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Topology Optimization Based on Deep Learning and toward Their Coevolution

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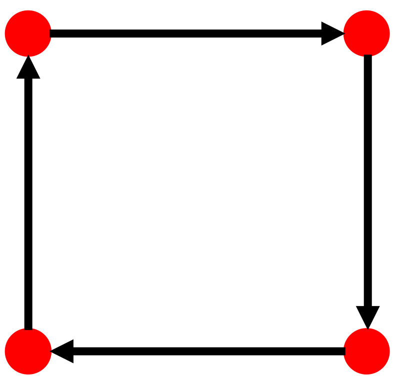
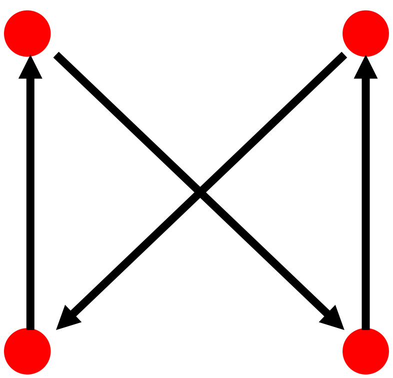
Traveling Salesman Problem (TSP)

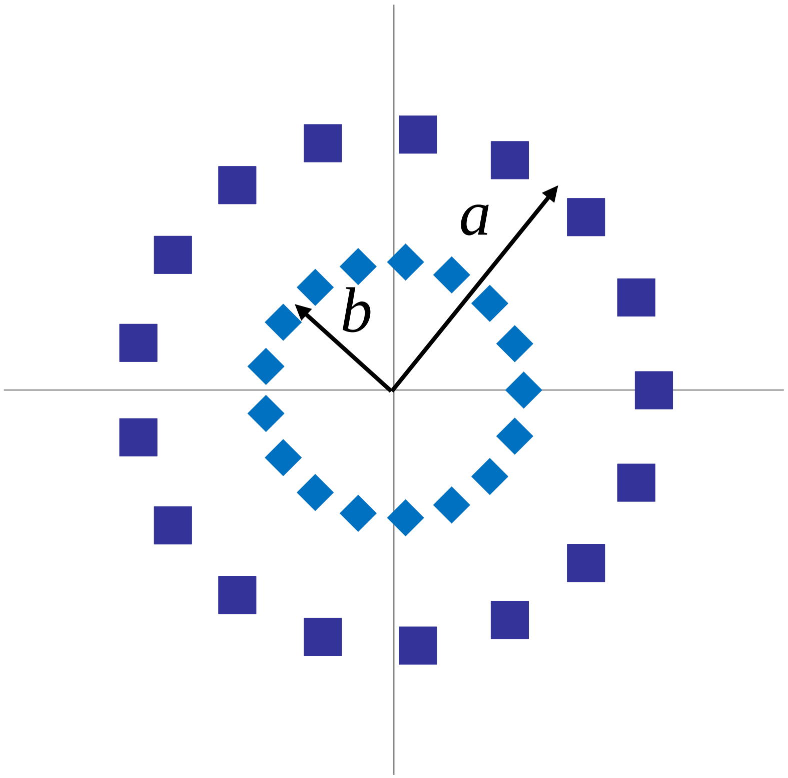
Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city and returns to the origin city? (WiKi)

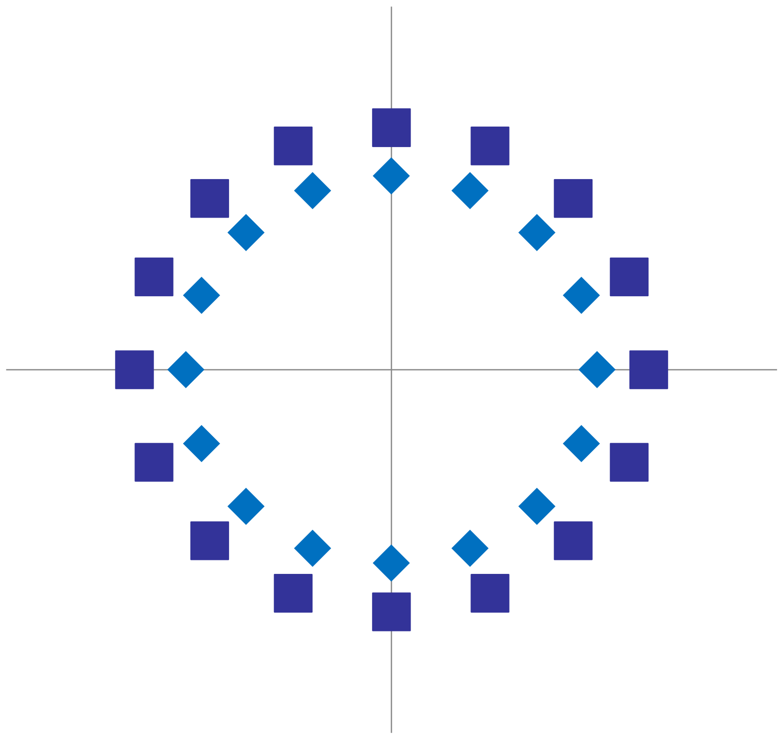




$$L_1 = 4 \quad < \quad L_2 = 2 + \sqrt{2}$$

TSP for cities on concentric circles





$$r = \frac{b}{a}$$

Complexity of TSP

Number of combinations to visit n cities is found to be

$$C = \frac{1}{2}(n-1)!$$

The value of $n!$ can be estimated by the Stirling approximation.
For example, when $n = 30, C$ is estimated to be

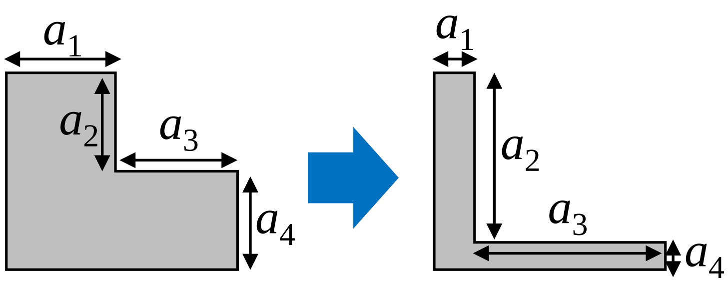
$$\begin{aligned} \log_{10} n! &\approx n(\log_{10} n - \log_{10} e) \\ &= n(\log_{10} n - 0.43) \approx 30 \end{aligned}$$

Core i7(10^6 Mips) executes an instruction for 10^{-12} sec.
Thus, roughly speaking, 10^{18} sec = 10^9 years (10億年)
lasts for 10^{30} computations, that is, 30 city-problem.

Shape Optimization

Parameter Optimization

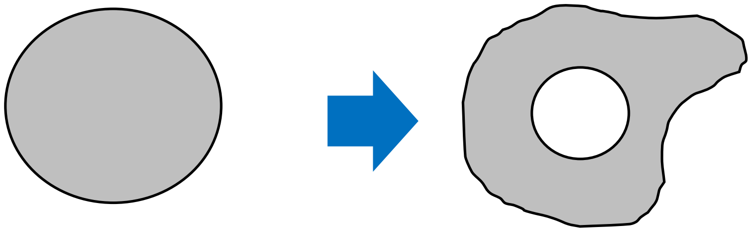
- Unknowns: design parameters



- Parameter design is necessary.
- Sound approach but little novelty

Topology Optimization

- Shape is free deformed. Holes can be generated or annihilated.



- No parameter design
- Novel design might be obtained.

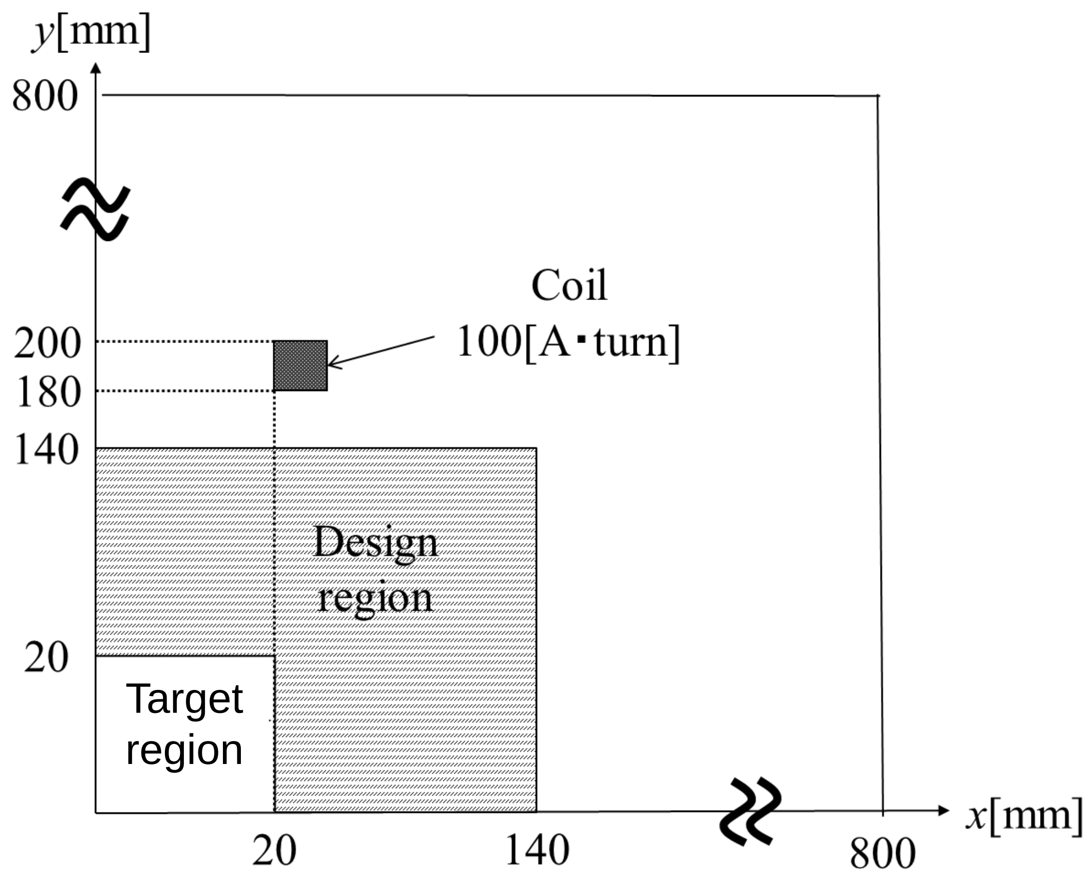
Example of Topology Optimization

- The present method is applied to magnetic shield model shown below.
- The purpose of this optimization is to minimize the flux density in the target region and core volume in the design region.

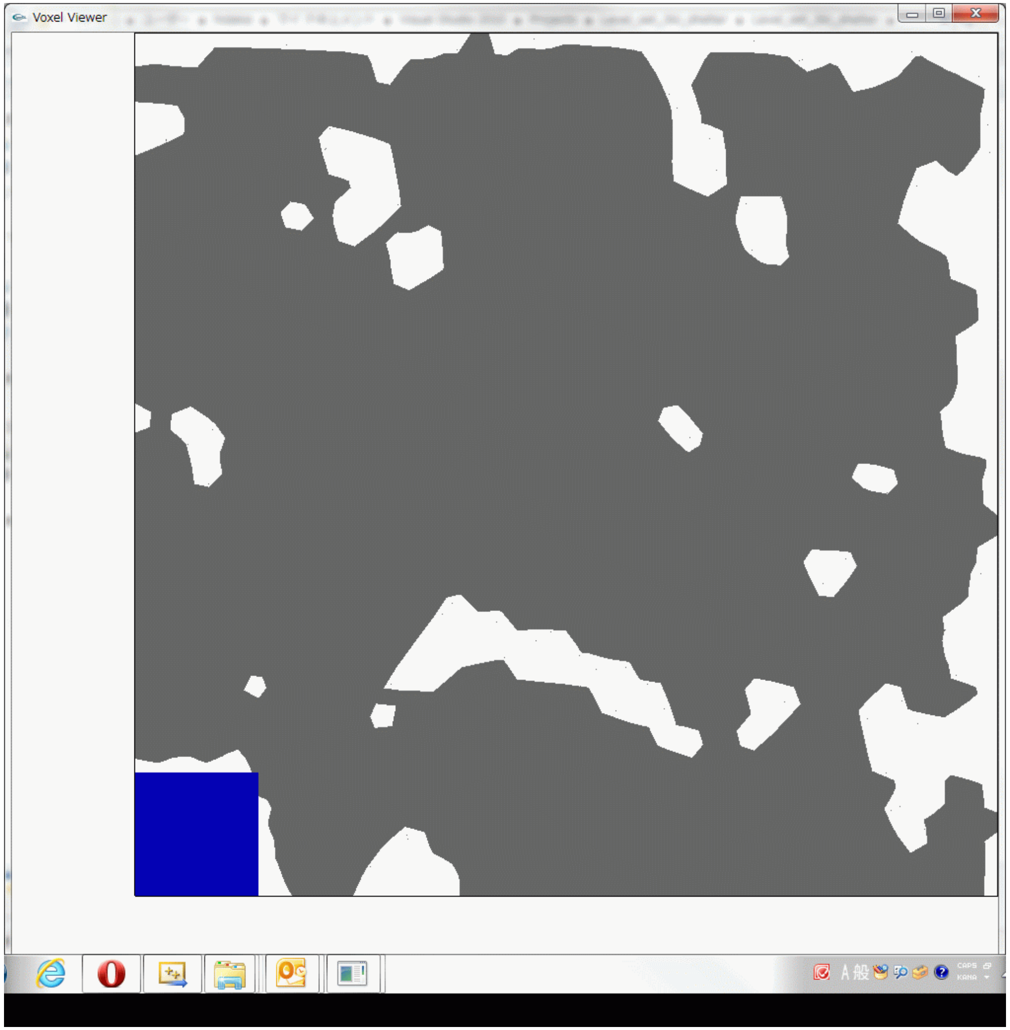
■Optimization Problem

$$F(\phi) = W_M \frac{|\boldsymbol{B}|_{average}}{10^{-5}} + \frac{S}{S_{design}} \rightarrow \text{Min.}$$

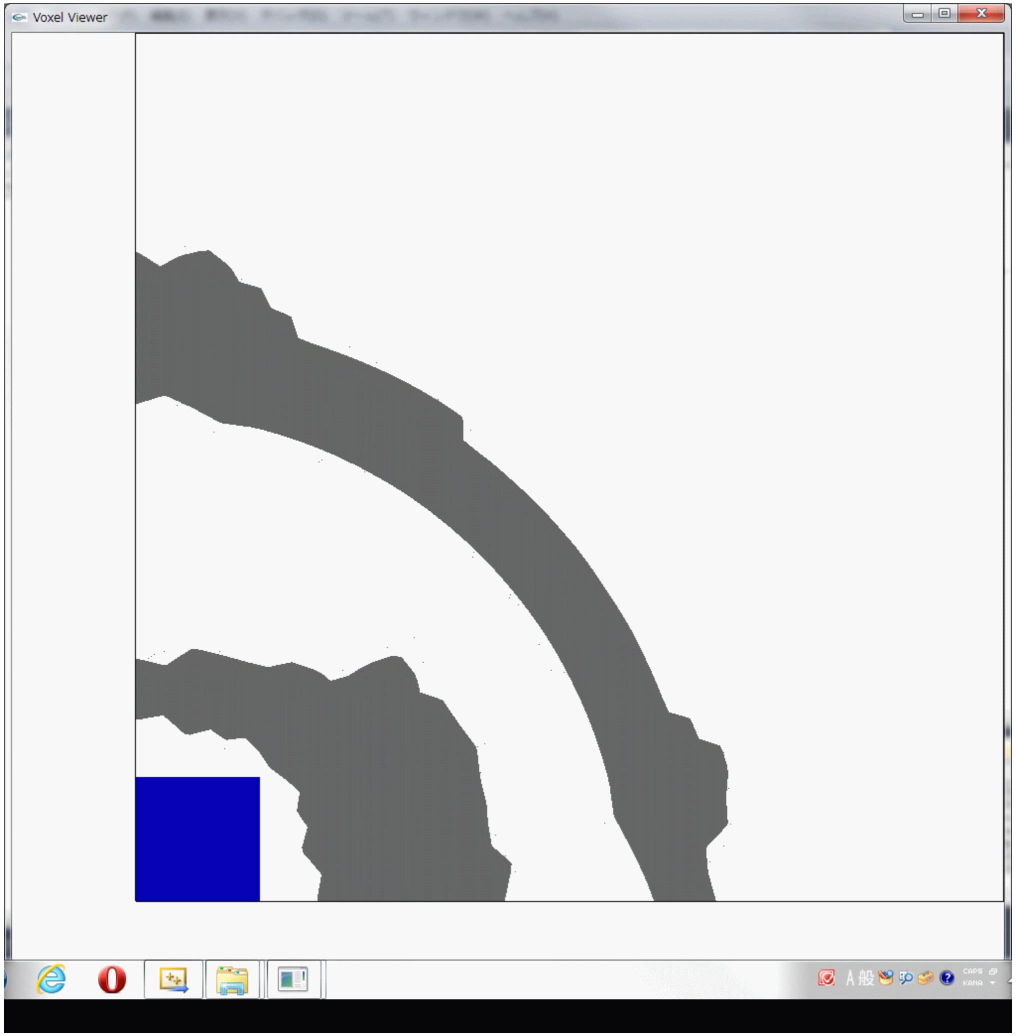
W_M : weighting coefficient
S : core volume
S_{design} : volume of the design region
$\boldsymbol{B}$: flux density of in the target region



Global search

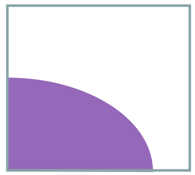
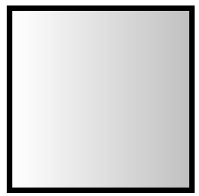
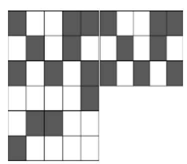
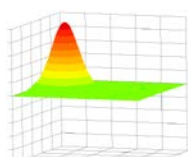


Local search

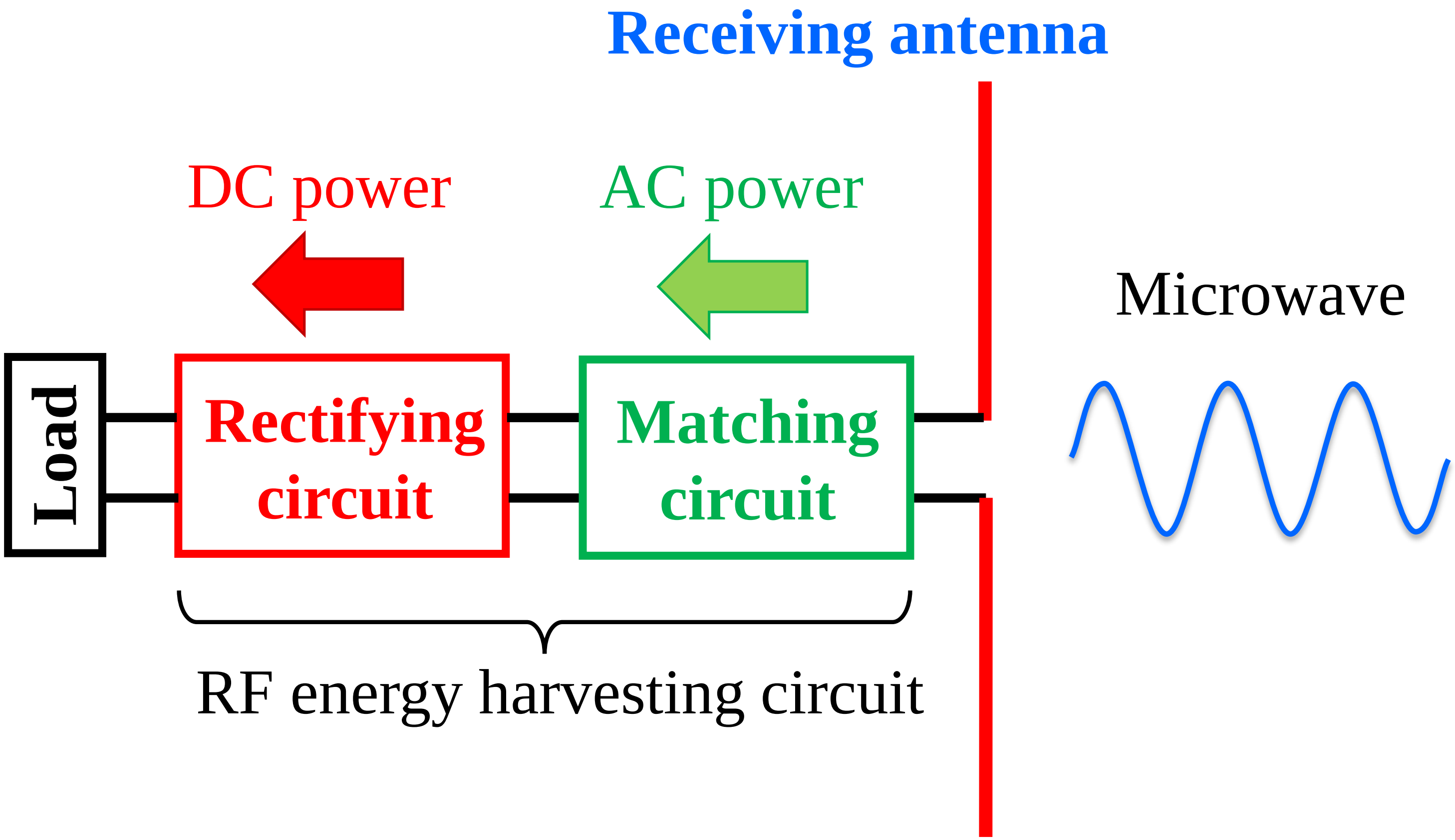


Y. Hidaka, T. Sato, H. Igarashi, "Topology Optimization Method Based on On–Off Method and Level Set Approach," IEEE Transactions on Magnetics, Volume:50, Issue:2, Article#7015204, 2014.

Methods for Topology Optimization

Methods		Optimization	Features
Level set		Sensitivity analysis	Small comp. cost Derivative computation Local search
Density			
ON/OFF		Stochastic algorithm, e.g. GA	Large computing cost No derivative comp. Global search
Basis function $\psi(\boldsymbol{x}) = \sum_n w_n G_n(\boldsymbol{x})$			

- The microwave energy-harvesting device is composed of a receiving antenna and RF energy harvesting circuit.

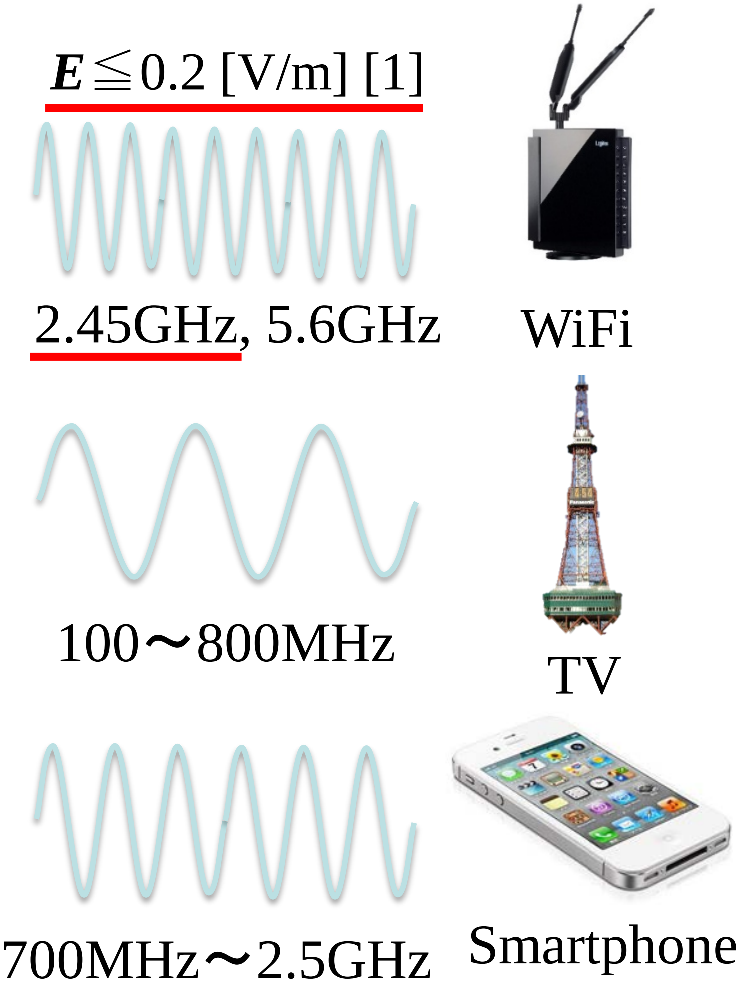


Microwave energy-harvesting device

- We optimize the shape of receiving antenna and circuit parameters using optimization algorithm based on evolution technique.

- We consider harvesting energy from microwave transmitted by wireless rooter.

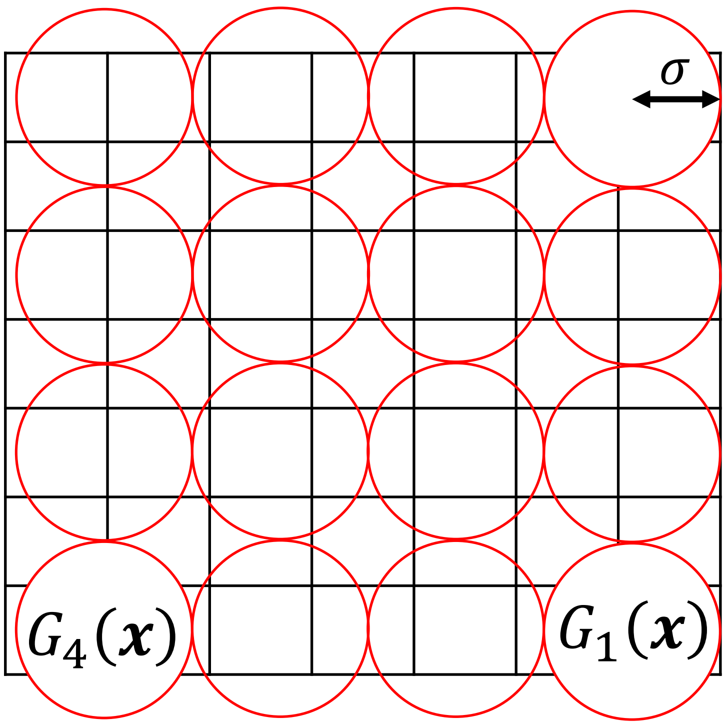
- The measured electric field intensity of 2.45GHz microwave is about 0.2V/m.



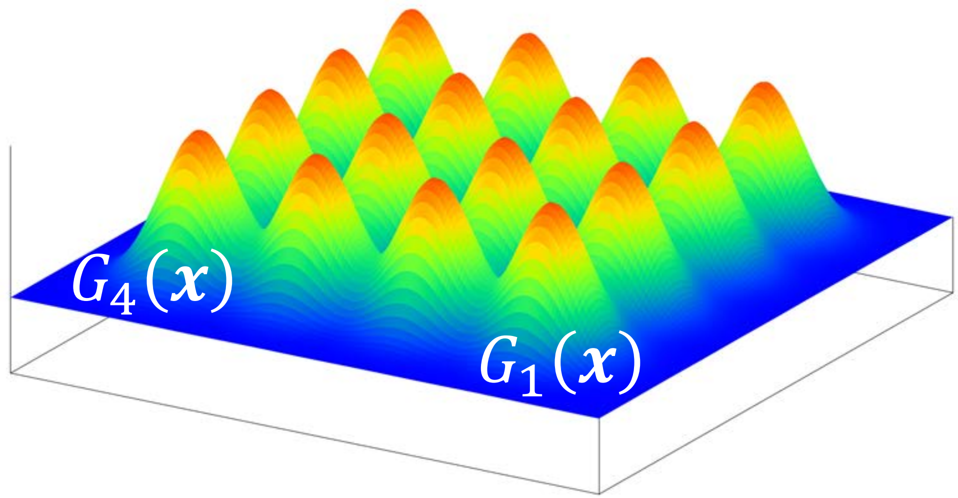
[1] Y. Kawahara, et al., “Power Harvesting from Microwavr Oven Electromagnetic Leakage”, *Proc. The 2013 ACM international Joint Conference on Pervasive and Ubiquitous Computing, pp. 373-382, 2013.*

NGnet on/off method

Gaussian functions are uniformly deployed so that the design region is covered by the support of the Gaussians.



Design region



Gaussian function

$$G_i(\boldsymbol{x}) = \frac{1}{(2\pi\sigma)^{\frac{3}{2}}} \exp\left\{-\frac{1}{2\sigma^2}|\boldsymbol{x}-\boldsymbol{x}_i|^2\right\}$$

σ :standard deviation

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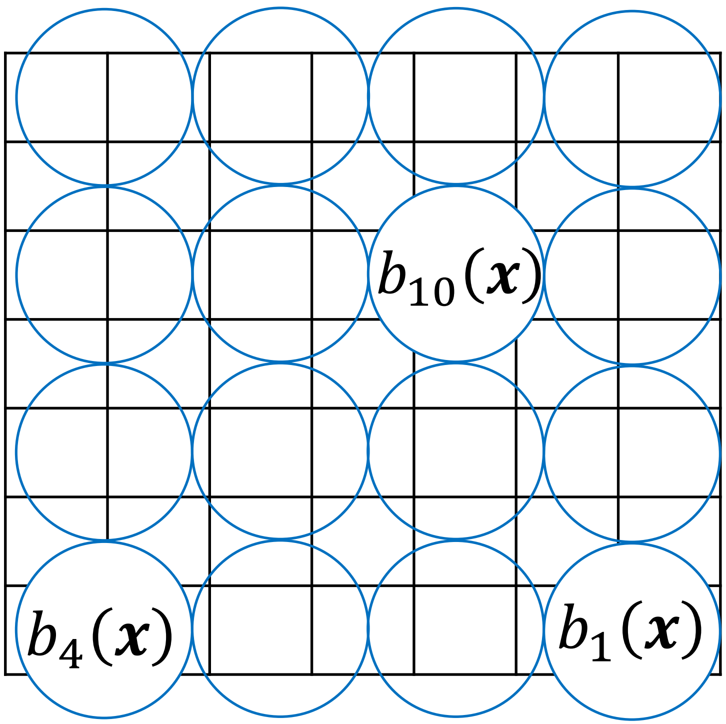
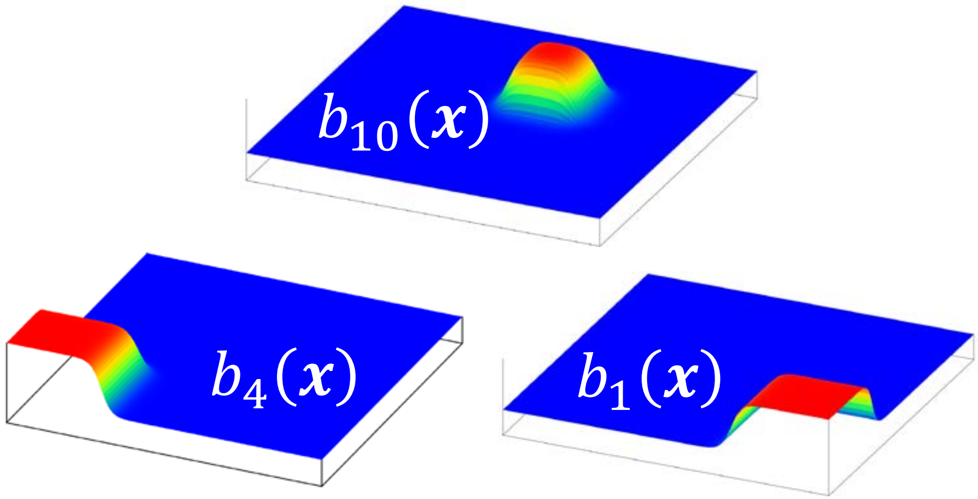
NGnet on/off method

Gaussian functions in the design region are normalized.



Design region

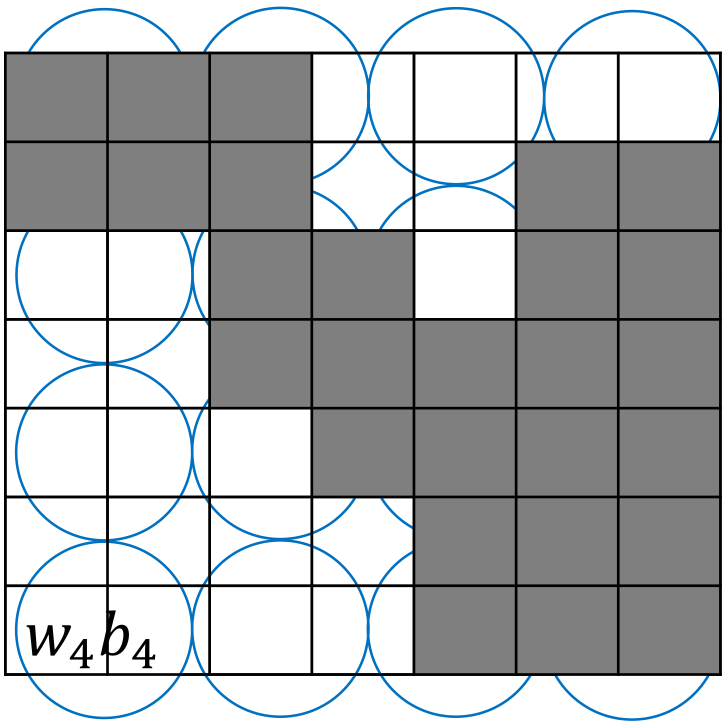


Normalization

$$b_i(\boldsymbol{x}) = G_i(\boldsymbol{x}) \Big/ \sum_{j=1}^{N} G_j(\boldsymbol{x})$$

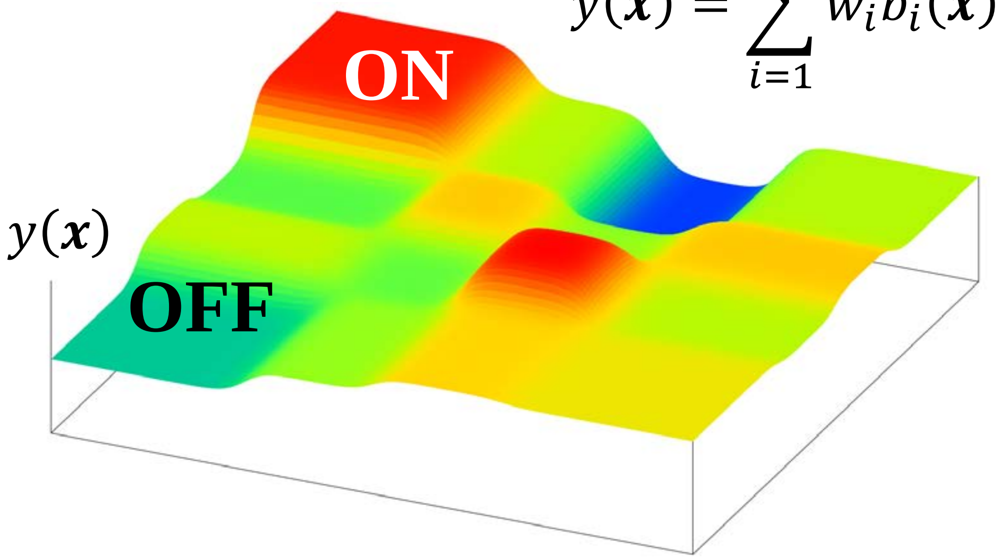
NGnet on/off method

To determine the material attribute in the design region, we use the output of the shape function $y(\boldsymbol{x})$.



Design region

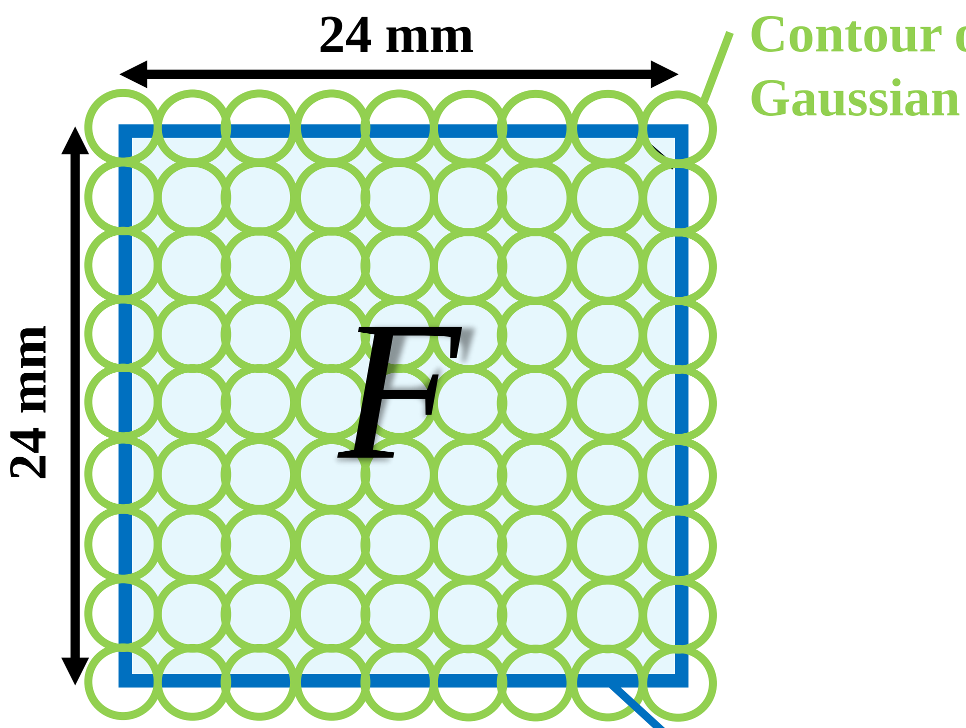
$$y(\boldsymbol{x}) = \sum_{i=1}^{N} w_i b_i(\boldsymbol{x})$$



Material attribute

$$M_e = \begin{cases} \text{ferrite (ON)} & y(\boldsymbol{x}) \geq 0 \\ \text{air (OFF)} & y(\boldsymbol{x}) < 0 \end{cases}$$

The Gaussian functions are uniformly deployed in the unit region whose direction is represented by “*F*”.



Distribution of
Gaussian functions

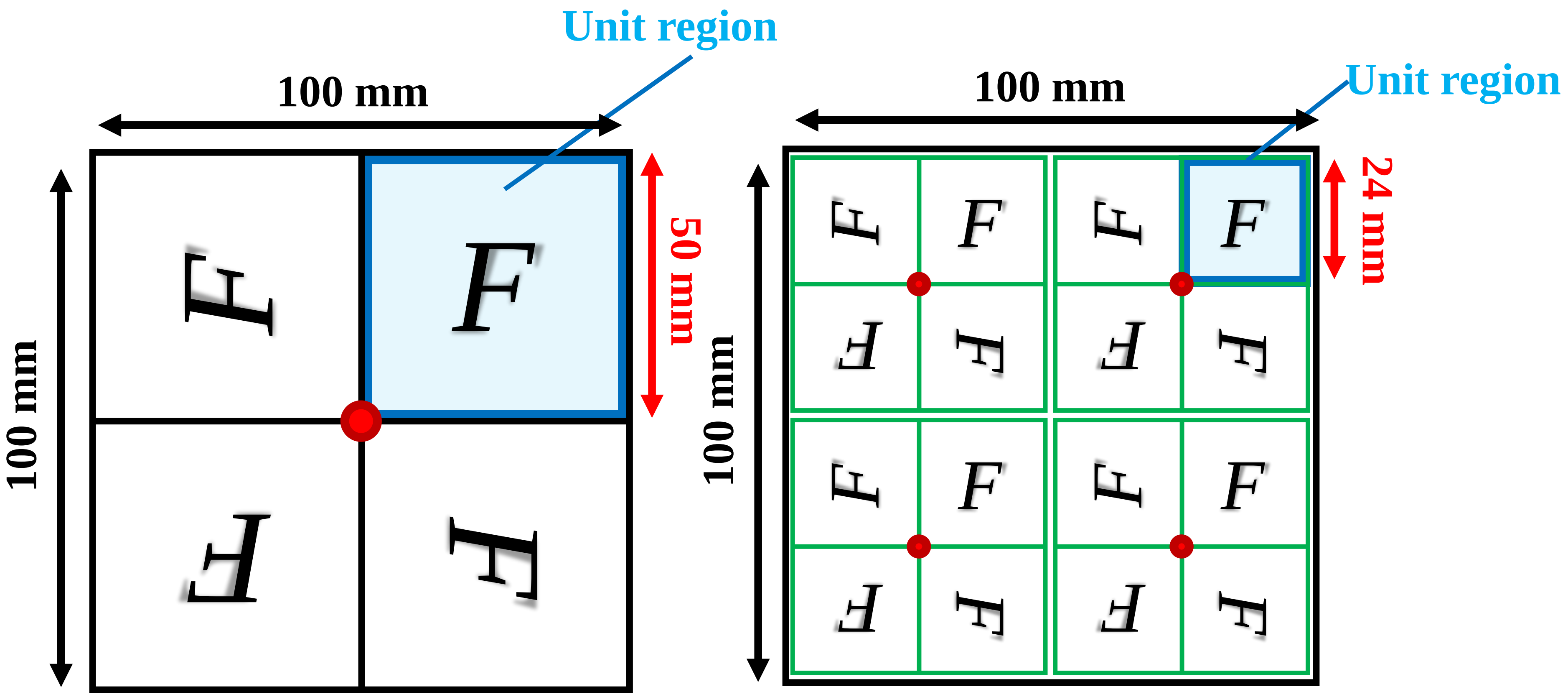
Shape function

$$y(\boldsymbol{x}) = \sum_{i=1}^{N} w_i b_i(\boldsymbol{x})$$

***N*=81**

The single antenna consists of four unit regions with C_4 symmetry.

The array antenna consists of four 4×4 unit regions with C_4 symmetry.



(a) single (b) array

Optimization Problem

The actual gain is maximized in the frequency period (1.5GHz, 3.5GHz).

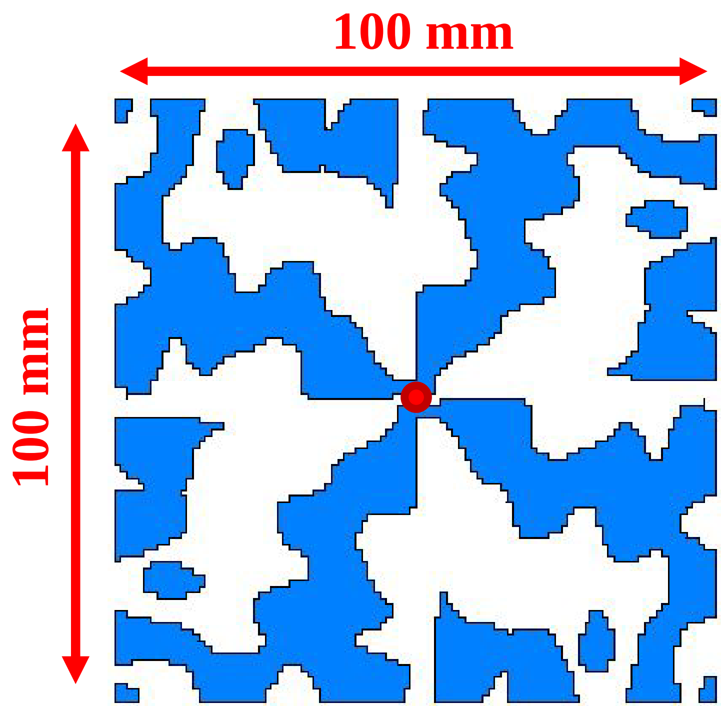
$$< G_{actual} >= \frac{\int_{f_0}^{f_1} G_{\mathrm{actual}}(f)\,df}{f_1 - f_0} \to \max$$

$$G_{\mathrm{actual}}(f) = \frac{1}{4}\sum_{k=1}^{4} G_{\mathrm{iso}}(f)\left(1 - \left|\frac{Z_{\mathrm{a}}^{k}(f) - Z_{\mathrm{c}}}{Z_{\mathrm{a}}^{k}(f) + Z_{\mathrm{c}}}\right|^2\right)$$

impedance matching

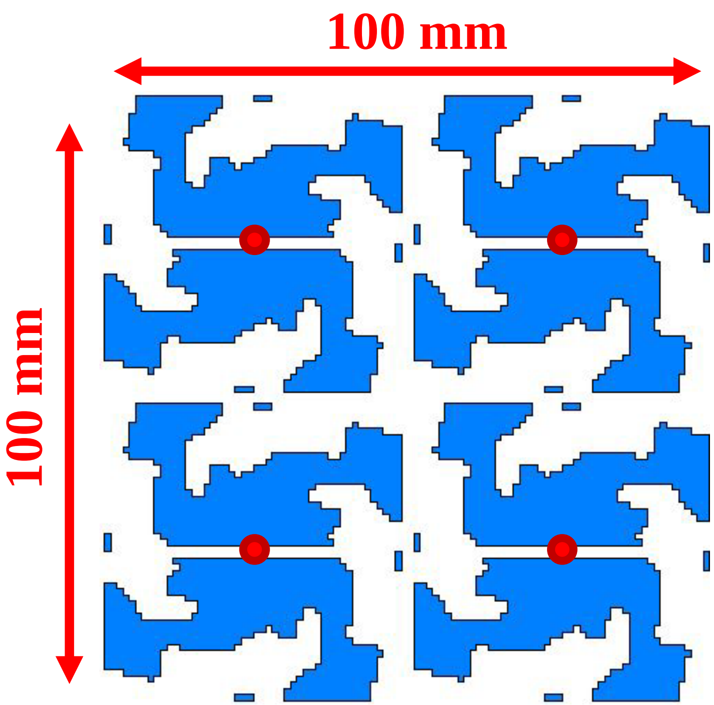
G_{actual} : actual gain
G_{iso} : absolute gain
Z_{a} : input impedance of antenna
Z_{c} = 50 Ω : input impedance of circuit
f_0 = 1.5 GHz
f_1 = 3.5 GHz

Optimal Shapes



(a) single

$\langle G_{actual} \rangle = 5.6 \text{ dBi}$

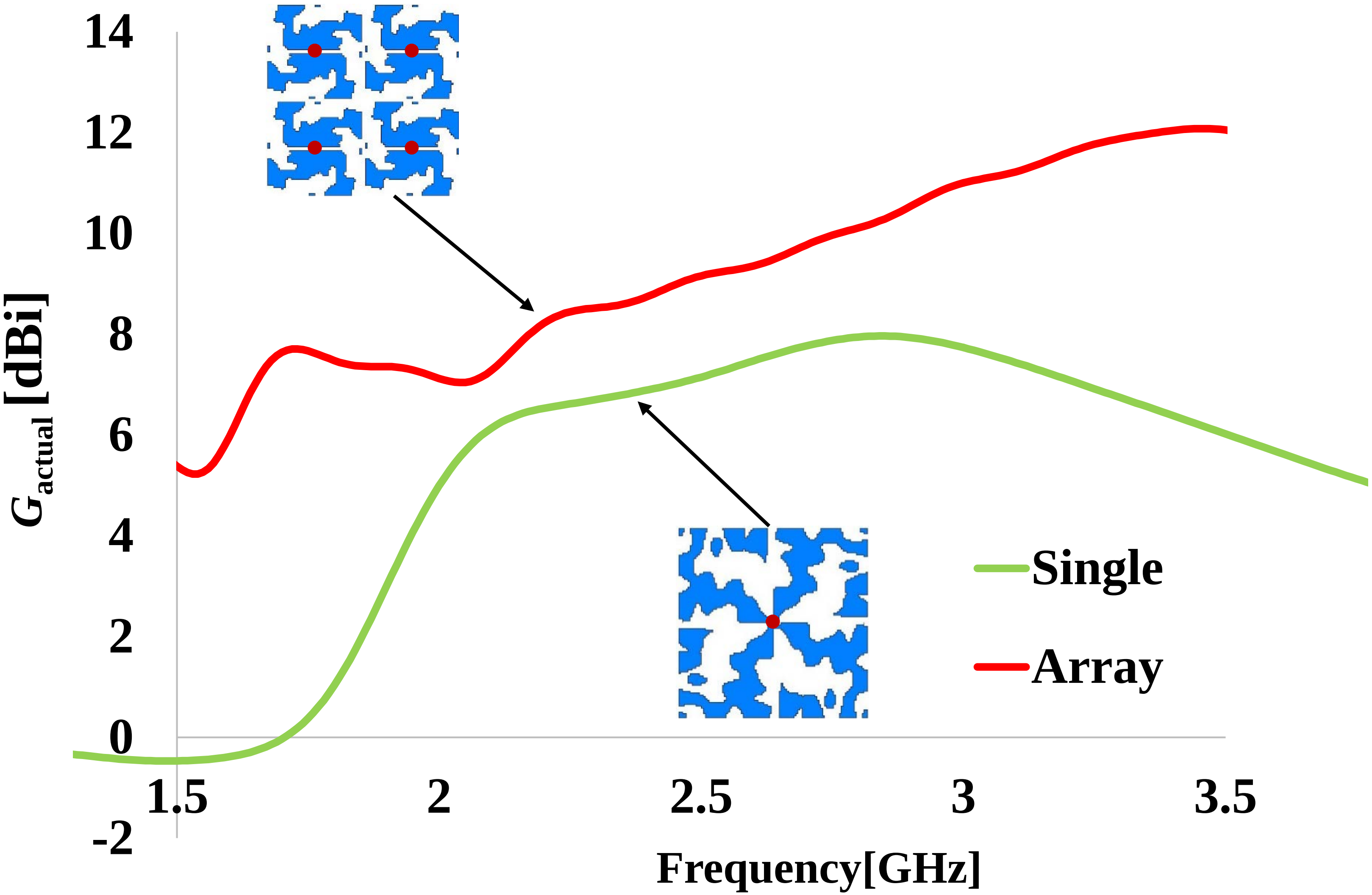


(b) array

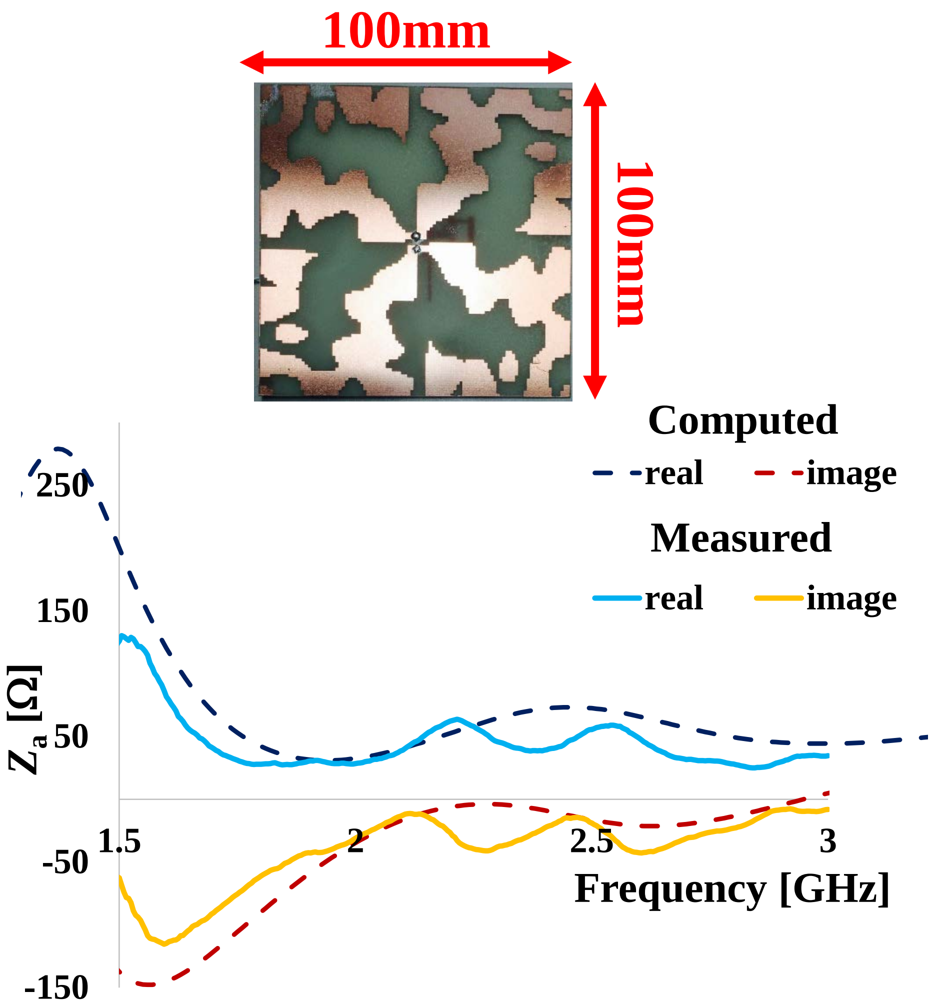
$\langle G_{actual} \rangle = 9.2 \text{ dBi}$

T. Mori, H. Igarashi, Topology optimization of wideband array antenna for microwave energy harvester, International Journal of Applied Electromagnetics and Mechanics, vol. 52, no. 1-2, pp. 631-639, 2016.

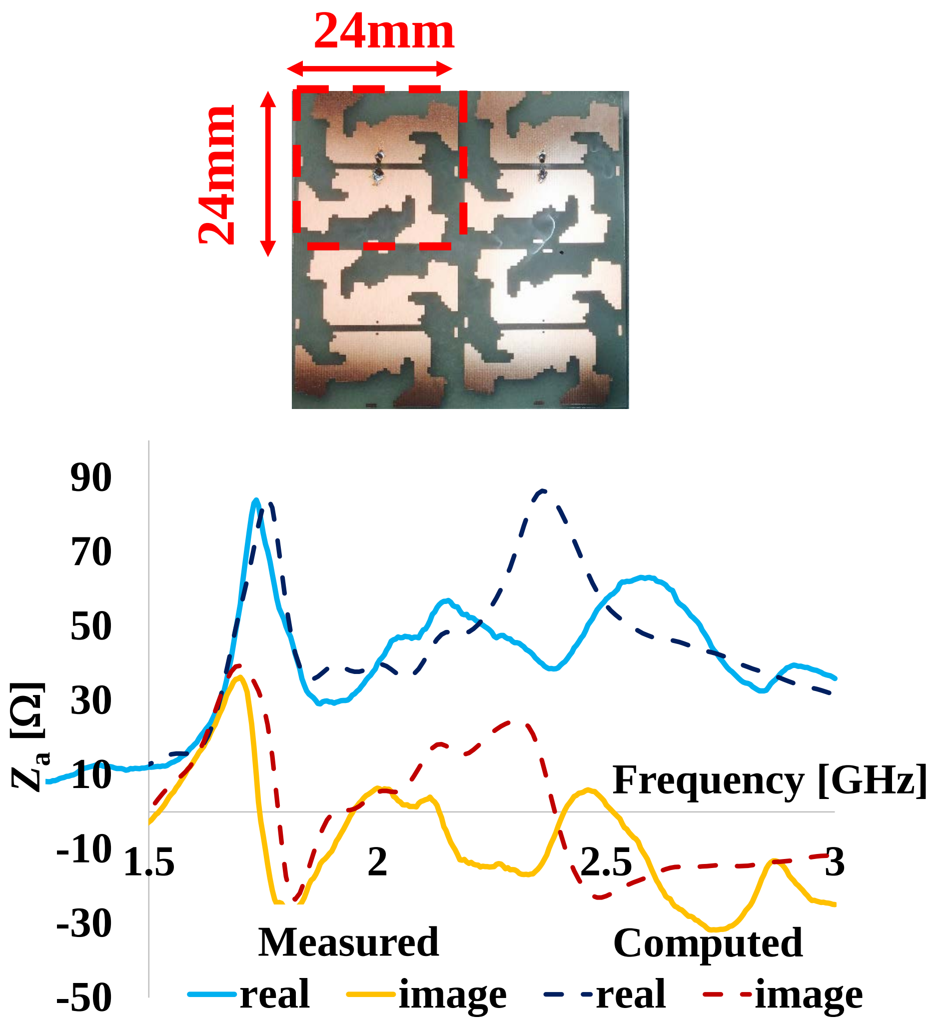
Optimization result



Computed and measured input impedance

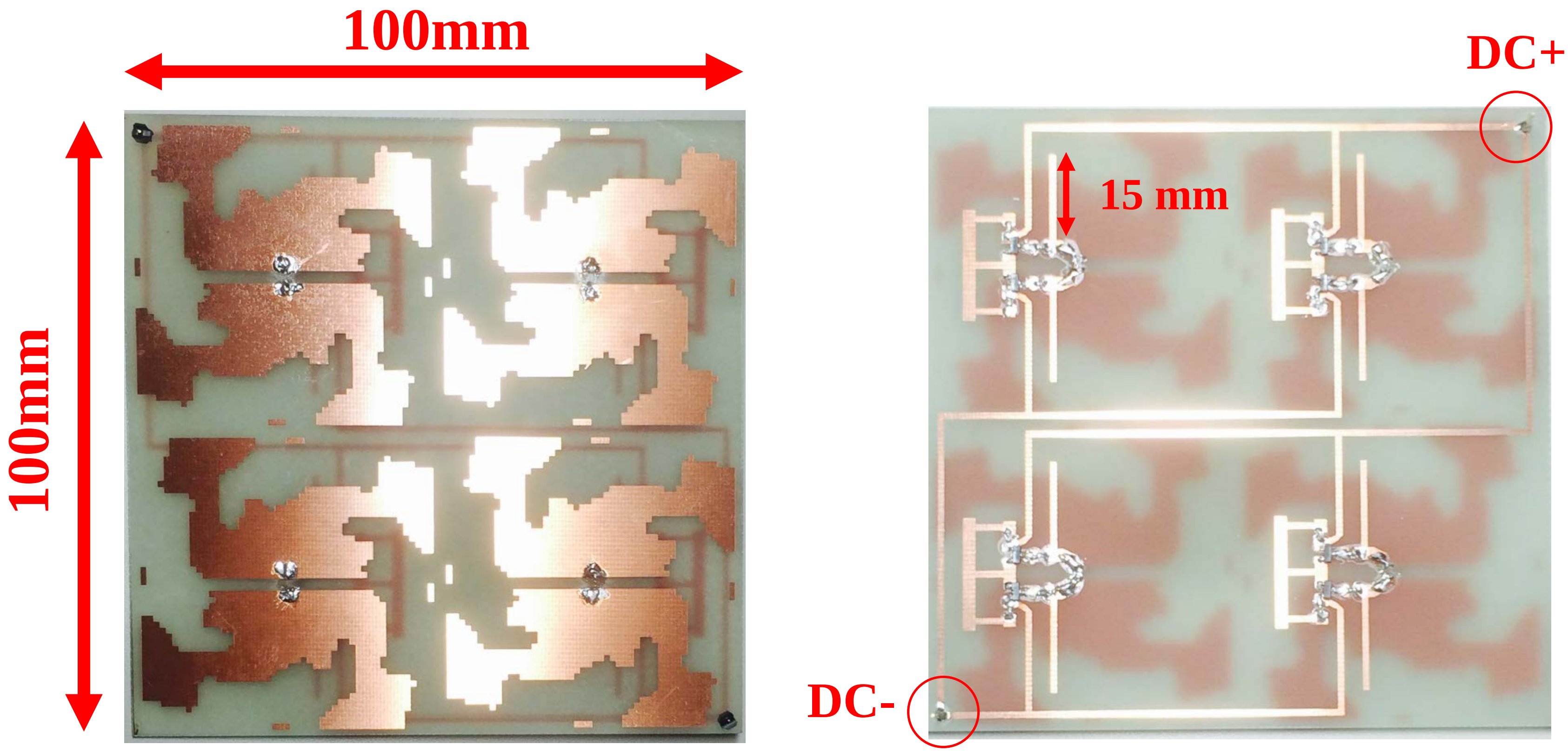


(a) single



(b) array

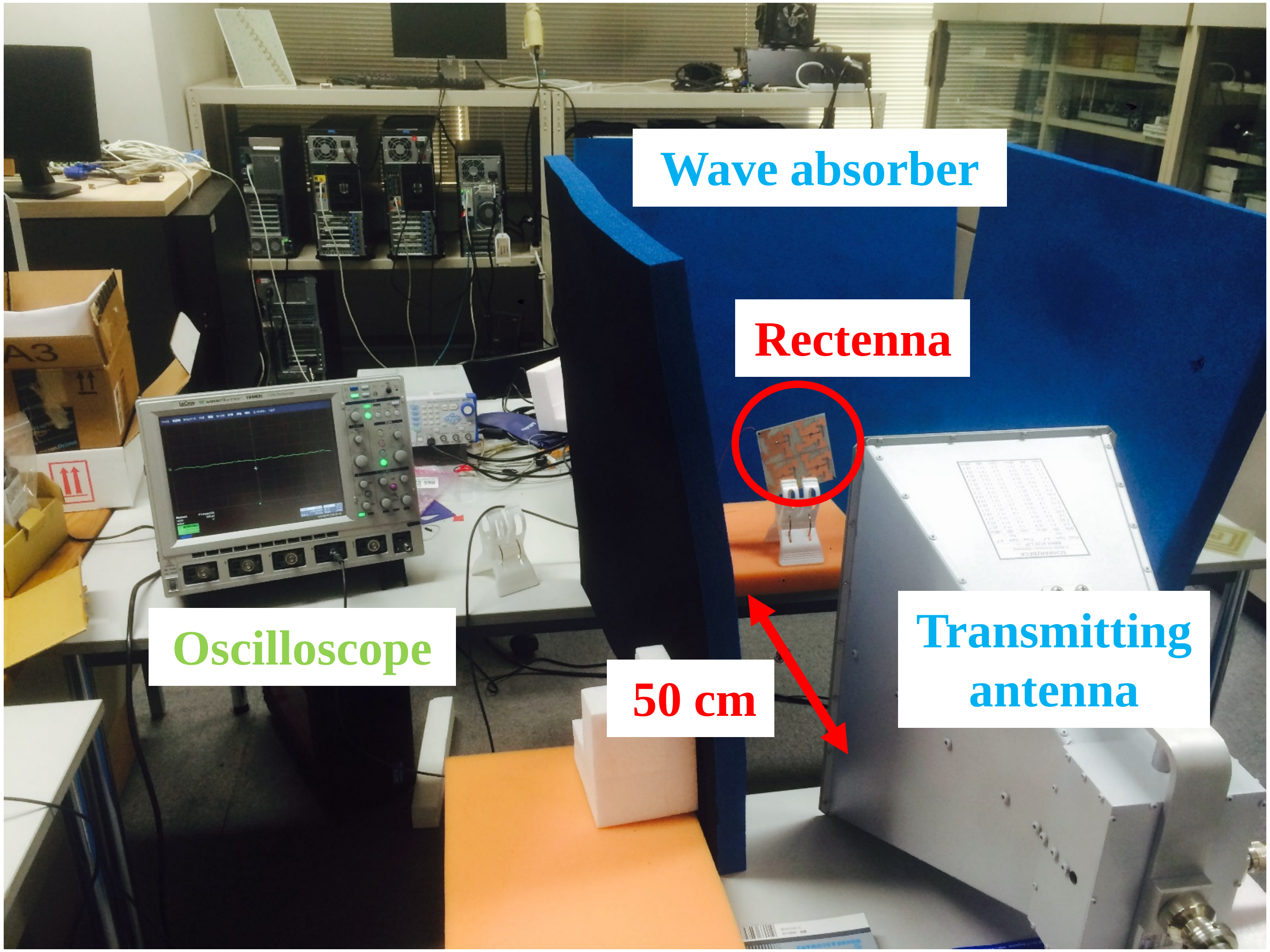
Realization of optimized antenna

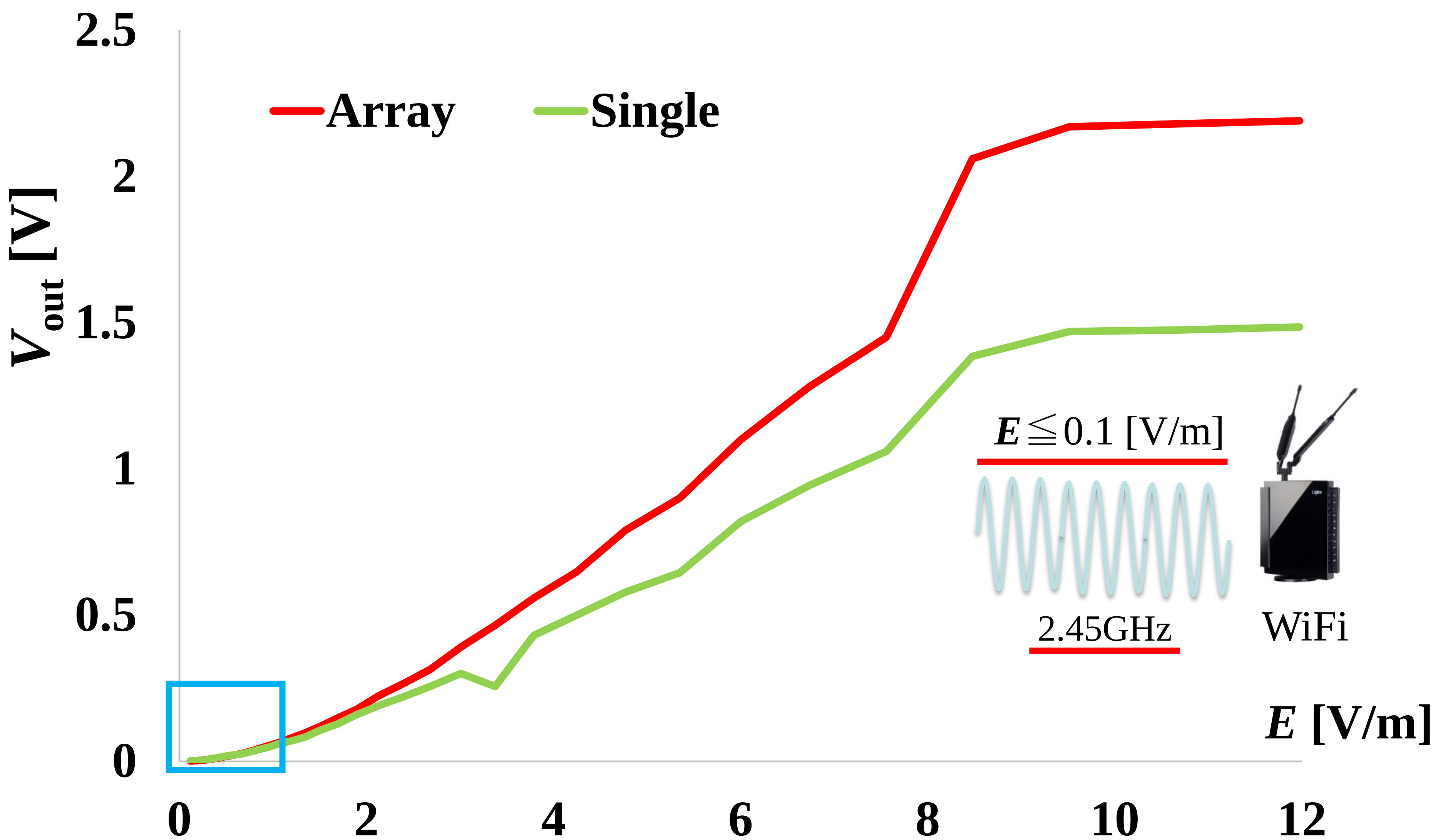


(a) front face (b) back face with circuit

Manufactured Array Antenna

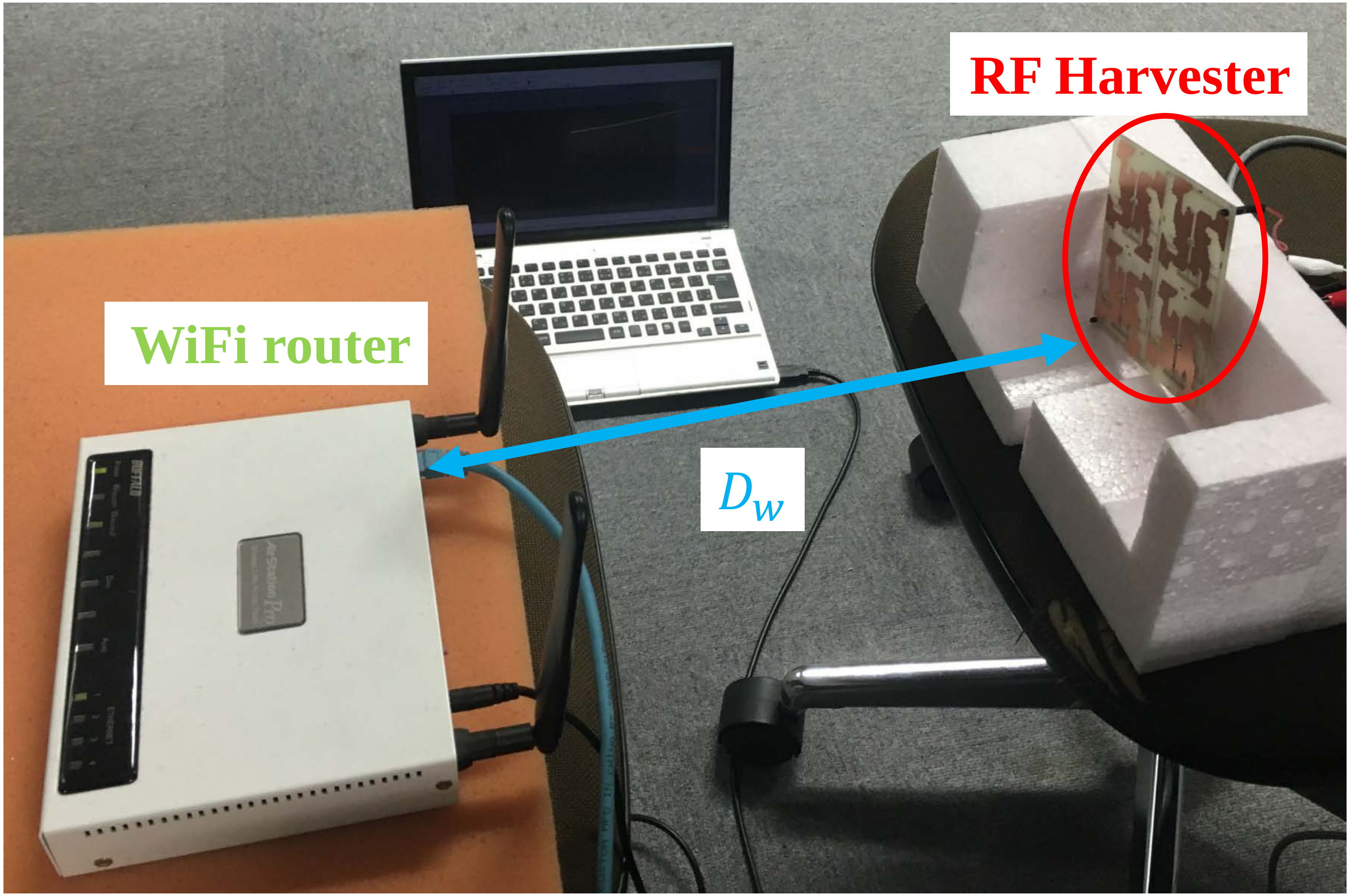
Measurement of output voltage



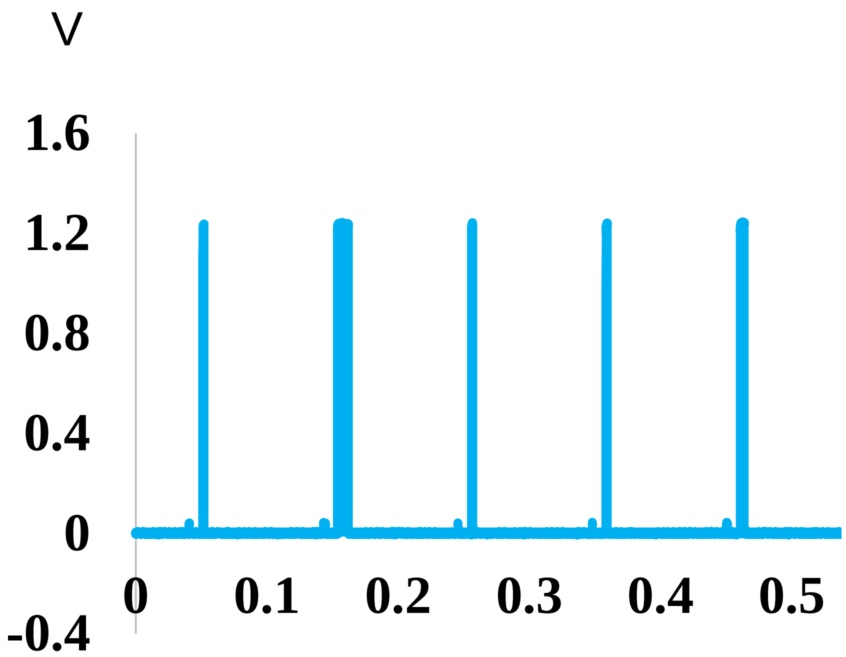


Output Voltage V_{out} (measured)

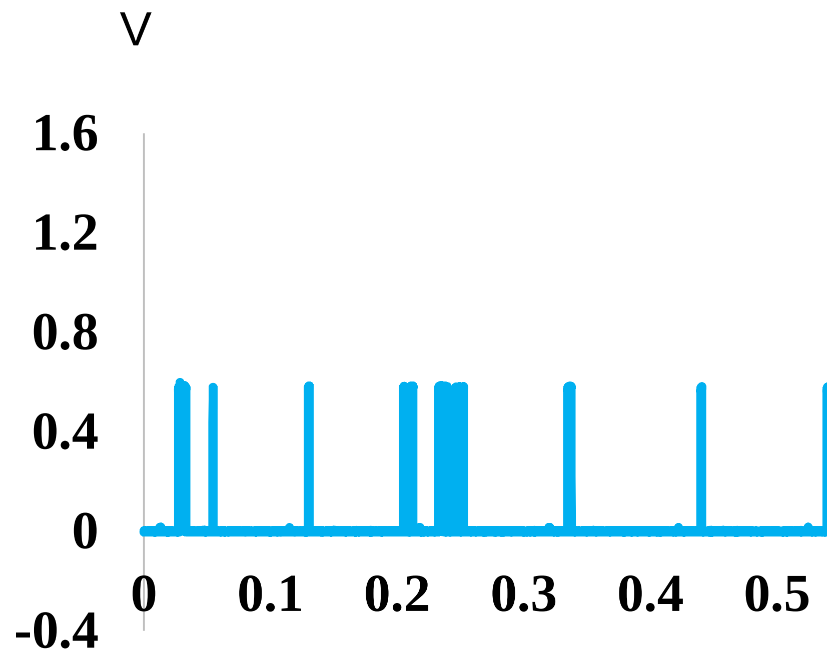
Operation test: RF harvester located near WiFi router



Voltage generated by harvester



$D_W = 15\text{cm}$



$D_W = 30\text{cm}$

From Hybrid Vehicle (HV) to Zero Emission Vehicle (ZEV)

For manufacturers with annual sales greater than 60,000 vehicles, at least 14% of the vehicles they produce and deliver for sale in California must meet ZEV requirements for 2015 through 2017.

Optimization of Wireless Power Transfer

- Wireless power transfer (WPT) for EVs is expected to expand rapidly.

WPT system for EVs

Y. Otomo, Y. Gong, H. Igarashi, 3-D Topology Optimization of Magnetic Cores for Wireless Power Transfer with Double-Sided Shielding Coils, presented at OIPE2018, submitted to Int. J. AEM.

Optimization problem

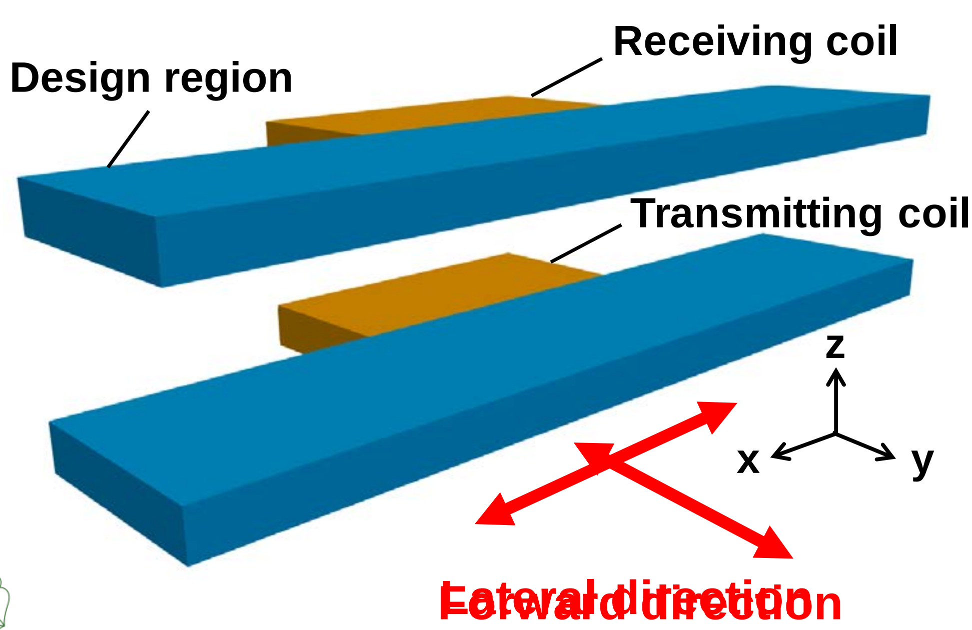
Optimization problem

$$\max_{\boldsymbol{w}} F(\boldsymbol{w}), \qquad F(\boldsymbol{w}) = \frac{1}{N_{\mathrm{P}}} \sum_{i=1}^{N_{\mathrm{P}}} k_i(\boldsymbol{w}), \qquad \text{sub. to } \Omega_{\mathrm{M}} \leq \frac{\Omega_{\mathrm{D}}}{2}$$

$k_i(\boldsymbol{w})$: coupling coefficient of the i-th misalignment

Ω_{M} : total volume of the magnetic core

Ω_{D} : volume of the design region



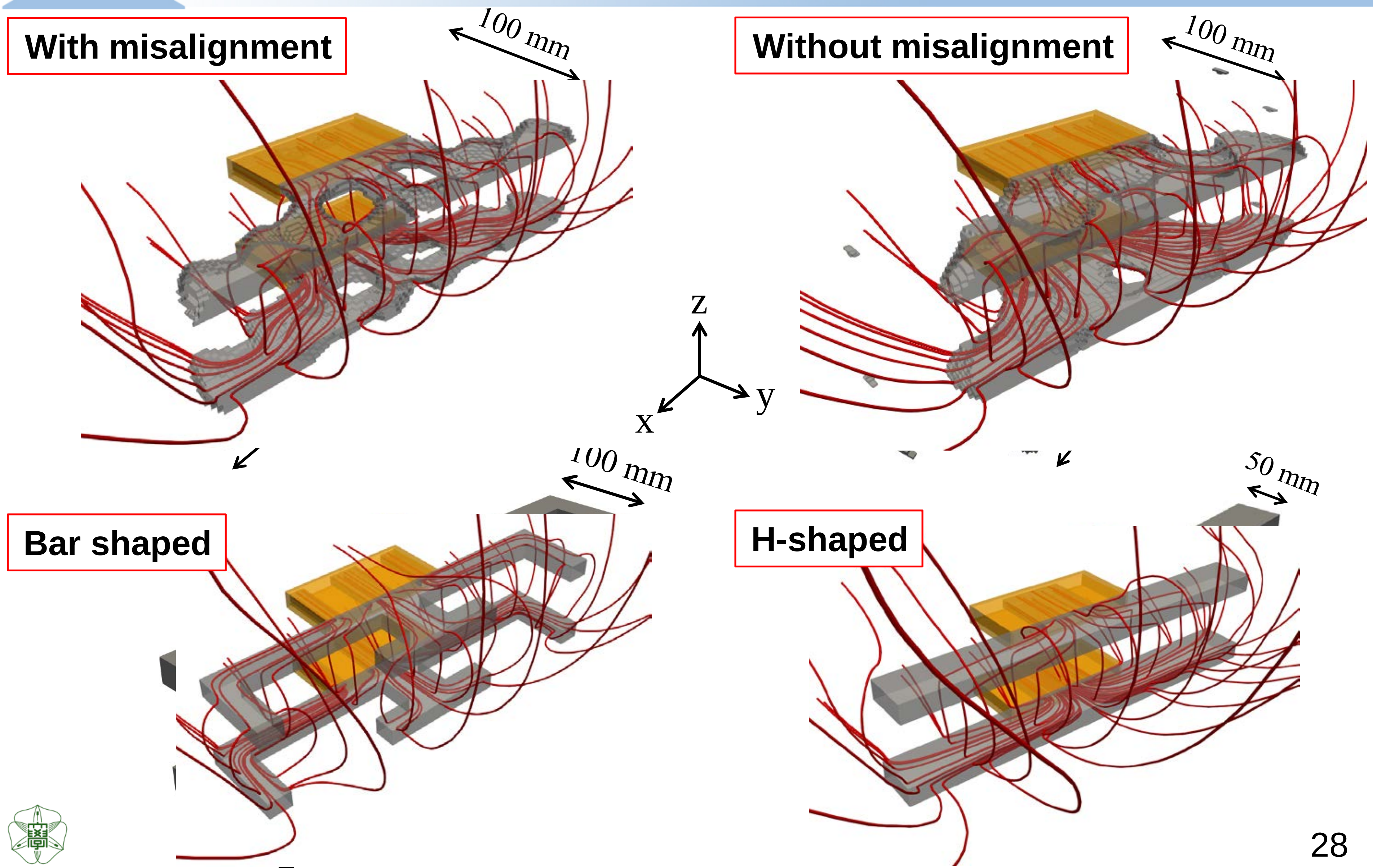
Three different misalignments

0 mm

150 mm

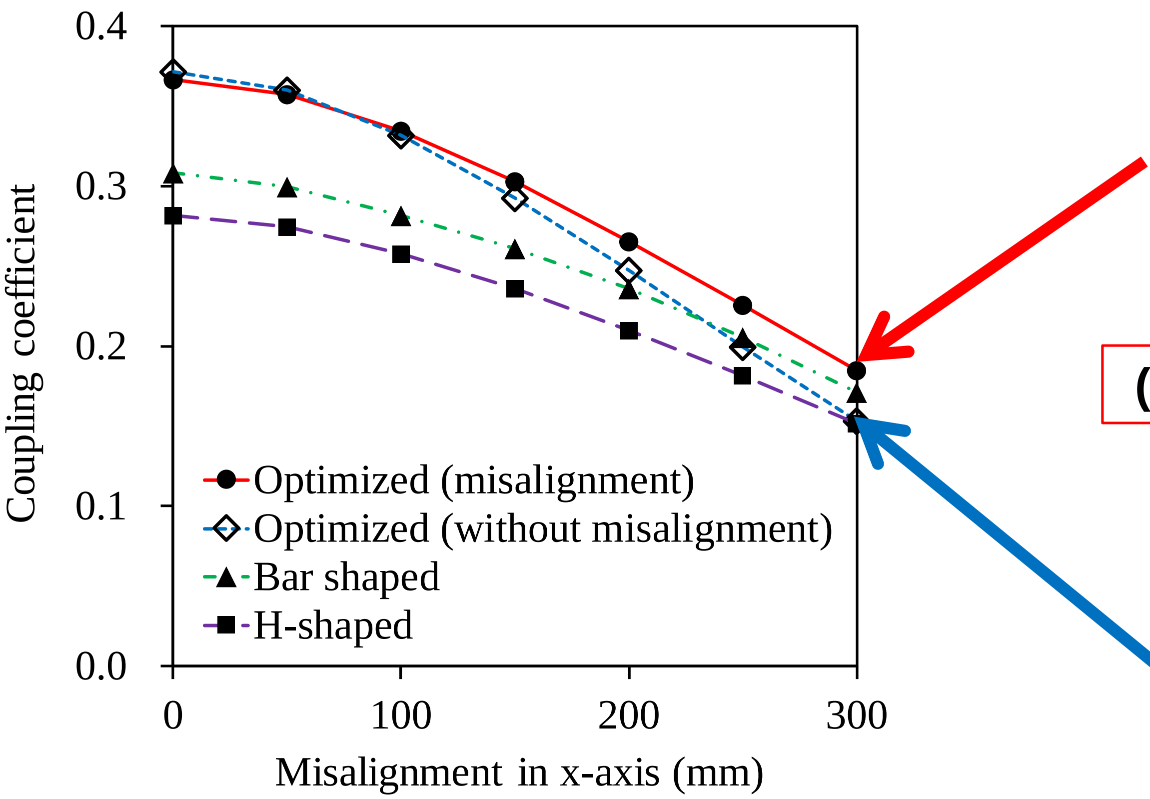
300 mm

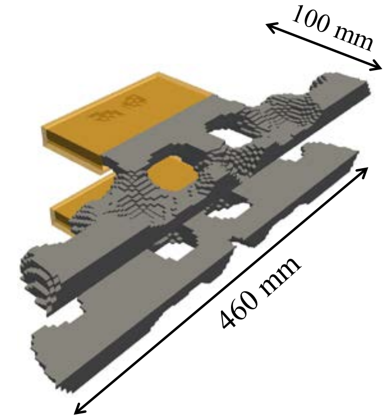
Optimized and conventional core shapes



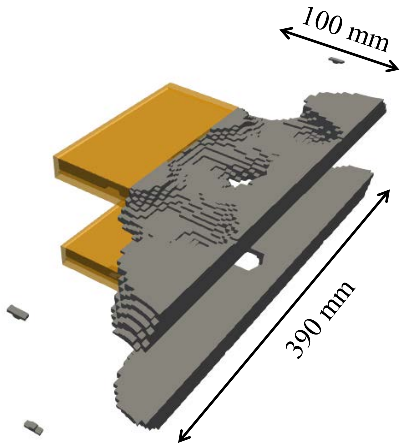
Coupling coefficient of each WPT core

- We can see that the optimized WPT cores have the good tolerance in the forward misalignment and air gap.



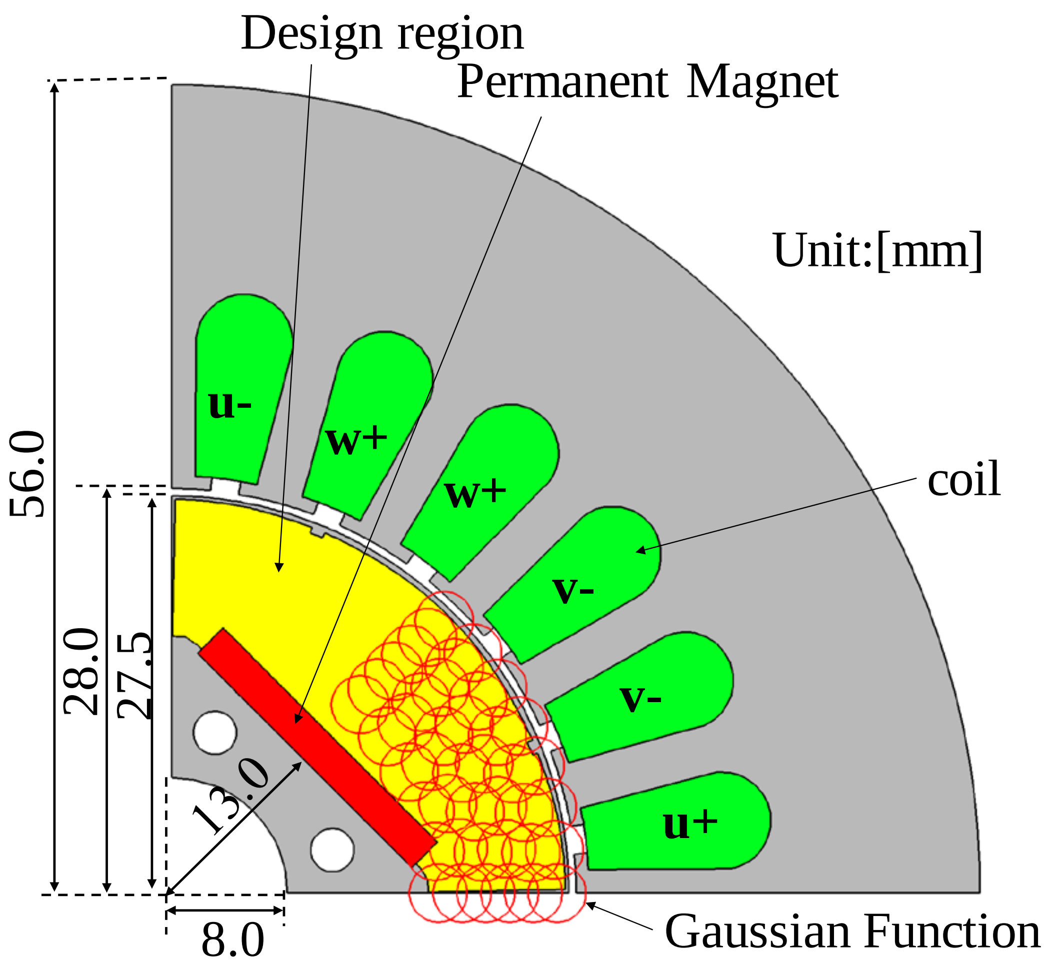


(a) with misalignment

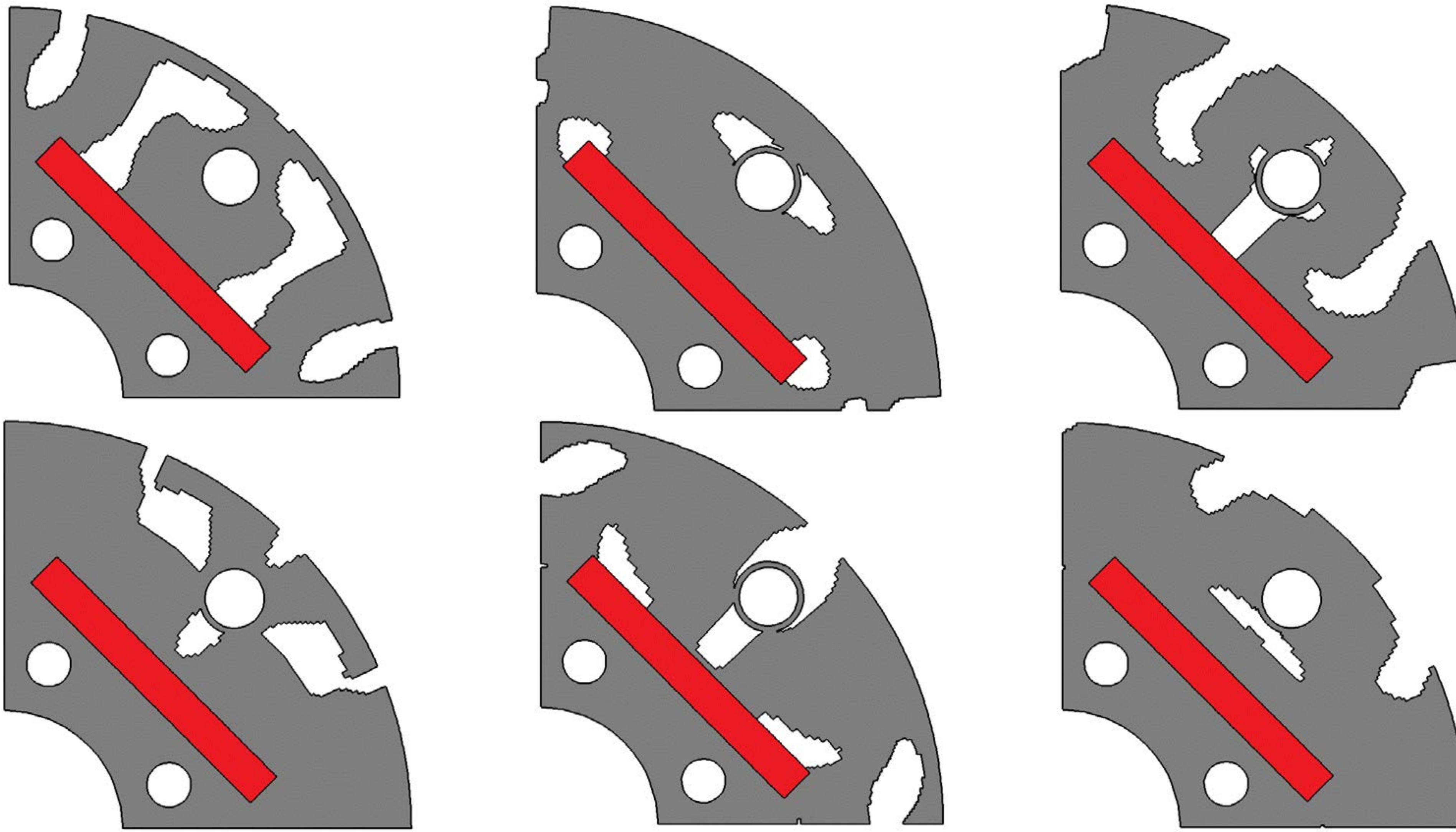


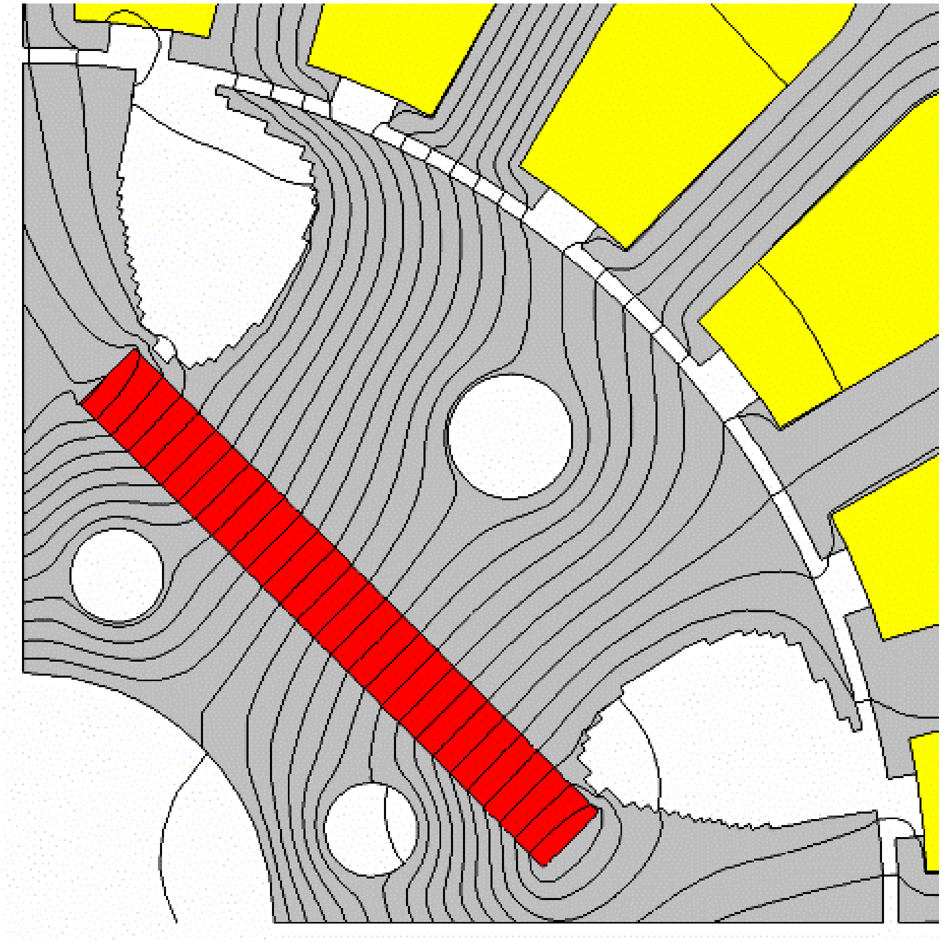
(b) without misalignment

Optimization of Interior Permanent Magnet (IPM) Motor



Initial individuals generated in the GA process





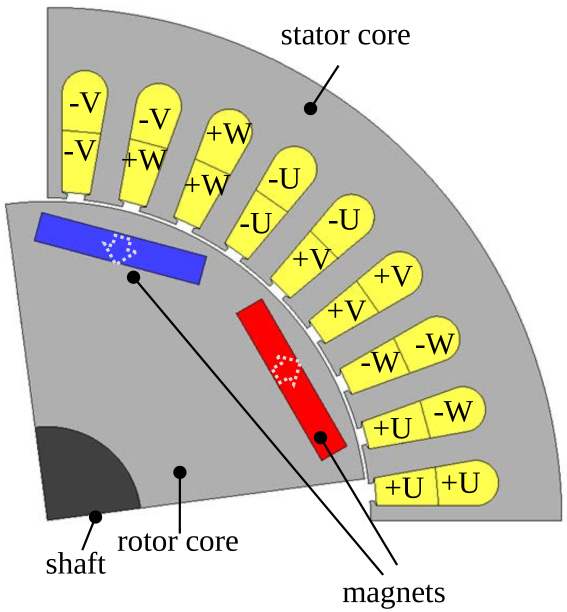
Optimization of Realistic IPM Motor

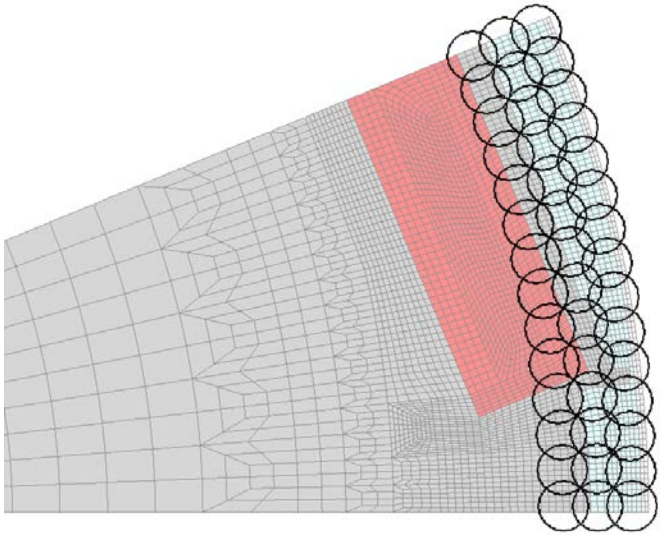
Maximization of torque and minimization of ripple

$$F = -T_{ave}/T_0 + 0.5T_{rp}/T_1 \rightarrow \text{minimize},$$

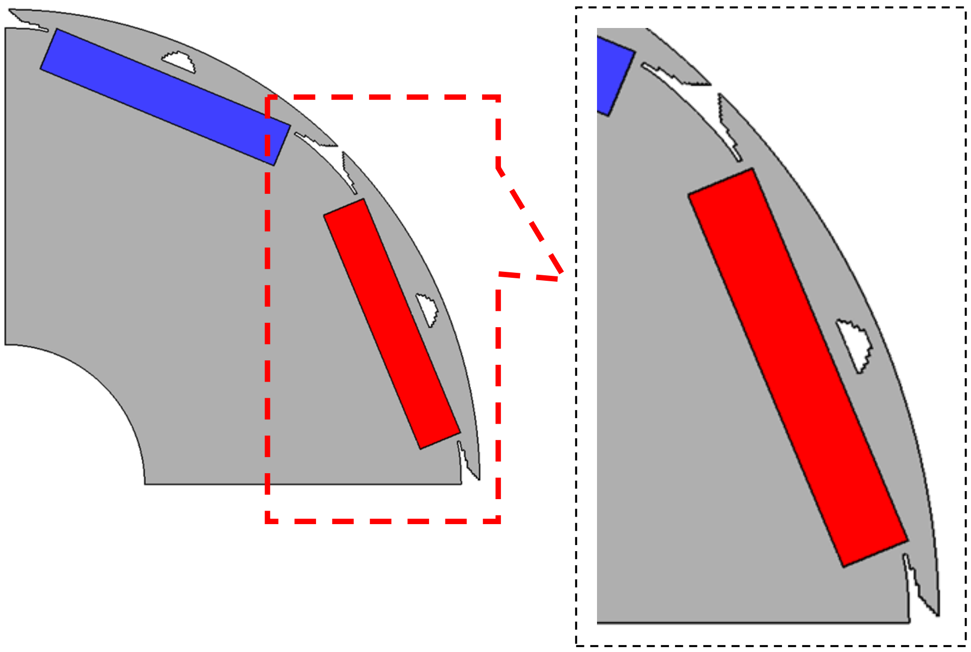
T_{ave} : average torque, T_{rp} : torque ripple

T_0=10.8Nm, T_1=8.5% : normalization constants

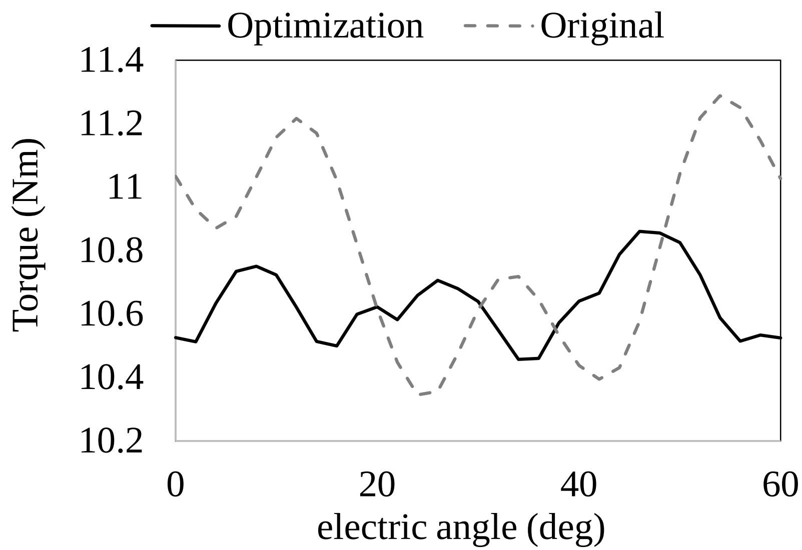




Optimization result

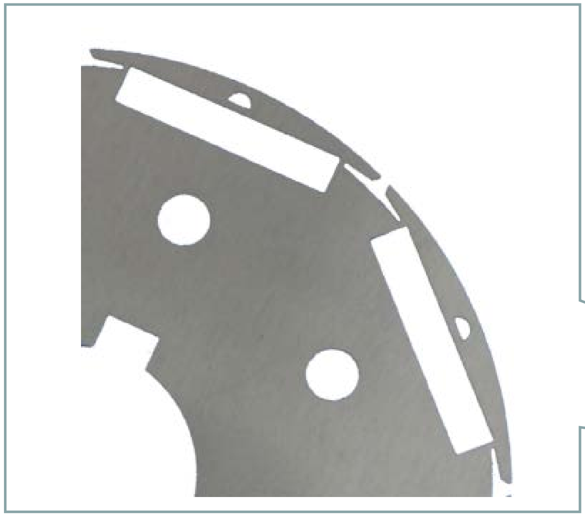


$T_{\mathrm{ave}}=0.96\boldsymbol{T_0}$, $T_{\mathrm{rp}}=0.25T_1$

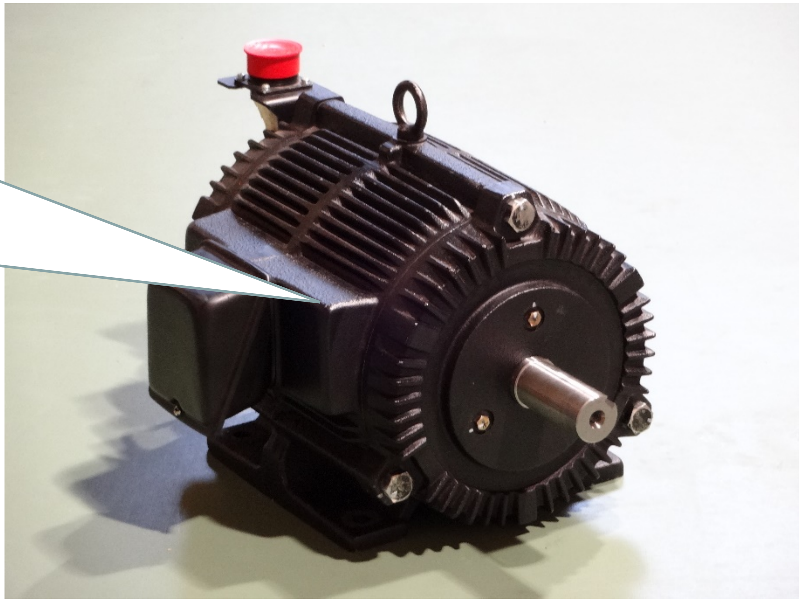


Torque ripple is greatly reduced by the optimization.

Realization of Optimized IPM Motor



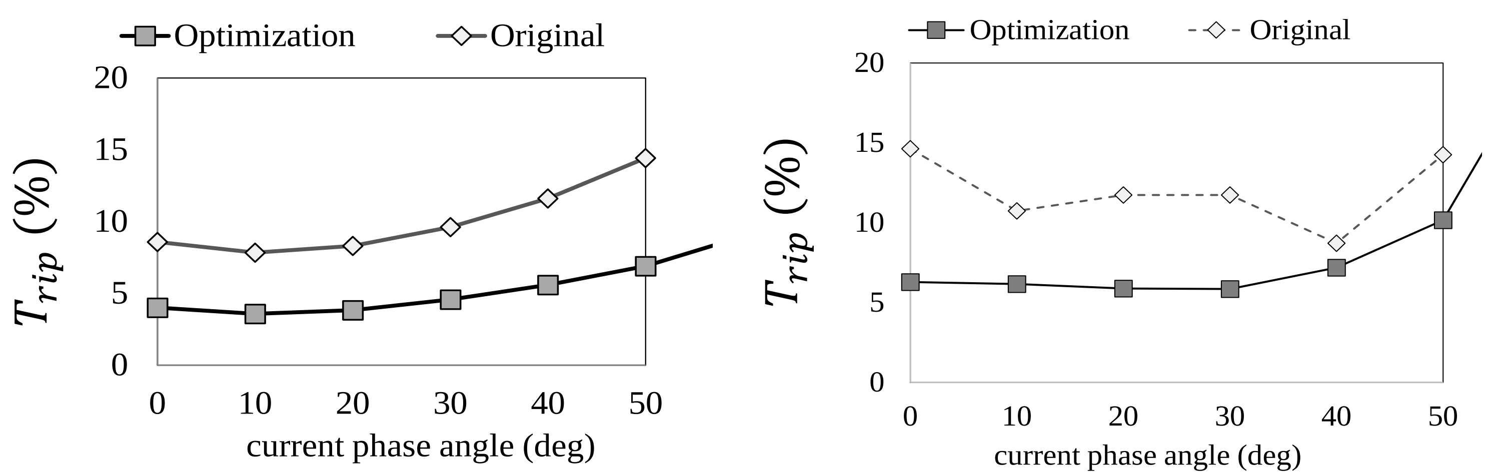
Manufactured rotor



Experimental results

It is found from the measurement that
the torque ripple is suppressed while
the average torque is kept almost unchanged.

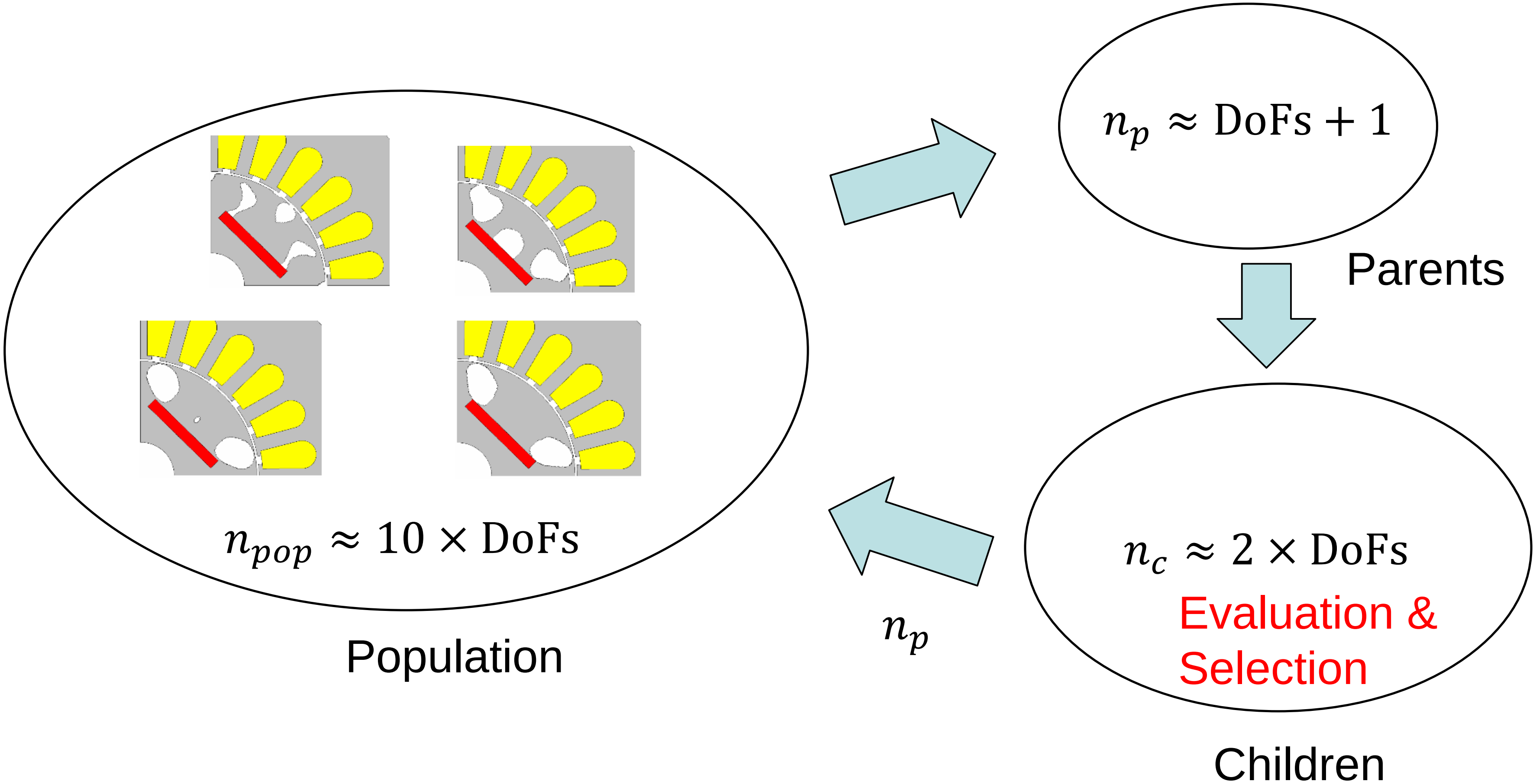
$$T_{rip} = \frac{T_{max} - T_{min}}{T_{average}}$$



(a) Computed (b) Measured

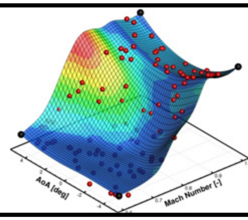
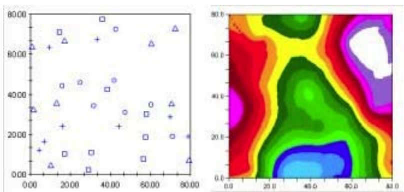
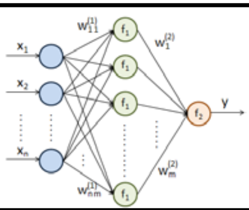
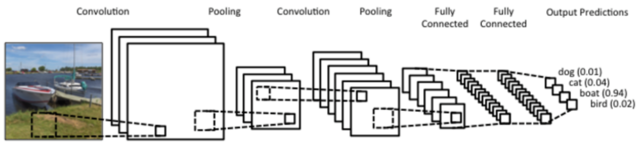
佐藤孝洋，五十嵐一，他，トポロジー最適化による埋込磁石同期モータの回転子形状最適化，
電気学会論文誌D，Vol. 135，No. 4，291,-298, 2015

Real-coded Genetic Algorithm (with REX)



Finite element analysis has to be performed for $2 \times \mathrm{DoFs}$ times a generation.

Surrogate Models (代理モデル)

Methods		Features
Response surface (応答曲面法)		They do not work well for high-dimensional Problems. 自由度が大きくなるとほぼ使えない
Kiriging		
Neural network		Feature engineering is necessary. 特徴量の定義が必要
Deep Learning		Feature is automatically obtained. 特徴量の定義が不要

GoogLeNet***

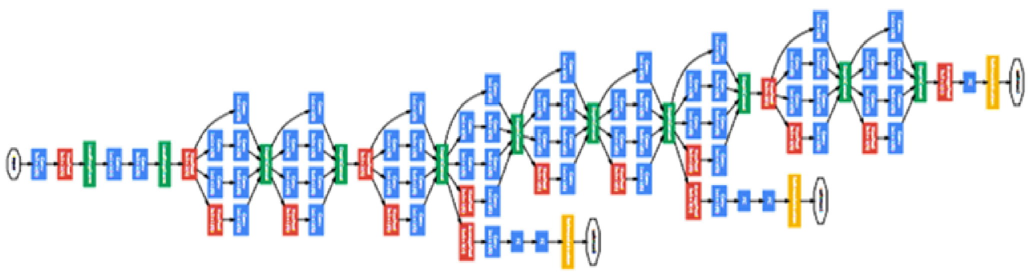
Convolutional neural network developed by Google.
This outperforms the conventional machine learning methods.

Classifier(分類器)

The IPM motors with different shapes are classified with respect to the average torque T_{ave} and torque ripple T_{rip}.

Input:
image of motor

Classifier



GoogLenet *

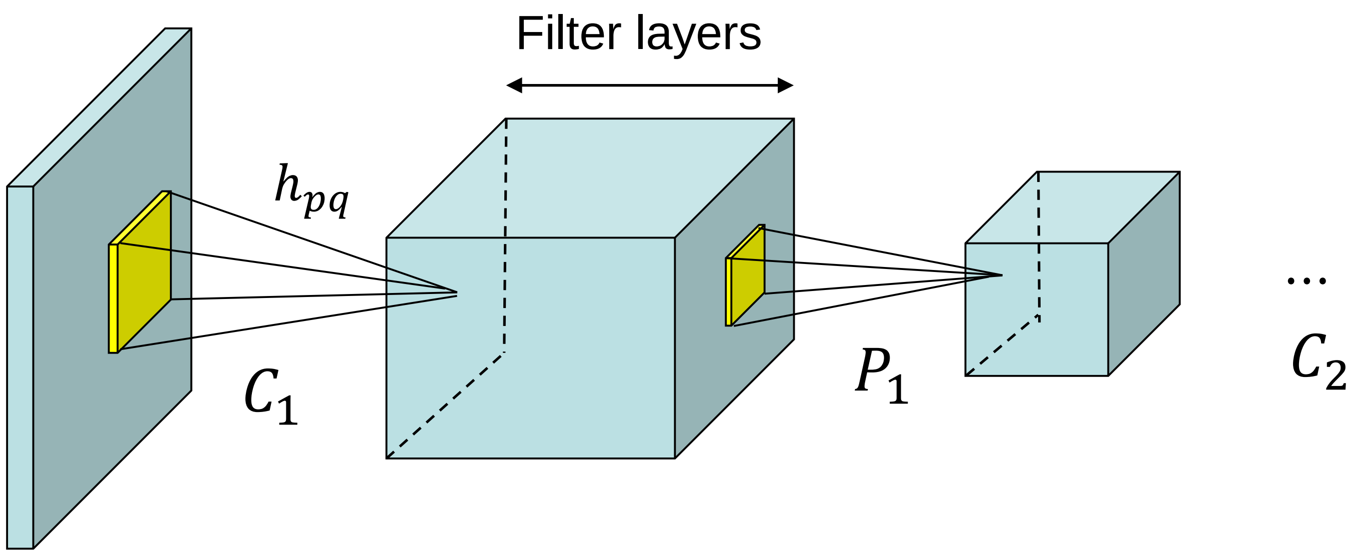
Output

T_{ave}

T_{rip}

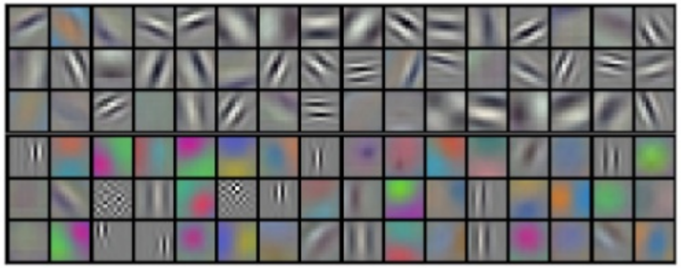
*Szegedy, Christian, et al. “Going deeper with convolutions.” Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

Convolutional Neural Network (CNN)



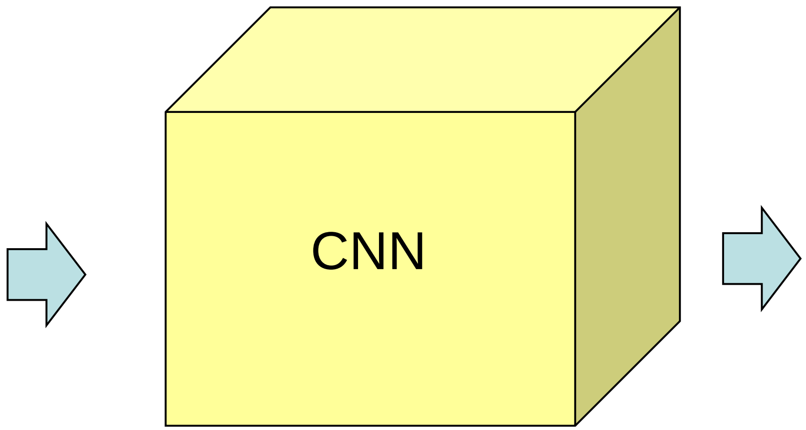
$$x_{ij} = \sum_{p,q} y_{i+p,j+q} h_{pq} + b$$

$$x_{ij} = \max_{p,q \in P_{ij}} y_{pq}$$



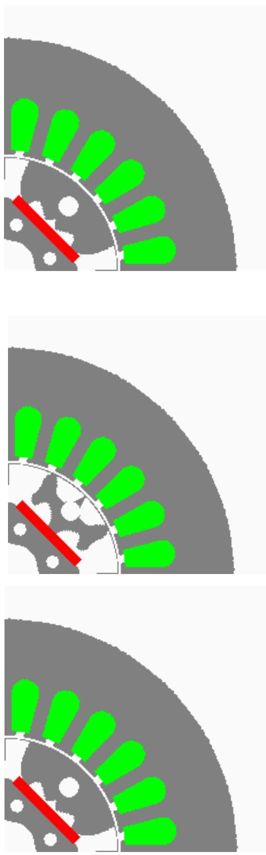
Deep Learning for Image Recognition

Internet

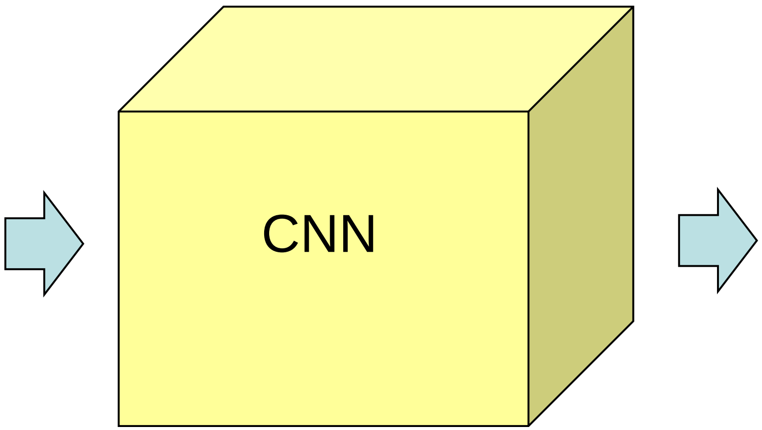


class
dog
wolf
fox
⋮

Deep Learning for Topology Optimization

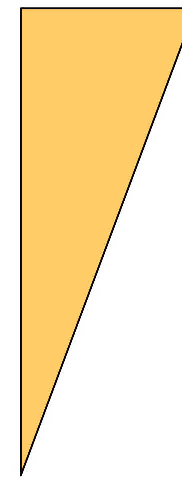


Topology optimization



Torque Class
A+
A
A-
⋮
F

Possibility in FE analysis



Generation of Data for DL with Topology Opt.

Training phase

Training of CNN with the result for optimization problem A.

Training of CNN with the result for optimization with small number of individuals.

Training of CNN. Optimization problems are generated for generalization of CNN.

Optimization phase

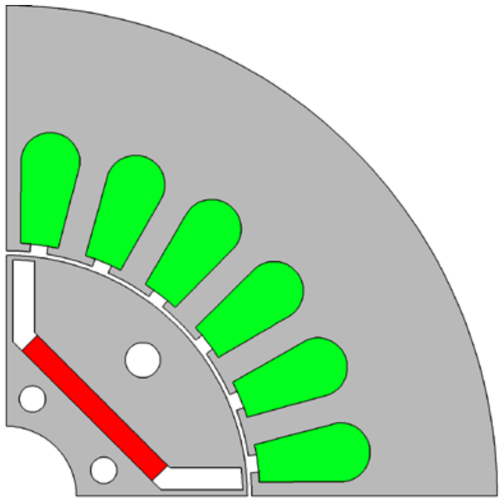
Optimization for different problems B, C, D… with CNN.

Optimization with large number of individuals with CNN.

Optimization with CNN for wide class of motors and problems.

Because the classification done by CNN is not perfect, posterior FE analysis is necessary for accurate evaluation. FE analysis is performed at high possibility for individuals in good classes.

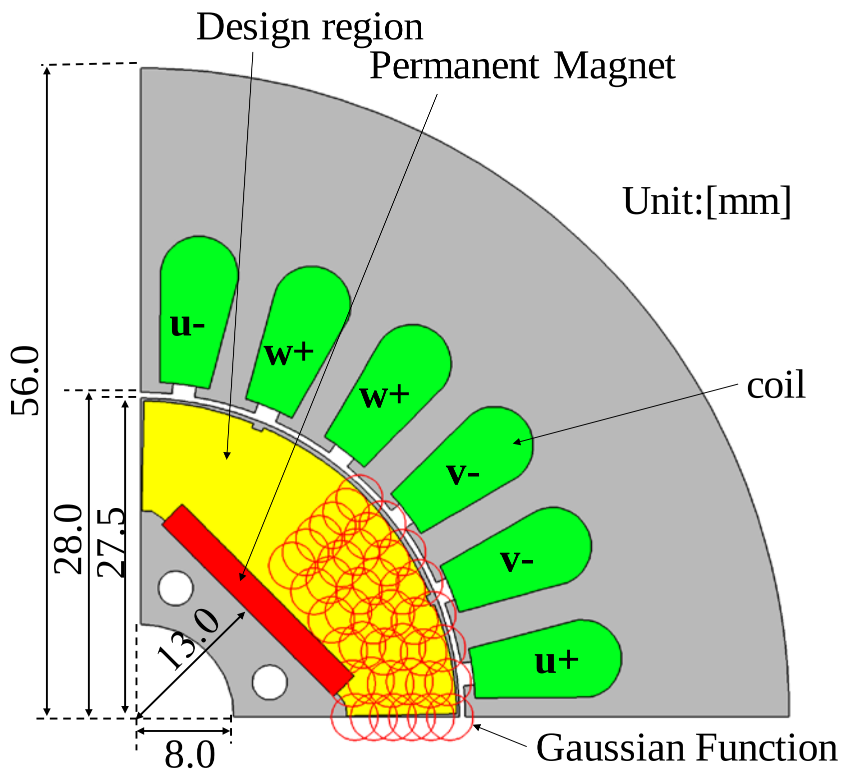
Optimization of IPM motor



$T^0 = 2.08$ Nm

$T^0_{rip} = 0.57$

Current phase angle [degree]	30
Current effective value [A]	4.2425
Number of turns [turn]	35
Residual flux density [T]	1.25



[4] Technical report of the institute of electrical engineering of Japan," *Industry application society*, No. 776, 2000.

Optimization Problem

$$\boxed{F = \frac{T}{T^0} \rightarrow \max.}$$

$$\text{Sub.to. } N_{\text{area}} < 2$$

T: Average torque

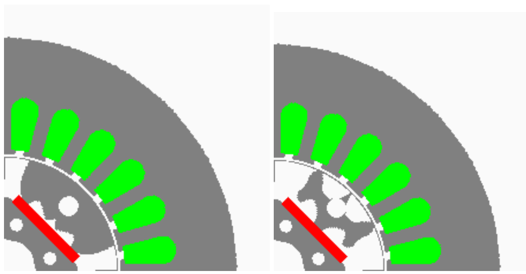
T^0: Average torque of original model

N_{area}: The number of separated rotor cores

Optimization setting

The number of genes	42
The number of individuals	800
The number of children	160

Training of CNN for classification of torque and torque ripple

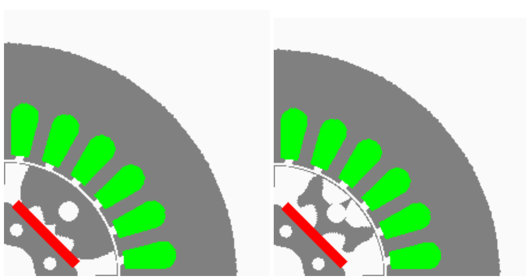


Bit map showing material distribution
(224 × 224)

4,000

CNN
Torque
Classifier

8 classes



Bit map showing material distribution
(224 × 224)

10,000

CNN
Torque Ripple
Classifier

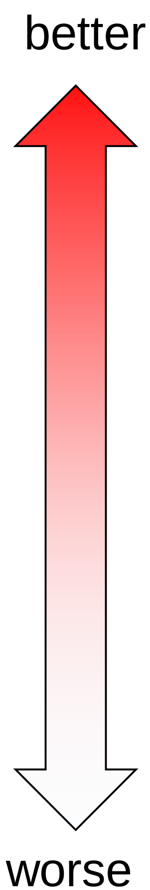
8 classes

■: Iron ■: Permanent magnetic ■: Copper □: Air

H. Sasaki, H. Igarashi, to be presented at CEFC2018 and submitted to IEEE Trans. Magn.

Classification of torque and torque ripple

Classification of Torque	
CNN	FEM
1.1	1.05~
1.0	0.95~1.05
0.9	0.85~0.95
0.8	0.75~0.85
0.7	0.65~0.75
0.6	0.55~0.65
0.5	0.45~0.55
0.0	~0.45



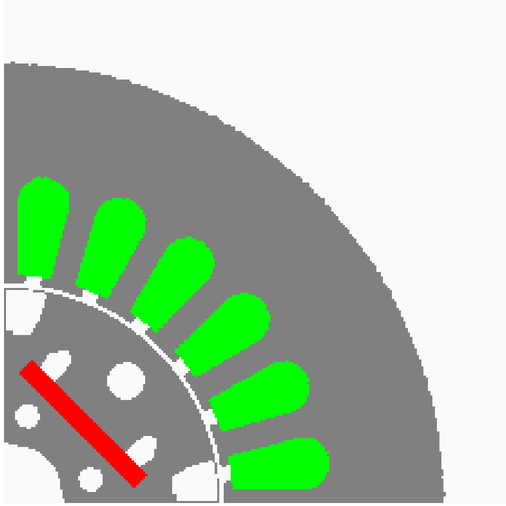
Classification of Ripple	
CNN	FEM
0.6	~0.65
0.7	0.65~0.75
0.8	0.75~0.85
0.9	0.85~0.95
1.0	0.95~1.05
1.1	1.05~1.15
1.2	1.15~1.25
1.3	1.25~

Accuracy in torque

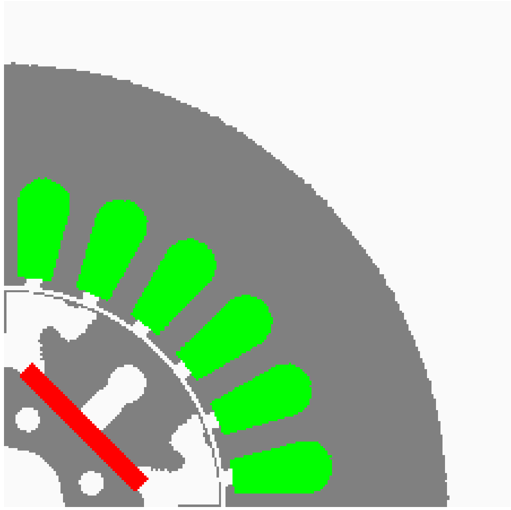
		Label by CNN $\hat{T}_{ave}^{CNN}$								
		0	0.5	0.6	0.7	0.8	0.9	1	1.1	**TOTAL**
Label by FEM $\hat{T}_{ave}^{FEM}$	0	**513**	46	10	6	2	7	0	0	584
	0.5	18	**397**	75	1	0	0	0	0	491
	0.6	0	83	**392**	79	0	0	0	0	554
	0.7	0	1	73	**462**	39	1	0	0	576
	0.8	0	0	0	32	**377**	29	0	0	438
	0.9	0	0	0	6	40	**463**	28	0	537
	1	0	0	0	0	0	21	**368**	26	415
	1.1	0	0	0	0	0	0	10	**395**	405
	TOTAL	531	527	550	586	458	521	406	421	4000

H. Sasaki, H. Igarashi, to be presented at CEFC2018 and submitted to IEEE Trans. Magn.

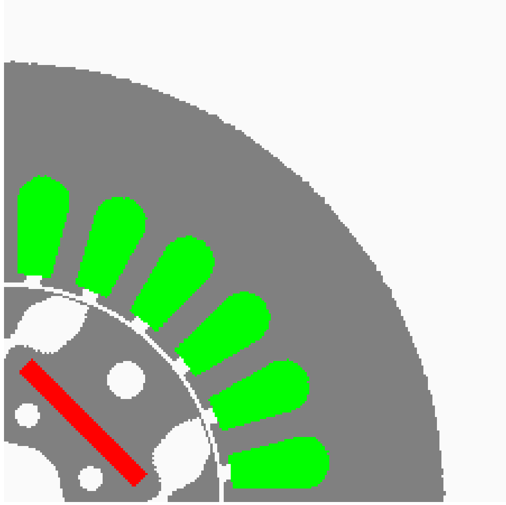
Examples



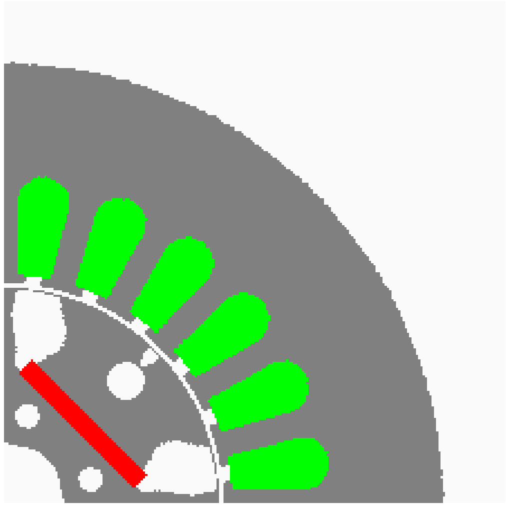
CNN: 0.50 FEM: 0.50



CNN: 0.90 FEM: 0.90



CNN: 0.70 FEM: 0.70



CNN: 1.10 FEM: 1.09

Torque ripple

		Label by CNN $\hat{T}_{\mathrm{rip}}^{CNN}$								
		0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	**TOTAL**
Label by FEM $\hat{T}_{\mathrm{rip}}^{FEM}$	0.6	**797**	246	36	1	11	10	12	19	1132
	0.7	169	**631**	164	99	20	33	21	29	1166
	0.8	21	200	**858**	128	37	24	16	18	1302
	0.9	7	114	139	**812**	122	136	41	12	1383
	1	8	27	44	148	**821**	125	61	15	1249
	1.1	5	36	29	115	108	**850**	250	27	1420
	1.2	9	20	37	38	64	295	**575**	107	1145
	1.3	21	19	32	26	33	36	240	**796**	1203
	TOTAL	1037	1293	1339	1367	1216	1509	1216	1023	10000

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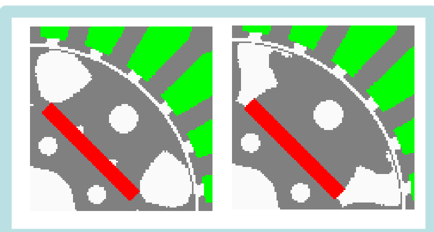
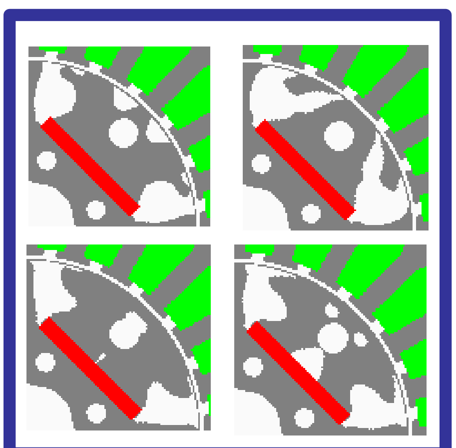
Torque ripple

Relationship between evaluation value by CNN and FEM





		Label by CNN $\hat{T}_{rip}^{CNN}$								
		0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	**TOTAL**
Label by FEM $\hat{T}_{rip}^{FEM}$	0.6	**797**	246	36	1	11	10	12	19	1132
	0.7	169	**631**	164	99	20	33	21	29	1166
	0.8	21	200	**858**	128	37	24	16	18	1302
	0.9	7	114	139	**812**	122	136	41	12	1383
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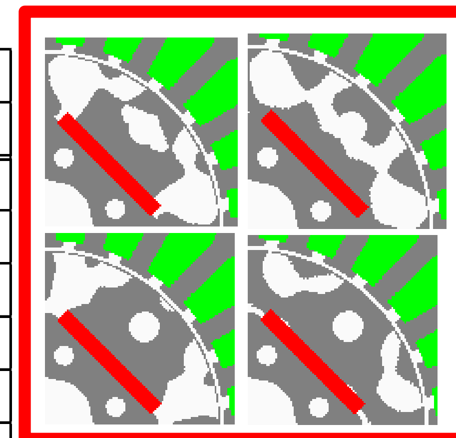
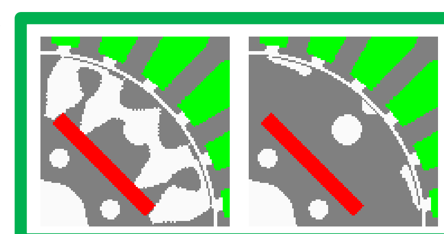
	TOTAL	1037	1293	1339	1367	1216	1509	1216	1023	10000

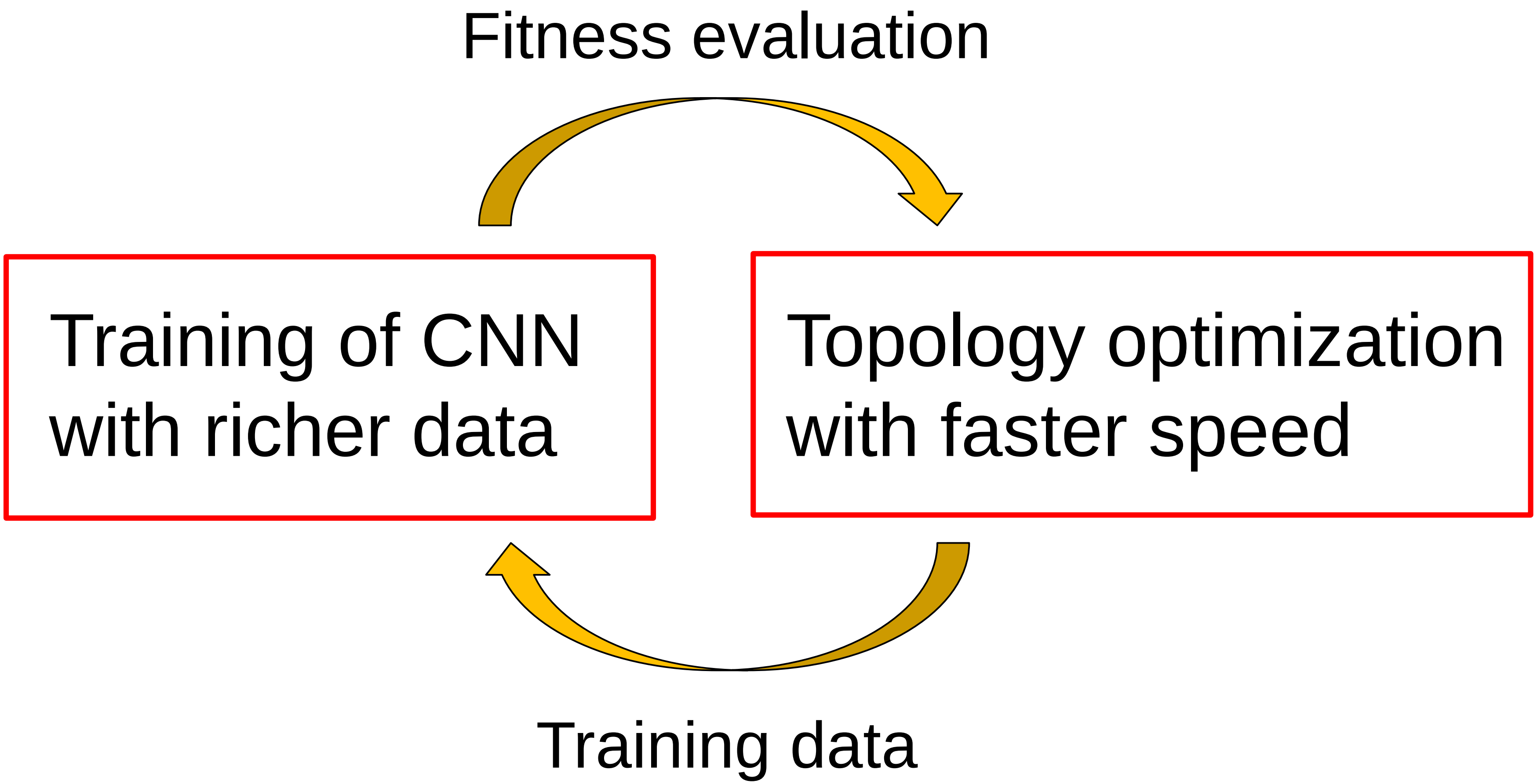




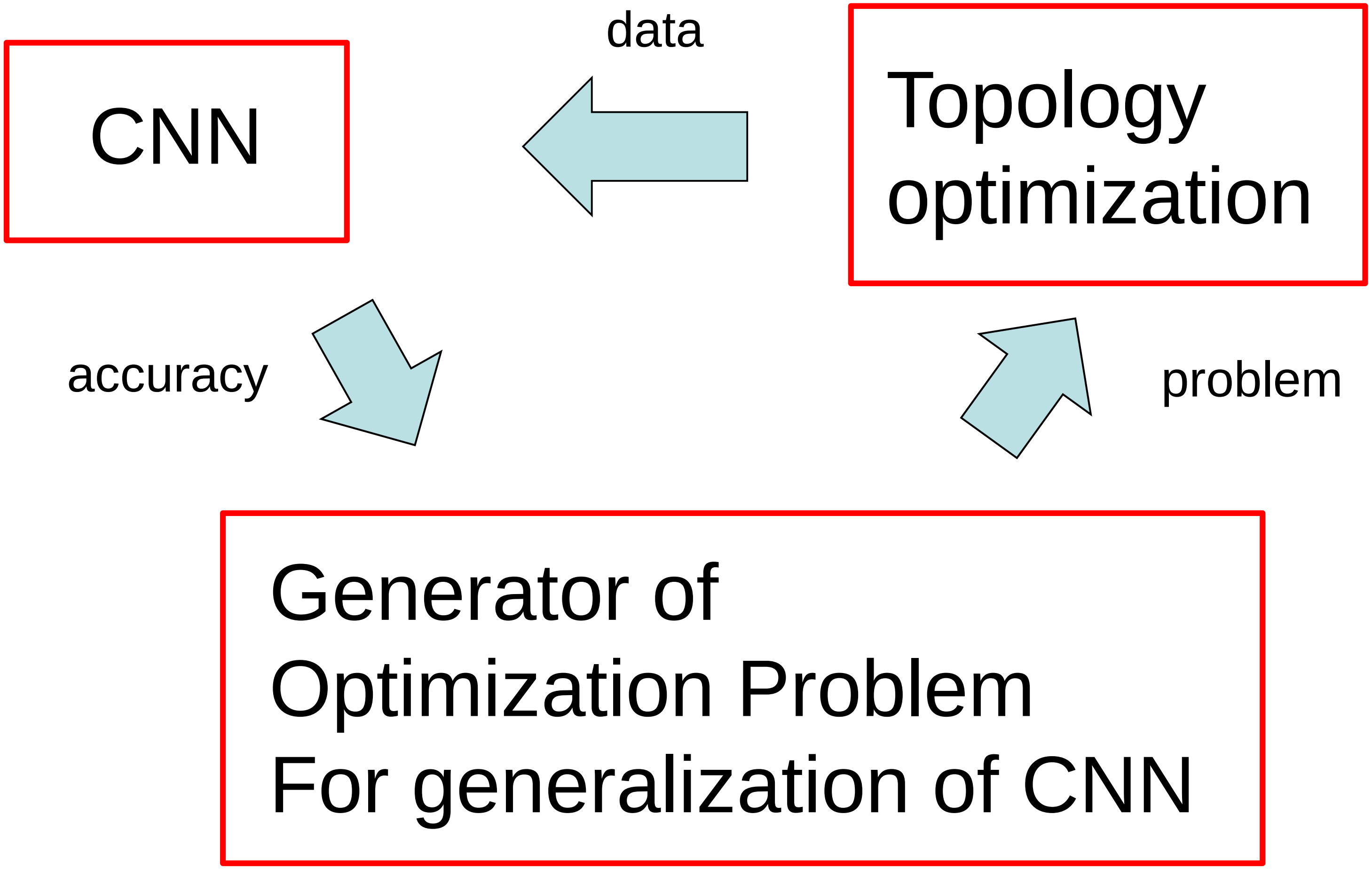
Coevolution in biology

Wiki: In biology, **coevolution** occurs when two or more species reciprocally affect each other's evolution.

Toward Coevolution of DL and TO



Building a Strong Classifier with DL



Conclusions

Topology optimization leads to new design to various electric and electronic apparatus as well as other mechanical and chemical Systems.

Deep learning is promising to reduce the computational cost of Topology optimization.

Topology optimization and deep learning can make coevolution. Using the topology optimization, we would be able to realize *a strong classifier with generality* of electric motors as well as other devices.