

"Evaluating the performance of LSTM Models for Glucose Prediction"

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INDEX

1. INTRODUCTION
2. STATUS OF THE QUESTION
3. MODEL
4. RESULTS
5. CONCLUSIONS AND FUTURE WORKS

INDEX

1. INTRODUCTION

2. STATUS OF THE QUESTION

3. MODEL

4. RESULTS

5. CONCLUSIONS AND FUTURE WORKS

¿WHAT?

- Predict glucose levels in Diabetic patients

¿HOW?

- Using a Machine Learning algorithm

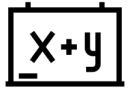
¿WHY?

- Digital transformation and Industry 4.0
- Importance of Diabetes management
- Benefits of Artificial Intelligence in medical processes

OBJECTIVES



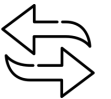
Develop a LSTM **model** that can predict glucose



Find the **optimal** set of **input variables** for that model



Optimize the model



Analyze the **transferability** to other patients



Propose potential **future work**

INDEX

1. INTRODUCTION

2. STATUS OF THE QUESTION

3. MODEL

4. RESULTS

5. CONCLUSIONS AND FUTURE WORKS

DIABETES MELLITUS



What is it?

Disease where the **body**
can't produce or use
insulin



Possible complications

Heart Disease, Stroke,
Nerve damage...



Types

Type 1, Type 2 and
Gestational



Increasing cases

2000 -> 4.6%
2023 -> 6.1%
2045 -> 10.9%



How to deal with it?

Insulin, Glucose
Monitoring, balanced
alimentation...

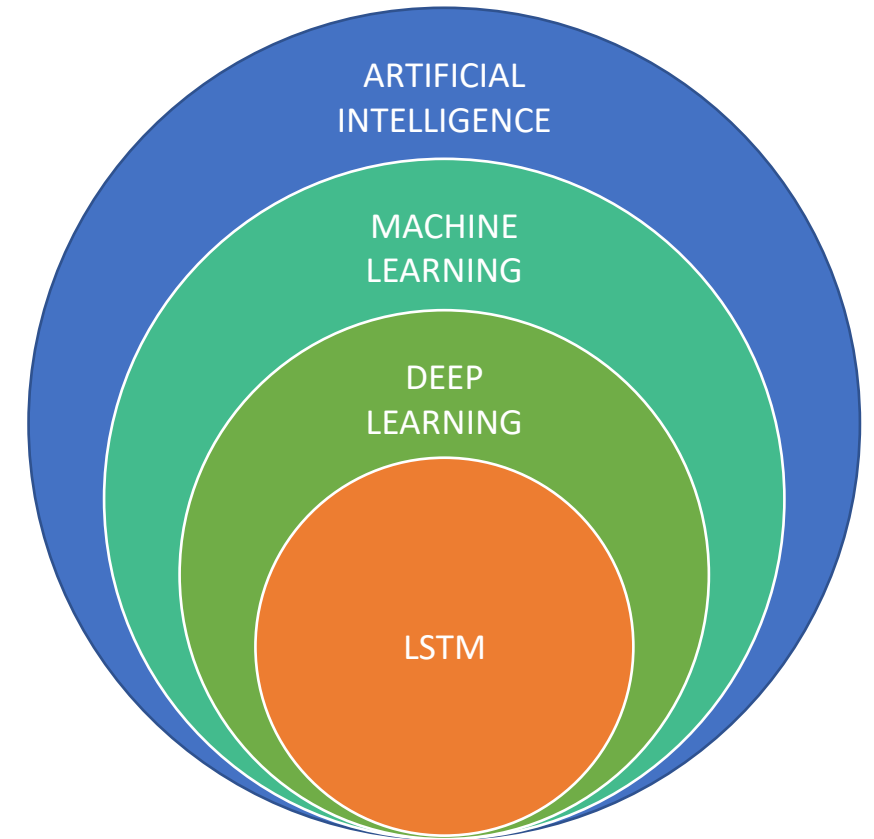
LSTM WITHIN ARTIFICIAL INTELLIGENCE

Artificial Intelligence is the broader field involving techniques that enable machines to imitate human behavior.

Machine Learning is a subset of A.I that uses statistical methods and mathematical models to make machines improve with experience.

Deep Learning is a subset of machine learning where computers try to imitate the human brain when processing data.

LSTM (Long Short-Term Memory) is a specialized architecture within deep learning, designed to handle and predict long-term dependencies in sequential data



WHY LSTM?

LSTM is a special architecture of recurrent neural networks, but...



What is a Recurrent Neural Network (RNN)?

A recurrent neural network is **deep learning algorithm** often used to work with sequential data, so...



Why don't we use RNN?

RNN struggle with long-term dependencies due to **vanishing and exploding gradient problems** (they give much more importance to the most recent data), making them less effective for long sequences compared to...



The solution, LSTM

LSTM is a variation of RNN that due to internal mechanisms can handle long sequences of data, which makes them more effective for tasks requiring long-term dependencies, and the best option for this study

MACHINE LEARNING AND GLUCOSE PREDICTIONS



Different **Machine Learning** techniques have been used to try to predict glucose signals; these techniques involve different algorithms and different input variables

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}}$$

$\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n$ are predicted values

y_1, y_2, \dots, y_n are observed values

n is the number of observations



RMSE (Root Mean Square Error) is a commonly used accuracy metric to evaluate the difference between values predicted by a model and the actual observed values

Best results within the different ML methods

Method	Authors	Input Variables	Best RMSE (mg/dL) obtained
Echo State Network	Li et al.	CGM signals	23.57
Causal CNN	Zhu et al.	CGM signals, insulin data and carbohydrate intake	21.7
Feed Forward NN	Zeccini et al.	CGM signals	7.45
SVR	Georga et al.	CGM signals, insulin data, meal intake and Energy exp.	5.7
RNN - LSTM	Mario Munoz	CGM signals, insulin data and carbohydrate (simulated)	3.45

INDEX

1. INTRODUCTION

2. STATUS OF THE QUESTION

3. MODEL

4. RESULTS

5. CONCLUSIONS AND FUTURE WORKS

MODELIZATION

DATASET

- Dataset used: D1NAMO dataset
- Contains **glucose**, **fast insulin** and **slow insulin** measures
- 20 healthy patients and 9 patients with Diabetes type I



MODEL OBJECTIVES

1. Compare **input variables** set
2. Compare **number of memory cells** and **future samples** performance
3. Tune model **hyperparameters**



MODEL ARCHITECTURE

- Environment: **Python**; relevant libraries: **TensorFlow**
1. Data loading and cleaning
 2. **Train test split** (70/30), Number of **future samples** (1, 6 and 12) , number of **memory cells** (5,10 and 15) and selection of **input variables** (glucosa, glucosa+fast insulin and glucosa+fast insulin+slow insulin)
 3. Build **Initial LSTM model**: 3 layers (64 cells, 32 cells and dropout layer), 20% dropout, 30 epochs, 0.001 learning rate -> hyperparameter optimization
 4. Model **evaluation** (RMSE) and **predictions**
 5. Visualization of results: **Predicted Values vs Real Values**



INDEX

1. INTRODUCTION

2. STATUS OF THE QUESTION

3. MODEL

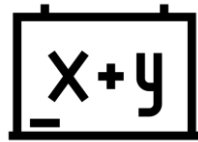
4. RESULTS

5. CONCLUSIONS AND FUTURE WORKS

EXPERIMENTS THAT HAVE BEEN CONDUCTED



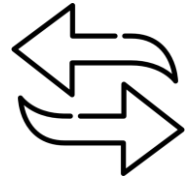
Optimal Number
of **memory cells**
(or past simples)



Best set of input
variables



Hyperparameter
Tunning



Analyze **transferability**
of the model

Model 1: Glucose as input variable

Model 2: Glucose + Fast insulin as input variables

Model 3: Glucose + Fasta Insulin + Slow Insulin as input variables



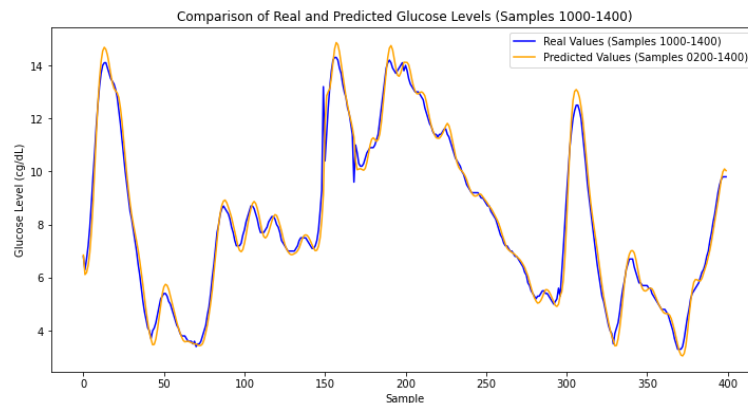
OPTIMAL NUMBER OF MEMORY CELLS FOR MODEL 1

Number of past samples	1 Future sample	6 future samples	12 future samples
5	0.61	1.52	2.6
10	0.54	1.4	2.56
15	0.5	1.4	2.52

RMSE in cg/dL

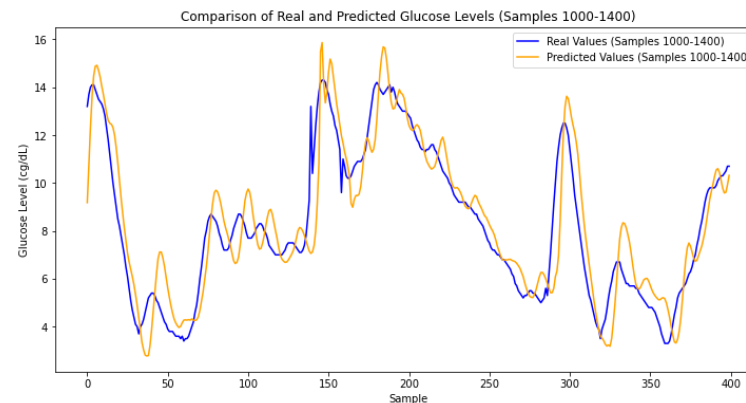
1 future sample: 5 minutes time horizon
 6 future sample: 30 minutes time horizon
 12 future sample: 60 minutes time horizon

Predicting 1 future sample

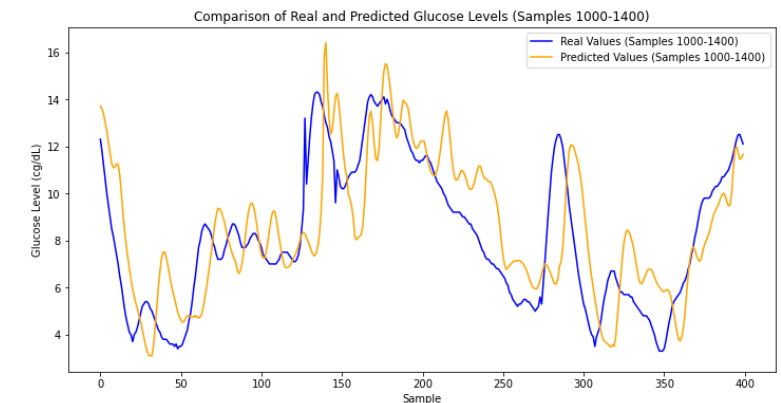


Real Values
 Predicted Values

Predicting 6 future samples



Predicting 12 future samples



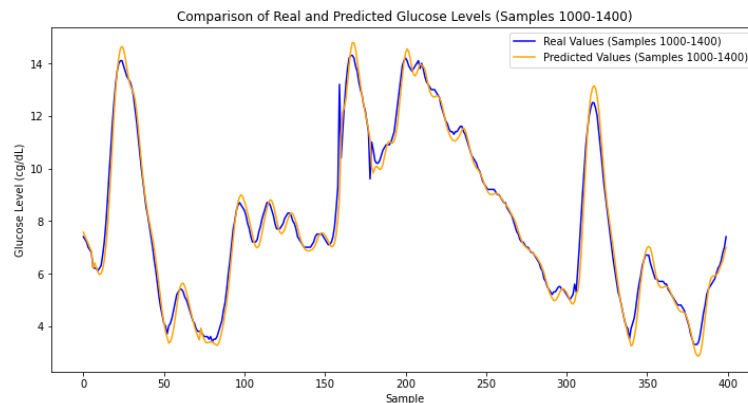
OPTIMAL NUMBER OF MEMORY CELLS FOR MODEL 2

Number of past samples	1 Future sample	6 future samples	12 future samples
5	0.51	1.39	2.55
10	0.5	1.36	2.45
15	0.55	1.37	2.65

1 future sample: 5 minutes time horizon
 6 future sample: 30 minutes time horizon
 12 future sample: 60 minutes time horizon

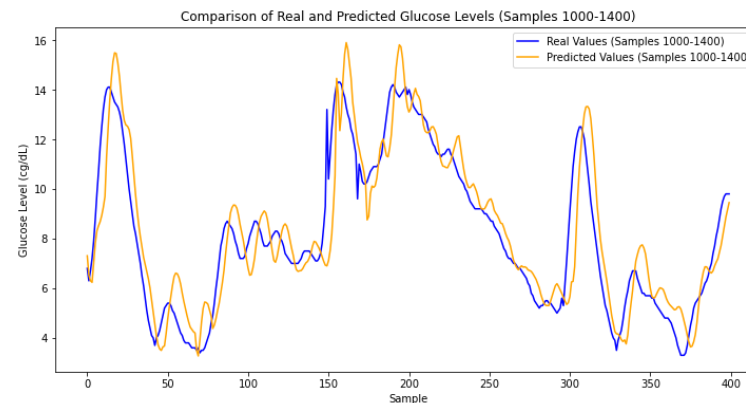
RMSE in cg/dL

Predicting 1 future sample

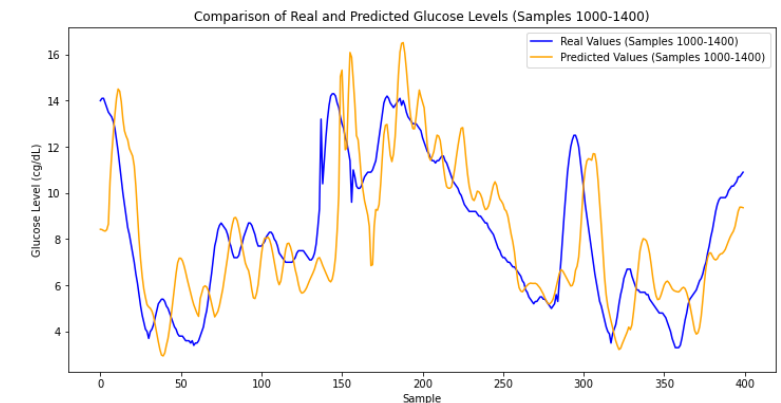


Real Values
 Predicted Values

Predicting 6 future samples



Predicting 12 future samples



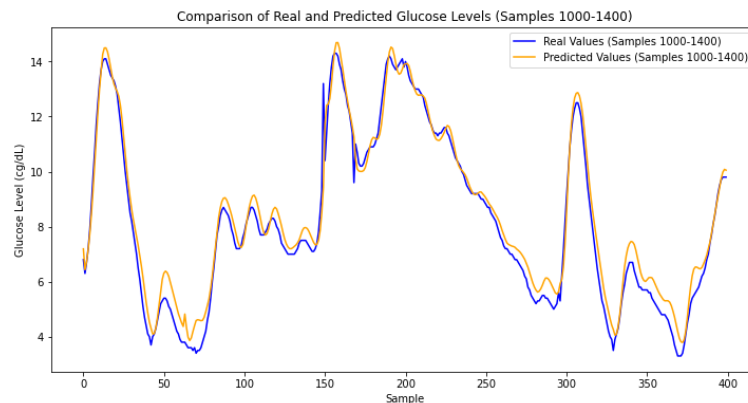
OPTIMAL NUMBER OF MEMORY CELLS FOR MODEL 3

Number of past samples	1 Future sample	6 future samples	12 future samples
5	0.51	1.4	2.62
10	0.5	1.4	2.61
15	0.49	1.38	2.6

RMSE in cg/dL

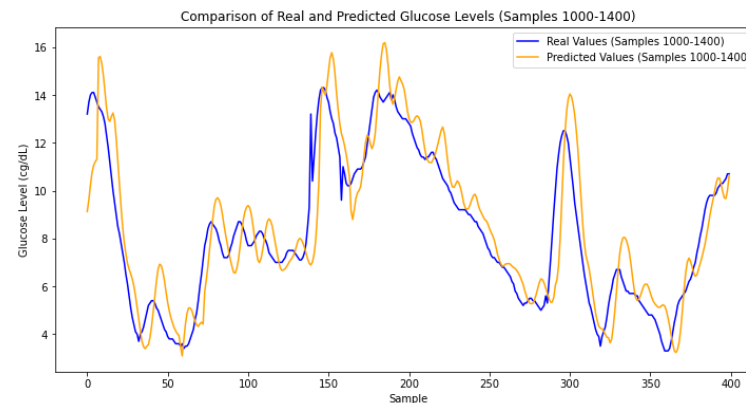
1 future sample: 5 minutes time horizon
 6 future sample: 30 minutes time horizon
 12 future sample: 60 minutes time horizon

Predicting 1 future sample

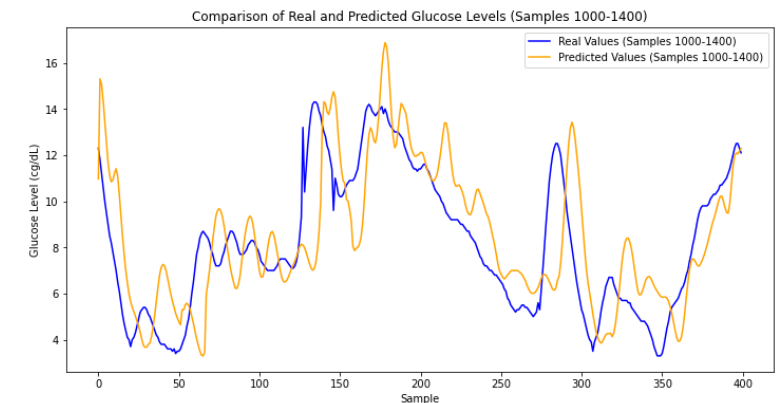


Real Values
 Predicted Values

Predicting 6 future samples

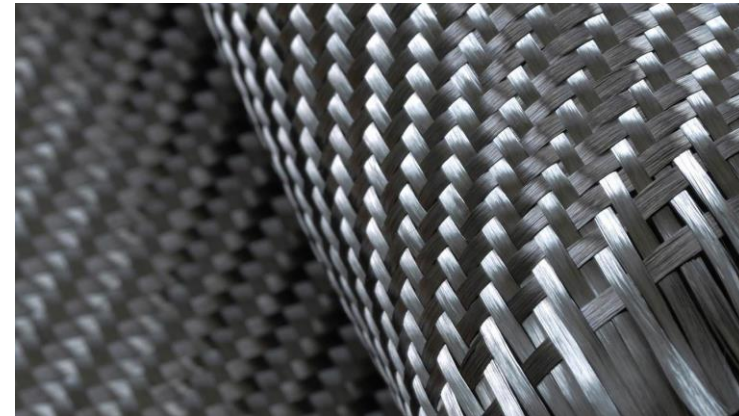
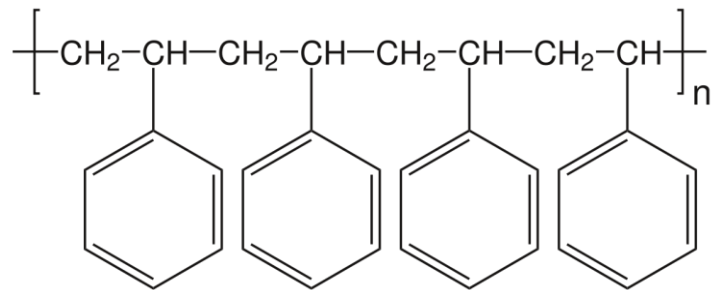


Predicting 12 future samples



¿Qué es un CFRP?

Matriz: Polimérica + Refuerzo: Fibra de Carbono

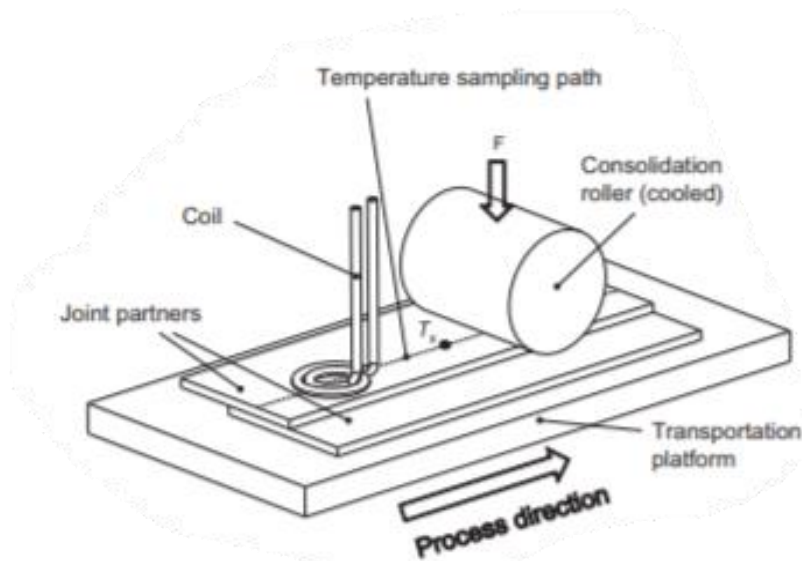


Calentamiento por inducción electromagnética

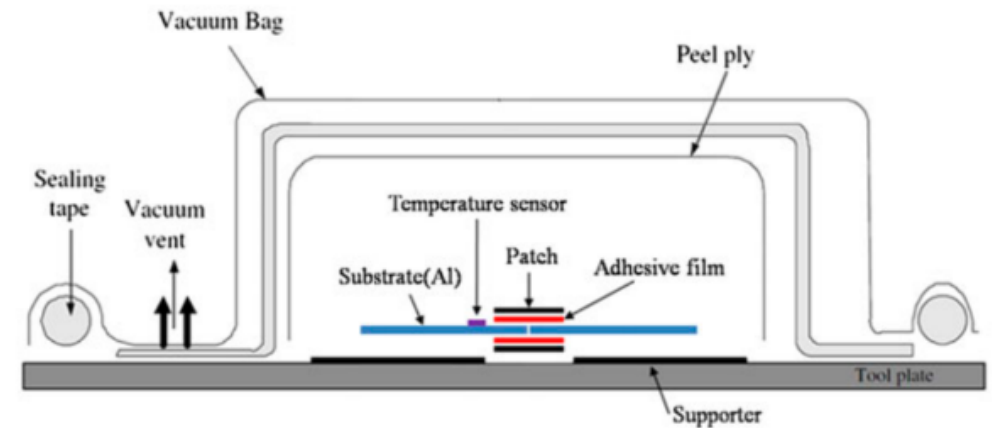


Aplicaciones del calentamiento por inducción

Soldadura por inducción electromagnética



Curación por inducción electromagnética



Análisis numérico

- Método de elementos finitos (MEF)
- Calculo estructural, Automóviles (BMW), Deporte (SPEEDO)...
- LS-DYNA



Índice:

1.- Introducción

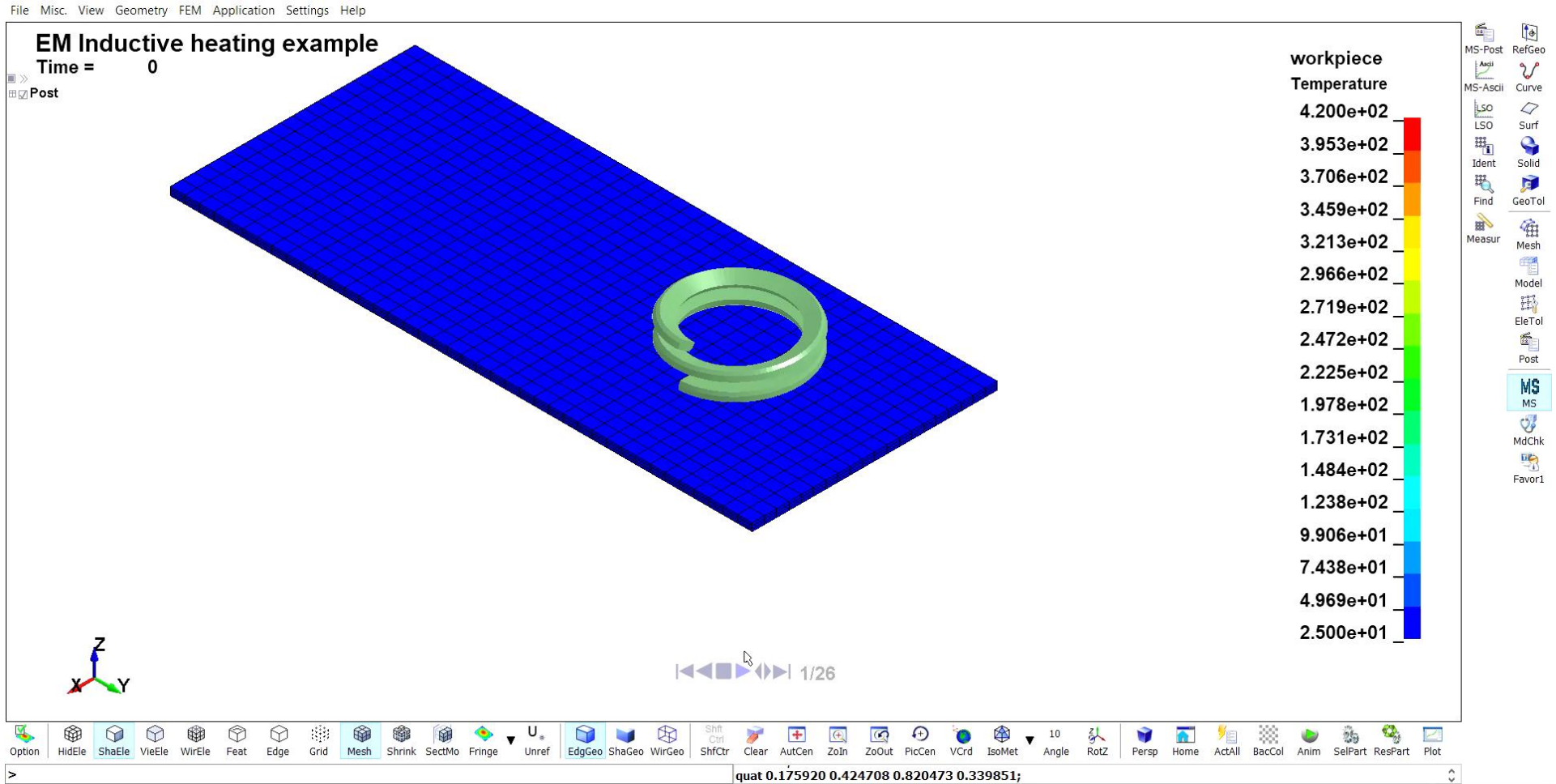
2.- Estado del arte

3.- Modelo

4.- Resultados

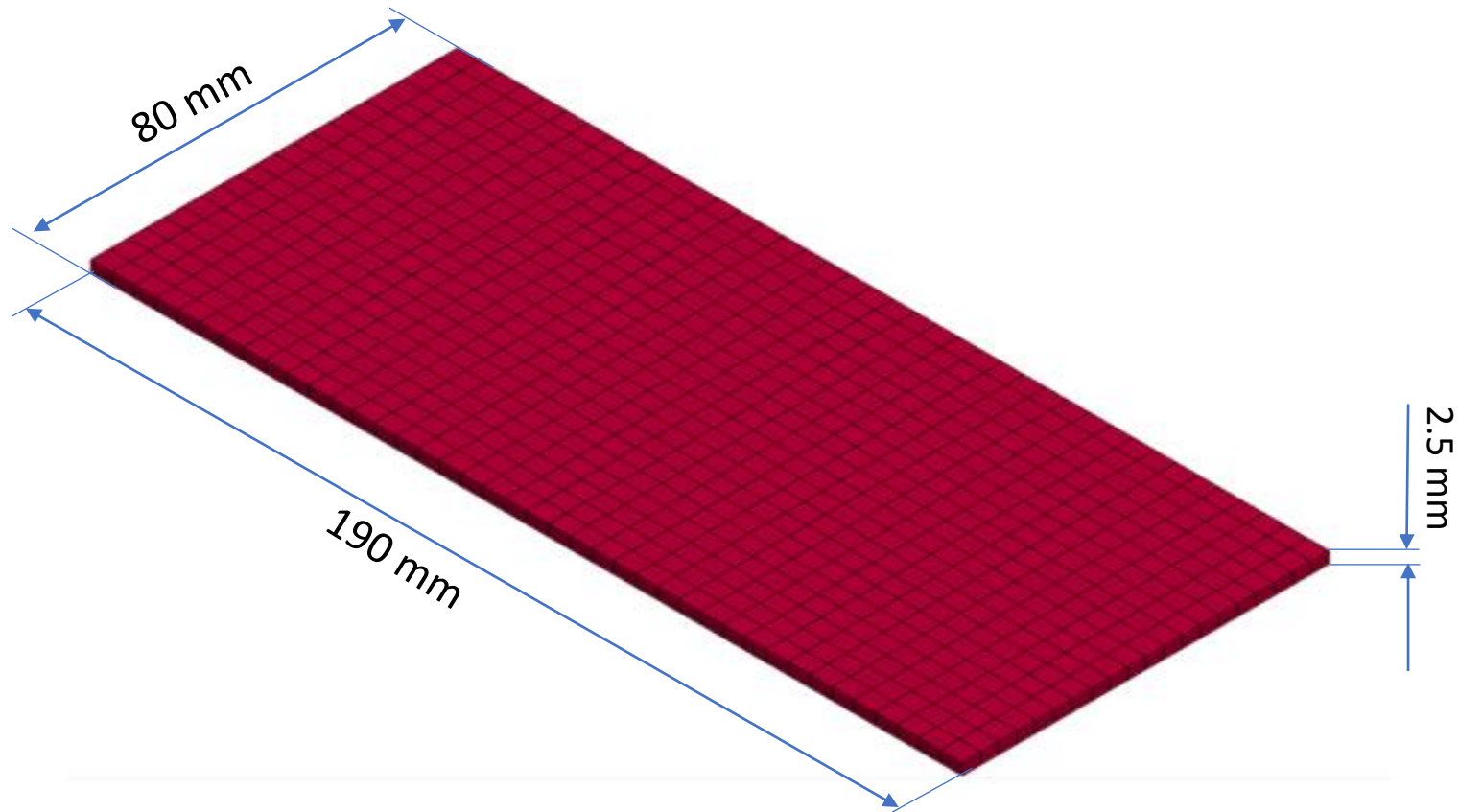
5.- Conclusiones y trabajos futuros

Ejemplo de simulación



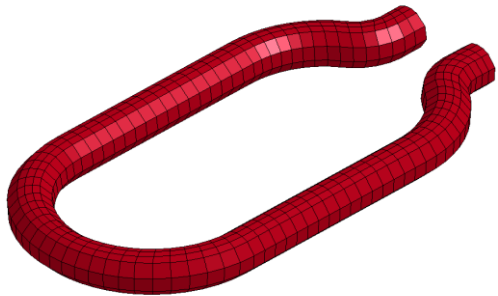
Geometrías y mallado

Placa de CFRP



Geometrías y mallado

Inductor tipo ovalo

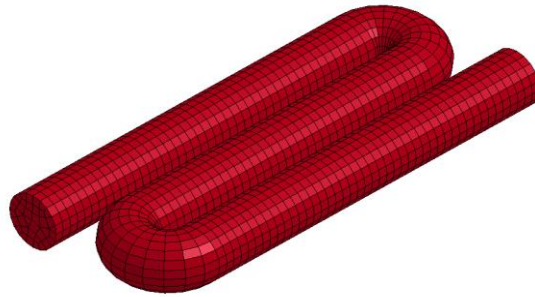


Sección: $\varnothing=5$ mm

Longitud=135 mm

Elementos: 792

Inductor tipo serpiente

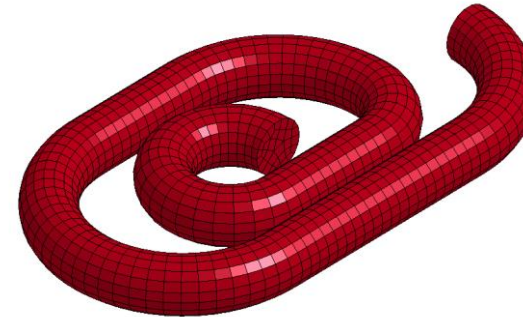


Sección: $\varnothing=5$ mm

Longitud=137 mm

Elementos: 5439

Inductor tipo clip

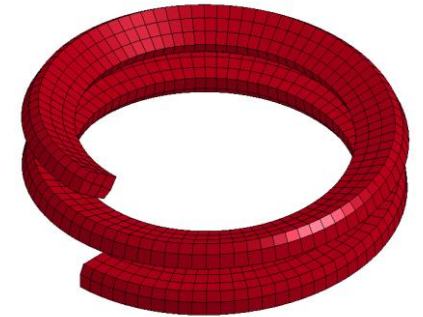


Sección: $\varnothing=4.5$ mm

Longitud=140 mm

Elementos: 4256

Inductor tipo hélice



Sección: $\square=5 \times 2.5$ mm

Longitud=220 mm

Elementos: 1020

Materiales

- Placa de CFRP: CF/PPS (50% FC)

Densidad	Mod.Young	Ratio Poisson	Cond.Termica	Cond.Electrica	Calor Específico
0.00157 g/mm ³	6.8x10 ⁹ Pa	0.22	X: 2.5 W/m×°C Y: 2.5 W/m×°C Z: 0.32 W/m×°C	X: 1.39x10 ⁴ S/m Y: 1.39x10 ⁴ S/m Z: 10 ⁻¹³ S/m	0.95 J/°C

- Inductor: Aleación de Cobre

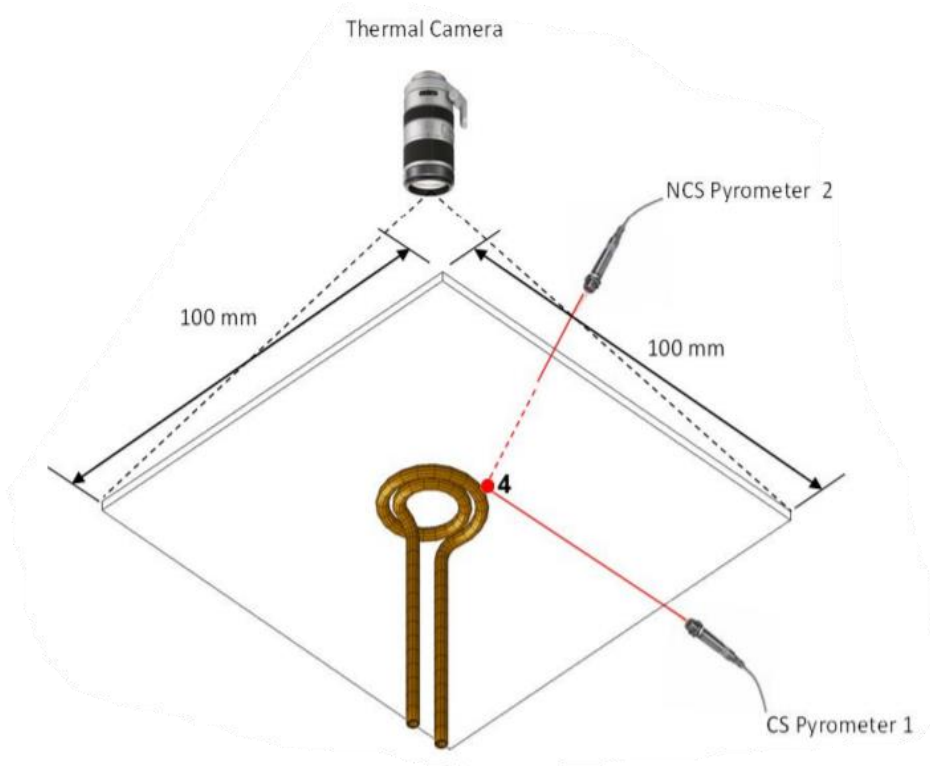
Densidad	Mod.Young	Ratio Poisson	Cond.Termica	Cond.Electrica	Calor Específico
0.00849 g/mm ³	2x10 ¹¹ Pa	0.33	238 W/m×°C	25x10 ⁶ S/m	0.896 J/°C

Aspectos relevantes

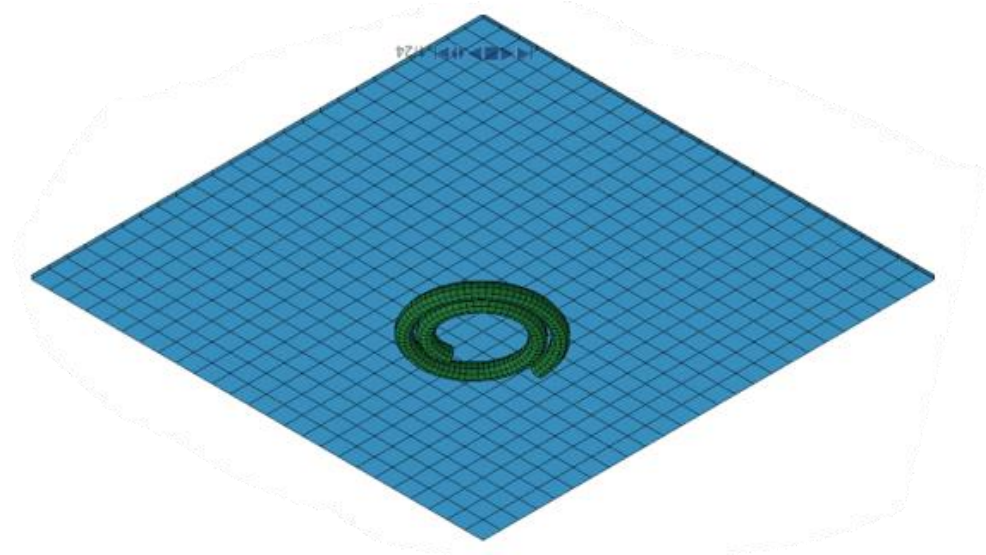
- Circuito del inductor: Intensidad (A) y Frecuencia (Hz)
- Temperatura inicial 25°C
- Velocidad constante en el eje y
- Tiempo de duración 20 s

Validación metodología de simulación

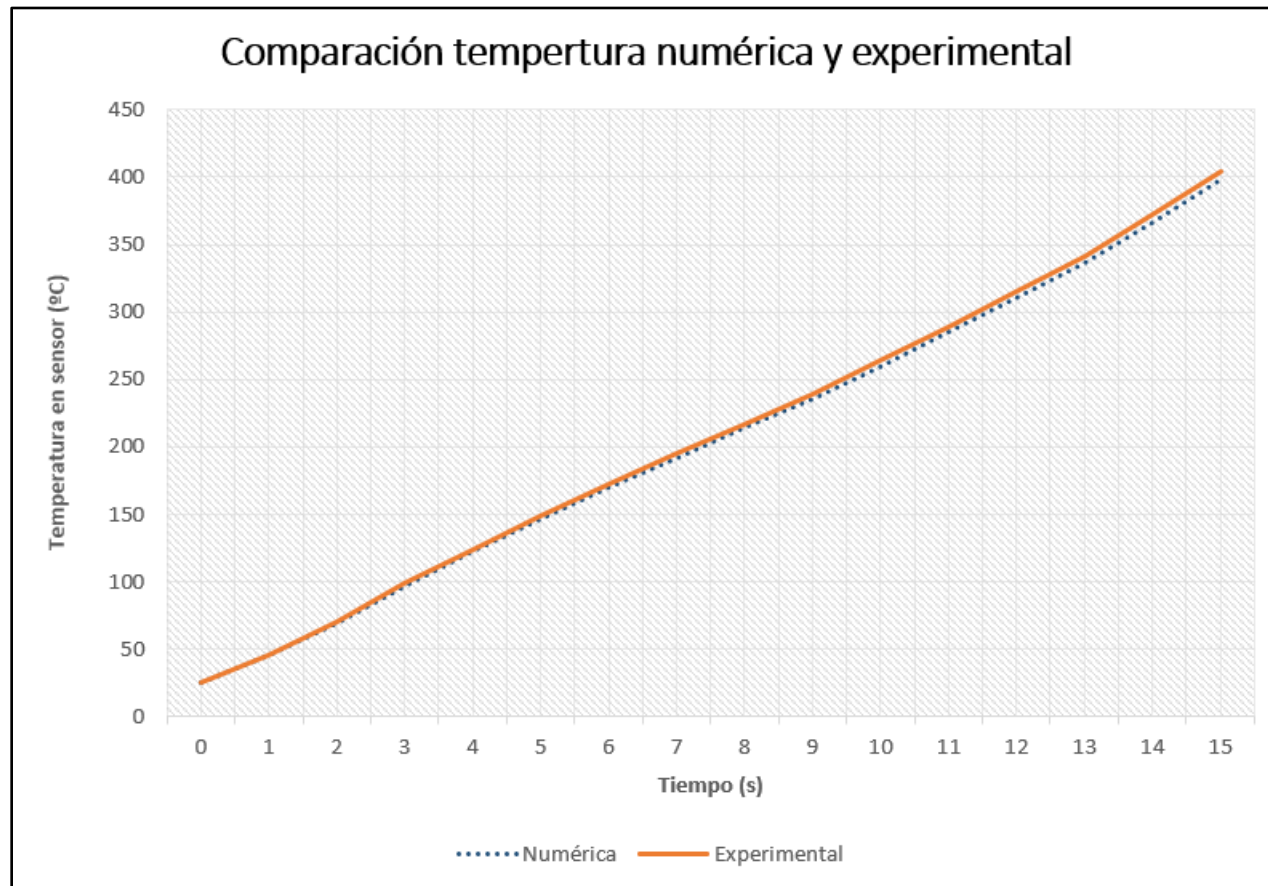
Experimento instituto *Verbundwerkstoffe*



Recreación en LS-DYNA



Validación metodología de simulación



T=15 s: $T_{\text{MAX Exp.}} = 404.3^{\circ}\text{C}$

$T_{\text{MAX Num.}} = 397.8^{\circ}\text{C}$

$$\text{Error relativo} = \frac{|\text{Valor experimental} - \text{Valor numérico}|}{\text{Valor experimental}}$$

Error relativo(%)=1.6%



Índice:

1.- Introducción

2.- Estado del arte

3.- Modelo

4.- Resultados

5.- Conclusiones y trabajos futuros

Introducción a los resultados

- Se analizan 4 variables (geometría, distancia, intensidad y frecuencia)
- Temperatura máxima Placa
- Temperatura del inductor
- Temperatura de trabajo [420;450] °C

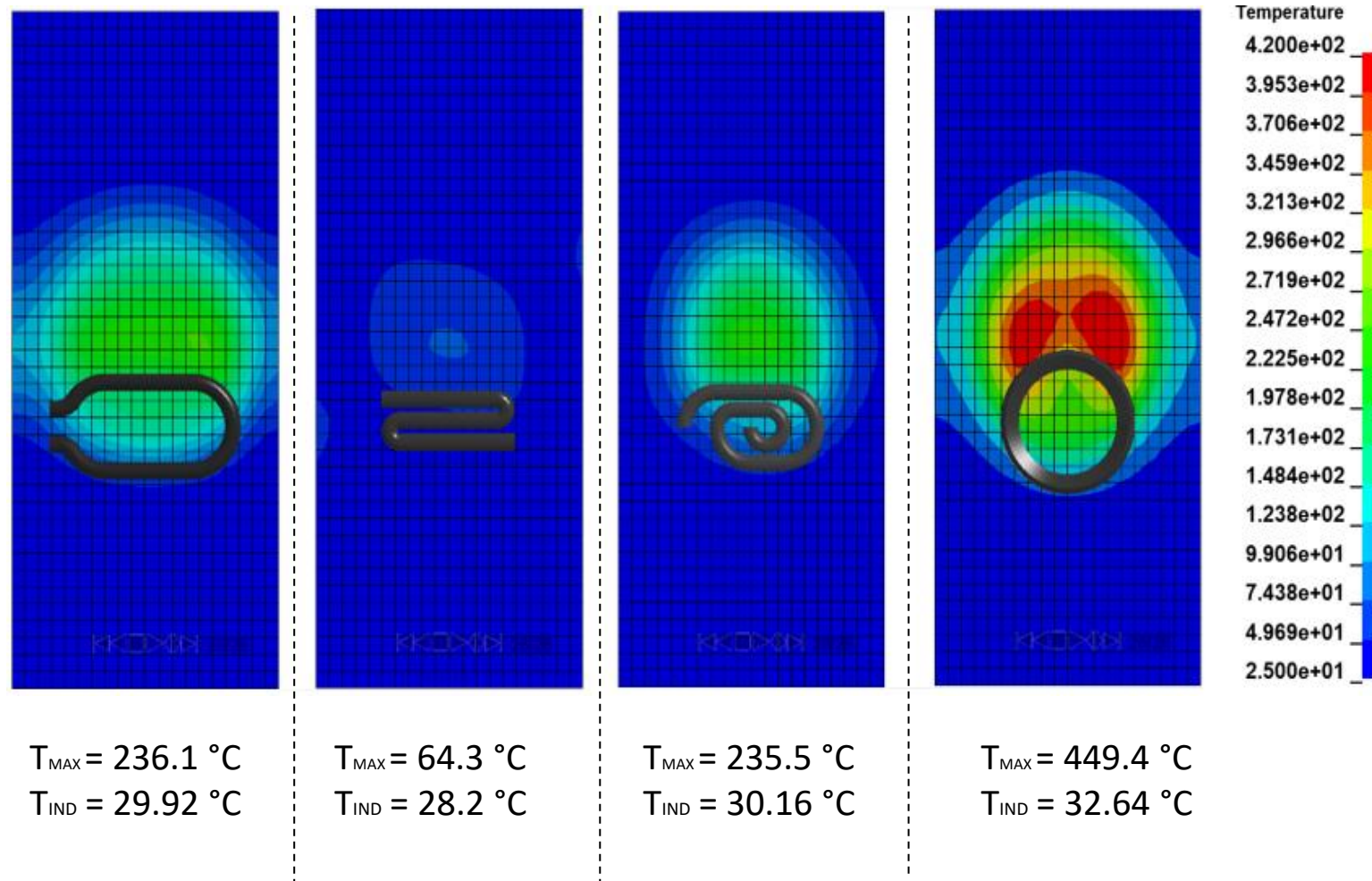
Comparación geometrías

- Análisis de 4 geometrías: Ovalo, clip serpiente y hélice

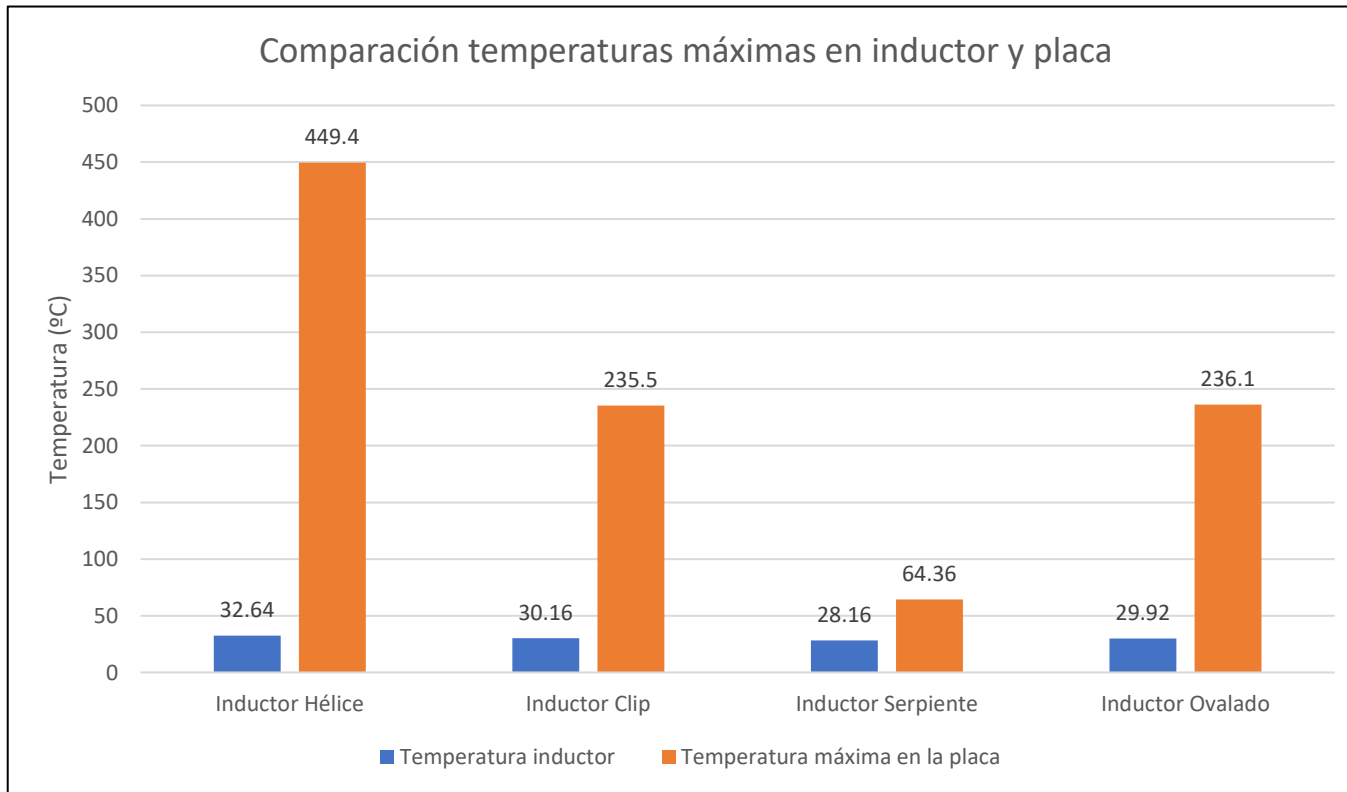
Condiciones iniciales

Distancia placa-inductor	5 mm
Frecuencia inductor	1 MHz
Intensidad inductor	100 A
Velocidad placa	2 mm/s

Comparación geometrías inductor



Comparación geometrías inductores



$$\text{Ratio aumento de temperaturas} = \frac{T_{\text{maxplaca}} - T_{\text{inicial}}}{T_{\text{maxinductor}} - T_{\text{inicial}}}$$

	Inductor ovalado	Inductor clip	Inductor serpiente	Inductor hélice
Ratio	42.9	40.79	12.45	55.55



Conclusiones (geometrías)

- Mayor temperatura en placa → Inductor tipo hélice
- Temperatura aceptable del inductor tipo hélice
- Mejor ratio aumento temperatura → Inductor tipo hélice

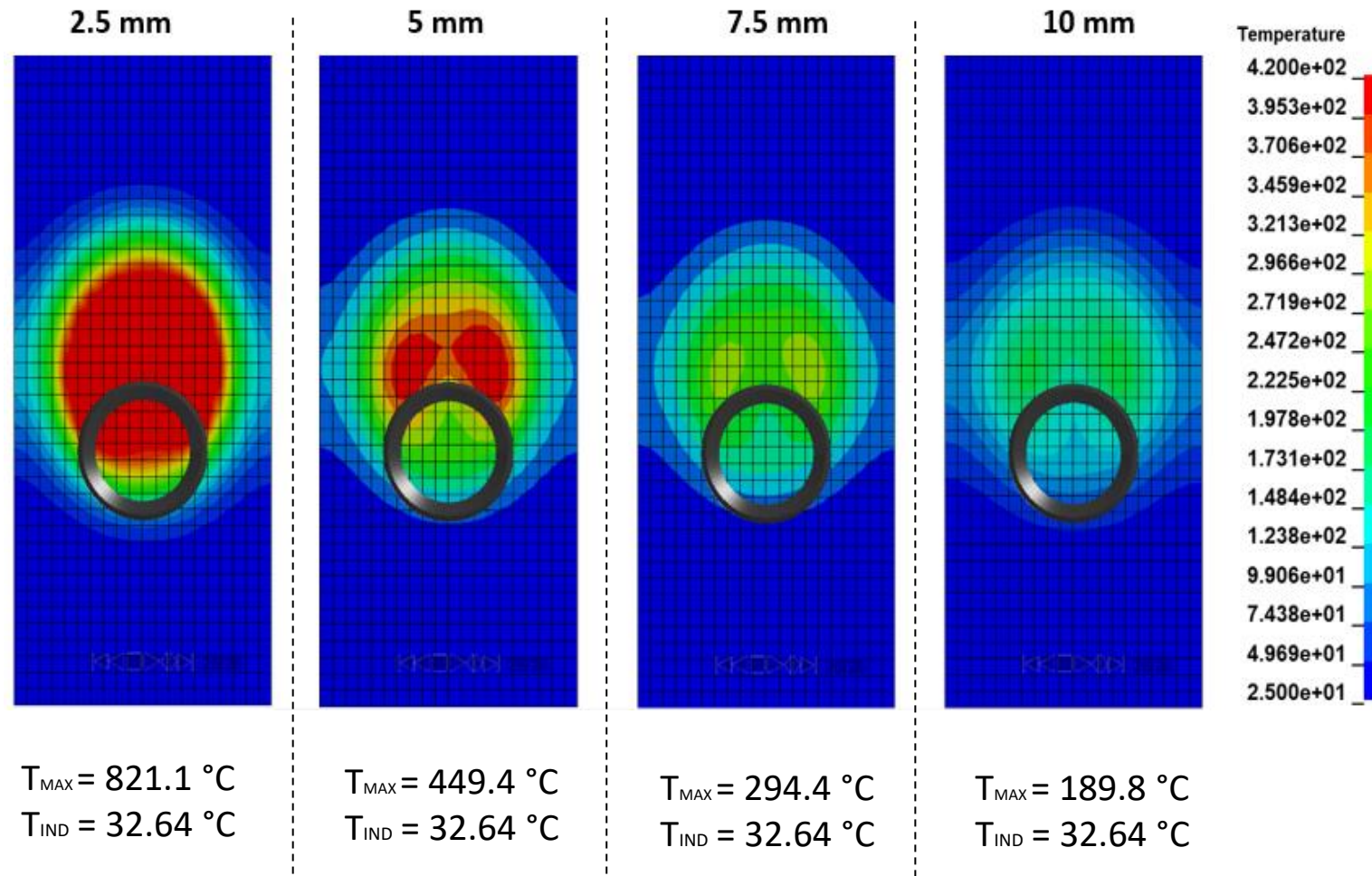
Comparación distancias placa-inductor

- Análisis 4 distancias: 2.5, 5, 7.5, 10 mm

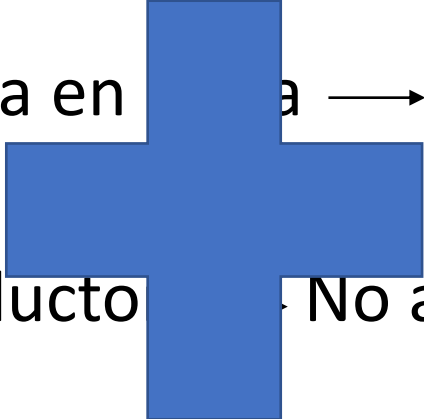
Condiciones iniciales

Geometría del inductor	Hélice
Frecuencia inductor	1 MHz
Intensidad inductor	100 A
Velocidad placa	2 mm/s

Comparación distancias placa-inductor



Conclusiones (distancias)

- 
- Mayor temperatura en placa \rightarrow Menor distancia (2.5 mm)
 - Distancia placa-inductor \rightarrow No afecta temperatura inductor
 - No hay inconvenientes

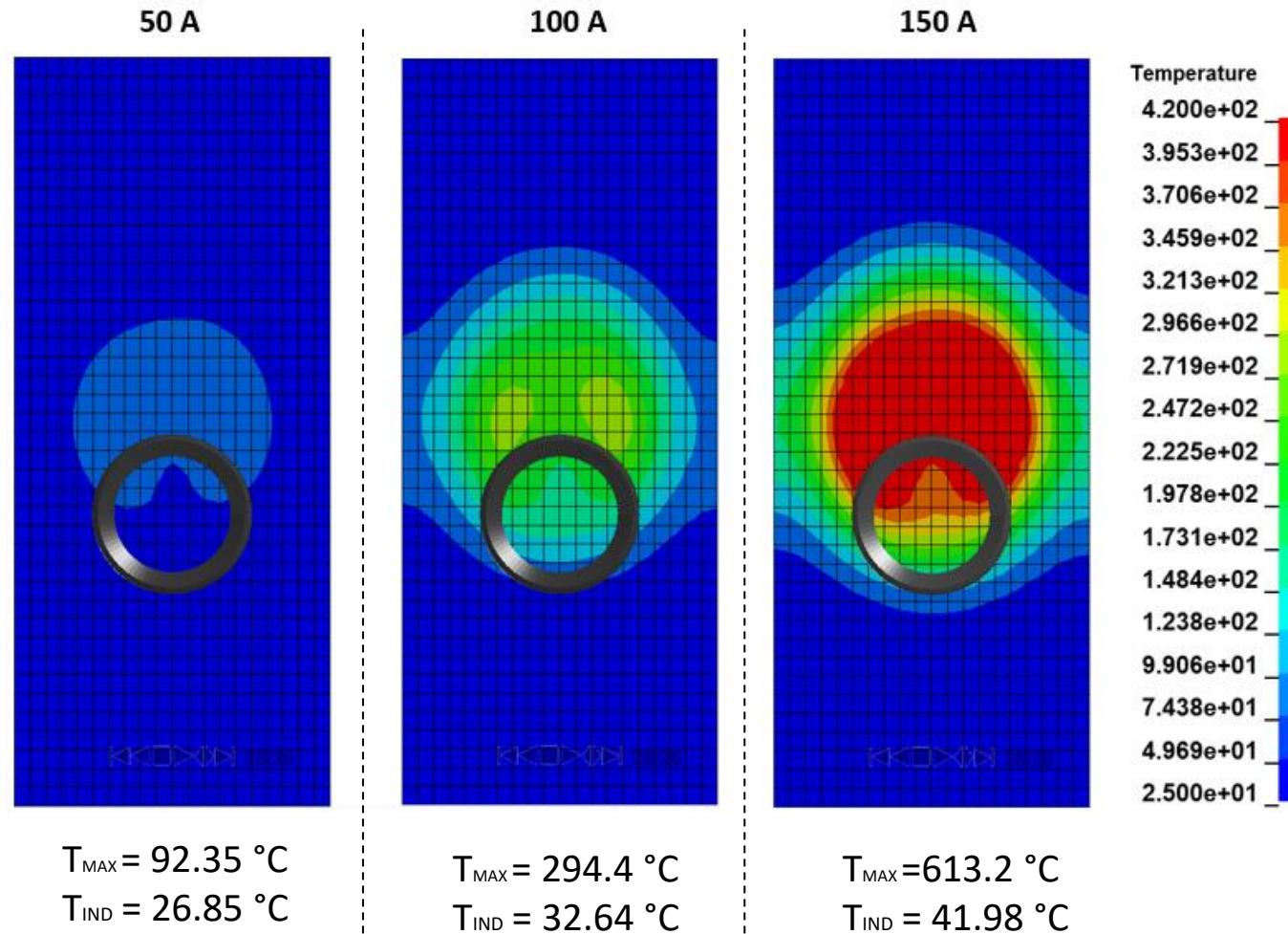
Comparación intensidades

- Análisis 3 intensidades: 50, 100, 150 A

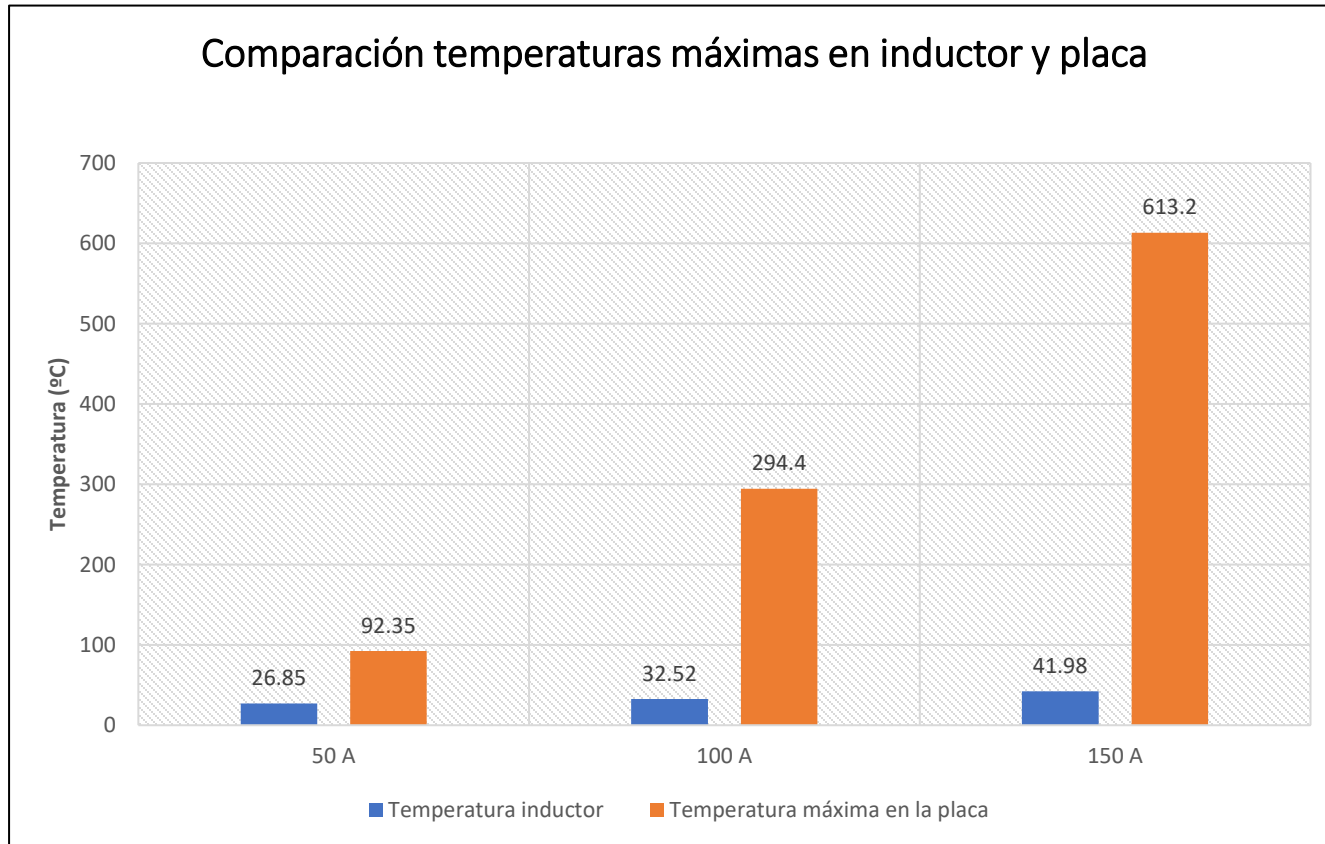
Condiciones iniciales

Geometría del inductor	Hélice
Frecuencia inductor	1 MHz
Distancia placa-inductor	7.5 mm
Velocidad placa	2 mm/s

Comparación intensidades



Comparación intensidades




$$\text{Ratio aumento de temperaturas} = \frac{T_{\text{maxplaca}} - T_{\text{inicial}}}{T_{\text{maxinductor}} - T_{\text{inicial}}}$$

	50 A	100 A	150 A
Ratio	36.4	35.82	34.64



Conclusiones (intensidades)

- Mayor temperatura en placa \longrightarrow Mayor intensidad (150A)
- Mejor ratio aumento temperatura \longrightarrow Menor intensidad (50A)
- Temperatura del inductor 

Comparación frecuencias

- Análisis 5 frecuencias: 0.5, 1, 1.5, 2 y 2.5 MHz

Condiciones iniciales

Geometría del inductor	Hélice
Distancia placa-inductor	5 mm
Intensidad inductor	100 A
Velocidad placa	2 mm/s

$$\delta = \sqrt{\frac{\rho}{\mu \cdot \pi \cdot f}}$$

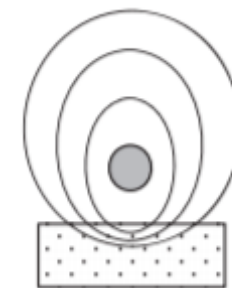
SKIN EFFECT

δ : profundidad de penetración

ρ : densidad

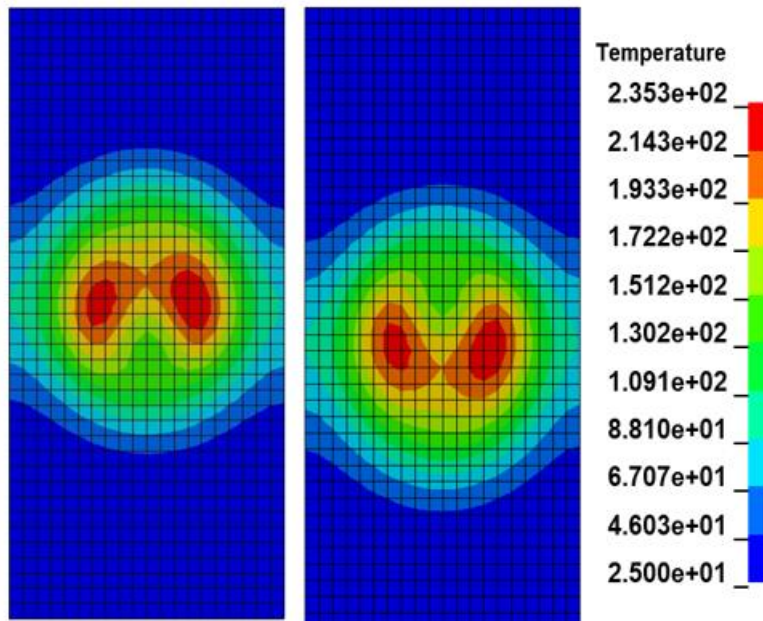
μ : permeabilidad magnética

f : frecuencia del inductor



Comparación de frecuencias (skin effect)

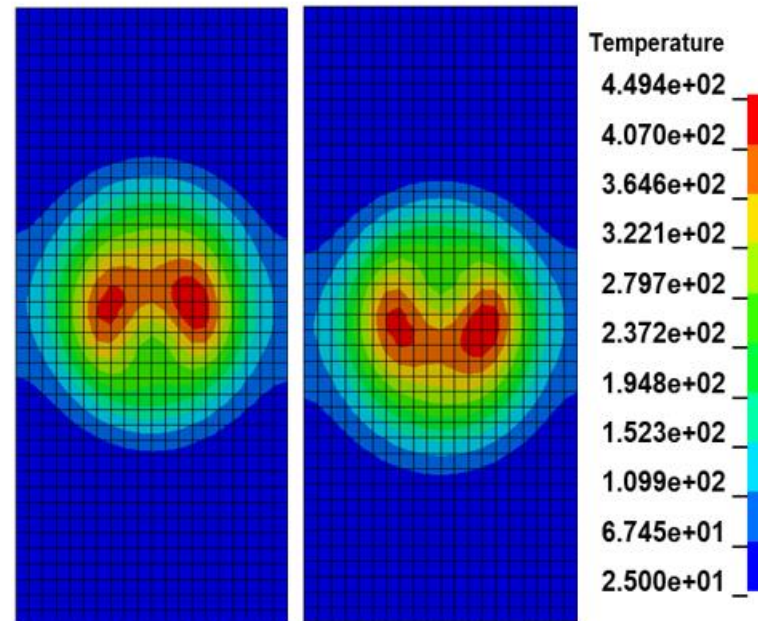
0.5 MHz



- Misma distribución de temperaturas
- Misma temperatura máxima

NO SKIN EFFECT

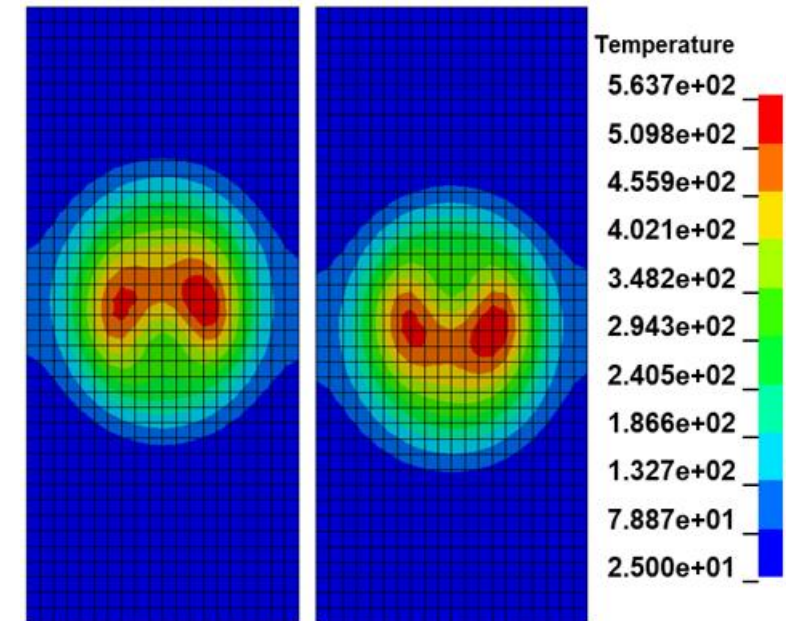
1 MHz



- Misma distribución de temperaturas
- Misma temperatura máxima

NO SKIN EFFECT

1.5 MHz

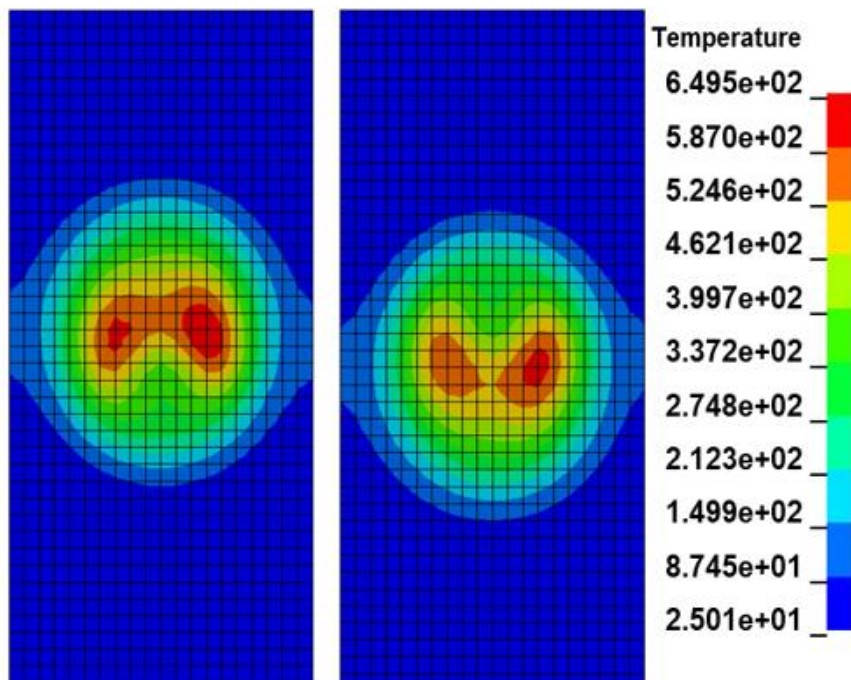


- Misma distribución de temperaturas
- Misma temperatura máxima

NO SKIN EFFECT

Comparación de frecuencias (skin effect)

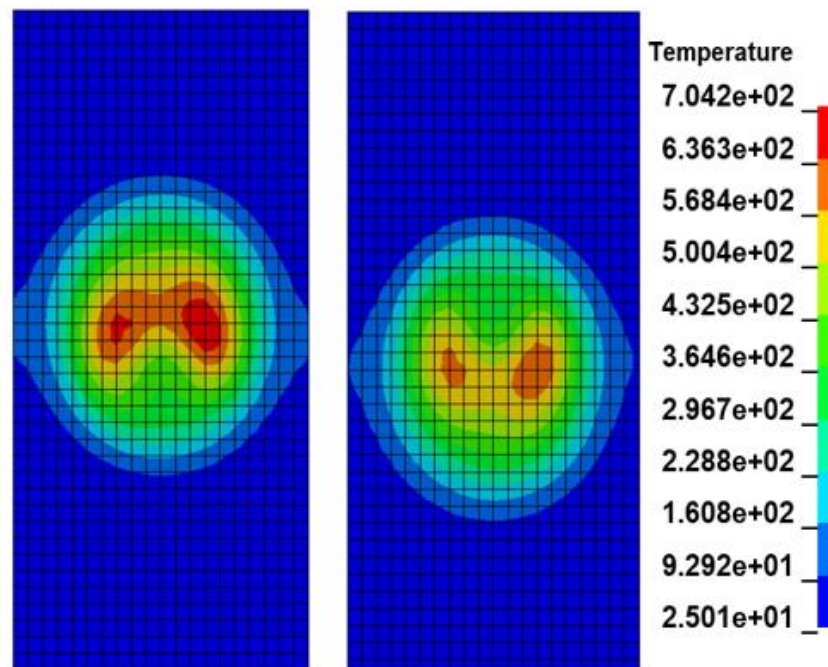
2 MHz



- Distinta distribución de temperaturas
- Misma temperatura máxima

SÍ SKIN EFFECT

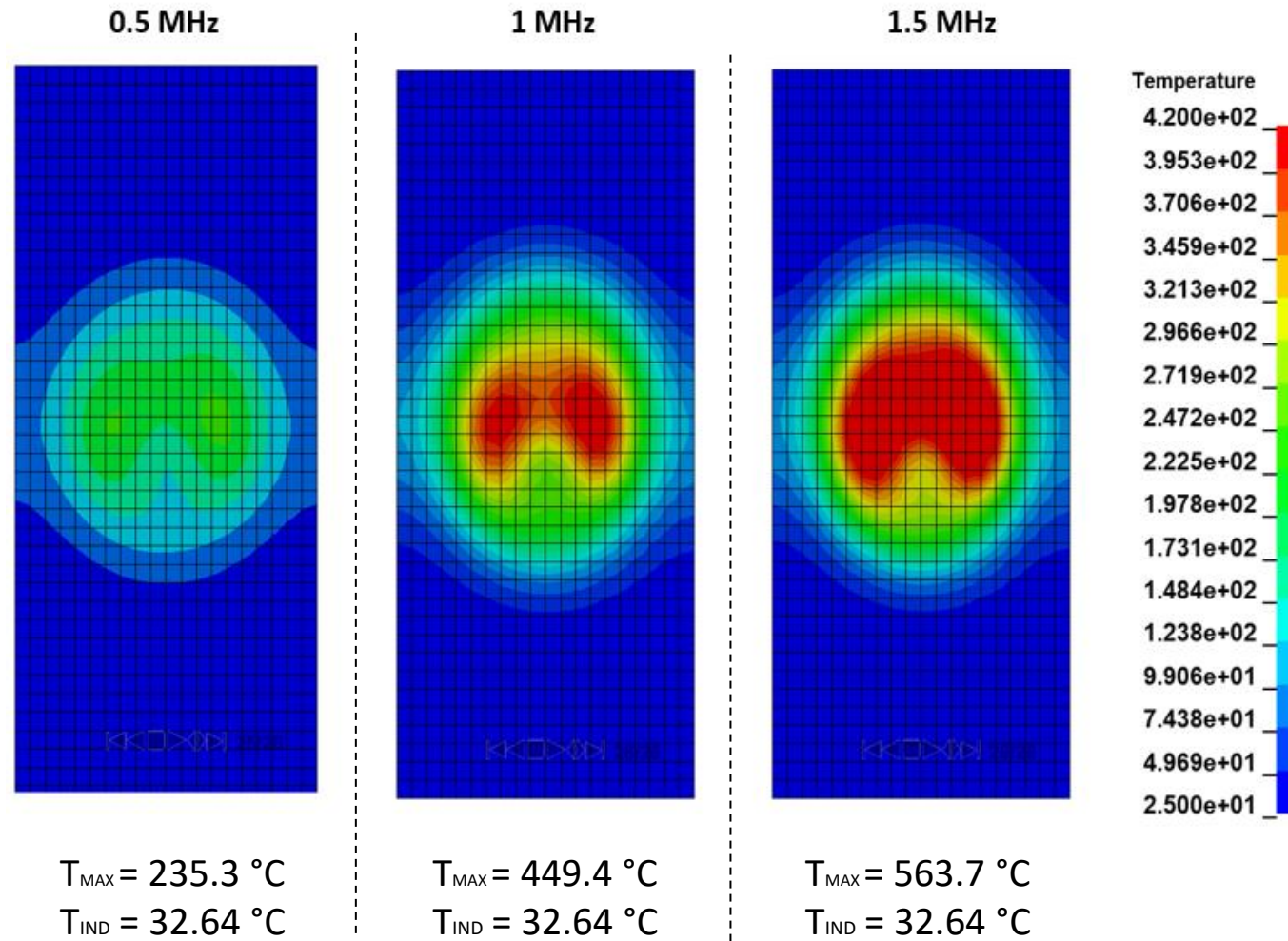
2.5 MHz




- Distinta distribución de temperaturas
- Distinta temperatura máxima

SÍ SKIN EFFECT

Comparación frecuencias



Conclusiones (frecuencias)

- Frecuencia más alta —→ mayor temperatura en placa
- No afecta temperatura factor
- Skin effect 
- Equilibrio temperatura-profundidad

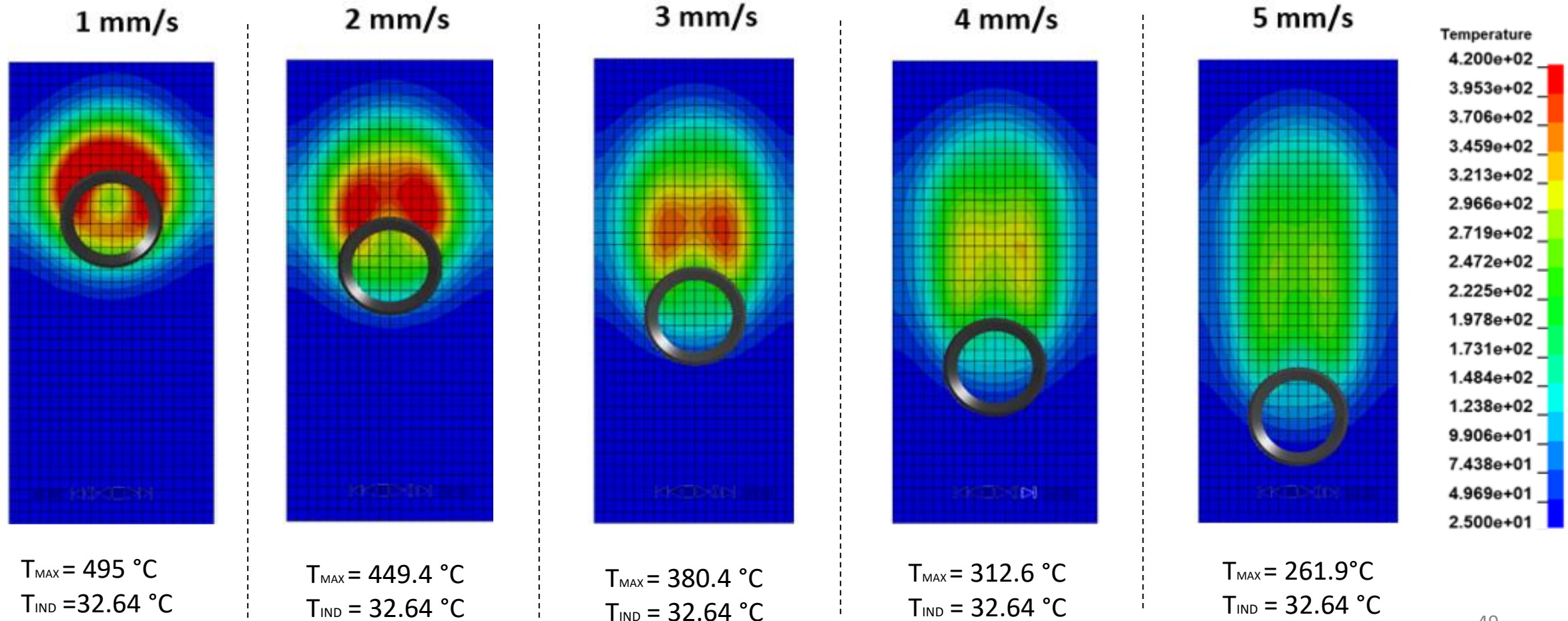
Comparación velocidades

- Análisis 5 velocidades: 1, 2, 3, 4 y 5 mm/s

Condiciones iniciales

Geometría del inductor	Hélice
Frecuencia inductor	1 MHz
Distancia placa-inductor	7.5 mm
Intensidad inductor	100 A

Comparación velocidades



Conclusiones (velocidades)

- Mayor velocidad \longrightarrow Mayor temperatura en placa
- Mayor velocidad \longrightarrow Mayor área calentada
- No afecta al inductor

Optimización calentamiento

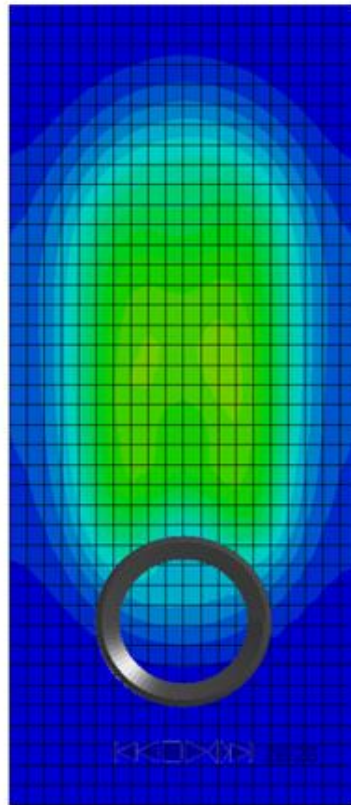
Condiciones	Geometría inductor	Intensidad inductor	Distancia placa-inductor	Frecuencia inductor	Velocidad	T _{MAX} placa
Iniciales	Hélice	100 A	5 mm	1 MHz	5 mm/s	261.9 °C



Condiciones	Geometría inductor	Intensidad inductor	Distancia placa-inductor	Frecuencia inductor	Velocidad	T _{MAX} placa
Iniciales	Hélice	150 A	2.5 mm	1.5 MHz	15 mm/s	432 °C

Optimización calentamiento

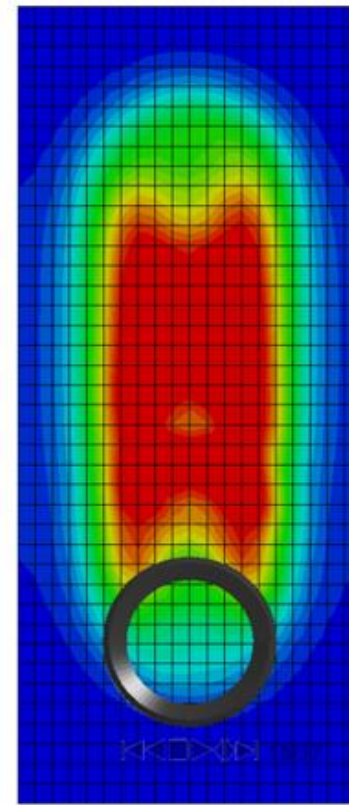
Probema inicial ($v=5$ mm/s)



$T_{\text{MAX}} = 261.9$ °C

$T_{\text{IND}} = 32.64$ °C

Problema optimizado ($v=15$ mm/s)



$T_{\text{MAX}} = 432$ °C

$T_{\text{IND}} = 41.98$ °C



Índice:

1.- Introducción

2.- Estado del arte

3.- Modelo

4.- Resultados

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Conclusiones

- Modelo numérico adaptable
- Estudiado diversas variables
- Optimizado de un proceso de calentamiento por inducción
- Estudio de las diferentes variables facilitará la implementación

Trabajos futuros

- Estudio de variables diferentes
- Estudio del efecto de la secuencia de apilamiento
- Aplicación de este estudio en soldadura electromagnética

Gracias por la atención

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Tutor: Jesús Pernas Sánchez

16/julio/2020, Madrid.