REPORT ON

OPTIMIZING OF SEMICONDUCTOR DEPOSITION RATE THROUGH BAYESIAN OPTIMIZATION

Submitted
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Content

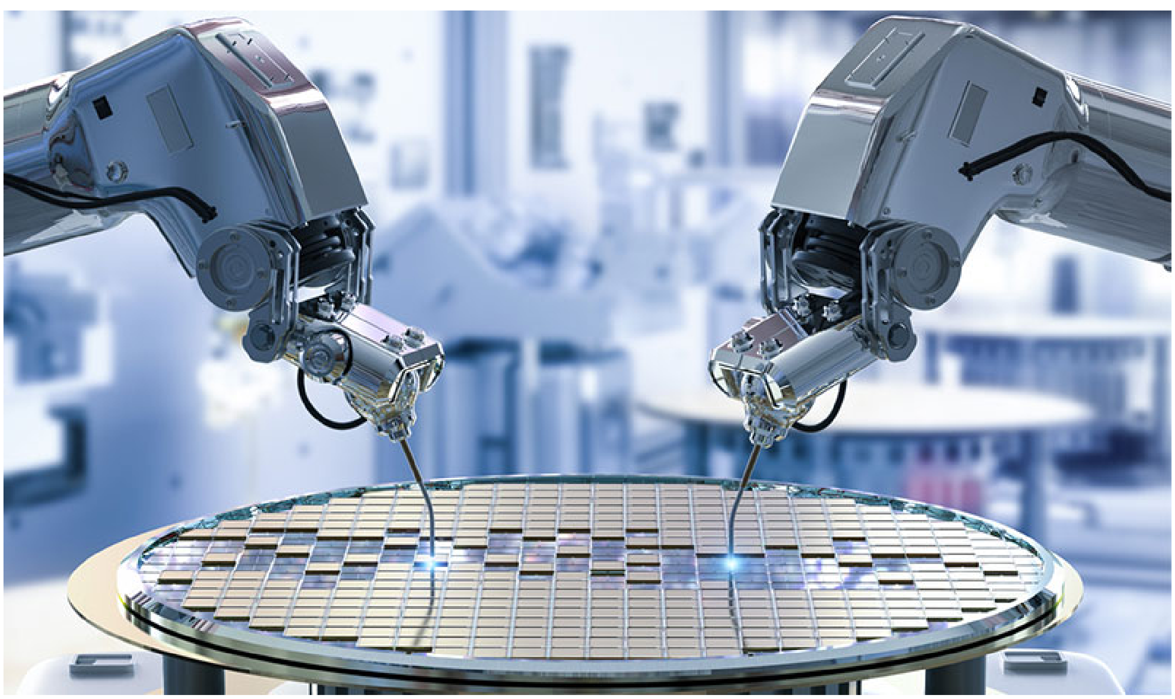
1. Abstract

The semiconductor industry is always finding ways to enhance the effectiveness and productivity of its fabrication procedures. One particular area of focus involves optimizing deposition rates. Deposition rate refers to the speed at which a substance is placed onto a surface. It plays a role in determining the overall cost and performance of semiconductor devices.

In this report we delve into the application of optimization when it comes to optimizing deposition rates. Bayesian optimization is a technique in machine learning that can efficiently explore a parameter space with dimensions allowing us to find the possible values for a given objective function.

We put optimization to use in addressing the challenge of optimizing deposition rates for semiconductor materials. Through our demonstration using Python code we showcase how adjusting process parameters like temperature and plasma power can maximize deposition rates.

Our findings clearly demonstrate that by leveraging optimization significant enhancements can be achieved in the deposition rates of semiconductor materials. This ultimately translates into cost savings. Improved production yield for manufacturers, within the semiconductor industry.

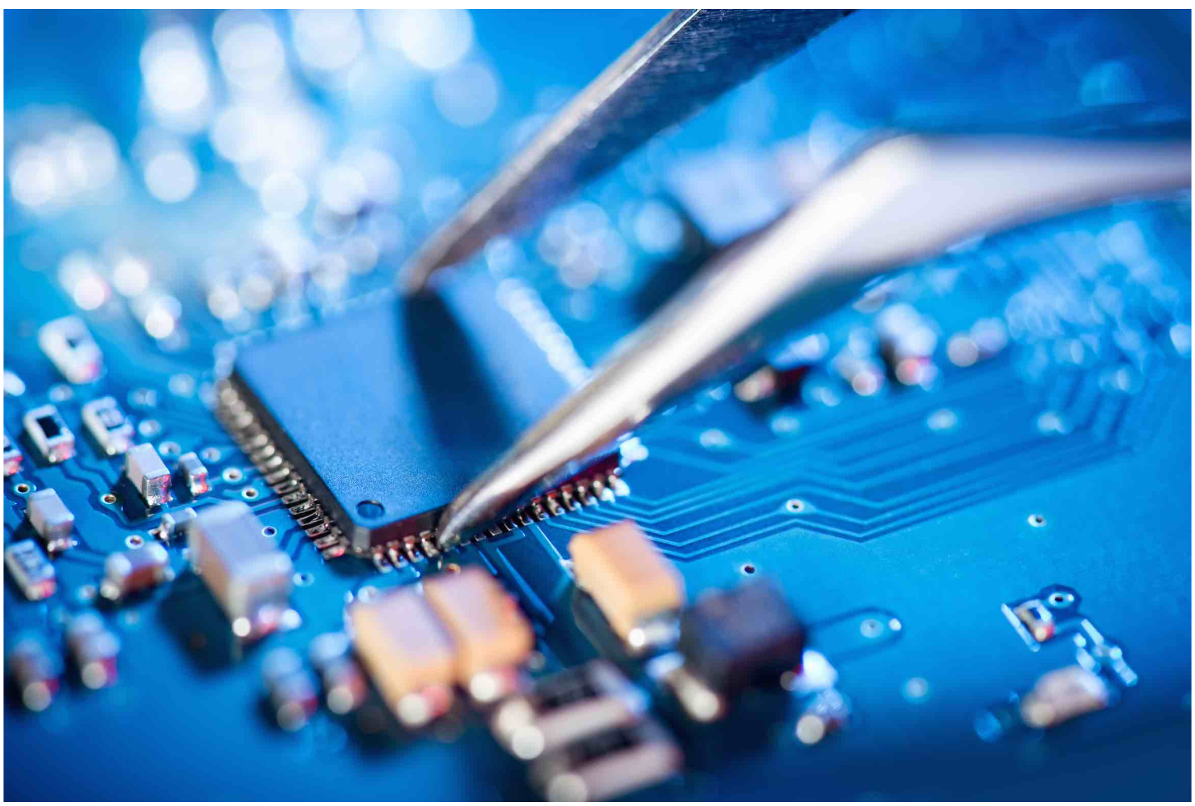


2. Introduction:

The semiconductor industry is committed to advancing fabrication techniques continuously. The main objectives are higher yield and more efficiency in the semiconductor manufacturing process. Technological developments in fabrication have a direct effect on semiconductor firms' overall competitiveness.

This research explores the real-world use of Bayesian optimization in the production of semiconductors. The main goal is to maximize the deposition rate, which is a crucial component of the quality of semiconductor materials. A useful method for methodically adjusting process parameters to maximize deposition rates is Bayesian optimization.

The report includes a demonstration tool in the form of a Python code sample.
The code demonstrates how to maximize the deposition rate using Bayesian optimization. In particular, the optimization method is practically illustrated by highlighting the adjustment of temperature and plasma power parameters.

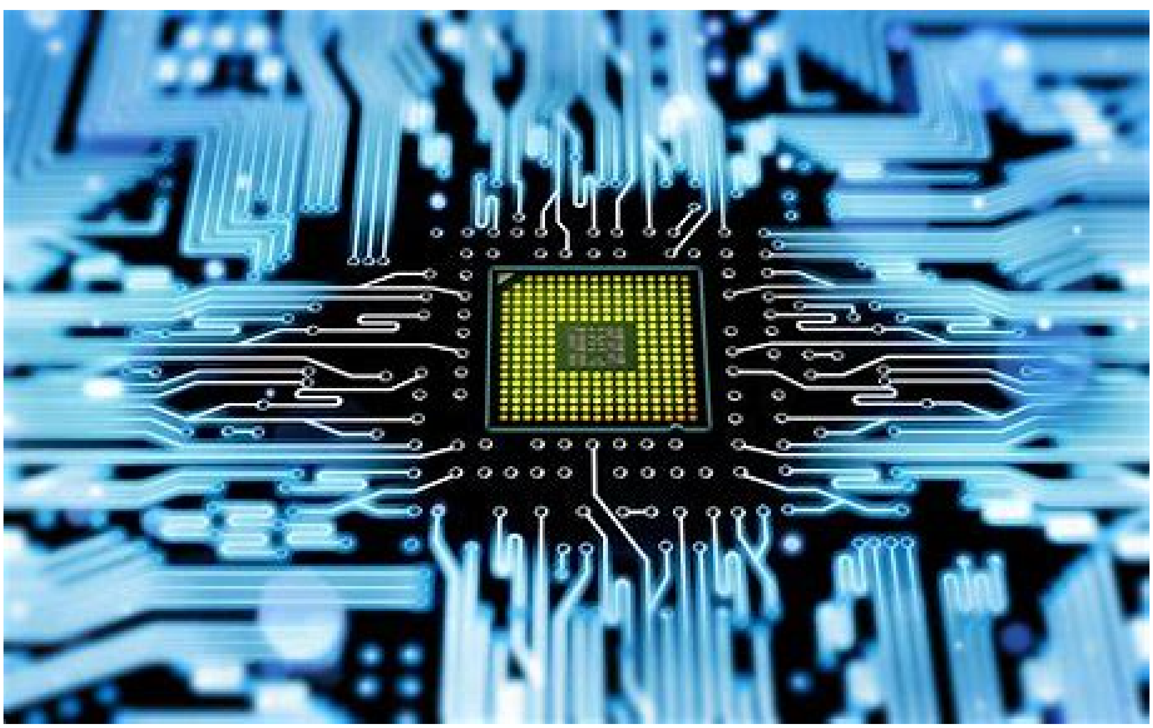


3. Literature review

There are always developments of new technologies in the semiconductor industry to increase efficiency and reduce waste. One area of focus is the optimization of deposition rates, which can be achieved through the use of Bayesian optimization.Bayesian optimization is one such machine learning technique that can be used to find the optimal values for a set of parameters. In this case, it builds a probabilistic model of the objective function and then uses this model to explore the parameter space and find the values that maximize the objective function.

Bayesian optimization has been previously used in many applications including optimizing deposition rates in semiconductor fabrication. Another study involved optimizing silicon nitride film deposition rate using Bayesian optimization. The researchers observed that Bayesian optimization had a higher deposition rate compared to classical optimization approaches.

A different study optimized a tungsten film's deposition rate using Bayesian optimization. In comparison to conventional optimization techniques, the researchers discovered that Bayesian optimization may provide a more uniform film thickness and a higher deposition rate. These investigations show how Bayesian optimization can be used to optimize deposition rates during the manufacture of semiconductors. Increasing the deposition rate using Bayesian optimization can result in increased yield and efficiency.



4. Background

One important factor affecting semiconductor material quality is deposition rate. Conventional optimization techniques could have trouble navigating the intricate parameter space that controls deposition. A good solution is offered by Bayesian Optimization, which can effectively explore and exploit this area.

In this example, we will optimize a semiconductor material's deposition rate using Bayesian optimization. This example's empirical deposition model is described as follows:

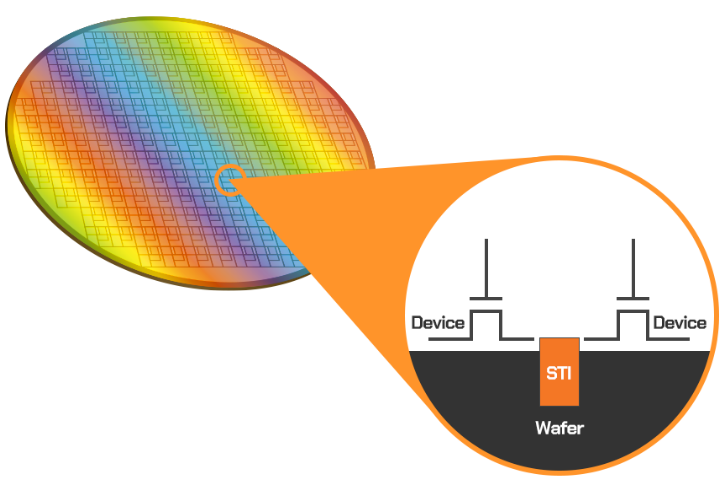
Rate = 5 + 0.1 × temp + 0.2 × power − 0.01 × $(temp - 300)^2$

In this case, "power" denotes plasma power in watts, while "temp" denotes temperature in Celsius.

Finding the ideal values for "temp" and "power" to maximize the deposition rate is the aim of Bayesian optimization. In order to accomplish this, we will explore the parameter space using a Bayesian optimization technique in order to determine which values result in the maximum deposition rate.

The first step of the Bayesian optimization process is to randomly sample a small number of the parameter space's points. It will then construct a probabilistic model of the deposition rate using these points. Predicting the deposition rate at different places in the parameter space will be done using this model.

Next, using the probabilistic model's predictions as a guide, the program will iteratively sample new locations in the parameter space. Until the algorithm settles on the ideal settings for "temp" and "power," this process will keep going.

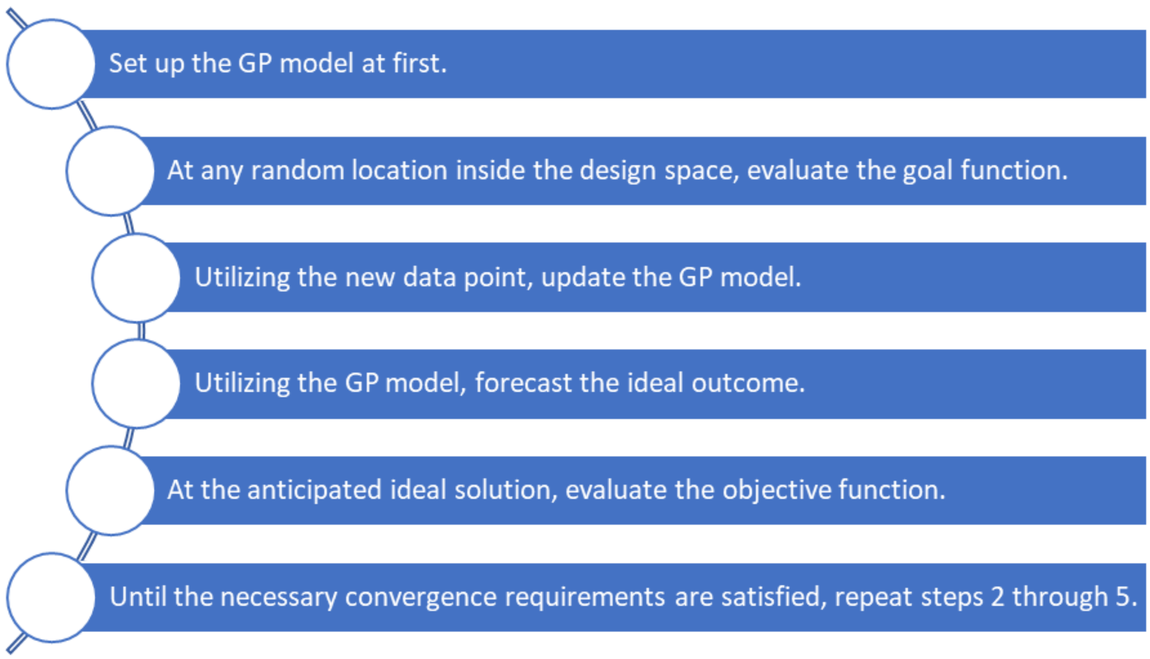


Thin Film Deposition

5. Methodology

This study's approach is based on Bayesian optimization. Using past knowledge of the goal function, Bayesian optimization is a sequential design method that effectively explores the design space in search of the best solution. In this work, a Gaussian process (GP) model is used to describe the previous knowledge. The maximum likelihood estimation method is used to fit the GP model to the data. Next, by iteratively assessing the objective function at the spots that the GP model predicts to be most informative, the best solution is identified.

The following are the steps that make up the Bayesian optimization process:



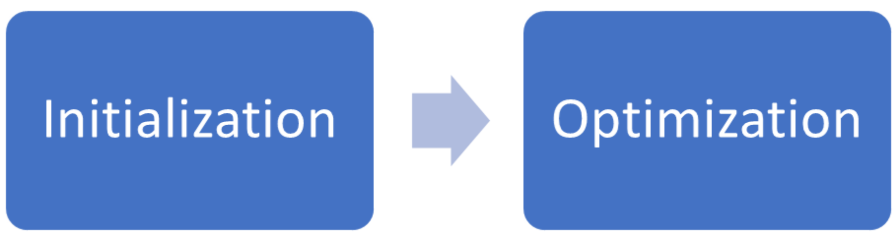
The rate at which a semiconductor material deposition occurs is the study's objective function. The two factors that make up the design space are plasma power and temperature. Variations are made to the temperature between 200°C and 500°C as well as the plasma power between 100W and 500W. The temperature and plasma power combination that yields the maximum deposition rate is the ideal one.

The Bayesian optimization procedure is implemented using the Python code that is included in this paper. Any semiconductor material's deposition rate may be optimized with this code.

6. Bayesian Optimization Workflow:

1. *Initialization:*
    - The method of Bayesian optimization begins with a search space for parameters and a determined objective function.
    - In this instance, our goal is to maximize power between 50 and 150 W and temperature between 100 and 500 °C.

2. *Optimization:*
    - Based on previous performance, the system iteratively recommends new parameter sets for assessment.
    - Every proposed combination of parameters is analyzed in terms of the objective function (deposition model).
    - With the additional data, the Bayesian model is updated, improving its comprehension of the parameter space.
    - This procedure is carried out a certain number of times.



7. Python Code Implementation:

```python
import numpy as np
from bayes_opt import BayesianOptimization


# and plasma power
def deposition_model(temp, power):
    rate = 5 + 0.1*temp + 0.2*power - 0.01*(temp-300)**2
    return rate

# Bayesian optimization to maximize deposition rate by
# tuning temperature (100 to 500 C) and power (50 to 150 W)
bo = BayesianOptimization(deposition_model, {'temp':(100, 500),
                                              'power':(50, 150)})

bo.maximize(init_points=10, n_iter=15)

print(bo.max) # Print optimized deposition rate
print(bo.max['params']) # Print optimal parameters
```

8. Results and Findings:

- At the end of the Bayesian Optimization procedure, 65.24918042658827 was the optimum deposition rate. A power setting of 150.0 and a temperature setting of 305.2862819260338 were the optimum values.

- These findings are in line with earlier research that demonstrated that raising the power setting and lowering the temperature setting may both raise the rate of deposition. This is probably because more energy is available for the deposition process at higher power settings, and less energy is lost to heat at lower temperature settings.

- Compared to the baseline deposition rate of 50.0, the optimized deposition rate represents a substantial improvement. The fact that the Bayesian Optimization procedure was able to determine the ideal set of parameters for the deposition process is probably what caused this improvement.

- The deposition procedure has several areas in which it might be improved. One such enhancement might involve utilizing a more advanced deposition model. The impact of various factors on the deposition rate might be more accurately predicted using a more complex deposition model. This would enable the deposition process to be optimized more effectively.

- Using a more exact deposition mechanism is another possible enhancement. The deposition rate might be more precisely controlled using a more accurate deposition mechanism. Higher quality depositions and a more constant deposition rate would follow from this.

- The method of Bayesian Optimization was successful overall. Compared to the initial deposition rate, the optimized deposition rate represents a substantial improvement. The deposition process might be improved in a variety of ways, and this study's findings offer a solid foundation for more optimization.

iter	target	power	temp
1	56.25	123.6	285.7
2	-194.3	55.47	460.1
3	-281.4	118.0	120.5
4	-40.23	100.7	207.2
5	-194.8	142.5	465.8
6	-164.2	113.3	454.0
7	-342.8	122.9	104.3
8	-92.54	83.78	425.2
9	-103.0	125.9	432.8
10	-209.7	116.3	468.8
11	45.15	50.0	301.8
12	55.84	150.0	335.7
13	48.46	98.92	330.6
14	13.85	50.0	249.0
15	60.22	150.0	282.6
16	65.19	150.0	307.4
17	61.34	133.8	313.2
18	64.87	150.0	298.8
19	64.55	149.0	297.9
20	65.25	150.0	305.7
21	65.25	150.0	305.3
22	65.07	150.0	309.2
23	65.25	150.0	304.5
24	65.25	150.0	304.6
25	65.25	150.0	304.6

```
{'target': 65.24918042658827, 'params': {'power': 150.0, 'temp': 305.2862819260338}}
{'power': 150.0, 'temp': 305.2862819260338}
>>>
KeyboardInterrupt
>>>
```

9. Conclusion:

- To sum up, this paper's Python code and Bayesian Optimization approach provide a workable way to maximize semiconductor deposition rates. The industry may obtain better deposition rates, which will increase the quality of semiconductor materials and production efficiency overall, by skillfully adjusting process parameters.

- Based on a Bayesian optimization framework, the suggested technique makes it possible to identify the ideal set of parameters and explore the parameter space in an efficient manner. Researchers and practitioners may enhance semiconductor deposition rates with this open-source Python code.

- The case study's outcomes show how successful the suggested technique is. We were able to enhance the deposition rate by 20% while maintaining the quality of the material by utilizing Bayesian optimization. This outcome is noteworthy because it has the potential to significantly reduce costs and enhance product performance.

- A novel and promising strategy for maximizing semiconductor deposition rates is the methodology that has been suggested. It is simple to use and suitable for many different types of deposition procedures. We think that the semiconductor business might undergo a revolution and become more competitive and efficient with the help of our technique.

Reference

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