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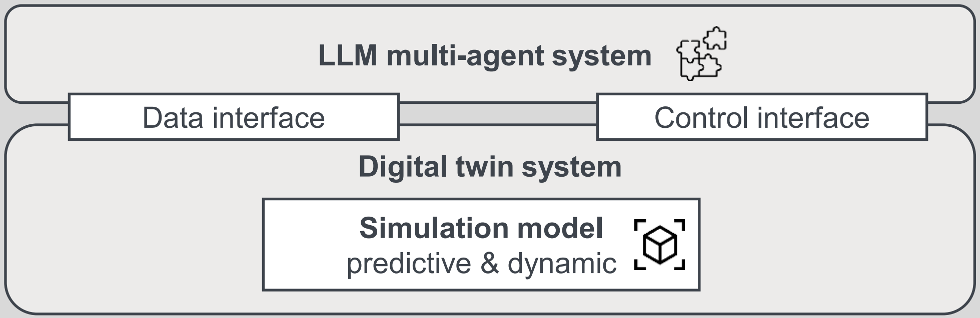

Integrating **Large Language Model Agents** with **Simulation Model** for Smart Oven Control

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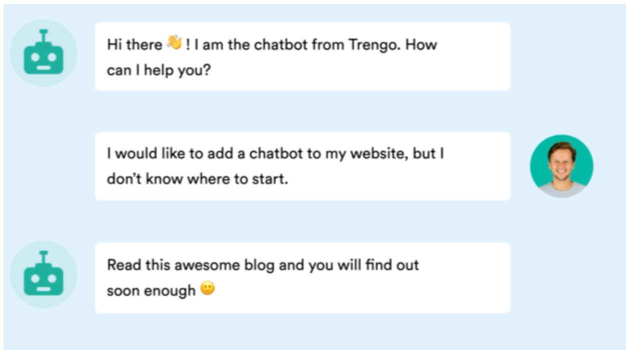
Examiner: Prof. Dr. Ing. Michael Weyrich

Introduction

- General Application of LLM
- Special Application
- LLM Agents

General applications

LLM for natural language processing and chatbot



Chatbot

ChatGPT — From OpenAI

Bard — From Google

Claude — From Anthropic

Natural Language/ Code/ etc. → LLM → Natural Language/ Code/ etc. (Text)

Special applications

LLM Agent Used in **Automation Tasks**

Coding in software engineering [1][2][3]

[1] Assessing the Capabilities of ChatGPT to Improve Additive Manufacturing Troubleshooting
[2] CodeT: Code Generation with Generated Tests
[3] CodeBERT: A Pre-Trained Model for Programming and Natural Languages

[4] ChatTwin: Toward Automated Digital Twin Generation for Data Center via Large Language Models
[5] Empowering digital twins with large language models for global temporal feature learning
[6] ProAgent: From Robotic Process Automation to Agentic Process Automation

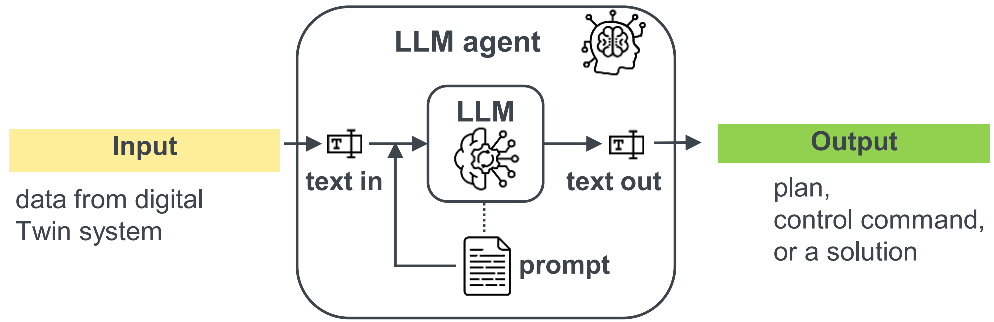
Interact with Industrial Digital Twin[4][5][6]

Perform specific tasks[7][8][9]

[7] LLMind: Orchestrating AI and IoT with LLM for Complex Task Execution
[8] Tidybot: Personalized robot assistance with large language models
[9] Large Language Models for Supply Chain Optimization

LLM Agent

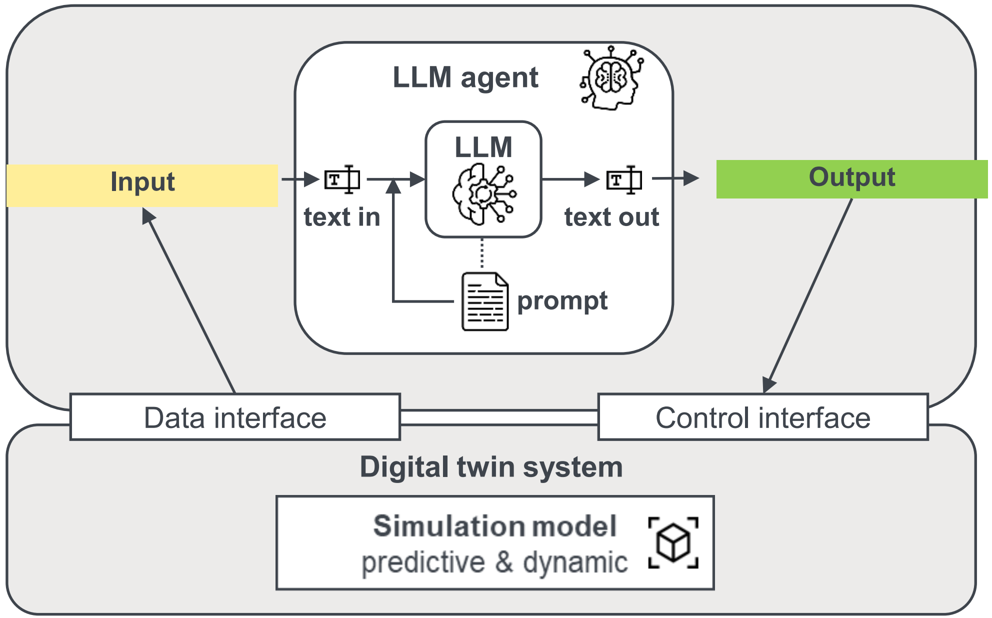
For automate tasks



Compared To Traditional Agent:

- Enhanced Capability of Natural Language Understanding
- Enhanced Capability of Handling **Variable** Tasks

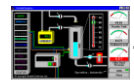
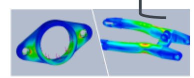
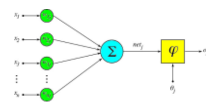
Apply LLM Agent to Interact with Simulation Model



Xia, Y., Dittler, D., Jazdi, N., Chen, H., & Weyrich, M. (2024). LLM experiments with simulation: Large Language Model Multi-Agent System for Process Simulation Parametrization in Digital Twins. https://arxiv.org/abs/2405.18092v1

Use Case

Simulation Model in This Research

- **Process control** 
  - **System Monitor**
  - **Planning**
  - **Control**
- Physical world model (CAD, FEA) 
- Mathematical models 
- etc.

Simulation model
predictive & dynamic

Case Study: Heating Process Simulation

- Heat treatment of metals
- Automotive Paint Baking
- **Household Oven** SIMULINK

Manufacturing process:

Heating and Ventilation

Home device:

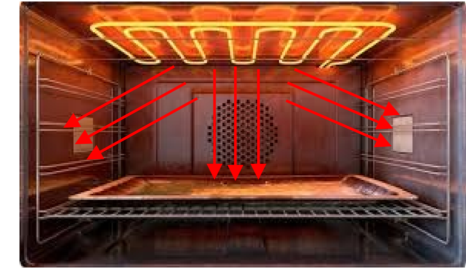
Cooking Oven

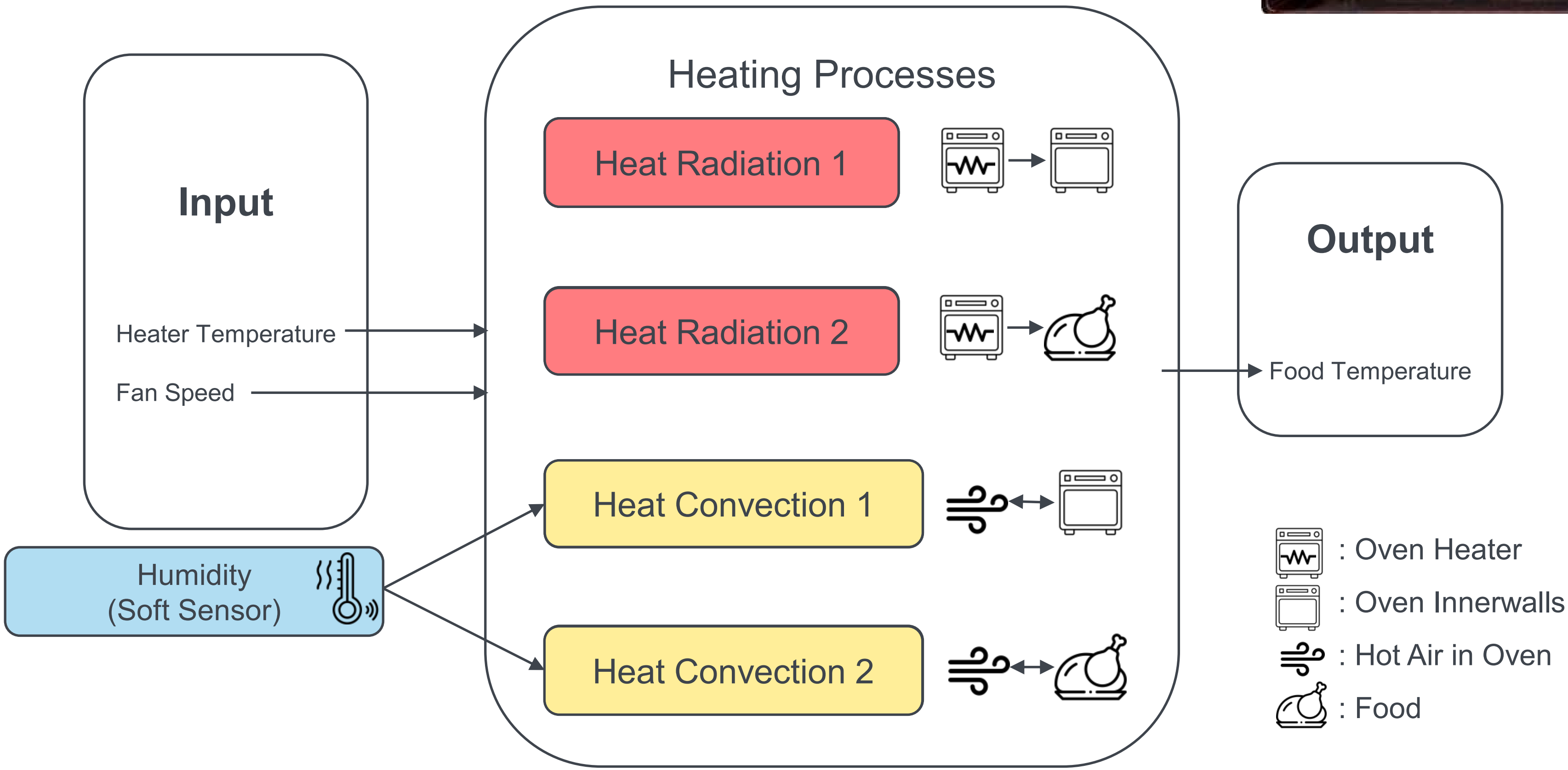
Simulation Model

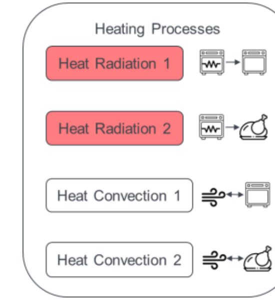
- Modeling
- Calibration
- Experimental validation

Simulation Model

Conceptual Diagram

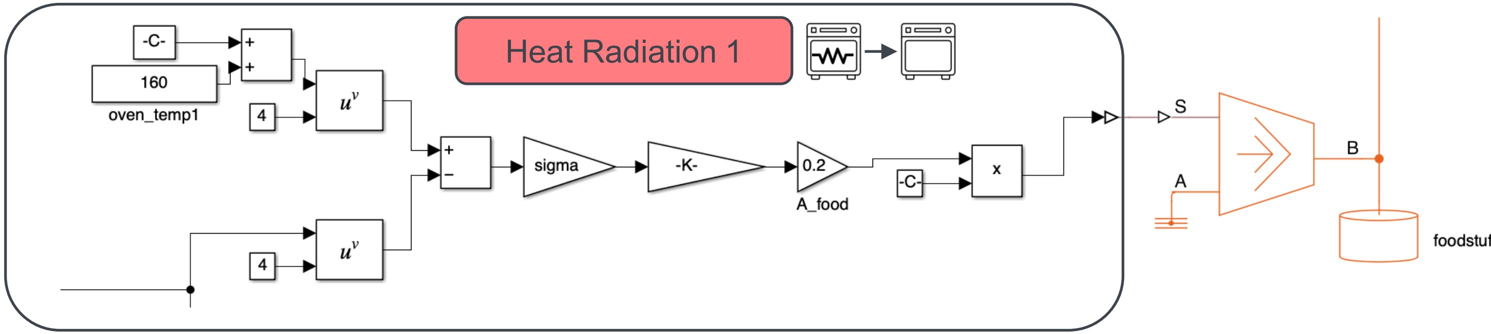




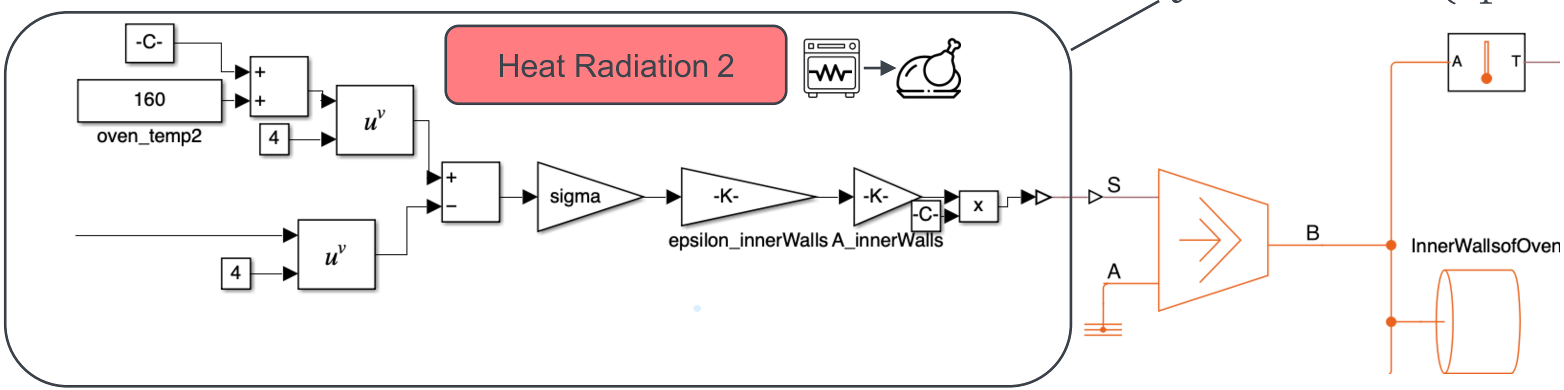


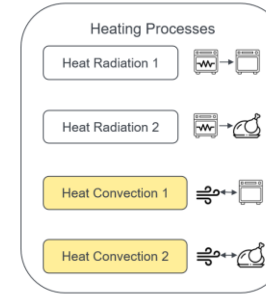
Simulation Model

Subsystems - Heat Radiation



$$Q = \varepsilon * \sigma * A * ({T_1}^4 - {T_2}^4)$$

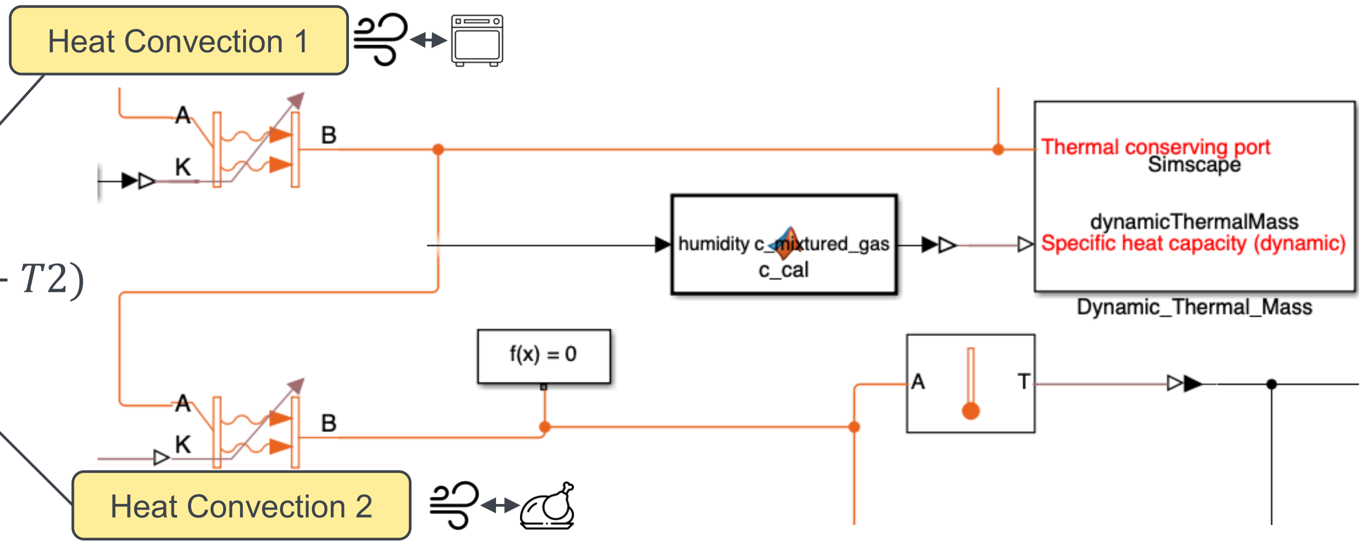




Simulation Model

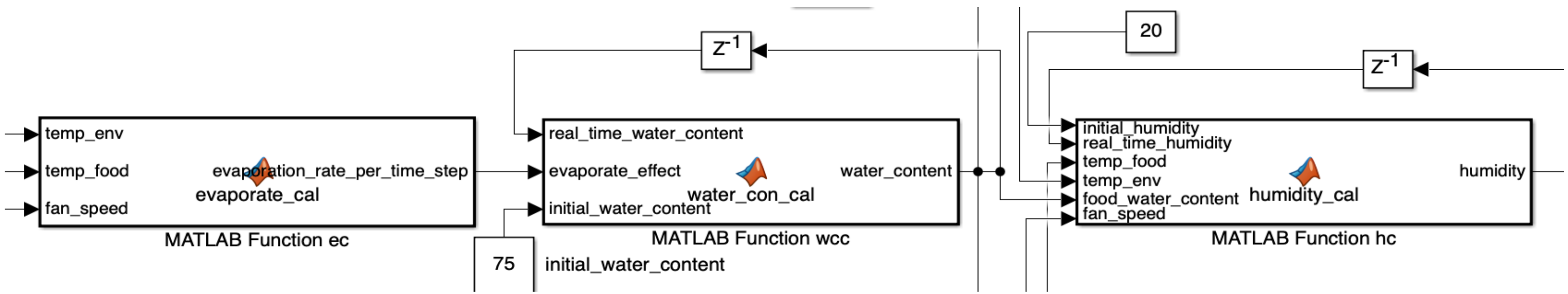
Subsystems - Heat Convection

$$Q = \mathrm{h} * A * (T1 - T2)$$



Simulation Model

Subsystems - Soft Sensor



Humidity
(Soft Sensor)

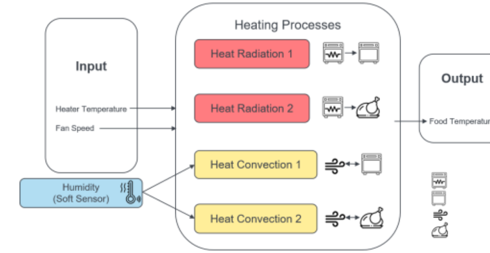
(Humidity Calculation System)

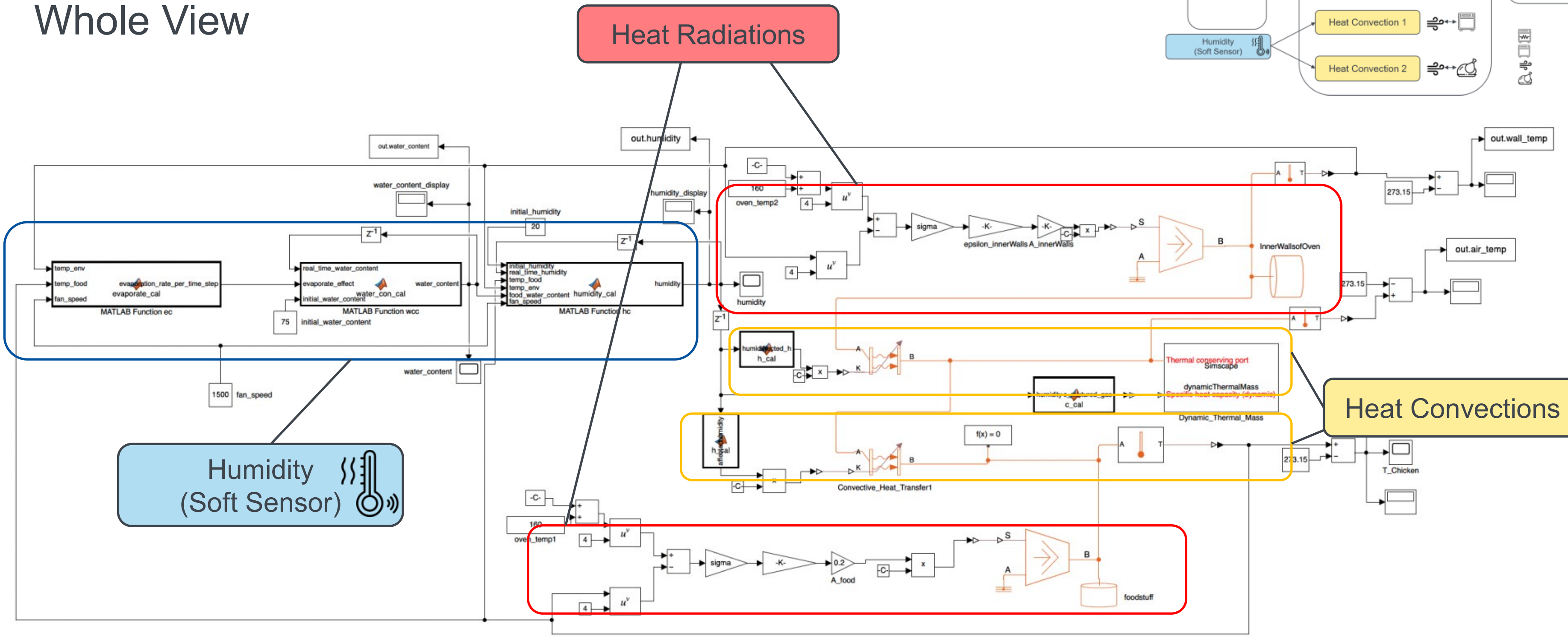
$$Evaporate\ Rate = k \cdot (T_{oven} - T_{ambient})$$

$$Humidity(t) = Initial\ Humidity + \int_0^t Evaporate\ Rate(t)dt$$

Simulation Model

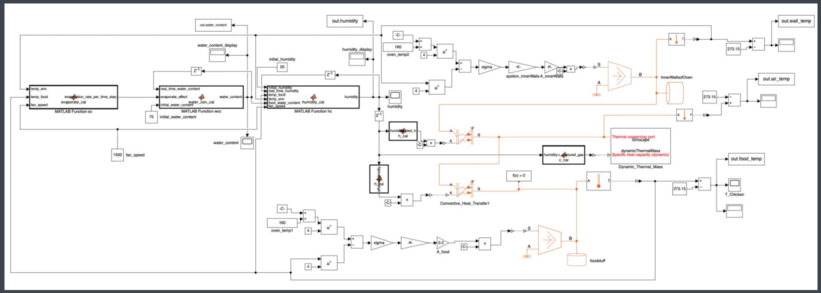
Whole View





Calibration and Validation

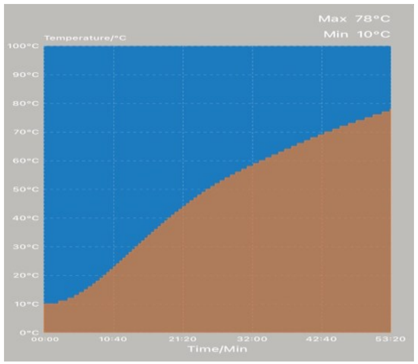
- Calibration
- Experimental validation



Simulation Calibration

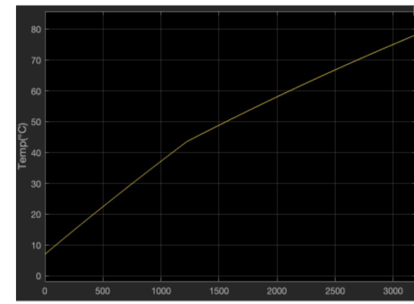
Roast Chicken Experiment

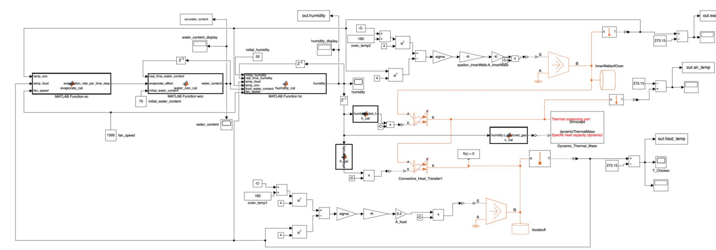
Real Experiment Measurement



Oven Setting:
0-1200s: 220℃, 2000r/min.
1200s-3200s: 160℃, 1200r/min.

Simulation Measurement After Calibration



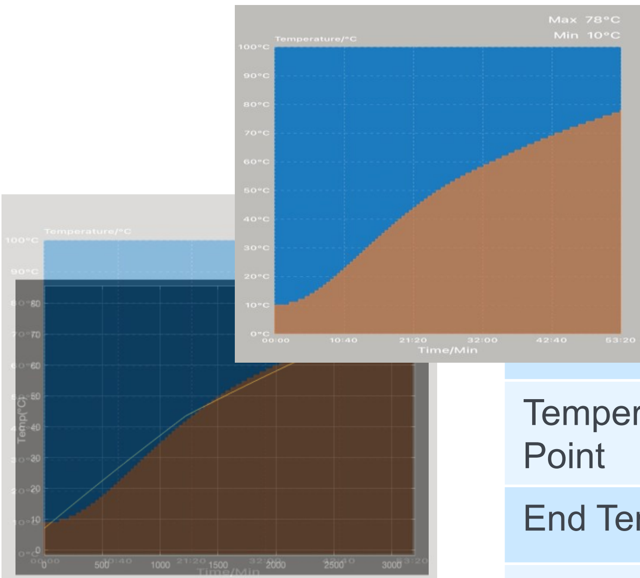


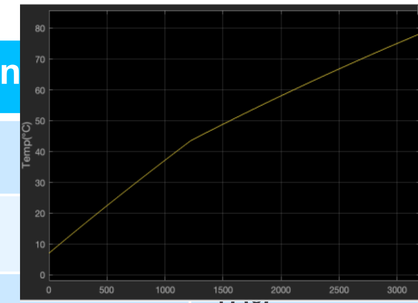
Calibration Evaluation

Calibration with a sample

Experiment Chicken Property:

Weight: 1.322kg,
Initial Temperature: 10°C





	Simulation	…urve
…ne		
…hanging Point		
…emperature	7℃	10℃
Temperature at Changing Point	42.9℃	42℃
End Temperature	78.5℃	78℃
Slope from 0s to 1200s	1.80℃/min	1.60℃/min
Slope from 1200s to 3200s	1.07℃/min	1.08℃/min

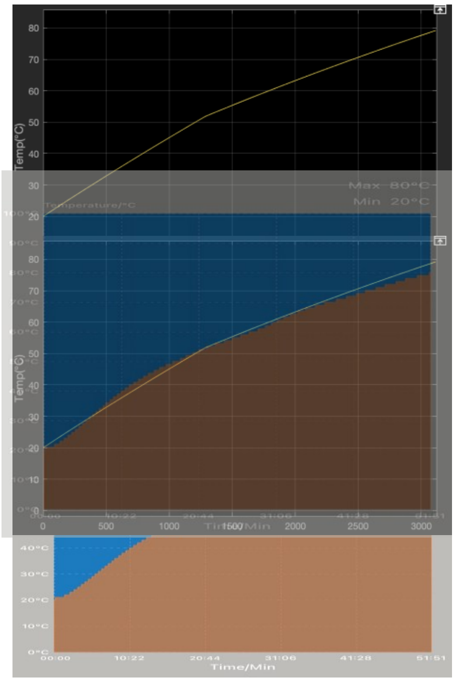
Calibration Error: 3.57%

Simulation Validation

Validation with a second sample

Experiment Chicken Property:

Weight: 1.322kg,
Initial Temperature: 10°C

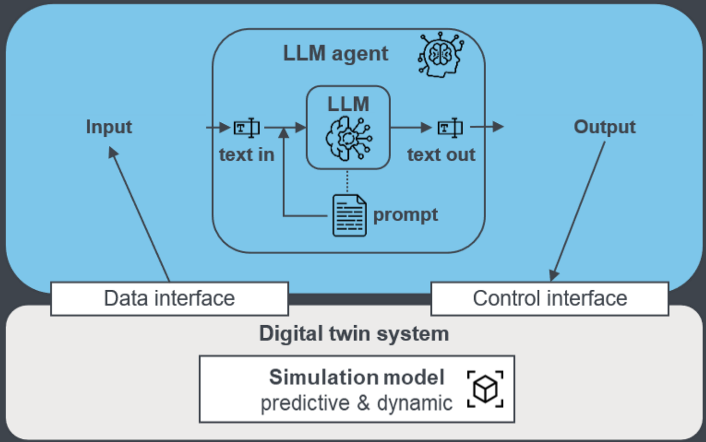


	Simulation Curve	Real Oven Curve
Grill Time	3120s	
Time Changing Point	1200s	
Initial Temperature	20℃	20℃
Temperature at Changing Point	53℃	49.8℃
End Temperature	79.2℃	80℃
Slope from 0s to 1200s	1.49℃/min	1.65℃/min
Slope from 1200s to 3200s	0.92℃/min	0.81/min

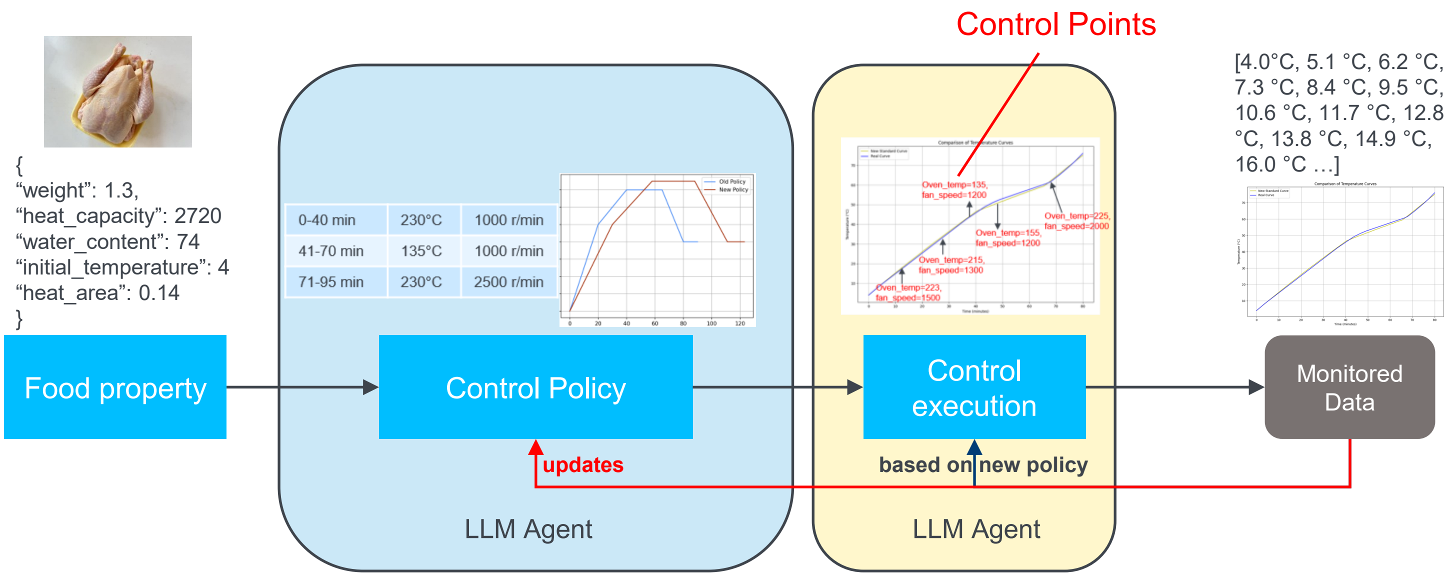
Calibration Error: 4.92% acceptable ✓

Control Modeling

- System Workflow



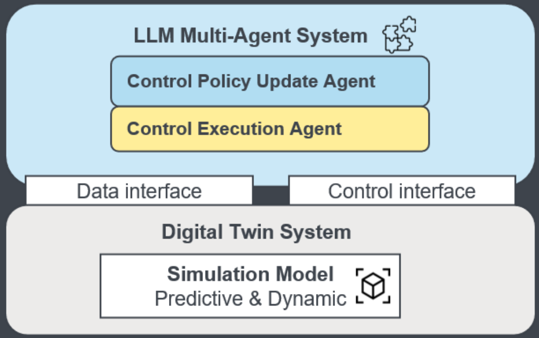
Control Workflow



0-40 min	230°C	1000 r/min
41-70 min	135°C	1000 r/min
71-95 min	230°C	2500 r/min

Use LLM agent to control Simulation Process Control

- Control Policy
- Two LLM Agents
- System Workflow



Control Policy

Control Policy

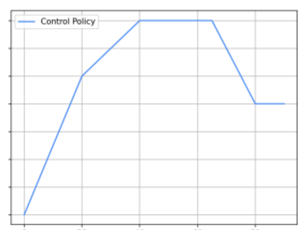
Food property

```
{
“weight”: 1.3,
“heat_capacity”: 2720
“water_content”: 74
“initial_temperature”: 4
“heat_area”: 0.14
}
```

determine

For Whole Chickens:

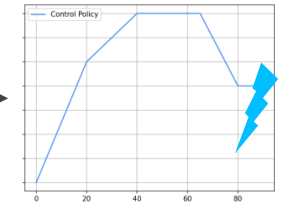
0-40 min	230°C	1000 r/min
41-70 min	135°C	1000 r/min
71-95 min	230°C	2500 r/min



as **reference** for food temperature control

Different Food Property

fail

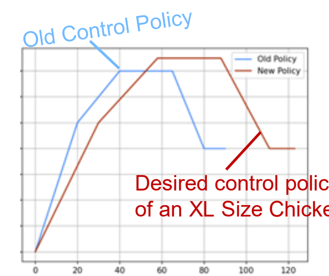


Old Policy

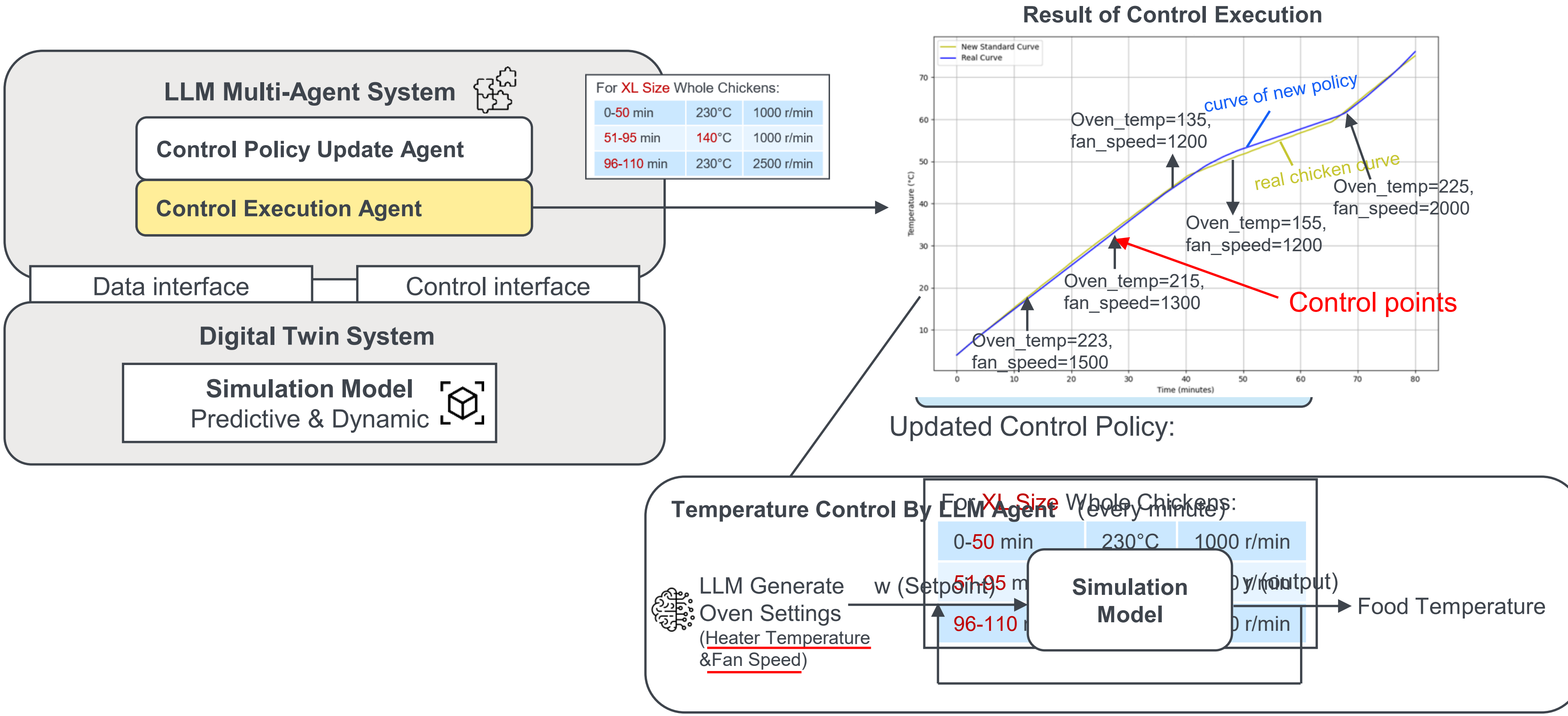
Updated Control Policy:

For XL Size Whole Chickens:

0-50 min	230°C	1000 r/min
51-95 min	140°C	1000 r/min
96-110 min	230°C	2500 r/min



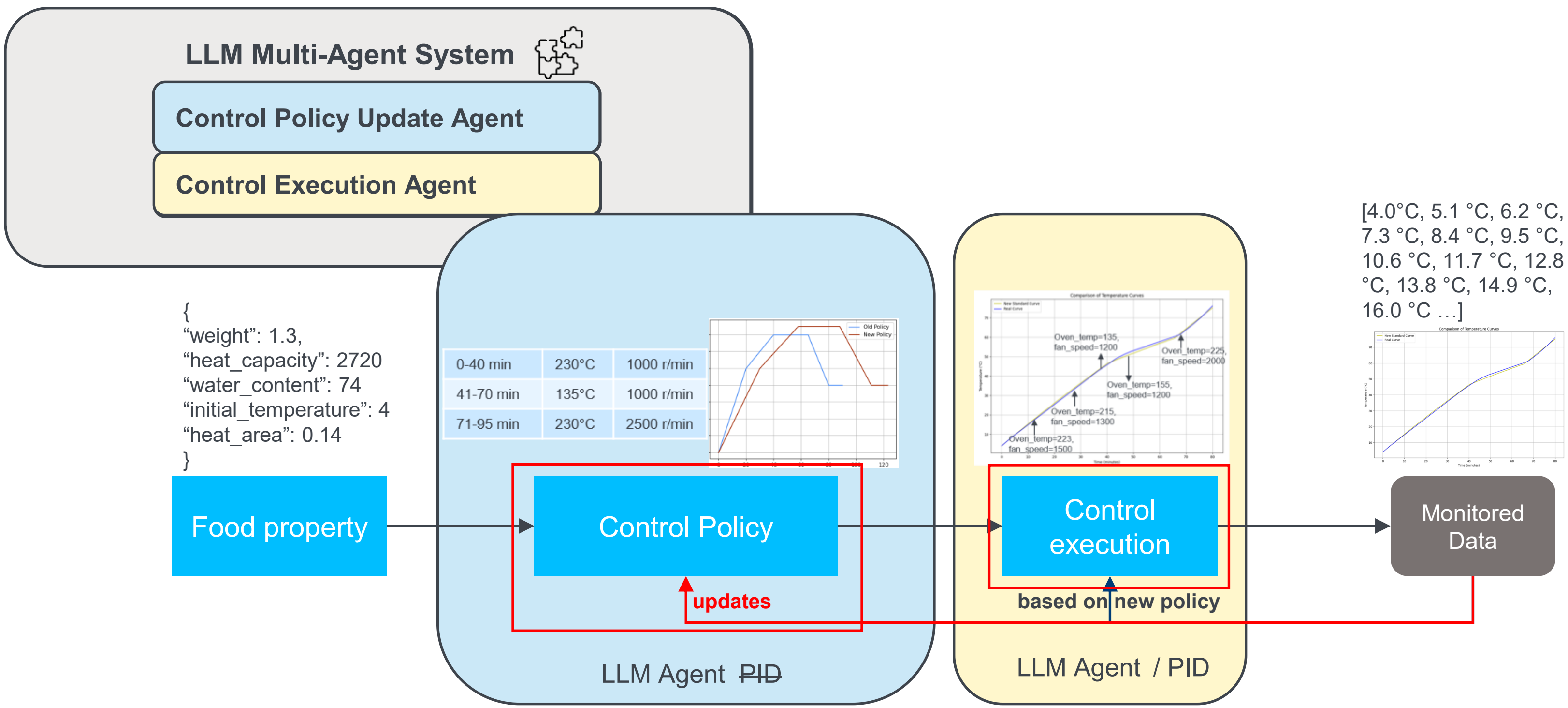
LLM Agent for Control Policy Update



For XL Size Whole Chickens:

0-50 min	230°C	1000 r/min
51-95 min	140°C	1000 r/min
96-110 min	230°C	2500 r/min

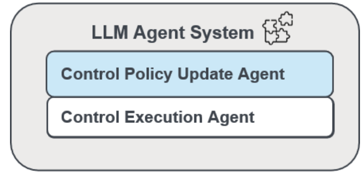
LLM Agent System



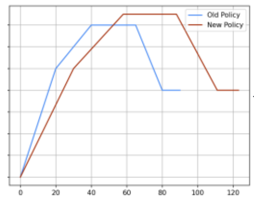
How can LLM update the control policy?

--It needs heuristical knowledge

How LLM Agent Update Policy



For simplicity:



cause ← Different Food Properties (weight, heat capacity, water content…)

2 Steps for LLM Agent
To Update the Control Policy

Step 1. Reason the error in food property

"m" = "1.3kg" ✗ "m" = "1.484kg" ✓

Step 2. Adjust the policy to compensate the effect caused by different food property

0-40 min	230°C	1000 r/min
41-70 min	135°C	1000 r/min
71-95 min	230°C	2500 r/min

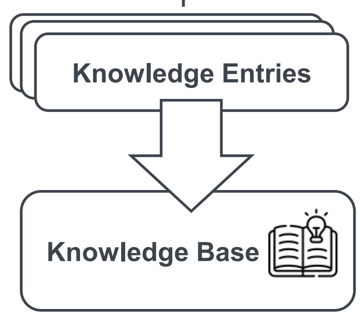
✗

For XL Size Whole Chickens:

0-50 min	230°C	1000 r/min
51-95 min	140°C	1000 r/min
96-110 min	230°C	2500 r/min

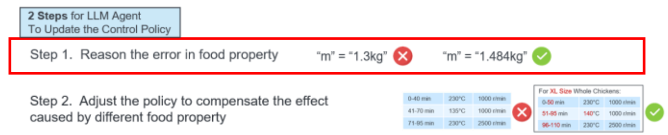
✓

Rules of how to complete the two steps



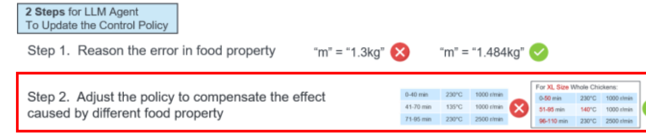
Knowledge Base Creation from Simulation Model

Curve Change Rules (First Step)

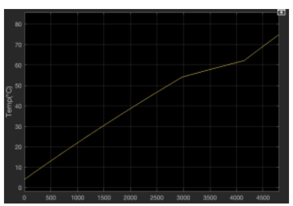


Knowledge Base Creation from Simulation Model

Oven Setting Adjustment Policy (Second Step)



Simulation Model → Run Multiple Times to Collect → Oven Setting Adjustment Methods

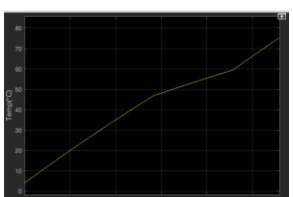


m ↗ 10%:

2. period ↗ 300s, T ↗ 10°C,

3. Period → T ↘ 10°C

…



C ↗ 10%:

2. period ↗ 400s, T ↗ 10°C

summerize → Understandable Texts

Knowledge Entries

If the weight increases 10%, For Second Period: time increases 300s, temperature rises 10°C
For Third Period: time remains, temperature drops 10°C

prompt → **LLM**

Experiment & Evaluation

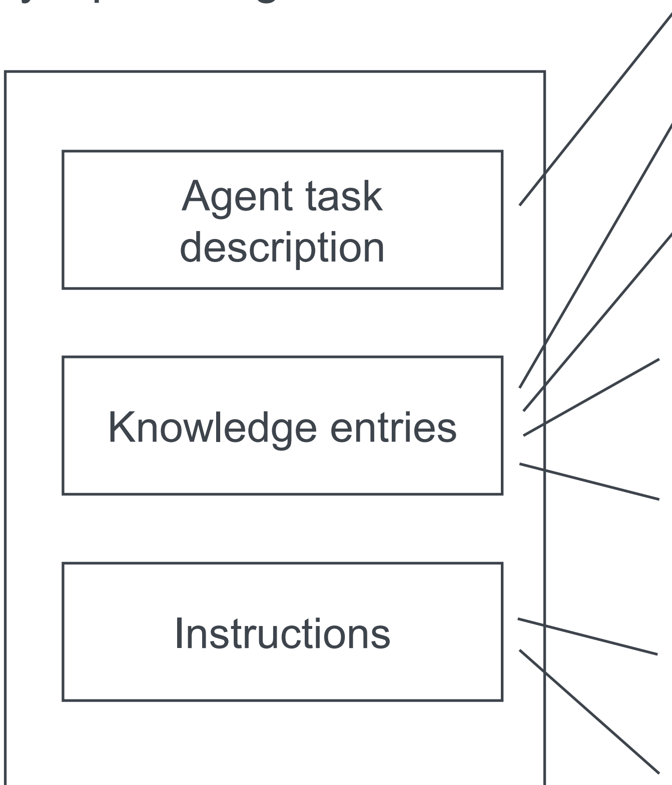
- LLM Prompt Design
- Experiments under Variate Food Properties

Prompt Design

Prompt Section	Definition	Typical Examples
Agent Task Description	Describe the role and the task responsibility of the LLM agent	*„You are an AI trained to analyze deviations between the current temperature curve of food in an oven and a standard curve"*
Knowledge Entries	Texts summarized from knowledge base, informing LLM to make inference and decision	*"For heat capacity, if the temperature difference is -0.76%, the true heat capacity should be 1% higher; if the temperature difference is +0.76%, the true heat capacity should be 1% lower."*
Instructions	Steps LLM should follow to complete the Task	*„Step 2: Update the corresponding parameters in the current oven settings (from info. 4) with the values determined in the previous step."*

Prompt Design

Policy Update Agent



You are an AI trained to analyze deviations between the current temperature curve of food in an oven and a standard curve. Your task is to determine the reason for these deviations based on changes in one or more of the following parameters: heat capacity and weight. You will then adjust the food parameters accordingly and develop a new baking plan that better aligns with the current food, resulting in an updated standard curve. You have the following informations available:

1.Food Type: Whole Chicken

2.Temperature Difference Between Current and Standard Curve in the Fifth Minute (Format: "Current Temperature ~ Standard Curve Temperature"): 9.0°C ~ 9.5°C (−5.556%, which means 5.556% lower than standard. Based on experience, the average difference will be the twice of the difference in fifth minute, which means in this situation, the average difference can be considered as −11.112%, which means 11.112% lower than standard.)

3.Impact of Food Parameters on Temperature Curve:
•There are coefficients (K) between the food parameters and the food temperature curve.
•For heat capacity, if the temperature difference is −0.76%, the true heat capacity should be 1% higher; if the temperature difference is +0.76%, the true heat capacity should be 1% lower.
•For weight, if the temperature difference is −0.84%, the true weight of food should be 1% higher; if the temperature difference is +0.84%, the true weight of food should be 1% lower.
Note: The temperature changes mentioned above apply to the change of a single parameter. If two parameters change simultaneously, the temperature change will be their combined effect. For example, if the heat capacity increases by 0.3% and the weight increases by 1% at the same time, the final temperature difference shown to you would be − (0.76 * 0.3 + 0.84%).

4.Oven Settings for the Standard Curve:
{'type of food': 'chicken', 'heat_capacity': '2720', 'm': '1.3', 'water_content': '74', 'initial_temp': '4', 'A': '0.14', 'first_period': '2400', 'first_period_temp': '200', 'first_period_fan_speed': '1000', 'second_period': '1200', 'second_period_temp': '135', 'second_period_fan_speed': '1000', 'third_period': '1600', 'third_period_temp': '230', 'third_period_fan_speed': '2000'}
Note: keys definition: "type of food", "heat capacity", "m", "initial_temp", "A" represent the properties of the food: type, heat capacity, weight, initial temperature, surface area. There are three grill phases specified in the setting, including its time duration, oven temperature and oven fan speed.

5.Principles for Modifying the Standard Curve:
The standard curve changes with variations in the three parameters (heat capacity, weight, surface area) as follows:
•If heat capacity increases by 10%, the second period time increases by +400s, and the temperature increases by +10°C.
•If heat capacity decreases by 10%, the first period time decreases by −400s.
•If weight (m) increases by 10%, leading to a 1% increase in surface area (A), the second period time increases by +300s, temperature by +10°C, and the third period temperature decreases by −10°C.
•If weight (m) decreases by 10%, leading to a 1% decrease in surface area (A), the second period time decreases by −400s, and the temperature by −10°C.

Now, strictly follow the steps outlined below to execute this task and output the process you did for each step :

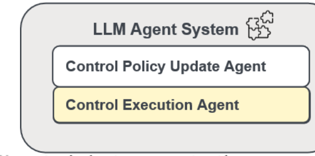
Step 1: Analyze the first three pieces of information (food type, temperature differences in the first five minutes, and the impact of food parameters on the temperature curve) to identify which parameter(s) differ from the standard curve. In this case, you can only take weight and surface area as the cause of temperature deviation. Quantitatively determine whether each parameter is higher or lower and by how much. Attention: The change of food weight always lead to its surface area change (one tenth of the weight change). If weight decreases, it can only leads to shorter grill time or lower grill temperature, so does the heat capacity. If you increase the temperature based on a smaller weighted food, you should do the inference again.

Step 2: Update the corresponding parameters in the current oven settings (from step 4) with the values determined in the previous step.

Step 3: Based on the changes in food parameters inferred in Step 2, and using the guidelines from information 5, calculate the necessary adjustments to the oven settings (including the duration and temperature for each period). Update the settings accordingly.

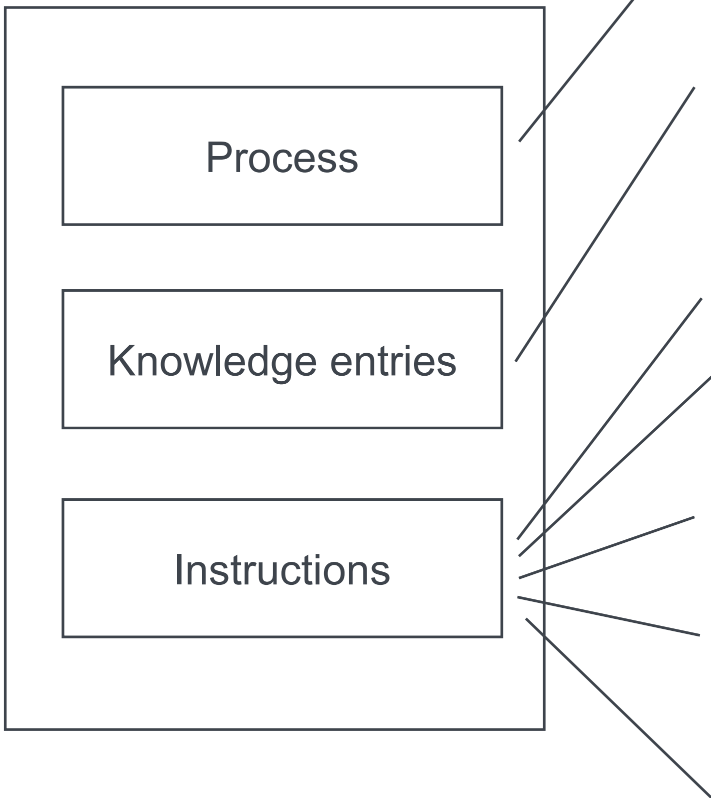
Step 4: Output the final oven settings in form of JSON: All keys and values must be enclosed in double quotes. Do not include any comments, additional explanations, or extra content.Produce only the pure JSON data structure.

Step 5: Output the result of your inference within the [INFERENCE][/INFERENCE] labels: Parameter(s) that you considered as the cause of the temperature difference, and how you changed the value of them



Prompt Design

Control Execution Agent




```
You are an AI designed to monitor and optimise the baking process in an oven. Your task is to generate the
most suitable oven settings (oven temperature and fan speed) for the moment by referring to the standard
curve. You need to follow the information that I provide and follow the steps that I lay out for you step by
step to complete the task.

Information:
1. The type of food is: Whole Chicken

2. Difference between the current food temperature curve and the standard curve:
Current Temperature Deviation: -2 degrees Celsius
Last Minute Temperature Deviation: -3 degrees Celsius
Note: Negative deviation represents that the current food temperature is lower than standard, Positive
deviation represents that the current food temperature is higher than standard.

3. Standard Curve Oven Settings:
Temperature: 180 degrees Celsius
fan_speed: 1800 r/min

4. Current Oven Settings:
Temperature: 220 degrees Celsius
fan_speed: 1200 r/min


Steps:
1. Food Type Consideration:
Pay attention to the type of food. Does this type of food often exhibit individual differences (such as
size, water content, specific heat capacity)? If significant individual differences are possible, the
temperature deviation may be influenced by both the individual differences and the oven settings.

2. Evaluate Current Temperature Deviation:
Evaluate the current temperature difference. Is the current temperature difference large or small for baking
this type of food? If it is large, improper oven settings are likely the cause, and significant adjustments
to the oven parameters are necessary. If the difference is small, it may be due to the food's inherent
characteristics, but small adjustments to the oven parameters can still eliminate the deviation.
Additionally, if the temperature difference shows that the current temperature is higher than the standard,
it is advisable to lower the oven temperature, and vice versa.

3. Observe Deviation Trend:
To observe the deviation trend, compare the current temperature deviation and the last minute temperature
deviation. If the deviation is decreasing, it indicates that the current oven settings are adequate, and
only minor adjustments are needed. If the deviation is increasing, more substantial adjustments to the oven
settings are required. If the deviation is decreasing then increasing (for example from -1 to +1), that
suggests that the last change of oven setting is too much.

4. Compare Oven Settings to Standard Curve:
Compare the current oven settings to the standard curve (considering whether you previously determined to
raise or lower the temperature). If the current temperature setting is higher than the standard temperature
setting but you intended to continue increasing the temperature, you might only raise the temperature
slightly to avoid significant impacts.

5. Specify New Oven Settings:
Specify the new values for oven temperature and fan speed. If no changes are needed, indicate NO CHANGE.
Format your output as a JSON file with the [CONTROL][/CONTROL] tags with the following structure:
[CONTROL]
{
  "Oven Temperature": <new_temperature_or_NO_CHANGE>,
  "fan_speed": <new_fan_speed_or_NO_CHANGE>
}
[/CONTROL]
```

Experiment

Errors in food weights

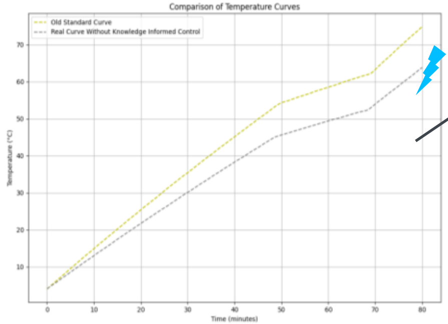
LLM Agent System

Control Policy Update Agent

Control Execution Agent

Input Weight: 1.3kg

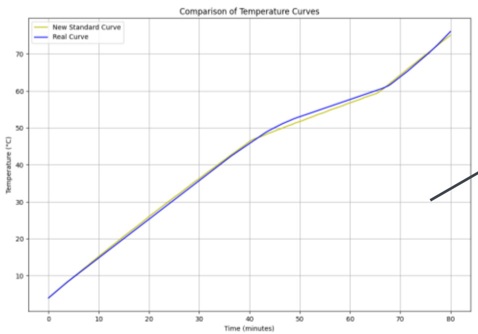
Real Weight: 1.5kg



0-40 min	200°C	1000 r/min
41-54 min	135°C	1000 r/min
55-78 min	230°C	2000 r/min

Knowledge Informed LLM Agent

0-40 min	200°C	1000 r/min
41-67 min	145°C	1000 r/min
68-105 min	220°C	2500 r/min




```
**Step 1: Analyze the information**

Given the temperature difference of -11.112% on average, we can infer the impact of the
weight on the temperature curve:
- The temperature difference is -11.112%, which is below the standard curve.
- For weight: A -0.84% temperature difference corresponds to a +1% increase in weight.
Thus, an -11.112% temperature difference suggests a 13.23% increase in weight (since
-11.112% / -0.84% = 13.23% increase in weight).

**Step 2: Update the corresponding parameters**

The weight (m) and surface area (A) of the chicken need to be updated:
- Original weight \( m = 1.3 \, \text{kg} \)
- New weight \( m \) = \( 1.3 \times (1 + 0.1323) = 1.484 \, \text{kg} \)

- Surface area \( A \) needs to increase by one-tenth of the weight change:
- Original surface area \( A = 0.14 \, \text{m}^2 \)
- New surface area \( A \) = \( 0.14 \times (1 + 0.01323) = 0.14185 \, \text{m}^2 \)

**Step 3: Adjust the oven settings**

With a 13.23% increase in weight, the following adjustments are made based on the
guidelines:
- **Second period**:
  - Time increases by \( 300 \times 1.323 = 396.9 \, \text{s} \), so new second period
time = \( 1200 + 396.9 = 1596.9 \, \text{s} \)
  - Temperature increases by \( +10^\circ \text{C} \), so new second period temperature =
\( 135 + 10 = 145^\circ \text{C} \)

- **Third period**:
  - Temperature decreases by \( -10^\circ \text{C} \), so new third period temperature = \
( 230 - 10 = 220^\circ \text{C} \)

**Step 4: Final oven settings JSON**

```json
{
  "type_of_food": "chicken",
  "heat_capacity": "2720",
  "m": "1.484",
  "water_content": "74",
  "initial_temp": "4",
  "A": "0.14185",
  "first_period": "2400",
  "first_period_temp": "200",
  "first_period_fan_speed": "1000",
  "second_period": "1597",
  "second_period_temp": "145",
  "second_period_fan_speed": "1000",
  "third_period": "1600",
  "third_period_temp": "220",
  "third_period_fan_speed": "2000"
}
```

Step 5: Inference

[INFERENCE]
Parameter(s) that you considered as the cause of the temperature difference: **Weight**
(m) and consequently **Surface Area** (A). The weight increased by 13.23%, which led to
the corresponding adjustment in the oven settings.
[/INFERENCE]
```

Knowledge informed:

LLM reasoning: actual weight is 1.484kg → changes control policy.

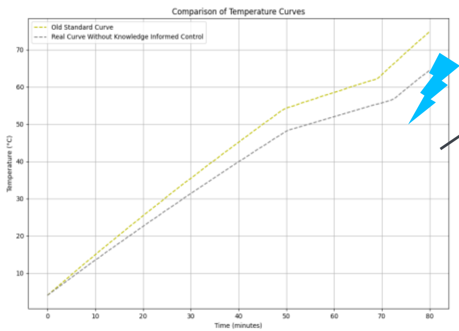
LLM Agent System

- **Control Policy Update Agent**
- Control Execution Agent

Experiment

Errors in food heat capacity

Input Heat Capacity: 2720J /(kg·K),
Real Heat Capacity: 2992J /(kg·K),



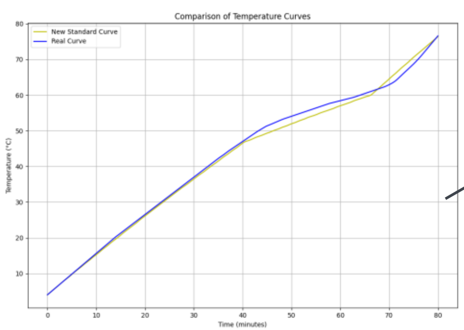
0-40 min	200°C	1000 r/min
41-54 min	135°C	1000 r/min
55-78 min	230°C	2000 r/min

↓

Knowledge Informed LLM Agent

↓

0-40 min	200°C	1000 r/min
41-67 min	145°C	1000 r/min
68-105 min	230°C	2500 r/min




```
### Step 1: Analyze the temperature difference and determine the parameter change

- **Food Type**: Whole Chicken
- **Temperature Difference in Fifth Minute**: 9.0°C (current) vs. 9.5°C (standard), with an average deviation of
-11.112%.

Given that the change in temperature difference is -11.112%, and considering the impact of food parameters on the
temperature curve:

- **Heat Capacity**: A -0.92% temperature difference corresponds to a +1% increase in heat capacity. Since the
temperature difference here is -11.112%, we can calculate the corresponding increase in heat capacity as follows:

  \[
  \text{Increase in Heat Capacity} = \frac{11.112}{0.92} \approx 12.08\%
  \]

Therefore, the heat capacity should be increased by approximately 12.08%.

### Step 2: Update the oven settings with the new parameters

The original heat capacity is 2720 J/kg·K. With a 12.08% increase, the updated heat capacity is:

\[
\text{Updated Heat Capacity} = 2720 \times (1 + 0.1208) \approx 3048.576 \text{ J/kg·K}
\]

### Step 3: Adjust the oven settings based on the new parameters

Using the guidelines provided:

- **Heat Capacity Increase by 10%**: The second period time increases by +400s, and the temperature increases by
+10°C.

Since the heat capacity increase is 12.08% (approximately 10%), the adjustments would be:

- **Second Period**:
  - Time: 1200s + 400s = 1600s
  - Temperature: 135°C + 10°C = 145°C

No further adjustments are necessary for the first and third periods, as the primary focus is on the second period due
to the heat capacity change.

### Step 4: Output the final oven settings in

```json
{
  "type of food": "chicken",
  "heat_capacity": "3048.576",
  "m": "1.3",
  "water_content": "74",
  "initial_temp": "4",
  "A": "0.14",
  "first_period": "2400",
  "first_period_temp": "200",
  "first_period_fan_speed": "1000",
  "second_period": "1600",
  "second_period_temp": "145",
  "second_period_fan_speed": "1000",
  "third_period": "1600",
  "third_period_temp": "230",
  "third_period_fan_speed": "2000"
}
```

Step 5: Inference Result

[INFERENCE]
- **Parameter(s) Considered**: Heat Capacity
- **Change Made**: Increased heat capacity by 12.08%, resulting in adjustments to the second period's time and
temperature.
[/INFERENCE]
```

Knowledge informed:

LLM reasoning:
actual heat capacity is 3048.576J/(kg·K)
→ changes control policy.

LLM Agent System

Control Policy Update Agent

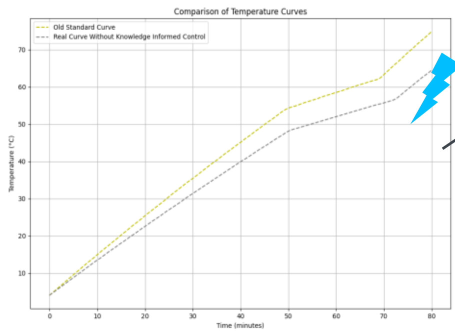
Control Execution Agent

Experiment

Errors in both food weight and heat capacity

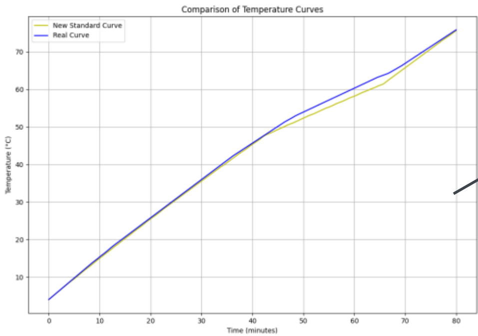
Input Heat Capacity: 2720J /(kg·K), Weight: 1.3kg

Real Heat Capacity: 2900J /(kg·K), Weight: 1.5kg



0-40 min	200°C	1000 r/min
41-54 min	135°C	1000 r/min
55-78 min	230°C	2000 r/min

Knowledge Informed LLM Agent



0-40 min	200°C	1000 r/min
48-75 min	145°C	1000 r/min
76-103 min	230°C	2500 r/min

~~~
**Step 1: Analysis of Deviations**

Given the temperature difference of -20.93% (current temperature being 20.93% lower than the standard curve), and based on the
relationship between heat capacity, weight, and temperature, I can infer the following:

- The temperature difference is negative, indicating that the current temperature is lower than the standard.
- Since the change in weight is assumed to be twice that of the heat capacity, we can set up equations to determine the exact
percentage change in both parameters.

Let the change in heat capacity be \( x \% \), then the change in weight is \( 2x \% \).

Using the coefficients provided:
- Heat capacity: A -0.88% temperature difference corresponds to a +1% heat capacity change.
- Weight: A -0.84% temperature difference corresponds to a +1% weight change.

The total temperature difference can be expressed as:
\[ \text{Total temperature difference} = -0.88x - 0.84(2x) \]

Given that the total temperature difference is -20.93%, we solve for \( x \):

\[ -0.88x - 1.68x = -20.93 \]
\[ -2.56x = -20.93 \]
\[ x = \frac{20.93}{2.56} \approx 8.18\% \]

So, the heat capacity has increased by approximately 8.18%, and the weight has increased by approximately 16.36%.

**Step 2: Update the Parameters**

- Heat Capacity: \( 2720 \times 1.0818 \approx 2942.5 \, \text{J/kg·K} \)
- Weight: \( 1.3 \times 1.1636 \approx 1.5127 \, \text{kg} \)
- Surface Area: \( 0.14 \times 1.01636 \approx 0.1423 \, \text{m}^2 \)

**Step 3: Adjust Oven Settings**

Given the guidelines:

- Heat capacity increased by 8.18%:
  - Increase the second period time by \( 400 \times \frac{8.18}{10} \approx 327.2 \, \text{s} \).
  - Increase the second period temperature by \( 10 \times \frac{8.18}{10} \approx 8.18 \, \text{°C} \).

- Weight increased by 16.36%:
  - Increase the second period time by \( 300 \times \frac{16.36}{10} \approx 490.8 \, \text{s} \).
  - Increase the second period temperature by \( 10 \times \frac{16.36}{10} \approx 16.36 \, \text{°C} \).
  - Decrease the third period temperature by \( 10 \times \frac{16.36}{10} \approx 16.36 \, \text{°C} \).

Final adjustments:
- Second Period Time: \( 1200 + 327.2 + 490.8 \approx 2018 \, \text{s} \)
- Second Period Temperature: \( 135 + 8.18 + 16.36 \approx 159.54 \, \text{°C} \)
- Third Period Temperature: \( 230 - 16.36 \approx 213.64 \, \text{°C} \)

**Step 4: Final Oven Settings JSON Output**

```json
{
  "type of food": "chicken",
  "heat_capacity": "2942.5",
  "m": "1.5127",
  "water_content": "74",
  "initial_temp": "4",
  "A": "0.1423",
  "first_period": "2400",
  "first_period_temp": "200",
  "first_period_fan_speed": "1000",
  "second_period": "2018",
  "second_period_temp": "159.54",
  "second_period_fan_speed": "1000",
  "third_period": "1600",
  "third_period_temp": "213.64",
  "third_period_fan_speed": "2000"
}
```

**Step 5: Inference Output**

[INFERENCE]
The temperature difference was due to an increase in both the heat capacity and weight of the chicken. The heat capacity increased by
approximately 8.18%, and the weight increased by approximately 16.36%. I adjusted the oven settings accordingly to account for these
changes.
[/INFERENCE]
~~~

Knowledge informed:

LLM reasoning:
heat capacity is 2942.5J/(kg·K),
weight is 1.5127kg
→ changes control policy.

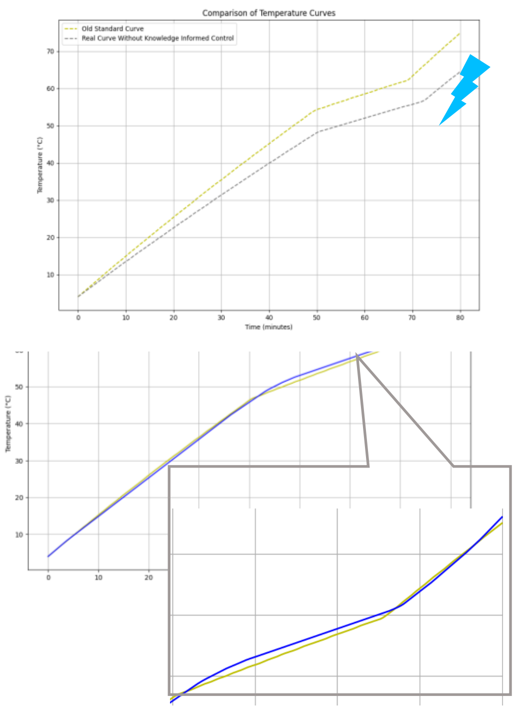
Different Hypothesis of LLM Agent

LLM agent's reasoning is not always correct

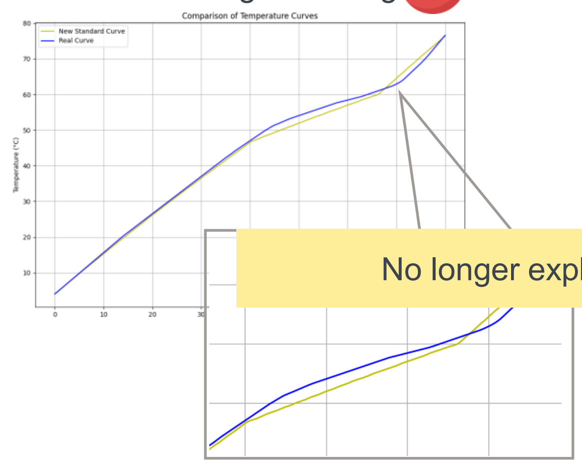
LLM Agent System
- Control Policy Update Agent
- Control Execution Agent

Real Situation: Food Weight -0.2kg, Heat Capacity +7%

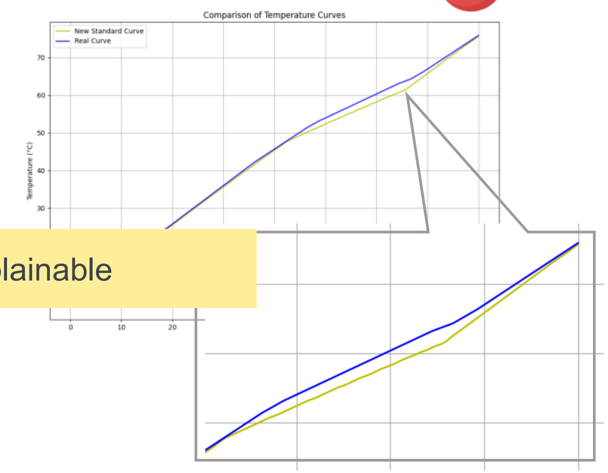
LLM perform tasks based on hypothetical reasoning



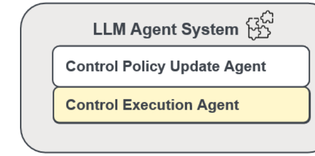
H2: Food Weight -0.38kg



H3: Heat Capacity +20.8%

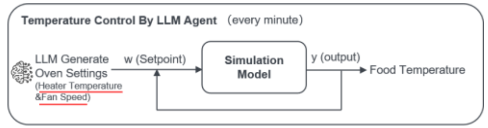


No longer explainable

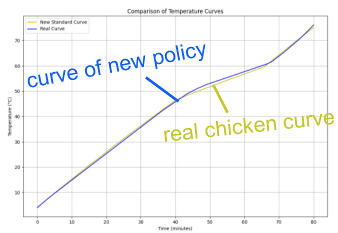


Evaluation of the Closed Loop Temperature Control

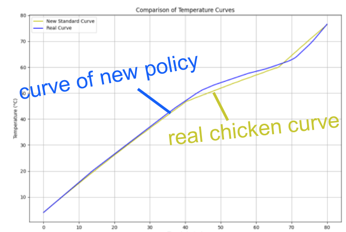
Control Execution Agent



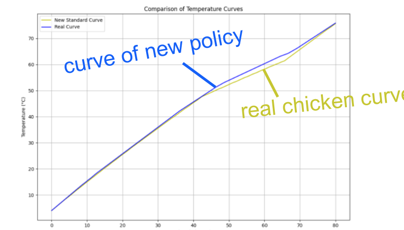
Errors in food weight:



Errors in food heat capacity:



Errors in both food weight and food heat capacity:

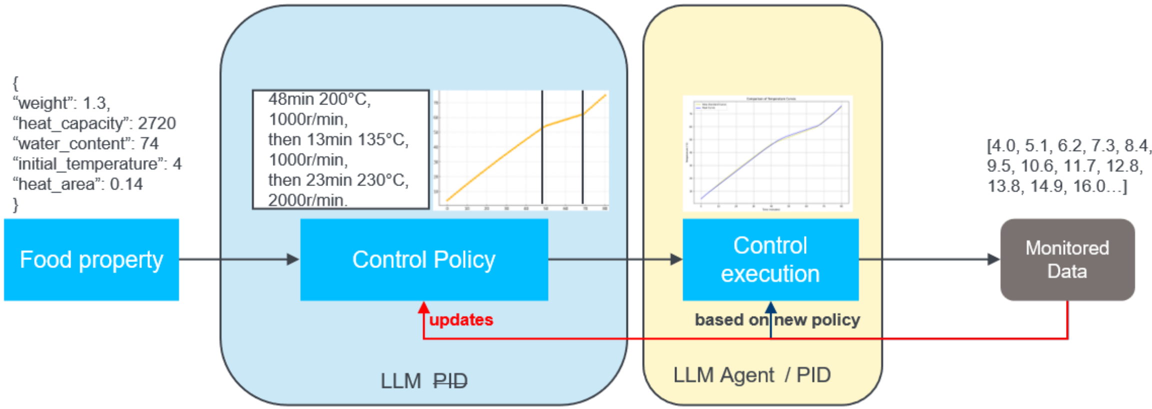


		Initial Temperature	End Temperature	Minimum Difference	Maximum Difference	Average Difference
m+0.2kg	Standard Curve	$4°C$	$76.2°C$	0%	3.66%	2.07%
	Real Curve	$4°C$	$76.1°C$			
c+10%	Standard Curve	$4°C$	$76.4°C$	0%	4.17%	2.03%
	Real Curve	$4°C$	$76.6°C$			
m+0.2kg & c+7%	Standard Curve	$4°C$	$75.7°C$	0%	2.69%	1.00%
	Real Curve	$4°C$	$75.9°C$			

Conclusion

- Task completed
- Future Work

Conclusion



Tasks Completed:

- Proof-of-Concept
- A feasible design using LLM to control simulation
- However, **limitations** observed
  - Simulation != Reality (calibration error)
  - Hypothesis not always correct (LLM need more information to confirm the hypothesis)

Future Work:

- Hypothesis validation
- Comparision with other smart control methods
- Automated knowledge base creation

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Institut of Industrial Automation
and Software Engineering

Thank you!

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