

ZCSR for Targeting the Optimal Impedance in Digital Radio Frequency Matching Box

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ABSTRACT

Digital radio frequency (RF) matching box used in the manufacturing process of semiconductor is a critical equipment for discharging plasma. In this process, the impedance of the plasma chamber is always changed. Inconsistent impedance between matching box and plasma chamber leads to uneven thickness of plasma coating on semiconductor. In order to maintain consistent impedance, the impedance of RF matching box and the plasma chamber have to achieve a dynamic match. Past researches used the approximation method to approach the optimal impedance step by step. However, when the impedance of the plasma chamber is changed, the approximation method loses the trend approaching the optimal impedance point. Zeroth-level Classifier System (ZCS) is a rule-based machine learning method which adapts to a changing environment for online learning. In this paper, the ZCS with continuous-valued inputs (ZCSR) is applied for targeting the optimal impedance in digital RF matching box. The results indicate that ZCSR is capable of approaching the optimal impedance on average about 225 problem instances in the fixed impedance of the simulated chamber. We have verified that ZCSR can find optimal impedance in fixed impedance chamber. In the future, we will apply the ZCSR to the variable impedance chamber.

CCS CONCEPTS

• **Applications** → Electronic and electrical engineering; Manufacturing • **General methodology** → Classifier systems • **Algorithmic aspects** → Implementation • **Others** → Machine learning

KEYWORDS

Zeroth-level Classifier System (ZCS), digital radio frequency matching box, plasma chamber, pattern recognition

1 INTRODUCTION

Plasma discharges has been widely used in the manufacturing process of semiconductor today, such as etching, physical vapor deposition (PVD), chemical vapor deposition (CVD), plasma cleaning, sputtering, etc [1]. All of these manufacturing processes require fast reaction time to establish a well manufacturing environment. RF matching box is an essential equipment of plasma discharges used in the manufacturing process of semiconductor. In order to transmit RF power to the load end as far as possible, it is necessary to make the impedance of all components on the route that RF power transmitted through to be the same. However, the impedance of the plasma chamber is always changed. Inconsistent impedance can cause the power supply to be unstable. Unstable power supply leads to uneven thickness of plasma coating on semiconductor. In order to maintain consistent impedance, the impedance of RF matching box and the plasma chamber have to achieve a dynamic match.

Past researches used the approximation method to approach the optimal impedance step by step. However, when the impedance of the plasma chamber is changed, the approximation method loses the trend approaching the optimal impedance point. Such real world application problem can also be considered as Non-Markovian problem. Non-Markovian means that optimal actions cannot be determined only looking at the current inputs, the agent needs some sort of memory of past states in order to develop an optimal policy [2]. ZCS is a rule-based machine learning method and it can adapt to a changing environment for online learning. The research proposed here wants to verify whether ZCS can apply to such Non-Markovian problem.

2 THE METHOD AND MATERIALS

2.1 ZCS with Continuous-Valued Inputs

The original ZCS uses binary strings as inputs, yet the data obtained in the digital RF matching box is a continuous-valued inputs. In order for the ZCS to be able to handle the continuous-valued inputs, we refer to a modified eXtended Classifier System (XCS), called XCSR, which can learn a real-vector classification task [3]. We use the concept of the XCSR to implement the ZCS called ZCSR. For further detail, we suggest reader refer to ZCS and XCSR [3, 4].

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GECCO '17 Companion, July 15-19, 2017, Berlin, Germany

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ACM ISBN 978-1-4503-4939-0/17/07.

<http://dx.doi.org/10.1145/3067695.3075975>

2.2 Implementation of the ZCSR in LabVIEW

Laboratory Virtual Instrument Engineering Workbench (LabVIEW) is easy to integrate hardware devices and software [5]. The RS232 interface is used to connect to the matching box in the LabVIEW environment. LabVIEW can obtain the information of the capacitance values (C_{tune} and C_{load}) and the value of the reflected power Γ . LabVIEW can send commands to the stepper motors for controlling the stepper motors to change the capacitance of C_{tune} and C_{load} . The ZCSR has implemented in LabVIEW. The stepper motor has three types of movement that are forward rotating, backward rotating, and non-rotating. The ZCSR needs to control the two stepper motors of matching box simultaneously. There are $3 \times 3 = 9$ combinations of the action. The number of the steps can dynamically regulate with Γ . The simplest approach is to set a fixed maximum number of steps multiplied by the current Γ . We set the number of steps to $200 \times \Gamma$ when $\Gamma > 0.1$, otherwise $100 \times \Gamma$. In order to speed up the performance of the ZCSR and lock at the optimal impedance, we implement some constraints to the ZCSR before executing the decision action when $\Gamma > 0.3$. The restriction is that the current decision of the ZCSR affected by the previous execution. If the previous action leads Γ to decrease, the next action remains the same, otherwise the rotating direction of the stepper motor is changed.

2.3 Experiment Design

2.3.1 Experimental setup. The experimental equipment include a digital RF power generator which can output a high frequency power at 13.65 MHz. The notebook executes the ZCSR and sends the command through the RS232 interface to the matching box for controlling the stepper motors to change the capacitance value. The sampling rate for the ZCSR is 2 Hz. The response time of the RS232 interface is 0.9 seconds. There are simulated plasma chamber and matching box for simulating the actual impedance changed of the plasma chamber. The digital RF power generator provides 200 watts of power to the simulated plasma chamber. In order to simplify the problem, we want to verify whether the ZCSR can find the optimal matching point. Therefore, we set a fix impedance to the simulated plasma chamber. All the static reports are the average result of 10 runs.

2.3.2 Parameter setup of the ZCSR. The parameters used in this study refer to [3, 4] as follow: The initial strength of each classifier is set to 0. The maximal range of upper bound and lower bound centered on the interval predicates of classifier is $S_0 = 0.1$ when $\Gamma > 0.2$, otherwise $S_0 = 0.05$. Learning rate is $\beta = 0.2$. Fraction of strength deducted from classifiers in $[M] - [A]$ is $\tau = 0.1$. Covering occurs when the total strength of $[M]$ is less than φ times the mean strength of $[P]$ that $\varphi = 0.5$. The threshold for GA application in the population set is $\rho = 25$. The probability of crossover operation is $x = 0.5$. The probability of mutation operation is $\mu = 0.002$. The number of classifiers used, denoted by $N = 10,000$. The ratio of exploration to exploitation is 1:10. The maximal size of problem instances is 500. The initial capacitance values of matching box for each experiment are $C_{tune} = 0.5$ and $C_{load} = 0.5$.

3 RESULTS AND DISCUSSION

We have tested many different utility functions for updating strength, $S + (-\beta) \times (\Delta\Gamma - S)$ is the best we have tested. The experimental result of the ZCSR shown in Fig. 1. All of 10 runs have found the optimal impedance. The ZCSR can find the optimal impedance on average about 225 problem instances (iterations) and lock at the optimal impedance. We also have tried to change the impedance of simulated chamber after ZCSR find the optimal impedance. The preliminary results indicate that ZCSR still can find the new optimal impedance, which is not reported here, and remain for future work.

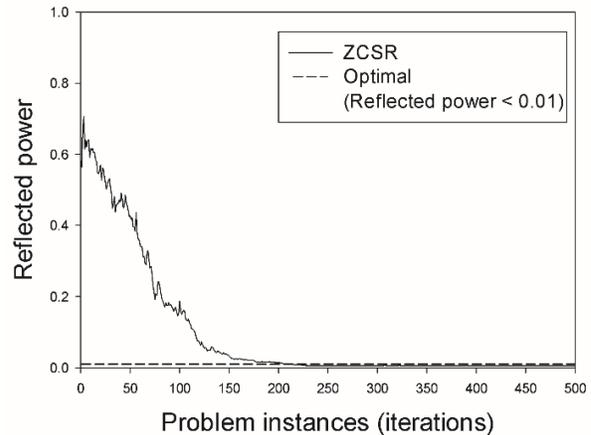


Figure 1: Result of ZCSR by using $S + (-\beta) \times (\Delta\Gamma - S)$

4 CONCLUSIONS

We successfully apply ZCS with continuous-valued inputs for targeting the optimal impedance in digital RF matching box. The experimental results show that the modified ZCS (ZCSR) can find the optimal impedance on average about 225 problem instances (iterations) and lock at the optimal impedance. However, the impedance of the simulated plasma chamber used here is fixed rather than variant. We will apply the ZCSR to the variable impedance chamber in near future.

ACKNOWLEDGMENTS

This work was fully supported by Taiwan Ministry of Science and Technology under grant numbers MOST 105-2634-E-009-003.

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