UNIVERSIDAD NACIONAL DE EDUCACIÓN A DISTANCIA

Máster en Ingeniería Avanzada de Fabricación

Trabajo Fin de Máster

TÍTULO	**Mejora de la calidad, eficiencia y sostenibilidad en los procesos de mecanizado mediante Inteligencia Artificial.**
AUTOR	Lourdes Martínez Molina.
TUTOR	Eva María Rubio Alvir.
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DEPARTAMENTO: Ingeniería de Construcción y Fabricación.

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(A rellenar por la Comisión Evaluadora)

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Este TFM ha sido desarrollado durante la estancia en la Universidad Federico II de Nápoles (UNINA) como parte del programa ERASMUS.

El TFM ha dado lugar a la participación, con una ponencia oral, en la 16th CIRP Conference on Intelligent Computation in Manufacturing Engineering – Innovative and Cognitive Production Technology and Systems celebrada del 13 -al 15 de julio de 2022 y que será publicada en la revista de Open Access CIRP Procedia.

Martínez, L., Teti, R., Rubio, E.M., Quality, efficiency and sustainability improvement in machining processes using Artificial Intelligence, CIRP Procedia, 2022. (In press).

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Puedes besar y despedirte de tu familia y amigos poniendo kilómetros de por medio, pero siguen estando contigo en tu corazón, en tus pensamientos. Porque no sólo vives en un mundo, sino que un mundo vive en ti (Frederick Buechner).

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RESUMEN GENERAL

1-INTRODUCCIÓN

1.1-RESUMEN

El sector industrial se encuentra en estos momentos en un periodo de recuperación a nivel global aun cuando se sigue haciendo frente a las consecuencias de la pandemia mundial COVID -19, el aumento de precio de la electricidad y del barril de petróleo, la escasez de materias primas y su aumento de precio, etc. La coyuntura industrial hace que el crecimiento sea contenido. Las empresas deben hacer frente a estos condicionantes y, además, mejorar su eficiencia para ser competitivas. En un mercado global, donde las compras de productos se hacen cada vez en lugares más lejanos, las organizaciones deben encontrar un equilibrio en el que el valor añadido que ofrezcan supere las ventajas de sus competidores.

Además, se deben considerar, por un lado, las políticas de sostenibilidad, que, si bien buscan la equidad social, el crecimiento y la reducción de impacto medio ambiental, suponen restricciones añadidas a los procesos industriales y por otro, los requisitos cada vez más exigentes del mercado y de los clientes.

Como se puede observar el entorno industrial es complejo por lo que las empresas deben buscar la eficiencia a través de nuevas herramientas y haciendo uso de las tecnologías disponibles.

Así, esta eficiencia pasa por realizar cambios estructurales que busquen:

- Reducción de costes.
- Mejora de la calidad percibida por el cliente.
- Optimización del uso de las materias primas.
- Aumento de la eficacia en la toma de decisiones.
- Mejora de la eficiencia de los procesos industriales.
- Uso eficiente de los recursos energéticos.
- Minimización y gestión adecuada de los residuos.
- Reducción del impacto ambiental de los procesos productivos.
- Impacto social positivo de las actividades industriales.
- Rápida adaptación a los entornos cambiantes.
- Plazos de entrega cada vez más exigentes.

Los cambios estructuras necesarios, factores limitantes para unos y oportunidades para otros, dirigen al sector industrial a su cuarta revolución. En ella, la información juega un papel determinante y las empresas más competitivas serán aquellas que empleen de manera eficaz esta información junto a los avances tecnológicos. Las organizaciones que se adapten mejor y más rápido a los cambios de la demanda, a la implantación de nuevas soluciones tecnológicas, cada vez más frecuentes, y usen la información generada y disponible en su favor, serán aquellas que tengan más posibilidades de sobrevivir en un entorno de competencia creciente.

De una manera más concreta, en este trabajo, se examinará la industria del mecanizado. Siendo esta una de las industrias fundamentales que sustenta y ofrece productos a muchos otros sectores.

Este estudio se centrará en aquellas mejoras de los procesos de mecanizado. Así, partiendo de la situación actual en uno de los países de la Union Europea como es España, se recorrerá los distintos avances disponibles para los procesos de mecanizado y se analizarán las necesidades actuales de la industria para la implantación de esos avances.

Hablar de los avances disponibles es hablar de la inteligencia artificial (AI) que está revolucionando el mundo tal y como lo conocemos. Desde la manera en la que buscamos información, nos comunicamos con los aparatos electrónicos hasta la previsión del ganador en un partido de tenis. Aunque a veces y como en este último ejemplo, el ser humano siguió sorprendiendo a las máquinas. Existen múltiples mejoras que la AI ofrece en el campo del mecanizado, pero si bien es cierto no será posible su implantación de la misma manera en todas las empresas del sector.

El objetivo de este trabajo es la de estudiar como la inteligencia artificial ayuda a los procesos de mecanizado para ser más competitivos sin olvidar la percepción ética del uso de estos avances y la situación de partida en España. De esta manera, se analizarán los parámetros que influyen en la eficiencia y sostenibilidad de los procesos de mecanizado y en la calidad final de las piezas para optimizarlos mediante el uso de la inteligencia artificial.

1.2-CLIMA INDUSTRIAL ESPAÑOL Y ESTADO DE LA DIGITALIZACIÓN

El informe de coyuntura industrial de enero de 2022 (MINCOTUR, 2022) muestra la recuperación y el crecimiento del índice de clima industrial (Figura 1.1- Figura 1.2) a niveles anteriores a la crisis del COVID 19.

Esto ofrece optimismo para el futuro, pero con trabajo por delante para incrementar la respuesta productiva nacional y la venta de la producción.

El informe publicado por la Comisión Europea sobre el Índice de Economía y Sociedad Digitales (EU, 2021) ofrece información sobre el Índice de Intensidad Digital (IID). El DII es un índice que mide el uso de diversas tecnologías digitales a nivel de empresa: Muestra el grado de penetración y la velocidad de despliegue de las tecnologías digitales a nivel nacional.

Las soluciones tecnológicas digitales adoptadas por empresas españolas e italianas se clasifican en su mayoría como de bajo nivel. En ambos países, menos del 2% de las empresas han adoptado medidas de tecnología digital avanzada como el uso de big data, el uso de robots industriales o robots de servicio, sistemas de fabricación avanzada como la impresión 3D, etc. (Figura 1.4).

España está por detrás de la media de la UE en cuanto a la aplicación de las herramientas fundamentales de digitalización (uso de cloud computing, análisis de Big Data y uso de inteligencia artificial) (Figura 1.5). Este informe muestra que España debe implementar varias medidas de calado para alcanzar la cuarta revolución industrial de forma favorable.

1.3-INTELIGENCIA ARTIFICIAL

La evolución de la digitalización ha pasado por varias etapas, desde una digitalización inicial para almacenar documentos sin ningún cambio en los procesos hasta la actualidad, donde lo físico y lo virtual convergen. (Qi *et al*., 2021) (Figura 1.6). En la actualidad, la inteligencia artificial se combina con otras herramientas para mejorar su rendimiento. La IA podría combinarse con Internet of Things para mejorar la precisión, realizar análisis predictivos, mejorar la satisfacción del cliente y aumentar eficiencia operativa (Mohanta *et al*., 2020). La IA también utiliza cloud computing para aumentar la conectividad.

La definición de inteligencia artificial dada por el Grupo de Expertos de Alto Nivel de la Comisión Europea sobre IA (UE, 2018) ofrece una primera visión del creciente impacto de su uso en diferentes dimensiones: *"Los sistemas de inteligencia artificial (IA) son sistemas de software (y posiblemente también de hardware) diseñados por humanos que, dado un objetivo complejo, actúan en la dimensión física o digital percibiendo su entorno a través de la adquisición de datos, interpretando los datos estructurados o no estructurados, razonando sobre el conocimiento o procesando la información de estos datos y decidiendo la mejor acción o acciones a realizar para alcanzar el objetivo fijado. Los sistemas de IA pueden utilizar reglas simbólicas o aprender un modelo numérico, y también pueden adaptar su comportamiento analizando cómo el entorno se ve afectado por sus acciones anteriores. Como disciplina científica, la IA incluye varios enfoques y técnicas, como el aprendizaje automático (del que el aprendizaje profundo y el aprendizaje por refuerzo son ejemplos específicos), el razonamiento automático (que incluye la planificación, la representación del conocimiento y el razonamiento, la búsqueda y la optimización) y la robótica (que incluye el control, la percepción, los sensores y los actuadores, así como la integración de todas las demás técnicas en sistemas ciberfísicos)"*.

Así, la utilidad de la inteligencia artificial es incuestionable, ya que está integrada en nuestra vida cotidiana y la competitividad de las empresas depende de ella. Tal y como se recoge en el Libro Blanco de la Comisión Europea sobre la Inteligencia Artificial: *"El crecimiento económico sostenible actual y futuro de Europa y el bienestar de la sociedad de Europa se basan cada vez más en el valor creado por los datos. La IA es una de las aplicaciones más importantes de la economía de los datos"* (UE, 2020). Por otra parte, su desarrollo ofrecerá tanto a la industria como a otros sectores posibilidades antes inimaginadas. La inteligencia artificial se ha desarrollado ampliamente y tiene un futuro prometedor en otros campos como la medicina. Pero esto no ha sido así, por ejemplo, en el ámbito industrial español, donde su introducción, hasta la fecha, ha sido poco notable y lenta. Además, existe una brecha importante entre el progreso de la investigación sobre el mecanizado, el uso de la inteligencia artificial en este campo y su aplicación, por ejemplo, en las industrias de mecanizado. Este trabajo incluye estudios sobre la aplicación de la inteligencia artificial en el sector del mecanizado, pero estas soluciones tecnológicas sólo están llegando parcial y lentamente a las empresas. La inteligencia artificial puede influir en la industria en muchos ámbitos (Fahle and Kuhlenkötter, 2020) (Figura 1.10).

1.4-MARCO DE TRABAJO DE LA INTELIGENCIA ARTIFICIAL EN LOS PROCESOS DE MECANIZADO

La inteligencia artificial ofrece un impacto positivo y un apoyo a la industria del mecanizado en la mejora de los siguientes aspectos:

- ✓ **Eficiencia.** La inteligencia artificial ofrece tres beneficios principales en este campo (Nishant *et al*., 2020):
    - Automatización de operaciones que aportan poco valor añadido, son consumidoras de tiempo y repetitivas. Además, el uso de la automatización permite que aquellas tareas con impacto ergonómico negativo sobre los trabajadores sean llevadas a cabo por dispositivos, robots, etc.
    - Análisis de los datos. Transformación de datos difíciles de analizar en información. Puede ser por su volumen, por no estar estructurados o por sus características (vídeos, fotografías, informes, etc.).
    - Capacidad de involucrar a un gran número de ordenadores y dispositivos y su capacidad de integrarse en otras soluciones tecnológicas que conforman la Industria 4.0.

- ✓ **Calidad.** Mejorar la precisión y reducir la variabilidad de las operaciones. Como se verá en este trabajo, la calidad en los procesos de mecanizado se caracteriza por el cumplimiento de las tolerancias dimensionales, el acabado superficial y la eliminación de defectos en las piezas mecanizadas. Hoy en día con la creciente importancia de la micro y nanofabricación, los equipos de ingeniería se están especializando en el diseño de piezas y productos cada vez más precisos y en la reducción de tolerancias de fabricación. De este modo, disminuyen los costes asociados a los desperdicios de material, la falta de calidad piezas rechazadas, etc. Un ejemplo de ello es el proyecto MIDEMMA, Minimización de Defectos en Aplicaciones de Microfabricación (MIDEMMA, 2014), que defiende y trabaja para conseguir una "fabricación con cero defectos". Esta visión se está generalizando a otros sistemas de fabricación y los requisitos procedentes de los clientes son cada vez más cada vez más exigentes. El uso de la inteligencia artificial permite lograr altos niveles de calidad en los productos y servicios.

- ✓ **Sostenibilidad.** Tal y como se recoge en el Libro Blanco de la Comisión Europea sobre la Inteligencia Artificial (UE, 2020): "El uso de sistemas de IA puede tener un papel importante en la consecución de los Objetivos de Desarrollo Sostenible y en el apoyo al proceso democrático y a los derechos sociales". La inteligencia artificial ayuda a gestionar los procesos de forma que se reduzcan su impacto ambiental y social. Por ejemplo, en el caso de los procesos de mecanizado reduce la cantidad de material utilizado y de residuos, optimiza el uso de energía, gestiona y controla los productos que afectan a los trabajadores, reduce el trabajo repetitivo, etc. La fabricación ecológica puede llegar a ser estratégica en términos de objetivos económicos de alto nivel y se centra en tres finalidades principales como (Mao *et al.,* 2019):

    - Reducir el consumo de energía y las emisiones contaminantes.
    - Supervisión de la seguridad de los procesos a lo largo del ciclo de vida y control de los riesgos.
    - Seguimiento y evaluación de la huella ambiental.

  Por otro lado, la huella de carbono y el impacto ambiental generado por el uso de AI debe ser considerado y se deben explorar fuentes de energía alternativas, menos impactantes, y optimizar los procesos de IA para reducir la cantidad de energía utilizada (Nishant *et al*., 2020).

2-USO DE LA INTELIGENCIA ARTIFICIAL EN LOS PROCESOS DE MECANIZADO

Hoy en día, considerando los condicionantes que rodean al sector industrial de fabricación, cuando las organizaciones se plantean sus principales líneas de actuación, siempre tienen en cuenta estos tres objetivos fundamentales, ya que son la clave de su competitividad. En este sentido, la industria del mecanizado está en continua evolución debido a (Albertí, 2010):

- Desarrollo de materiales para herramientas.

- Mejor conocimiento de los mecanismos de formación de viruta y desgaste de la herramienta.
- Desarrollo de las máquinas herramienta y de las condiciones de mecanizado.
- Crecimiento constante de la demanda de eficiencia en tiempo y costes.
- Desarrollo de nuevos materiales difíciles de mecanizar.
- La demanda de una mayor calidad del producto.
- La demanda de tiempos de producción más cortos mediante flujos simplificados.
- La reducción del ciclo de vida del producto.
- El aumento de las superficies multifuncionales en los componentes.

Para hacer frente a cada uno de los puntos mencionados, la inteligencia artificial es una herramienta esencial. En las siguientes subsecciones se analizará la implicación de la inteligencia artificial en diferentes aspectos del mecanizado:

1. Selección de materias primas, herramientas y equipos y operaciones de mecanizado.
2. Algoritmos de IA para optimizar el proceso de mecanizado.
3. Monitorización del proceso de mecanizado.
4. Sostenibilidad del proceso.

Se enumerarán las diferentes soluciones propuestas por varios autores, que nos llevan a entender el futuro del mecanizado en manos de la inteligencia artificial

2.1-SELECCIÓN DE MATERIAS PRIMAS, HERRAMIENTAS Y EQUIPOS Y OPERACIONES DE MECANIZADO.

El mecanizado engloba una gran variedad de procesos cuya finalidad es dar forma a las piezas mediante eliminación de material, ya sea por mecanizado, abrasión, vaporización, ataque químico, etc. Debido a esta variedad de operaciones, la caracterización de los procesos es difícil. Más aún con la introducción de nuevos materiales que exigen requisitos operativos especiales.
Así, determinar las condiciones de los procesos de mecanizado, aunque sean convencionales, es muy compleja. Estas condiciones son la selección del material adecuado, el proceso y los parámetros de mecanizado adecuados, y los equipos y herramientas necesarios.

2.1.1-MATERIAS PRIMAS.

La elección correcta del material es esencial, ya que puede mejorar la productividad, la utilización del material reduciendo los residuos y la flexibilidad, fiabilidad y repetibilidad del proceso (Zeynali *et al*., 2012). En consecuencia, esto conduce a un proceso más eficiente y un ahorro de costes, mejores plazos de entrega y una mayor calidad del producto y del servicio.

Existen multitud de características a tener en cuenta, no solo en cuanto al material en sí mismo, sino también en cuanto a cómo afecta ese material al proceso. Además, los nuevos materiales que están surgiendo en la industria deben ser tenidos en cuenta, y que en algunos casos suponen la sustitución de materiales tradicionales por sus ventajosas propiedades. Todo esto hace que la selección de materiales sea cada vez más compleja debido a nuevos materiales, nuevos conocimientos, nuevos desarrollos de procesos, la necesidad de ahorrar costes y de reducir el impacto medioambiental. Con el fin de realizar una selección exitosa de materiales, es necesario hacer uso de los métodos de inteligencia artificial disponibles. De este modo, los autores que citados en la tabla 4.1 proponen el uso de inteligencia artificial en la fase de elección de materiales. Se destacan los siguientes estudios:

- Zeynali y sus colaboradores (Zeynali *et al*., 2012) consideran la selección de la combinación de materiales como una toma de decisiones de criterios múltiples (MCDM). En su estudio, el proceso de jerarquía analítica difusa (AHP) se utiliza para calcular el peso de cada criterio que conduce a la selección de los materiales más adecuados y, posteriormente, se aplica la Técnica Difusa de Preferencia de Orden por Similitudes a la Solución Ideal (TOPSIS) para obtener los resultados optimizados.
- Denkena y sus colaboradores (Denkena *et al*., 2020) proponen la identificación de diferentes materiales durante una operación de mecanizado, lo cual es muy útil para ajustar los parámetros de la operación. El estudio se basa en los cambios en la vibración y la fuerza causados por diferentes materiales. Los resultados mostraron que las redes neuronales (RNA) son capaces de clasificar los materiales en función de los parámetros de corte en torneado. (Figura 2.5)

2.1.2-MÁQUINAS Y HERRAMIENTAS.

La selección adecuada de las máquinas-herramienta, las herramientas y sus soportes son esenciales para obtener el producto deseado, en términos de conformación y calidad, y para lograr las condiciones óptimas del proceso, por ejemplo, la precisión dimensional y el tiempo de ciclo (Albertí, 2010). Para ello, hay que definir los factores para poder discernir entre las alternativas disponibles.

La elección de la máquina-herramienta es una decisión difícil para las empresas tanto en el momento de la compra, ya que deben tener muy claro lo que buscan y compararlo con las existentes en el mercado, como en el momento de tomar la decisión de llevar a cabo un proceso de fabricación, ya que deben analizar las prestaciones de las máquinas-herramienta disponibles en sus instalaciones.

Actualmente, la mayoría de las empresas hacen su elección basándose en la experiencia y los conocimientos de los de los responsables. El uso de la inteligencia artificial permite considerar una mayor cantidad de información de forma objetiva.

Una elección inadecuada puede generar costes adicionales (costes de funcionamiento, costes de inversión, etc.), impactos negativos en la productividad, la precisión, la flexibilidad y la capacidad de respuesta de la empresa. Todo esto repercute en la calidad, el coste y el plazo. (Ayağ y Özdemir,2006).

Por ello, la búsqueda de la máquina-herramienta ideal tiene como objetivo:

- La reducción de la variabilidad del proceso.
- Aumento del control de los parámetros de corte.
- Optimización de la dinámica de funcionamiento y de la trayectoria.
- Mejoras en el mantenimiento de la máquina herramienta (plazos y costes).
- Mejora de las capacidades.

Debido a que la selección adecuada de la máquina, herramienta y su secuencia de uso es esencial para la eficiencia de las operaciones de mecanizado, muchos autores han buscado la mejor manera de optimizar esta tarea y hacerlo conjuntamente con las herramientas que proporciona la inteligencia artificial. En este trabajo se han presentado una serie de ejemplos de estudios con diferentes enfoques, pero con el objetivo común de mejorar esta tarea (Tabla 4.1). Especial mención se debe hacer a los siguientes trabajos:

- Keung y sus colaboradores (Keung *et al*., 2001) decidieron emplear algoritmos genéticos para la elección del centro de mecanizado abordando la programación en un sistema de fabricación flexible (Figura 2.6).
- Alam y sus colaboradores (Alam *et al*., 2003) utilizan también algoritmos genéticos con el objetivo de reducir el tiempo de ciclo.
- Ayağ y Özdemir (Ayağ y Özdemir.,2006) incluyen la selección de la máquina herramienta en el ámbito de la toma de decisiones con criterios múltiples (MCDM). El enfoque AHP difuso permite una toma de decisiones más precisa, ya que sirve para ponderar las alternativas en función de varios atributos, como los pertenecientes a las categorías de productividad, flexibilidad espacio, adaptabilidad, precisión, fiabilidad, seguridad, medio ambiente, mantenimiento y servicio. Posteriormente, se lleva a cabo un análisis beneficio/coste, a partir del cual se obtiene la opción de máquina-herramienta más adecuada.
- Önüt y sus colaboradores aplican un modelo de dos etapas: 1-Procedimiento AHP difuso 2-TOPSIS difuso para la selección del centro de centro de mecanizado CNC más adecuado entre los propuestos en una empresa turca (Önüt *et al*., 2008).

- Ic y Yurdakul [8] también aplicaron AHP difusa y TOPSIS difusa para crear un sistema de apoyo a la decisión de forma intuitiva para las empresas usuarias (Ic y Yurdakul, 2009) (Figura 2.9).
- Taha y Rostam (Taha y Rostam, 2011) presentan un sistema de decisión basado en un proceso de jerarquía analítica difusa complementado con el Método para la organización de la clasificación de preferencias para el enriquecimiento de la evaluación. (PROMETHEE). El método AHP difuso ayuda a proponer los pesos de cada una de las categorías de selección, mientras que el método PROMETHEE realiza la clasificación final.
- Albertí y sus colaboradores (Albertí *et al.*, 2011) utilizan redes neuronales para modelar un sistema de selección de centros de mecanizado de alta velocidad. Partiendo de tres variables relacionadas con el producto, con la configuración de la máquina y la propia operación. La selección de la máquina se basa en la relación precisión/error, el error, el tiempo y el coste del proceso y el coste de la máquina herramienta (Figura 2.7-Figura 2.8).

La selección de las herramientas de corte es también es importante. Esta elección repercute en los costes de explotación, el tiempo de ciclo y la calidad del producto obtenido. Una de las características que puede verse directamente afectada por la herramienta escogida es su propio desgaste, que influye en las métricas anteriores. Hay varios factores que determinan la selección de las herramientas de corte (Albertí, 2010):

- Propiedades mecánicas (dureza, resistencia, tenacidad, etc.).
- Aplicabilidad.
- Stock de reposición.
- Requisitos de precisión y acabado.
- Tipo de máquina-herramienta utilizada.
- Requisitos de producción en función de las velocidades de corte y de avance.
- Condiciones de funcionamiento como esfuerzo de corte, temperaturas, etc.
- Costes por pieza.

El portaherramientas también debe ser seleccionado adecuadamente (Albertí, 2010) ya que debe garantizar un rápido cambio entre herramientas y proporcionar estabilidad en el proceso. Un portaherramientas inadecuado puede provocar defectos de mecanizado, falta de precisión dimensional, mala calidad de acabado e incluso una reducción de la vida útil de la herramienta. Varias investigaciones han utilizado la inteligencia artificial para la tarea de selección de herramientas y portaherramientas y su secuenciación (Tabla 4.1). Entre ellas destacan:

- Gjelaj y sus colaboradores (Gjelaj *et al.*, 2013) proponen una mejora en la selección de herramientas en centros de mecanizado CNC basada en el uso de algoritmos genéticos (Figura 2.10).
- Kunaparaju y sus colaboradores (Kunaparaju *et al*., 2016) sugieren un modelo que, partiendo de una base de datos de herramientas y datos de operación, utilizan un sistema neuro difuso adaptativo para obtener una lista de herramientas adecuada para la operación de mecanizado y un algoritmo genético para optimizar la selección de herramientas y parámetros de mecanizado. Esta optimización se basa en maximizar la tasa de eliminación de material y la vida útil de la herramienta y minimizar su coste (Figura 2.11).
- Ahmad y sus colaboradores (Ahmad *et al.,* 2010) proponen un nuevo método para obtener una secuencia de herramientas bajo un coste óptimo para el mecanizado de cajeras de 2,5 ejes aplicando algoritmos genéticos. Los datos de entrada considerados son la geometría de la cajera y de la pieza, el conjunto de herramientas disponibles los parámetros de corte y la geometría del portaherramientas (Figura 2.12-Figura 2.13).
- Para Yao y sus colaboradores, el enfoque para optimizar la secuencia de herramientas para el fresado en 2,5 -D es a través del tiempo, tanto del tiempo de proceso como del tiempo de carga de la herramienta (Yao *et al*., 2003). En su estudio, mediante algoritmos geométricos se extrae la región de mecanizado objetivo, el área que puede cubrir cada una de las herramientas y finalmente, mediante el algoritmo de Dijkstra, se obtiene la secuencia óptima.
- Lim y sus colaboradores abordan la optimización de la secuencia de herramientas empleando algoritmos geométricos que favorecen la herramienta más grande, capaz de realizar un vaciado volumétrico más completo (Lim *et al*., 2010) (Figura 2.14).

2.1.3-PROCESOS DE MECANIZADO Y SU SECUENCIA.

Los responsables de producción o los técnicos designados son los encargados de determinar los procesos de mecanizado a realizar para la fabricación de una pieza y también establecer la secuencia de las operaciones. Esta decisión es el resultado de sus conocimientos y experiencia (Kang *et al*., 2016). Por otro lado, cada vez son más los técnicos que confían en los sistemas CAD/CAM para la fabricación de piezas, siendo el módulo CAP un enlace estratégico entre ellos que da soporte a la decisión de secuenciar los procesos de mecanizado. Hay que tener en cuenta que la aparición de nuevos materiales, tanto de trabajo como de utillaje, nuevos procesos de mecanizado y la evolución de las máquinas herramienta, hace que la toma de decisiones sea más compleja, más lenta y menos eficiente. La inteligencia artificial en esta fase es crucial ya que educe el error humano en el proceso de selección, mejora la eficiencia, reduce el tiempo y considera todos los datos relacionados con los procesos de mecanizado.

En la elección de los procesos de mecanizado adecuados, los responsables buscan obtener la calidad requerida en el menor tiempo y al menor coste posible, incluyendo el aumento de la vida útil de las herramientas. La correcta secuenciación de las operaciones reduce el tiempo y el número de preparaciones, el tiempo de ciclo, el coste del ciclo y conduce a un mejor mantenimiento de la máquina-herramienta.

Los autores han utilizado diversas estrategias para lograr una selección óptima del proceso y secuencia de mecanizado (Tabla 4.1). Es importante mencionar las siguientes:

- Aproximación a la selección y secuenciación de procesos de mecanizado mediante modelos ontológicos (Eum *et al*., 2013) (Kang *et al*., 2016).
- Ahmad (Ahmad, 2001) propone un modelo CAPP que abarca desde el diseño de la pieza, la extracción de características y la optimización de los parámetros del proceso mediante algoritmos genéticos (Figura 2.15).
- Ahmad y Haque (Ahmad y Haque, 2002) emplean redes neuronales para selección de procesos de mecanizado de superficies cilíndricas (Figura 2.16).
- Desarrollo de una nueva red neuronal de retropropagación para piezas rotacionalmente simétricas (Deb *et al*., 2006) (Figura 2.17).
- Wong y sus colaboradores (Wong *et al*., 2003). resuelven la decisión de la selección y secuenciación de procesos de mecanizado con un enfoque híbrido mediante un sistema experto difuso (ES) y algoritmos genéticos (AG). Este enfoque optimizó la secuenciación con un modelo de tolerancia de costes (Figura 2.18).
- Deja y Siemiatkowski (Deja y Siemiatkowski, 2018) proponen el uso de algoritmos para la selección del proceso de mecanizado y su secuenciación según la configuración mostrada en la figura 2.19. Basándose en las características del mecanizado y los atributos de la pieza, y considerando las máquinas herramienta disponibles, el algoritmo realiza la selección de la operación más adecuada y su secuenciación.
- Nallakumarasamy y sus colaboradores realizan una aproximación utilizando algoritmos genéticos superhíbridos y la técnica de annealing simulado. El algoritmo genético proporciona una solución óptima a la técnica de annealing simulado con el objetivo de obtener un resultado de mayor calidad y reducir el tiempo computacional (Nallakumarasamy *et al*., 2011).

2.2-ALGORITMOS PARA OPTIMIZAR LOS PROCESOS DE MECANIZADO.

La selección del proceso de mecanizado óptimo consiste en determinar los parámetros de proceso ideales para maximizar la productividad y el ahorro, reducir el coste del proceso, el impacto medioambiental y cumplir los requisitos del cliente en términos de calidad, alcance, tiempo y coste. La consecución de estos parámetros de funcionamiento óptimos ha sido objeto de numerosos estudios, ya que es uno de los aspectos clave de la eficacia del proceso (Tabla 4.1). Son significativos:

- Bakhtiyari y sus colaboradores sugieren métodos híbridos de inteligencia artificial, como el modelo GA-ANN, para lograr la optimización del mecanizado por rayo láser, centrándose en los aspectos de calidad y rendimiento (Bakhtiyari *et al.*, 2021) (Figura 2.27).
- Boga y Koroglu (Boga y Koroglu, 2021) también emplean un enfoque de inteligencia híbrida consistente en redes neuronales ajustadas mediante un algoritmo genético para estimar la rugosidad superficial de una pieza compuesta de fibra-carbono en un proceso de fresado (Figura 2.28).
- Muthuram y Frank (Muthuram y Frank, 2021) integran la técnica de redes neuronales en algoritmos genéticos para encontrar la combinación de parámetros que maximiza la tasa de eliminación de material (MRR) y minimiza la rugosidad superficial (Figura 2.29).
- Lee y Yarng ya estudiaron, en el año 2000, la selección de los parámetros de corte adecuados para un proceso de torneado multipaso con el objetivo de optimizar el coste de explotación, maximizando la tasa de producción o minimizando el coste de producción (Lee y Yarng, 2000). Utilizaron redes polinómicas para modelar el proceso (Fig. 2.30).
- Cus y Balic (Cus y Balic, 2003). intentaron optimizar el coste y el tiempo de operación encontrando los valores óptimos para los parámetros de corte. Para ello, emplearon algoritmos genéticos en los que se consideran varias funciones objetivo y restricciones (Tabla 2.3) (Figura 2.31).
- D'Addona y Teti (D’Addona y Teti, 2013) también trabajaron en el proceso de torneado con algoritmos genéticos. Las funciones objetivo se centran principalmente en minimizar el coste de producción y maximizar la producción y el beneficio.
- Zuperl y sus colaboradores (Zuperl *et al.*, 2004) proponen un sistema híbrido para este fin. El sistema híbrido se desarrolla gracias a redes neuronales y a la rutina TOPSIS (Figura 2.32-Figura 2.33).
- Una perspectiva interesante es la desarrollada por La Fé-Perdomo y sus colaboradores (La Fé-Perdomo *et al.*, 2018) en la que, además de la visión técnico-económica incorporan la dimensión ambiental en la selección de los parámetros ideales para un proceso de torneado multipasos. Las variables de decisión elegidas se basan en los parámetros de corte: velocidad, avance y profundidad de corte. Además, se consideraron dos funciones objetivo. La primera representa los costes del proceso, mientras que la segunda refleja el impacto medioambiental a través del consumo de energía y la vida útil de la herramienta (desgaste de la herramienta). La optimización para obtener los parámetros adecuados se llevó a cabo mediante dos técnicas diferentes: el algoritmo genético no clasificado II y la optimización multiobjetivo por enjambre de partículas. Ambas proporcionaron resultados eficaces resultados eficaces

en términos de optimización sostenible. Sin embargo, los algoritmos genéticos presentaron una respuesta superior en términos de calidad y eficiencia computacional.

- Es importante mencionar también la nueva perspectiva de Yoo y Kang (Yoo y Kang, 2021) sobre la búsqueda de optimización de procesos de mecanizado basada en la estimación de costes de fabricación mediante el uso de deep Learning. No se basa en los parámetros de corte sino en el material, la forma final de la pieza y los costes del proceso (Figura 2.34-Figura 2.35).

2.3-MONITORIZACIÓN DE LOS PROCESOS DE MECANIZADO.

La gran relevancia de la monitorización en los procesos de mecanizado es evidente por el gran número de artículos científicos y estudios relacionados con ella. El ámbito de la monitorización es el análisis de f (Teti *et al*., 2010):

- Condiciones de la herramienta.
- Condiciones de la viruta.
- Condiciones del proceso.
- Integridad de la superficie.
- Estado de la máquina.
- Detección de vibraciones, etc.

La aplicación de herramientas de IA permite analizar todos los datos recogidos por los sensores de forma rápida, fiable y precisa.
El uso de técnicas de inteligencia artificial sobre la base de datos ya procesada favorece una estimación más rápida y autónoma de, por ejemplo, el desgaste de la herramienta, la calidad de la pieza y fallos catastróficos. La aplicación de estas técnicas, por tanto, lleva el proceso hasta sus límites haciéndolo más eficiente, lo que conlleva un ahorro de costes y un menor número de defectos al reducir la intervención humana. A continuación, se presentan una selección de estudios sobre el uso de la IA en la monitorización de los procesos de mecanizado (Tabla 4.1).

2.3.1-MONITORIZACIÓN DEL DESGASTE DE LA HERRAMIENTA Y SU FALLO.

El desgaste de las herramientas es un aspecto muy importante con respecto a productividad, el tiempo de proceso, la calidad de la pieza producida y el coste total de la operación de mecanizado. También existe la posibilidad de un fallo prematuro, que provoca pérdidas de material, retrasos en la producción, etc. El cambio de herramientas depende, sobre todo, de los conocimientos y la experiencia del operario y de los responsables del proceso de mecanizado. La predicción del desgaste de las herramientas es una tarea muy compleja debido al gran número de variables que intervienen. Varios autores consideran que la IA es una gran ayuda en este campo:

- Caggiano y sus colaboradores (Caggiano *et al.*, 2017) presentan el uso de redes neuronales en la predicción del desgaste y calidad de la pieza en un proceso de taladrado de un plástico reforzado con fibra de carbono.
- Centrándose en el desgaste y, sobre todo, en cómo maximizar la vida de la herramienta en operaciones de taladrado de plásticos reforzados con fibra de carbono, Caggiano y sus colaboradores (Caggiano *et al.*, 2018) profundizan en la combinación de análisis de señales de fuerza y par de corte y redes neuronales para la estimación del estado (Figura 2.38).
- También estudian las operaciones de taladrado Zhu y sus colaboradores (Zhu *et al.*, 2021) empleando una red neuronal de propagación para estimar la fuerza de taladrado en un material SiCp/Al y tomando datos de velocidad de corte y avance.
- Si hablamos de otro tipo de operación de mecanizado como como el pulido, el trabajo de D'Addona y sus colaboradores (D'Addona *et al.*, 2016) muestra que las redes neuronales (redes neuronales de retropropagación) presentan un resultado aceptable en cuanto a la estimación del desgaste de una muela basándose en las señales de vibración.
- También hay que mencionar los trabajos de Corne y sus colaboradores (Corne *et al.*, 2017) y Drouillet y sus colaboradores (Drouillet *et al.*, 2016) que también utilizan redes neuronales para la predicción del desgaste de las herramientas. En ambos casos, el estudio se realiza utilizando señales de potencia del husillo.
- D'Addona y Teti (D'Addona y Teti, 2013) desarrollan una metodología para determinar el desgaste de la herramienta mediante imágenes captadas por una cámara de cámara de vídeo y utilizando redes neuronales de retropropagación.
- Bergs y sus colaboradores (Bergs *et al.*, 2020) presentan la aplicación del aprendizaje profundo para detección de desgaste de herramientas a partir de imágenes digitales (Figura 2.39). El aprendizaje profundo está representado por dos redes neuronales con dos tareas diferentes:
    - Redes neuronales convolucionales (CNN) que se utilizan para la clasificación de imágenes para la identificación de tipos de herramientas y
    - Redes Convolucionales Completas (FCN) que permiten la detección de la zona de desgaste de la herramienta.
- El trabajo de Brili y sus colaboradores (Brili *et al.*, 2021) tiene como objetivo estimar el desgaste de la herramienta y su posible fallo mediante CNN en operaciones de torneado en seco. Además de la información visual, se ha propuesto implementar una cámara que proporciona información termográfica para supervisar el proceso de mecanizado (Tabla 2.5-Figura 2.41-Figura 2.42).
- Basándose en las señales de temperatura, He y sus colaboradores (He *et al.*, 2021) proponen un modelo de aprendizaje profundo (Deep Learning) para la predicción del desgaste de la herramienta durante el torneado CNC. Como técnica de Deep Learning,

utilizan los autocodificadores dispersos con una red neuronal de retropropagación para el modelo de regresión (Figura 2.43-Figura 2.44).

- La mayoría de los trabajos se centran en la detección del desgaste gradual desgaste gradual de la herramienta (GTW) y, en segundo lugar, en el fallo catastrófico de la herramienta (CTF). Sin embargo, Bombiński y sus colaboradores (Bombiński *et al*., 2022) tienen como objetivo identificar desgaste acelerado de la herramienta (ATW) en el torneado utilizando la fuerza de corte en diversas ventanas de tiempo. Para lograr su objetivo, se emplean algoritmos preentrenados para detectarlo automáticamente (Figura 2.45-Figura 2.46).

2.3.2-MONITORIZACIÓN DEL DESEMPEÑO DE CALIDAD.

El objetivo de cualquier proceso de mecanizado es conseguir productos que cumplan los requisitos técnicos con la calidad suficiente para satisfacer al cliente en el menor tiempo y coste posible. Aunque la calidad es un asunto de gran relevancia, existe un número limitado de artículos que discuten directamente el uso de la inteligencia artificial con ese fin. Es cierto que hay un gran número de artículos cuyo objetivo es supervisar el desgaste de las herramientas con un doble propósito: el de alargar la vida de la herramienta y el de asegurar la calidad de la pieza.
La rugosidad superficial actúa como indicador de la calidad del producto obtenido y también del comportamiento del proceso.

Como estudios destacados en esta área se enumeran a continuación:

- Correa y sus colaboradores (Correa *et al*., 2008) demostraron el uso ventajoso de las redes bayesianas sobre las redes neuronales para estimar la calidad superficial en procesos de fresado de alta velocidad (Tabla 2.6-Figura 2.47).
- Babu y sus colaboradores (Babu *et al*., 2018) emplean la lógica difusa para predecir la rugosidad de la superficie en la operación de taladrado de aceros templados en aceite sin contracción (Figura 2.48).
- Moreira y sus colaboradores (Moreira *et al*., 2019) utilizan un sistema adaptativo de interferencia neuro-fuzzy (ANFIS) para la determinación de la rugosidad superficial en una máquina CNC mediante un sistema de monitorización integrado (Figura 2.49-Figura 2.50-Tabla 2.7).
- Cabe mencionar de igual manera el trabajo de Chen y Kudapa (Chen and Kudapa, 2020) en el que se presentan dos modelos para la estimación de la rugosidad basados no sólo en los parámetros de corte sino también en la corriente. El primero es un sistema de inferencia difusa (FIS), en el que las reglas son establecidas por expertos, y el segundo es un sistema neurofuzzy (ANFIS). El resultado experimental muestra que el modelo ANFIS es más preciso en su estimación.

- El trabajo de Wang y sus colaboradores (Wang *et al*., 2019) es digno de mención porque presenta un enfoque de inteligencia artificial no supervisada para estimar la calidad geométrica en un proceso de mecanizado por descarga eléctrica de hilo. A veces, la rugosidad no es tan crítica como las tolerancias dimensionales. Este trabajo es novedoso por la integración de estos cuatro factores: mecanizado no convencional, calidad entendida como el cumplimiento de las tolerancias geométricas, el uso de la inteligencia artificial no supervisada en este campo y la elección de la variable: la distribución del tiempo de ionización en lugar de la tensión.

2.3.3-SUPERVISIÓN DE LAS ANOMALIAS DE LA MÁQUINA.

Normalmente, la supervisión de los procesos de mecanizado se centra en los parámetros de corte y el estado de la herramienta, pero la detección temprana de las anomalías de las máquina- herramienta no debe dejarse de lado, ya que su mal funcionamiento también influye en el coste, el tiempo de entrega y la calidad de la pieza. Netzer y sus colaboradores (Netzer *et al*., 2020) propusieron un sistema basado en el algoritmo mean shift cluster para la detección de anomalías. El estudio demostró que las técnicas no supervisadas pueden ser una herramienta muy válida para la detección de anomalías en entornos con alta incertidumbre ya que no tienen ningún conocimiento a priori de las condiciones variables o el funcionamiento de la máquina.

2.4-SOSTENIBILIDAD DEL PROCESO.

La sostenibilidad de los procesos de mecanizado pasa por reducir su impacto medioambiental, principalmente en lo que respecta a los recursos energéticos y el consumo de productos tóxicos. Para reducir el impacto, es necesario llevar a cabo una adecuada selección y control de los productos tóxicos utilizados y del consumo de energía.

2.4.1-SELECCIÓN Y CONTROL DE LA REFRIGERACIÓN Y LA LUBRICACIÓN.

La lubricación y la refrigeración son esenciales en las operaciones de mecanizado, ya que reducen la temperatura, retrasan el desgaste de la herramienta, protegen la pieza, aumentan su calidad, permiten la evacuación de la viruta, reducen la fricción y eliminan las partículas metálicas. Existen varias áreas en las que la IA puede ser un factor diferenciador:

- Selección de la estrategia de lubricación/refrigeración.
- Control del consumo de fluido de corte o lubricación.
- Control del rendimiento de la estrategia de refrigeración.
- Ajuste de la formulación de los fluidos de corte a las condiciones de proceso.

- Posibilidad de combinar diferentes estrategias de mecanizado en la configuración óptima.

2.4.2-MONITORIZACIÓN DEL CONSUMO ENERGÉTICO.

La Agenda 2030 considera la gestión del consumo energético como un objetivo esencial para el desarrollo sostenible. Además, el precio actual de la electricidad y de los combustibles fósiles hace que el control del consumo sea decisivo.

- Kant y Sangwan (Kant y Sangwan, 2015) describen el uso y comparan dos técnicas para estimar el consumo de electricidad: redes neuronales artificiales y regresión de vectores de apoyo (Tabla 2.11).
- Wang y sus colaboradores (Wang *et al*., 2015) también utilizan redes neuronales artificiales para definir las relaciones entre los parámetros iniciales, el consumo de energía y la calidad de la superficie en los procesos de fresado (Figura 2.70 – Figura 2.71-Figura 2.72).
- Lee y sus colaboradores (Lee *et al*., 2017). proponen un método de optimización del consumo energético en procesos de mecanizado utilizando una Máquina-Herramienta Virtual y Algoritmos Genéticos (Figura 2.73-Figura 2.74-Figura 2.75).
- He y sus colaboradores (He *et al*., 2020) proponen el uso de deep learning para estimar la cantidad de energía consumida en dos procesos: rectificado y fresado (Figura 2.76).
- Brillinger y sus colaboradores (Brillinger *et al*., 2021) comparan tres herramientas de aprendizaje automático para la predicción del consumo de energía por operación de mecanizado CNC (Figura 2.77-Figura 2.78).

3-INDUSTRIA DEL MECANIZADO: SITUACIÓN Y POLITICAS DE DESARROLLO.

3.1-SITUACIÓN DE LA INDUSTRIA DEL MECANIZADO ESPAÑOL.

El perfil mayoritario (80%) de empresa en el sector de mecanizado español es el de ser organizaciones poco integradas que solo aportan mecanizado o algún proceso adicional y son subcontratadas por otras que gestionan el producto final. Sólo el 17% fabrica su propio producto (Project AVIVA, 2012).

Además, se trata de empresas de portafolio de negocio regional o nacional en su mayoría. Sólo el 3% de las empresas declaran más del 80% de su facturación a clientes de otros países. El 54% de las empresas vende menos del 20% fuera de su región (Project AVIVA, 2012).

Por todo ello, España necesita dar un paso adelante en materia de digitalización y fortalecimiento del sector, para aumentar su competitividad frente a otros países europeos y activar la internacionalización.

Hay dos factores que podrían determinar la evolución de la transformación industrial en el sector del mecanizado español: la maquinaria y los trabajadores.

En cuanto a la maquinaria, los datos del proyecto AVIVA (2012) (Project AVIVA, 2012) muestra que las máquinas de las empresas de mecanizado españolas tenían mayoritariamente entre 2 y 10 años en el momento del estudio, pero un alto porcentaje eran máquinas con más de 10 años de antigüedad.

Además, la mayoría de estas empresas tienen menos de 10 trabajadores, con edades comprendidas entre los 30 y 40 años para los trabajadores y entre 40 y 50 años para el equipo directivo. En relación con la formación de los trabajadores, el 63% de las empresas confirman la dificultad de encontrar personal cualificado, pero también es significativo que el 36% no tiene un plan de formación y el 39% improvisa la formación durante el año. Es aún más remarcable que para el 51% de las empresas, la formación es necesaria pero no se realiza por falta de tiempo. Comprobando los datos aportados por el proyecto sobre innovación, se observa que, aunque el 65% de las empresas consideran que la I+D es un factor de competitividad, su transformación en iniciativas es poco significativa. Sólo el 37% de las empresas ha invertido en innovación en los últimos tres años en procesos de mecanizado y el 33% en procesos empresariales clave.

3.2-POLITICAS DE DESARROLLO EUROPEAS Y ESPAÑOLAS

Desde las instituciones europeas y españolas se han lanzado diversas estrategias y programas para abordar los retos que la implantación de las nuevas tecnologías supone.

Desde las instituciones europeas se lanzaron las siguientes iniciativas:

- *Europa 2020* fue la estrategia de digitalización lanzada por los organismos de la UE para el periodo 2010-2020.
- El programa *Europa Digital* para el periodo 2021-2027 se publicó junto al programa *Horizonte Europa* y los *Fondos Estructurales y de Inversión* Europeos.
- Además, en 2020 el Consejo y la Comisión, junto con el Parlamento Europeo, adoptaron una hoja de ruta para recuperación tras la pandemia mundial COVID - 19 (Tribunal de Cuentas de la UE, 2020). En el momento del informe, los avances habían sido limitados y el Tribunal de Cuentas instaba a la Comisión y a los Estados miembros a tomar medidas ejecutivas para mejorar la consecución de los objetivos fijados. La Comisión Europea

destaca dos transiciones vitales entre los seis objetivos clave del plan de recuperación (https://ec.europa.eu): la transición ecológica y la transición digital. La transición ecológica para convertirse en un continente neutro desde el punto de vista climático y la transición digital que tiene como objetivo capacitar a las personas con una nueva generación de tecnologías. Por ejemplo, la tiene previsto invertir 1.000 millones de euros en IA con cargo a los programas Europa Digital y Horizonte Europa para atraer más de 20.000 millones de euros de inversión total en IA al año durante la próxima década. (Comisión Europea).

- La Brújula Digital 2030 de la Comisión Europea de marzo de 2021 (UE, 2021) establece que el 20% del Mecanismo de Recuperación y Resiliencia se dedicará a la transición digital de los miembros. El Mecanismo de Recuperación y Resiliencia es el programa de desarrollo europeo post-pandémico de la UE con claros objetivos económicos, ecológicos, de innovación y de empleo.

Los organismos europeos se han dado cuenta de que el futuro lo está escribiendo la inteligencia artificial y están creando un marco para garantizar que Europa no se quede atrás en esta carrera.

Por su parte las instituciones españolas han puesto en marcha los siguientes mecanismos:

- A través del Plan de Recuperación, Transformación y Resiliencia (GOB ESP 2021), el Gobierno articula la estrategia de España para la recuperación económica tras las pandemias, creando un futuro sostenible y digital. De este modo, traslada el Mecanismo de Recuperación y Resiliencia de la UE al Estado español. Este plan se basa en 7 pilares: transición ecológica, digitalización, protección social, educación y formación profesional, turismo sostenible, empleo y ciencia (Figura 3.7).
- En 2020, el gobierno español presentó el Plan España Digital 2025 (GOB ESP 2020), que se basaba en 10 ejes estratégicos. Entre ellas existen objetivos definidos para el desarrollo de la inteligencia artificia. El desarrollo digital es un reto ambicioso y necesario para España. Uno de los ejes principales es el impulso de la inteligencia artificial, que se articula en la transformación hacia la economía de los datos, en la potenciación de la inteligencia artificial como motor de innovación y crecimiento sostenible, preparando al país para la transformación y creando un marco legislativo y marco moral compartido con la UE.
- La estrategia nacional de inteligencia artificial (MIAETD, 2020), que se basa en trabajos anteriores y está financiada por el Estado con 600 millones de euros, nació de este plan. La estrategia nacional se articula en 6 ejes y 30 medidas. Los 6 ejes principales son:
    - Promover la investigación científica, el desarrollo tecnológico y la innovación en IA.

  - Promover el desarrollo de las capacidades digitales, impulsar el talento nacional y atraer el talento en inteligencia artificial.
  - Desarrollar plataformas de datos e infraestructuras tecnológicas que apoyen la IA.
  - Integrar la IA en las cadenas de valor para transformar la infraestructura económica.
  - Potenciar el uso de la IA en la administración pública y en las misiones estratégicas nacionales.
  - Establecer un marco ético y normativo que refuerce la protección de los derechos individuales y colectivos, con el fin de garantizar la inclusión y el bienestar social.
- Así, en septiembre de 2021, el Gobierno puso en marcha un programa de renovación para subvencionar la modernización de las máquinas-herramienta de las pequeñas y medianas empresas por valor de 50 millones de euros (https://www.lamoncloa.gob.es).

En otras palabras, España se está organizando para abordar una decisiva transformación. La industria deberá estar preparada para asimilar esta transformación y la tecnología instalada debe ser capaz de acoger las nuevas soluciones digitales y de inteligencia artificial.

Tanto a nivel europeo como nacional, se han introducido diversos planes y estrategias para la evolución de la tecnología, la digitalización y la inteligencia artificial. Además, se han creado medidas para que estos avances lleguen a la industria, que es el principal objetivo.

Si estas medidas son suficientes para hacer de España un país competitivo se comprobará en los próximos años. No obstante, la principal conclusión es que la inteligencia artificial está en el presente y futuro de la industria y que es un área de conocimiento muy prometedora para ser desarrollar y aplicar adecuadamente.

4-ANALISIS DE RESULTADOS.

4.1- MEJORA DE LA CALIDAD, LA EFICIENCIA Y LA SOSTENIBILIDAD MEDIANTE TÉCNICAS DE AI

Los autores han aplicado diferentes técnicas de inteligencia artificial para abordar los distintos factores que pueden mejorar los procesos de mecanizado. La tabla 4.1 muestra un resumen de los métodos utilizados por cada uno de los autores en cada uno de los aspectos mencionados en los apartados anteriores.

4.2- VISION SOCIAL

El Eurobarometro 516 (EU 2021) sobre nuevas tecnologías muestra que el 18% de los encuestados de la Unión Europea (UE) cree que la IA tendrá un efecto muy positivo dentro de 20 años, el 43% bastante positivo, mientras que el 33% cree que no tendrá ningún efecto o un efecto negativo. En España, el 31% de los encuestados piensa que tendrá un efecto muy positivo. Cabe destacar que el 25% de los de los encuestados españoles opina que no tendrá ningún efecto o que su efecto será bastante o muy negativo. El porcentaje de encuestados con una respuesta muy negativa es del 11% (Figura 4.1). En cuanto a la opinión sobre las posibilidades de creación de empleo basadas en la automatización y la IA, el 33% de los encuestados españoles cree que proporcionarán más puestos de trabajo de los que destruirán, mientras que el 60% tiene una opinión neutra o negativa sobre el tema (Figura 4.2).

Según la V Encuesta sobre la percepción social de la innovación en España (COTEC, 2022), el 66% de la población encuestada opina que la sociedad española no está preparada para asumir los avances tecnológicos y en 2021, más del 80% de los encuestados consideran que la inversión pública en España es insuficiente, destacando que el porcentaje de personas que está muy de acuerdo con esta afirmación ha aumentado en los últimos 5 años. Por último, el 56,2% cree que la innovación genera desigualdad, y este porcentaje ha ido aumentando desde 2018.

La IA conlleva una cierta vulnerabilidad personal que no genera ninguna confianza entre los usuarios y la población en general. El Eurobarómetro 518 (EU 2021) sobre derechos y principios digitales refleja que el 87% de los encuestados europeos considera importante incluir la protección contra el riesgo o las aplicaciones no éticas de las tecnologías digitales, incluida la IA. De ese porcentaje, el 54% lo considera muy importante.

Nazareno y Schiff (Nazareno y Schiff, 2021) destacan en la investigación los posibles impactos en la esfera personal de los trabajadores. Mientras que la automatización y la IA pueden tener un impacto en el estrés, reduciéndolo, es a costa de perder el sentido e importancia del trabajo, volverse más insatisfecho, e incluso empeorar la salud (Figura 4.8).

Jarrahi (Jarrahi, 2018) evidencia la sinergia que puede crearse entre los humanos y la IA en la toma de decisiones (Figura 4.9) y Makarius y sus colaboradores (Makarius *et al*., 2020) destacan la falta de información y formación de los empleados y directivos respecto a la IA. Esta falta de información conduce a una falta de comprensión y, por tanto, a una percepción negativa. Este estudio aboga por una mayor comprensión e integración de la IA para que los trabajadores y los directivos puedan centrarse en las oportunidades que ofrecen estas técnicas y crear un marco de socialización para una integración eficaz en el entorno laboral (Figura 4.10).
Ostheimer y sus colaboradores (Ostheimer *et al*., 2021) afirman que la confianza es un pilar fundamental para la implantación y la aceptación de la IA.

5-CONCLUSIONES

5.1-CONCLUSIONES GENERALES

Se ha comenzado el trabajo poniendo en contexto la situación industrial, haciendo hincapié en la industria española, para conocer las perspectivas y las demandas de un mercado cada vez más exigente. Una de las claves para que la industria española sea más competitiva es la adopción de la inteligencia artificial y las nuevas tecnologías.

Se han revisado las virtudes de la inteligencia artificial en los procesos de mecanizado y de la mano de diferentes autores se ha ido recorriendo cada uno de los aspectos en los que puede ser un elemento diferenciador para mejorar estos procesos en calidad, sostenibilidad y eficiencia. Así es claro su significativo desempeño en la selección de materiales, herramientas, máquinas y operación, en la optimización y monitorización de los procesos de mecanizado y la mejora de la sostenibilidad. Están claras las ventajas de la inteligencia artificial, pero, ¿Está la industria del mecanizado española y sus trabajadores preparados para su adopción? La situación de la industria del mecanizado pone en relieve que el parque de maquinaria no se renueva como se debería y que los trabajadores, no se forman adecuadamente.

Existen diferencias significativas entre los avances académicos, lo que se requiere por los diseñadores y la respuesta que puede dar a día de hoy la industria del mecanizado. La UE y el gobierno de España han lanzado varios programas para integración de la digitalización de las empresas, el desarrollo de la inteligencia artificial y la renovación de la maquinaria. El efecto de estas políticas se verá en un corto medio plazo.

Por otro lado, se debe tener en cuenta la visión social de la cuarta revolución industrial o Industria 4.0 en la que la inteligencia artificial es un pilar básico. Esta transformación afectará a los trabajadores, a las organizaciones y a los ciudadanos. Es una transformación total que tiene muchas implicaciones. La acogida de esta transformación no es homogénea y está claro que no es todo lo positiva que debiera. La desinformación y la posibilidad de que se vulneren los derechos de los trabajadores y de las personas no ayudan a potenciar las oportunidades de crecimiento que ofrece la inteligencia artificial. Hay que poner en marcha programas de calidad para informar y educar a los trabajadores y ciudadanos y crear un marco legal que los proteja, como ha empezado a hacer la UE. Las empresas deben estar preparadas para una recepción menos traumática. Además, hay que establecer límites y procedimientos de trabajo para que los trabajadores se sientan protegidos. Queda mucho por hacer a nivel académico, empresarial y político.

A nivel académico, los estudios sobre el uso de la inteligencia artificial en el mecanizado no han llegado a extenderse en la medida en que lo han hecho en otros campos, como puede ser la medicina. Además, aunque el coste y la productividad son factores clave que determinan la viabilidad de las operaciones, es hora de incorporar la sostenibilidad de los procesos como elemento decisional. Existen futuras vías de estudio y de desarrollo del uso de la inteligencia artificial. Adicionalmente, es necesario acercar los avances que proporcionan estos estudios a las empresas, no sólo a las grandes, si no sobre todo a las pequeñas y medianas. De esta manera, podrán ir cambiando su perfil de organización y podrán competir en igualdad.

A nivel de empresa, es necesario vincularse con la vida académica, para poder observar el sentido en el que se producen los avances y los criterios que demandarán los clientes del futuro. Es imprescindible crear un marco de formación para los trabajadores de manera que se les prepare para las nuevas tecnologías y para el cambio que sufrirá su trabajo. Es necesario incorporar innovación y establecer planes estratégicos en los que las compañías marquen la dirección de sus decisiones. Se han de formular acuerdos con los gobiernos para que las empresas de pequeño y mediano tamaño no se queden atrás. Y, además, de manera definitiva deben incluir la sostenibilidad en esos planes estratégicos, no solo de palabra sino en sus acciones.

A nivel político, en España cuatro deben ser los marcos en los que sostener la adopción de la inteligencia artificial:

- *Marco de innovación y desarrollo.* Además de creer en la innovación se ha de invertir en ella. Se han de crear centros de excelencia en inteligencia artificial donde varias especialidades puedan colaborar para desarrollarla al máximo.
- *Marco legal* de protección de los derechos como ciudadanos y trabajadores. Buscar la excelencia a través de la confianza.
- *Marco formativo.* Establecer nuevas enseñanzas para los trabajadores del futuro que versen sobre inteligenciar artificial. Incluir la inteligencia artificiar en los recorridos académicos ya existentes. Esto ayudará a cambiar la percepción sobre la inteligencia artificial a una más positiva y que los ciudadanos sean responsables en el uso y a la hora de demandar leyes que les protejan.
- *Marco de incentivos a la industria.* España debe desarrollar una industria de calidad, no vertebrada por su territorio. Para ello se deben tomar decisiones políticas estructurales que apoyen a las empresas independientemente de su tamaño en la adopción de las nuevas tecnologías y, sobre todo, en la implantación de la inteligencia artificial.

El papel de la inteligencia artificial en el futuro es indiscutible. La clave será colocar los límites al potencial que tiene para que su uso sea sostenible con respecto al medio ambiente y a las personas. También es responsabilidad de los ciudadanos ser críticos y exigir el cumplimiento de esos límites. Por eso es necesaria que la información y la formación llegue a todos.

5.2-CONCLUSIONES PARTICULARES

5.2.1-USO DE A INTELIGENCIA ARTIFICIAL EN LOS PROCESOS DE MECANIZADO.

En este trabajo se han revisado las propuestas de diversos autores para la aplicación de la AI en distintas fases de los procesos de mecanizado:

- Selección de materiales de partida.
- Selección de equipos y herramientas.
- Selección y secuenciación de las operaciones.
- Optimización de los procesos mediante la selección de los parámetros de corte.
- Monitorización de las operaciones.
    - Monitorización del desgaste y fallo de la herramienta.
    - Monitorización de la calidad.
    - Monitorización de anomalías en las máquinas.
- Selección de refrigeración y lubricación.
- Monitorización del consumo eléctrico.

Todos los autores presentaban como objetivo común el aumento de la eficiencia de los procesos de mecanizado. Si bien cada uno se centraba en alguno de los puntos antes mencionados, no se ha planteado una solución global a la optimización de los procesos de mecanizado que tenga en cuenta todos los aspectos.

Se ha comprobado como la AI es un factor clave en el desarrollo de la industria del mecanizado al ofrecer soluciones más eficientes y rentables a los problemas de toma de decisiones y de control de esta industria. Tradicionalmente estas dificultades se han solventado mediante la experiencia y el conocimiento de personal cualificado. La AI permite realizar la toma de decisiones en base una mayor cantidad de datos procedentes de un mayor número de fuentes y de una manera más precisa, reduciendo la incertidumbre del proceso, estando actualizada de una manera periódica y eficaz y dando respuesta a requerimientos cada vez más complejos y restrictivos.

Los distintos autores han escogido diferentes técnicas de IA (Tabla 4.1) para resolver las cuestiones antes mencionadas dando a conocer distintas formas de abordar estos problemas de toma de decisiones complejos. En los distintos estudios se han ido escogiendo aquellas técnicas que se consideraban más idóneas con respecto al aspecto a tratar. Algunos de ellos, también han comparado diversas técnicas para determinar cuál era la más apta.

Es muy significativa la cantidad de artículos relacionados con la monitorización de las operaciones de mecanizado transmitiendo la importancia que tiene su control para la obtención de piezas que cumplan con los requisitos de calidad y que a la vez maximice la productividad y minimice costes y tiempos. Dentro de la monitorización hay además muchos métodos de adquisición de señales que están relacionados con determinados parámetros de la operación. Esto hace que sea un verdadero desafío técnicamente hablando. La AI puede favorecer en gran medida la monitorización y por ello, muchos autores han decido tratar este tema.

Varios autores han dado un paso hacia delante integrando la inteligencia artificial en el mecanizado en sistemas inteligentes como por ejemplo usando sensores virtuales, o incorporando la monitorización y las inspecciones de calidad en un sistema cloud manufacturing, en modelos ciber-físicos y desarrollando la simulación, el mecanizado virtual y los gemelos digitales. Sin duda, es el objetivo de la industria 4.0. poder ofrecer tecnologías avanzadas e integradoras para cada uno de los pasos de la cadena productiva. Esto ayudará en gran medida a automatizar las tareas que aportan poco valor añadido al proceso productivo y reducir los errores e incertidumbres del proceso.

También es necesario destacar la poca proliferación de estudios sobre el uso de la AI en la selección de la lubricación y refrigeración de las operaciones de mecanizado. Por otro lado, una gran proporción de número de estudios buscan la eficiencia a través del aumento de la calidad a menor coste y tiempo dejando atrás las variables ambientales como factores decisivos. Entre los posibles factores ambientales, se deberían considerar el consumo eléctrico de las operaciones, ya que es el impacto ambiental más notable, y el tipo de refrigeración / lubricación. Ambas afectan al coste, a la viabilidad de la operación, la calidad de la pieza obtenida, el desgaste de la herramienta y el tiempo de proceso. Por lo tanto, estas variables no solo deben ser consideradas por el impacto ambiental que generan, sino que además se deben tener en cuenta en cumplimiento de la legislación ambiental y por la propia eficiencia del proceso de mecanizado.

5.2.2-INDUSTRIA DEL MECANIZADO EN ESPAÑA Y VISIÓN SOCIAL.

Según se ha mencionado las empresas españolas presentan un perfil estratégico bajo que se caracteriza por realizar trabajos de mecanizado con algún aporte de procesos adicionales a una escala mayoritariamente regional y nacional. Sería recomendable que un porcentaje significativo de estas lleguen a ser incluidas en los grupos G3 -G4 donde se aporta un gran valor al proceso al crear productos propios ya sea subcontratando aquellas operaciones que no sean de mecanizado o bien integrándolas en la compañía. Estas empresas serían generadoras de riqueza y valor. Para que esas organizaciones aumenten su perfil estratégico es necesario que apuesten por la innovación y el desarrollo de las competencias internas. Es difícil que las empresas españolas puedan competir con las del este de Europa en flexibilidad, cercanía a los países de centro Europa y costes por lo que se hace imprescindible elevar el perfil para asegurar la pervivencia y para crear oportunidades en industrias adyacentes.

Existen varios elementos que limitan este proceso:

- Edad de la maquinaria. Las máquinas no actualizadas no estarán preparadas para integrarse en la industria 4.0. por ello, se han lanzado varios planes por parte del gobierno para facilitar la sustitución de los equipos.
- Edad de los trabajadores. El personal cualificado es un personal maduro que no está completamente adaptado a la era digital. Por tanto, la formación y actualización de contenidos es esencial en esta industria.
- Planes de formación. Los datos reflejan que se realizan de forma genérica y en un gran porcentaje no se plantean como una formación continua. La formación debe impartirse de manera adaptada a las necesidades de cada trabajador o grupo de trabajadores con las mismas carencias y debe llevarse a cabo de manera continua y planificada para actualizar los conocimientos con los últimos avances y tecnologías.
- Innovación y desarrollo. No solo los trabajadores de la empresa deben tener conocimiento de las últimas tendencias; el equipo gerencial debe estar atento y generar un ambiente de innovación y desarrollo. De esta manera, se podrá general un mayor valor a nivel empresa e industria y ser empresas altamente cualificadas y bien posicionadas competitivamente.
- Digitalización. Las empresas españolas no se encuentran entre las mejores posicionadas en cuanto a digitalización por lo que será muy importante el aprovechamiento de las acciones y fondos destinados a ello que han lanzado tanto las instituciones europeas como las nacionales.

Es destacable la percepción de la sociedad española ante la innovación y la inteligencia artificial. Mayoritariamente se considera la innovación como algo positivo, así como los efectos de la inteligencia artificial a medio-largo plazo, pero este porcentaje decae al responder si la inteligencia artificial generará trabajo. También un porcentaje significativo de población española considera la innovación como un agente de desigualdad social. Por delante debe haber un gran trabajo de información, de protección y de integración por parte de las entidades académicas, empresariales e institucionales, como se ha comentado en las conclusiones generales.

5.3-OPORTUNIDADES PARA FUTUROS ESTUDIOS

Como futuras oportunidades de investigación se han detectado las siguientes:

- Optimización de los procesos de mecanizado de manera global empleando inteligencia artificial. Es un reto muy importante porque supone no encontrar la mejor solución en cada una de las áreas que se han visto en este trabajo, sino una solución que sea la mejor para todas ellas. Pero al conseguirlo estaremos ante procesos realmente mejorados y equilibrados.

- Estudios sobre la aplicación de la inteligencia artificial en la selección y optimización de la lubricación y la refrigeración de los procesos de mecanizado.
- Pocos han sido los estudios encontrados en los que se emplee el uso de la inteligencia artificial en los procesos no tradicionales de mecanizado. Con la incorporación de nuevos materiales y las soluciones que aportan estos procesos, será necesario profundizar en este aspecto.
- El uso de la inteligencia artificial en la determinación de la calidad geométrica, dimensional y funcional de las piezas obtenidas.
- Inclusion de los factores ambientales como elementos decisionales en la optimización de los procesos de mecanizado.

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DEPARTAMENTO: Ingeniería de Construcción y Fabricación.

TITLE	**Quality, efficiency and sustainability improvement in machining processes using Artificial Intelligence.**
AUTHOR	Lourdes Martínez Molina.
TUTOR	Eva María Rubio Alvir.
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LIST OF ABBREVIATIONS AND ACRONYMS.

AHP	Analytic hierarchy process method.
AI	Artificial Intelligence.
ANFIS	Neuro-Fuzzy System.
ANN	Artificial Neural Network.
ANP	Analytic network process.
ATW	Accelerated Tool Wear.
BP NN	Backpropagation neural network.
CNC	Computer numeric control.
CNN	Convolutional Neural Network.
CTF	Catastrophic Tool Failure.
DII	Digital Intensity Index.
DT	Digital Twin.
ETSII	Senior Technical School of Industrial Engineers. Escuela Técnica Superior de Ing. Ind.
FCN	Fully Convolutional Network.
FIS	Fuzzy Interference System.
FMS	Flexible manufacturing system.
GTW	Gradual Tool Wear.
ICI	Industrial Climate Indicator.
IPI	Index of Industrial Production.
ICT	Information and communication technology.
KBES	Knowledge -based expert systems.
LBM	Laser Beam Machining.
MCDM	Multiple-criteria decision making.
ML	Machine Learning.
OMT	Operation-Machine-Tool.
PCA	Principal component analysis.
R&D	Research and development.
SSAE	Stacked sparse autoencoders.
SVR	Support Vector Regression.
TCM	Tool Condition Monitoring.
TCMS	Tool Condition Monitoring System.
TFM	Master's Thesis. (Trabajo Fin de Máster.)
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution.
TP	Tutor of the work. (Tutor del Trabajo.)
UNED	National University of Distance Education. Univ. Nacional de Educación a Distancia.
VMT	Virtual Machine Tool.

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You can kiss and say goodbye to your family and friends by putting miles between you, but they are still with you in your heart, your thoughts. For you not only live in a world but a world lives in you (Frederick Buechner).

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CHAPTER 1. INTRODUCTION.

1.1-ABSTRACT.

The industrial sector is currently in a period of global recovery, even though it is still facing the consequences of the global pandemic COVID-19, the electricity and oil price increases, the shortage of raw materials and their increasing price, etc. This industrial climate leads to weak growth. Companies must face these constraints and improve their efficiency in order to be competitive. In a global market, where products are increasingly purchased from further afield, organisations must find a balance in which the added value they offer outweighs the advantages of their competitors.

In addition, sustainability policies and the increasingly demanding requirements of the market and customers must be considered. Although sustainability polices seek social equity, growth and the reduction of environmental impact, imply added restrictions to industrial processes.

As could be seen, the industrial environment is complex, and organizations must seek efficiency through new tools and by making use of available technologies.

Thus, this efficiency involves making structural changes with the aim of:

- Cost reduction.
- Improving the quality perceived by the customer.
- Optimisation of the raw materials use.
- Increased efficiency in decision-making.
- Improving the efficiency of industrial processes.
- Efficient use of energy resources.
- Minimisation and appropriate management of waste.
- Reduction of the environmental impact of production processes.
- Positive social impact of industrial activities.
- Rapid adaptation to changing environments.
- Increasingly demanding delivery deadlines.

The necessary structural changes, limiting factors for some and opportunities for others, are leading the industrial sector towards its fourth revolution. In it, information plays a decisive role, and the most competitive companies will be those that make effective use of this information together with technological advances. The organisations that adapt best and fastest to changes in demand, to the implementation of new technological solutions, which are becoming more and more frequent, and use the information generated and available to their advantage, will be those that have the best chances of surviving in an environment of growing competition. Industry 4.0, increasing connectivity and digitisation of organisations, supports this industrial revolution based on smart manufacturing.

More specifically, the machining industry will be examined in this work. This is one of the key industries that underpins and provides products to many other sectors.
This study will focus on improvements in machining processes. Thus, starting from the current situation in one of the European Union countries, Spain, the different advances available for machining processes will be reviewed and the current needs of the industry for the implementation of these advances will be analysed.

To talk about the advances available is to talk about artificial intelligence (AI), which is revolutionising the world as we know it. From the way we search for information, communicate with electronic devices to predicting the winner of a tennis match. But sometimes, as in this last example, humans continue to surprise machines. There are many improvements that AI offers in the field of machining, but it is true that it will not be possible to implement it at the same level in all companies in the sector.

The aim of this work is to study how artificial intelligence helps machining processes to be more competitive without forgetting the ethical perception of the use of these advances and the starting situation in Spain. Thus, the objective is to study the parameters that influence the efficiency and sustainability of machining processes and the final quality of the parts to optimise them through the use of artificial intelligence.

Il settore industriale sta attualmente in un periodo di ripresa globale, anche se sta ancora affrontando le conseguenze della pandemia globale COVID-19, l'aumento del prezzo dell'elettricità e del petrolio, la carenza di materie prime e il loro aumento di prezzo, ecc. Il clima industriale fa che la crescita sia contenuta. Le aziende devono affrontare questi vincoli e anche migliorare la loro efficienza per essere competitive. In un mercato globale, dove i prodotti sono sempre più acquistati da più lontano, le organizzazioni devono trovare un equilibrio in cui il valore aggiunto che offrono supera i vantaggi dei loro concorrenti.

Inoltre, bisogna considerare, da un lato, le politiche di sostenibilità che, cercando l'equità sociale, la crescita e la riduzione dell'impatto ambientale, implicano restrizioni aggiuntive ai processi industriali e, dall'altro, le richieste sempre più esigenti del mercato e dei clienti.

Come si può vedere, l'ambiente industriale è complesso e le aziende devono cercare l'efficienza attraverso nuovi strumenti e facendo uso delle tecnologie disponibili.

Questa efficienza implica fare cambiamenti strutturali che cercano:

- Riduzione dei costi.
- Migliorare la qualità percepita dal cliente.
- Ottimizzazione dell'uso delle materie prime.
- Maggiore efficienza nel processo decisionale.
- Migliorare l'efficienza dei processi industriali.
- Uso efficiente delle risorse energetiche.
- Minimizzazione e gestione appropriata dei rifiuti.
- Riduzione dell'impatto ambientale dei processi produttivi.
- Impatto sociale positivo delle attività industriali.
- Rapido adattamento agli ambienti che cambiano.
- Termini di consegna sempre più esigenti.

I necessari cambiamenti strutturali, fattori limitanti per alcuni e opportunità per altri, stanno portando il settore industriale verso la sua quarta rivoluzione. In esso, l'informazione gioca un ruolo decisivo e le aziende più competitive saranno quelle che faranno un uso efficace di questa informazione insieme ai progressi tecnologici. Le organizzazioni che si adattano meglio e più velocemente ai cambiamenti della domanda, all'implementazione di nuove soluzioni tecnologiche, che stanno diventando sempre più frequenti, e utilizzano le informazioni generate e disponibili a loro vantaggio, saranno quelle che avranno le migliori possibilità di sopravvivere in un ambiente di crescente concorrenza. L'industria 4.0 che aumenta la connettività e la digitalizzazione delle organizzazioni supporta questa rivoluzione industriale e sosterrà la produzione intelligente.

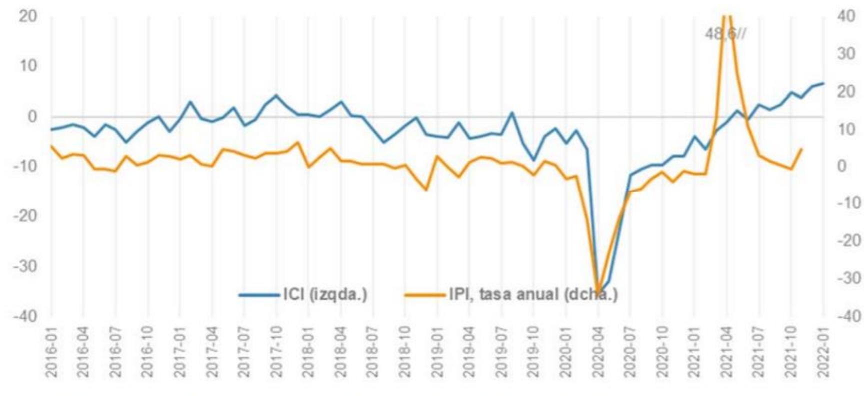
Più specificamente, in questa tesi verrà esaminata l'industria della lavorazione (machining industry). Questa è una delle industrie chiave che sostiene e fornisce prodotti a molti altri settori.
Questo studio si concentrerà sui miglioramenti dei processi di lavorazione (machining processes). Così, partendo dalla situazione attuale in un paese dell'Unione Europea, Spagna, si passeranno in rassegna i diversi progressi disponibili per i processi di lavorazione e si analizzeranno le esigenze attuali dell'industria per l'implementazione di questi progressi.

Parlare dei progressi disponibili significa parlare di intelligenza artificiale (AI), che sta rivoluzionando il mondo come lo conosciamo. Dal modo in cui cerchiamo informazioni, comunichiamo con i dispositivi elettronici fino a prevedere il vincitore di una partita di tennis. Ma a volte, come in quest'ultimo esempio, gli umani continuano a sorprendere le macchine. Ci sono molti miglioramenti che l'AI offre nel campo della lavorazione, ma è vero che non sarà possibile implementarla allo stesso modo in tutte le aziende del settore.

L'obiettivo di questo lavoro è studiare come l'intelligenza artificiale aiuta i processi di lavorazione ad essere più competitivi senza dimenticare la percezione etica dell'uso di questi progressi e la situazione di partenza in Spagna. Così, l'obiettivo del lavoro è quello di studiare i parametri che influenzano l'efficienza e la sostenibilità dei processi di lavorazione e la qualità finale dei pezzi al fine di ottimizzarli attraverso l'uso dell'intelligenza artificiale.

1.2-SPANISH INDUSTRY CLIMATE AND DIGITISATION SITUATION.

The January 2022 industrial conjuncture report (MINCOTUR, 2022) shows the recovery and growth of the Spanish industrial climate index (ICI) surpassing pre-COVID-19 levels, followed by the industrial production index (IPI) (Fig 1.1)

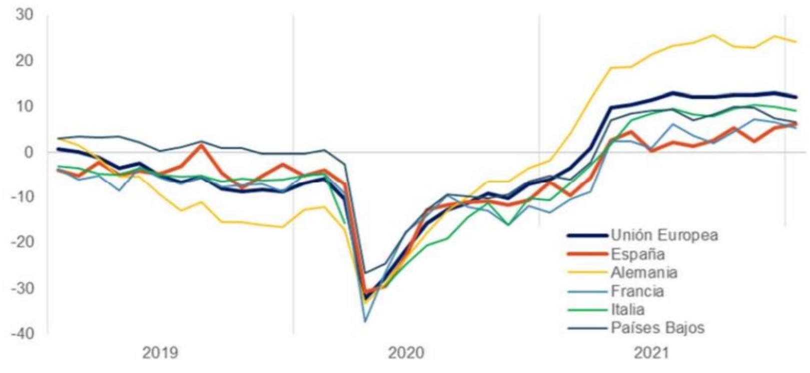


Fuente: Subdirección General de Estudios, Análisis y Planes de Actuación (MINCOTUR) e INE

Figure 1.1- Spanish Industrial Climate Indicator (ICI) and Index of Industrial Production (IPI).

The industrial climate indicator is based on the level of organisations' orders, stock levels and production expectations.

The report reflects the evolution of the ICI in the EU and in certain countries such as Spain, Germany, France, Italy and the Netherlands:



Fuente: Subdirección General de Estudios, Análisis y Planes de Actuación (MINCOTUR) y Comisión Europea

Figure 1.2- UE Industrial Climate Indicator (ICI) and Index of Industrial Production (IPI)

Figure 1.3- Industrial Climate Indicator (ICI) for UE, Germany, France, Spain, Italy and Netherlands from November-20 to January-21.

As could be seen in the figures above, Germany is in the lead within the EU environment while Spain is the only country where the indicator has continued to grow in the last month, but remains below the rest of the countries, including Italy. This gives optimism for the future, but with a lot of work ahead for Spain to increase the country's productive response and the sale of its products.

With these prospects, the next step is to find out how far EU countries are in terms of digitisation to cope with this growth and even the degree of implementation of artificial intelligence.

The report issued by the European Commission on the Digital Economy and Society Index (EU, 2021) provides information on the Digital Intensity Index (DII) by level as a percentage of companies. The DII is an index that measures the use of various digital technologies at the enterprise level: It shows the degree of penetration and the speed of deployment of digital technologies in enterprises at the national level.

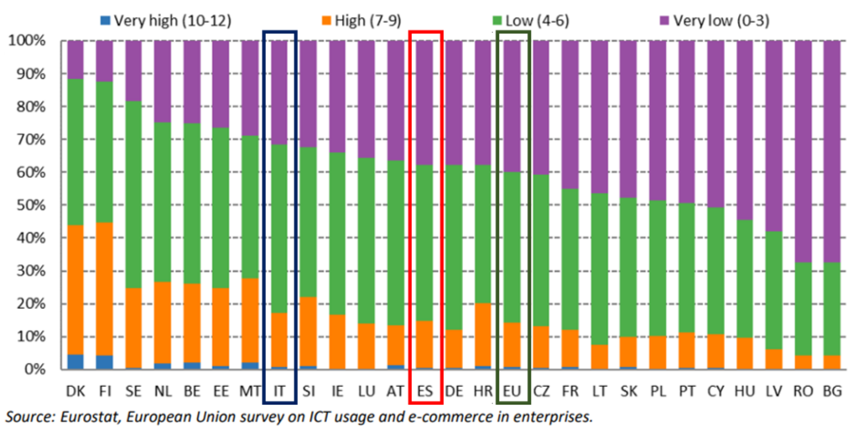


Figure 1.4- Digital Intensity Index by level (% of enterprises), 2020.

Comparing Spain and Italy with other EU countries digital technology solutions adopted by Spanish and Italian companies are mostly classified as low level, which implies some implementation of technological tools such as having a website, use of computers connected to the Internet by at least 50% of employees, use of portable devices connected to the Internet by at least 20% of employees, etc. In both countries, less than 2% of companies have adopted advanced digital technology measures such as the use of big data, the use of industrial or service robots, advanced manufacturing systems such as 3D print, etc. Spanish digitisation lags behind the result obtained by Italy, while both are above the European average.

Regarding the use of the fundamental aspects of digitisation:

- Use of cloud computing services.
- Analysis of Big Data.
- Use of AI.

The percentage of enterprises that have adopted these three technological solutions in each of the EU countries is shown in the following figure:

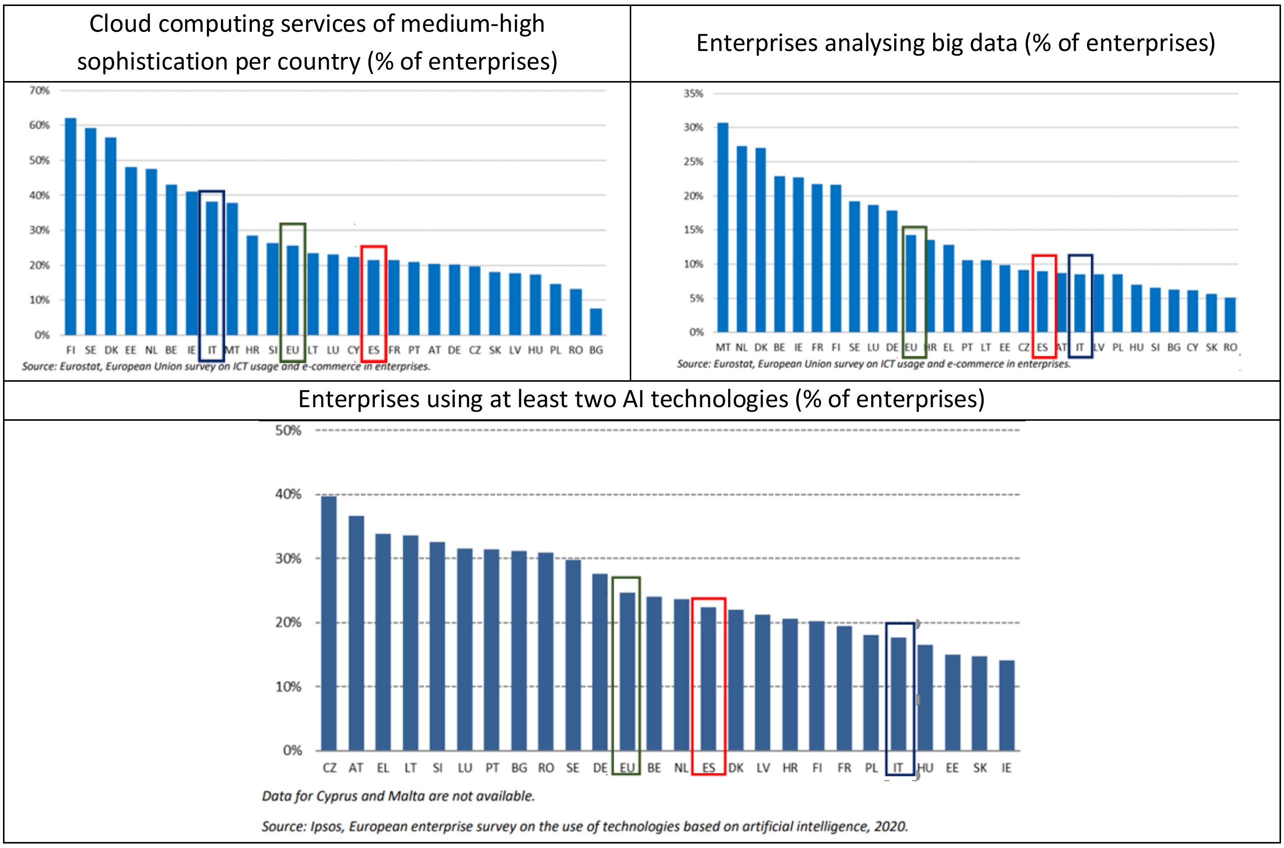


Figure 1.5- Use of digitisation technology solutions per country (% companies).

Spain lags behind the EU average in terms of implementation of these fundamental digitisation tools. Italy exceeds this value in the use of cloud computing, but the percentage of companies using AI and analysing Big Data is lower than in Spain.
This report shows that both Spain and Italy must implement several measures to reach the fourth industrial revolution in a favourable way.

1.3-ARTIFICIAL INTELLIGENCE.

The evolution of digitisation has gone through several stages from an initial digitisation to store documents without any change in processes to the present day where the physical and the virtual converge. (Qi *et al.*, 2021). At present, artificial intelligence is combined with other tools to achieve this integration and improve the performance that the different systems, the different tools, offer. Additionally, AI could be combined with the use of the Internet of Things to improve accuracy, perform predictive analytics, improve customer satisfaction and increase operational efficiency (Mohanta *et al*., 2020). AI also use cloud computing to increase connectivity. The following figure shows the evolution of digitalisation since 1946 (Qi *et al.*, 2021):

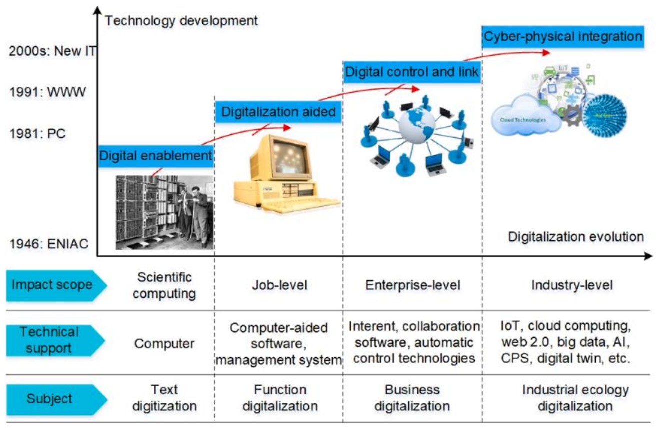


Figure 1.6-Digitalization evolution.

The definition of artificial intelligence given by the European Commission's High-Level Expert Group on AI (EU, 2018) offers a first insight into the growing impact of its use in different dimensions: *"Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions. As a scientific discipline, AI includes several approaches and techniques, such as machine learning (of which deep learning and reinforcement learning are specific examples), machine reasoning (which includes planning, scheduling, knowledge representation and reasoning, search, and optimization), and robotics (which includes control, perception, sensors and actuators, as well as the integration of all other techniques into cyber-physical systems)."* In this sense, the way in which an IA system acts can be schematised in the following figure:

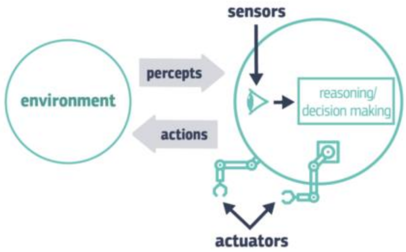


Figure 1.7-Schematic depiction of an AI system.

In this way, the reality to be studied, or environment, is *perceived* by a series of sensors (such as measurement probes, cameras, microphones, etc.). The information collected by these sensors is *analysed* and used in the *decision-making* process carried out by the main module of the intelligence systems. This is the module that interprets the data collected by the sensors, translates it into information and based on this information, makes decisions determining the best action to be taken. This action will be executed by a series of *actuators*, which can be physical (robots, machines, etc.) or not (execution of a programme module, etc.).
In terms of data collection, it is important to distinguish between *structured data* according to a set of pre-established rules and *unstructured data*, which are not organised in any way.
This system has three main capabilities: perception, reasoning/decision making and action, which leads us to the main artificial intelligence techniques that can be divided into two groups, analysis and reasoning and learning. Robotics would be the third group. This paper will focus mainly on the first two.

The group of ***reasoning techniques*** allows the translation of data collected by sensors into information available for analysis, decision making, solution finding, process planning and optimisation, etc. through the use of symbolic rules.

On the other hand, ***learning techniques*** are used in cases where the solution cannot be obtained by means of symbolic reasoning rules and are based on perception. In consequence, it is used when the rules governing the phenomenon are too complex or constantly changing, or even when it is the data itself that is continuously adjusting (https://es.mathworks.com). Through these techniques, the system learns each time it is executed. In this way, its actions are refined and become more precise. We can find several techniques such as Machine Learning, Deep Learning, etc. that can go beyond perception. The difference between Machine Learning and Deep Learning lies in accuracy (https://es.mathworks.com). Deep Learning is much more accurate and requires a large amount of data and a great deal of computing power. It is called Deep Learning because it uses a much larger number of hidden layers in neural networks, and this means that manual feature extraction is not necessary.

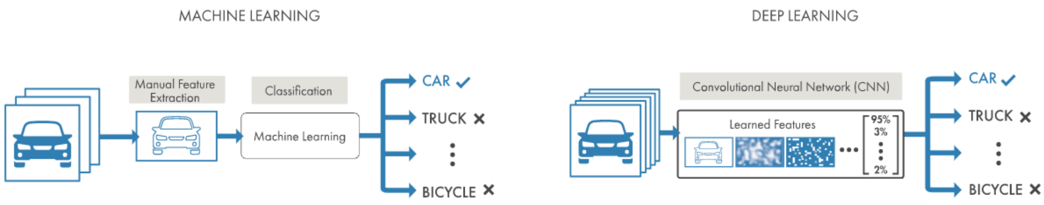


Figure 1.8-Comparison of Machine Learning and Deep Learning approaches to vehicle categorisation.

Machine Learning techniques use a mathematical model to calculate the decision from the collected data. The most commonly used Machine Learning approaches are supervised learning, unsupervised learning and reinforcement learning. Thus, the Matlab guide on Machine Learning shows the techniques used in each of them:

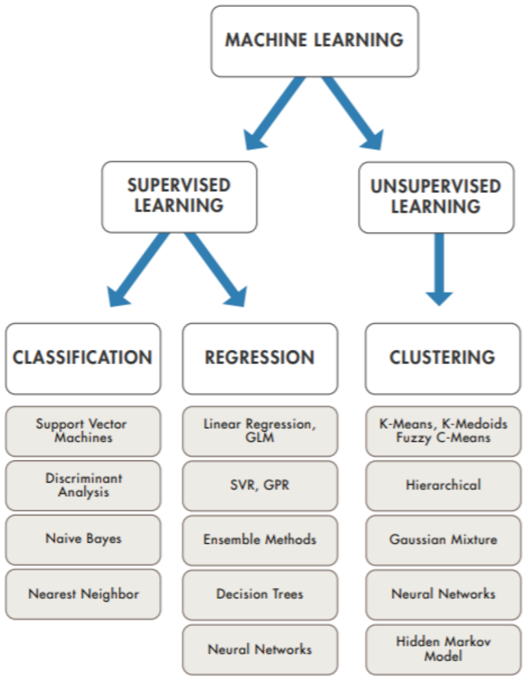


Figure 1.9- Tools used in Machine Learning systems.

- *Supervised learning.* Where the system is provided with examples of source data and its response for the algorithm to generalise and extrapolate to other cases by predicting discrete responses in the case of classification techniques (discerning whether an email is true or spam, whether a tumour is malignant or not, etc.) or continuous responses in the case of regression techniques (changes in temperature or fluctuations in electricity demand, etc.).
- *Unsupervised learning.* The system finds hidden patterns or intrinsic structures. The system is provided with inputs to the system, but no example outputs. The most common set of techniques belongs to the clustering group and are capable of object recognition, genetic sequence analysis, etc.

The third group focuses on ***robotics***, which is the physical action part of artificial intelligence. The control architecture combines the aforementioned capabilities with other disciplines to govern the robots and to execute their designated operations.

The usefulness of artificial intelligence is unquestionable, as it is integrated into our daily lives and the competitiveness of companies depends on it. As written in the European Commission's White Paper on Artificial Intelligence: "Europe's current and future sustainable economic growth and societal wellbeing increasingly draws on value created by data. AI is one of the most important applications of the data economy." (EU, 2020). Moreover, its development will offer both industry and other sectors previously unimagined possibilities. Artificial intelligence has been widely developed and has a promising future in other fields such as medicine. But this has not been the case in, for example, the Spanish industrial field, where its introduction has, to date, been unremarkable and slow. Furthermore, there is a significant gap between the progress of machining research and the use of artificial intelligence in this field and its application for example in the machining industries. This work includes studies on the application of artificial intelligence in the machining sector, but these technological solutions are only partially and slowly reaching companies.

The usefulness of artificial intelligence in industry influences the following areas (Fahle and Kuhlenkötter, 2020):

Manufacturing process planning
- Scheduling.
- Cost prediction.
- Parameter optimization for energy and resource efficient manufacturing chain design and operation.
- Classification of workers' localization.
- Forecasting the load of the factory.

Quality Control
- Reducing quality assurance cost.
- Optimization the quality assurance.
- Identifiying root cause for quality deviations of the manufacturing processes.
- Definition the final product key parameters to optimize the manufacturing process.
- Quality process classification.

Predictive maintenance
- Predicting the remaining useful lifetime.
- Fault estimation.
- Equipment failure modelling.

Logistics
- Scheduling.
- Logistics prediction.
- Logistics packaging classification and estimation.

Robotics
- Human robot collaboration.
- Path Planning.
- Improve automation tasks.

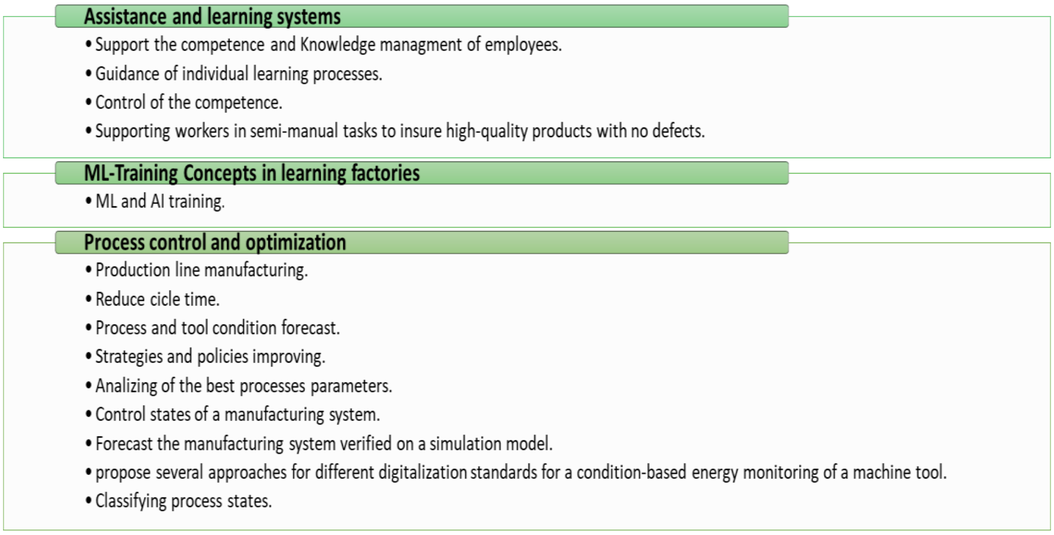


Figure 1.10- Areas of action for artificial intelligence in industry.

1.4-ARTIFICIAL INTELLIGENCE WORKFRAME IN THE MACHINING PROCESSES.

The usefulness of artificial intelligence in machining processes is clear and important as it optimises them and makes them more competitive. Artificial intelligence offers a positive impact on these processes by improving:

- ✓ ***Efficiency.*** Figure 1.10 shows the areas where artificial intelligence can bring improvements and thus increase process efficiency. Artificial intelligence offers three main benefits (Nishant *et al.*, 2020):

    - o Automation of operations that provide little added value, are time consuming and repetitive. In addition, the use of automation means that tasks that are not ergonomic for workers can be carried out through the use of devices, robots, etc.
    - o Data analysis. Transformation into information of data that is difficult to analyse, either because of its volume or because it is not structured or because it requires human management due to its characteristics (videos, photographs, reports, etc.).
    - o Capacity to involve a large number of computers and devices and their ability to be integrated into other technological solutions that comprise Industry 4.0.

- ✓ ***Quality.*** Improving precision and reducing variability in operations. As will be seen in this work, quality in machining processes is characterised by compliance with dimensional tolerances, surface finish and the elimination of defects in the machined parts. Nowadays, with Micro and Nano-manufacturing becoming increasingly important, engineering teams are specialising in designing ever more precise parts and products and reducing manufacturing tolerances. In this way, costs associated with material waste, non-quality, rejected parts, etc. are reduced. An example of this is the MIDEMMA project, Minimizing

Defects in Micro-Manufacturing Applications (MIDEMMA, 2014), which advocates and works to achieve "Zero-defect manufacturing". This vision is being generalised to other manufacturing systems and the requirements coming from customers are becoming more and more demanding. Therefore, the use of artificial intelligence makes it possible to achieve high levels of product and service quality.

- ✓ ***Sustainability***. As written in the European Commission's White Paper on Artificial Intelligence (EU, 2020): "The use of AI systems can have a significant role in achieving the Sustainable Development Goals, and in supporting the democratic process and social rights." Artificial intelligence helps to manage processes in a way that reduces their environmental and social impact. For example, in the case of machining processes, it reduces the amount of material used and waste, reduces waste, optimises the use of energy, manages and controls products that affect workers, reduces repetitive work, etc. Green manufacturing can become strategic in terms of high-level economic objectives and focuses on three main objectives such as (Mao *et al.*, 2019):

    - Reducing energy consumption and pollutant emissions.
    - Monitoring the safety of processes throughout the life cycle and controlling risks.
    - Monitoring and evaluation of the environmental footprint.

  Although progress has been made in this direction and international and national legislation is becoming increasingly restrictive, industry is still a long way from green manufacturing. In this respect, artificial intelligence plays a key role in improving process safety management and the intelligent use of raw materials and energy. Mao and collaborators note that there are problems in green manufacturing, grouped into three categories, which could be solved by using artificial intelligence:

    1. Information integration. Knowledge graphs are suggested as a tool.
    2. Process risk analysis and decision support. In this case, they propose the Bayesian networks as a technique to be used.
    3. Early warning. For this category they recommend the use of Deep Learning.

  However, the carbon footprint, environmental impact, generated by the use of IA should also be taken into account, and alternative, less impactful energy sources should be explored and IA processes themselves optimised to reduce the amount of energy used (Nishant *et al.*, 2020).

To achieve this integrative objective, artificial intelligence acts in the following aspects:

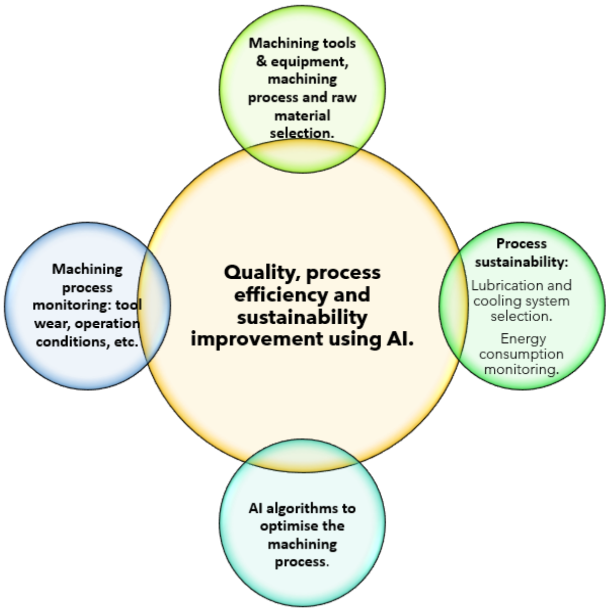


Figure 1.11-AI framework in the machining processes.

This paper will analyse each of these aspects, showing the opportunities that artificial intelligence offers in each of them.

CHAPTER 2. USE OF AI IN THE MACHINING PROCESSES.

In the following subsections we will analyse various aspects in which artificial intelligence helps machining processes with three fundamental objectives of improving:

- ✓ Quality. reducing the machining defects and fulfilling the client requirements (dimensional and geometrical tolerances and surface roughness).
- ✓ Improving sustainability, reducing the negative impact on the environment, workers and society.
- ✓ Improve the efficiency of these processes.

Nowadays, with all the conditioning factors that surround the manufacturing sector, when organisations consider their main lines of action, they always take these three fundamental objectives into consideration, as they are key to their competitiveness. With these three objectives in mind, machining processes and the equipment used are evolving due to (Albertí, 2010):

- Development of tool materials.
- Better knowledge of the mechanisms of chip formation and tool wear.
- Development of machine tools and the machining conditions.
- Constant growth in the demand for time and cost efficiency.
- Development of new materials that are difficult to machine.
- The demand for higher product quality.
- The demand for shorter production times through simplified flows.
- The reduction of the product life cycle.
- The increase in multifunctional surfaces in components.

In order to deal with each of the aforementioned points, artificial intelligence is an essential tool. The following subsections will analyse the involvement of artificial intelligence in different aspects of machining:

1. Machining tools & equipment, machining process and raw material selection.
2. AI algorithms to optimise the machining process.
3. Machining process monitoring.
4. Process sustainability.

The different solutions proposed by various authors will be listed, which lead us to understand the future of machining in the hands of artificial intelligence.

2.1- RAW MATERIAL, MACHINING TOOLS & EQUIPMENT AND MACHINING PROCESS SELECTION.

The machining encompasses a wide variety of processes whose purpose is to shape parts by removing material, either by machining, abrasion, vaporisation, chemical attack, etc. Due to this variety of operations, the characterisation of the processes is difficult. Even more so with the introduction of new materials that demand special operating requirements.
Thus, determining the conditions of the machining processes, even if they are conventional ones, is very complex. These conditions are the selection of the appropriate material, the suitable machining process and parameters, and the necessary equipment and tools.

2.1.1-RAW MATERIAL SELECTION.

As with the selection of tool-machine and tools, the right choice of material is essential as it can improve productivity, material utilisation by reducing waste and the flexibility, reliability and repeatability of the process (Zeynali *et al*., 2012). Consequently, this leads to a more efficient process and cost savings, better lead times and higher product and service quality.

Also as in the previous case, there are a multitude of characteristics to consider, not only in terms of the material itself but also how that material affects the process. Additionally, the new materials that are emerging in the industry must be taken into account, and which in some cases mean the replacement of traditional materials due to their advantageous properties.
In recent years, the needs in various industries have changed and the challenges they face are different. These challenges also impact to parts manufacturing plants. For example, in recent years the aeronautics and automotive industries have advocated making their fleets lighter, with the aim of reducing energy consumption, saving costs and reducing CO2 emissions. Consequently, new materials have been developed to fulfil these purposes with increased recyclability and adequate mechanical properties with respect to their function (Rubio *et al.*, 2020). All this makes material selection increasingly complex due to new materials, new knowledge and process developments, the need for cost savings and reduced environmental impact. With the purpose of making a successful material selection, it is necessary to make use of available artificial intelligence methods. In this way, the following authors propose the use of artificial intelligence in the phase of material election:

- Merayo and collaborators (Merayo *et al*., 2019) also show how artificial intelligence can help designers to select the right material for each application and production process. This allows the system to work under increasingly extreme conditions, in the sense of bringing the system to the optimal possible point, reducing maintenance costs and increasing performance and safety. It is also important to highlight how artificial intelligence techniques can examine very diverse materials with not only an economic-technical vision but also incorporating an environmental and performance perspective. They work in the Machine Learning environment comparing the results offered by supervised and unsupervised learning techniques in the selection of materials:

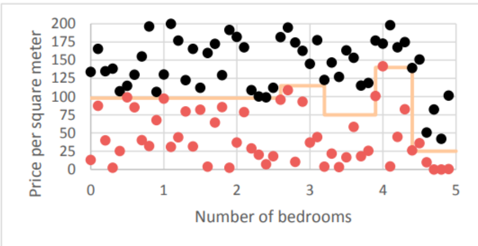
<table>
<tr><th colspan="3">Supervised Learning.</th></tr>
<tr><th>Description</th><th>Strengths</th><th>Weakness</th></tr>
<tr><th colspan="3">Decision Tree</th></tr>
<tr><td>It starts from a source population or root node and branches according to the algorithm used so that each branch represents each of the possible categories (or set of possible values of an input variable) while the leaf node represents a value or range of values of the target variable.</td><td>❖The computational requirements are low.
❖Decision trees don’t require data pre-processing and the learning process is usually fast.</td><td>- Trees are very given to overfitting and tend to have bias if a class dominate.
-Learning the optimal decision tree is known to be an NP-complete problem (nondeterministic polynomial time).</td></tr>
<tr><td colspan="3">

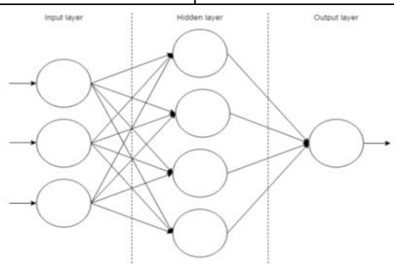
Figure 2.1-Decision tree example in a 2-dimensional space.</td></tr>
<tr><td colspan="3">Decision of industrial material. Based on the materials used in other installations (e.g. fluid pipelines), the algorithm is trained to obtain the most suitable material (pipeline).</td></tr>
<tr><th>Description</th><th>Strengths</th><th>Weakness</th></tr>
<tr><th colspan="3">Neural network-Multi layer perceptron.</th></tr>
<tr><td>It learns a non-linear function by training an algorithm from inputs and outputs. In this way, once trained, it will correlate an input data with its label (output).</td><td>❖Capable of learning non-linear models.
❖Capable of reaching great complexity.</td><td>-. Neural networks are prone to finding local minima and its training is a slow and complex task.
- Requires tuning very relevant parameters before starting the training.</td></tr>
<tr><td colspan="3">There are three types of layers: the input layer with the initial data, the hidden layer, which is the one that relates the input data with the results, and the output layer, which includes the result information.


Figure 2.2-Neuronal network example.</td></tr>
<tr><td colspan="3">Application: Any industrial component based on all known characteristics and all stated boundary conditions.</td></tr>
</table>

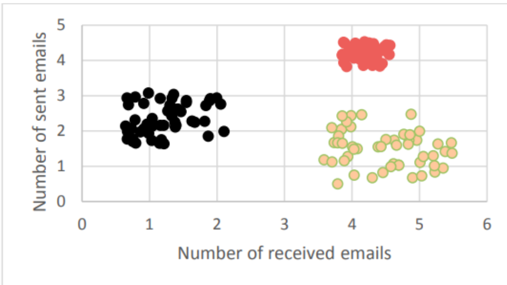
<table>
<tr><th colspan="3">Unsupervised Learning.</th></tr>
<tr><th>Description</th><th>Strengths</th><th>Weakness</th></tr>
<tr><th colspan="3">K-Means clustering algorithms.</th></tr>
<tr><td>It aims to divide a dataset into different homogeneous packages (clusters) to create subsets of data that share common characteristics, usually corresponding to proximity criteria. The K-means method groups data using a strategy that separates samples into subsets of the same variance, minimising intra-cluster inertia.</td><td>❖There are efficient polynomial complexity heuristics that can solve these problems.
❖K-means is generally very fast but there are bad cases where convergence is delayed.</td><td>-. K-means is proud to sub-optimal results and is known to be a NP-complex problem.
- K-means is proud to find clusters of equal size and the number of clusters is an input.</td></tr>
<tr><td colspan="3">

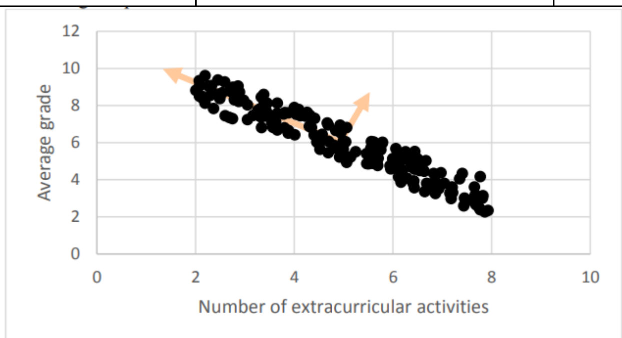
Figure 2.3-K-means clustering algorithm example in a 2-dimensional space.</td></tr>
<tr><td colspan="3">Application: Grouping of components that share similar functionalities or are subject to similar working conditions.</td></tr>
<tr><th>Description</th><th>Strengths</th><th>Weakness</th></tr>
<tr><th colspan="3">Principal Component Analysis (PCA)</th></tr>
<tr><td>They are a group of techniques that assist other classification tools by performing dimensional reduction of the data or by increasing the speed of other algorithms.</td><td>❖PCA allows to reduce data dimensionality.
❖PCA is a polynomial algorithm.</td><td>- PCA assumes data linearity and that the observed data are a linear combination of a certain base.
- PCS relies on the average and variance, which can produce statistical problems.</td></tr>
<tr><td colspan="3">

Figure 2.4-PCA algorithm example in a 2-dimensional space.</td></tr>
<tr><td colspan="3">Application: To stablish the most important parameters to materials selection.</td></tr>
</table>

Table 2.1-Supervised and unsupervised techniques for material selection.

- Zeynali and collaborators (Zeynali *et al.*, 2012) state that the selection of the combination of materials to be employed in the production process can be viewed as multiple criteria decision making (MCDM). This approach has been used in the case of the choice of the machine tool and, as in that case, a Fuzzy AHP approach is used to calculate the weight of each of the criteria that leads to the selection of the most suitable materials and, subsequently, the Fuzzy TOPSIS method is used to obtain the optimised results, i.e., the most appropriate final decision. Linguistic variables are introduced in the study to help define situations that are too complex to be defined by traditional quantitative expressions. The key phase in material selection by means of Fuzzy AHP & Fuzzy TOPSIS method is to establish the critical functional characteristics of the part to be manufactured. In the design phase a compromise will have to be found between:
    - Mechanical properties of the material to be used including hardness and machinability.
    - Characteristics of the process and its risks such as the concentration of heat for plastic materials or the generation of fire in the machining of magnesium, etc.
    - The available production capacity considering the tool- machines and tools available, most efficient sequences, etc.

- A step beyond material selection and from a very interesting perspective, the identification of different materials in a machining operation is proposed (Denkena *et al*., 2020). Increasingly, industry needs to develop high-performance components and this leads to the use of material combinations in parts. This results in the need to adjust the machining parameters during the operation to ensure a correct finish and compliance with the performance metrics imposed for the process. Hybrid materials have been developed mainly for the automotive and aeronautical industries to reduce fuel consumption and CO2 emissions. To carry out this material recognition during operation, Denkena and collaborators rely on the changes in vibration and force caused by different materials in machining processes. These parameters are measured using two acceleration sensors, one on the tool turret and one on the tool, and a dynamometer (Fig 2.5). From the measured signals, training sets for the machine learning algorithm were determined. Subsequently, the materials identification efficiency was tested. It was thus possible to demonstrate that the neural networks are capable of classifying materials according to the cutting parameters (feed rate, speed and depth of cut) in a turning process. Likewise, due to the high cost of dynamometers and extra sensors, the identification was carried out with the machine tool's own sensors, obtaining a classification rate of 99.7% with a constant depth of cut. These values are sufficiently accurate. If the depth of cut varies, the classification rate can be increased from 93.2% to 98.9% with the use of an additional acceleration sensor in combination with the machine own control signals.

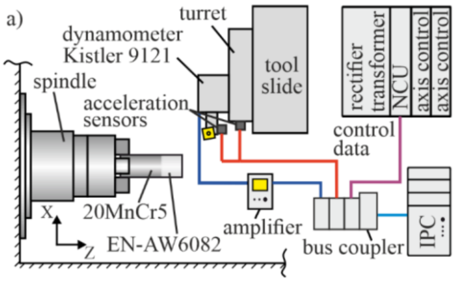


Figure 2.5-Measuring setup.

2.1.2-EQUIPMENT AND TOOLS SELECTION.

The appropriate selection of machine tools, tools and their supports are essential to obtain the desired product, in terms of forming and quality, and to achieve optimum process conditions, for example, dimensional accuracy and cycle time (Albertí, 2010). To this end, the essential factors must be defined to be able to discern between the available alternatives.

The choice of machine tool is a difficult decision for companies both at the time of purchase, as they must be very clear about what they are looking for and compare it with the existing ones on the market, and when the decision is taken to carry out a manufacturing process, as they must compare it with the performance of the machine tools in the company's layout.

Currently, most companies make their choice based on the experience and knowledge of the people in charge. The use of artificial intelligence makes it possible to consider more information objectively.

An inappropriate choice may lead to extra costs (operating costs, investment costs, etc.), negative impacts on productivity, accuracy, flexibility and responsiveness of the company, all of which have an impact on quality, cost and time. (Ayağ and Özdemir,2006).

For this reason, the search for the ideal machine tool is aimed at:

- Reduction of process variability.
- Increased control of cutting parameters.
- Optimisation of the dynamics of operation and trajectory.
- Improvements in the maintenance of the machine tool (deadlines and costs).
- Improved capabilities.

With the aim of having a positive impact on cost, lead time and quality.

Therefore, it must be considered (Alberti *et al.*, 2011):

- Machine configuration, which determines its dynamic behaviour.
- Productivity criteria.

- Quality criteria.
- Technological criteria:
    - Cutting conditions.
    - Trajectories programmed so that they are correctly executed by the machine tools. Basically, three different types of interpolations are used to define the points on the path: Linear interpolations, circular interpolations and polynomial interpolations. The proper selection of the interpolation to be used has a direct impact on the cycle time. (Flores *et al.*, 2007).

Taking all these aspects into account, there are several studies on the use of artificial intelligence in the selection of machine tools:

- ❖ Application of a decisional algorithm to select the appropriate machining process. The machining processes considered are high speed machining, electrical discharge machining or a combination of both (Alam *et al.*, 2002).

- ❖ The optimisation of the selection of machine tools, cutting tools and cutting conditions by means of genetic algorithms with the aim of reducing the cycle time is proposed by Alam and collaborators (Alam *et al.*, 2003).

- ❖ Ayağ and Özdemir (Ayağ and Özdemir,2006) include machine tool selection in the scope of multiple-criteria decision making (MCDM) due to the existence of multiple quantitative-qualitative attributes. They propose to solve this indecision by means of the analytic hierarchy process (AHP) method based on pairwise comparison. Due to the subjectivity of this method and its imprecision, they complement this method with fuzzy logic. This fuzzy AHP approach allows for more accurate decision making as it serves to weight the alternatives under various attributes such as those belonging to the categories of productivity, flexibility, space, adaptability, accuracy, reliability, safety and environment, and maintenance and service. Subsequently, a benefit/cost analysis is carried out, from which the most suitable machine-tool option is obtained. In 2011 (Ayağ and Özdemir,2011) proposed the use of analytic network process (ANP) instead of AHP as it is more general and does not analyse the interconnection between elements of different levels. In this way, the selection of machines among those existing in the market is carried out through a fuzzy ANP approach.

- ❖ Use of genetic algorithms for the choice of machining centre by addressing scheduling in a flexible manufacturing system (FMS) as it shown in Fig 1.17 (Keung *et al.*, 2001). Genetic algorithms are based on the idea that the fittest survive, which is why it is a system that provides better answers each time. A system is proposed in which tool exchanges between the magazine and the automatic tool interchanging device and tool exchanges in the machining centre itself must be minimised. The aim of this study is to solve the problems of machine tool allocation and scheduling in a tool sharing environment.

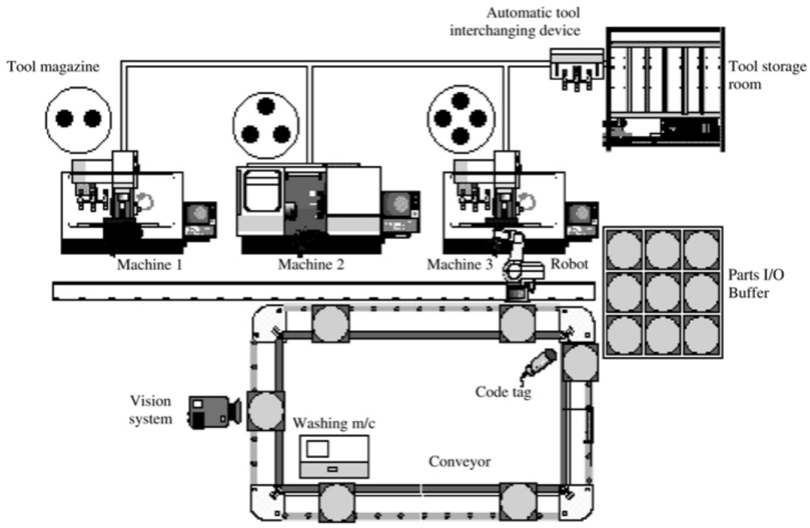


Figure 2.6-FMS layout.

❖ Taha and Rostam (Taha and Rostam, 2011) present a decision system based on a fuzzy analytic hierarchy process complemented with the PROMETHEE method. The fuzzy AHP method helps to propose the weights of each of the selection categories while the PROMETHEE method performs the final ranking of the machines in order of suitability among the existing alternatives in the market, whose data have been previously entered into a database. This study focuses on turning centres and its criteria are Work envelope-main spindle, components-headstock spindle, Tooling Carrier, Axes specification, general specifications as machine weight, floor layout and mill-drill function. Although this method can obviously be used for other machining processes.

❖ Development of neural networks to model a selection system for high-speed machining centres (Alberti *et al.*, 2011). Starting from three types of variables such as those related to the product (material, dimensional accuracy, size, etc.), those related to the machine configuration (acceleration, although the layout is fixed with the type of machine) and those related to the operation itself (type of interpolation and feed rate). Machine selection is based on accuracy/error ratio, process error, process time, process cost and machine tool cost. The use of neural networks, systems that consist of a series of neurons and weighted connections whereby the input information, introduced by the user, gives a series of responses that reflect the information acquired in those connections during training. A multilayer system has at least three levels: an input layer, a hidden layer and an output layer, Fig 2.7. The neural network learns and adjusts the weights of the neural connections. This provides increasingly reliable predictions and results.

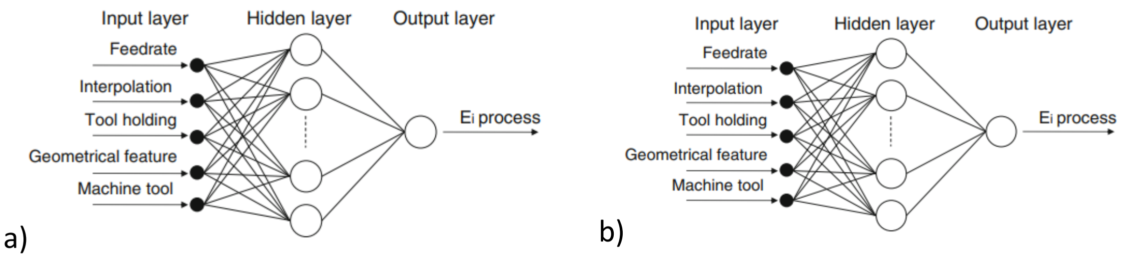


Figure 2.7-Architecture of multilayer feed-forward neural network used for: a) predicting process error b) time process prediction.

The flow chart of machine tool selection proposed is:

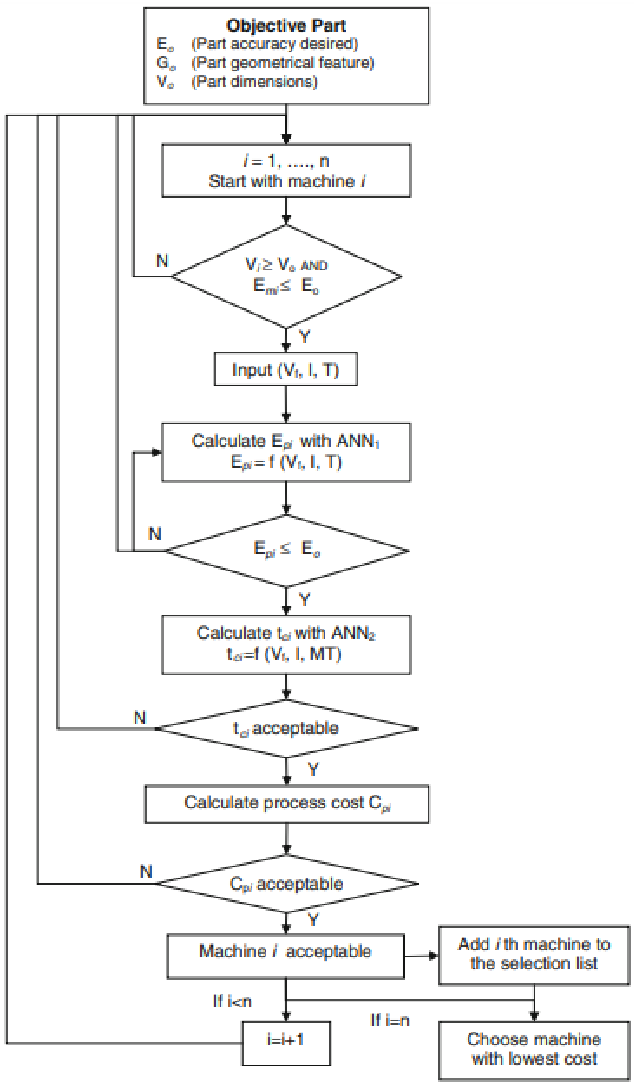


Figure 2.8-Flow chart for the machine tool selection model.

❖ Önüt and collaborators apply a two-stage model: 1-Fuzzy AHP procedure 2-Fuzzy TOPSIS for the selection of the most suitable CNC machining centre among the proposed in a Turkish company (Önüt *et al*., 2008). The Fuzzy AHP method is proposed to establish the weight of each of the chosen criteria while TOPSIS is one of the MCDM methods that has been widely used whereby the best alternative is the one that has the best levels for all the established criteria while the anti-ideal solution is the one that has the worst levels. The aspects evaluated for the determination of their weighted weights have been cost, operative flexibility, installation easiness, maintainability & serviceability, productivity, compatibility, safety and user friendliness.

❖ Ic and Yurdakul (Ic and Yurdakul, 2009) also considered Fuzzy AHP and Fuzzy TOPSIS logics to create a decision support system in an intuitive way for user companies. Thus, the key decision of choosing a machining centre among the existing ones in the company is carried out by a programme that offers as a result the best centre(s) to perform a certain application. Figure 2.9 shows the process of the decision support system called MACSEL:

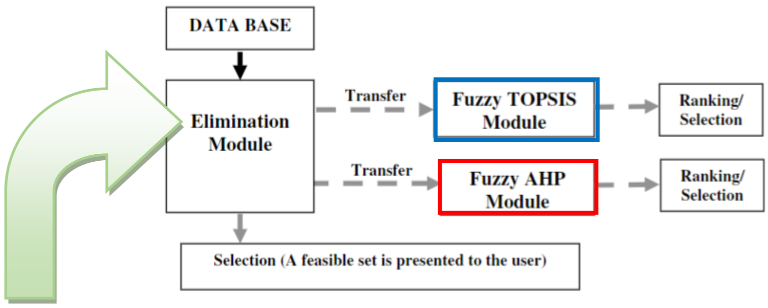


Figure 2.9a-MACSEL Structure.

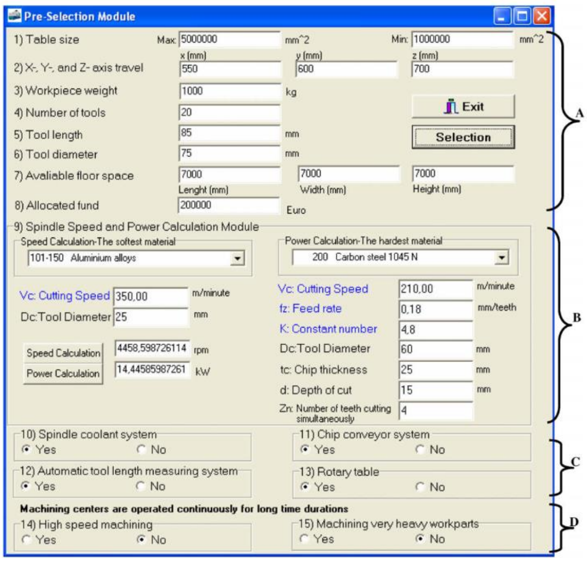
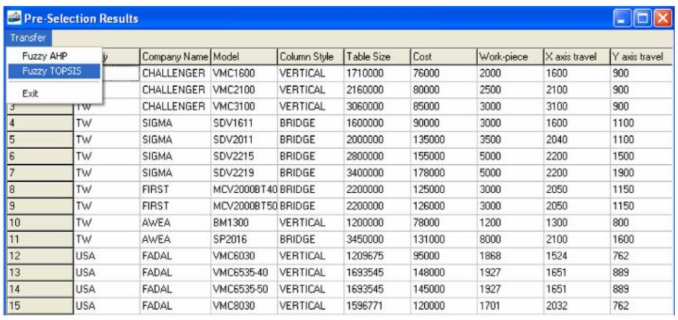


Fig 2.9b-Elimination module.



	y	Company Name	Model	Column Style	Table Size	Cost	Work-piece	X axis travel	Y axis travel
		CHALLENGER	VMC1600	VERTICAL	1710000	76000	2000	1600	900
		CHALLENGER	VMC2100	VERTICAL	2160000	80000	2500	2100	900
3		CHALLENGER	VMC3100	VERTICAL	3060000	85000	3000	3100	900
4	TW	SIGMA	SDV1611	BRIDGE	1600000	90000	3000	1600	1100
5	TW	SIGMA	SDV2011	BRIDGE	2000000	135000	3500	2040	1100
6	TW	SIGMA	SDV2215	BRIDGE	2800000	155000	5000	2200	1500
7	TW	SIGMA	SDV2219	BRIDGE	3400000	178000	5000	2200	1900
8	TW	FIRST	MCV2000BT40	BRIDGE	2200000	125000	3000	2050	1150
9	TW	FIRST	MCV2000BT50	BRIDGE	2200000	126000	3000	2050	1150
10	TW	AWEA	BM1300	VERTICAL	1200000	78000	1200	1300	800
11	TW	AWEA	SP2016	BRIDGE	3450000	131000	8000	2100	1600
12	USA	FADAL	VMC6030	VERTICAL	1209675	95000	1868	1524	762
13	USA	FADAL	VMC6535-40	VERTICAL	1693545	148000	1927	1651	889
14	USA	FADAL	VMC6535-50	VERTICAL	1693545	145000	1927	1651	889
15	USA	FADAL	VMC8030	VERTICAL	1596771	120000	1701	2032	762

Fig 2.9c-Elimination module output.

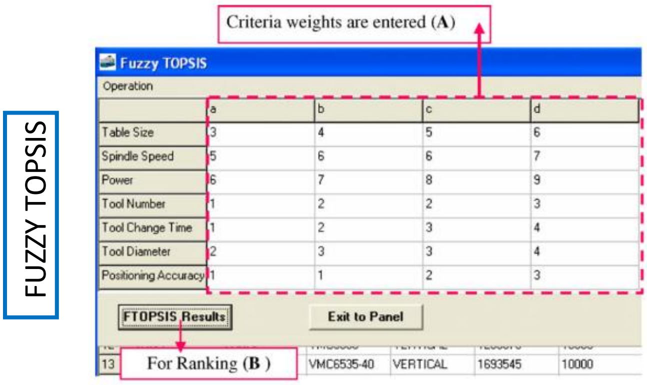


Fig 2.9d-Criteria weights inputs-Fuzzy TOPSIS.

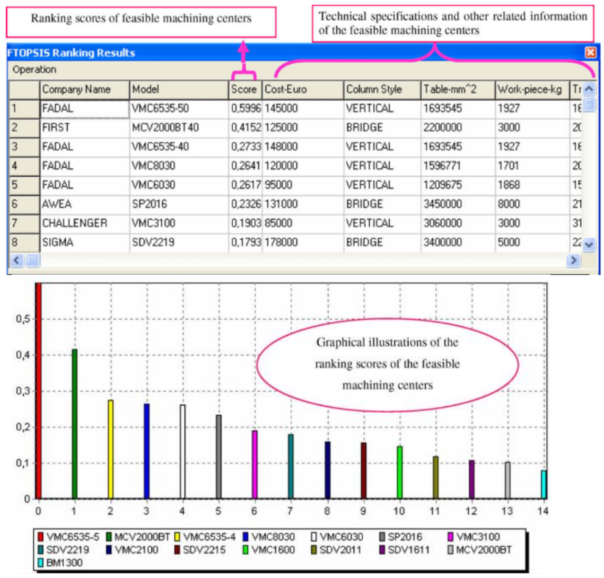


Fig 2.9e- Classification of machining centres.

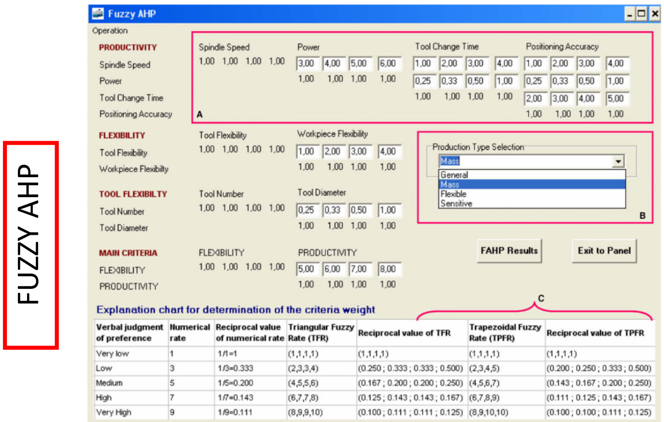


Fig 2.9f-Fuzzy AHP Input Screen.

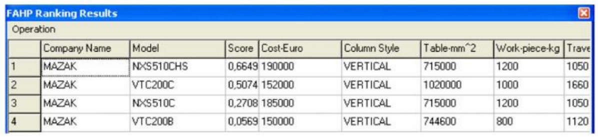


Fig 2.9g-Fuzzy AHP ranking results.

Figure 2.9- MACSEL functionality.

The elimination module, Fig 2.9b, allows the user to enter the process data in section A and the spindle speed and power by entering the weakest material and the hardest material to be machined in section B. The program proposes values for the cutting parameters that could be modified manually. The user shall also enter process and operation information in sections C and D. After entering this data, the program proposes a response in which machining centres in the database that do not meet these input requirements are not displayed. The output information is shown in Figure 2.9c. Following, a choice is made between a Fuzzy AHP or Fuzzy TOPSIS system to obtain the ranking of machining centres ordered by suitability. As can be seen, the Fuzzy AHP system presents a higher complexity when entering the weight of the criteria.

These studies show how the use of artificial intelligence techniques help in making decisions regarding the selection of machining centres. These decisions are still largely made by the experience and decisions of the people in charge, without taking advantage of the ability of these techniques to use a greater amount of information in an objective manner.

In addition to determining the appropriate machining centre, the selection of cutting tools is also important. This choice has an impact on operating costs, cycle time and the quality of the product obtained. One of the characteristics that can be directly affected by choosing the wrong tool is its own wear, which influences the above metrics. There are several factors that determine the selection of cutting tools (Albertí, 2010):

- Mechanical properties (hardness, strength, toughness, etc.).
- Applicability.
- Replenishment stock.
- Accuracy and finishing requirements.
- Type of machine-tool used.
- Production requirements dependent on cutting and feed rates.
- Operating conditions such as cutting effort, temperatures, etc.
- Costs per part.

The tool holder must also be suitably selected (Albertí, 2010) as it must ensure a quick changeover between tools and provide stability in the process. An inadequate tool holder can cause machining defects, lack of dimensional accuracy, poor finishing quality and even a reduction in tool life. These systems can be mechanical, hydraulic or thermal. This choice must be made on the basis of cost and the attributes required to achieve the process objectives.

- Gjelaj and collaborators proposed an improvement in tool selection on CNC machining centres based on the use of genetic algorithms (Gjelaj *et al.*, 2013). The ultimate goal is to reduce human intervention in these decision processes, reduce product cost, reduce cycle time and obtain higher process efficiency. Initially, the tools to be used and in what sequence were determined by the operators themselves; later, the introduction of CAD/CAM systems has helped in this task. In fact, CAD/CAM systems feature modules for the selection of tools, tool length-path, type of work material and machine tool. But all these intelligent systems have not completely replaced human action in making selection decisions. The use of genetic algorithms, as it has been mentioned, is a widely used method for problem solving and is based on the survival of those solutions that provide the best solution (survival of the fittest):

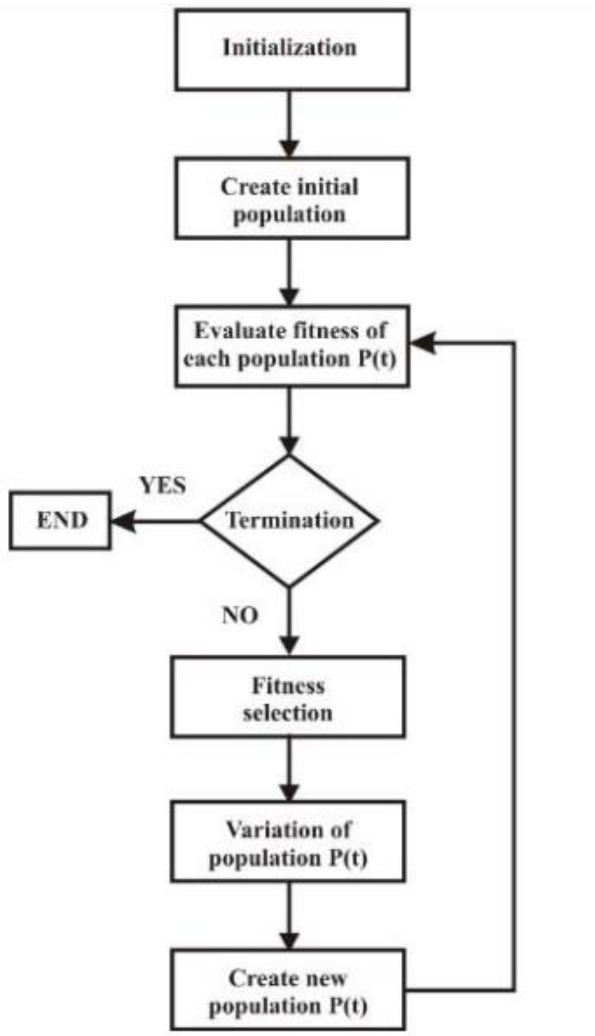


Figure 2.10- Flowchart of the evaluation process using GAs for tool selection.

This model is based on the machining parameters and the workpiece design.

- Kunaparaju and collaborators highlighted how the choice of tools for machining processes through catalogues and databases of manufacturing companies is an inefficient task in terms of cost and time (Kunaparaju *et al*., 2016). In addition, a great deal of knowledge is required to be able to choose the best alternative. Knowing also that the importance of proper tool selection is fundamental, the use of intelligent decision-making and optimisation methods is necessary. This study presents the use of several artificial intelligence techniques such as fuzzy logic, artificial neural networks and genetic algorithms for the optimal selection of both tools and machining parameters:

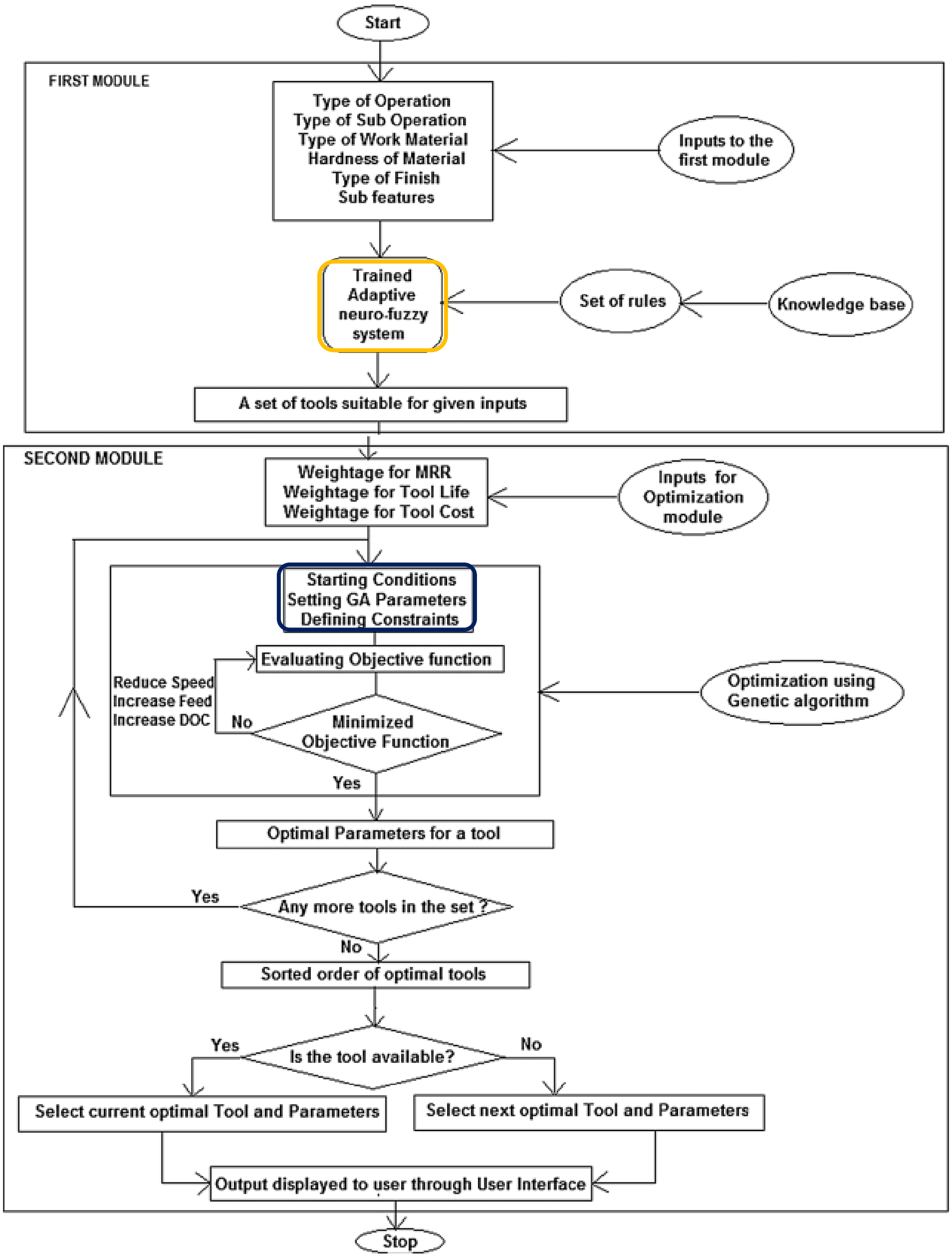


Figure 2.11- Flowchart of the AI based optimal cutting tool and parameters selection system.

The proposed model starts from a database of tools and data on the type of operation, the work material and its hardness, the finishing requirement, etc. and uses an adaptive neuro-fuzzy system to obtain a list of tools suitable for the machining operation. Subsequently, the second module is advanced to optimise tool selection and machining parameters (speed, feed and depth of cut). This optimisation is based on maximising the material removal rate and tool life and minimising tool cost. In order to fulfil this purpose, a compromise between the tool and the chosen parameters is essential. In other words, an inadequate tool versus ideal parameters or vice versa, leads to process inefficiency. Under these premises, the system offers the most suitable tool and the optimum machining conditions.

❖ A new method to obtain a cost-optimal tool sequence, by applying genetic algorithms, for 2.5-axis pocket machining is proposed by Ahmad and collaborators (Ahmad *et al.,* 2010). The input data considered are the geometry of the pocket and the part, the set of available tools, the cutting parameters and the geometry of the tool holder. A set of rules for tool selection is also established:

- Tools will be used in the decreasing order of diameters
- Each tool will machine whatever it can reach up to the extent of its accessible area
- For any two tools, the accessible area of a larger tool is always the geometric subset of the accessible area of the smaller tool.

On this basis, the problem is stated as follows: *"Find the cheapest tool sequence to machine a pocket, given a tool set arranged in the decreasing order of diameters T = t1, t2 ... tn, associated cutting parameters (width of cut, depth of cut, feed, speed), tool holder geometry, and a 2.5-axis pocket defined by the B-Rep of its bottom face 'p', depth 'h' and the B-Rep 'I' of the intermediate stock after the pocket has been machined*.". To solve this problem, three geometric algorithms are developed to define the most suitable tools. Subsequently, genetic algorithms are used to find the optimal tool sequence. In this study, two selection methods were applied to eliminate the less suitable alternatives:

- *Roulet Wheel Method*, whereby the solution is selected by spinning a "roulette" of solutions and where the share of each solution is set according to its suitability.

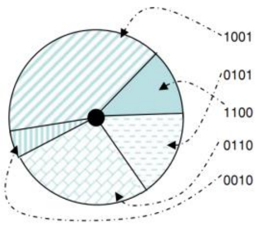


Figure 2.12-Roulet Wheel Method: Response sector angle distribution.

- *Elitist Method*, whereby the best response from one generation will be in the next. In this case, the sequence of tools is set in increasing order of cost.

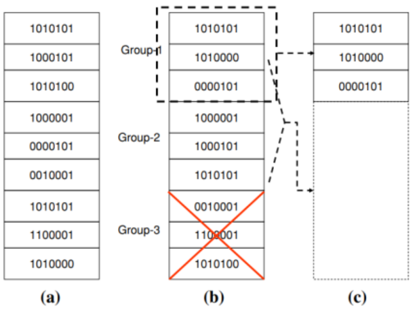
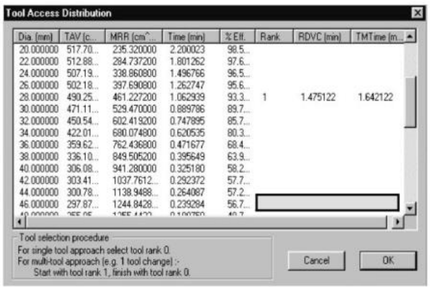


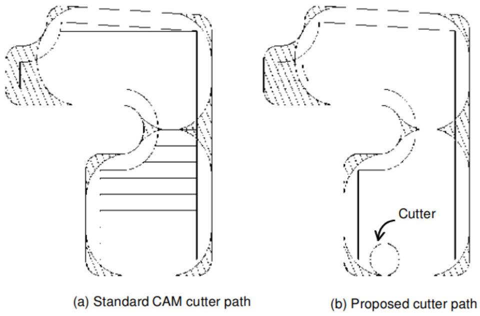
Figure 2.13-Elitist Method: a) Population in ith generation. b) classification and selection. c) (i+1)th generation.

- ❖ For Yao and collaborators, the approach to optimising the tool sequence for 2.5-D milling is through time, both process time and tool loading time (Yao *et al*., 2003). In milling, tool size is essential as it significantly affects machining time. While a small tool size is able to handle a larger number of machining geometries, it is true that it increases the process time. In this way, geometric algorithms are used to extract the target machining region, the area that can be covered by each of the tools and finally, by means of Dijkstra's algorithm, the optimum sequence is obtained.

- ❖ Approach to tool sequence optimisation by employing geometric algorithms that favour the largest tool capable of more complete volumetric clearance, i.e. tends to reduce residual material (Lim *et al*., 2010):



a)



b)

Figure 2.14- a) Optimal tool selection and tool change sequence. b) Improved cutter path.

Due to the fact that the appropriate selection of tool and their sequence of use is essential for the efficiency of machining operations, many authors have searched for the best way to optimise this task and to do so jointly with the tools provided by artificial intelligence. In this work a series of examples of studies with different approaches but with the common objective of improving this task have been presented.

2.1.3-MACHINING PROCESS SELECTION.

The production managers or designated technicians are responsible for determining the machining processes to be carried out for the manufacture of a part and also establish the sequence of operations. This decision is the result of their knowledge and experience (Kang *et al.*, 2016). On the other hand, more and more technicians are relying on CAD/CAM systems for the manufacture of parts, with the CAPP module being a strategic link between them that provides support for the decision to sequence the machining processes.

It should be considered that the appearance of new materials, both working and tooling materials, new machining processes and the evolution of machine tools, renders decision making more complex, slower and less efficient. Artificial intelligence in this phase is crucial as it reduces human error in the selection process, improves efficiency, reduces time and considers all data related to machining processes.

In the election of the proper machining processes, those responsible seek to obtain the required quality in the shortest possible time and at the lowest possible cost, including the increase in tool life. Proper sequencing of operations reduces setup time and number, cycle time, cycle cost and leads to improved machine-tool maintenance.

The authors have used various strategies to achieve an optimal process selection and machining sequence:

- ❖ Approach to machining process selection and sequencing using ontological models (Eum *et al*., 2013) (Kang *et al*., 2016). This method requires knowledge of machining features and capabilities and the relationships between them. The decision-making logic is modelled by rules that connect the characteristics of machining processes and a particular process.

- ❖ Ahmad (Ahmad, 2001) proposes a CAPP model covering from part design, feature extraction to optimisation of process parameters by means of genetic algorithms. (Fig. 2.15)

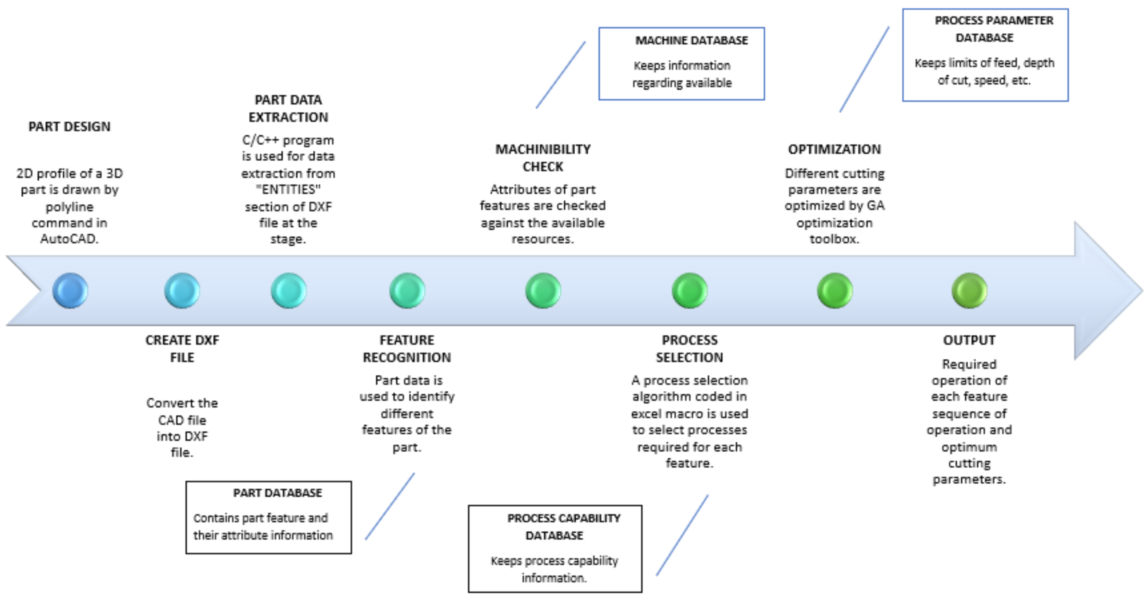


Figure 2.15-CAPP system.

The selection of the machining process for rotational components is carried out by means of an algorithm that considers the attributes required for the part like surface shape and finish. There are limitations in this work, as in addition to considering only symmetrical parts of revolution and the algorithm does not consider all the conditioning factors of the machining processes (times, tool cost, etc.).

- ❖ Ahmad and Haque (Ahmad and Haque, 2002) employ neural networks for cylindrical surface machining process selection.

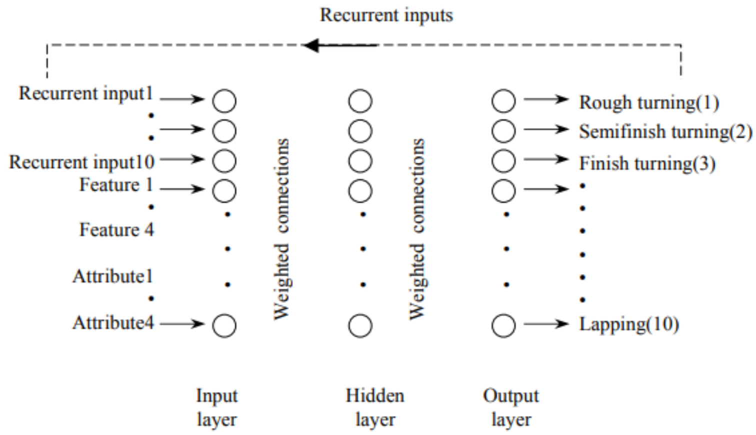


Figure 2.16-Neuronal network to process selection.

The system considers as input neurons 10 recurrent input neurons, 4 neurons corresponding to the surface types (horizontal, vertical, inclined and curved) with the attributes to be met including length, surface type, tolerance and finish. The output layer consists of 10 neurons with each of the machining processes. By using neural networks, Ahmad and Haque addressed some of the limitations of his previous work.

- ❖ Development of a new back-propagation neural network for rotationally symmetrical parts (Deb *et al.*, 2006). The proposed neural network model is:

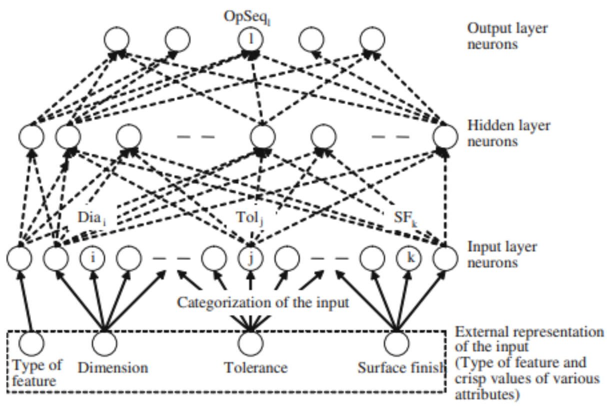


Figure 2.17-Rotationally symmetrical parts neural network model.

The model starts from all possible sequences to determine the most suitable one depending on the availability of the machine tool, the cutting tool, the manufacturing cost and the constraints of the operation.

❖ Wong and collaborators solve the decision of the selection and sequencing of machining processes with a hybrid approach through Fuzzy Expert System and Genetic Algorithms (GA) (Wong *et al*., 2003). This approach optimized the sequencing with a cost-tolerance model.

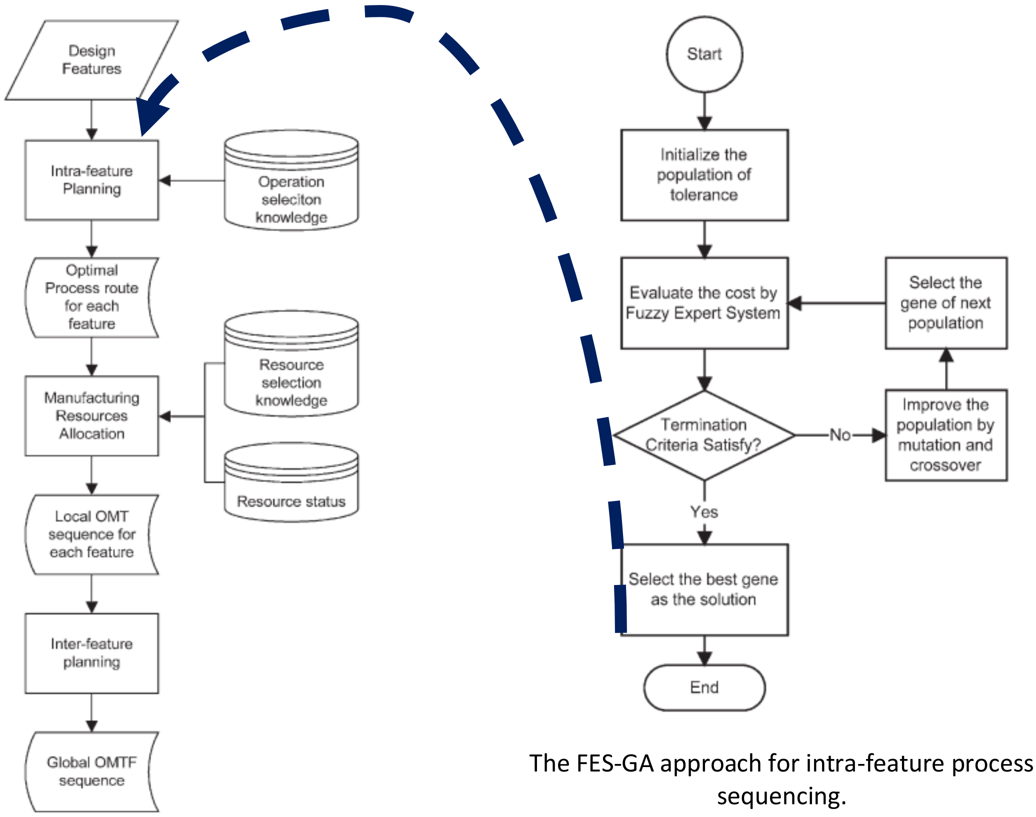


Figure 2.18-Fuzzy Planning System.

Intra-feature planning focuses on the selection of the optimal machining process using fuzzy cost evaluation integrated in a genetic algorithm. Consequently, the optimal process is chosen based on the cost for each feature. Machines and tools assigned to each selected operation to form an operation-machine-tool (OMT). While through inter-feature planning, which considers the relationships between all operations, the sequencing is adjusted. Sequencing optimisation is performed through a genetic algorithm using fuzzy numbers.

❖ Deja and Siemiatkowski (Deja and Siemiatkowski, 2018) propose the use of algorithms for the selection of the machining process and subsequent sequencing. Based on the machining characteristics and part attributes, and considering the available machine tools, the algorithm performs the selection of the most suitable operation and its sequencing. The following figure shows the flowchart of the proposed system and the information it takes into consideration:

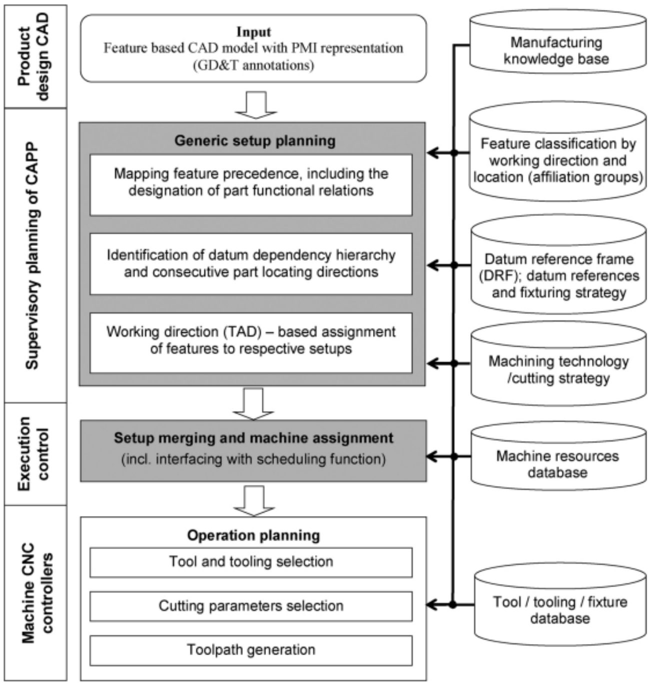


Figure 2.19-System solution outline for optimal process plan selection in CAPP applications.

The system proposes a series of alternative sequences as shown in Figure 2.20 for the turning-milling of a part. The alternatives include: performing all operations on machine m_1 (alternative a), on machine m_2 and then finishing the part on machine m_3 (alternative b) or m_2 and forcing a change of machine in a previous operation to machine m_3.

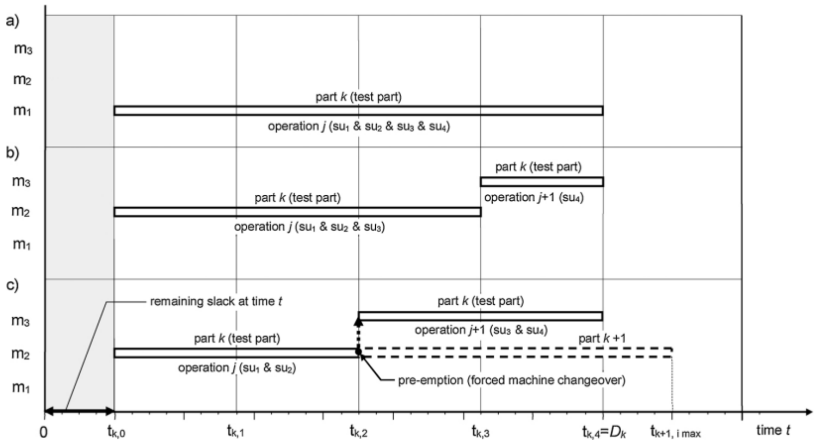


Figure 2.20-Alternative schedule solutions.

❖ Nallakumarasamy and collaborators perform an approach using a superhybrid genetic algorithms - simulated annealing technique which incorporates solution space reduction technique (SSRT) (Nallakumarasamy *et al.*, 2011). The method starts by evaluating the part in terms that recognises the features to be machined by considering the dimensional tolerances, geometries and the required finishing. For each feature a selection of suitable operation, tools and cutting parameters is produced considering the constraints. From the knowledge of previous machining processes, a cost matrix is run where changes of machine, tools, set-up and parameters are considered. The genetic algorithm provides an optimal solution to the simulated annealing technique with the aim to obtain a higher quality result and reduces the computational time.

❖ Selection of machining strategy on the environmental variable using a life cycle assessment program (LCA software: GaBi 6) (De Souza *et al*., 2019). Although it does not directly mention artificial intelligence as a tool, the study by De Souza and collaborators is worth mentioning for its environmental perspective. The results obtained by the LCA software could be incorporated into the aforementioned artificial intelligence techniques for selecting the optimal machining strategy. In other words, not only technical and economic aspects would be considered, but also the sustainability of the process would be taken into account.

In this study, five different machining alternatives have been compared. The first is a standard milling operation of a low-alloy steel while the other four are shown in the following table:

Tool configuration	Tool material	Machine	Feed rate (mm/min)	Energy consumption (MJ)
Ball end mill, Ø4.76 mm, 30° helix	TiN-coated carbide	Mory Seiki NVD1500 DCG, 7.5HP, 40,000 rpm	882	3.09 ± 0.02
			433	4.98 ± 0.02
		Haas VF0B, 20HP, 7,500 rpm	433	16.93 ± 0.05
	Uncoated high-speed steel	Mory Seiki NVD1500 DCG, 7.5HP, 40,000 rpm	35	47.87 ± 0.61

Table 2.2-Machining alternatives based on different tool materials, machine size and speed.

As can be observed, two distinct tool materials, two different machines and two speeds are involved in the generation of the alternatives. The energy consumption is exponentially influenced by the feed rate, so that slower processes have a higher consumption. Larger and heavier machines, such as the Hass compared to the Mory Seiki, also have a superior consumption.

The standard methodology provided by the programme was used, considering as environmental risk factors those shown in the following figure (Fig 2.21):

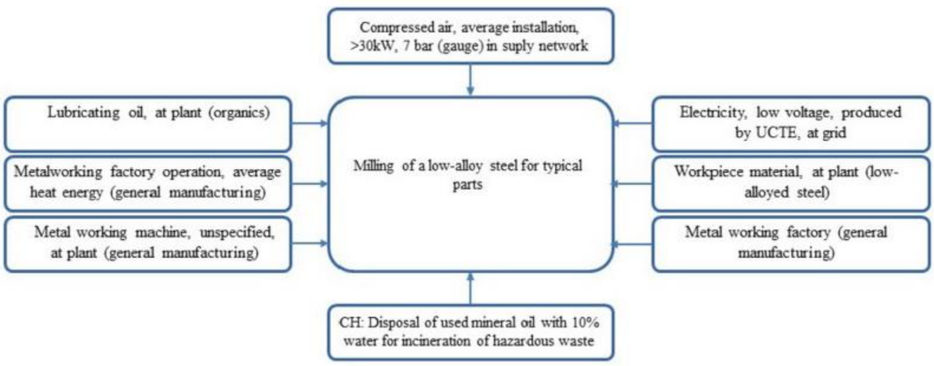


Figure 2.21-Inputs for a milling operation in LCA software inventory.

The impact created by each of these categories is shown in Fig 2.22. The two most impactful categories are working material and factory operations. Therefore, by working on both aspects, the overall impact of the process is reduced by more than 80%. This is the reason why it is so important to continue to look for more sustainable working materials and machining strategies. To accomplish this, companies need to be aware of all the technological tools available. In this context, the integration of the environmental variable in the selection of machining strategies, by means of, for example, the use of LCA software or its integration with CAD/CAM programmes, shall be a priority for all companies and not only for large ones.

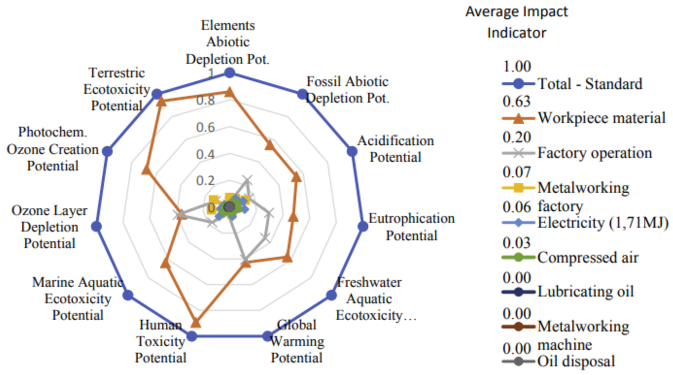


Figure 2.22-Impact areas and percentage impact indicator for each input for a milling operation in LCA software inventory.

For the different alternatives the LCA software calculates their impact area and impact indicator value based on energy consumption (Fig 2.23):

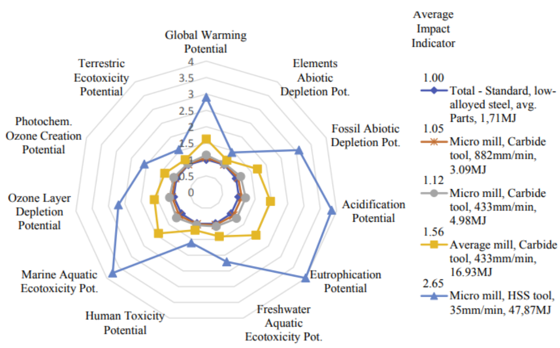


Figure 2.23- Impact areas and average impact indicators based on actual energy consumption for the standard milling operation and the four other strategies.

The least impacting strategy is the one with the Mory Seiki machine, the TiN-Coated carbide tool and a feed rate of 882 mm/min. The least efficient strategy is the one carried out on the largest machine with HSS tools at 35 mm/min.

It should be noted that it is a visual, easy to understand and useful tool to obtain information on the environmental impact of different machining strategies. It should be an additional input when selecting the optimal machining process. Furthermore, at a time when electricity prices are reaching record highs, it will help to choose strategies with lower energy costs.

The study points also out as a weakness the high standard deviation of the inventory data which was corrected by introducing actual energy consumptions.

2.2-AI ALGORITHMS TO OPTIMISE THE MACHINING PROCESS.

The selection of the optimal machining process is about determining the ideal process parameters to maximise productivity and savings, reduce process cost, environmental impact and meet customer requirements in terms of quality, scope, time and cost. Achieving these optimum operating parameters has been the subject of many studies, as it is one of the key aspects of process efficiency.

- Following Park and Kim (Park and Kim 1998), these studies can be characterised as CAD-based, operations research and AI-based approaches. Within the artificial intelligence approach, a distinction can be made between:
  - ***Knowledge -based expert systems (KBES).*** These systems copy human problem-solving strategies to produce recommendations. They employ various AI techniques. Based on sensor feedback of machining variables, KBES can keep parameters within critical operating ranges and can push them to their limits to optimise the process.

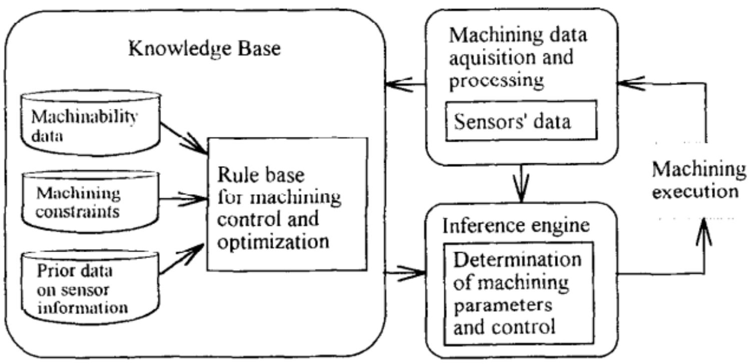


Figure 2.24-KBES structure for machining control.

  - ***Neural Networks.*** Compared to the previous approach, neural networks create their own knowledge by learning. In addition, they can respond to source data that has not been entered before or is incomplete. Park and Kim propose that once the system is trained, using the backpropagation algorithm, the optimal control phase of the process is addressed. The objective of this phase is to determine the machining parameters that optimise the performance index of the process. The backpropagation algorithm minimises the global error of the system by adjusting the learning parameters.

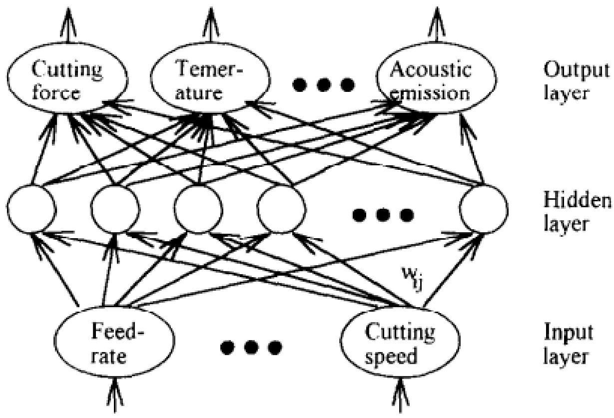


Figure 2.25-A neural net structure for machining process.

Subsequently, the optimal set of values is found, establishing the conditions and calculating the performance index.

- *__Probabilistic inference__*. An influence diagram is used to graphically display complex decision problems based on incomplete or imprecise information. They depict the relationships between the different variables. The circular nodes incorporate the certain or uncertain states, the square or decision nodes are the variables whose value is chosen by the decision maker while the diamond-shaped nodes represent the objective to be maximised by the decision analysis. In this case, it would be the material removal rate. The probability of the solutions is incorporated by means of numerical information. Once the diagram is completed, it is evaluated to define the optimal decision strategy.

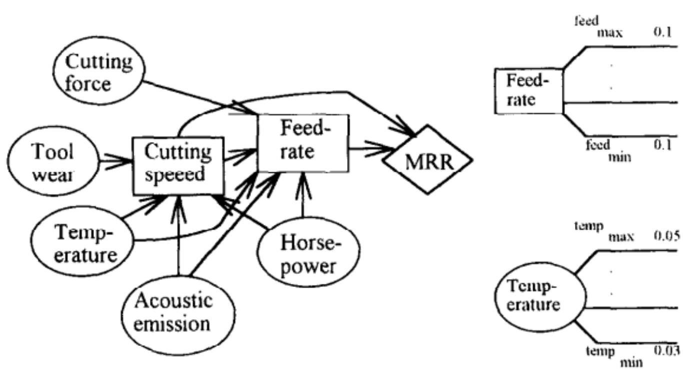


Figure 2.26-An influence diagram for determining machining parameters.

❖ Artificial intelligence techniques to achieve laser beam machining optimisation focusing on quality and performance aspects (Bakhtiyari *et al*., 2021) (Fig 2.27 a)):

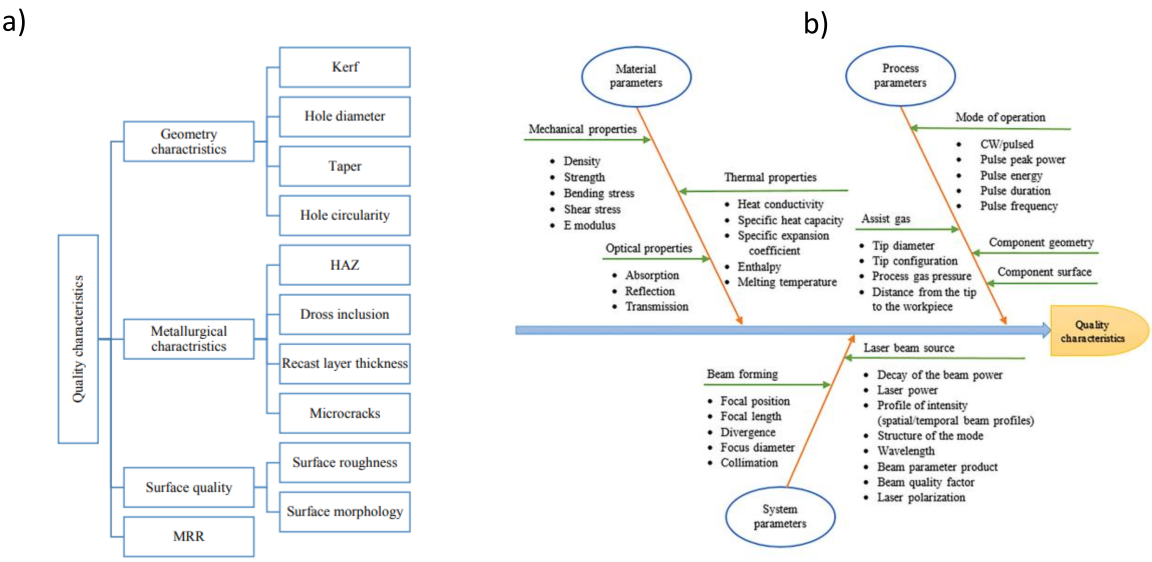


Figure 2.27-LBM Aspects and parameters: a) Key aspects of optimisation. b) Influential parameters.

The critical parameters that influence the machining process can be categorised into three distinct groups: process, material and system parameters (Fig 2.27b)). From these, the authors' conclusions are that, although AI techniques such as ANN and fuzzy logic provide an adequate response to feature optimisation, they have a number of disadvantages that can be overcome by the combined use of both techniques. They highlight how these hybrid methods offer more efficient and accurate results. This is also observed in combined modelling-optimisation methods such as the hybrid GA-ANN model.

❖ Boga and Koroglu (Boga and Koroglu, 2021) use one of these hybrid methods to estimate the surface roughness of a fibre-carbon composite part in a milling process. The surface roughness is an indicator that allows the evaluation of the final quality of the product and even provides information on the machining performance. This hybrid intelligence approach consists of neural networks whose parameters are adjusted by means of a genetic algorithm with the final objective of estimating the surface roughness:

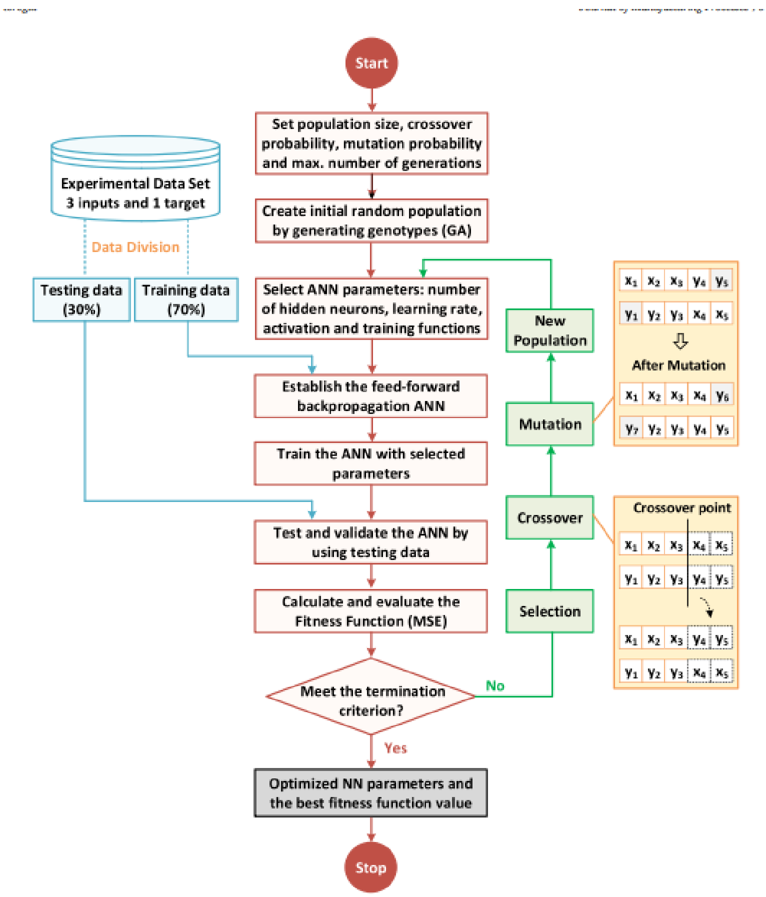


Figure 2.28-Hybrid ANN-GA algorithm flowchart.

For this purpose, the following cutting parameters were chosen: cutting tool used, spindle speed and feed rate. By means of a statistical ANOVA analysis, it was observed that the tool and feed rate parameters had a greater effect on the surface roughness of the composite material. In addition, surface roughness was estimated using a feed-forward backpropagation ANN model with assisted parameter setting by GA. The incorporation of genetic algorithms provides greater efficiency in effort and time in the selection of optimal parameters. This study shows how hybrid systems provide very good results in the optimisation of machining processes.

❖ As Boga and Koroglu (Boga and Koroglu, 2021), Muthuram and Frank (Muthuram and Frank, 2021) integrate the ANN technique into genetic algorithms to find the combination of parameters that maximises the MRR and minimises the surface roughness. The ANN results have been compared with other prediction models (Fig. 2.29) showing its performance. This performance is based on its ability to identify non-linear and complex relationships and could be improved by adjusting hyperparameters such as its activation function, learning rate, etc. This gives it an advantage over other models.

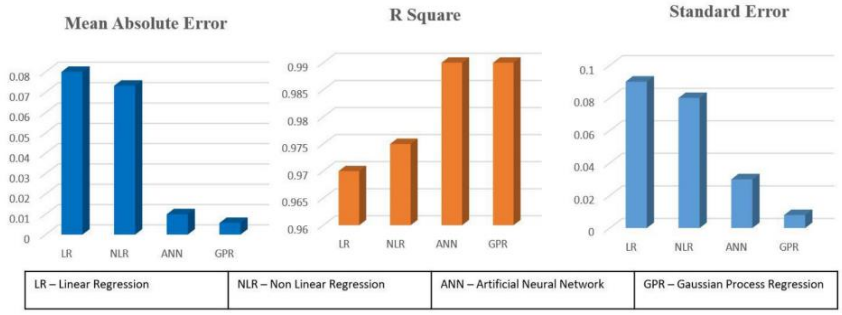
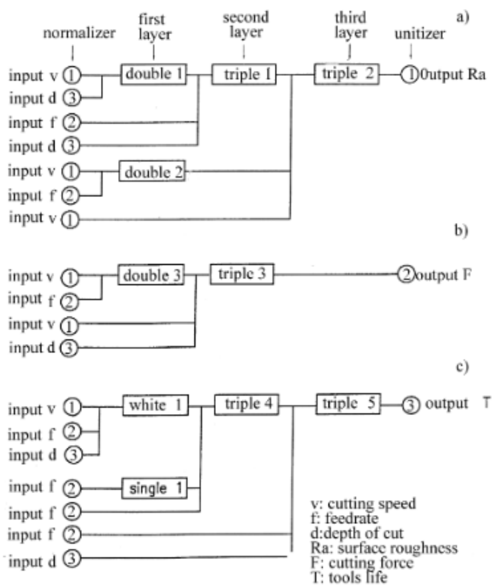
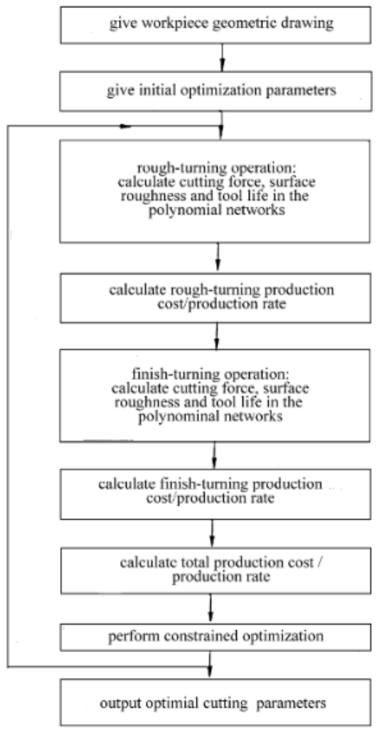


Figure 2.29-Performance of different models.

- Lee and Yarng already in 2000 studied the selection of suitable cutting parameters for a multipass turning process with the aim of optimising the operating cost by maximising the production rate or minimising the production cost (Lee and Yarng, 2000). They used polynomial networks to model the process, due to the relationships between the input data and the outputs of the process (Fig 2.30 a). They chose polynomial networks as they have higher accuracy and less need for internal connections to provide adequate solutions than back-propagation networks. Having obtained a set of initial parameters suitable for the process, an optimisation algorithm called the sequential quadratic programming method is used. The process flow chart is represented in the figure (Fig 2.30 b)).



a) Polynomial networks for predicting cutting performance: (a) surface roughness; (b) cutting force; (c) tool life.



b) Optimization flow chart.

Figure 2.30-Polynomial networks for predicting cutting performance and optimization flow chart.

❖ Cus and Balic aimed to optimise cost and operation time by finding the best values for the cutting parameters (Cus and Balic, 2003). To this end, genetic algorithms are employed in which several objective functions and constrains are considered (Tab 2.3).

Functions	Constrains	Optimization
• *Production Rate* (as the time of manufacturing, including material removal rate and tool life). • *Operation cost*. • *Cutting Quality* (based on Roughness).	• Cutting conditions stablished by the tool. • Cutting power and cutting force limited by the machine. • Mechanical properties of the work material.	**Minimize cycle time.** **Minimize Operation cost.** **Minimize roughness.**

Table 2.3-Constrains and objective functions of cutting parameters optimization.

From this information, the genetic algorithm is applied to optimise the parameters. The following figure shows the process flow that can even be integrated into an online system within the framework of smart manufacturing.

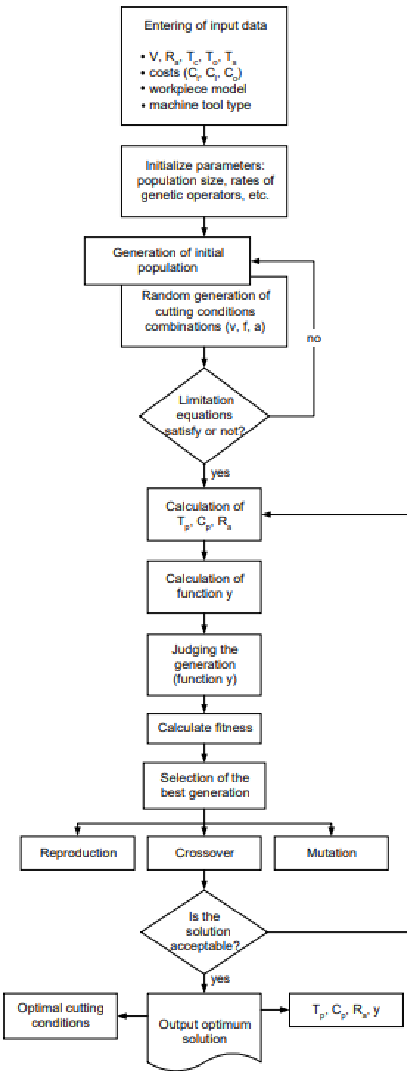


Figure 2.31-GA solution flowchart.

❖ D'Addona and Teti also worked on turning process with the purpose of the cutting parameters optimization by means of genetic algorithm (D'Addona and Teti, 2013). The objective functions are mainly focus on minimize production cost and maximize production and profit rate. Process constrains should also be taken into account, such as: tool-life, cutting force, power, stable cutting region, chip-tool interface temperature, surface finish and roughing and finishing parameter relationship. This study aims to minimise production time while respecting process constraints. The production time is expressed by the ratio of the setup time, the tool change time, the time during which the tool does not cut, the tool life, the volume of material removed and the material removal rate (MRR). The evaluation of the process result is done by the roughness obtained. Considering the technological and material constraints, the possible results are obtained and optimised by means of GA.

❖ Zuperl and collaborators propose a hybrid system for this purpose . The hybrid system is developed thanks to ANN and the TOPSIS routine. In this study the objective functions and constraints are similar to those considered by Cus and Balic (Cus and Balic, 2003):

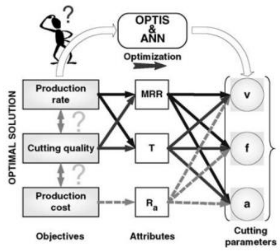


Figure 2.32- Objectives, attributes and cutting parameters logical representation.

The following figure shows the combined strategy for obtaining the best results in terms of cutting parameters.

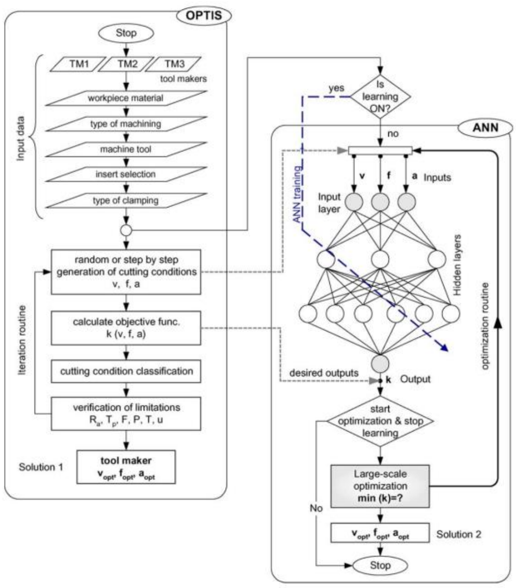


Figure 2.33-Optimization strategy flowchart.

This strategy was compared with others such as the use of genetic algorithms and its effectiveness was highlighted.

❖ An interesting perspective is developed by La Fé-Perdomo and collaborators (La Fé-Perdomo *et al.*, 2018) in which, in addition to the technical-economic vision, they incorporate the environmental dimension in the selection of the ideal parameters for a multipass turning process. The decision variables chosen are based on the cutting parameters: speed, feed and depth of cut. In addition, two objective functions were considered. The first one represents the process costs while the second one reflects the environmental impact through energy consumption and tool life (tool wear). Finally, the process constraints are defined, establishing the working ranges of the parameters depending on the tool, limitation of the cutting force, the maximum roughness to be reached in the last pass, etc. As a result of the linear programming, a set of appropriate solutions were obtained for the process described. The optimisation to obtain the suitable parameters was carried out using two different techniques to be compared: the non-sorting genetic algorithm II and the multi-objective particle swarm optimization. Both provided effective results in terms of sustainable optimisation. However, the genetic algorithms presented a superior response in terms of quality as well as computational efficiency.

The new perspective of Yoo and Kang (Yoo and Kang, 2021) on the search of optimisation of machining processes based on manufacturing cost estimation using deep learning should finally be highlighted. It is not based on the cutting parameters but in the material, final piece form and costs of the process. The different phases of this study are shown in the figure below:

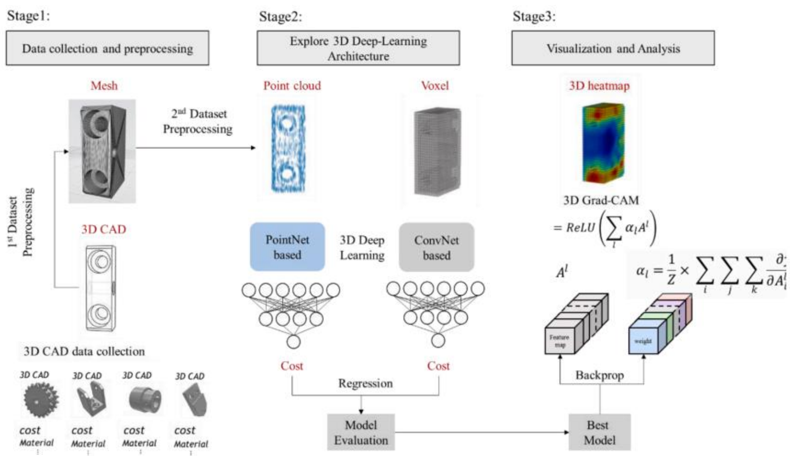


Figure 2.34-Research framework.

Stage 1 collects all information on materials, processes and costs and studies it. Thus, the output of information on volume, materials and costs is the input for deep learning. Stage 2 is where the 3D Deep Learning architecture model is developed in which features are extracted and regression techniques are used. A deeper model than previous authors is proposed in this work. Finally, the third stage is the 3D Grad-CAM in which once the 3D CNN has been trained, it can perform cost estimation of new parts.

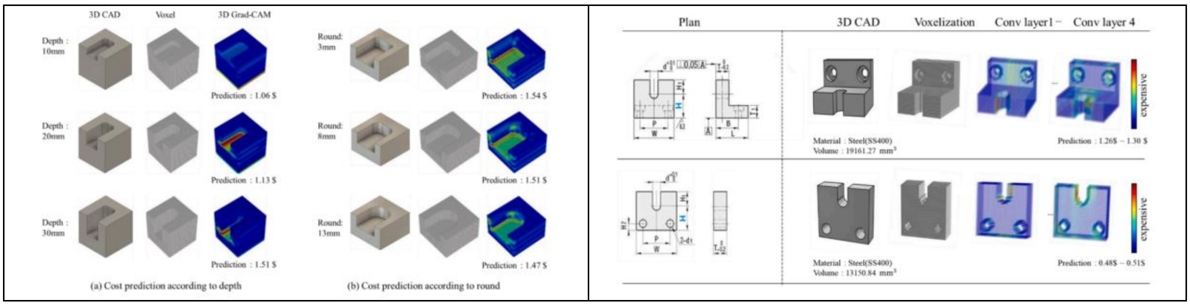


Figure 2.35-Cost prediction.

This study determines the value of the machining operation evaluating the final piece characteristics, allowing designers to make decisions based on cost.

Possible future research could be the inclusion of environmental variables as an impact cost. Therefore, it could be possible to select the design with the lowest cost and the lowest environmental impact.

2.3- MACHINING PROCESS MONITORING.

The great relevance of monitoring in machining processes is evident in the large number of scientific articles and studies related to it. The scope of monitoring is the analysis of (Teti *et al*., 2010):

- Tool conditions: wear, breakage, geometry, temperature.
- Chip conditions: form, disposal, breakage.
- Process conditions: faults, variations, state, simulation and cutting variables.
- Surface integrity: finish and roughness, white layer formation, surface integrity, plucking and smearing, delamination.
- Machine tool state: feed drives wear, fault diagnosis and maintenance planning, spindle bearings.
- Chatter detection: chatter state, chatter onset, chatter vibration.
- Other scopes as work material heat treatment conditions, workpiece mass, tool-workpiece contact, workpiece diameter, cutting force measurements, product conditions, process, tool and workpiece states, ultra-precision machining conditions, collision detection, machining environment monitoring.

This makes it a very interesting subject. The application of artificial intelligence tools makes these advantages even greater, as they allow all the data collected by the sensors to be analysed more quickly, reliably and accurately than with human intervention alone. If in other cases, the use of AI techniques is more than demonstrated, in the case of monitoring it is even more so. Artificial intelligence allows for more objective and data-driven decision making.

Monitoring techniques have traditionally been classified into two categories (Teti *et al*., 2010):

- *Direct.* Are those that directly measure the variable to be studied: tool wear, the quality of the part by measuring the final finish or dimensions, etc. The measurement is carried out using cameras, radioactive isotopes, laser beams, electrical resistances. Due to their cost and complexity, their use is mostly restricted to academic environments.

- *Indirect.* The target variable is obtained by measuring other parameters to which it is related. These methods are less precise, but less expensive and can be more easily implemented in industrial environments, although they are not widely used. The variables usually measured in this approach are those related to the engine and the process, as shown in the figure below:

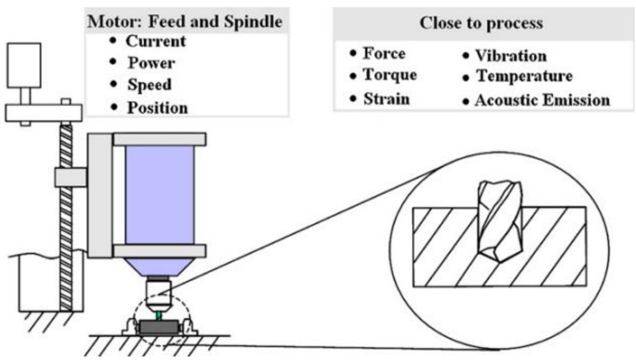


Figure 2.36-Measurable phenomena for online sensor monitoring.

The signals collected by sensors must be processed so that the relevant data can be decisive in decision making. The signals must be pre-processed, which consists of filtering, amplification, conversion, segmentation and transformation. Subsequently, the next stage is the extraction of signal or signal transformation features that vary with tool or process conditions. Finally, the selection of the relevant features is a critical phase as these are the ones that will be used in the diagnosis of the process and/or tool condition and the making – decision stage (Teti *et al*., 2010). Although in the signal processing stage, the machining data have been represented as time series, as the measurements are taken over a period of time. Shafae and collaborators propose the spatial point cloud representation to be able to analyse spatial correlations as well. Thus, monitoring provides a better understanding of the machining processes and allows us to act on any anomalies that arise (Shafae *et al*., 2021).

Each signal acquisition method has its advantages and limitations as shown below (Nath, 2020):

Data acquisition methods (no. of article)	Till 1989	1990-99	2000-09	2010-19	Advantages	Limitations
Optical measurement or wear texture analyses (29)	3	7	5	14*	Very accurate (~97%), can map all wear modes, offline and online	On-machine inspection, multiple tools mapping
Radioactive (6)	6				Accurate	Slow response, radiation, unsafe
Electrical resistance (2)	2				Accurate	Misleading results
Force / torque (88)	11	18	27	32	Accurate flank wear and tool breakage	Complex relationship with wear, not suitable for other wear modes, installment of sensors and wiring for individual tools
Vibration / acceleration (45)	7	6	18	14	Accurate, cheap, low energy, easy to install and use	Sensitive to neighbor system vibrations
Displacement (4)	1	1	2		Fairly accurate	Sensitive to part size, needs special setup, process delay, mainly for turning
Acoustic emission (38)	6	2	14	16	Accurate detection of almost all wear/failure and other outputs, cheap, low energy	Sensitive to lacing location(s), ambient noise, sensor alignment, fouling from chip and coolant
Current/power (19)	2	2	3	12	Accurate, cheap, easy to install and use, low energy	Availability of suitable hardware, Still a bit less accurate than force, Complex relationship with wear
Audible sound (15)	1	4	5	6	Accurate, cheap, easy to install and use	Sensitive to ambient noises, cannot detect all wear modes
Tool temperature and thermal imaging (14)	4	3	4	3	Remote infrared ray (IR) application	Installment issue at tool-chip interface, limited to estimate only flank and crated wear, inaccurate with IR signals, complex relationship with wear
Surface roughness & texture / dimension error (12)		2	6	4	Fairly accurate	Limited to only flank wear, no chip information, hard for in-situ application, process delay, modeling-based estimation

Table 2.4-Signal acquisition methods and their TCMS feasibility in industry applications (*majority tending towards machine vision).

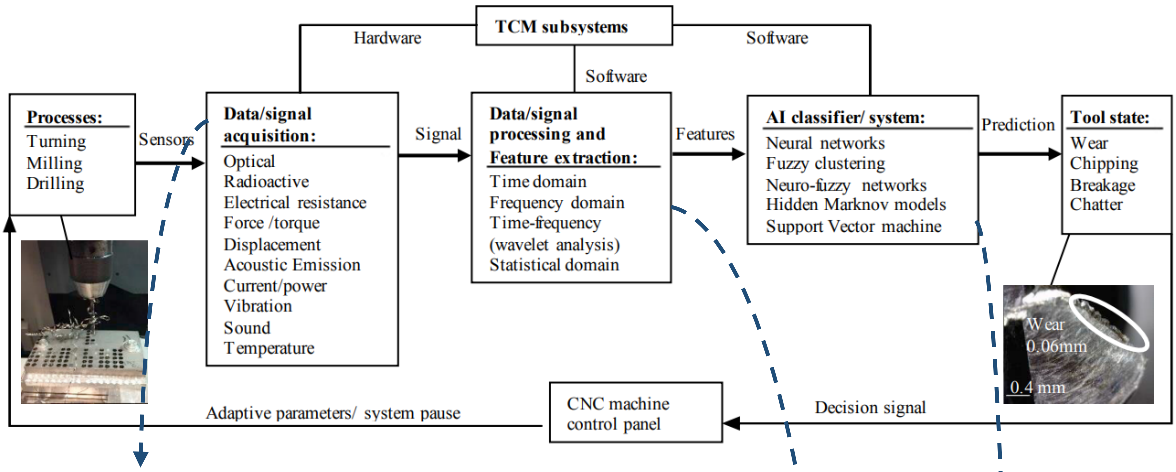
The use of artificial intelligence techniques on the basis of already processed data favours a faster and more autonomous estimation of, for example, tool wear, workpiece quality and catastrophic failures. The application of these techniques, therefore, drives the process to its limits, making it more efficient and bringing associated cost savings and fewer defects by reducing human intervention. A selection of studies on the use of IA in monitoring are presented as follows.

2.3.1-TOOL WEAR AND FAILURE MONITORING.

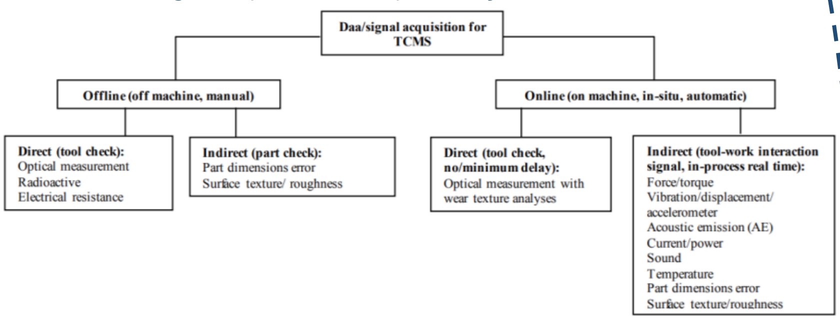
Tool wear is a very important aspect with respect to productivity, process time, quality of the part produced and the total cost of the machining operation. Tool change is mostly dependent on the knowledge and experience of the operator and those responsible for the machining process. Thus, it is possible to maintain preventive policies that do not achieve the maximum benefit from the tools or cost saving policies that take them to their maximum, putting the quality of the part at risk and incurring in production malpractice. In addition to all this, there is the possibility of premature failure, which causes unexpected material losses, production delays, machine and workers 'downtime, workers frustration, etc.

Tool wear prediction is a very complex task due to the large number of variables involved; from the tool itself (material, geometry, surface finish, coatings, etc.) to the cutting parameters, lubrication and cooling methods, the machines, tool holders, etc. Consequently, systems have been developed that help to monitor wear and thereby reduce production costs and increase productivity. These are the machining condition monitoring systems, which are composed of the following modules (Nath, 2020):

TCM system overview.



Signal acquisition techniques classification.



Applicability and limitations of data/signal processing.

Extractors	Applicability and key factors	Limitations
Time (43)	Suitable with force, AE and surface roughness data	Prone to disturbances. Limited analyses on power and vibration data
Frequency (49)	Suitable with vibration, sound, force, AE, and roughness signals. Good prediction accuracy.	Difficult to identify the characteristic spectral bands
Wavelet (19)	Vibration, force, AE signals. High prediction accuracy, Less processing time.	Limited study. Hard to estimate exact contribution of specific frequencies.
Statistical (38)	Vibration, sound, force, AE, wear image, surface roughness. Good to estimate wear rate. Fairly high accuracy, less computation efforts	Hard to identify the random tool wear features. Model-based detection

Applicability advantages and limitations of AI classifiers.

AI classifiers	Applicability and advantages	Limitations
Artificial neural networks (43)	Accurate prediction (reported 97%), nonlinear and complex functionality, high fault tolerance and adaptability, and noise suppression capability	Needs data for prior training, time-consuming process, larger error with new data, requires retraining if parameters/environments changed.
Fuzzy logic (10)	Accurate prediction, nonlinear and complex functionality, tested for vibration and force signals, simpler and faster processing	Difficult to establish input-output relationship, needs expertise, ability to estimate the prediction error.
Neuro-fuzzy (9)	Combination of NNs and FLs, Accurate prediction, tested for force signals, Simpler and faster processing without expertise,	Requires retraining if parameters/ environments changed, still tested only for force signals.
Hidden Marknov (9)	Higher accuracy, vibration signals	Limited study
Support vector (6)	Higher accuracy, AE / surface texture signals	Limited study
Statistical/ regression model (3)	Fairly acceptable, ease of modeling	Least accurate, Limited for online TCMS

Figure 2.37-TCM system overview.

Prediction using AI is quite accurate, but there are limitations to be taken into account when applying these techniques. However, the constraints of ANNs and fuzzy logic are reduced when work in combination.

Several works using artificial intelligence in tool wear monitoring will be presented below:

- As early as 1997, the ANN method for the detection of tool condition, distinguishing between worn or sharp, was addressed (Dimla *et al*., 1997). The cutting force and vibration signals are collected using a dynamometer and an accelerometer. An accuracy of more than 75% was obtained for the single layer perceptron neural network while for the multiple layer perceptron neural network it was more than 95%. These results show that ANN can be a valid technique for tool condition monitoring.

- Caggiano and collaborators also present the use of ANN in the prediction of wear and workpiece quality (Caggiano *et al*., 2017); in this case, a drilling process of a carbon fibre reinforced plastic. The drilling of this type of material is quite delicate due to:

    - The anisotropy of the material whereby the cutting direction determines the chip formation mechanism and the surface quality.

    - The concentration of stresses and heat generated in the process that can cause damage to the part, deformations and rapid tool wear increased by the abrasive nature of the carbon fibre.

  In the study, several cutting parameter values were selected for their influence on wear and piezoelectric dynamometers were used to monitor the force and cutting torque. The Fast Fourier Transform algorithm was utilised to cover the collected frequency domain signals while ANNs were selected to find the correlations between the tool wear and the selected frequency domain characteristics. The training of the neurons was carried out by the Levenberg-Marquardt optimization algorithm. This study confirmed the possibility of automation of drilling operations.

- Focusing on wear and, above all, on how to maximise tool life in carbon fibre reinforced plastic drilling operations, Caggiano and collaborators delve into the combination of force and cutting torque signal analysis and ANNs for condition estimation (Caggiano *et al*., 2018). This study compares the analysis and extraction of key features using three different techniques: fractal analysis, conventional statistical analysis and the combination of both. The strategies adopted in the study are:

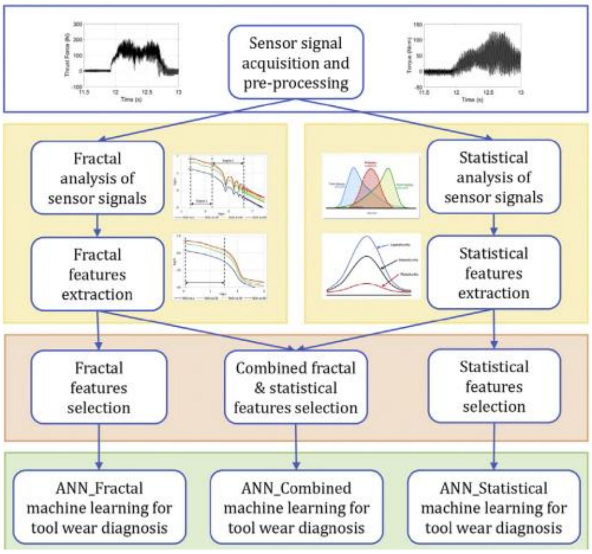


Figure 2.38-Tool wear analysis strategies.

Fractal analysis identifies changes in the behaviour of the signals and extracts key features to be further analysed by ANNs.

After the experiment, it was found that the combination of statistical and fractal analysis together with ANNs more accurately predicts tool life, increasing the efficiency of the process and saving significant costs. It also shows that pure fractal analysis is more reliable than conventional statistical techniques.

❖ Also studying drilling operations in composites, the back propagation neural network to estimate the drilling force in a SiCp/Al material was studied (Zhu *et al*., 2021). This work considered the cutting speed and feed rate data and is a good foundation for the study of tool wear and surface quality from drilling force.

❖ If we talk about another type of machining operation such as polishing, the ANNs (Back propagation neural networks) present an acceptable result in terms of wear estimation of a grinding wheel, based on vibration signals (D'Addona *et al*., 2016).

❖ Mention should equally be made of the works regarding the prediction of tool wear using spindle power signals for drilling Inconel 625 (Corne *et al*., 2017) and milling stainless steel (Drouillet *et al*., 2016).

An interesting group of papers involve the use of images for tool wear prediction, among which the most important are:

❖ A methodology to determine tool wear: flank or crater wear by means of images captured by a video camera and using Back-propagation Neural Networks (D'Addona and Teti, 2013). The difficulty lies in the fact that there is no homogeneity between the images and this complicates the prediction. The model presented is fully valid and very useful. The limitations in terms of image processing are now much easier to deal with new technologies.

- Application of deep learning for tool wear detection from digital images (Bergs *et al*., 2020). Deep learning is represented by two neural networks with two different tasks:

  - *Convolutional Neural Networks (CNN).* It is used for the classification of images for the identification of tool types.

  - *Fully Convolutional Networks (FCN).* Allows the detection of the tool wear area.

  The result of their study shows an accuracy of 95.6% in the identification of tool types while the tool wear detection shows a result of 0.73 in the Intersect over joint coefficient (Jaccard index). This solution is a step towards full automation of tool wear analysis by incorporating microscopes as shown in the figure below:

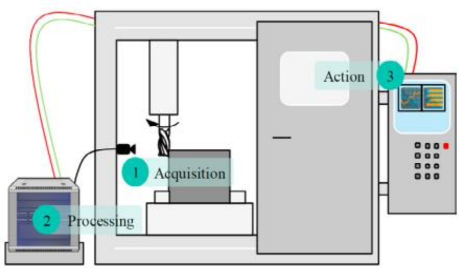


Figure 2.39-Schematic representation of a fully automated tool wear analysis system within machine tools.

- The work of Brili and collaborators aims to estimate tool wear and possible tool failure by means of CNN in dry turning operations (Brili *et al.*, 2021). A camera that provides thermographic information in addition to visual feedback has been proposed to monitor the machining process.

  The authors selected the thermographic camera because wear correlates with the thermal load of the operation. Thus, higher operating temperatures exhibit higher tool wear and higher speeds lead to increases in temperature. As considered in previous sections, the correct selection of cutting parameters is crucial for the efficiency of the operation; if a high productivity and high-speed strategy is adopted, tool life decreases, and part quality will suffer:

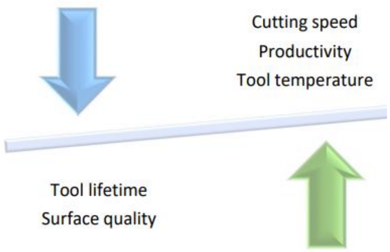


Figure 2.40-Inverse proportionality of machining characteristics.

In this study, the temperature at the point of contact between the chip and the tool is calculated, taking into account that doubling the cutting speed (from 100 m/min to 200 m/min) leads to a 20% increase in temperature while doubling the feed rate (from 0.1mm/rev to 0.2mm/rev) only increases it by 10%.

Each tool condition category was trained with about 2000 images. The four wear categories were established using the dimensional deviations on the workpiece:

Wear Level	Dimensional Deviations of the Workpiece
No wear	$\Delta D < 0.02$ mm
Low wear	$0.02 \text{ mm} \leq \Delta D < 0.04$ mm
Medium wear	$0.04 \text{ mm} \leq \Delta D < 0.07$ mm
High wear	$0.08 \text{ mm} \leq \Delta D$

Table 2.5-Values of wear level.

The approach of the CNN-thermographic system is schematized in the following figure:

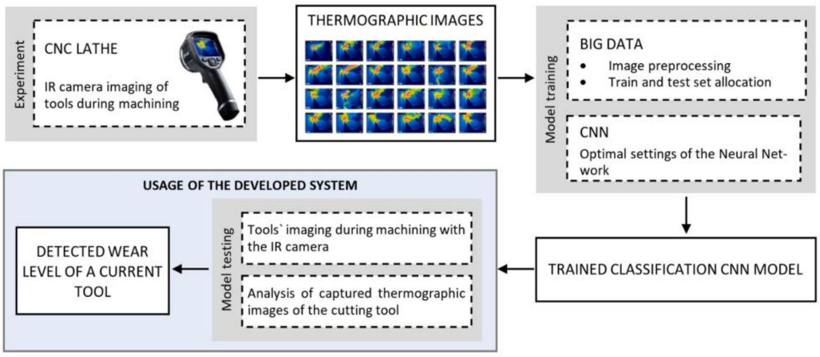
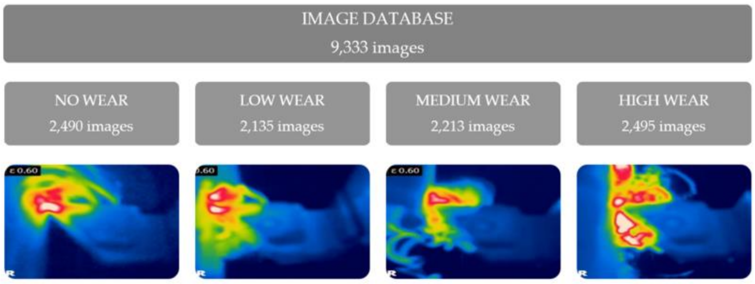


Figure 2.41-CNN-Thermografic system.

The results showed high accuracy when moving from four categories to three.
Thus, this model is less accurate in distinguishing between medium and high wear:



	ACTUAL					
	No Wear	Low Wear	Medium Wear	High Wear	Sum	Precision
No wear	216	1	7	0	224	96.4%
Low wear	1	219	0	0	220	99.5%
Medium wear	3	0	194	13	210	92.4%
High wear	0	0	19	207	226	91.6%
Sum	220	220	220	220		
Recall	98.2%	99.5%	88.2%	94.1%		

	ACTUAL				
	No Wear	Low Wear	High Wear	Sum	Precision
No wear	218	1	0	219	99.5%
Low wear	2	219	0	221	99.1%
High wear	0	0	220	220	100.0%
Sum	220	220	220		
Recall	99.1%	99.5%	100.0%		

Figure 2.42-CNN-Thermografic system results.

The results show that this model can be of great utility in both academic and industrial settings, and furthermore its investment cost is modest.

❖ Based on temperature signals, a Deep Learning model for tool wear prediction during CNC turning operation was proposed by He and collaborators (He *et al.*, 2021). As a Deep Learning technique, they use the stacked sparse autoencoders with a backpropagation neural network for regression model. The effectiveness of this model was compared with other machine learning techniques such as backpropagation neural network and support vector regression with manual feature extraction. An experiment was conducted by varying the cutting parameters (cutting speed, feed rate and Depth of cut) in which data is collected through embedded sensors. It is important to study the phenomenon of temperature as it feeds back into the wear itself. In other words, tool wear causes an increase in cutting temperature, while an increase in cutting temperature increases tool wear. The tool wear patterns are photographed after each cutting cycle:

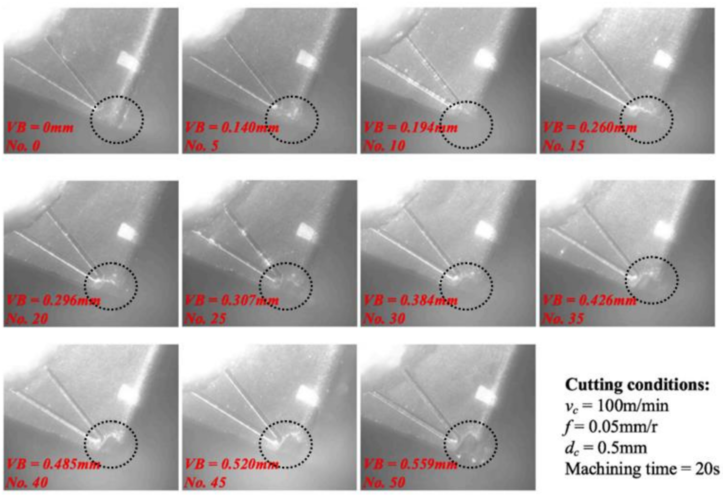


Figure 2.43-Tool wear progression.

The proposed Deep Learning model is shown in the figure below:

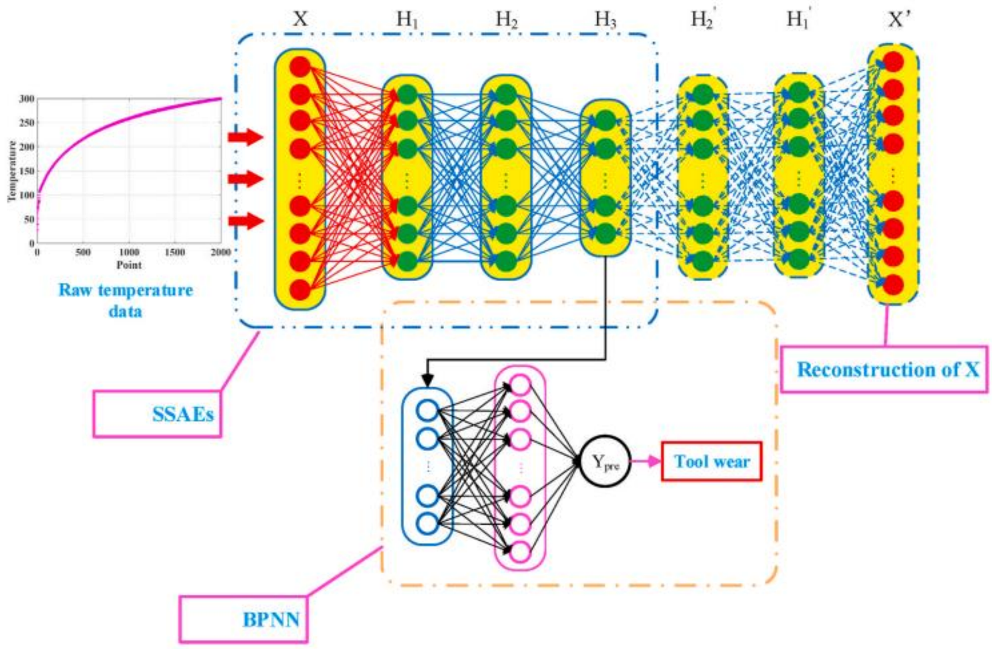


Figure 2.44-Deep learning model.

The standard autoencoder model belongs to the group of unsupervised techniques containing an encoder consisting of an input layer and a hidden layer and a decoder composed of a hidden layer and an output layer. Both the input and output layers must have the same number of neurons. The AE model constantly adjusts the weights of the connection layers in a way that minimises the reconstruction error between the input and output layers by means of a backpropagation algorithm, which subsequently reconstructs the original data. The sparse model adds some sparsity to the hidden layer to ensure that important features are considered.

The results showed that the proposed method performed more accurately in wear prediction than the other machine learning techniques tested.

- Most of the works are focused on the detection of gradual tool wear (GTW) and secondarily on catastrophic tool failure (CTF). However, Bombiński and collaborators aim to identify accelerated tool wear (ATW) in turning using the cutting force in diverse time windows (Bombiński *et al.*, 2022). To achieve its goal, pre-trained algorithms to automatically detect the ATW without human intervention are employed. ATW occurs prior to catastrophic failure and is defined by the loss of cutting ability of the tool. Visually, the three types of tool life ends are differentiated:

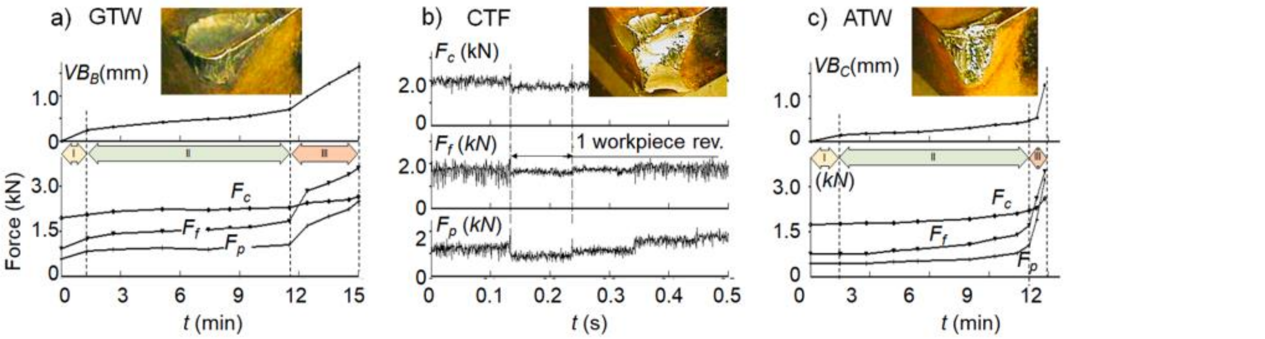


Figure 2.45- Ending of tool life: a) Gradual Tool Wear, b) Catastrophic Tool Failure, c) Accelerated Tool Wear.

The operator can determine the tool life end criteria and the sensitivity of the system, so that any catastrophic failure can be prevented. Graphically, it can be shown as:

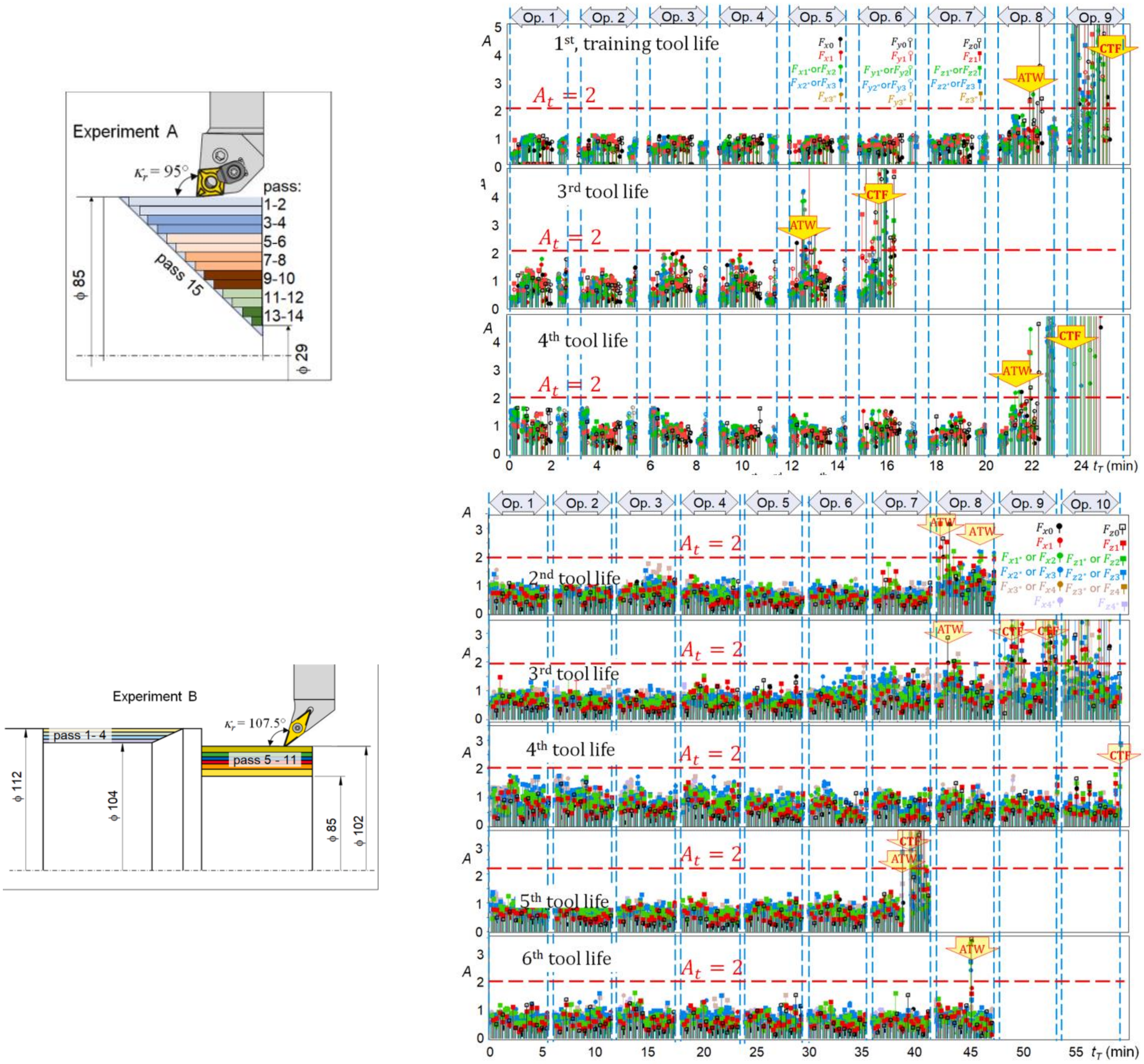


Figure 2.46-ATW Detection on experiments.

2.3.2-QUALITY PERFORMANCE MONITORING.

The aim of any manufacturing process, and therefore of any machining process, is to achieve products that meet the technical requirements with sufficient quality to satisfy the customer in the shortest possible time and at the lowest possible cost. In previous sections, preventive solutions to achieve this compliance have been presented. In this section, quality monitoring during the process will be presented.

It is relevant to note that even though this is an issue of great relevance for customers and the machining industry, there are a limited number of articles where the use of artificial intelligence in quality monitoring is discussed directly. It is true that there are a large number of articles whose aim is to monitor tool wear with the dual objective of extending tool life and ensuring workpiece quality.

Surface roughness acts as an indicator of the quality of the product obtained and also of the behaviour of the process. It reflects both the appropriate selection of machine tool, tool, cutting parameters, etc. and the condition of the cutting tool and the machine itself. In other words, if the cutting tool is worn, it will not be able to achieve the required roughness - surface finish - and may even cause damage to the workpiece.

Usually, the surface finish is checked once the operation has been completed, which sometimes means that it is necessary to rework the workpiece, with the associated costs and lead times. Or even, it can be observed that having reached the maximum dimensional or geometric tolerance, the surface finish does not meet the technical requirements. This forces a decision to be made on whether to comply with the surface finish or the dimensional or geometric compliance, when normally both are important for the correct functioning of the workpiece.

The prospect of online roughness monitoring then becomes very interesting as it therefore allows to meet the necessary quality by increasing productivity. However, online real-time monitoring has its disadvantages (Carou *et al*., 2017):

- Some signals may be redundant.
- Inaccurate predictions may lead to measurement errors.
- The cost of the monitoring system is relatively high.
- Sometimes signals are altered by the frequency range causing the results to be useless.

It is therefore necessary to devise an appropriate monitoring strategy, choosing the signals, the processing method and the analysis and decision-making tools. In this respect, artificial intelligence is once again becoming importance.

❖ Correa and collaborators tested the advantageous use of Bayesian networks over neural networks for estimating surface quality in high-speed milling processes (Correa *et al*., 2008).

As the article states, the study of roughness is of great interest since it is related to the fatigue of the part, corrosion, stress concentration and finally, the service life of the part.

For the first experiment, 8 variables were selected: feed per tooth (fz) cutting speed (Vc), axial depth of cut (ap), tool diameter (diam), radial depth of cut (ae) and novelty, material hardness (HB), geometry radius (Radius) and geometry curvature (Geom). The roughness classes were determined using ISO 1302. In the second, those variables essential for the determination of surface roughness were discarded, leaving 5 of them: feed per tooth (fz), tool diameter (diam), radial depth of cut (ae), material hardness (HB) and the combination of radius and curvature of the geometry (Geom). After several experiments were carried out in which both Bayesian networks and neural networks predicted the roughness conditions of the workpiece, the results showed that Bayesian networks performed more reliably:

Medida	RB	RNA
Tasa verdaderos positivos (Casos correctamente clasificados)	1216 (96.35%)	1197 (94.84%)
Tasa falsos positivos (Casos incorrectamente clasificados)	46 (3.64%)	65 (5.15%)
Estadístico Kappa	0.94	0.92
Error medio absoluto (MAE)	0.03	0.04
Raíz error cuadrático medio (RMSE)	0.13	0.14
Error absoluto relativo (RAE)	10.41%	13.05%
Raíz error cuadrático relativo (RRSE)	32.66%	33.70%

Table 2.6-Experiment results.

Bayesian networks have certain advantages over neural networks. The first is that they are much more visual, showing the relationships that connect the variables, whereas neural networks are a black box. This makes them more easily interpretable. Bayesian networks are a graphical probabilistic model that allow us to answer, through their connections, questions about the response variable, but also about the source variables. On the other hand, they minimise the expected rate of misclassified cases. This study used the following Bayesian network model:

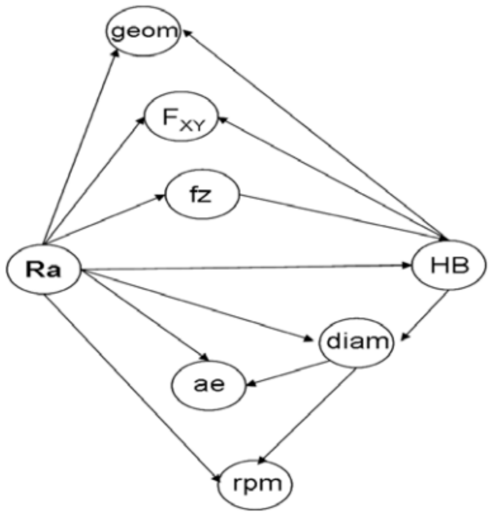


Figure 2.47-Bayesian network model: TAN network.

The use of Bayesian networks allows to deepen the cause-effect relationship of the machining operation and to work on the causal variables to improve the process.

- Another work was carried out appliying Fuzzy logic to predict surface roughness in the drilling operation of Oil Hardened Non - Shrinking Die Steel, which is a steel used in the chemical, nuclear, shipbuilding and automotive industries (Babu *et al*., 2018). The input variables are cutting speed, feed rate and drill diameter:

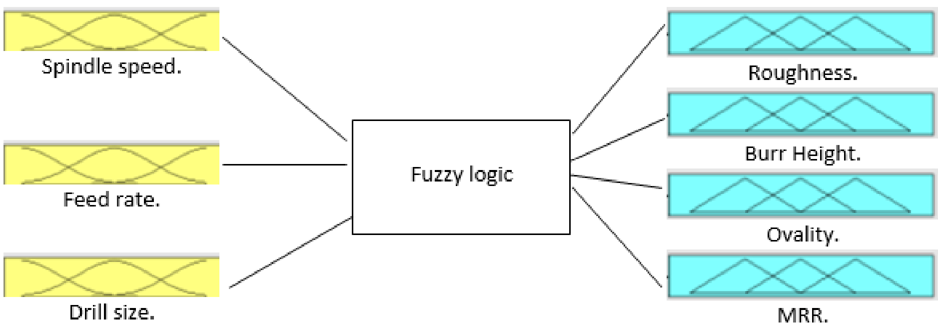


Figure 2.48-Fuzzy proposal.

The study reached two conclusions: 1) Both feed rate and cutting speed are crucial factors in roughness. 2) Fuzzy logic helps predict the roughness of a workpiece accurately within a range of parameters.

- The work of Moreira and collaborators also develop fuzzy logic using an Adaptive neuro-fuzzy interference system (ANFIS) for the determination of surface roughness on a CNC machining machine by means of an integrated monitoring system (Moreira *et al*., 2019):

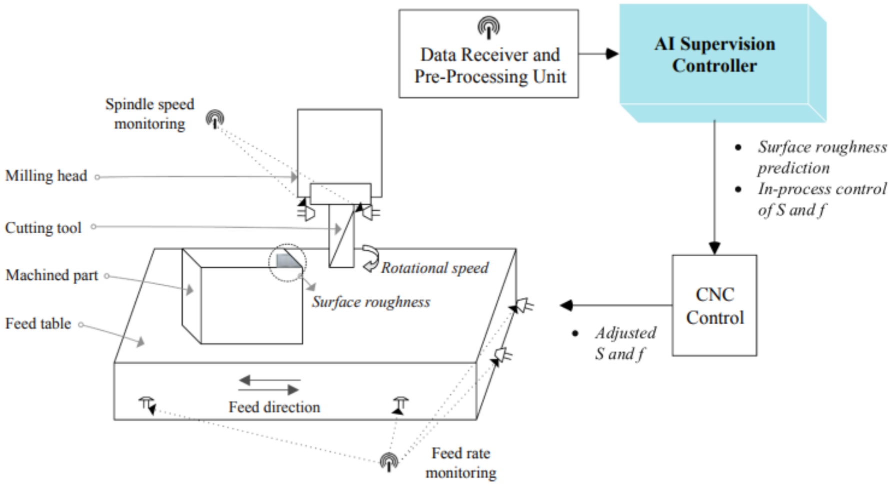


Figure 2.49-CNC machining supervision controller for surface quality assurance.

First, an experimental environment was created for system design and data collection. For this purpose, a BS EN24T (AISI 4340) material was milled under various strategies, in which the spindle speed and feed rate were varied. The following conclusions were drawn:

1. Roughness varies up to 3.5 µm with variations of spindle speed (s) while this value increases to 7.4 µm when it comes to feed rate (f) showing its greatest influence. These ratios are taken into account when determining the fuzzy logic.
2. Both spindle speed and feed rate influence the roughness while only the feed rate influences the operating time, increasing the MRR.
3. Higher spindle speeds would decrease surface roughness but not through a linear relationship.
4. Lower feed rates lead to better surface qualities, but again the correlation is not linear.

The neuro-fuzzy roughness prediction model proposed by Moreira and collaborators is illustrated as follows:

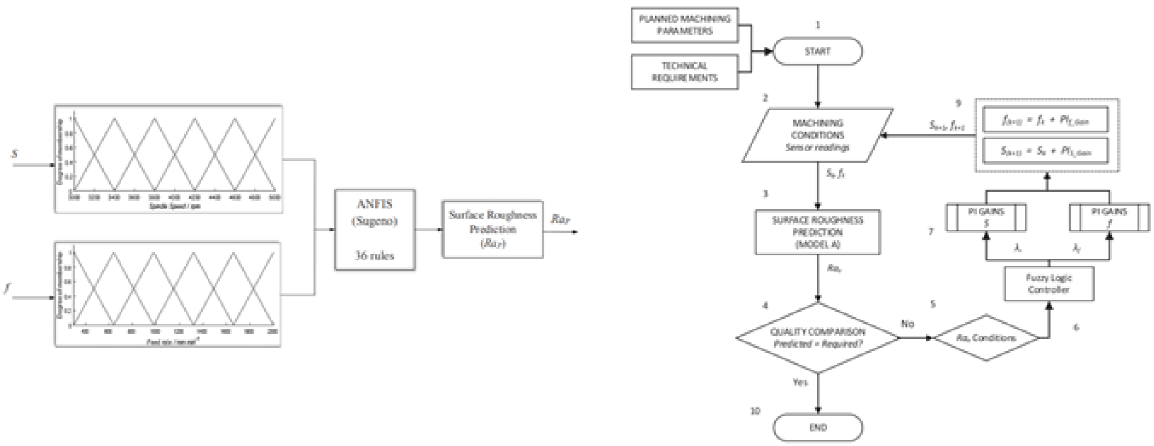


Figure 2.50-Neuro-fuzzy prediction model.

As can be seen in the figure, the machining operation starts with the machining parameters and the technical requirements. The speed and feed data are collected by the monitoring system. With this data, the surface roughness is estimated and compared with that established by the technical requirements. If it complies with them, the operation is concluded, while if it does not comply, it enters the cycle again by means of the fuzzy logic controller.

Subsequently, this system was validated in a case study showing significant improvements over the operator's decision:

Technical Requirement (Ra_D)/µm	Planned Parameters (Machinists' decision)				AI Supervision Controller			
	S/rpm	f/mm min^{-1}	Absolute Error (Ra_e)/µm	Ra_e/%	Adjusted S/rpm	Adjusted f/mm min^{-1}	Absolute Error (Ra_e)/µm	Ra_e/%
(a) 0.5	5000	300	0.1	20	4128	300	0.002	0.43
(b) 1	5000	600	0.99	98.7	5000	600	0.99	98.7
(c) 3	4000	1200	3.6	118.8	4969	1053	0.12	4
(d) 4.5	3500	1680	0.88	19.6	4818	1579	0.001	0.02
(e) 6	3000	1800	2	33.6	4177	1801	0.095	1.6
(f) 7	3000	2000	2.9	40.7	4172	1947	0.006	0.1

Table 2.7-Validation results.

It is remarkable that the adjustment of the proposed system is significantly more accurate than the supervision of trained and experienced personnel and is therefore a further step towards automation.

As future work, it was proposed to include wear in the model in addition to the roughness prediction, thus completing the original model.

- Mention should also be made of the work of Chen and Kudapa (Chen and Kudapa, 2020) in which two models are presented for roughness estimation based not only on the parameters but also on the cutting current. The first is a fuzzy inference system (FIS), in which the rules are set by experts, and the second is a neuro-fuzzy system (ANFIS), as seen in Moreira and collaborators study, in which the rules are set by the system itself. The experimental result shows that the ANFIS model is more accurate in its estimation.

- So up until now, quality has been viewed through the prism of roughness in conventional machining processes. The work of Wang and collaborators is noteworthy because it presents an unsupervised artificial intelligence approach for estimating geometric quality in a wire electrical discharge machining process (Wang *et al.*, 2019). Sometimes roughness is not as critical as dimensional tolerances can be. This work is novel because of the integration of these three factors: non-conventional machining, quality understood as compliance with geometric tolerances, the use of unsupervised artificial intelligence in this field and the choice of the variable: distribution of ionization time instead of voltage. The machine learning techniques tested were K-Means and Hierarchical clustering. Although an improvement was observed with respect to tolerance monitoring, the results were limited. Nevertheless, their contribution to the development of new studies in these novel fields is important.

2.3.3-MACHINE ANOMALIES.

Typically, the monitoring of machining processes is focused on cutting parameters and tool condition, but the early detection of machine tool anomalies should not be left behind, as their malfunctioning also influences cost, lead time and workpiece quality. With these problems in mind, a system based on the mean shift cluster algorithm for anomaly detection was developed (Netzer *et al*., 2020). The data collected during the machining operation is assigned to a category: normal operation or malfunction in a self-organising map. One of the problems of this unsupervised system is to properly determine the state of the machines, especially as the patterns are changing. Even so, the study showed that unsupervised techniques can be an effective tool for detecting anomalies in environments with high uncertainty since they do not have any a priori knowledge of the variable conditions or operation of the machine.

2.3.4-INTEGRATION OF MONITORING IN INTELLIGENT SYSTEMS.

This section presents selected studies that aim at integrating monitoring into intelligent systems and provide technical solutions for their implementation in industry.

- *Use of virtual sensors.* As Bustillo and collaborators highlight that in some industrial environments it is not possible to install certain sensors on the tools (Bustillo *et al.,* 2011). With the aim to propose an alternative, a virtual sensor that collects two variables such as the power consumption of the feed drive and operation time for each workpiece was developed. The work chart of this system is as follows:

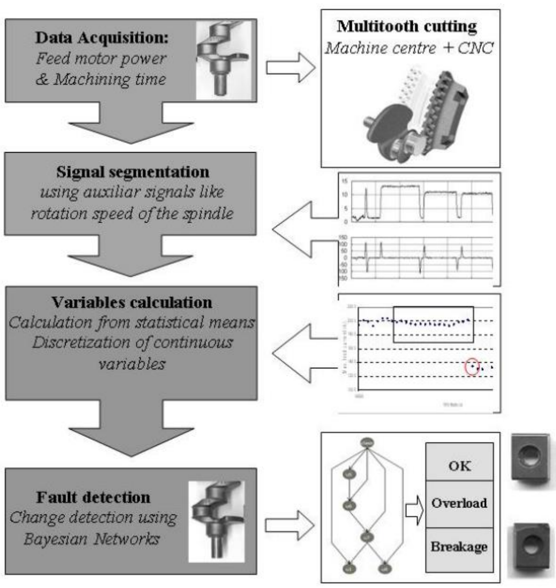


Figure 2.51-Virtual sensor flowchart.

Bayesian networks are used to distinguish between different states of the tool. Thus, this virtual sensor is useful for the industry because it can detect critical cases, failures with high accuracy and also to promote preventive maintenance in an autonomous way.

- *Cloud manufacturing*. Using cloud solutions, data, resources, technologies, knowledge, etc. can be shared with machines, people, etc. that are located at great distances. Another advantage is that it centralises analysis and decision making, allowing more data and more generalised models to be used. It also allows this step to be continuously improved as more information is received from different locations.

    - The work of Caggiano and collaborators presents a framework based on the cloud manufacturing paradigm for the intelligent monitoring of machining processes (Caggiano *et al.*, 2016). In this way, all the machines will be connected, establishing three levels: the physical resources in the workshop, the local server in the same factory and the cloud server. In this way, it will be possible to monitor the machining conditions online in real time.

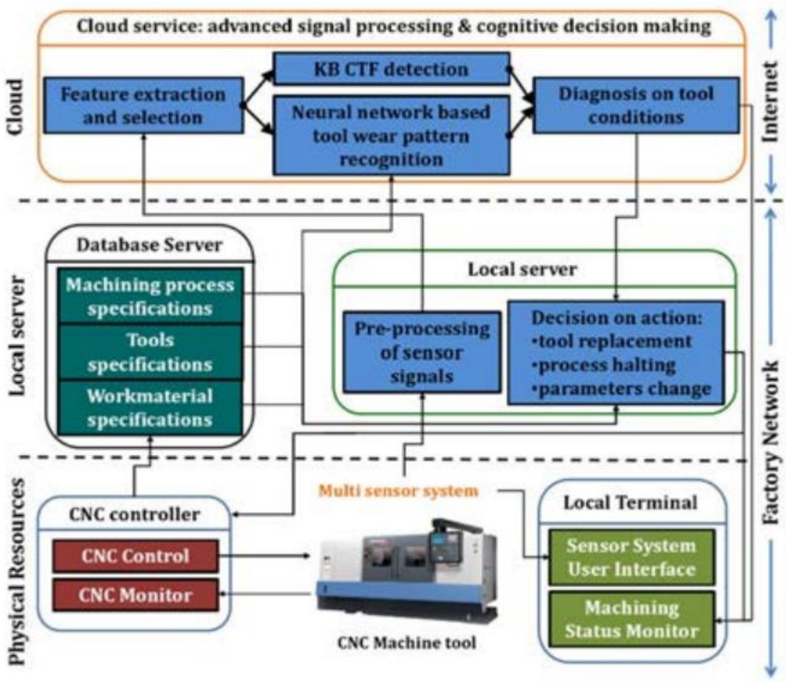


Figure 2.52-Cloud monitoring system.

It is also suggested the use of neural networks for the detection of the residual life of the tool and its possible failure. In this way, based on this diagnosis, the local server performs the necessary preventive action such as tool change, parameter variation, etc.

- Further in the integration of non-contact quality inspection systems, a laser-based reverse engineering (RE) and ultrasonic non-destructive inspection were incorporated into a Claud manufacturing system (Caggiano *et al.,* 2018):

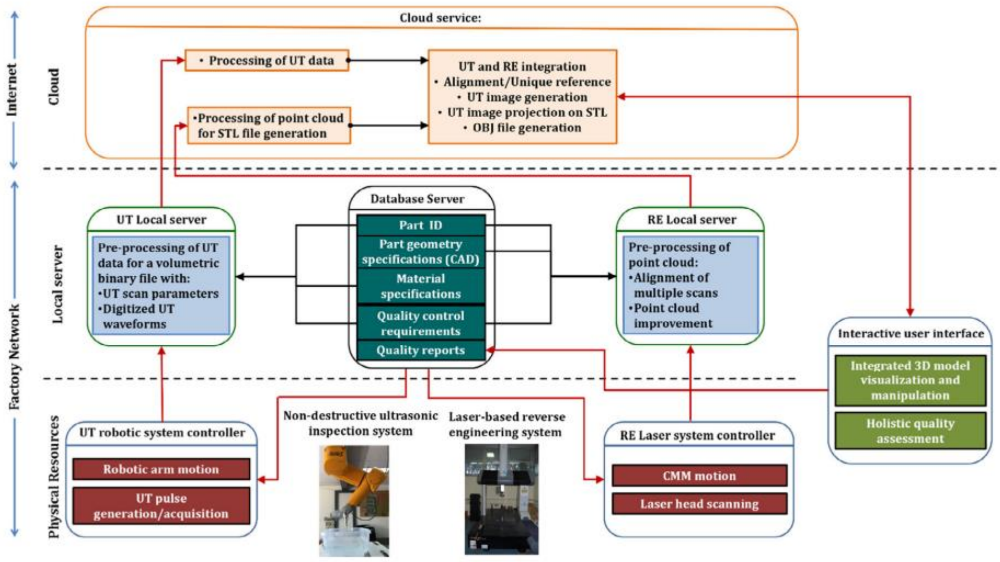


Figure 2.53-Cloud quality monitoring system.

It is a very interesting perspective that can be extended to many more inspection procedures that can interact at the same time and in real time, offering great possibilities in terms of cost and time savings, elimination of rework, etc.

- *Cyber-Physical models.* The cybernetic field offers and will offer many possibilities for the development of real time monitoring, as examples the following works:

  - Open architecture approach to the layout and connection of machine tools in order to achieve higher accuracy, higher efficiency and lower consumption (Deng *et al.*, 2018). Subsequently, a cyber-physical model with the use of Wireless Sensor Networks that allow real-time monitoring of machining processes remotely was proposed. This model is associated with the incorporation of new technologies such as the Internet of things and cloud computing, favouring interconnection and the use of common resources.

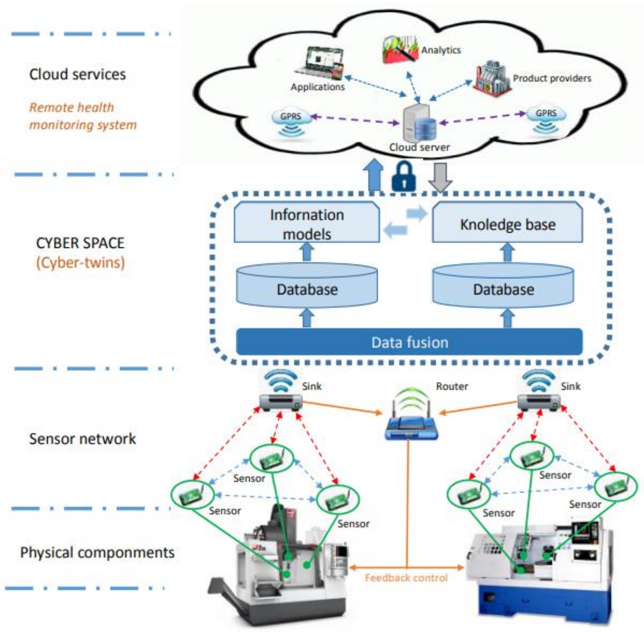


Figure 2.54-Real monitoring system for cyber physical machine tools proposal.

Therefore, the knowledge that can be extracted from several machining centres is used to make better decisions and there is a clear vocation for the intelligent system to be able to optimise itself, to learn and to carry out preventive maintenance.

- Möhring and collaborators introduced a cybernetic system into the tool, making it intelligent (Möhring *et al*., 2020). The data collection is performed on the tool and is sent via Bluetooth to the data analysis station which can reach any end-user device. The users can receive a message indicating the end of life of the tool. The tool prototype and the intelligent logic data processing are presented as follows:

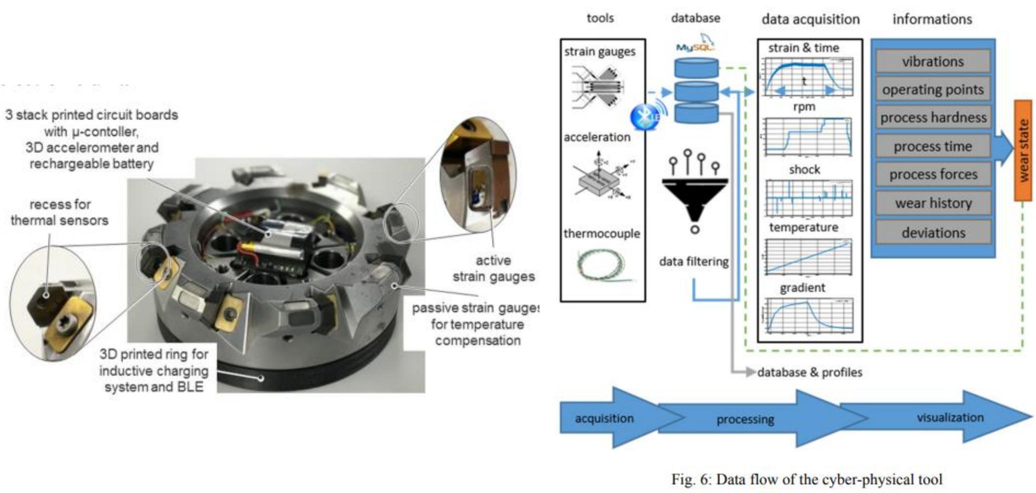


Figure 2.55-Cyber-physical cutting tool prototype and data flow.

The remarkable aspect of this proposal is the ability to send the processed data to end-users on any device and to have more information on the process in real time.

Figure 2.56-Draft design of the app with start page, setting and live display in line view and bar chart for several tools.

- *Simulation, virtual machining and digital twins*. The simulation, virtualisation and the creation of digital twins of the machining processes and their monitoring permit the operation to be visualised from the very first moment and the parameters, monitoring ranges, etc. to be adjusted when moving to real conditions and from the very first workpiece. It is clear that they reduce the uncertainty of the process, saving costs and time.

    - Denkena and Koeller (Denkena and Koeller, 2013) introduce a model for teachless monitoring by means of simulation of machining processes:

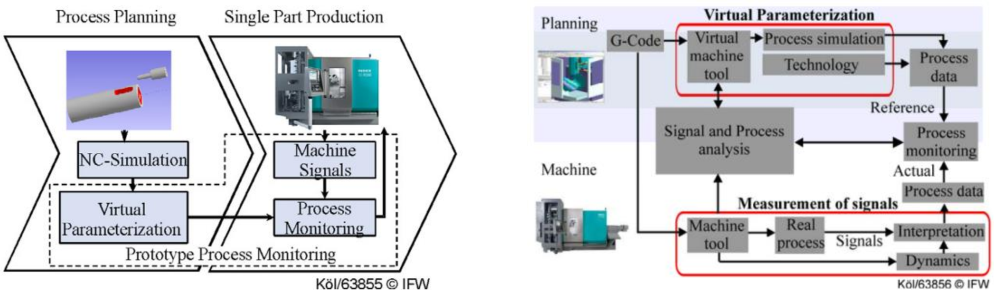


Figure 2.57-Basic and detailed concept of teachless process monitoring.

It is important to note that no prior learning is required in this model to set the limits for monitoring the machining operation, so this approach is capable of generating reference data.

    - Denkena and collaborators return to the importance of monitoring without prior learning for the first part or for single batch productions (Denkena *et al*., 2014). The search for process confidence from the first piece is one of the objectives of this work. For this reason, they replace the learning of monitoring limits by simulation.

- Also, a virtual machining technology model was introduced to examine the behaviour of machining operations and optimise it before it is brought into production by monitoring the condition of the tool (Heo *et al.*, 2017). As mentioned, virtual machining simulation provides initial data that can serve as a frame of reference for monitoring and warning of abnormalities, especially when the production is of single parts, expensive parts or single batches. In addition, virtual machining can be considered further in time without affecting the real part, which allows a more accurate diagnosis of the machining status at any given time. However, this approach has the disadvantage that it cannot guarantee a real time calculation, nor can it ensure an accurate correlation between the measurement and the process in time. The limitations offered by each of the alternatives must be considered in order to select them accordingly:

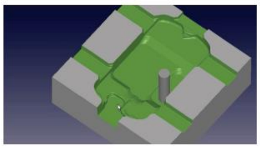
	Virtual machining data	CNC data	Sensor data
Illustration			
Pros	What, Why, Where	Where, When, What	When, What
Cons	When	Why	Where, Why
Real-time	No	Near	Yes

Table 2.8-Virtual machining, CNC and sensor data pros and cons.

Virtual machining data can response to the physical phenomena (what), in a certain tool location (where) based on a mechanical modelling (why) whereas CNC data can give evidence about the phenomena, the location and slightly delayed time (when) but not about the mechanical model. Sensor can provide information about the physical phenomena at no delayed time (when).

With the increasing capacity of computers, virtual machining is one of the areas to be developed in an interesting direction.

- A digital twin is a model that imitates a physical system with the help of other technological solutions, so that it allows simulations, learning, etc. Tests can be carried out on it to check its behaviour under changing conditions without having to test the physical system itself. Qiao and collaborators create data-driven model for digital twin process for tool condition estimation (Qiao *et al*., 2019). Deep learning techniques are employed to perform the prediction. Digital twins are characterised by the following aspects:

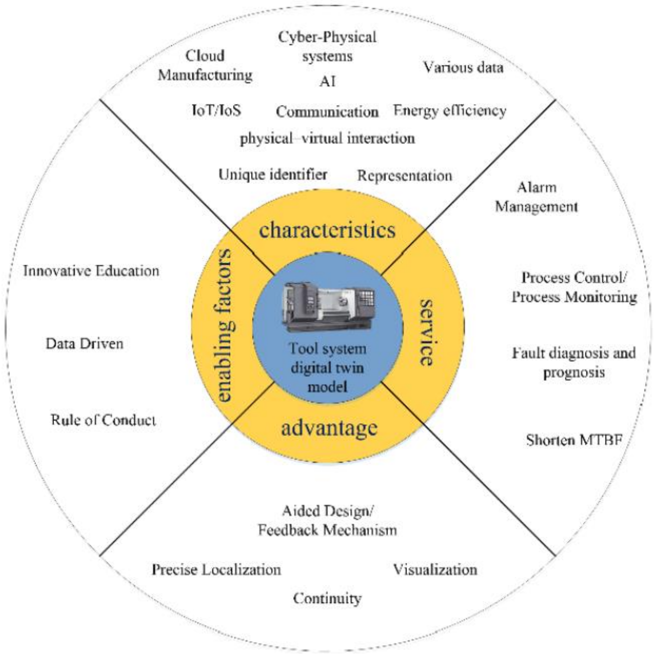


Figure 2.58-Tool system digital twing model: Characteristics, service, enabling factors and advantages.

In previous work, three-dimensional digital twins predominated, considering the entity model, the virtual model and their connections, while Qiao and collaborators develop a five-dimensional digital model that favours speed and accuracy of prediction.

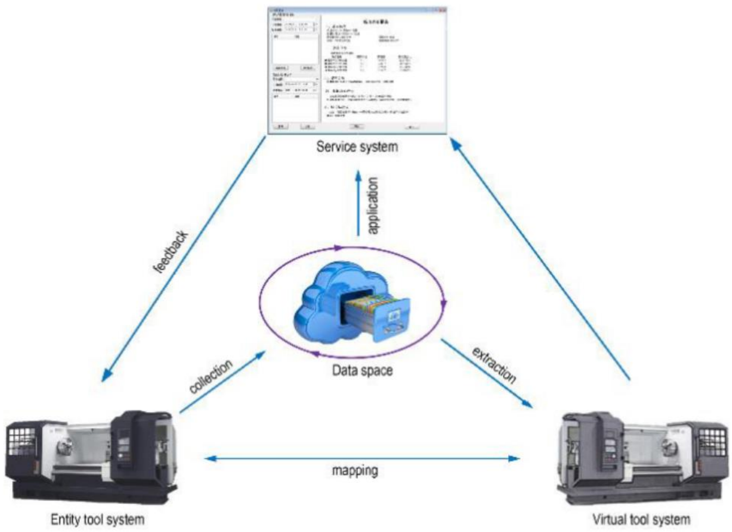


Figure 2.59-Five-Dimensional Digital Twin model of tool system.

The digital twin is able to integrate information from the physical system and its management to promote a new form of process monitoring. Artificial intelligence significantly improves the tool condition prediction.

- Armendia and collaborators assess the applicability of the digital twin concept in the industrial environment with the aim of providing an accurate view of machining processes to improve their management and monitoring (Armendia *et al*., 2019). It is based on the concept of the digital twin as a model of the physical system where the process, wear conditions, energy consumption, etc. can be simulated and which relates to the physical world in a bidirectional way in which it receives real data in exchange for more accurate predictions of the system's performance.

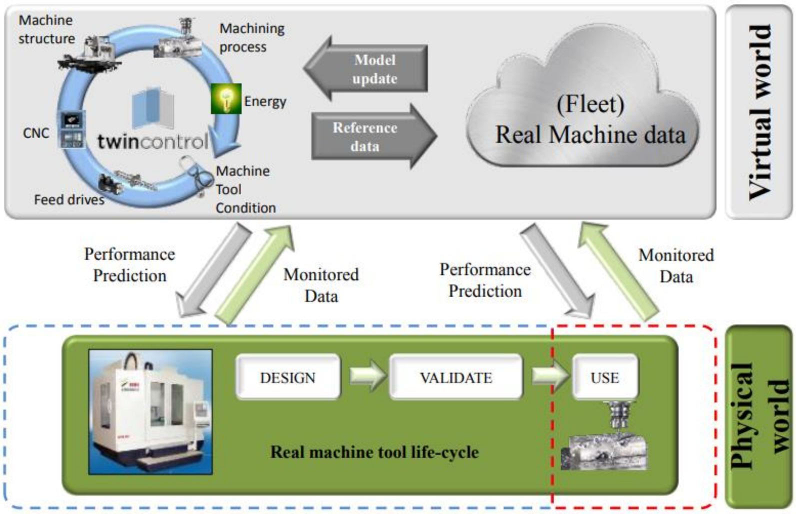


Figure 2.60-Twin-Control concept.

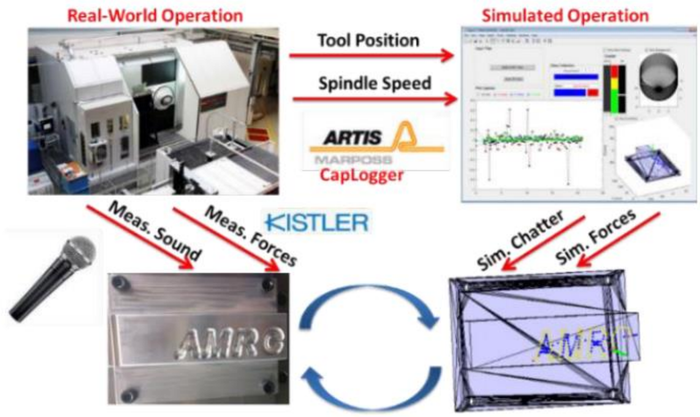
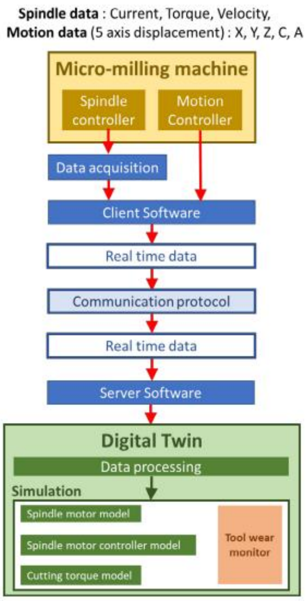
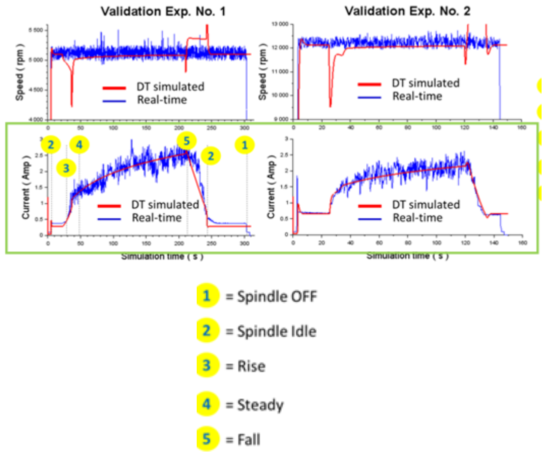


Figure 2.61-Real data flow in the application of the digital twin in industrial environments.

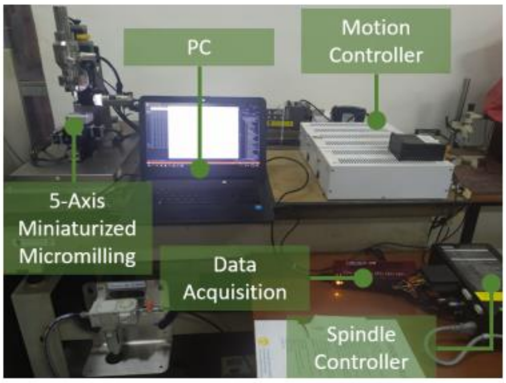
- Christiand and Kiswanto (Christiand and Kiswanto, 2020) develop a digital twin to predict tool wear in micro-milling operations, focusing on the current data provided by the spindle motor.



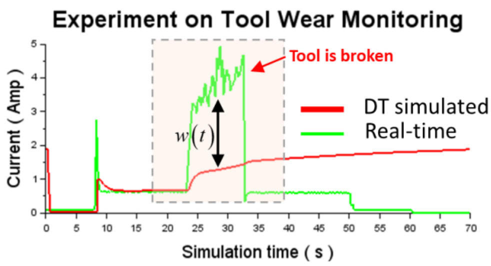
a) Digital twing tool wear monitoring flowchart.



c) Model Validation.



b) Tool wear monitoring system.



d) Tool wear monitoring with the digital twing (DT).

Figure 2.62-Digital twin model proposal and results.

Figure 2.62 shows the result of one of the experiments where a 10 times higher feed rate was forced, causing a precipitous tool breakage. The digital twin model recorded an occurrence in the second 22nd. The use of DT for tool wear prediction and abnormality monitoring is very encouraging.

- A digital twin for high-speed machining on CNC machines was developed that allows autonomous control of machining operations and integration with the real system, favouring the exchange of information (Ward *et al.*, 2021). A significant contribution is that in addition to monitoring and simulation, it can detect and control chatter and, through MIRS control, to control the residual stress values in the machined parts. This study takes a step forward in terms of the autonomy of machining processes and introduces a novel approach to stress control.

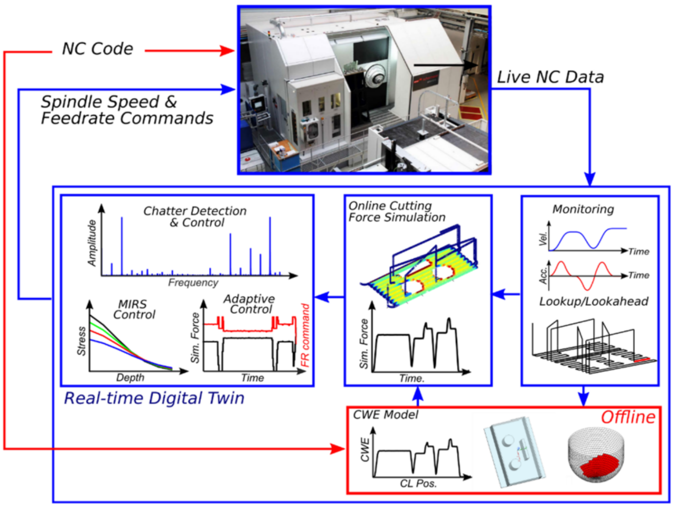


Figure 2.63-System architecture.

2.4- PROCESS SUSTAINABILITY.

The environmental damage that has occurred in recent decades, together with social gaps that have not yet been closed, have led governments and institutions around the world to take protective measures in all sectors and areas. One of them, of course, is the implementation of sustainability policies in industry to guide the different production processes. In fact, goal 12 of the 2030 agenda endorsed by the UN promotes the adoption of sustainable practices by companies and organisations.

Naim Shaikh and Ali (Naim Shaikh and Ali, 2021) show in their work which aspects need to be addressed to make these processes sustainable.

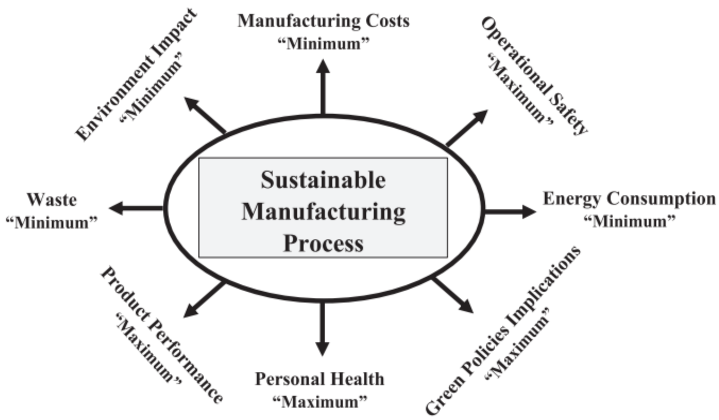


Figure 2.64-Sustainable Manufacturing Process aspects.

The sustainability of machining processes involves reducing their environmental impact, mainly in terms of the consumption of energy resources, which are transformed into emissions and therefore CO2 footprint, consumption and generation of toxic waste for the environment and for the health of workers. In order to reduce the impact, it is necessary to carry out an adequate selection and control of the toxic products used and energy consumption. Both factors are decisive when calculating the costs of the machining process, so in addition to favouring the impact reduction of the process, it will also benefit the cost savings.

It is essential to know the flow of materials and energy throughout the process in order to be able to act on it and reduce its impact. Energy consumption occurs both in the main machining operation and in the cleaning and cutting fluid recovery processes. Hazardous waste is generated after the latter two processes. It is the amount of cutting fluid that shall be disposed of and treated appropriately.

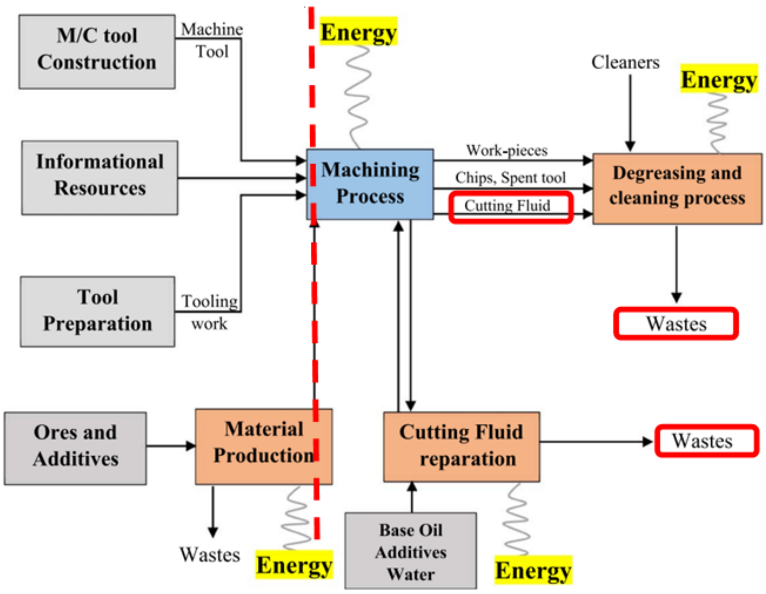


Figure 2.65-Machining Process Flow: Materials, Energy and Waste. (Naim Shaikh and Ali, 2021)

2.4.1- COOLING AND LUBRICATION SELECTION AND CONTROL.

Lubrication and cooling are essential in machining operations as they lower the temperature, delay tool wear, protect the workpiece, increase its quality, allow chip evacuation, reduce friction and remove metal particles. The advantages they provide are very significant, but they also have some important disadvantages associated with them, such as: cost, environmental impact and risk to workers' health (Benedicto *et al*., 2017).

In recent years, more sustainable lubrication/cooling systems have been developed. Of these, biodegradable cutting fluids are closest to the vision of traditional lubrication/cooling.

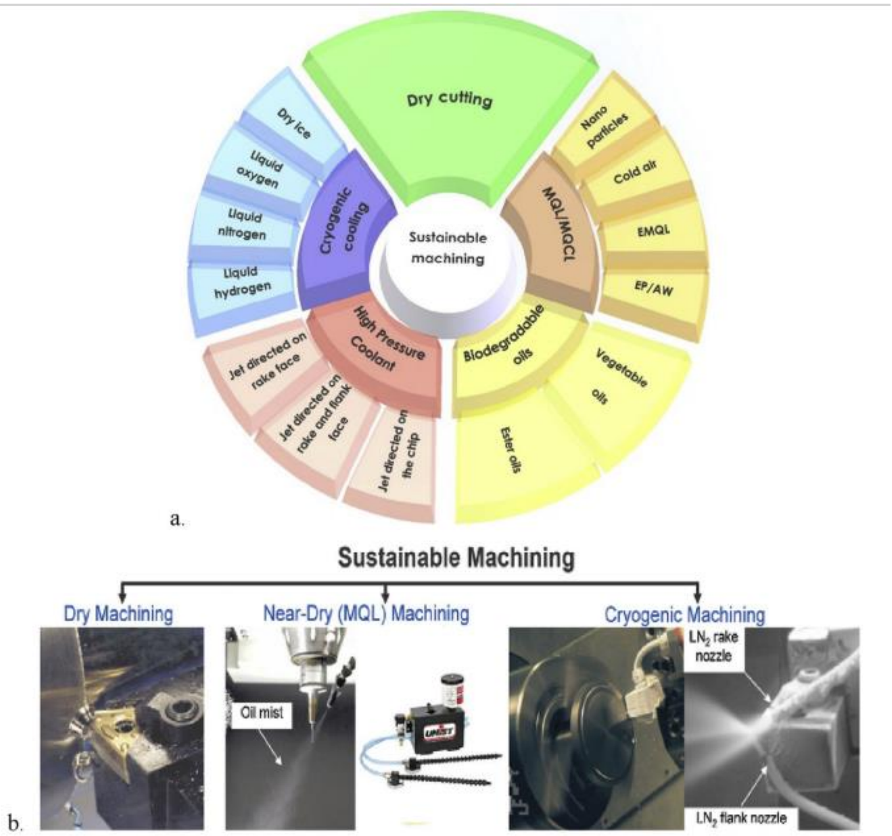


Figure 2.66- Cooling/lubrication technologies for sustainable machining. (Mia *et al.*, 2022)

The different strategies have their advantages and disadvantages that must be considered when making the right choice for the machining operation to be carried out.

Lubrication/ cooling systems	Advantages	Drawbacks
Dry cutting	No need for cutting fluid Easier chip collection for recycling Minimal environmental impact	High cutting temperature generation High tendency of workpiece microstructural alterations Reliable results for limited cutting parameters Poor tool life and surface finish Problematic chip evacuation
MQL	Reduction in cutting fluid Less costly method in comparison to other systems Good results in terms of cutting forces, tool wear, surface roughness are noted	Poor chip evacuation Poor cooling capacity Mist formation Very sensitive to MQL supply system
Cryogenic cooling	Eliminate the use of cutting fluid No need to clean the chips and improved chip breakability Promote improvements in surface integrity Improved tool life	Highly sensitive to tool–material pairs. The production cost of the cryogen is very high compared to cutting fluids Special Dewar is needed for cryogenic supply Overcooling lead to embrittlement of workpiece
Cold compressed air	Absence of cutting fluid Chips can be collected in dry form	Additional energy is required to produce compressed air
Sustainable cutting fluids	Can be totally biodegradable and renewable Less costly compared to cryogenic cooling Chip evacuation Effective removal of heat	Vegetable oils have low oxidation stability Formulation difficulties

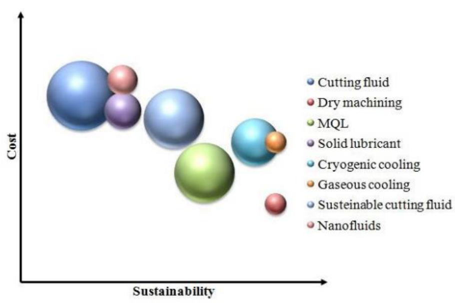


Figure 2.67- Sustainable machining strategies advantages and disadvantages (Benedicto *et al.*, 2017) and sustainable-cost relationship (Benedito *et al.*, 2021).

Conventionally, selection and control are left to the experience and knowledge of the operator or manager, who tends to apply conservative policies of using too many cutting fluids or cost saving policies. Both of these policies do not optimise the process and therefore need to be addressed. The differentiating effect of controlling and selecting the proper lubrication/cooling strategy suggests that artificial intelligence could offer a great opportunity in the efficiency of machining processes in this field.

Areas where artificial intelligence can be a differentiator factor are:

- Selection of the most sustainable and suitable lubrication/cooling strategy for the process to be carried out, also considering the workpiece material, tool material and cost.
- Control of the amount of cutting fluid or lubrication/cooling system in the process.
- Cooling strategy performance monitoring. For example, the effect of cooling on stone cutting performance based on process power consumption through a hybrid GA-ANN approach (Hosseini *et al*., 2019).
- Adjust the formulation of cutting fluids to the process conditions: tool material, work material, process, etc. For example, the use of artificial intelligence in tribology (Rosenkranz *et al*., 2021). The fields of monitoring, material composition design, lubricant formulation and prediction of film formation and friction behaviour are highlighted in their research. With the data that can be provided from the machining industry, tribology can develop more suitable cutting fluids for the processes and materials to be machined, especially for new materials that are not easily machinable.
- Possibility to combine different machining strategies in the most optimal configuration.

It is true that no studies have been found on machining aimed at improving these areas using artificial intelligence. This will no doubt be an approach to be addressed in future research.

2.4.2- ENERGY CONSUMPTION MONITORING.

The 2030 Agenda of the United Nations considers the management of energy consumption, especially from fossil fuels, as an essential target for the sustainable development of nations. This is reflected in goals 12 and 13 of the agenda itself.

Energy consciousness coupled with the current price of electricity and fossil fuels means that consumption monitoring for decision making aimed at reduction and optimisation becomes more than urgent and necessary.

The work of Ahmad and collaborators shows how artificial intelligence is the key to the energy sector, which is becoming increasingly complex and data-intensive (Ahmad *et al.*, 2021). The beneficial use of AI tools in three aspects of predictive maintenance control and energy trading that can be extrapolated to the manufacturing industry, such as: Maintenance decision-making, prognosis and diagnosis and forecasting and monitoring. Due to the high energy prices, it would be good to plan the demand and optimise the operations:

❖ Analysing the factors involved in energy consumption and studying their relationship using ANN (Borgia *et al.*, 2014). In addition, the authors developed an energy simulator composed of 4 modules:

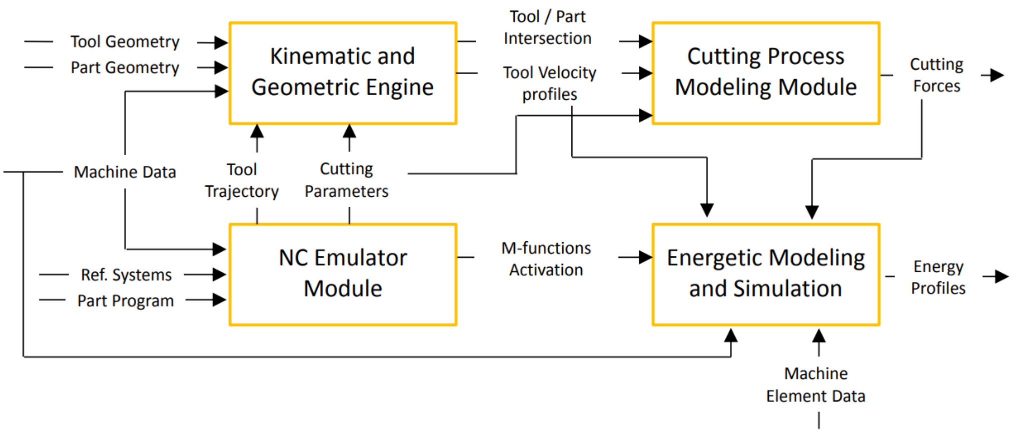


Figure 2.68-Energy simulator architecture.

- *Kinematic and Geometric Engine.* The MRR, depth of cut and the tool/workpiece intersection are calculated with the initial information about the tool, workpiece and cutting conditions.
- *Cutting Process Modelling Module.* A model of the cutting process designed for energy analysis is developed. The cutting forces are calculated.
- *Energetic Modeling and Simulation*. Taking into account the input data, it performs an energy simulation of the whole machine for the given process.
- *NC Emulator Module*. It interprets the program and calculates the trajectory and velocity of each axis in each trajectory. This information feeds the Kinematic and Geometric Engine module and also the energy simulation module.

First, the parameters that influence the prediction of the machine's energy consumption must be selected. These parameters are those associated with the operation, the part and the machine:

Parameter	Meas. Unit	Notation	Value range
Surface length	[mm]	L	350 – 450
Surface width	[mm]	W	120 – 180
Depth	[mm]	B	1 – 3

a) Workpiece parameter.

Parameter	Meas. Unit	Notation	Value range
Cut angle	[rad]	Ac	$0 - \pi$
Width of cut	[mm]	K	$W/3 - W$
Tool diameter	[mm]	D	$2K - K$
Cutting velocity	[m/min]	Vc	150 –600
Feed per tooth	[mm/tooth rev]	T	0.03 – 0.2
Teeth number	-	Z	2 – 8

b) Machining operation parameters.

Table 2.9-Workpiece and operational parameters for energy estimation.

Parameter	Meas.Unit	Notation	Value range
Axes max velocity	[mm/min]	$ax.V_{MAX}$	20000 – 60000
Axes max acceleration	[m/s^2]	$ax.A_{MAX}$	2.5 – 5
Axis static friction	[Nm]	$ax.T_{Fr}$	3 – 6
Axis motor rated torque	[Nm]	$ax.T_N$	1.5 – 20
Axis motor rated velocity	[rpm]	$ax.\varpi_N$	1500 – 6000
Axis transmission ratio (screw lead)	[mm]	$ax.\rho$	7 – 30
Machine basal power consumption	[W]	$mu.P_B$	1000 – 3500
Machine moving total inertia	[kg·m^2]	$mu.M$	0.05 – 0.07
Spindle motor rated torque	[Nm]	$sp.T_N$	45 – 160
Spindle motor rated velocity	[rpm]	$sp.\ \varpi_N$	2500 – 4000
Spindle static friction (bearings)	[Nm]	$sp.T_{Fr}$	0.4 – 0.8

Table 2.10-Machine parameters for energy estimation.

The relationship of these parameters to the energy required for the process and its relevance is represented through feed forward neural network:

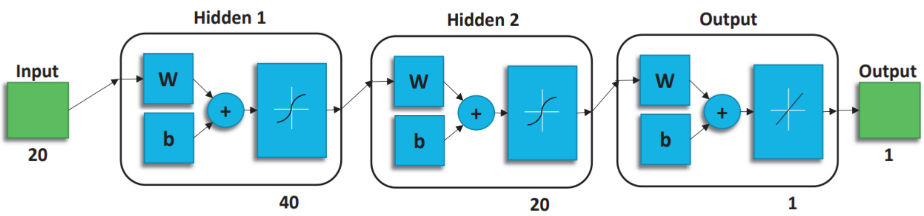


Figure 2.68-ANN design.

The network has been trained prior to simulation using Bayesian regularization back propagation to minimise the error function. The accuracy of the energy prediction is significant making it a very suitable tool for designers to make decisions on executing the least energy-impacting machining strategies.

- Kant and Sangwan (Kant and Sangwan, 2015) highlight that machine tools have an energy efficiency of less than 30% and that more than 99% of the environmental impact they produce is due to electricity consumption. With these data, it is necessary to take action to make machining processes more sustainable. The paper describes the use and comparison of two techniques for estimating electricity consumption: Artificial Neuronal Networks and Support Vector Regression. The results showed that neural networks have a better prediction performance. They can be used in the search for optimal parameters in order to reduce consumption.

Response	Models	Mean	SE Mean	Std dev.	Range
Power	ANN	1.749	0.705	2.821	9.796
	SVR	1.86	1.41	5.63	22.74

Table 2.11-Descriptive statistics for error comparisons: ANN -SVR.

Likewise, Kant and Sangwan (Kant and Sangwan, 2015) again rely on ANNs for energy estimation of the machining process. It is emphasised that this technique can be used in sustainable process planning during the manufacturing phase of life cycle of a machine tool.

❖ Another work also uses ANN to define the relationships between initial parameters and energy consumption and surface quality in milling processes (Wang *et al.*, 2015). This study applies other techniques such as Pattern Search, Genetic Algorithm and Simulated Annealing to find the optimal solutions. This two-step approach is shown in the following figure:

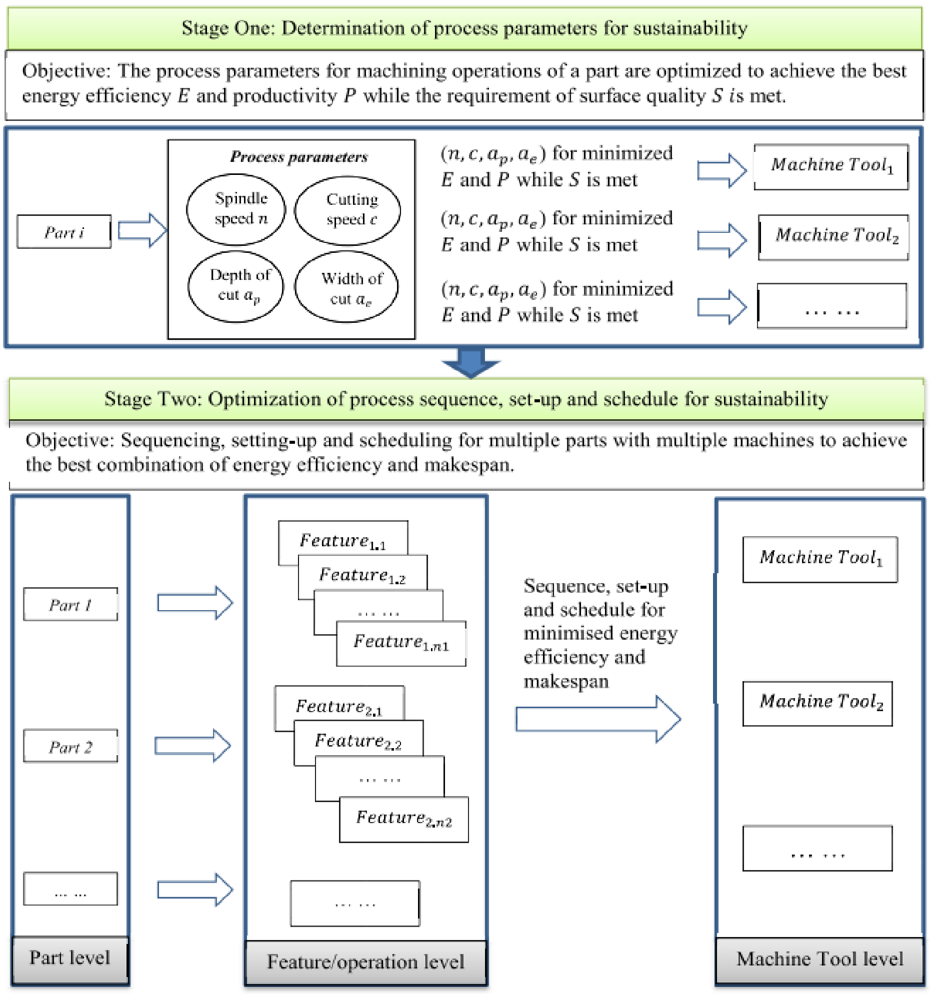


Figure 2.70-Two stages of sustainable process planning and scheduling optimization.

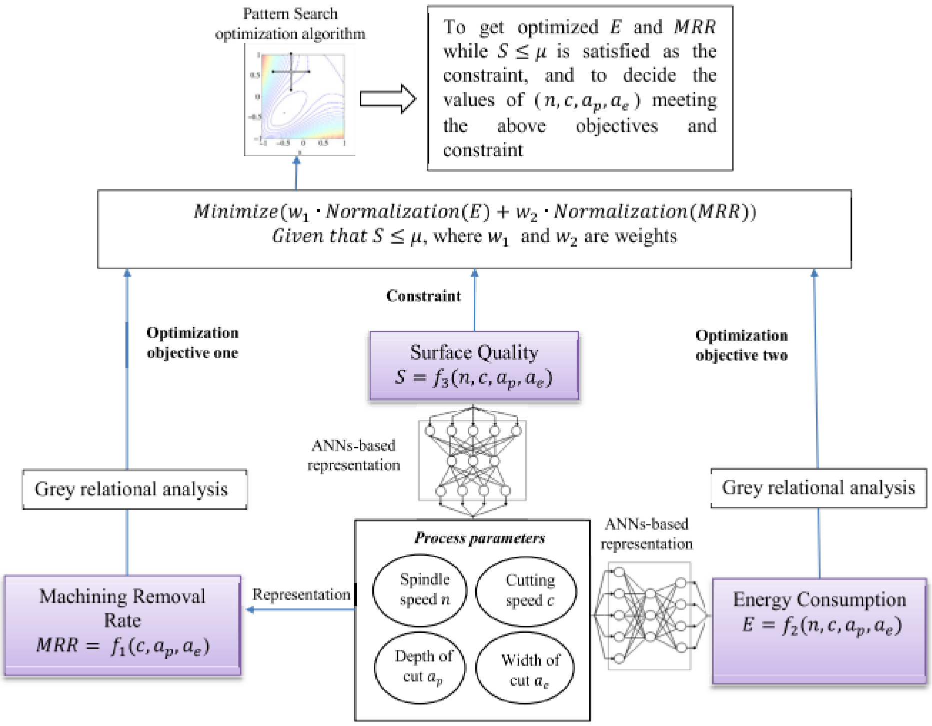
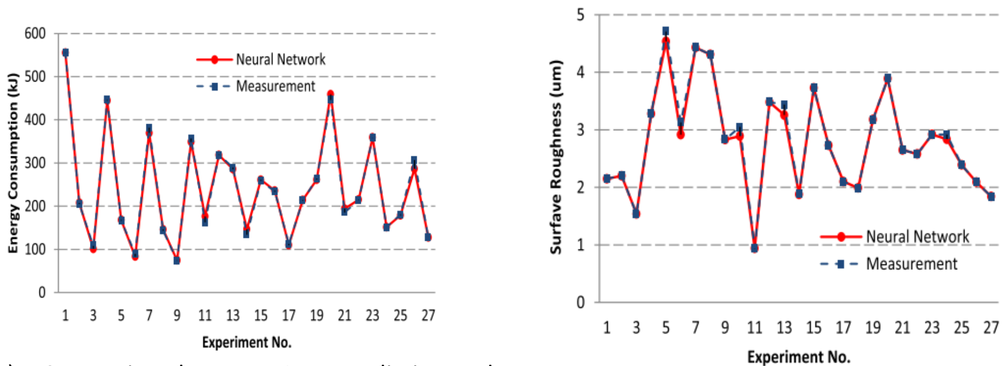


Figure 2.71-Optimization of milling indicators and process parameters.

After experimenting with this model in a case study, it is observed that the prediction of both energy consumption and surface quality is very accurate. In addition, the values obtained for the three selected optimisation algorithms can be compared:



a) Comparison between ANN prediction and measured energy consumption.

b) Comparison between ANN prediction and surface roughness measurement.

Result comparison of the three optimization algorithms.

Algorithms	Average time (s)	Best solutions (3 trials with $S \leq 2.5$ μm)		
Pattern Search	9.23	0.3377	0.3377	0.3377
Genetic Algorithm	24.25	0.3376	0.3406	0.3410
Simulated Annealing	152.84	0.3364	0.3392	0.3409

c) Comparison of the optimization algorithms.

Figure 2.72-Models result.

In conclusion, the proposed model meets the objectives set by the study and the pattern search algorithm is more stable and more rigorous in optimisation.

- Lee and collaborators propose a method of optimising energy use in machining processes that produces savings of up to 13% using a Virtual Machine Tool and genetic algorithms (Lee *et al.*, 2017). The input data are the machining parameters and the program. The VMT estimates energy consumption and other process variables. Based on these data the genetic algorithm is able to find the energetically optimal spindle speed and feed rate condition for each line of the program. System constraints and the cost function are considered.

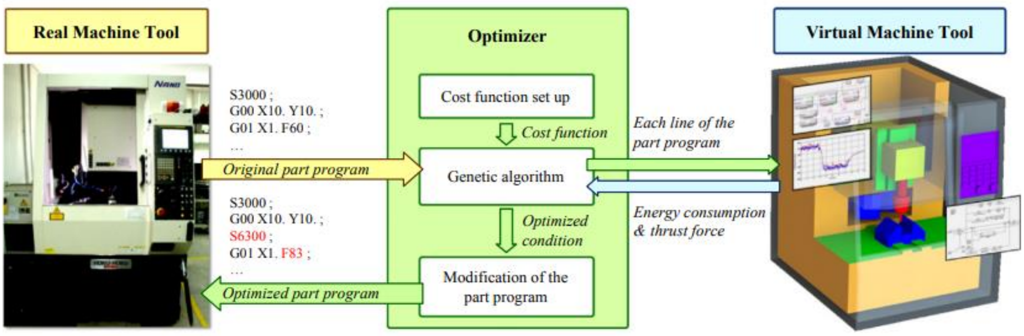


Figure 2.73-Simulation-based method for optimizing machining condition.

The VMT is conceived as follows:

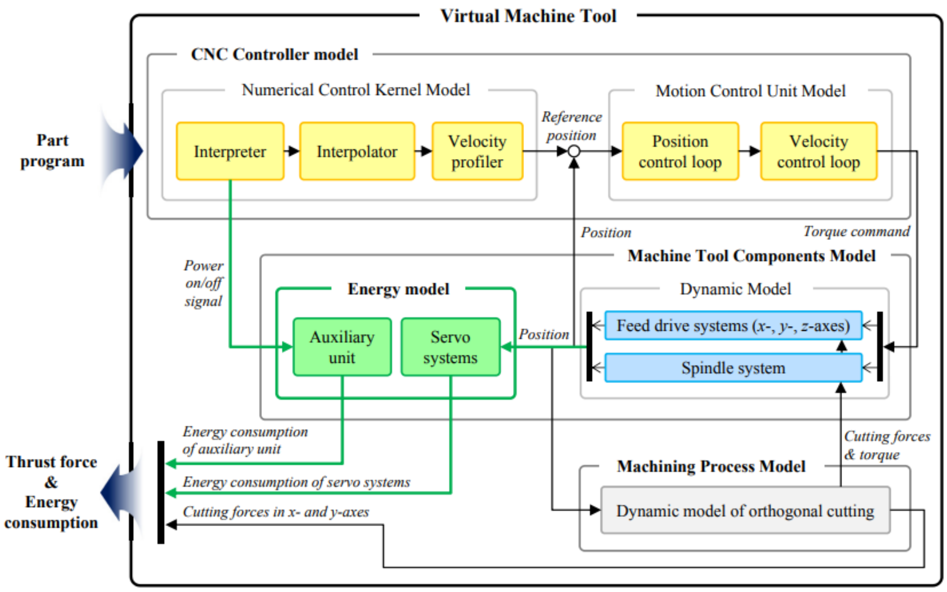
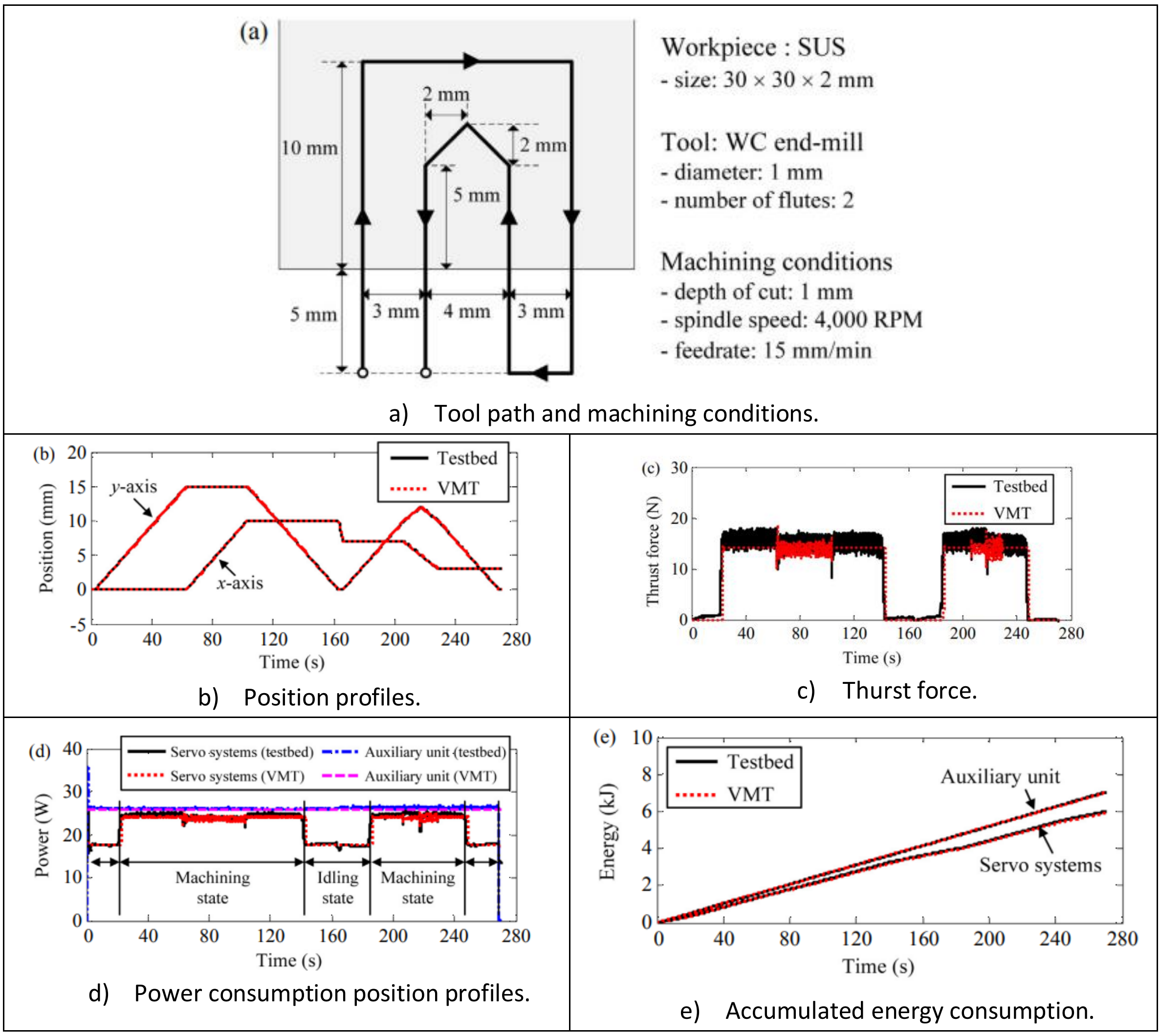


Figure 2.74-VMT structure.

In addition to energy savings of up to 13%, the results showed that the prediction of the energy consumption and the cutting force prediction obtained an accuracy of 99.7% and 96.7% respectively. The proposed model is therefore very effective.



a) Tool path and machining conditions.

b) Position profiles.

c) Thurst force.

d) Power consumption position profiles.

e) Accumulated energy consumption.

Figure 2.75-Experimental verification of VMT.

❖ Using the deep learning to estimate the amount of energy consumed (He *et al.*, 2020). They studied two processes: grinding and milling. In this case the initial parameters were extracted directly from the tool-machine. Their model can be extrapolated to other machines. Four prediction techniques are used: support vector regression, Gaussian process regression, extreme learning machine and convolutional neural network.

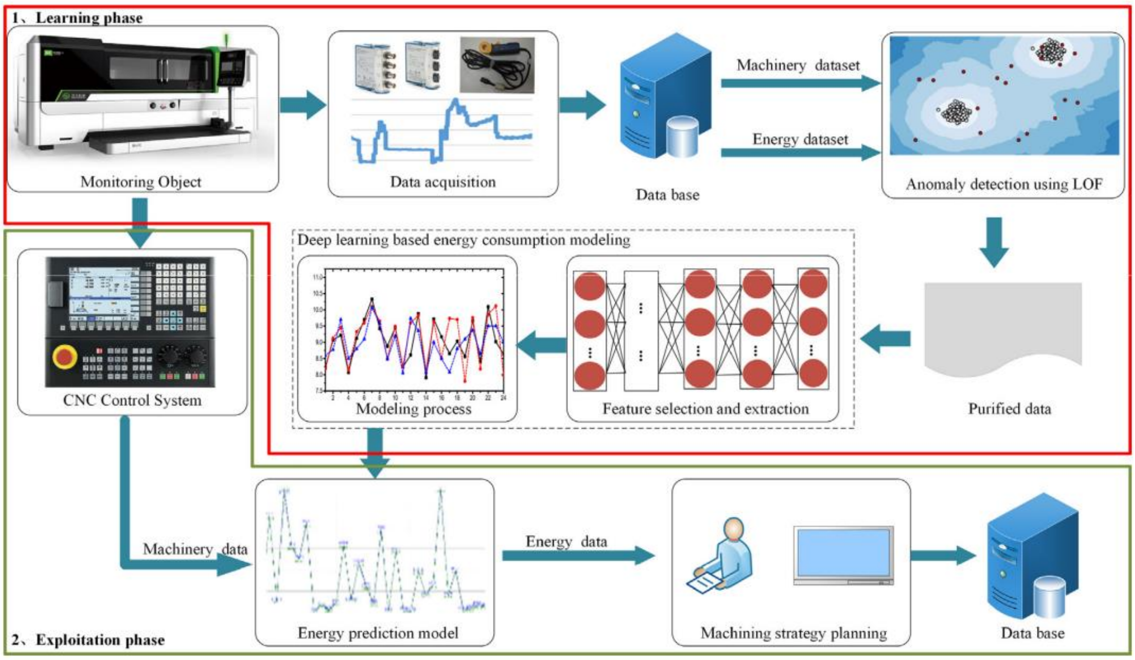


Figure 2.76-General framework of the energy prediction method based on deep learning.

The model is shown to be effective in estimating energy consumption considering that only data from the machine is used. This model can be implemented with little effort and without a great deal of prior knowledge. The CNN algorithm shows a good behaviour allowing the estimation of energy consumption to be carried out without human intervention.

- Brillinger and collaborators compare three machine learning tools for the prediction of power consumption by CNC machining operation (Brillinger *et al.*, 2021). Three clear objectives are established:
  - Determine the low-energy machining strategy considering the geometrical characteristics.
  - Predict energy demand and optimise consumption from the design phase.
  - Contribution to the stability of the energy consumption of the installations as peak demand is controlled.

In this study, only one machine tool is used, a material in a dry machining process. It has been proven that the machining strategy has a major influence on energy consumption; so, in this case, the energy prediction has been limited. For the three machine learning tools the approach is as follows:

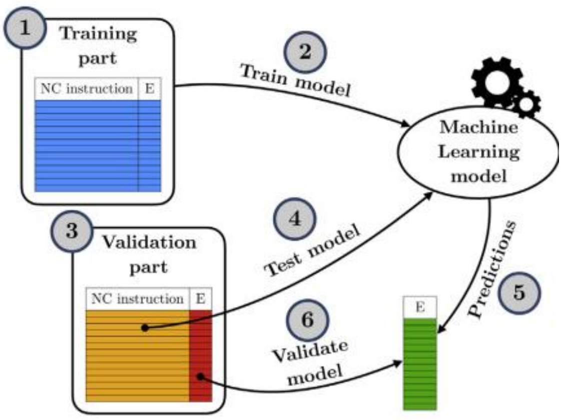
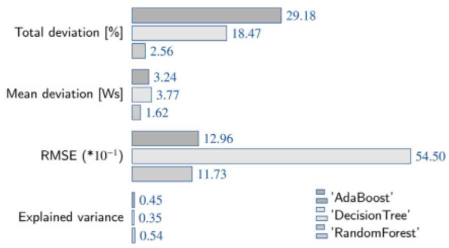
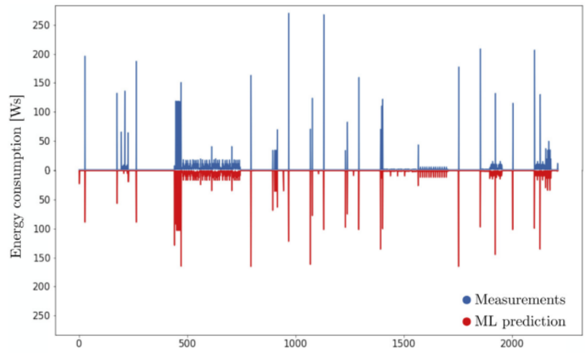


Figure 2.77-Study approach.

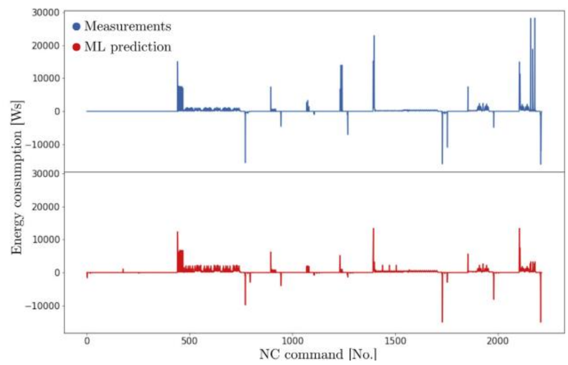
The model is trained and validated as observed in previous studies. Models were created to compare the results of the three Machine Learning tools:



a) Comparision of the prediction quality of different machine learning techniques.



b) Comparision of the prediction quality for the whole machining cycle.



c) Comparision of the prediction quality for the spindle aggregate for the whole machining cycle.

Figure 2.78-Study results.

The results demonstrate that the tools that the model employed can be used to accurately predict energy consumption. The most accurate tool is the Random Forest algorithm.

CHAPTER 3. MACHINING INDUSTRY: SITUATION AND DEVELOPMENT POLICIES.

3.1-SPANISH MACHINING INDUSTRY SITUATION.

The machining industry in Spain could be characterised by 4 groups of companies that make up the sector, according to the information provided by the Aviva Project (Project AVIVA, 2012). These are:

1. Group 1 (G1). These are the companies that only contribute machining to the final product.
2. Group 2 (G2). These are companies that, in addition to machining, include other processes such as cutting, forming, welding, assembly, etc.
3. Group 3 (G3). Companies with their own product, but which only carry out machining operations while the other operations are subcontracted.
4. Group 4 (G4). Companies with their own product and which integrate a large number of manufacturing processes for the completion of their products.

The percentage of companies in each of the groups is as follows:

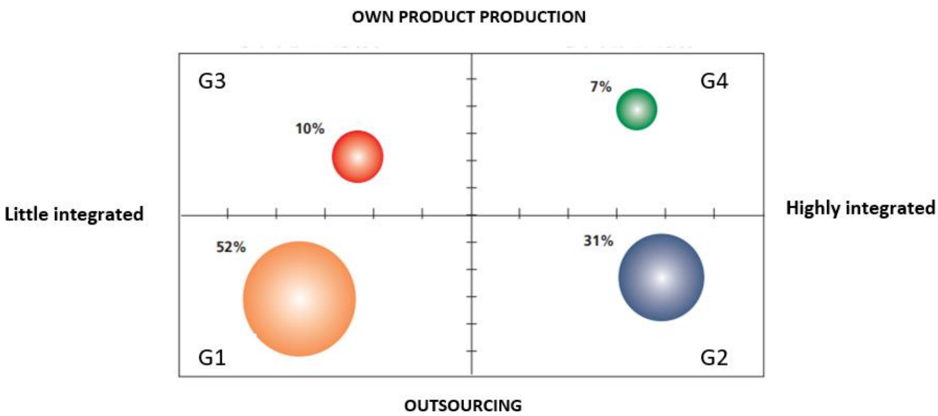


Figure 3.1-Classification of Spanish machining companies. (% companies).

More than 80% are companies that only do machining or machining with some other additional process and are subcontracted by others who manage the final product. Only 17% manufacture their own product.
Comparing these data with the other EU countries, the following information is obtained:

TERRITORY	G1 (%)	G2 (%)	G3 (%)	G4 (%)
SPAIN	52	31	10	7
CENTRAL - EASTERN EUROPE	50	41	5	5
WESTERN EUROPE	24	40	16	20

Table 3.1-Classification of European machining companies (% companies).

Western European companies (France, Germany, Italy, etc.) have a more integrated strategic profile; they are larger companies than the Spanish ones. Western European companies can take on larger projects with a higher technological value, while Spanish companies are more flexible as they have lower fixed costs. Eastern European companies have a similar strategic profile to Spanish companies, but with a series of advantages that make them more competitive. These advantages are cheaper labour, lower transport costs and a little more integrated profile. In fact, 80% of Spanish companies sell less than 20% outside the country. Only 3% of companies report more than 80% of their turnover to customers in other countries. Therefore, we are dealing with a sector of mainly national and regional consumption. 54% of companies sell less than 20% outside their region. For all these reasons, Spain needs to take a step forward in terms of digitisation and strengthening of the sector, to increase its competitiveness compared to other European countries and to activate the internationalisation.

There are two factors that could determine the evolution of industrial transformation in the Spanish machining sector. These two factors are machinery and workers.
With regard to machinery, the data from the AVIVA project show that the machines in Spanish machining companies were mainly between 2 and 10 years old at the time of the study. It should be noted that 45% of the companies did not have new machinery and that a high percentage of companies had machines that were more than 10 years old.

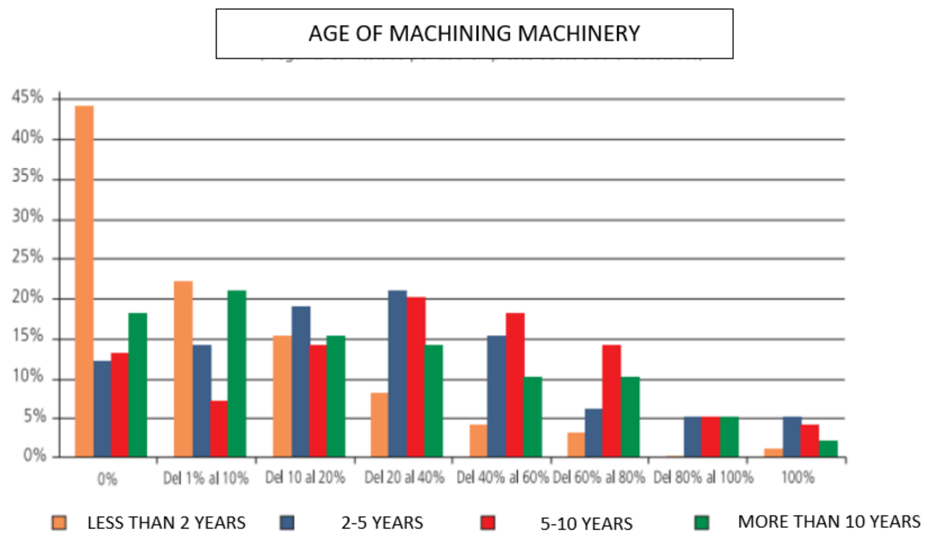
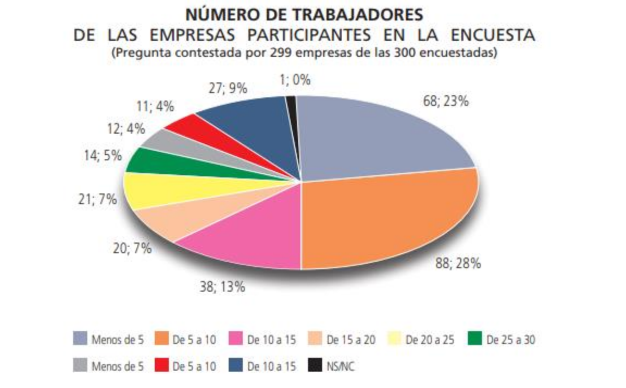


Figure 3.2-Age of the machinery (Spanish Machining Industry).

In addition, most of these companies have less than 10 workers aged between 30 and 40 years for the workers and between 40 and 50 years for the management team.

Nº WORKERS PER COMPANY.



AGE OF WORKERS IN MACHINING COMPANIES.

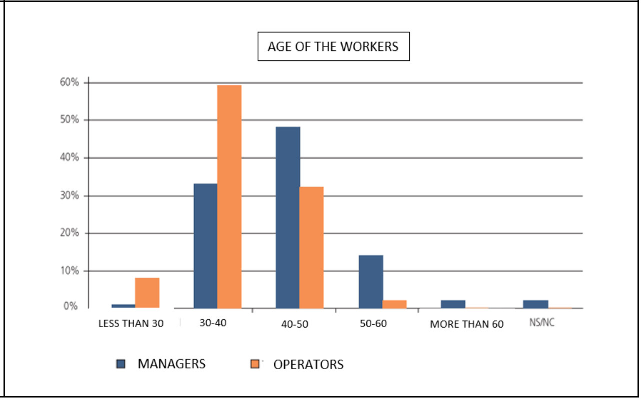


Figure 3.3-Number and age of workers in machining enterprises.

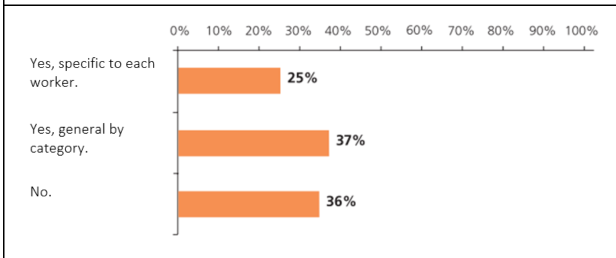
3.2-SPANISH MACHINING INDUSTRY PERSONNEL TRAINING AND RESEARCH AND DEVELOPMENT.

Investment in innovation and continuous staff training help companies to be prepared for the rapid changes that are taking place in the industry and that mark its evolution. Knowing the current trends and how the different technological, manufacturing, management, etc. solutions are being introduced in the market helps organisations to position themselves more advantageously in relation to their competitors, as well as being able to introduce important improvements in their own production processes.

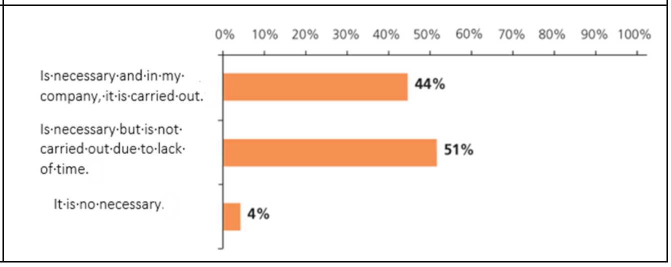
The AVIVA project provides information on how Spanish machining companies deal with these two aspects.

In relation to the training of workers, 63% of the companies confirm the difficulty of finding qualified personnel, but it is also significant that 36% do not have a training plan and 39% improvise training during the year. It is even more demonstrative that for 51% of companies, training is necessary but is not carried out due to lack of time.

TRAINING PROGRAMME.



CONTINUOUS TRAINING.



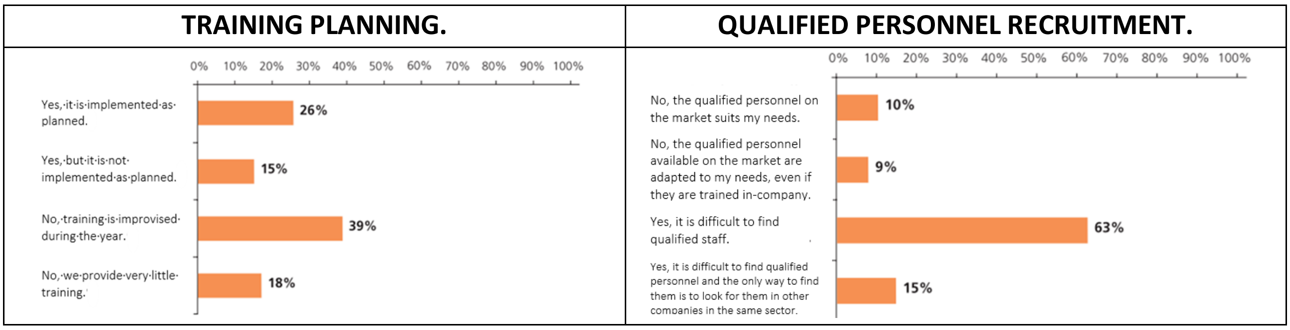


Figure 3.4-Training and workers qualification in the Spanish Machining Industry.

Looking at the data provided by the project on innovation, it can be seen that, although 65% of the companies consider R&D to be a key factor in competitiveness, its transformation into initiatives is not very significant. Only 37% of companies have invested in innovation in the last three years in machining processes and 33% in key business processes. In terms of new products developed through R&D in the last 5 years, 34% of companies confirm that they have developed them, and they account for a percentage of their turnover. Furthermore, 56% of companies have not received information on aid for the renewal of machinery, while only 23% have received and used it. Finally, only 12% of companies have a written strategic plan which they follow faithfully, while 56% do not have one.

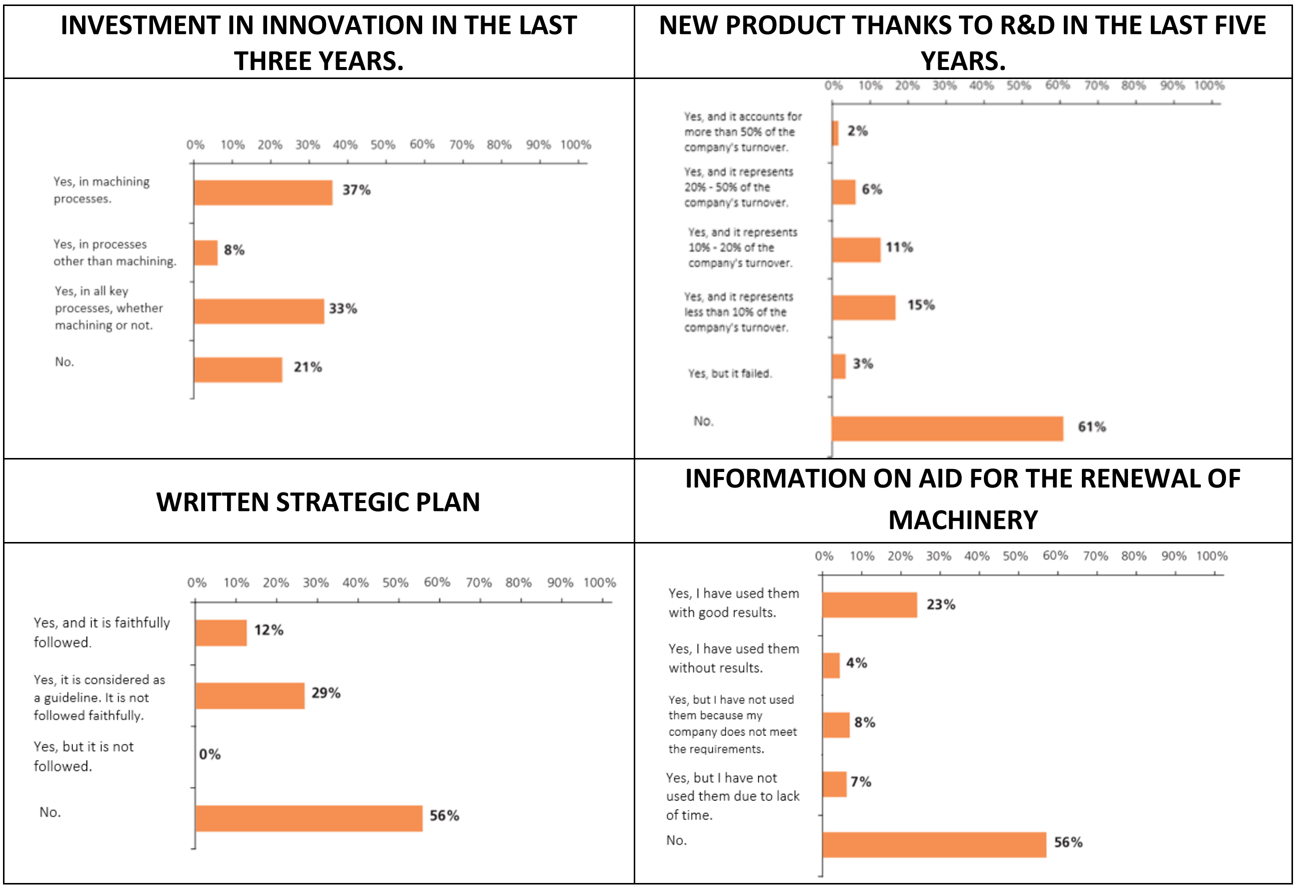


Figure 3.5-R&D in the Spanish Machining Industry.

3.3-EUROPEAN AND SPANISH DEVELOPMENT POLICIES

3.3.1-EUROPEAN DEVELOPMENT POLICIES.

Europe 2020 was the digitalisation strategy launched by EU bodies for the period 2010-2020. The European Court of Auditors found in the special report on the state of digitalisation in 2020 that EU companies were not maximising the opportunity of digitalisation and potential innovation in technology, including artificial intelligence (EU Court of auditors, 2020). Disparities were also found in that 54% of large companies have a high degree of digitisation compared to 17% of small and medium-sized companies. Considering that 99% of European companies belong to the latter group, this places Europe in a difficult position for the future.

The *Digital Europe programme for the period 2021-2027* was released in addition to the *Horizon Europe programme* and the *European Structural and Investment Funds*. Futhermore, in 2020, the Council and the Commission together with the European Parliament adopted a roadmap for recovery after the global pandemic COVID - 19 (EU Court of auditors, 2020). At the time of the report, progress has been limited and the Court of Auditors urges the Commission and Member States to take executive action to improve the achievement of the targets set.

The European Commission's website highlights two vital transitions among the six key objectives in the *recovery plan* (https://ec.europa.eu): the ecological transition and the digital transition. The ecological transition to become a climate-neutral continent and the digital transition aims to empower people with a new generation of technologies. For instance, the commission plans to invest EUR 1 billion in AI from the *Digital Europe* and *Horizon Europe* programmes to attract more than EUR 20 billion of total investment in AI per year over the next decade. (EU Commission).

European bodies have realised that the future is being written by artificial intelligence and are creating a framework to ensure that Europe is not left behind in this race. The Commission advocates for European excellence in IA and has formulated four main objectives (https://ec.europa.eu):

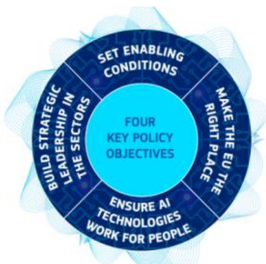


Figure 3.6- EU Commission main objectives of promoting excellence in IA.

The *European Commission's Digital Compass 2030* of March 2021 (EU, 2021) states that 20% of the Recovery and Resilience Mechanism will be dedicated to the digital transition of member states. The *Recovery and Resilience Mechanism* is the EU's post-pandemic European development programme with clear economic, ecological, innovation and employment objectives. The digital compass sets out four objectives:

1. A tech-savvy continent in which all people are digitally empowered.
2. High-level, reliable and secure digital infrastructures.
3. A continent with a high proportion of digitised companies.
    a. 75 % of European enterprises will have incorporated:
        - cloud computing services (2020 baseline: 26 %).
        - big data (2020 baseline: 14%).
        - artificial intelligence (2020 baseline: 25%).
    b. More than 90 % of SMEs should reach at least a basic level of digital intensity (2019 baseline: 60.6%).
    c. Europe will expand the number of its innovative growth companies and improve their access to finance, leading to a doubling of the number of "unicorns", both companies created after 1990 that have had an IPO or sale of more than USD 1 billion and companies that have been valued at that amount or more in their last round of private financing. (2021 baseline: 122).
4. Modernisation of public services to respond to society's demands.

3.3.2-SPANISH DEVELOPMENT POLICIES.

Through the *Recovery, Transformation and Resilience Plan* (GOB ESP 2021), the government articulates Spain's strategy for economic recuperation after the pandemics, creating a more sustainable and digital future. It thus transfers the EU Recovery and Resilience Mechanism to the Spanish state. This plan is based on 7 pillars: ecological transition, digitalisation, social protection, education and vocational training, sustainable tourism, employment and science. The investments of the plan are distributed in the following actions:

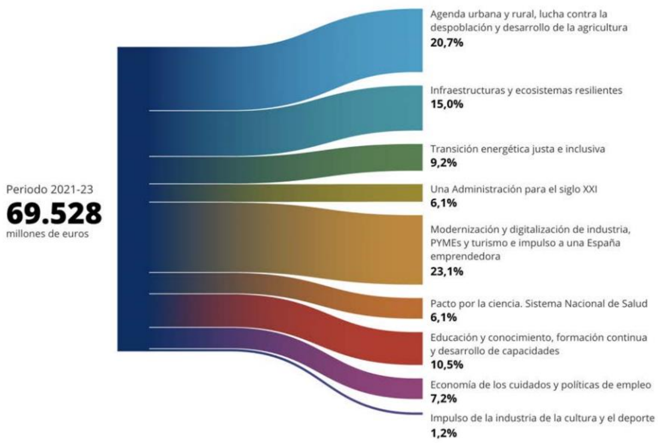


Figure 3.7- Recovery, Transformation and Resilience Plan investment.

23.1% of the investment is directed to the digitalisation and modernisation of industry, small and medium-sized enterprises and tourism and the promotion of an entrepreneurial Spain, 10.5% to education and knowledge, lifelong learning and skills development and 9.2% to a just and inclusive energy transition, with the aim of generating a competitive economic and industrial network and training professionals in line with market demands.

In 2020, the Spanish government presented the *Digital Spain 2025 Plan* (GOB ESP 2020), which is based on 10 strategic axes:

1. Guarantee adequate digital connectivity for 100% of the population, promoting the disappearance of the digital divide between rural and urban areas (target 2025: 100% of the population with 100 Mbps coverage).
2. Continue to lead the deployment of 5G technology in Europe, encouraging its contribution to increased economic productivity, social progress and territorial structuring (2025 target: 100% of the radio spectrum prepared for 5G).
3. Strengthening the digital skills of workers and citizens as a whole (2025 target: 80% of people with basic digital skills, of which 50% will be women).
4. Strengthen Spain's capacity in cybersecurity, consolidating its position as one of the European poles of business capacity (target 2025: 20,000 new specialists in cybersecurity, AI and Data).
5. Boost the digitisation of Public Administrations (target 2025: 50% of public services available on mobile apps).
6. Accelerate the digitalisation of companies, with special attention to micro-SMEs and start-ups.(target 2025: 25% contribution of e-commerce to SME turnover).
7. Accelerate the digitisation of the production model through sectoral transformation projects that generate structural effects (2025 target: 10% reduction of CO2 emissions due to the effect of digitisation).
8. Improve Spain's attractiveness as a European platform for business, work and investment in the audiovisual field (2025 target: 30% increase in audiovisual production in Spain).
9. Favour the transition to a data economy, guaranteeing security and privacy and taking advantage of the opportunities offered by the Artificial Intelligence (target 2025: 25% of companies using AI and Big Data).
10. Guarantee citizens' rights in the new digital environment (2025 target: a national charter on digital rights).

Digital development is an ambitious and necessary challenge for Spain. One of the main axes is the promotion of artificial intelligence, which is articulated in the transformation towards the data economy, in the empowerment of artificial intelligence as a driver of innovation and sustainable growth, preparing the country for the transformation and creating a legislative and moral framework shared with the EU. The *national artificial intelligence* strategy (MIAETD 2020), which builds on previous work and is funded by the state to the tune of 600 million euros, was born out of this plan. The national strategy is articulated in 6 axes and 30 measures. The 6 main axes are:

- To promote scientific research, technological development and innovation in AI.
- Promote the development of digital capabilities, boost national talent and attract global talent in artificial intelligence.
- Develop data platforms and technological infrastructures that support AI
- Integrate AI into value chains to transform the economic infrastructure.
- Enhance the use of AI in public administration and national strategic missions.
- Establish an ethical and regulatory framework that reinforces the protection of individual and collective rights, in order to ensure social inclusion and well-being.

In other words, Spain is organising itself to tackle a decisive economic, social and technological transformation.

The industry shall be prepared to assimilate this transformation and the installed technology must be able to accommodate the new digital and artificial intelligence solutions. Thus, in September 2021, the government launched a renovation programme to subsidise the modernisation of machine tools in small and medium-sized enterprises to the tune of 50 million euros (https://www.lamoncloa.gob.es). One of the following conditions should be fulfilled (https://www.mincotur.gob.es):

- Involve an expansion of the production capacity of an existing establishment.
- Diversify production by creating new products.
- Involve an essential change in the overall production process of an existing establishment.

At both European and national level, various plans and strategies have been introduced for the evolution of technology, digitalisation and artificial intelligence. In addition, measures have been created to ensure that this progress reaches industry, which is the main objective.

Whether these measures are sufficient to make Spain a competitive country will be verified in the following years. Nevertheless, the main conclusion is that artificial intelligence is in the present and future of industry and that it is a very promising area of knowledge to be developed and properly implemented in the industry.

CHAPTER 4. ANALYSIS OF RESULTS.

4.1-QUALITY, EFFICIENCY AND SUSTAINABILITY IMPROVEMENT USING AI TECHNIQUES.

The authors have applied different artificial intelligence techniques to address the various factors that can improve machining processes. The following table shows a summary of the methods used by each of the authors in each of the aspects mentioned in the previous sections.

	Raw material selection	**Equipment and tool selection**	**Machining process selection**	**Cutting parameters optimization**	**Monitoring**	**Energy consumption monitoring.**
Decision tree	Merayo *et al.*, 2019					Brillinger *et al.*, 2021
ANN	Merayo *et al.*, 2019 Denkena *et al.*, 2020	Alberti *et al.*, 2011	Ahmad and Haque, 2002 Deb *et al.*, 2006		Dimla *et al.*, 1997 Caggiano *et al.*, 2017 Caggiano *et al.*, 2018 Zhu *et al.*, 2021 D'Addona *et al.*, 2016 D'Addona and Teti, 2013 Corne *et al.*, 2017 Drouillet *et al.*, 2016 Caggiano *et al.*, 2016	Kant and Sangwan, 2015 Borgia *et al.*, 2014 Wang *et al.*, 2015
ANN + GA				Boga and Koroglu, 2021 Muthuram and Frank, 2021		
ANN + TOPSIS				Zuperl *et al.*, 2004		
SSAEs structure with BPNN					He *et al.*, 2021	
CNN				Yoo and Kang, 2021	Brili *et al.*, 2020	He *et al.*, 2020
CNN+ FCN					Bergs *et al.*, 2020	
Bayesian networks					Correa *et al.*, 2008 Bustillo *et al.*, 2011	
Genetic Algorithms		Alam *et al.*, 2003 Keung *et al.*, 2001 Gjelaj *et al.*, 2013 Ahmad *et al.*, 2010	Ahmad,2001	Cus and Balic, 2003 D'Addona and Teti, 2013 La Fé-Perdomo *et al.*, 2018		Lee *et al.*, 2017 Wang *et al.*, 2015
Genetic algorithms + Simulated annealing technique			Nallakumarasamy *et al.*, 2011			
Fuzzy AHP & Fuzzy TOPSIS	Zeynali *et al.*, 2012	Önüt *et al.*, 2008 Ic and Yurdakul, 2009				
Fuzzy AHP		Ayağ and Özdemir,2006				

Fuzzy ANP		Ayağ and Özdemir,2011				
Fuzzy logic					Babu *et al.*, 2018	
Fuzzy AHP + PROMETHEE Method		Taha and Rostam, 2011				
Neuro Fuzzy system + Genetic algorithms		Kunaparaju *et al.*, 2016				
Fuzzy expert system + Genetic algorithms			Wong *et al.*, 2003			
Neuro-Fuzzy system					Moreira *et al.*, 2020 Chen and Kudapa, 2020	
Fuzzy interference system					Chen and Kudapa, 2020	
PCA	Merayo *et al.*, 2019					
Geometrics Algorithms		Yao *et al.*, 2003 Lim *et al.*, 2010	Deja and Siemiatkowski, 2018		Bombiński *et al.*, 2022	
Polynomial network + Sequential quadratic programming method				Lee and Yarng, 2000		
Decisional algorithms.		Alam *et al.*, 2002				
Simulated annealing						Wang *et al.*, 2015
K-Means clustering alg.	Merayo *et al.*, 2019				Wang *et al.*, 2019	
Hierarchical clustering					Wang *et al.*, 2019	
Mean shift cluster algorithm					Netzer *et al.*, 2020	
Random forest						Brillinger *et al.*, 2021
AdaBoost + Decision Tree						Brillinger *et al.*, 2021
Support Vector regression						Kant and Sangwan, 2015 He *et al.*, 2020
Pattern search						Wang *et al.*, 2015
Extreme learning machine						He *et al.*, 2020
Gaussian process regression						He *et al.*, 2020

Table 4.1- AI techniques used to improve the quality, efficiency and sustainability of machining processes.

4.2- SOCIAL PERCEPTION.

Artificial intelligence is often associated only with robotics. The general public is unaware that they are surrounded by it and that common everyday actions are performed by this innovative technology. This ignorance generates mistrust, as it remains a black box. Moreover, it is related to the transfer of data, especially personal data, so it is perceived as a distant technology that appropriates privacy and work. For all these reasons, artificial intelligence is not as popular as it should be if truthful information were provided to the population.

The European Barometer 516 (EU 2021) on new technologies shows that 18% of EU respondents believe that artificial intelligence will have a very positive effect in 20 years' time, 43% quite positive while 33% think it will either have no effect or a negative effect.

In Spain, 31% of respondents believe that it will have a very positive effect, compared to 25% in Italy. It is worth noting that 25% of Spanish respondents believe that it will either have no effect or that its effect will be quite or very negative. The percentage of very negative respondents is 11%, while in Italy it is 8%.

It is surprising to note that German respondents are more suspicious of the effect of artificial intelligence in the future.

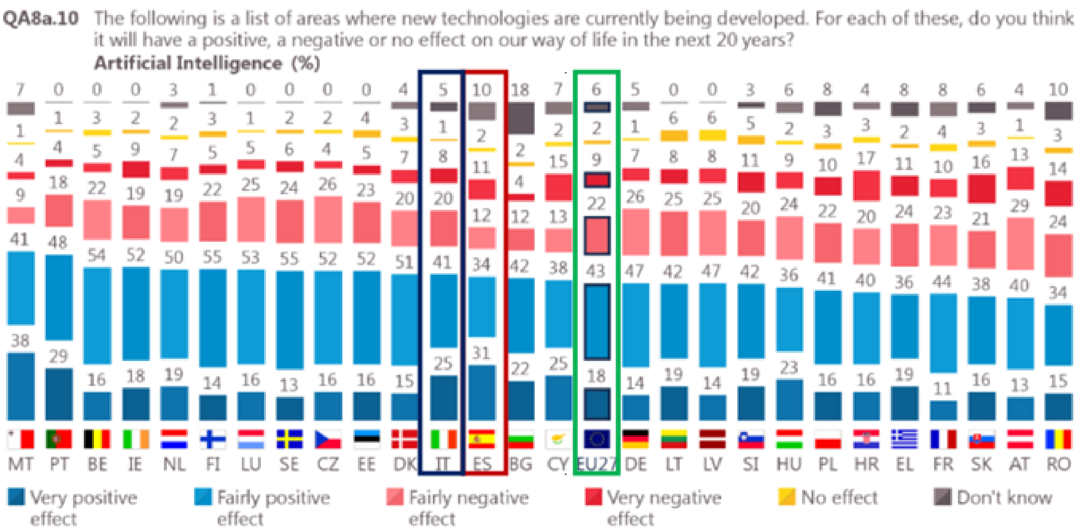


Figure 4.1-Survey on the effect of IA in 20 years' time. European Barometer 516.

The barometer also shows that 66% of men have a positive opinion compared to 57% of women on the impact of the improvements that IA will bring in the next 20 years. This opinion is shared by 64% of inhabitants of large towns and 55% of those living in rural areas.

Regarding the opinion on the possibilities of job creation based on automation and artificial intelligence, 33% of Spanish respondents believe that they will provide more jobs than they will destroy, while 60% have a neutral or negative opinion on the subject. The opinion of German respondents is again surprising, as it is one of the leading countries.

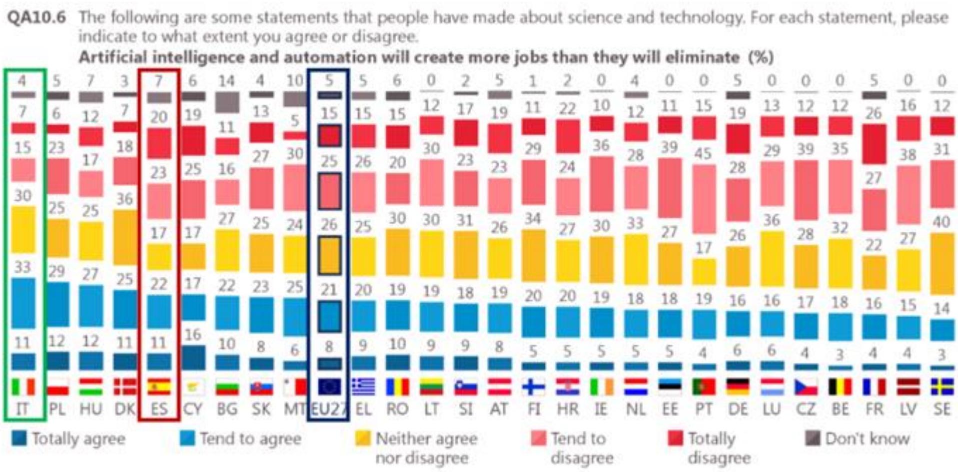


Figure 4.2- Survey about AI and automation jobs creation. European Barometer 516.

The V survey on the social perception of innovation in Spain (COTEC, 2022) provides very interesting data collected between December 2021-January 2022 on the opinion of Spanish citizens:

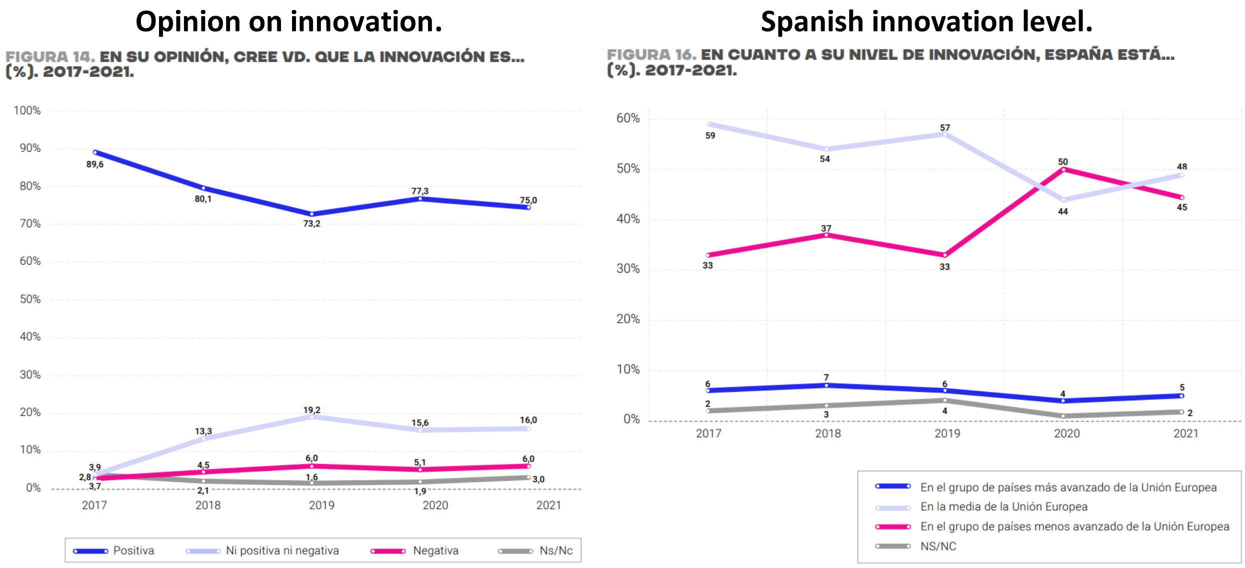


Figure 4.3-Opinion on innovation and Spanish innovation level.

Positive opinion on innovation is in the majority, exceeding 70% of respondents over the 5 years of the study. However, it is noteworthy that the percentage of positive opinion has decreased since 2017. With regard to whether Spain is an innovative country, from 2017 to 2019 it was mostly valued as the average of the European Union. In 2020 this perception decreased and the percentage who believe that Spain is one of the least advanced countries increased. In 2021, the percentages of both categories were very close.

Are small and medium-sized Spanish companies innovative?.	Are large Spanish companies innovative?.

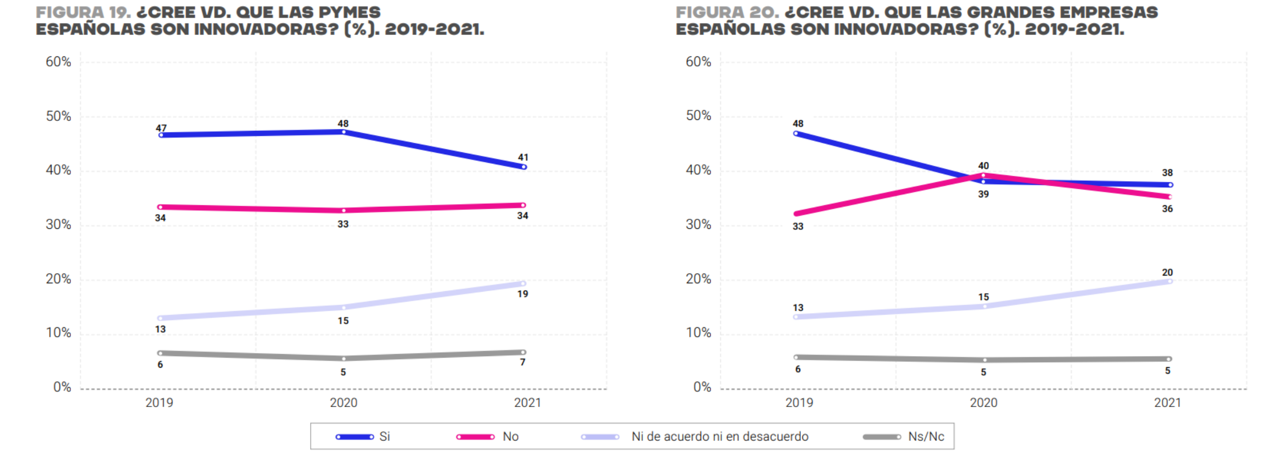


Figure 4.4- Survey on whether Spanish small – medium sized and large enterprises are innovative.

Even with the perception of Spain as a country that does not stand out among the most advanced, the opinion on whether small-medium and large companies are innovative is mostly positive, although closely followed by the negative response. It is also noted that this positive perception has declined over the last 5 years.

It is very characteristic how 66% of the surveyed population is of the opinion that Spanish society is not ready to take on technological advances, but only 38% consider themselves not prepared. Thus, a majority of 59% consider that they are well prepared to enter the market of automation and ICT tools.

Adequate preparation of Spanish society for the impact of technology on employment.	It is able to compete in an automated market with a strong ICT presence?

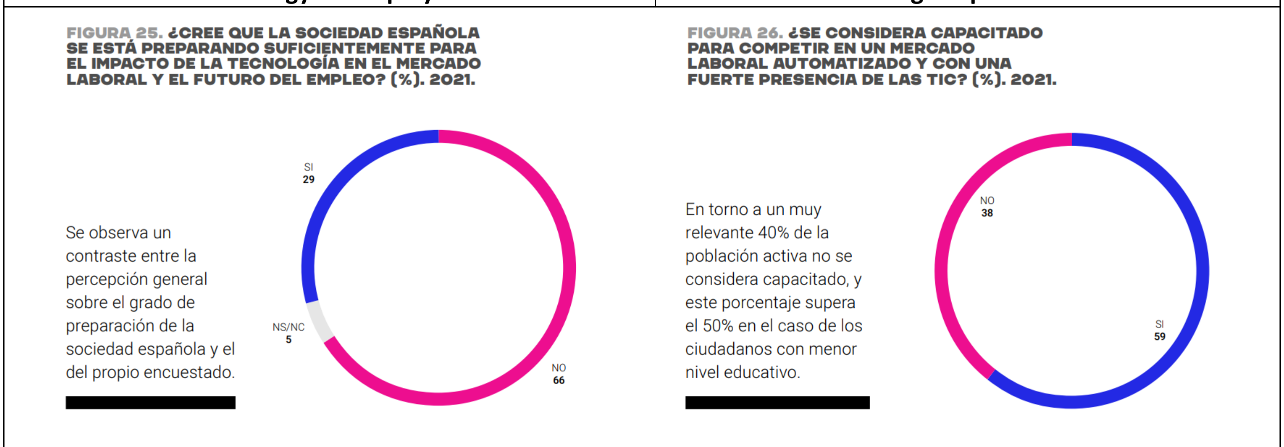


Figure 4.5- Survey on technology impact proper preparation of the Spanish society.

In 2021, more than 80% of respondents consider that public investment in Spain is insufficient, highlighting that the percentage of people who strongly agree with this statement has increased in the last 5 years. Finally, 56.2% believe that innovation generates social inequality and this percentage has been increasing since 2018.

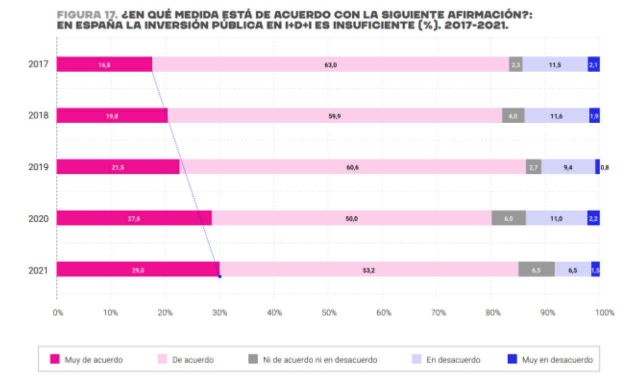
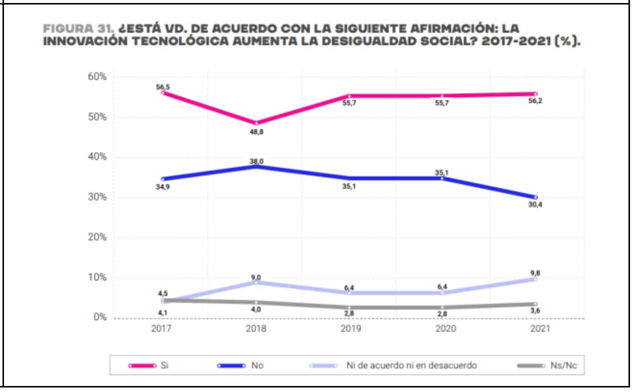
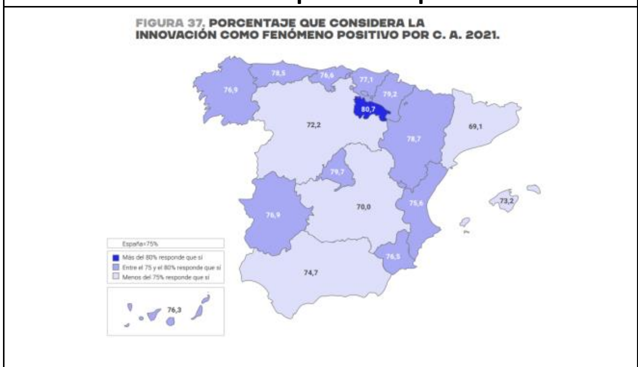
Opinion on the adequacy of public R&D investment.	Social inequality.
	

Figure 4.6- Survey regarding the adequacy of public R&D investment and social inequality.

This study also shows the vertebration of Spain in the face of innovation:

- Respondents from all the autonomous communities recognise the positive impact of innovation at a rate of over 70%.
- The innovation scoreboard shows that the innovation pole communities are the Basque Country and Madrid while Extremadura, Andalusia and Castilla La Mancha are in a modest position.
- Respondents from the east coast of Spain together with the Basque Country, Aragon and Madrid believe that their companies are innovative. Respondents from the rest of the regions responded negatively.
- Respondents in these same autonomous communities, together with Andalusia, believe that innovation will promote the generation of more jobs than it will destroy.

Innovation positive impact.	Innovation Scoreboard.
	

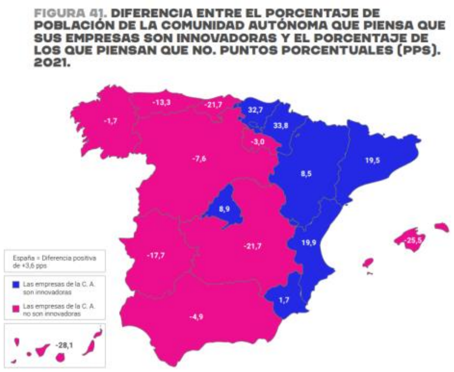
Opinion on innovative companies in your region.	Job losses due to automation.
	

Figure 4.7-Results by autonomous communities on innovation.

The conclusions drawn by Albarrán and collaborators (Albarrán *et al.*, 2021) are thus applicable to artificial intelligence and can be extrapolated to innovation:

1. It is crucial for companies to create programmes for the inclusion of workers in jobs where artificial intelligence and innovative technological solutions are being used.
2. It is essential to explain the influence of artificial intelligence and automation on job creation.
3. Consumer perceptions must be improved by conveying the benefits it brings.
4. With regard to legislators, it is important to create a legislative framework that covers users' privacy.

Artificial intelligence carries with it a certain personal vulnerability that generates no confidence among users and the general population. It is legislators' responsibility to create a legislative framework where users, workers and citizens in general feel protected.

The Eurobarometer 518 (EU 2021) on digital rights and principles reflects how 87% of European respondents consider important to include protection against risk or unethical applications of digital technologies, including artificial intelligence. Of that percentage, 54% consider it very important.

92% of respondents who use the Internet on a daily basis and have a student or manager profile believe that information on the use of digital technologies is important.

It is necessary to improve the perception about artificial intelligence. To achive this goal, a legal framework that protects the users and reliable information, that educates the citizens as autonomous and responsible users of new technologies, is required.

The European Commission in 2020 issued the report "White paper: On Artificial Intelligence - A European approach to excellence and trust" (EU, 2020) with the aim of making artificial intelligence more trustworthy and laying the foundations for a future that respects the values and principles of the European Union. The development of AI is intended to take place in a ecosystem of trust and in an ecosystem of excellence, for all the benefits that can revert to citizens and public and private organisations. Within the ecosystem of excellence are included the actions related to:

- The strengthening of relations with other member states by creating a co-ordinated plan on IA.
- The creation of innovation and research centres.
- Reinforcement of the necessary skills to develop IA in a safe environment.
- Supporting small and medium sized enterprises in the implementation.
- Create a partnership with the private sector.
- Create a plan for the incorporation of IA in the public sector.
- Promote responsible data management, creating a secure environment.
- Work in coordination with other countries and international organizations on the responsible use and development of IA.

The ecosystem of trust works to create a legal framework that protects users, citizens and organisations against risks of violations of their fundamental rights, including protection of their personal data, protection of privacy and non-discrimination.

Nazareno and Schiff (Nazareno and Schiff, 2021), who based their study on five hypotheses on which automation and artificial intelligence would have a direct effect, stand out in the research on the possible impacts on the personal sphere of workers. In their work, they include the conceptual framework on which their study is based:

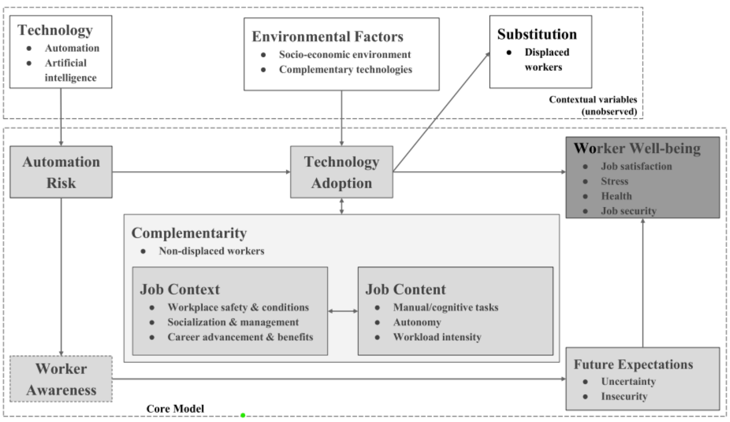


Figure 4.8-AI and automation impact concept framework.

The five hypotheses regarding the workers well-being on which the study was based are:

1. *Creative freedom hypothesis*. Automation and artificial intelligence can take over the most repetitive and routine tasks, making way for the most creative and high-value activities.
2. *Cognitive overload hypothesis.* As repetitive tasks are reduced, the number of more complex tasks with a higher load of cognitive demand will increase.
3. *Loss of meaning hypothesis.* Workers may lose some of the work that identifies them.
4. *Surveillance and control hypothesis.* Artificial intelligence and automation may exert control and surveillance over workers.
5. *Hypotheses of job insecurity*, due to rapid job change or simply because of the risk of being relegated.

The impact of new technologies, automation and artificial intelligence on the well being is a very complex phenomenon and not homogeneous for all workers. While automation and artificial intelligence can have an impact on stress by reducing it, it is at the cost of losing meaning, becoming more dissatisfied with work and even making health worse. Perhaps training alone will not be enough to prevent worker discomfort. The academic world will have to convey the complexity of the impact of new technologies on the well-being of workers in order for the business and political world to make the necessary decisions and create pro-worker policies.

Several works rely on cooperation between technological solutions and people. They believe in partnerships and symbiosis as the future of the relationship between humans and machines. In this way, adaptation to new markets and ways of working will be less traumatic and frustrating.

Jarrahi (Jarrahi, 2018) evidences the synergy that can be created between humans and artificial intelligence in decision-making. Decision-making is characterised by uncertainty, complexity and equivocality. In each of these, artificial intelligence and human capacity can bring their advantages:

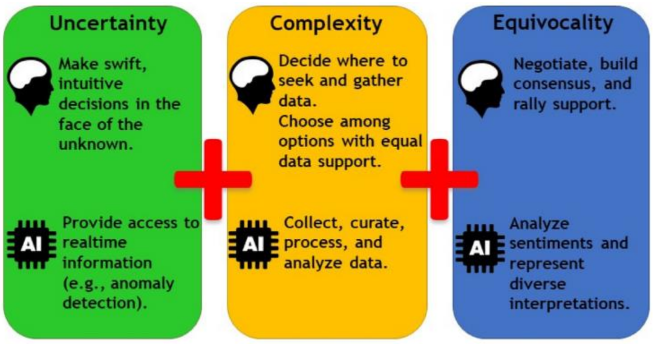


Figure 4.9-Complementarity of humans and AI in decision-making situations scheme.

Jarrahi proposes synergy between systems so that each contributes what it is best at; artificial intelligence provides analysis and objectivity while humans have intuition as a distinctive element.

Makarius and collaborators (Makarius *et al.*, 2020) highlights the lack of information and training of employees and managers regarding artificial intelligence, its benefits and its uses. This deficiency of information leads to a lack of understanding and therefore to a negative understanding. This study advocate for greater understanding and integration of AI so that workers and managers can focus on the opportunities that these techniques offer and create a socialisation framework for effective integration into the work environment:

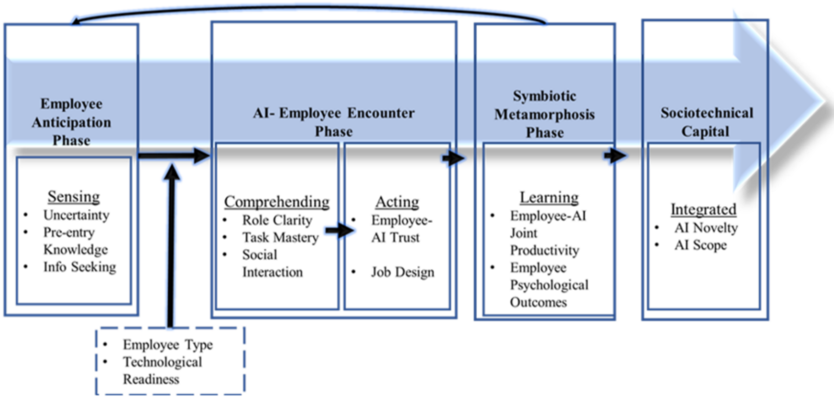


Figure 4.10-AI socialization framework.

This model advocates gradually adopting, adapting and assimilating AI systems to achieve a positively valued transformation. It is time to design collaborative working procedures with artificial intelligence as it will transform the future of the working environment.

Trust is a fundamental pillar for the successful implementation and acceptance of artificial intelligence and work must be done along the lines of hybrid intelligence that combines artificial intelligence and human decisions (Ostheimer *et al.*, 2021). Human-in-the-loop (HITL) computing is a fusion of human and data-derived decision making. In addition, they set out eight fundamental principles of Design Science Research:

Principle 1- Principle of client-designer relationship. A communication relationship must be created between designers and stakeholders. In this way, HITL computing will be able to integrate all the necessary knowledge and the opinion of all participants.

Principle 2- Principle of sustainable design. Align design with client requirements and prepare for future changes in the environment.

Principle 3 -Principle of extended vision. Experts should be involved in the design of algorithms. Consideration should be given to the objectives of the design but also and essentially to the constraints, especially when talking about the legal framework.

Principle 4- Principle of AI-Readiness. Organisations must be prepared to embrace the transformation brought about by artificial intelligence.

Principle 5- Principle of hybrid intelligence. The advantages of the use of artificial intelligence must be explained until a hybrid decision-making system is reached.

Principle 6- Principle of use case-marketing. It is essential to align the design with the client's expectations.

Principle 7- Principle of power relationship. It is human intelligence that gives meaning to artificial intelligence, so there is unequal power in favour of humans.

Principle 8- Principle of Human-AI trust. For hybrid systems to work, it is essential to create a relationship of trust. Otherwise, implementation will not be effective and the full opportunities that artificial intelligence offers will not be realised.

Surveys and studies show how workers and citizens perceive new technologies and artificial intelligence. A large percentage believe that they will risk their jobs or at least what makes them meaningful. It is also worth noting with respect to Spain that the majority of respondents believe that there is not enough investment in innovation. A large percentage revealed that it is not a country where companies are innovative, which is a very significant reflection of the country's structure, and that as a society they are not prepared to embrace technological advances.

Several authors advocate synergy and alliance between humans and artificial intelligence. In this way, it will be possible to make use of the most advantageous and differentiating qualities of each. Even creating a framework of sociability between them. It is true that the use of artificial intelligence must be based on trust and the principles governing this collaboration must be established.

CHAPTER 5. CONCLUSIONS.

5.1- GENERAL CONCLUSIONS.

The work began by putting the industrial situation in context, with an emphasis on Spanish industry, in order to understand the prospects and challenges of an increasingly demanding market. One of the keys to making Spanish industry more competitive is the adoption of artificial intelligence and new technologies.

The virtues of artificial intelligence in machining processes have been reviewed and each of the aspects in which it can be a differentiating element to improve these processes in terms of quality, sustainability and efficiency have been explored by different authors. Thus, its significant performance in the selection of materials, tools, machines and operation, in the optimisation and monitoring of machining processes and the improvement of sustainability is clear. The advantages of adopting artificial intelligence are evident, but is the Spanish machining industry and its workers ready for its adoption? The situation of the machining industry highlights that the machinery parquet is not renewed as it should be and that workers are not adequately trained.

There are significant differences between academic developments, what is required by designers and the response that the machining industry can provide today. The EU and the Spanish government have launched several programmes for the integration of the digitalisation of companies, the development of artificial intelligence and the renewal of machinery. The effect of these policies will be seen in the short to medium term.

On the other hand, the social vision of the fourth industrial revolution or Industry 4.0, in which artificial intelligence is a basic pillar, must be taken into account. This transformation will affect workers, organisations and citizens. It is a total transformation that has many implications. The reception of this transformation is not homogeneous and it is clear that it is not as positive as it should be. Misinformation and the possibility that workers' and people's rights may be violated do not help to enhance the growth opportunities offered by artificial intelligence. Quality programmes must be put in place to inform and educate workers and citizens and create a legal framework to protect them, as the EU has started to do. Companies must be prepared for a less traumatic reception. In addition, boundaries and working procedures must be established so that workers feel protected. Much remains to be done at the academic, business and political levels.

At academic level, studies on the use of artificial intelligence in machining have not expanded to the extent that they have in other fields, such as medicine. Furthermore, although cost and productivity are key factors that determine the viability of operations, it is time to incorporate process sustainability as a decision-making element. There are future opportunities to study and develop the use of artificial intelligence. In addition, it is necessary to bring the advances provided by these studies closer to companies, not only large companies, but especially small and medium-sized ones. In this way, they will be able to change their organisational profile and compete on an equal basis.

At business level, it is necessary to link up with academic life, in order to be able to observe the direction in which developments are taking place and what criteria the customers of the future will demand. It is essential to create a training framework for workers in order to prepare them for new technologies and for the changes that their work will undergo. It is necessary to incorporate innovation and establish strategic plans in which companies set the direction of their decisions. Agreements with governments must be formulated so that small and medium-sized enterprises are not left behind. And they must definitely include sustainability in these strategic plans, not just in words but in their actions.

At political level, there should be four frameworks in Spain to support the adoption of artificial intelligence:

- *Innovation and development framework.* As well as believing in innovation, we must invest in it. Centres of excellence in artificial intelligence must be created where various specialities can collaborate to develop it to the maximum.
- *Legal framework* for the protection of rights as citizens and workers. Search for excellence through trust.
- *Training framework.* Establish new training for the workers of the future in artificial intelligence. Include artificial intelligence in existing academic courses. This will help change the perception of artificial intelligence to a more positive one and help citizens to be responsible in its use and in demanding laws to protect them.
- *Incentive framework for industry*. Spain needs to develop a quality industry, not one that is vertebrated by its territory. To this end, structural political decisions must be taken to support companies, regardless of their size, in the adoption of new technologies and, above all, in the implementation of artificial intelligence.

The role of artificial intelligence in the future is indisputable. The key will be to place limits on its potential so that its use is sustainable with respect to the environment and people. It is also the responsibility of citizens to be critical and to demand compliance with these limits. This is the reason why information and education must reach everyone.

Il lavoro è iniziato contestualizzando la situazione industriale, con particolare attenzione all'industria spagnola, per capire le prospettive e le sfide di un mercato sempre più esigente. Una delle chiavi per rendere l'industria spagnola più competitiva è l'adozione dell'intelligenza artificiale e delle nuove tecnologie.

Le virtù dell'intelligenza artificiale nei processi di lavorazione sono state esaminate e ciascuno degli aspetti in cui può essere un elemento di differenziazione per migliorare questi processi in termini di qualità, sostenibilità ed efficienza sono stati esplorati da diversi autori. Così, la sua performance significativa nella selezione dei materiali, degli utensili, delle macchine e del funzionamento, nell'ottimizzazione e nel monitoraggio dei processi di lavorazione e nel miglioramento della sostenibilità è chiara. I vantaggi dell'adozione dell'intelligenza artificiale sono evidenti, ma l'industria meccanica spagnola e i suoi lavoratori sono pronti per la sua adozione? La situazione dell'industria della lavorazione evidenzia che il parquet dei macchinari non è rinnovato come dovrebbe e che i lavoratori non sono adeguatamente formati.

Ci sono differenze significative tra gli sviluppi accademici, ciò che è richiesto dai progettisti e la risposta che l'industria della lavorazione può fornire oggi. L'UE e il governo spagnolo hanno lanciato diversi programmi per l'integrazione della digitalizzazione delle aziende, lo sviluppo dell'intelligenza artificiale e il rinnovo dei macchinari. L'effetto di queste politiche si vedrà nel breve e medio termine.

D'altra parte, bisogna tener conto della visione sociale della quarta rivoluzione industriale o Industria 4.0, in cui l'intelligenza artificiale è un pilastro fondamentale. Questa trasformazione riguarderà i lavoratori, le organizzazioni e i cittadini. È una trasformazione totale che ha molte implicazioni. La ricezione di questa trasformazione non è omogenea ed è chiaro che non è così positiva come dovrebbe essere. La disinformazione e la possibilità che i diritti dei lavoratori e delle persone possano essere violati non aiutano a valorizzare le opportunità di crescita offerte dall'intelligenza artificiale. Bisogna mettere in atto programmi di qualità per informare ed educare i lavoratori e i cittadini e creare un quadro giuridico che li protegga, come ha iniziato a fare l'UE. Le aziende devono essere preparate per un'accoglienza meno traumatica. Inoltre, devono essere stabiliti i confini e le procedure di lavoro in modo che i lavoratori si sentano protetti. Molto resta da fare a livello accademico, aziendale e politico.

A livello accademico, gli studi sull'uso dell'intelligenza artificiale nella lavorazione non si sono ampliati nella misura in cui lo hanno fatto in altri campi, come la medicina. Inoltre, sebbene il costo e la produttività siano fattori chiave che determinano la redditività delle operazioni, è ora di incorporare la sostenibilità del processo come elemento decisionale. Ci sono opportunità future per studiare e sviluppare l'uso dell'intelligenza artificiale. Inoltre, è necessario avvicinare i progressi forniti da questi studi alle aziende, non solo quelle grandi, ma soprattutto quelle piccole e medie. In questo modo, potranno cambiare il loro profilo organizzativo e competere alla pari.

A livello aziendale, è necessario collegarsi con la vita accademica, per poter osservare la direzione in cui stanno avvenendo gli sviluppi e quali criteri richiederanno i clienti del futuro. È essenziale creare un quadro di formazione per i lavoratori al fine di prepararli alle nuove tecnologie e ai cambiamenti che il loro lavoro subirà. È necessario incorporare l'innovazione e stabilire piani strategici in cui le aziende stabiliscano la direzione delle loro decisioni. Si devono formulare accordi con i governi affinché le piccole e medie imprese non siano lasciate indietro. E devono assolutamente includere la sostenibilità in questi piani strategici, non solo a parole ma nelle loro azioni.

A livello politico, ci dovrebbero essere quattro framework in Spagna per sostenere l'adozione dell'intelligenza artificiale:

- *Framework di innovazione e sviluppo.* Oltre a credere nell'innovazione, dobbiamo investire in essa. Si devono creare centri di eccellenza nell'intelligenza artificiale dove varie specialità possano collaborare per svilupparla al massimo.
- *Framework giuridico* per la protezione dei diritti dei cittadini e dei lavoratori. Ricerca dell'eccellenza attraverso la fiducia.
- *Framework di formazione*. Stabilire una nuova formazione per i lavoratori del futuro nell'intelligenza artificiale. Includere l'intelligenza artificiale nei corsi accademici esistenti. Questo aiuterà a cambiare la percezione dell'intelligenza artificiale in una più positiva e aiuterà i cittadini ad essere responsabili nel suo uso e nel richiedere leggi che li proteggano.
- *Framework di incentivi per l'industria.* La Spagna ha bisogno di sviluppare un'industria di qualità, non una vertebrata dal suo territorio. A tal fine, devono essere prese decisioni politiche strutturali per sostenere le imprese, indipendentemente dalle loro dimensioni, nell'adozione di nuove tecnologie e, soprattutto, nell'implementazione dell'intelligenza artificiale.

Il ruolo dell'intelligenza artificiale nel futuro è indiscutibile. La chiave sarà porre dei limiti al suo potenziale in modo che il suo uso sia sostenibile rispetto all'ambiente e alle persone. È anche responsabilità dei cittadini essere critici ed esigere il rispetto di questi limiti. Questo è il motivo per cui l'informazione e l'educazione devono raggiungere tutti.

5.2- PARTICULAR CONCLUSIONS.

5.2.1-PARTICULAR CONCLUSIONS: USE OF AI IN MACHINING PROCESSES.

This work has reviewed the proposals of various authors for the application of IA in different phases of machining processes:

- Selection of materials.
- Selection of equipment and tools.
- Selection of operations and its sequencing.
- Optimisation of processes through the selection of cutting parameters.
- Monitoring.
    - Monitoring of tool wear and failure.
    - Quality monitoring.
    - Monitoring of machine anomalies.
- Selection of cooling and lubrication.
- Monitoring of electrical consumption.

All the authors presented as a common objective the increase in the efficiency of machining processes. Although each focused on one of the above-mentioned points, a global solution to optimising machining processes, that takes all aspects into account, has not been provided.

It has been shown that IA is a key factor in the development of the machining industry by offering more efficient and cost-effective solutions to the decisional and control problems of this industry. Traditionally, these difficulties have been solved through the experience and knowledge of skilled personnel. IA allows decision making based on a greater amount of data from a greater number of sources and in a more precise manner, reducing the uncertainty of the process, being updated periodically and efficiently, and responding to increasingly complex and restrictive requirements.

Different authors have chosen different AI techniques (Table 2.12) to solve the aforementioned questions, providing different ways of dealing these complex decisional problems. The different studies have chosen those techniques that were considered most suitable with respect to the issue to be addressed. Some of them have also compared different techniques to determine which was the most convenient.

There is a significant number of articles related to the monitoring of machining operations, conveying the importance of their control in order to obtain workpieces that meet quality requirements and at the same time maximise productivity and minimise costs and time. Within monitoring there are also many methods of signal acquisition that are related to certain parameters of the operation. This makes it a real challenge technically speaking. IA can greatly support monitoring and therefore, many authors have decided to address this topic.

Several authors have taken a step forward by integrating artificial intelligence and machining in intelligent systems, for example by using virtual sensors, or by incorporating monitoring and remote quality inspections in a cloud manufacturing system, in cyber-physical models and by developing simulation, virtual machining and digital twins. It is undoubtedly the goal of Industry 4.0 to be able to offer advanced and integrative technologies for every step of the production chain. This will greatly help to automate tasks that add little value to the production process and reduce errors and uncertainties in the process.

It is also worth noting that there is little proliferation of studies on the use of IA in the selection of lubrication and cooling for machining operations. On the other hand, a large proportion of studies seek efficiency through increased quality at lower cost and time, leaving behind environmental variables as decisive decisional factors. Among the possible environmental factors, the electrical consumption of the operations, as it is the most notable environmental impact, and the type of cooling/lubrication should be assessed. Both affect the cost, the feasibility of the operation, the quality of the obtained workpiece, the tool wear and the process time. Therefore, these variables should not only be considered for the environmental impact they generate but should also be taken into account in compliance with environmental legislation and for the efficiency of the machining process itself.

In questo lavoro, sono state esaminate le proposte di vari autori per l'applicazione dell'IA in diverse fasi dei processi di lavorazione:

- Selezione dei materiali.
- Selezione di attrezzature e strumenti.
- Selezione delle operazioni e la sua sequenza.
- Ottimizzazione dei processi attraverso la selezione dei parametri di operazione.
- Monitoraggio delle operazioni.
    - Monitoraggio dell'usura e dei guasti degli utensili.
    - Monitoraggio della qualità.
    - Monitoraggio delle anomalie della macchina.
- Selezione del raffreddamento e della lubrificazione.
- Monitoraggio dei consumi elettrici.

Tutti gli autori hanno presentato come obiettivo comune l'aumento dell'efficienza dei processi di lavorazione. Sebbene ciascuno di essi si sia concentrato su uno dei punti sopra citati, non è stata presentata una soluzione globale per l'ottimizzazione dei processi di lavorazione che tenga conto di tutti gli aspetti.

È stato dimostrato che l'IA è un fattore chiave per lo sviluppo dell'industria della lavorazione, in quanto offre soluzioni più efficienti ed economiche ai problemi decisionali e di controllo di questo settore. Tradizionalmente, queste difficoltà sono state risolte grazie all'esperienza e alle conoscenze di personale specializzato. L'IA consente di prendere decisioni basate su una maggiore quantità di dati provenienti da un maggior numero di fonti e in modo più preciso, riducendo l'incertezza del processo, aggiornandosi periodicamente e in modo efficiente e rispondendo a requisiti sempre più complessi e restrittivi.

Diversi autori hanno scelto diverse tecniche di IA (Tabella 2.12) per risolvere i quesiti sopra citati, fornendo modi diversi di affrontare questi complessi problemi decisionali. I diversi studi hanno scelto le tecniche ritenute più adatte rispetto al tema da affrontare. Alcuni di loro hanno anche confrontato diverse tecniche per determinare quale fosse la più idonea.

Esiste un numero significativo di articoli relativi al monitoraggio delle operazioni di lavorazione, che trasmettono l'importanza del loro controllo per ottenere pezzi che soddisfino i requisiti di qualità e allo stesso tempo massimizzino la produttività e minimizzino costi e tempi. Nell'ambito del monitoraggio esistono anche molti metodi di acquisizione dei segnali che sono legati a determinati parametri dell'operazione. Questo lo rende una vera sfida dal punto di vista tecnico. L'IA può essere di grande aiuto per il monitoraggio e per questo molti autori hanno deciso di affrontare questo tema.

Diversi autori hanno fatto un passo avanti integrando l'intelligenza artificiale nella lavorazione in sistemi intelligenti come l'uso di sensori virtuali, o incorporando il monitoraggio e le ispezioni di qualità in un sistema di produzione cloud, in modelli cyber-fisici e sviluppando la simulazione, la lavorazione virtuale e i gemelli digitali. L'obiettivo dell'Industria 4.0 è senza dubbio quello di poter offrire tecnologie avanzate e integrative per ogni fase della catena produttiva. Questo aiuterà notevolmente ad automatizzare le attività che aggiungono poco valore al processo produttivo e a ridurre gli errori e le incertezze nel processo.

Vale la pena di notare che gli studi sull'uso dell'IA nella scelta della lubrificazione e del raffreddamento per le operazioni di lavorazione sono poco numerosi. D'altra parte, una buona parte degli studi cerca l'efficienza attraverso l'aumento della qualità a costi e tempi ridotti, tralasciando le variabili ambientali come fattori decisionali decisivi. Tra i possibili fattori ambientali, occorre valutare il consumo elettrico delle operazioni, che è l'impatto ambientale più rilevante, e il tipo di raffreddamento/lubrificazione. Entrambi incidono sul costo e, sulla fattibilità dell'operazione, sulla qualità del pezzo ottenuto, sull'usura degli utensili e sul tempo di processo. Pertanto, queste variabili non devono essere considerate solo per l'impatto ambientale che generano, ma anche per la conformità alla legislazione ambientale e per l'efficienza del processo di lavorazione stesso.

5.2.2-PARTICULAR CONCLUSIONS: SPANISH MACHINING INDUSTRY AND SOCIAL VISION.

As mentioned above, Spanish companies have a low strategic profile characterised by machining work with some additional processes on a mainly regional and national scale. It would be advisable for a significant percentage of these companies to be included in the G3 - G4 groups, where great value is added to the process by creating their own products, either by subcontracting operations other than machining or by integrating them into the company. These companies would be generators of wealth and value. In order for these organisations to increase their strategic profile, they need to be committed to innovation and the development of internal competencies. It is difficult for Spanish companies to compete with Eastern European companies in terms of flexibility, proximity to Central European countries and costs, so it is essential to raise their profile in order to ensure their survival and to create opportunities in adjacent industries.

There are several elements that limit this process:

- Age of machinery. Machines that are not up to date will not be ready to be integrated into Industry 4.0. The government has launched several plans to facilitate the replacement of equipment.
- Age of workers. The skilled workforce is a mature workforce that is not fully adapted to the digital era. Therefore, training and updating of content is essential in this industry.
- Training plans. The data show that they are carried out in a generic way and in a large percentage of cases they are not considered as continuous training. Training should be provided in a way that is adapted to the needs of each worker or group of workers with the same deficiencies and should be carried out in a continuous and planned way in order to update knowledge with the latest advances and technologies.
- Innovation and development. It is not only the company's employees who must be aware of the latest trends; the management team must be attentive and generate an environment of innovation and development. In this way, it will be possible to generate greater value at company and industry level and to be highly qualified and competitively well-positioned companies.
- Digitalisation. Spanish companies are not among the best positioned in terms of digitalisation, so it will be very important to take advantage of the actions and funds for this purpose that have been launched by both European and national institutions.

Spanish society's perception of innovation and artificial intelligence is remarkable. The majority consider innovation as something positive, as well as the effects of artificial intelligence in the medium to long term, but this percentage drops when answering whether artificial intelligence will generate jobs. A significant percentage of the Spanish population also considers innovation to be an agent of social inequality. There is a great deal of work ahead in terms of information, protection and integration on the behalf of academic, business and institutional entities, as discussed in the general conclusions.

Come già detto, le aziende spagnole hanno un profilo strategico basso, caratterizzato da lavorazioni meccaniche con alcuni processi aggiuntivi su scala prevalentemente regionale e nazionale. Sarebbe opportuno che una percentuale significativa di queste aziende fosse inclusa nei gruppi G3 - G4, dove aggiungono un grande valore al processo creando prodotti propri, sia subappaltando operazioni diverse dalla lavorazione, sia integrandole nell'azienda. Queste aziende sarebbero generatrici di ricchezza e valore. Per aumentare il loro profilo strategico, queste organizzazioni devono impegnarsi nell'innovazione e nello sviluppo delle competenze interne. È difficile per le imprese spagnole competere con quelle dell'Europa orientale in termini di flessibilità, vicinanza ai Paesi dell'Europa centrale e costi, per cui è essenziale aumentare il loro profilo per garantire la loro sopravvivenza e creare opportunità nei settori adiacenti.

Ci sono diversi elementi che limitano questo processo:

- Età dei macchinari. Le macchine non aggiornate non saranno pronte per essere integrate nell'Industria 4.0. Il governo ha lanciato diversi piani per facilitare la sostituzione delle attrezzature.
- Età dei lavoratori. La forza lavoro qualificata è una forza lavoro matura che non si è completamente adattata all'era digitale. Pertanto, la formazione e l'aggiornamento dei contenuti sono essenziali in questo settore.
- Piani di formazione. I dati dimostrano che sono svolti in modo generico e in un'ampia percentuale di casi non sono considerati come formazione continua. La formazione deve essere erogata in modo adeguato alle esigenze di ciascun lavoratore o gruppo di lavoratori con le stesse carenze e deve essere svolta in modo continuo e pianificato per aggiornare le conoscenze con i progressi e le tecnologie più recenti.
- Innovazione e sviluppo. Non sono solo i dipendenti dell'azienda a dover essere consapevoli delle ultime tendenze; anche il management deve essere attento e generare un ambiente di innovazione e sviluppo. In questo modo, sarà possibile generare maggior valore a livello aziendale e di settore ed essere aziende altamente qualificate e ben posizionate dal punto di vista competitivo.

- Digitalizzazione. Le aziende spagnole non sono tra le meglio posizionate in termini di digitalizzazione, quindi sarà molto importante sfruttare le azioni e i fondi lanciati a questo scopo dalle istituzioni europee e nazionali.

La percezione che la società spagnola ha dell'innovazione e dell'intelligenza artificiale è notevole. La maggioranza considera positiva l'innovazione e gli effetti dell'intelligenza artificiale nel medio-lungo termine, ma la percentuale scende quando si risponde se l'intelligenza artificiale genererà posti di lavoro. Una percentuale significativa della popolazione spagnola considera l'innovazione un agente di disuguaglianza sociale. C'è molto lavoro da fare in termini di informazione, protezione e integrazione da parte di enti accademici, aziendali e istituzionali, come é stato discusso nelle conclusioni generali.

5.3-FUTURE RESEARCH OPPORTUNITIES.

The following future research opportunities have been identified:

- Optimisation of machining processes globally using artificial intelligence. This is a very important challenge because it means not finding the best solution in each of the areas that have been seen in this work, but a solution that is the best for all of them. But if this is achieved, we will have truly improved and balanced processes.
- Studies on the application of artificial intelligence in the selection and optimisation of lubrication and cooling in machining processes.
- Few studies have been found that employ the use of artificial intelligence in non-traditional machining processes. With the incorporation of new materials and the solutions provided by these processes, this aspect will need to be explored further.
- The use of artificial intelligence in determining the geometric, dimensional and functional quality of the workpieces obtained.
- Inclusion of environmental factors as decision-making elements in the optimisation of machining processes.

Sono state individuate le seguenti opportunità di ricerca futura:

- Ottimizzazione dei processi di lavorazione a livello globale grazie all'intelligenza artificiale. Si tratta di una sfida molto importante perché non significa trovare la soluzione migliore in ciascuna delle aree che sono state viste in questo lavoro, ma una soluzione che sia la migliore per tutte. Ma se si riuscirà a raggiungere questo obiettivo, avremo processi veramente migliorati ed equilibrati.
- Studi sull'applicazione dell'intelligenza artificiale nella selezione e nell'ottimizzazione della lubrificazione e del raffreddamento nei processi di lavorazione.

- Sono pochi gli studi che impiegano l'intelligenza artificiale in processi di lavorazione non tradizionali. Con l'incorporazione di nuovi materiali e le soluzioni offerte da questi processi, questo aspetto dovrà essere approfondito.
- L'uso dell'intelligenza artificiale per determinare la qualità geometrica, dimensionale e funzionale dei pezzi ottenuti.
- Inclusione dei fattori ambientali come elementi decisionali nell'ottimizzazione dei processi di lavorazione.

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