] has proposed a matrix to decide the optimal preventive maintenance strategy based on the individual maintenance times of all the components, their approximate location (global operation condition (GOC)) in the machine, and two key performance indicators (KPIs). The results of both papers describe situations where the component may have different maintenance strategies. If a component fails multiple times, a failure mode and effect analysis (FMEA) can be the solution for finding a design error in the machine, in the component, or an inadequate component selection for the normal operation condition required by the machine. In this way, T. Yuk-Ming [12] has highlighted the importance of product design in the future reliability of the components that must work within certain operating conditions. Product design and functional performance have been shown to be the main research foci in this area.

Predictive maintenance strategies have been shown to be able to avoid unexpected failures by monitoring the operation of the machine using sensors (P. Ponce [13]) and machine learning algorithms to know the normal behavior of the components or of the machine. Dolatabadi, S.H. [14] has provided an overview of past articles highlighting the major expectations, requirements, and challenges for small and medium-sized enterprises (SMEs) regarding the implementation of predictive maintenance (PdM). Normally, the PdM based on algorithms have several steps: data acquisition, data manipulation, configuration, aggregation, and prediction model (the condition monitoring sub-model); and maintenance decision-making, scheduling, and status (the maintenance sub-model). Sometimes, the main algorithm or calculating process is embedded in a PLC, as discussed in Cavalieri, S. [15] and Bouabdallaoui, Y.S. [16].

The study by Garcia, F.J.Á. and Salgado, D.R. [17] described a way to present the available strategies for multistage industrial machines. Their paper describes preventive strategies (with or without stock) and developed predictive strategies like digital behavior twin (DBT), composed of an algorithm with no need to learn normal behavior. S. Givnan [18] studied the normal behavior of the components of an industrial machine for early failure detection by using a machine learning model based on feed-forward neuronal networks trained to identify normal and abnormal behavior. One of the best advantages of the algorithms and the machine learning models is the time necessary to train the model to identify the normal behavior of the machine. Industries need, to the degree possible, simple, fast and reliable systems to take decisions about the availability of their machines in order to avoid unexpected failures. M.M.L. Pfaff [19] developed and tested an adaptive algorithm in a real environment. This algorithm created a dynamic limit value using an adaptive characteristic value segmentation. The paper also studied the location of the sensors for predictive maintenance and confirmed that location can significantly affect the measurement result and, thus, has a direct impact on the outcome of the data analysis. One of the advantages of this research is that there is no need to train the algorithm; the application does not require in-depth process knowledge.

As the technical decisions to take maintenance actions can be provided by the analysis of technical data, normal behavior trained, or not trained, by the adopted predictive algorithm, some authors have mixed the machine learning study with the cost of the maintenance to take global predictive maintenance decisions, as in E. Florian [20] and S.Arena [21], by using, in this case, the Decision Tree technique (DTs) process of implementing predictive maintenance (PdM) and also detecting potential failures (identified through FMEA analysis) and evaluating direct and indirect maintenance costs. It is very important to evaluate a FMEA analysis where a possible failure design of the machine can be the reason of repeated failures.

The digital twin (DT) concept, based on cyber physical systems (CBS) (C. Stary [22]), is a good way to study predictive maintenance and the behavior of the machine if it works under different operating conditions. J. O'Sullivan [23] studied the adoption of digital twins by the maintenance engineering industry to aid in predicting problems before they occur. The algorithm used provided three alarm levels to identify action before a failure.

But not all MSTM can be modelled with a digital twin, due to the fact that these machines normally are highly customized and adapted to the needs of each end user, and therefore since they are not mass-produced, they would require the development of their specific digital twin.

New models embedded in industry 4.0 and created to control corrective maintenance actions are based on a system built on the augmented reality (AR) or computer vision (CV). These systems are used when the machine must be maintained with non-expert operators, and the support of the system can drive the maintenance action with the most success, and in the optimal time. As it can understand the machine, this supporting system minimizes the MTTR and lets the availability of the machine remain in the highest degree possible. Similarly, the work of Konstantinidis, F.K. [24] and Z. Haihua [25] also attempts to solve unexpected failures that are not stored in the maintenance-experience database.

Little of the literature focuses on the simultaneous study of different preventive and predictive maintenance strategies at the same time in the same system. In the case of the MSTM, such studies are non-existent. An interesting paper of H. Wang [26] focuses on a DT-enabled integrated optimization problem of flexible job shop scheduling and flexible preventive maintenance (PM), considering both machine and worker resources. This approach is interesting, particularly if it is possible to open a flexible window to preventive maintenance actions and let the system constantly work with the monitoring of predictive maintenance policy. The architecture of a DT-enhanced job shop is developed, and then the end user has a method to take decisions for the maintenance actions.

This research aims to present a model to identify the component that has failed before its MTTF and, depending on whether or not the cause of the failure is known and the time to restart the normal functioning of the machine, propose the use of a predictive maintenance strategy and further decision-making to ensure the highest possible value from the machine's operating time. For this research, a real case study has been characterized component-by-component, studying the individual maintenance times to obtain the time lost production (TLP) for each component. Figure 1 shows the features of a multistage machine and the conditions on which the proposed maintenance strategies are based.

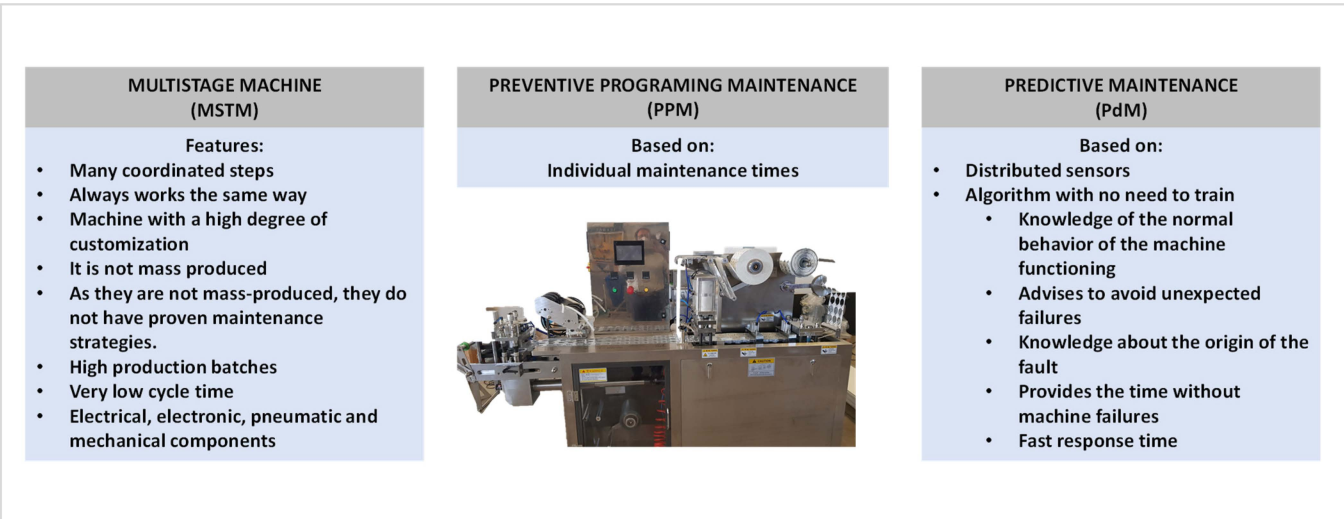

Figure 1. Features of a MSTM and main conditions of maintenance policy.

This approach determines the focus of the maintenance strategies, which are always aimed at rapid response, and calculated to avoid unexpected failures, and minimize TLP.

2. Materials and Methods

The machine worked for a year with a preventive maintenance system based on the previously characterized components. An algorithm for predictive maintenance was adopted in the beginning, but only to advise if a component had failed before its MTTF. The authors used a digital behavior twin algorithm [17] for predictive maintenance in this case. A comparison of the components that presented failures before their MTTF is given below. The results allow future users to add predictive maintenance for the components needing supervision to avoid unexpected failures and probable industrial costs for lost production time and quality production.

Below is the methodology used in this research, ordered by steps:

- Step One: The multistage thermoforming machine was selected as the case study. This machine was characterized, and all the components were identified and classified by type. See Section 2.1.
- Step Two: Reliable maintenance times were defined for each component. Importantly, an adequate MTTF was established for each component. See Section 2.2.
- Step Three: Possible preventive maintenance strategies were defined, and predictive maintenance strategies adopted. See Section 2.3.
- Step Four: The components that presented a failure before their MTTF after a year of working were studied. See Section 2.4.
- Step Five: For all of the components, the advice shown by the DBT predictive algorithm was presented to ascertain which failures could be identified before occurring unexpectedly. The advice does not entail a change of maintenance strategy. The only purpose of these dates was for use in data logging. See Section 2.5.
- Step Six: The authors proposed a procedure to make decisions for possible maintenance strategy changes in the components studied by looking for the cause of the failure and then by evaluating two key performance indicators (KPIs). See Section 2.6.

The results, discussion, conclusions, and future research are shown in Sections 3–5.

2.1. The Case Study: A Multistage Thermoforming Machine

Thermoforming and tub filling machines are one of many cases, and this study covers this type of machine. Figure 2 shows the MSTM and the placement of the components. The seven steps are identified, together with the main operation in each of them.

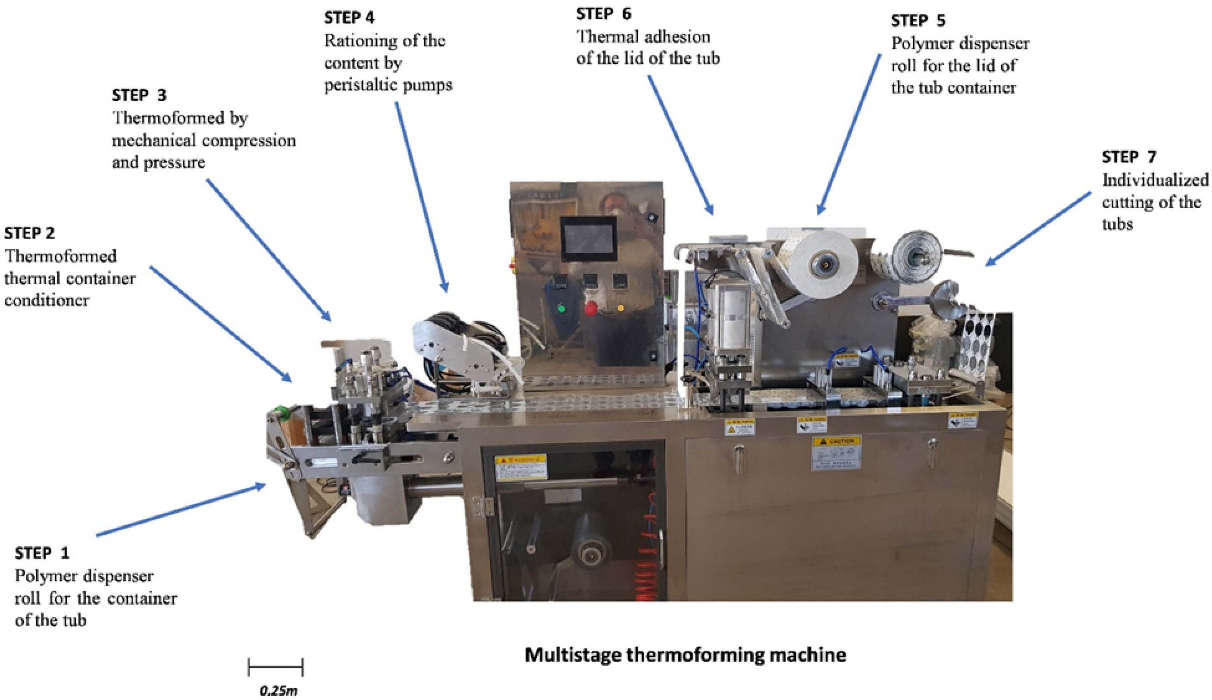

Figure 2. A multistage thermoforming machine of six terrines per cycle and its type of components.

This machine has a cycle time of 4 s, and the thermoforming mold allows the manufacture of 6 terrines for each cycle time. So, for each cycle time, seven steps constantly work in coordination.

The proper sequence of steps depends on the programmable logic controller (PLC) inside the electrical panel. The PLC receives all the information provided by sensors and takes decisions for all the actuators at the correct moment.

All the steps may have electrical, electronic, mechanical, and pneumatic components distributed for the whole industrial multistage machine. The adequate state of all the components allows for the correct functioning of the machine and avoids unexpected failures. It is easy to understand that the accumulated work time may affect the state of the components. Due to this and other considerations such as ambient conditions, power supplier events, normal degradation of mechanical components, compressed air system failure or jams in the peristaltic pumping system (step 4), unwanted mechanical shocks can be the origin of unexpected failures in the components and consequently in the industrial multistage machine.

The components of this machine and their type can be seen in Table 1. Many components may have a number greater than one. Also, the figure indicates the possible failure source and the consequences of the failure event.

Table 1. List of components in the industrial multistage machine.

Type of Component	Component	Cause of Failure	Failure Event
Electrical	Master power switch	Ambient condition, Power supplier event	Stop
	Plug-in relay	Ambient condition, Power supplier event, Unexpected hit	Malfunction Stop
	Command and signalling	Ambient condition, Power supplier event	Stop
	Safety limit switch	Ambient condition, Power supplier event, Unexpected hit	Stop
Electronic	PLC	Ambient condition, Power supplier event	Stop
	HMI	Ambient condition, Power supplier event	Stop
	Chromatic sensor	Ambient condition, Power supplier event	Stop
	Safety relay	Ambient condition, Power supplier event	Stop
	Temperature controller	Ambient condition, Power supplier event, Unexpected hit	Stop
	Solid state relay	Ambient condition, Power supplier event	Stop
	Belt drive	Ambient condition, Power supplier event	Malfunction
	Pressure sensor	Pressure failure, Global fatigue	Malfunction
	Servo drive peristaltic pump	Ambient condition, Power supplier event	Stop
	Absolute encoder	Global fatigue, Mechanical hit	Malfunction
Mechanical	Safety button	Ambient condition, Power supplier event	Stop
	Thermal resistance	Ambient condition, Power supplier event	Malfunction
	Thermocouple sensor	Global fatigue	Malfunction
	Belt motor	Global fatigue	Stop
	Bronze cap	Global fatigue	Malfunction
	Linear axis	Global fatigue	Malfunction
	Linear bearing	Global fatigue	Malfunction
	Peristaltic pump	Ambient condition, Power supplier event, compressed air system failure	Stop
	Terrine cutter	Global fatigue	Malfunction
Pneumatic	Pneumatic valve	Global fatigue	Malfunction
	Pneumatic cylinder	Pressure failure, Failure valve	Malfunction

2.2. Maintenance Times for Each Component

Once the industrial thermoforming machine has been characterized, the individual maintenance times required for each component must be studied to adopt the most appropriate preventive maintenance strategy policy accordingly. For this purpose, many individual times and equations are used and presented in this study, which has been provided by J. Jiři [27] and G. Liberopoulos [28].

- TTRP Time to replace a component
- TTC Time to configure
- TTMA Time to mechanical adjustment
- TTPR Time to provisioning
- MTTR Mean time to repair
- MTTF Mean time to failure

- MTBF Mean time between failure
- TTLR Line restart time, defined by expert knowledge
- TLP Time lost production

MTTR (1), TLP (2), and MTBF (3) can be calculated with these equations. Efficiency and availability are used as indicators of success in preventive maintenance.

$$\text{MTTR} = \text{TTRP} + \text{TTC} + \text{TTMA} + \text{TTPR} \quad (1)$$

$$\text{TLP} = \text{MTTR} + \text{TTLR} \quad (2)$$

$$\text{MTBF} = \text{MTTR} + \text{MTTF} \quad (3)$$

After defining the times and expressions, Table 2 presents the individual maintenance times in seconds for each component in this research. For this machine, the end users and original equipment manufacturer (OEM) have suggested, with their knowledge based on the experience of use, manufacture and maintenance, the fixing of individual maintenance as its shown in Table 2 and global TTLR at 14,400 s.

Table 2. Individual maintenance times in s for all the components in the industrial multistage machine.

Component	MTTR	TTPR	MTTF	TLP
Master power switch	14,400	10,800	9,999,999	28,800
PLC	435,600	345,600	9,999,999	450,000
HMI	435,600	345,600	9,999,999	450,000
Chromatic sensor	176,520	172,800	5,000,000	190,920
Plug-in relay	14,400	10,800	5,000,000	28,800
Command and signalling	14,400	10,800	5,000,000	28,800
Safety limit switch	14,400	10,800	9,999,999	28,800
Safety relay	14,400	10,800	9,999,999	28,800
Safety button	14,400	10,800	9,999,999	28,800
Temperature controller	435,600	345,600	9,999,999	450,000
Solid state relay	176,400	172,800	5,000,000	190,800
Thermal resistance	25,500	10,800	3,700,800	39,900
Thermocouple sensor	14,700	10,800	3,700,800	29,100
Belt drive	435,600	345,600	9,999,999	450,000
Belt motor	187,200	172,800	5,000,000	201,600
Bronze cap	288,000	172,800	7,750,000	302,400
Linear axis	288,000	172,800	7,625,000	302,400
Linear bearing	288,000	172,800	7,500,000	302,400
Pneumatic valve	176,400	172,800	9,999,999	190,800
Pneumatic cylinder	176,400	172,800	9,999,999	190,800
Pressure sensor	176,700	172,800	5,000,000	191,100
Servo drive peristaltic pump	435,600	345,600	9,999,999	450,000
Peristaltic pump	547,200	518,400	5,000,000	561,600
Terrine cutter	288,000	172,800	9,999,999	302,400
Absolute encoder	360,000	172,800	5,000,000	374,400

For this type of machine, both components used at the beginning, as well as those that have presented failures, are completely new units, not ones restored by the technical service of each component manufacturer. For necessary components replacements, only in the case of the pneumatic cylinder is it possible to repair the unit by substituting internal components for new components. All other components are replaced by new units.

2.3. Maintenance Strategies

In this section, two preventive maintenance strategies are presented, and one predictive maintenance strategy is used:

- Preventive maintenance, based on the MTTF of each component, to avoid unexpected failures during the work process.

- Improved preventive maintenance, based on the above but minimizing the TTPR of each component.
- Digital behavior twin (DBT) for predictive maintenance.

2.3.1. Preventive Programming Maintenance (PPM)

This strategy is based on the MTTF of each component and proposes inspecting and replacing the component once the worked time reaches the MTTF. This is the maintenance strategy adopted for all the components at the beginning of this study.

Once the decision to replace a component is taken, a decision based on its MTTF, lost production time is necessary for the corresponding maintenance operation. As shown by Equation (1), if the MTTR is higher than the value of TTPR, a new maintenance policy can be used to minimize the MTTR. This policy entails an increase in security stocks. Figure 3 shows the ratio TTPR/MTTR in this machine. The values are provided by the machine manufacturers and shown in [17].

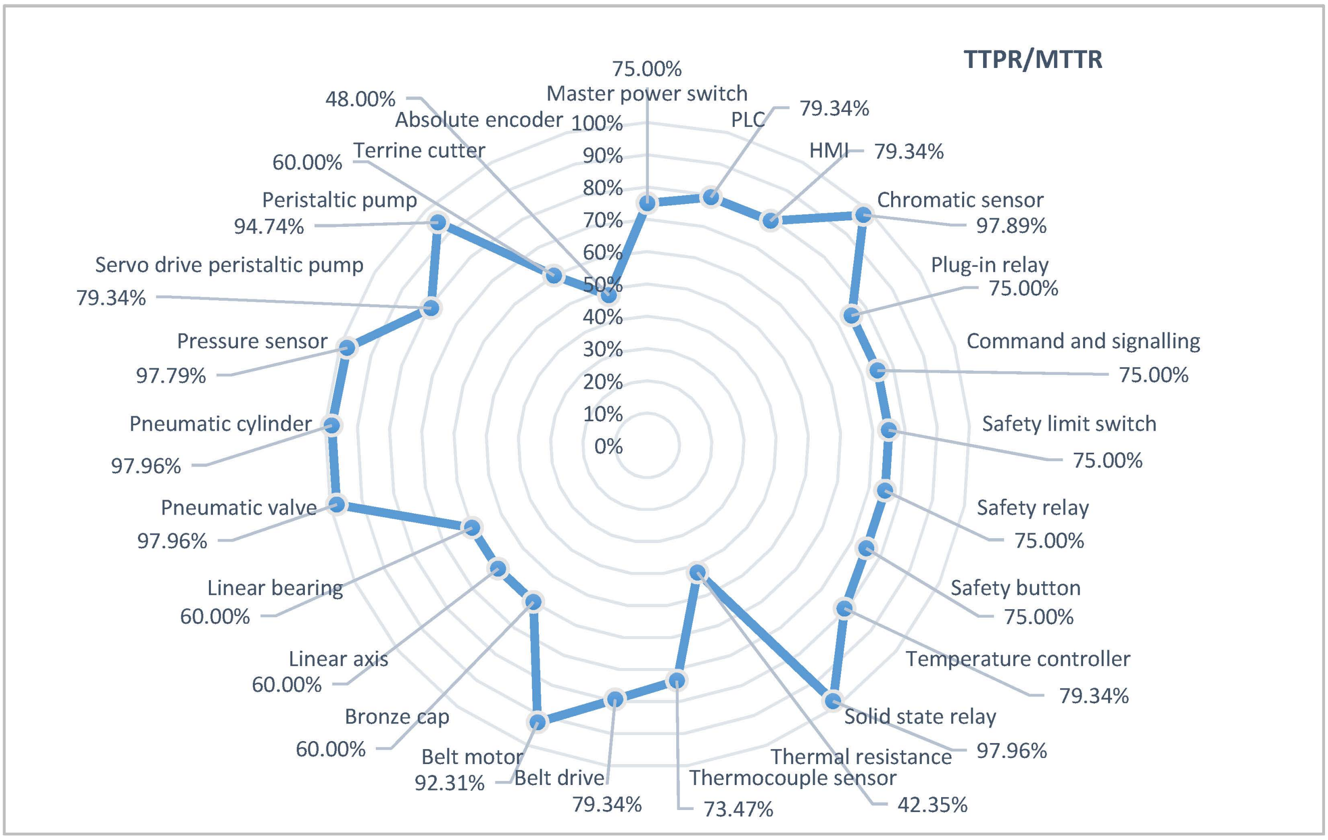

Figure 3. Comparison between TTPR and MTTR for the components of the case study.

The significant influence of TTPR value in MTTR is notable. The authors consider this ratio interesting. In Section 2.6, KPI_1 and KPI_2 will be defined by using TTPR value to propose a change in preventive maintenance strategy.

2.3.2. Improved Preventive Programming Maintenance (IPPM)

This strategy is based on the PPM strategy. When a component has a higher value of TTPR, this strategy can be used to minimize the TLP of the industrial multistage machine. In this case, the TTPR is replaced by a residual time fixed in 300s, which is the time it takes the end user of the machine to collect it from its replacement stock. Garcia, F.J.Á. and Salgado, D.R. [11] proposed a matrix to decide on the most appropriate preventive maintenance strategy but not on the component that needs a predictive maintenance strategy.

2.3.3. Digital Behaviour Twin (DBT)

This strategy is based on the sensors placed on the machine. These sensors give their values to a PLC, and the PLC uses an algorithm that triggers maintenance recommendations to avoid unexpected failures. A human interface machine (HMI) is used to show these recommendations.

This algorithm uses the signals received from the sensors and refers them to the position of a central axis by means of an absolute encoder. Since the normal operating condition is known, the algorithm detects normal operation without the need for learning, provides warnings of possible faults, and can provide the number of work cycles performed without faults.

Figure 4 shows the conceptualization of this strategy in the cited industrial multistage machine.

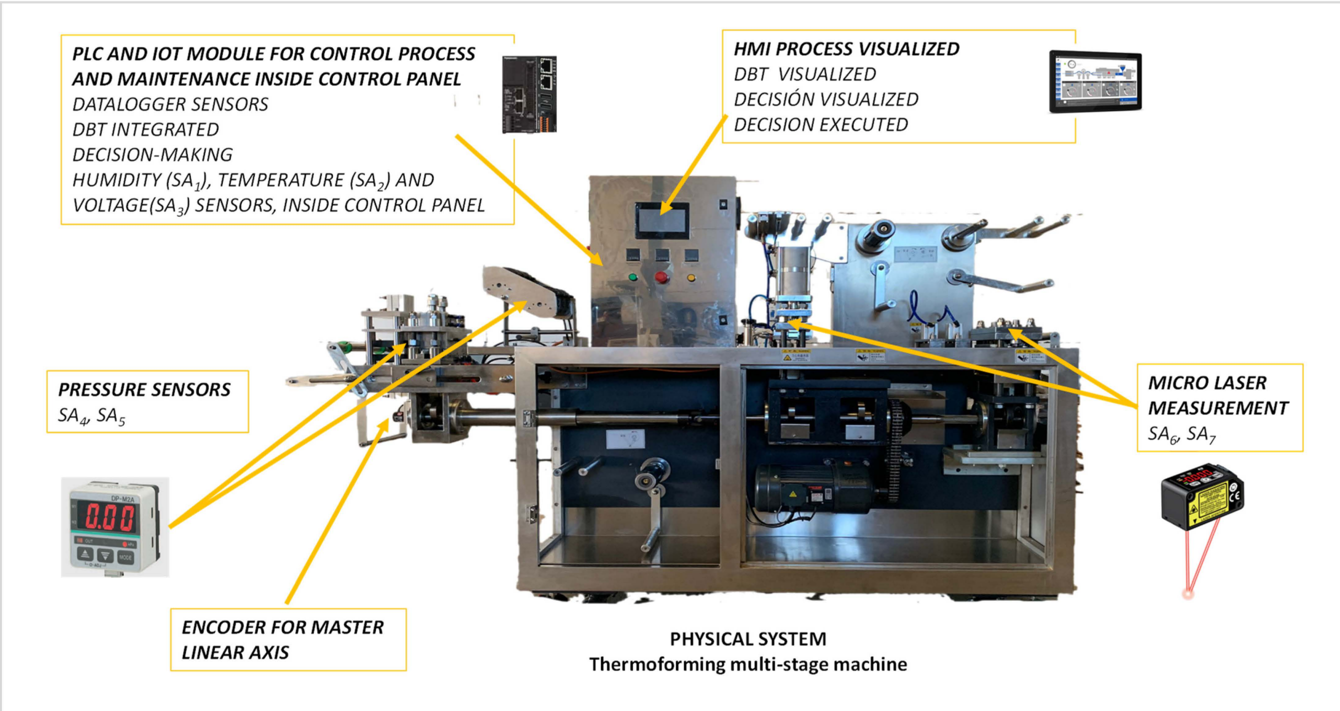

Figure 4. Conceptualization of the DBT predictive maintenance strategy.

Garcia, F.J.Á. and Salgado, D.R. [17] described this predictive maintenance strategy in detail. The objective of their research was not to define the predictive algorithm but to use it to propose a method to decide on a change of maintenance strategy from preventive to predictive.

This strategy has already been tested in this industrial multistage machine and allows the detection of potential failures within each cycle of operation of the whole machine.

2.4. Recovered Data after a Year of the Machine Working

The industrial multistage machine worked without stopping, 8 h per day, Monday to Friday, for one year, with the PPM in place and the DBT functioning only for data logging advice. Table 3 shows the list of components with the corrected MTTF if the component had failed before its MTTF and whether the cause of the failure was known or unknown.

Table 3. Individual component failures occurring within one year of the machine's working. Times in s.

Component	Fails before MTTF	Cause of Failure	Corrected MTTF
Chromatic sensor	1	Known	3,998,750
Plug-in relay	1	Known	4,056,010
Temperature controller	1	Known	7,934,710
Solid state relay	1	Known	4,678,034
Thermal resistance	1	Unknown	3,067,090
Thermocouple sensor	1	Unknown	2,890,760
Bronze cap	1	Unknown	6,500,453
Linear bearing	1	Unknown	6,375,010
Pressure sensor	1	Unknown	4,575,102
Peristaltic pump	1	Known	4,434,090
Terrine cutter	1	Unknown	8,750,778
Absolute encoder	1	Known	4,756,002

Table 3 shows that many components have presented failures before their MTTF. Figure 5 shows the results by type of component. The pneumatic components have not presented failures before their MTTF, unlike the rest of the components.

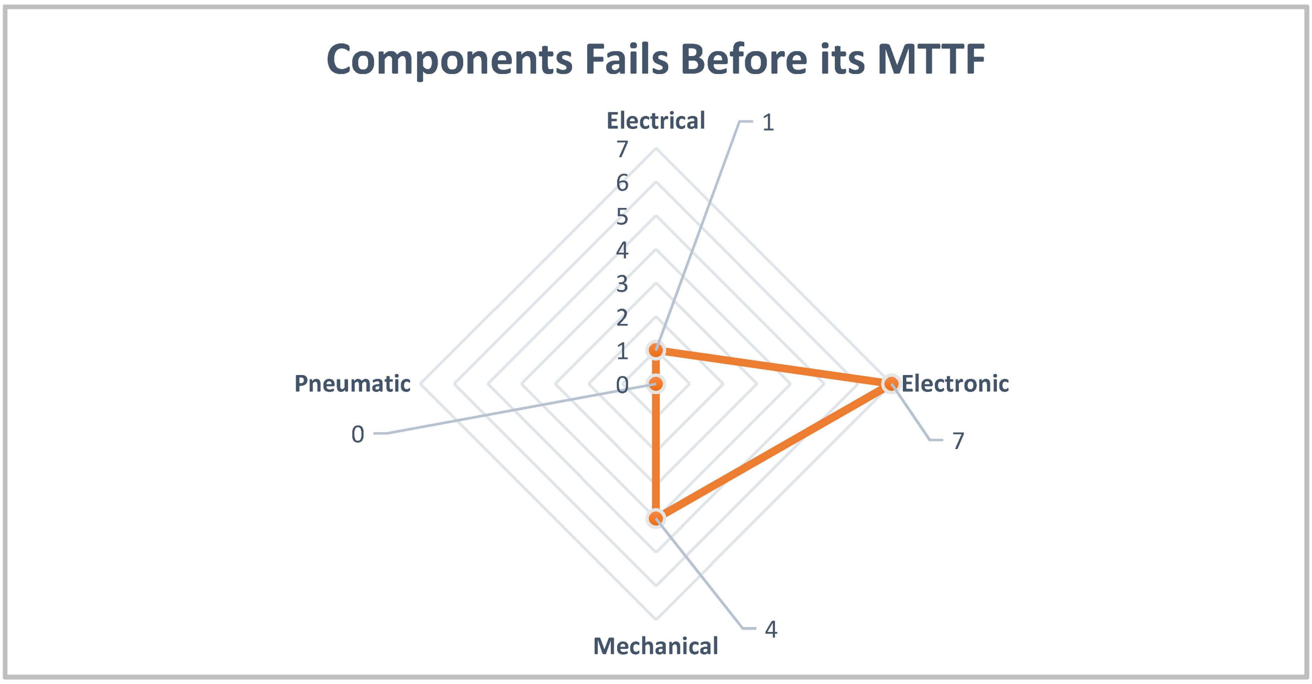

Figure 5. Component failures before their MTTF.

Table 4 shows the description of the cause of the failure of the components that presented a failure before their MTTF and also indicates, for these components, whether the cause is due to an occasional (infrequent) situation or a normal situation.

In the case of the plug-in relay, the authors believe that this component was not completely new at the beginning of the experiment. To verify this, a quality test was carried out. The rest of the components shown in Table 4, presented a failure-for-occasional-situation. In Section 2.6 a procedure to avoid the same situation is proposed.

These failures were registered. The DBT algorithm used only for data logging the advice for an unexpected failure will be compared below.

Table 4. Registered known causes of failure in components that presented a failure before their MTTF.

Component	Situation	Description of the Known Cause of Failure
Chromatic sensor	Occasional situation	The supplier of the film for the terrine lid changed the color without prior notice and made it darker and more reflective. This caused the sensor to stop seeing the mark correctly.
Plug-in relay	Normal situation	The number of commutations exceeded the mechanical endurance.
Temperature controller	Occasional situation	Mixed events of voltage RMS and high level of humidity.
Solid state relay	Occasional situation	The higher level of humidity and air dust caused a short circuit.
Peristaltic pump	Occasional situation	A higher density of fluid dosed in the terrine caused a jam.
Absolute encoder	Occasional situation	Accidental mechanical shock.

2.5. DBT Predictive Algorithm Warnings of Failure Recovered

The DBT algorithm matched the real failures that occurred when the machine was working. Table 5 shows the warning of failures obtained for the DBT predictive maintenance strategy. This table only shows components that presented failures.

Table 5. DBT warnings of failures by components within the operation time studied.

Component	DBT Warning of Failures
Chromatic sensor	1
Plug-in relay	1
Temperature controller	1
Solid state relay	1
Thermal resistance	1
Thermocouple sensor	1
Bronze cap	1
Linear bearing	1
Pressure sensor	1
Peristaltic pump	1
Terrine cutter	1
Absolute encoder	1

The coincidence of warning of failures provided by DBT and shown in Table 5 and components that failed before their MTTF, as shown in Table 3, suggests using the DBT algorithm if a component requires predictive maintenance. Due to this coincidence, a scorecard must be designed to make decisions about changes in the component maintenance strategy.

2.6. Method Proposal to Take Decisions for Maintenance Strategy Decisions

As Section 2.3.1 set forth, the PPM strategy had been adopted for all the components at the beginning of the study. With all the accumulated dates compared to the actual event, and the warning advice given by the DBT algorithm, this section explains how to make decisions for a possible change of maintenance strategy.

The objective is to identify the components that need predictive maintenance. For this purpose, there are two key questions:

- Has the component failed before its MTTF?
- Do we know why it failed?

Two key performance indicators are studied to ascertain whether the reason is known. The expressions for KPI_1 (4) and KPI_2 (5) are the following:

$$KPI_1 = (MTTR - TTPR)/MTTR \tag{4}$$

$$KPI_2 = TTPR\ /TLP \tag{5}$$

KPI_1 is used to ascertain the influence of TTPR in the MTTR for each component. If this ratio presents a small value, the TTRP will be higher, which is considered an important piece of information with reference to changing the maintenance strategy.

KPI_2 is used to assess the influence of TTPR in Time TLP because this ratio shows the availability and efficiency decrease for a higher value of TTPR.

2.6.1. Procedure to Set KPI_1 and KPI_2 Values

The procedure to set initial values of KPI1 and KPI2 is the following:

- Calculate KPI1 interval between PPM and IPPM strategies.
- Calculate KPI2 interval between PPM and IPPM strategies.
- Calculate average value of KPI1 and KPI2, assuming PPM strategy.
- Calculate average value of KPI1 and KPI2, assuming IPPM strategy.
- Calculate average value of TTPR/MTTR ratio assuming PPM strategy.

Individual times for PPM strategy are shown in Table 2. In the case of IPPM strategy, only TTPR is modified for a constant value fixed in 300s (see Section 2.3.2).

Table 6 shows all of the calculated values.

Table 6. Calculated ratios to define fixed values of KPI_1 and KPI_2.

Strategy	Ratio	Average KPI_1	Average KPI_2	Average TTPR/MTTR
PPM	Value Interval	22.92% [2.04–57.65%]	63.14% [27.07–92.31%]	77.08%
IPPM	Value Interval	96.04% [92.31–99.84%]	0.99% [0.15–1.64%]	3.96%

As can be observed, the intervals for KPI_1 and KPI_2 values in PPM and IPPM strategies have no common points. For initial, fixed KPI's points, we must be within the intervals provided by PPM strategy. Whether KPI_2 is considered the average ratio between TTRP and MTTR due to the TLP depends on a constant value (TTLR equal to 14,400 s) and the MTTR value (see Equation (2))

Figures 6 and 7 show the fixed KPI_1 and KPI_2 values for decision-making. A large dispersion of KPI_1 and KPI_2 values is observed in the case study. The correct functioning of the fixed values is evaluated by the minimization of TLP and stock cost in case of adopting IPPM strategy. The final value fixed in the case of KPI_1 is 25% and in the case of KPI_2 is 70% (value obtained by comparing average KPI2 with average TTPR/MTTR).

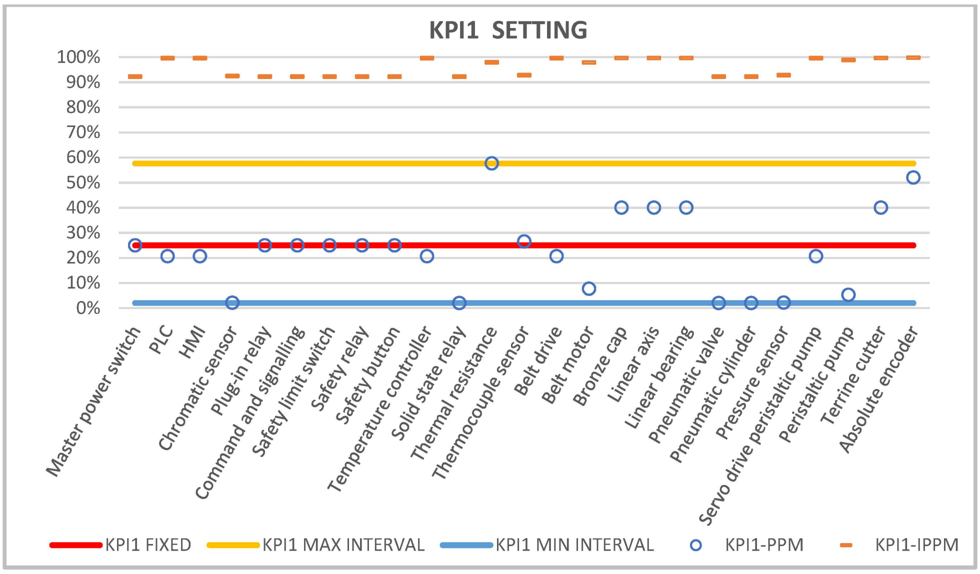

Figure 6. Comparison of KPI_1 values for each component in PPM and IPPM strategies, KPI_1 interval in PPM strategy and fixed value 25% of KPI_1.

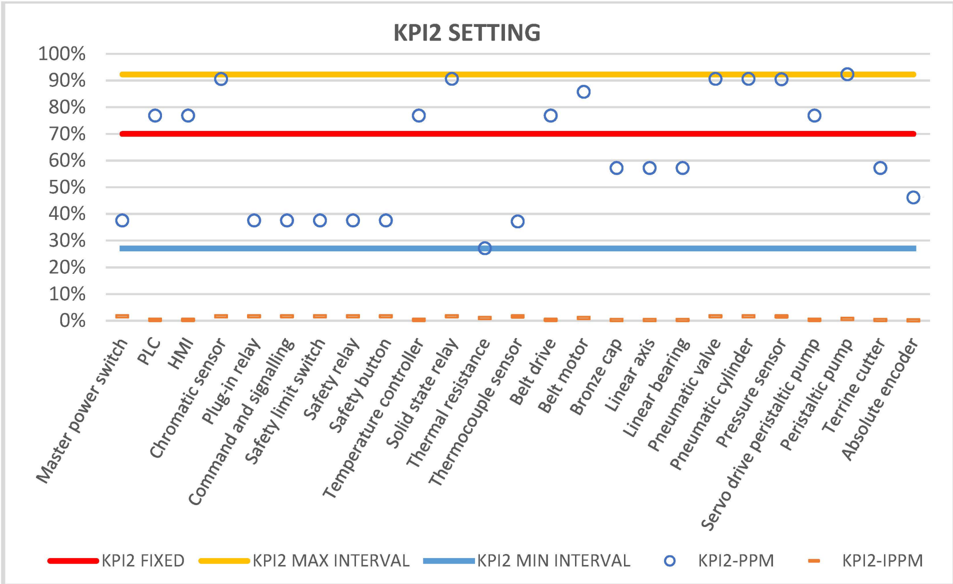

Figure 7. Comparison of KPI_2 values for each component in PPM and IPPM strategies, KPI_2 interval in PPM strategy and fixed value 70% of KPI_1.

With the fixed values, decision-making to change maintenance strategy can be adopted. So:

- If $KPI_1 < 25\%$ and $KPI_2 > 70\%$, the improved preventive maintenance strategy can be proposed, with a previous GOC evaluating the component;
- If $KPI_1 > 25\%$ and $KPI_2 < 70\%$, a preventive maintenance strategy change is unnecessary.

Of course, if a component presents a failure before its MTTF and the cause of the failure is unknown, and the value of $KPI_1 < 25\%$ and $KPI_2 > 70\%$, several changes must be made in the maintenance strategy.

2.6.2. Proposed Method for Maintenance Strategy Adoption

Figure 8 shows the method proposed by a PPM strategy adopted for all the components of the industrial multistage machine initially and the possible decisions to be taken depending on the knowledge of the fault and the KPI values.

The proposed method can be used in this machine when assessing whether to change the maintenance strategy if a component fails before its MTTF. However, feedback is useful to control the real evolution of the machine in every possible way. The authors consider that this feedback is only useful if the cause of the failure is known.

With the proposed method, all the components start operating with a PPM strategy, and if any fail before their MTTF, a change to IPPM or IPPM with DBT may be appropriate.

As mentioned in Section 2.5, if it is necessary to use a predictive maintenance strategy, DBT can be used, due to the good results offered with the advice shown in Table 5. In this way if a component fails before its MTTF, and the cause is unknown, IPPM will be adopted regardless of the value of KPIs. Later, an inspection of the location and other factors to find the cause of the failure with DBT monitoring enables a new value of MTTF to be set. If the cause of the failure is found, the method returns to starting point. If the component does not fail before its new MTTF, the maintenance strategy will be PPM. Otherwise, the way depends on the knowledge of the second failure.

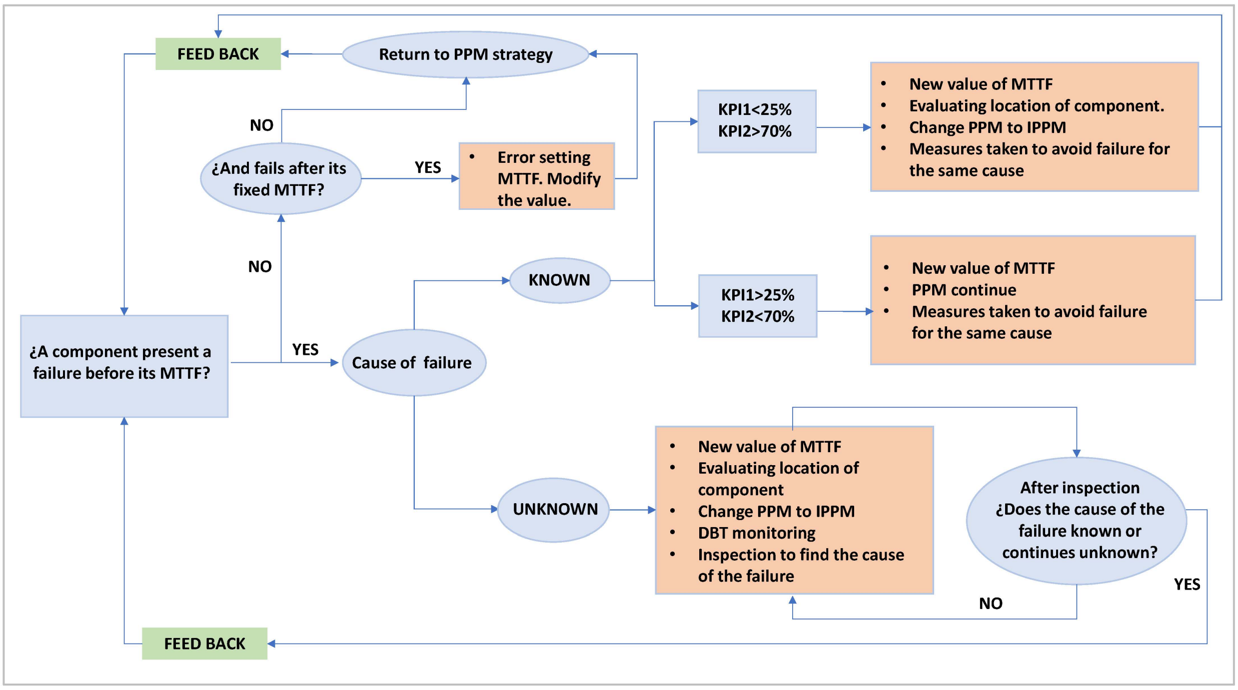

Figure 8. Proposed method to switch from a preventive maintenance strategy to a predictive strategy with a DBT algorithm.

According to the proposed method it i considered that the principal object and benefit of adopting a DBT predictive maintenance strategy is to determine the reason of a component failure before its MTTF by using distributed sensors that are part of the DBT predictive maintenance strategy. Also, when DBT monitoring is used, the behavior of the whole machine is monitored to guarantee the correct functioning of the MSTM. So, as Figure 5 shows, if the cause of the failure is found, the replaced component returns to the starting point of the proposed method and the DBT monitoring continues until the next failure of the same component. Otherwise, the method does not continue towards the starting point, and the model waits instead for a better result of the main actions proposed to find the reason of the failure.

The final object of this dynamic method is the default selection of PPM strategy for all components, and only IPPM if KPI1 < 25% and KPI2 > 70% at the same time if these components fail before its MTTF. Nevertheless, the real situations involving these types of machines, located in important factories and parts of a production process, indicates to us the need for a predictive maintenance strategy if, due to an occasional (infrequent) situation, a component fails before its initial MTTF.

3. Results

The application of the proposed method for possible maintenance strategy changes is shown in Table 7. The initial maintenance strategy was PPM for all the components. The next column shows the maintenance strategy to be adopted if the component fails before its MTTF.

The results show different changes in maintenance strategies. The PPM strategy of all the components that failed before their MTTF due to unknown causes was changed to IPPM with DBT monitoring (pressure sensor, thermal resistance, thermocouple sensor, bronze cap, linear bearing, and terrine cutter). The maintenance strategy of two components with known causes of failure remained unchanged (plug-in relay and absolute encoder), and the maintenance strategy of four components (chromatic sensor, temperature controller, solid state relay, and peristaltic pump) was changed to IPPM.

Of course, the initial PPM strategy of components that did not fail remained the same.

Table 7. Maintenance strategies for all components after a year in operation using the proposed method.

Component	KPI_1	KPI_2	Maintenance Strategy after a Year of Work
Master power switch	0.25	0.38	PPM
Plug-in relay	0.25	0.38	PPM
Command and signalling	0.25	0.38	PPM
Safety limit switch	0.25	0.38	PPM
PLC	0.21	0.77	PPM
HMI	0.21	0.77	PPM
Chromatic sensor	0.02	0.91	IPPM
Safety relay	0.25	0.38	PPM
Temperature controller	0.21	0.77	IPPM
Solid state relay	0.02	0.91	IPPM
Belt drive	0.21	0.77	PPM
Pressure sensor	0.02	0.90	IPPM + DBT monitoring
Servo drive peristaltic pump	0.21	0.77	PPM
Absolute encoder	0.52	0.46	PPM
Safety button	0.25	0.38	PPM
Thermal resistance	0.58	0.27	IPPM + DBT monitoring
Thermocouple sensor	0.27	0.37	IPPM + DBT monitoring
Belt motor	0.08	0.86	PPM
Bronze cap	0.40	0.57	IPPM + DBT monitoring
Linear axis	0.40	0.57	PPM
Linear bearing	0.40	0.57	IPPM + DBT monitoring
Peristaltic pump	0.05	0.92	IPPM
Terrine cutter	0.40	0.57	IPPM + DBT monitoring
Pneumatic valve	0.02	0.91	PPM
Pneumatic cylinder	0.91	0.91	PPM

4. Discussion

The proposed method for changing the maintenance strategy for all the components that failed does not provide a static decision criterion. For example, the same component can fail first due to an unknown cause, and again a second time due to a known cause. The method allows taking different decisions according to whether or not the cause of the failure is known.

The authors consider knowing the cause of the failure critical. An industrial multistage machine must not operate with unknown failures. Also, once the cause is known, the manufacturer must take action to avoid an unexpected failure due to the same cause. If these actions are correct and there is feedback, the industrial multistage machine can restart operating with adequate functionality guarantees.

The values of KPI_1 and KPI_2 are used to assess whether a change of preventive maintenance strategy is required. As mentioned in Section 2.6, the extreme values of both are fixed to show whether the preventive maintenance strategy should be changed from PPM to IPPM. However, if the value of time to provisioning (TTPR) of a component goes up or down, the value of its KPI_1 and KPI_2 will also change. In this scenario, if a failure occurs in this component, the method will use another way to make decisions, in a further evaluation.

A continuous application of this method for the same industrial multistage machine will allow greater failure control and higher levels of operation time without failures.

If a component supplier is changed for market reasons, the proposed method must be reassessed, and the KPIs and MTTR must be recalculated. Also, the value of MTTF must be changed accordingly before the machine resumes its operation.

The authors consider the following assessment critical, ascertaining the trust level in the component manufacturer by evaluating the ratio between the corrected and initial MTTF of all the components that failed before their initial MTTF. Table 8 shows this ratio:

Table 8. Trust levels in component manufacturers by comparing the initial and corrected MTTF in components that failed before their initial MTTF.

Type of Component	Component	Trust Level
Electronic	Chromatic sensor	79.98%
Electrical	Plug-in relay	81.12%
Electronic	Temperature controller	79.35%
Electronic	Solid state relay	93.56%
Electronic	Thermal resistance	82.88%
Electronic	Thermocouple sensor	78.11%
Mechanical	Bronze cap	83.88%
Mechanical	Linear bearing	85.00%
Electronic	Pressure sensor	91.50%
Mechanical	Peristaltic pump	88.68%
Mechanical	Terrine cutter	87.51%
Electronic	Absolute encoder	95.12%

This assessment, therefore, allows for a long operating time with an adequate selection of component manufacturers. Figure 9 shows the average trust level (ATL) by component type. The authors consider that the compared values must be similar. This indicates that the machine maintenance team is adequate for the whole machine. Obviously, the optimal value of this ATL is 100%. As the pneumatic components did not fail before their MTTF, they have not been included in Figure 9.

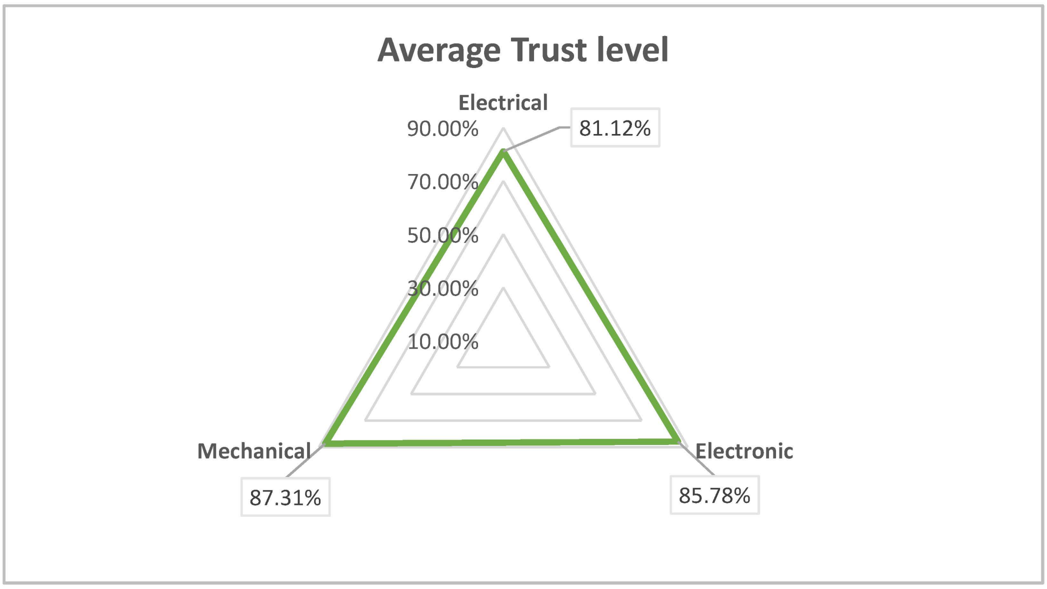

Figure 9. Average Trust level of components that failed before their initial MTTF.

The authors consider that one way to further this research would be if an ATL were to be fixed for all the components for possible decisions to change component manufacturers. Also, a new result would be obtained if the cost of the component were to be used in this proposed future research.

5. Conclusions

The proposed method for possible maintenance strategy changes for components in the same industrial multistage machine provides ways to change the maintenance strategy for PPM to IPPM or IPPM with DBT monitoring. The authors consider that this method will be useful for other industrial multistage machines.

The predictive maintenance strategy is used for constant component monitoring if an unexpected failure has occurred, so if the cause is known and the measures for avoiding a new failure for the same cause are taken, the component will probably fail at its new MTTF and will then go back to having preventive maintenance like PPM or IPPM.

If a component presents many consecutive failures before its initial MTTF and the actions proposed by the method are taken, then the ATL of the component manufacturer should be revisited to decide on whether to change the manufacturer with an objectively higher quality in this component. In this case, this could be another way to start a failure mode and effect analysis (FMEA) to redesign the function, location, and work of this stage of the machine.

All the components can be included in the study of ATL by component type. In this case, the average value will be higher than that shown in Figure 9. The authors only included the components that failed to avoid wrong results in the machine maintenance team's evaluation.

As the trust level, or the ATL, depends on the ratio between initial MTTF and real MTTF of the component or type of components, these values do not improve with a maintenance strategy change; they only improve to 1 or 100% if the actions necessary to take for avoid occasional (infrequent) situations that end with an unexpected failure work correctly. In the case of trust level or ATL improvement up to 100% the authors suggest an incorrect initial MTTF fixed at starting point of the machine's use. The proposed method suggests this way (see Figure 8)

Industrial multistage machines need a long working time without unexpected failures, so a global method for taking the appropriate decisions for maintenance strategies is needed, and adequate changes must be made to avoid such unexpected failures. The proposed method allows reaching this objective. Nevertheless, some comments for its application in the context of other multistage machines must be related:

- The case study is a multistage thermoforming machine. This machine has an absolute encoder. Its position is constantly sent to the PLC for synchronization and management of all the coordinated steps in the correct order. This encoder allows the use of a digital behavior twin algorithm for predictive maintenance strategy. Not all of the multistage machines have an encoder for this special function, so the normal behavior of the machine must be referred to with a more precise physical analogue.
- Due to the fact that the cycle time is only 4 s, the algorithm for predictive maintenance must be speedy and certain. Other machines with longer cycle times could use predictive maintenance based on the time;
- As Figure 1 indicates, the preventive maintenance strategy depends upon the individual maintenance times. It would be interesting to evaluate the sensibility of the method for an incipient change of TTPR in some components due to global market conditions.

The main contributions highlighted in this article are:

- Providing a method for deciding when to use predictive maintenance strategy and when to stop it in different components of a MSTM.
- Providing a dynamic global method to establish the maintenance strategy of any component of an MSTM.
- Providing a confidence level of a component or type of components in an MSTM that indicates whether the MTTF of said component operating in said machine is reliable.
- Because of the above, obtaining information on the reliability of the components of a MSTM to avoid unexpected failures during its operating time.

Table 9 shows the results of the comparison between the introduction citations and the proposed method. Due to the singularity of this type of multistage machine, the cited references are not alternative methods that can be used to provide other maintenance strategies for the same machine in the same working conditions, with the same components and the same evaluation time (1 year). Due to this, the comparison offered in the following table focuses on the most significant aspects found in each citation that are related to the methodology developed in this study. This comparison is, therefore, in qualitative terms, and not able to offer numerical comparisons. The first column indicates the item or relevant aspect to be compared. The second column indicates the highlighted references compared. The third column is a qualitative comparison between the cited item (column 1) in the reference (column 2) and the method proposed in this article.

Table 9. Qualitative comments highlighted between the proposed method and the state of art. (*) Improve options.

Item	References	Qualitative Comments after Comparison
Minimizing security stocks	[1,2]	Correct selection of fixed KPIs allows the optimization of stock and provides the adequate preventive maintenance policy
Stops to settings, removal actions. Imperfect maintenance	[3,4]	Settings only at the start time of the machine functioning by the temperature controller, thermal resistance, and thermocouple sensor. The maintenance actions must perform the machine functioning. The system can evaluate if the actions in each component or each type of component are imperfect by trust level or ATL.
Mathematical model for Preventive maintenance	[5–8]	Complex, very theoretical and many variables to manage. Simple, sensitive to variations of individual maintenance times.
MTTF reliable Reliability and law degradation	[9–11]	Initial MTTF fixed for all components; reliability functions not used. Possibility to change MTTF value if real MTTF lower or upper than initial MTTF fixed.
Product design and operation conditions	[12]	If a component exhibits repeated failures, an immediate FMEA analysis procedure is initiated to find design errors or component selection errors.
Mathematical model for Predictive maintenance	[13–18]	Uses PLC with embedded DBT algorithm. No need training and learning time. Quick response Very useful for a machine with fast cycle time.
Location components	[19]	(*) Possible improvement. Can be evaluated for this application
Mixed cost and technical analysis	[20,21]	(*) Possible improvement. Also is citated in future research. Coincidence in the use of FMEAS analysis
Digital Twin	[22,23]	The behavior of the machine always is the same and does not need a real digital twin since the characterization is special for each MSTM and operation conditions are always are the same. Coincidence in the event failure advises, no training and utilization of FMEAS analysis.
Augmented Reality and Computer Vision	[24,25]	(*) Possible improvement. Not used. ATL is used for evaluating the maintenance operator actions required for maintenance policy. But it is used after a maintenance action.
Preventive actions in flexible windows time. Predictive maintenance always running Method for decision-making	[26]	(*) Possible improvement to use flexible windows time for preventive maintenance actions. Predictive maintenance only works if a component fails before its MTTF, and the cause of the failure is unknow. Coincidence in the contribution of a method for decision-making
Individual preventive maintenance Times	[27,28]	Used in the article and performed by developing KPIS for preventive maintenance decisions

The method proposed is appropriate for the MSTM but can improve with respect to some items.

Future research:

- Study the influence of a fixed ATL and cost assessment for possible component manufacturer changes;

- Utilization of DBT monitoring for combined supervision in parallel of the same machine system to use Predictive Maintenance and use the advice for one machine to start DBT monitoring in other machines of the system working in the same operating conditions;
- Global cost analysis of the components, DBT monitoring system, and their influence on possible maintenance strategies for all the components in an industrial multistage machine;
- Mixed method for maintenance strategies using technical parameters and cost terms.

Author Contributions: Conceptualization, F.J.Á.G. and D.R.S.; methodology, F.J.Á.G.; software, F.J.Á.G.; validation, D.R.S. and F.J.Á.G.; formal analysis, F.J.Á.G.; investigation, F.J.Á.G. and D.R.S.; resources, F.J.Á.G.; data curation, F.J.Á.G.; writing—original draft preparation, D.R.S. and F.J.Á.G.; writing—review and editing, F.J.Á.G. and D.R.S.; visualization, F.J.Á.G.; supervision, D.R.S.; project administration, D.R.S.; funding acquisition, D.R.S. and F.J.Á.G. All authors have read and agreed to the published version of the manuscript.

Funding: This study has been carried out through the Research Project GR-21098 linked to the VI Regional Research and Innovation Plan of the Regional Government of Extremadura.

Data Availability Statement: Not applicable.

Acknowledgments: The authors wish to thank the European Regional Development Fund "Una manera de hacer Europa" for their support of this research. This study has been carried out through the Research Project GR-21098 linked to the VI Regional Research and Innovation Plan of the Regional Government of Extremadura.

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

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6

Otros Méritos relacionados

PAPER • **OPEN ACCESS**

Maintenance management and Optimization of the thermoforming process for the agri-food industry using the S^2 model

To cite this article: F J Álvarez *et al* 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1193** 012112

Maintenance management and Optimization of the thermoforming process for the agri-food industry using the S^2 model

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Abstract: The agri-food industry has been greatly enhanced in recent years with the introduction of process control and the automation [1] of certain links in the production chain. The seasons of the year in which these machines must be operational and show robust and reliable operation, have short durations (2 to 4 months) and are therefore greatly affected by unexpected failures that cause stops on the production lines. This paper attempts to expose a comparative advantages that can be obtained in terms of availability and efficiency in the thermoforming process. With the introduction of Industry 4.0 [2, 4] and the S^2 model [5] and actuator control and early action, it is possible to optimize availability and efficiency ratios on thermoformer machines. Results show that it's possible to reduce unexpected failures by means of this optimization tools. Two improvement strategies are outlined. Maintenance Management improvement model improves response to failures but does not optimize the useful life of the components. Algorithm life optimization based on S^2 model optimizes service life and improves response to failure.

Keywords: Thermoforming process, Availability, Industry 4.0, IoT, Efficiency.

1. Introduction

Online manufacturing processes require high levels of availability and reliability for high productions in short seasonal periods of the year. It is very important to control and define the stops times to avoid the sudden appearance of breakdowns causing unexpected stops and non-compliance with manufacturing commitments.

In the agri-food sector [1] the manufacture of many products is carried out in periods of time closely linked to harvests and collections. This is a reality that must be borne in mind when designing and structuring the entire production process. Currently, factories must be prepared to meet an extraordinary volume of production and demand, always controlling quality and compliance with the correct sanitary measures required by the administration.

The advantages of IoT [2] enable real-time management in the cloud, making decisions based on the comparison proposed by algorithms developed to maximize the useful life of the components, guaranteeing the reliability of these decisions.

The final objective of this research is to obtain a relationship between the production function and the availability of the machines, so that the study of the reliability of their equipment provides an availability status that allows guaranteeing production function and avoiding unexpected failures or not controlled during a production batch. In this way, the value chain [3] obtains the benefits of a more reliable service, with better quality and information [4] about their orders.

2. Case study and methodology

2.1. Thermoforming and tubs filling machines

Thermoforming and tubs filling machines are one case among the many that exist. This type of machines is the object of this study. These machines are composed of several sub-processes from the management of the polymer film to the container and lid, as well as the dosage and final cut.

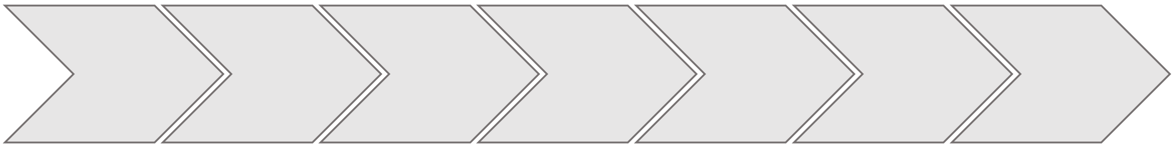

Figure 1. Sub process in thermoforming and terrine filling machines.

The sub processes involved in this machine are the following (see figure 1):

- Polymer dispenser roll for the container of the tub.
- Thermoformed thermal container conditioner.
- Thermoformer by mechanical compression and pressure.
- Rationing of the content by peristaltic pumps.
- Polymer dispenser roll for the lid of the tub container.
- Thermal adhesion of the lid of the tub to the thermoforming and filling container.
- Individualized cutting of the tubs for their subsequent logistical packaging.

The cycle time can vary between 6 and 12 tubs per second, depending on whether the machine is designed to manufacture 3, 6, 9 or up to 12 tubs simultaneously. Normally, the production is usually two rows simultaneously, then in a cycle, twice a series of 3, 6, 9 or 12 tubs can be manufactured. This affects the size, mold of the thermoformer, number of peristaltic pumps, rails for the row passage, size of the thermal bonder of the lid and size of the tub cutter.

Normal operation requires the constant coordination of all sub processes since a failure in one of them, means the loss of ongoing production.

From the thermal conditioner of the polymer for the thermoformer of the container, to the cutter for finished tubs, there is an axis in the lower part of the machine that with cams in synchronized positions, allow coordinated movements so that the process is controlled and at constant speed.

2.2. Description of the typical faults in the components

Table 1 shows a basic decomposition of the components of the machine subject to failure in the present work. A distinction is made between static or moving elements, the possible origin of a failure and the consequence of its failure.

Table 1. Basic decomposition of components and faults.

Nº	Component	Type	Fault Source	Failure
1	Master power switch	Power Machine/static	Ambient condition, Power supplier event	Stop
2	PLC	Control/static	Ambient condition, Power supplier event	Stop
3	HMI	Control/static	Ambient condition, Power supplier event, Crash	Stop
4	Cromatic sensor	Sensor/static	Ambient condition, Power supplier event, Crash	Malfunction
5	Plug-in relay	Control device/static	Ambient condition, Power supplier event	Stop
6	Command and signalling	Control	Ambient condition, Power supplier event, Crash	Stop
7	Safety limit switch	Security/Static	Ambient condition, Power supplier event	Stop
8	Safety relay	Security/Static	Ambient condition, Power supplier event	Stop
9	Safety button	Security/Static	Ambient condition, Power supplier event, Crash	Stop
10	Temperature controller	Control/static	Ambient condition, Power supplier event	Stop
11	Solid state relay	Actuator/Static	Ambient condition, Power supplier event	Malfunction
12	Thermal resistance	Actuator/Dynamic	Global fatigue	Malfunction
13	Thermocouple sensor	Control/Dynamic	Global fatigue	Stop
14	Tape drive	Actuator/Static	Ambient condition, Power supplier event	Stop
15	Tape Motor	Motor/Dynamic	Global fatigue	Stop
16	Bronze cap	Structure/Dynamic	Global fatigue	Stop
17	Linear axis	Structure/Dynamic	Global fatigue	Stop
18	Lineal bearing	Structure/Dynamic	Global fatigue	Stop
19	Pneumatic valve	Actuator/Dynamic.	Pressure failure, failure valve	Malfunction
20	Pneumatic cylinder	Actuator/Dynamic	Pressure failure, cylinder failure	Malfunction
21	Pressure sensor	Control/static	Ambient condition, Power supplier event	Stop
22	Servo drive peristaltic pump	Actuator/Dynamic	Ambient condition, Power supplier event	Stop
23	Peristaltic pump	Actuator/Dynamic	Global fatigue	Stop

2.3. Analysis of times and ratios used

The times involved in the favorable resolution of the failures and their mathematical expressions are the following:

- TT_{RP} Time to replace component
- TT_C Time to configure
- TT_{MA} Time to mechanical adjustment
- TT_{PR} Time to provisioning
- *MTTR* Main time to repair
- *MTTF* Main time to failure
- *MTBF* Main time between failure
- TT_{LR} Line restart time, defined by expert knowledge
- T_{LP} Time lost production

$$MTTR = TT_{RP} + TT_C + TT_{MA} + TT_{PR} \quad (1)$$

$$T_{LP} = MTTR + TT_{LR} \quad (2)$$

$$MTBF = MTTR + MTTF \quad (3)$$

With these times, two concepts are used, efficiency (4) and availability (5). Both concepts will be used as indicators of success in the preventive control of machine failures.

$$Efficiency = \frac{T_{LP}}{MTTR+MTTF} \quad (4)$$

$$Availability = \frac{MTBF}{MTBF+MTTR} \quad (5)$$

Setting the line restart time at 7200 seconds and with stable market values are used for the times in this machine, the following results are shown in table 2.

Table 2. Complete display of times, efficiency and availability. Times in seconds.

Component	*MTTR*	*TT_{RP}*	*TT_C*	*TT_{MA}*	*TT_{PR}*	*MTTF*	*T_{LP}*	*Efficiency*	*MTBF*	*Availability*
Máster power switch	14400	3600	0	0	10800	9999999	28800	99.71%	10014399	99.86%
PLC	435600	3600	86400	0	345600	9999999	450000	95.69%	10435599	95.99%
HMI	435600	3600	86400	0	345600	9999999	450000	95.69%	10435599	95.99%
Cromatic sensor	176520	3600	120	0	172800	4999999	190920	96.31%	5176520	96.70%
Plug-in relay	14400	3600	0	0	10800	4999999	28800	99.43%	5014400	99.71%
Command and signalling	14400	3600	0	0	10800	4999999	28800	99.43%	5014400	99.71%
Safety limit switch	14400	3600	0	0	10800	9999999	28800	99.71%	10014399	99.86%
Safety relay	14400	3600	0	0	10800	9999999	28800	99.71%	10014399	99.86%
Safety button	14400	3600	0	0	10800	9999999	28800	99.71%	10014399	99.86%
Temperature controller	435600	3600	86400	0	345600	9999999	450000	95.69%	10435599	95.99%
Solid state relay	176400	3600	0	0	172800	4999999	190800	96.31%	5176400	96.70%
Thermal resistance	25500	14400	0	300	10800	3700800	39900	98.93%	3726300	99.32%
Thermocouple sensor	14700	3600	0	300	10800	3700800	29100	99.22%	3715500	99.61%
Tape drive	435600	3600	86400	0	345600	9999999	450000	95.69%	10435599	95.99%
Tape Motor	187200	14400	0	0	172800	4999999	201600	96.11%	5187200	96.52%
Bronze cap	288000	28800	0	86400	172800	7750000	302400	96.24%	8038000	96.54%
Linear axis	288000	28800	0	86400	172800	7625000	302400	96.18%	7913000	96.49%
Lineal bearing	288000	28800	0	86400	172800	7500000	302400	96.12%	7788000	96.43%
Pneumatic valve	176400	3600	0	0	172800	9999999	190800	98.13%	10176399	98.30%
Pneumatic cylinder	176400	3600	0	0	172800	9999999	190800	98.13%	10176399	98.30%
Pressure sensor	176700	3600	300	0	172800	4999999	191100	96.31%	5176700	96.70%
Servo drive peristaltic pump	435600	3600	86400	0	345600	9999999	450000	95.69%	10435599	95.99%
Peristaltic pump	547200	14400	0	14400	518400	4999999	561600	89.88%	5547200	91.02%

Using the exponential model (6) the reliability of all the components is calculated in a time equal to MTTF. Figure 2 show the results.

$$R_{(t)} = e^{-\lambda t} \quad (6)$$

Where λ factor is the inverse value of MTBF if we consider we are in constant fatigue of components.

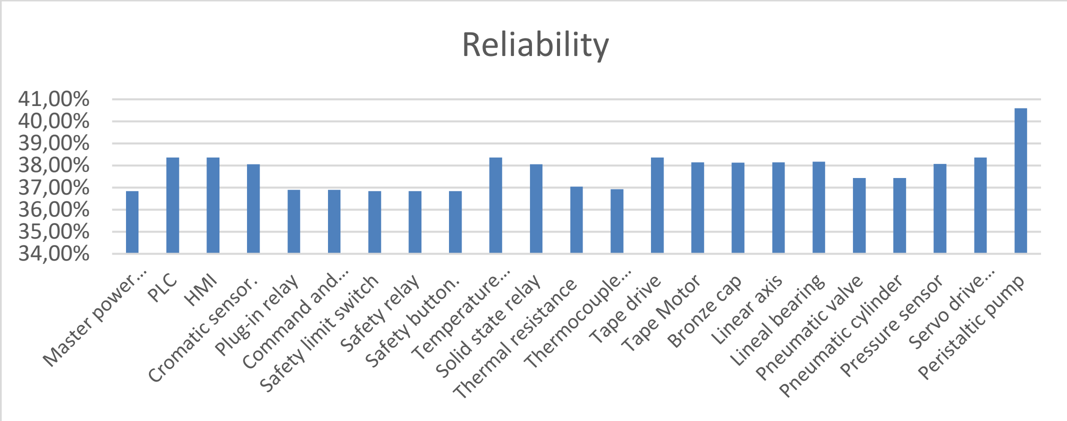

Figure 2. Reliability calculated at MTTF with exponential model (6).

Table 3. Proposed Strategies.

Strategy	Costs	New materials	MTTF	MTTR	S^2 model	YWF
MMI	Increased	Not necessary	Not modified	Improved	Not necessary	Improved
AOP	Not necessary	Necessary	Improved	Improved	Necessary	Optimized.

Table 4. Results of maintenance management improvement model application.

COMPONENT	*Without MMI*		*With MMI*		*AV MMI*	
	Efficiency	*Availability*	*Efficiency*	*Availability*	*Efficiency*	*Availability*
Máster power switch.	99.71%	99.86%	99.82%	99.96%	0.10%	0.10%
PLC	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
HMI	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
Cromatic sensor.	96.31%	96.70%	99.63%	99.92%	3.32%	3.22%
Plug-in relay	99.43%	99.71%	99.63%	99.92%	0.21%	0.21%
Command and signalling	99.43%	99.71%	99.63%	99.92%	0.21%	0.21%
Safety limit switch	99.71%	99.86%	99.82%	99.96%	0.10%	0.10%
Safety relay	99.71%	99.86%	99.82%	99.96%	0.10%	0.10%
Safety button.	99.71%	99.86%	99.82%	99.96%	0.10%	0.10%
Temperature controller	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
Solid state relay	96.31%	96.70%	99.63%	99.92%	3.32%	3.22%
Thermal resistance	98.93%	99.32%	99.21%	99.60%	0.28%	0.28%
Thermocouple sensor	99.22%	99.61%	99.50%	99.89%	0.28%	0.28%
Tape drive	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
Tape Motor	96.11%	96.52%	99.42%	99.71%	3.31%	3.19%
Bronze cap	96.24%	96.54%	98.35%	98.55%	2.11%	2.01%
Linear axis	96.18%	96.49%	98.32%	98.53%	2.14%	2.04%
Lineal bearing	96.12%	96.43%	98.29%	98.51%	2.18%	2.07%
Pneumatic valve	98.13%	98.30%	99.82%	99.96%	1.69%	1.66%
Pneumatic cylinder	98.13%	98.30%	99.82%	99.96%	1.69%	1.66%
Pressure sensor	96.31%	96.70%	99.63%	99.92%	3.32%	3.22%
Servo drive peristaltic pump	95.69%	95.99%	98.96%	99.11%	3.27%	3.12%
Peristaltic pump	89.88%	91.02%	99.14%	99.42%	9.26%	8.40%

3. Strategies to follow to improve results

The following table shows the best strategies proposed to achieve better results. The objective is to reduce the lost production time as much as possible but guaranteeing the proper functioning of the components.

- *MMI:* Maintenance management improvement model.
- *AOP:* Algorithm life optimization based on S^2 model [5] with maintenance advises.

The MMI strategy is based on having stocks in advance, then it supposes a better response to unexpected failures, but it does not allow optimizing the useful life of the components before being replaced. This aspect is resolved by the AOP strategy, which also improves MTTF. The use of new materials can increase the useful lifetime.

The *YWF* parameter is defined as years without failures, and it is used to monitor that the mean time between failures corresponds to more than one productive year, so that any preventive action can be planned at the best times without causing production stoppages.

4. Maintenance management improvement (MMI) model

This is a strategy based on the supply of components, would suppose a considerable reduction in the value of MTTR, and consequently, in the value of the efficiency and the availability. Table 4 shows the results of substituting the supply time for a residual search time in own stock.

The comparison of proposed scenarios provides an average increase in efficiency more than 7.5% and availability by 8.5%.

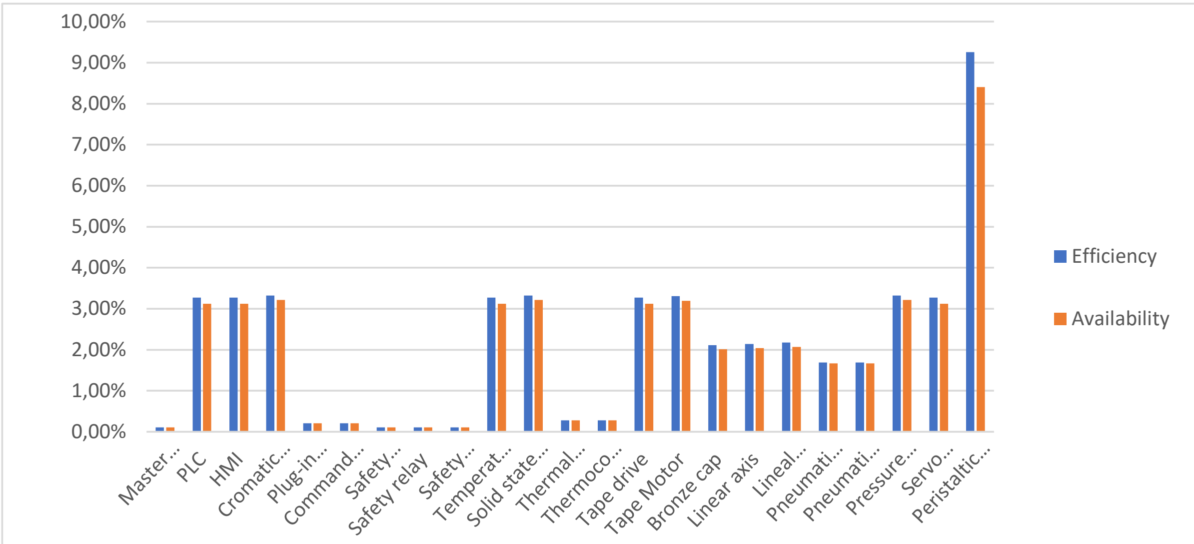

Figure 3. Improvements in efficiency and availability using MMI strategy.

Table 5. Sensors and components used for the model.

Sensor	*Description*	*Components affected*
SA1	% Humidity inside control panel	1, 2, 3, 5, 8, 10, 11, 14
SA2	Cª temperature inside control panel	1, 2, 3, 5, 8, 10, 11, 14
SA3	Voltage RMS in IGBT	1, 2, 3, 4, 5, 8, 10, 12, 14, 15, 19, 20, 21, 22, 23
SA4	Vacuum sensor for Thermoformer tub	10, 12, 13, 16, 18, 19, 20, 21
SA5	Volumetric sensor for peristaltic pumps	22, 23
SA6	Micro laser measurement, side front	14, 15, 16, 17, 18
SA7	Micro laser measurement, side rear	14, 15, 16, 17, 18

5. Algorithm life optimization (AOP) with maintenance advises

This strategy allows to modify the MTTF by analyzing the behaviour of measurements from various

IOP Conf. Series: Materials Science and Engineering 1193 (2021) 012112 doi:10.1088/1757-899X/1193/1/012112

sensors, a reasonable modification of the MTTF of each component can be established. In this way, it could be possible to optimize the useful life of each component. The operation of this strategy is compatible with maintenance decisions, so that conclusions of the previous strategy can be applied at certain times. Table 5 indicates proposed sensors and component group that they affect.

All sensors provide an analog output signal. A datalogger oversees monitoring, recording, and treating the signals in real time.

5.1. Mathematical model of the algorithm

The system records a value every 10 duty cycles. Later it calculates its average value and saves them (7). This operation is carried out 100 times, so that at the end of cycle 1000, 100 average values will be available for each parameter.

$$\mathrm{T}_{1,\mathrm{SA1}} = \frac{\sum_{1}^{10} \mathrm{SA1}_{\mathrm{i},}}{10}\,;\ \mathrm{T}_{2,\mathrm{SA1}} = \frac{\sum_{11}^{20} \mathrm{SA}_{\mathrm{i},1}}{10}\,;\ \ldots\ \mathrm{T}_{100,\mathrm{SA1}} = \frac{\sum_{91}^{100} \mathrm{SA1}_{\mathrm{i},}}{10} \tag{7}$$

Each sample of 100 values is evaluated for whether there is a dispersion of values that indicates that an error may occur in the measurement or in the sensor. Rejection criteria such as Chauvenet or similar are used for them. Once the sample is validated, the statistical values corresponding to a Normal Gaussian distribution are calculated, as the average (8) and the variance (9)

$$\bar{X}_{SA1,100} = \frac{\sum_{1}^{100} T_{i,SA1}}{100} \tag{8}$$

$$\sigma^2_{SA1,100} = \frac{\sum_{1}^{100} \left(T_{i,SA1} - \bar{X}_{SA1,100}\right)^2}{100-1} \tag{9}$$

The following expression (10) is the dynamic adjustment factor, *DFA* of MTTF, and is obtained for each component.

$$DFA = \frac{\left[A - \left(\bar{X}_{SA1,100} - \sigma_{SA1,100} \times 0{,}67\right)\right]}{k} \tag{10}$$

where:

- *A* is the nominal value of the measurement in correct operation.
- *k* is the model adjustment value that differs in each given sensor according to the amount of valid values that in each case may be correct.
- The value 0.67 corresponds, according to the normal Gaussian distribution with a confidence level of 50%. A restrictive level is initially proposed. This value admits correction up to the value 3 which would suppose a confidence interval of 99.7%.

To correct any anomaly that arises unexpectedly, it is proposed to use an alarm value (11) in each sensor that is active during the entire operating time of the machine. Each sensor has a coefficient ***S*** that defines the alarm level.

$$ALARM\ VALUE\ SA_1 = S \times A \tag{11}$$

The final objective of this model is to obtain the reliability of each component every 1000 cycles by adding sensors whose evolution of values and dispersions may indicate a malfunction of the system. Exponential or Weibull calculation models can be used for this purpose, depending on the actual state of wear of each component.

6. Results and conclusions

Most of the machines that process products and have complex threads, must have an adequate management of their maintenance that, as far as possible, leads to high rates of efficiency, availability, and reliability.

Strategy MMI can only minimize the established times for provisioning, repair, configuration and/or mechanical adjustments. Its use brings extra costs, benefits but the improvement is limited. In this case an average increase in efficiency more than 7.5% and availability by 8.5%.

Strategy AOP make it possible to optimize the operating time of the components, monitoring sensor values whose value management can extend the useful life of the components and predict the ideal replacement time based on known repaired or programmed stop times.

The implementation of process availability and quality control techniques provide factories with the ability to adapt on demand, respond with constant quality and report in real time the status of compliance with their commitments. Therefore, factories increase their competitiveness in the market.

Acknowledgements
The authors wish to thank the European Regional Development Fund "Una manera de hacer Europa" for their support towards this research. This study has been carried out through the Research's Projects GR-18029 and GR-18059 linked to the VI Regional Research and Innovation Plan of the Regional Government of Extremadura.

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