Design of 3-Layers Ogive Radome via Surrogate Assisted Optimization

M. Salucci, G. Oliveri, M. A. Hannan and A. Massa

Contents

1 Synthesis of a 3-Layer Ogive Radome (low density core)

1.0.1 Selecting the proper correlation model

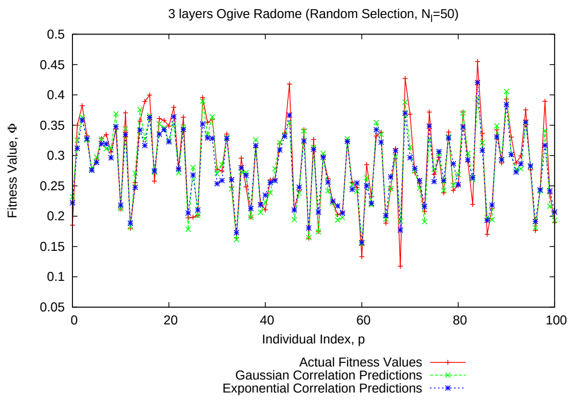
Kriging (Gaussian Process Regressor) parameters

- Regression model: constant (Ordinary Kriging);
- Correlation models:
  - Exponential ($p = 1$);
  - Gaussian ($p = 2$);
- Initial guess for hyper-parameters θ_h: $\theta_{h,0} = 0.5$, for $h = 1, ..., K$;
- Lower bound for hyper-parameters θ_h: $min\left\{\theta_h\right\} = 0.1$, for $h = 1, ..., K$;
- Upper bound for hyper-parameters θ_h: $max\left\{\theta_h\right\} = 20.0$, for $h = 1, ..., K$;

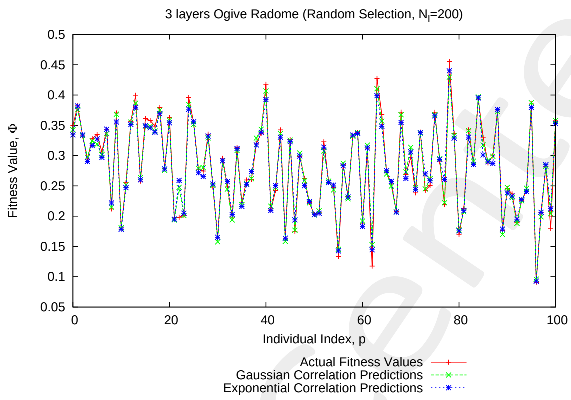
Incremental training parameters

- Number of available simulations: $S = 2000$ (LHS sampling);
- Dimension of the training sets: $N_1 = 50$, $N_{max} = N_L = 1500$, step $\Delta N = 50$;

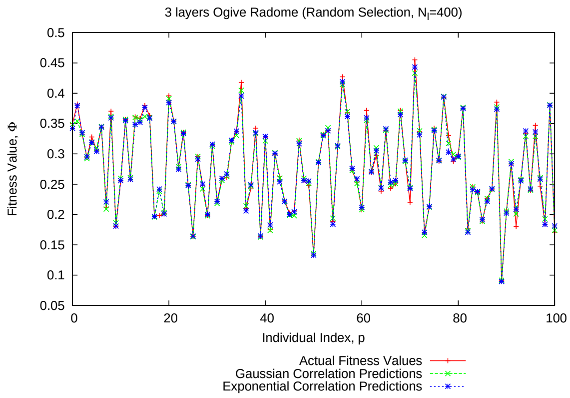
Predicted Fitness Values



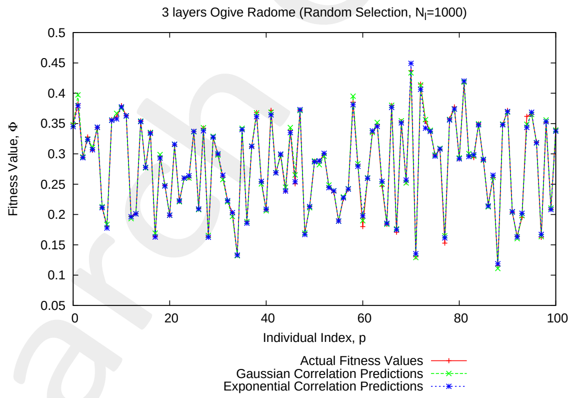
(a) $N = 50$



(b) $N = 200$



(c) $N = 400$



(d) $N = 1000$

Figure 1: *(3-layer ogive radome optimization)* – Actual and predicted functional values of 100 random individuals for different training sizes (N): (a) $N = 50$, (b) $N = 200$, (c) $N = 400$ and (d) $N = 1000$.

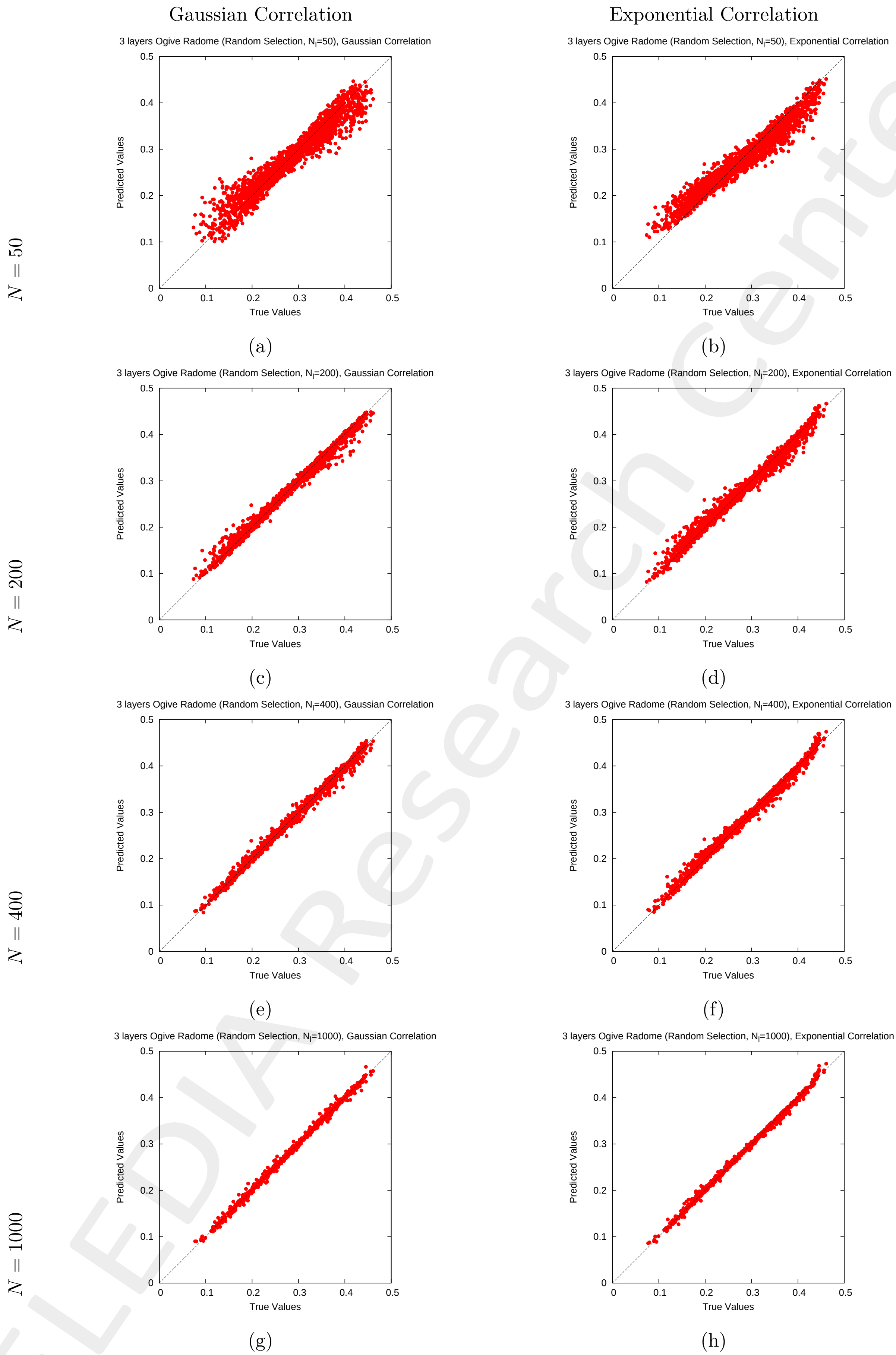
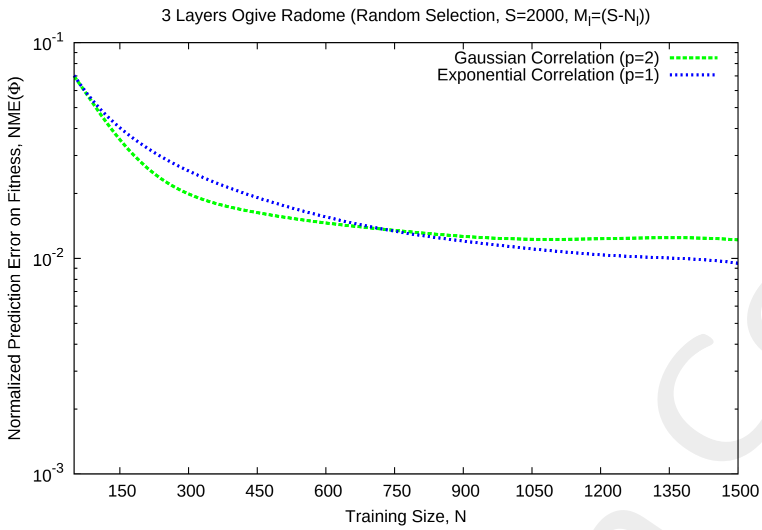
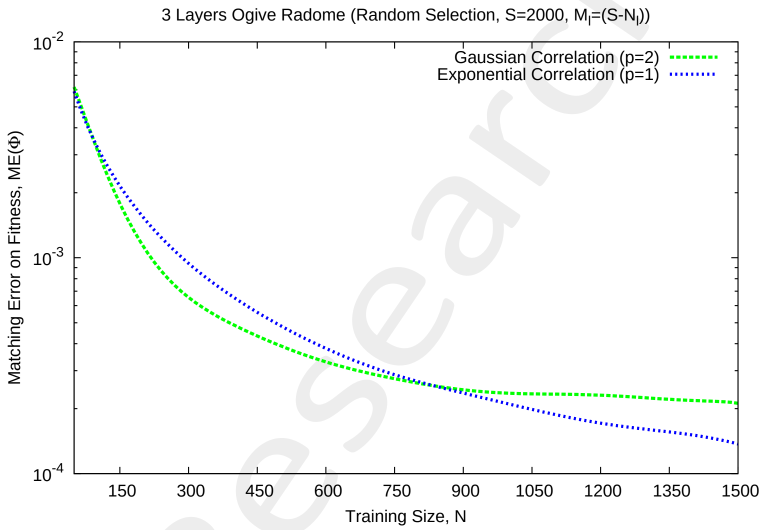


Figure 2: *(3-layer ogive radome optimization)* – Plot of predicted vs actual values for (a), (c), (e), (g) Gaussian Correlation Model and (b), (d), (f), (h) Exponential Correlation Model for different training sizes (N): (a),(b) $N = 50$, (c),(d) $N = 200$, (e),(f) $N = 400$ and (g),(h) $N = 1000$.

Prediction Error vs Training Size



(a)



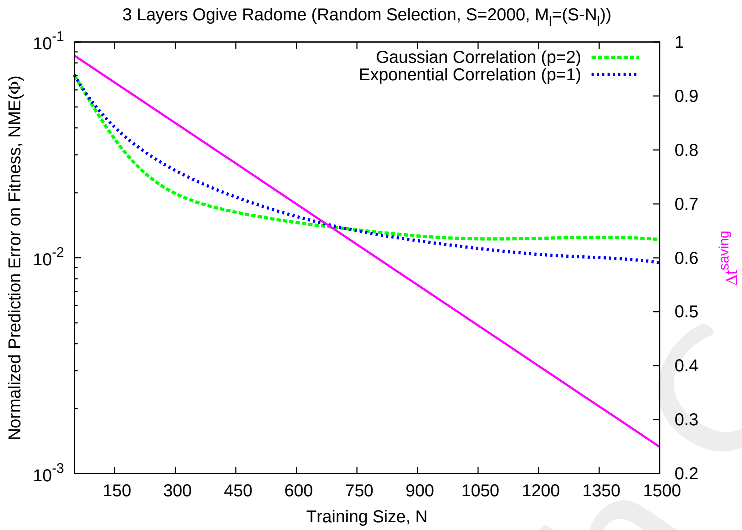
(b)

Figure 3: *(3-layer ogive radome optimization)* – (a) Normalized Mean Error (NME) and (b) Matching Error (ME) vs training size (N) when considering an incremental training with random selection of N_l training samples form a set of S available simulations and testing the corresponding Kriging model on a test set made by the remaining $M_l = (S - N_l)$ simulations.

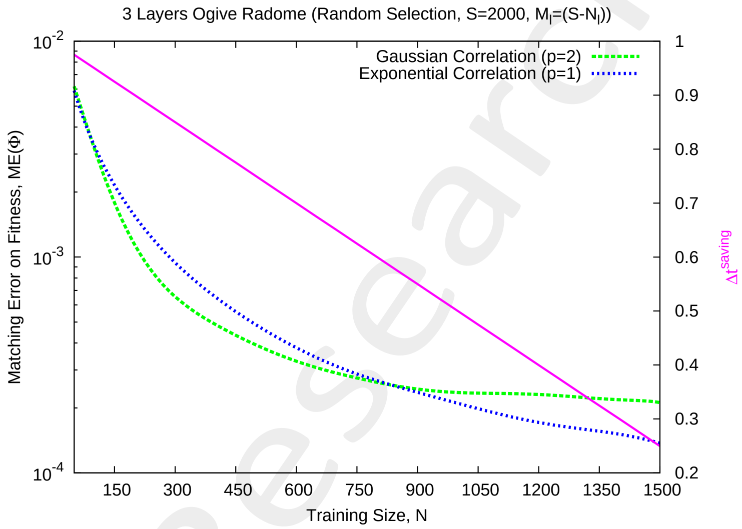
	Gaussian Correlation		Exponential Correlation	
N	NME	ME	NME	ME
50	6.99×10^{-2}	6.18×10^{-3}	7.04×10^{-2}	5.91×10^{-3}
200	2.50×10^{-2}	9.63×10^{-4}	3.28×10^{-2}	1.51×10^{-3}
400	1.73×10^{-3}	5.28×10^{-4}	2.04×10^{-2}	6.45×10^{-4}
1000	1.18×10^{-3}	2.20×10^{-4}	1.10×10^{-2}	2.00×10^{-4}

Table I: *(3 layer ogive radome optimization)* – Normalized Mean Error (NME) and Matching Error (ME) vs training size (N).

Time Saving Analysis

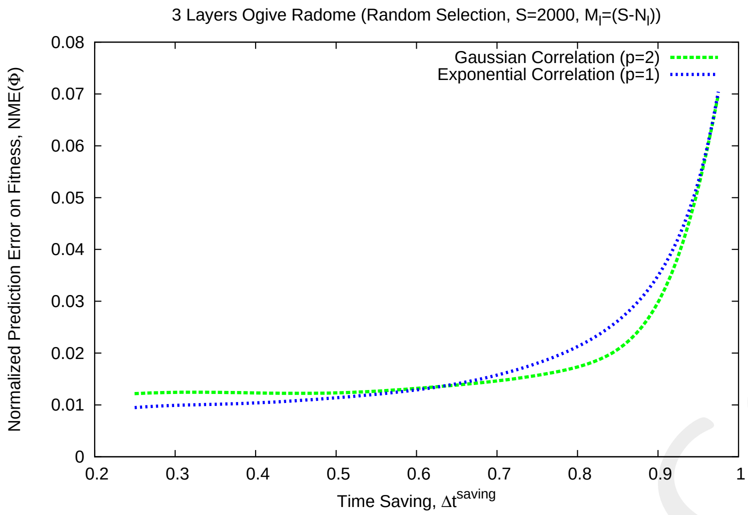


(a) NME

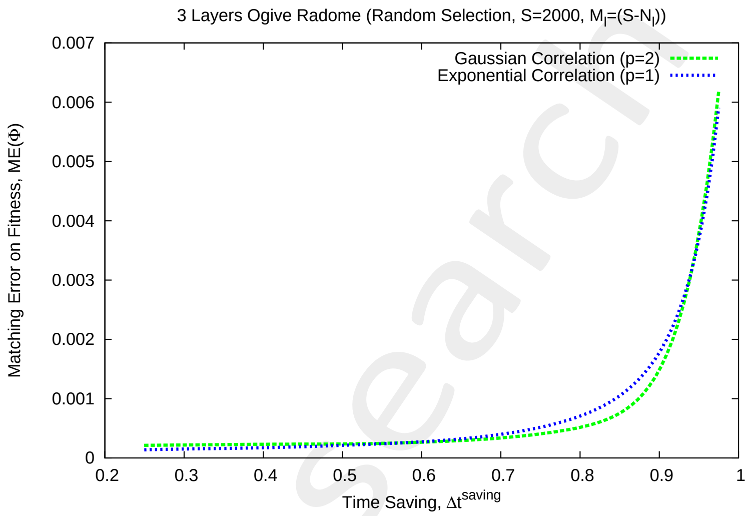


(b) ME

Figure 4: *(3-layer ogive radome optimization)* – Plot of Time Saving (Δt^{saving}) with (a) Normalized Mean Error (NME) and (b) Matching Error (ME) vs training size (N) when considering an incremental training with random selection of N_l training samples form a set of S available simulations and testing the corresponding Kriging model on a test set made by the remaining $M_l = (S - N_l)$ simulations.



(a) NME



(b) ME

Figure 5: *(3-layer ogive radome optimization)* – Plot of (a) Normalized Mean Error (NME) and (b) Matching Error (ME) vs Time Saving (Δt^{saving}).

1.0.2 Optimization

Parameters

Optimization targets

- Functional dimension: $J = 1$;
- Target frequencies:
  1. $f_1 = 200.0$ [MHz];

$SADE$ **parameters**

- Number of variables: $K = 6$;
- Population dimension: $P = 30$;
- Scaling factor: $Q = 0.6$;
- Crossover probability: $P_c = 0.8$;
- Primary parent selection mode: $SADE/RAND/1$;
- Maximum number of iterations: $I = 1000$;
- Fitness threshold: $\Phi^{th} = 10^{-20}$;
- Dimension of the training set: $\tau = 150$;
- Initialization strategy: ELEDIA (random P individuals + $(\tau - P)$ generated via LHS);
- Pre-screening strategy: LCB, $\omega = 2$;
- Update strategy: most promising individual overwrites itself;
- Random seed: $S = 1$;

Kriging (Gaussian Process Regressor) parameters

- Regression model: constant (Ordinary Kriging);
- Correlation models:
  - Exponential ($p = 1$);
  - Gaussian ($p = 2$);
- Initial guess for hyper-parameters θ_h: $\theta_{h,0} = 0.5$, for $h = 1, ..., K$;
- Lower bound for hyper-parameters θ_h: $min\{\theta_h\} = 0.1$, for $h = 1, ..., K$;

- Upper bound for hyper-parameters θ_h: $max\,\{\theta_h\} = 20.0$, for $h = 1, ..., K$;

Not-optimized (static) radome parameters

- Radome length: $L = 1.75\ [m] \simeq 1.17\lambda$;
- Radome base diameter: $D = 1.6\ [m] \simeq 1.07\lambda$;
- Curvature type: $\nu = 1.449$ (tangent ogive);
- Loss tangent of the layers: $tan\delta = 0.00$;

Antenna Parameters

- Dipole centered in $(x, y, x) = (0, 0, 0)$ and directed along $\hat{\mathbf{y}}$;
- Dipole length: $l_d = 0.75\ [m] = \frac{\lambda}{2}$;

Optimized parameters boundaries

Parameter	Description	Min	Max	Measure unit
ε_1	Relative permittivity of the layer 1	3.00	6.00	//
ε_2	Relative permittivity of the layer 2	1.10	3.00	//
ε_3	Relative permittivity of the layer 3	3.00	6.00	//
t_1	Thickness of the layer 1	1.00×10^{-2}	5.00×10^{-2}	[m]
t_2	Thickness of the layer 2	1.00×10^{-2}	5.00×10^{-2}	[m]
t_3	Thickness of the layer 3	1.00×10^{-2}	5.00×10^{-2}	[m]

Table II: *(3-layer ogive radome optimization)* – List of all considered boundaries for the optimized radome descriptors.

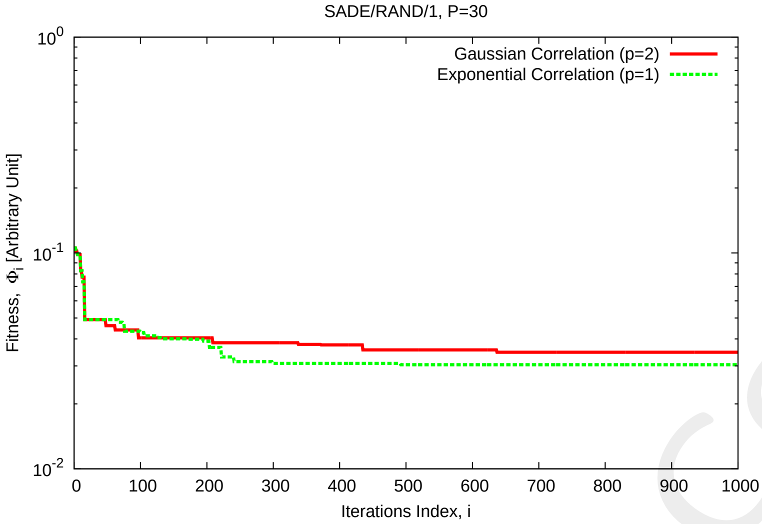
Results of the optimization

- Number of performed $SADE$ iterations: $I_{tot} = I = 1000$;
- Final value of the fitness:
  - Gaussian correlation: $\Phi^{(i=I_{tot})} = 3.47 \times 10^{-2}$;
  - Exponential correlation: $\Phi^{(i=I_{tot})} = 3.04 \times 10^{-2}$;
- Total number of $FEKO$ simulations: $E = (\tau + I_{tot}) = 150 + 1000 = 1150$;

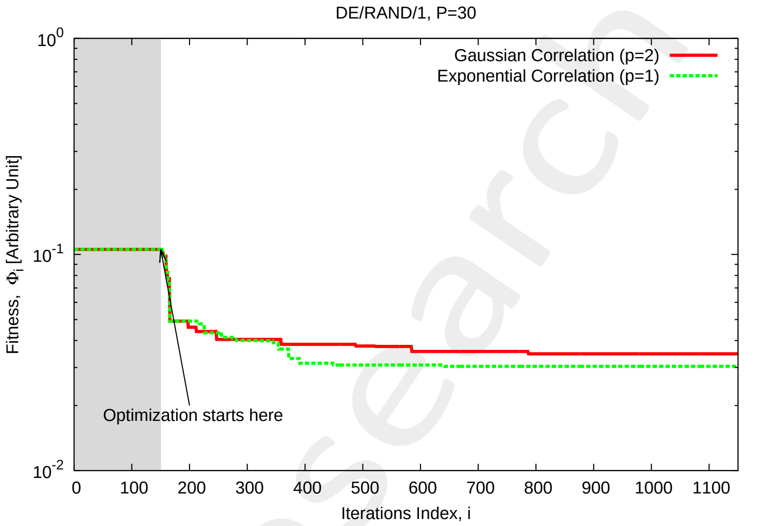
Computational time (@eledialab22-Intel(R) Core(TM) i5 CPU 650 @ 3.20GHz, 4-GB-Ram)

- Average time to compute the fitness associated to a trial solution (**1 core-simulation**): $\Delta t_{avg}^{sim} \simeq 150$ [sec];
- Time for training a Kriging surrogate model with $\tau = 150$ $K = 6$-dimensional training samples: $\Delta t^{train}\rvert_{N=\tau=100} \simeq 0.3$ [sec];
- Time for testing $P = 30$ $K = 6$-dimensional trial solutions using a Kriging surrogate model (built on $\tau = 150$ training samples): $\Delta t^{test}\rvert_{M=P=20} \simeq 0.04$ [sec];
- Real total duration of the optimization: $\Delta t^{tot} \simeq 48$ [hours].

Fitness



(a)



(b)

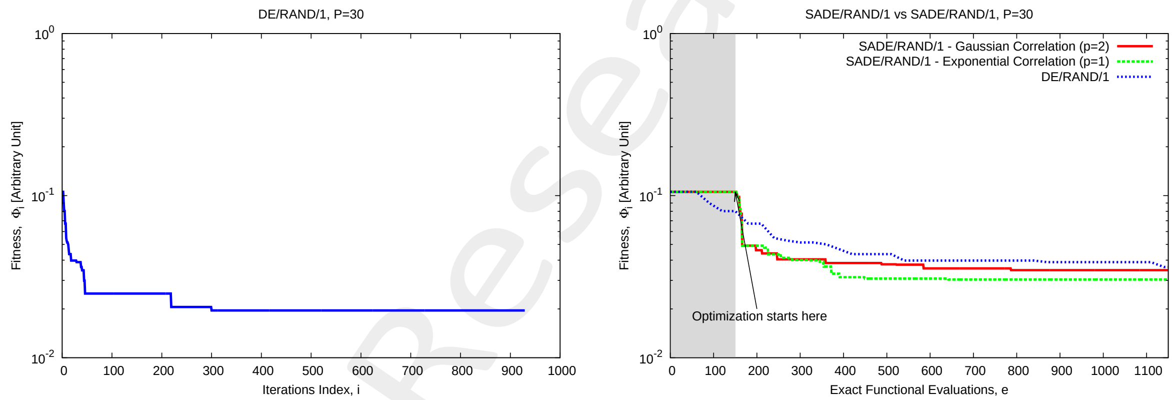
Figure 6: *(3-layer ogive radome optimization)* – Total fitness evolution; (a) evolution vs iteration index during the SADE optimization; (b) evolution vs number of exact function evaluations.

Comparison: $SADE/RAND/1$ vs $DE/RAND/1$

The same optimization (i.e., by using the same parameters, such as the random seed and, thus, forcing the same initial population) has been executed using a classic Differential Evolution (DE) algorithm. In particular, the following parameters have been set for DE:

- Population dimension: $P = 30$;
- Scaling factor: $Q = 0.6$;
- Crossover probability: $P_c = 0.8$;
- Primary parent selection mode: $DE/RAND/1$;
- Maximum number of iterations: $I = 1000$;
- Fitness threshold: $\Phi^{th} = 10^{-20}$;
- Random seed: $S = 1$ (same initial population).

Fitness



(a) (b)

Figure 7: Total fitness evolution; (a) evolution vs iteration index during the DE optimization; (b) evolution vs number of exact function evaluations (simulations with $FEKO$) for both $SADE/RAND/1$ and $DE/RAND/1$ executions.

Computational time

- Theoretical total duration of the optimization:
  - $SADE$ algorithm ($\tau = 100,\ I_{tot} = 1000$):

    $\Delta t^{tot}_{SADE} \simeq \tau \times \Delta t^{\Phi}_{avg} + I_{tot} \times \left(\Delta t^{train}\big|_{N=\tau=200} + \Delta t^{test}\big|_{M=P=50} + \Delta t^{\Phi}_{avg}\right) \simeq 48$ [hours];
  - DE algorithm ($I_{tot} = 1000,\ P = 30$):

    $\Delta t^{tot}_{DE} \simeq I_{tot} \times P \times \Delta t^{\Phi}_{avg} \simeq 1250$ [hours] ($\simeq 52$ [days]);

Evolution of the simulated individuals stored inside the database

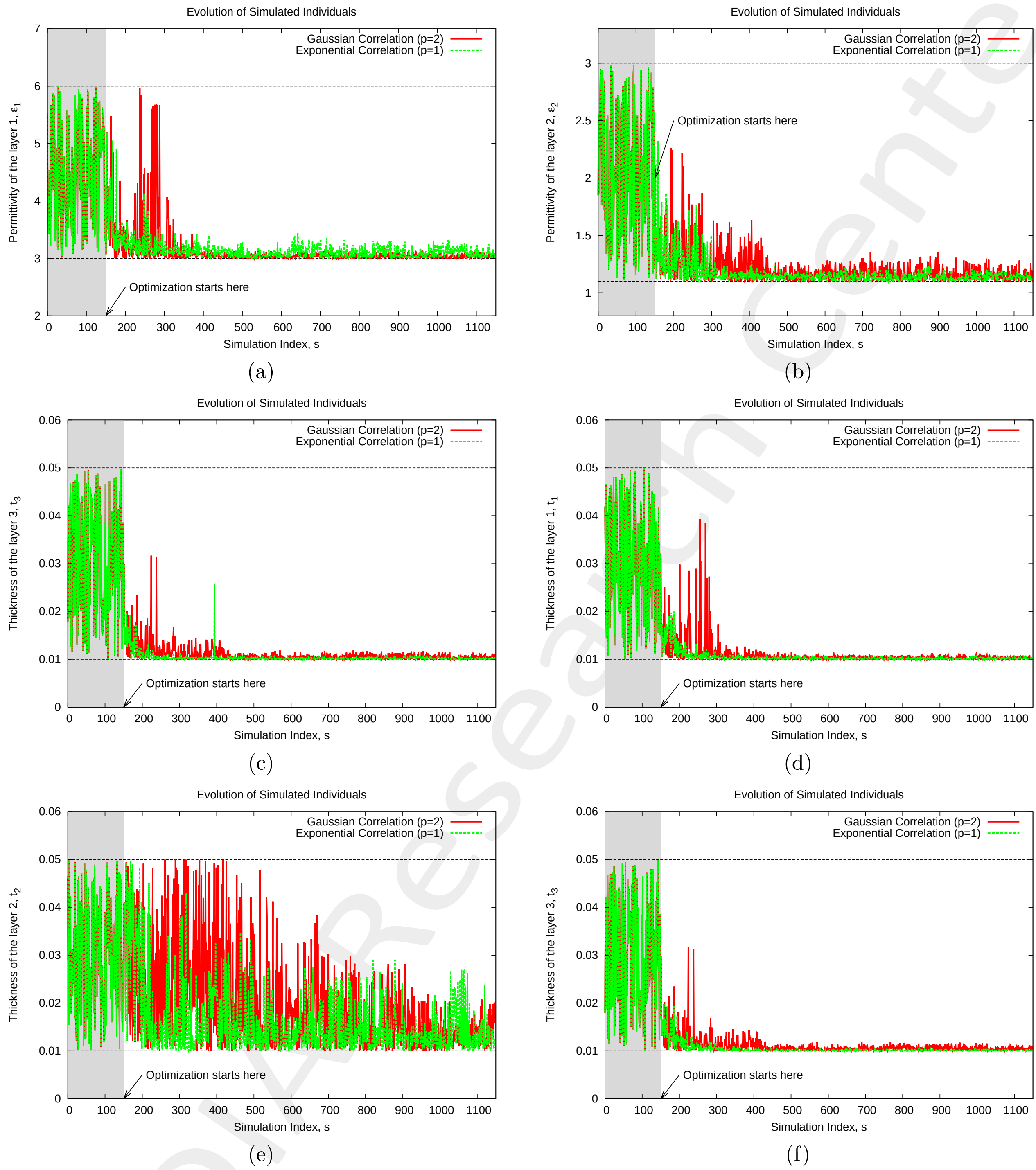


Figure 8: *(3-layer ogive radome optimization)* – Evolution of simulated individuals stored inside the database: parameter (a) ε_1, (b) ε_2, (c) ε_3, (d) t_1, (e) t_2 and (f) t_3.

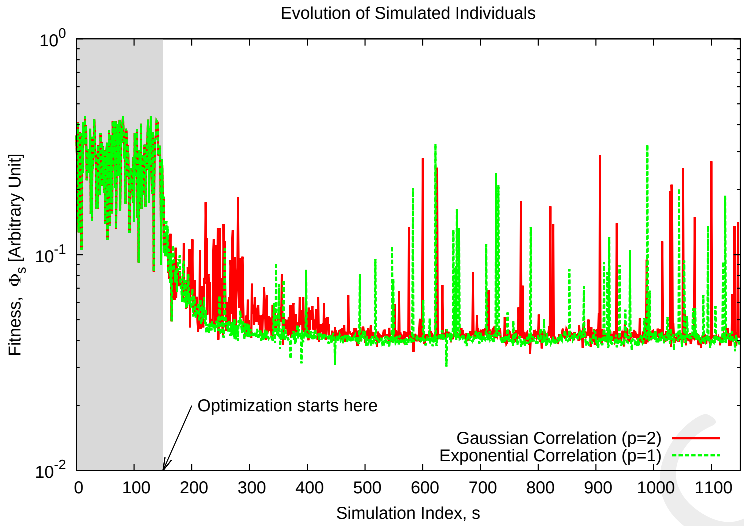
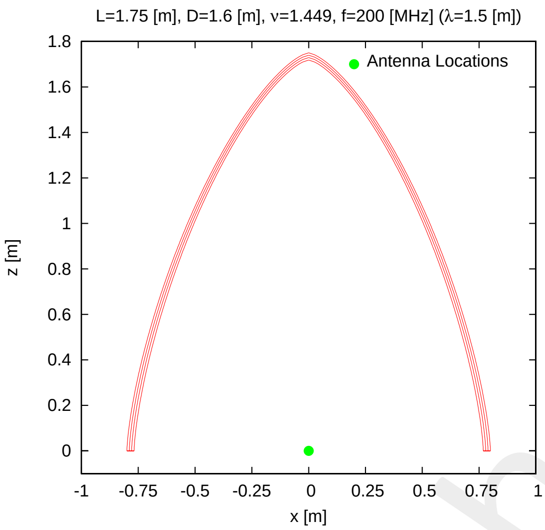


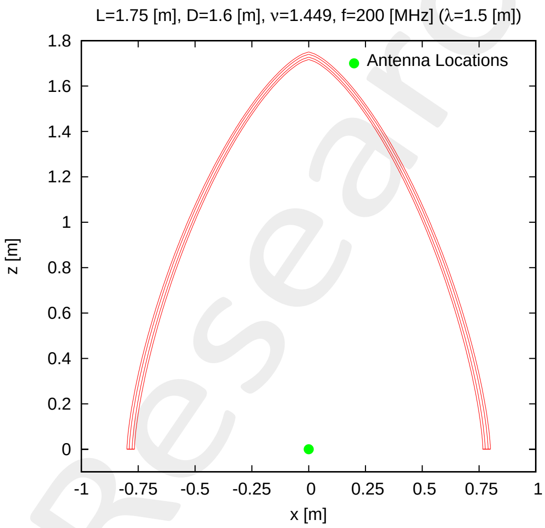
Figure 9: *(3-layer ogive radome optimization)* – Evolution of the fitness of the individuals stored inside the database.

Analysis of the optimal individual

Optimized Model



(a)



(b)

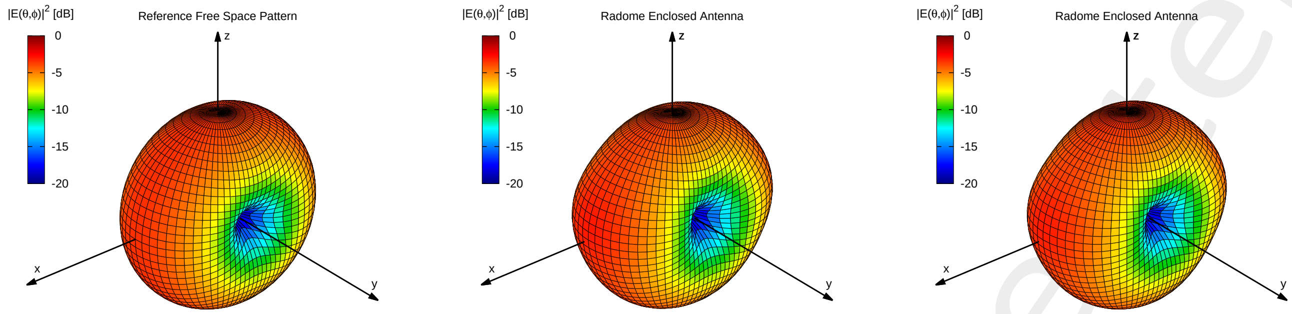
Figure 10: *(3-layer ogive radome optimization)* – Geometry of the optimized radome: (a) Gaussian correlation solution and (b) Exponential correlation solution.

- Total thickness of the structure:
  - Gaussian Correlation: $t = t_1 + t_2 + t_3 \simeq 3.16 \times 10^{-2}$ $[m]$
  - Exponential Correlation: $t = t_1 + t_2 + t_3 \simeq 3.11 \times 10^{-2}$ $[m]$

Parameter	Description	Value - Gauss. Corr. $(p = 2)$	Value - Exp. Corr. $(p = 1)$
ε_1	Relative permittivity of the layer 1	3.01	3.23
ε_2	Relative permittivity of the layer 2	1.13	1.19
ε_3	Relative permittivity of the layer 3	3.00	3.01
t_1	Thickness of the layer 1	1.04×10^{-2} [m]	1.02×10^{-2} [m]
t_2	Thickness of the layer 2	1.03×10^{-2} [m]	1.07×10^{-2} [m]
t_3	Thickness of the layer 3	1.09×10^{-2} [m]	1.02×10^{-2} [m]

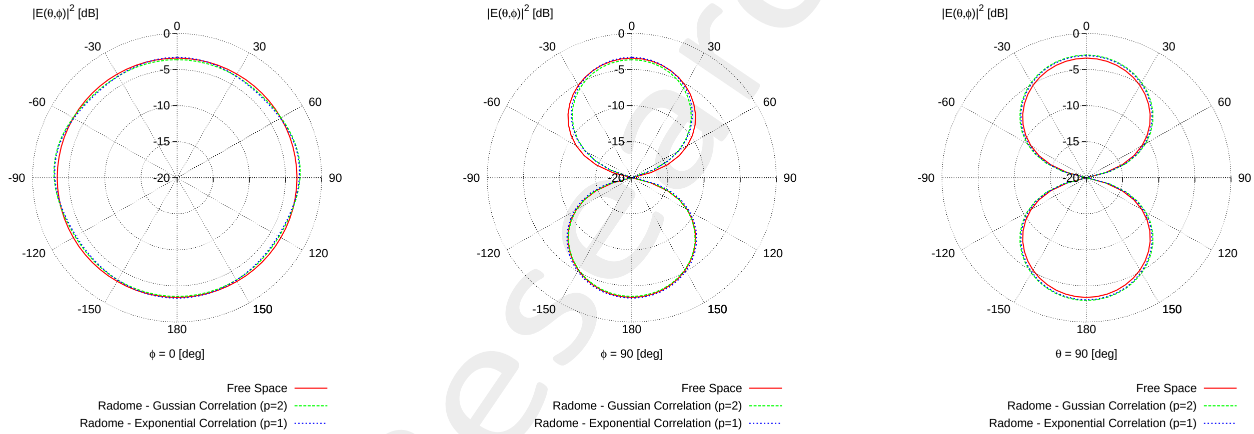
Table III: *(3-layer ogive radome optimization)* – Optimized values for all considered radome descriptors.

Radiation Diagrams



(a) (b) (c)

Figure 11: *(3-layer ogive radome optimization)* – 3D plot of the power pattern of (a) the antenna in free-space, (b) the antenna enclosed in the optimized radome (Gaussian Correlation solution) and (c) the antenna enclosed in the optimized radome (Exponential Correlation solution).



(a) (b) (c)

Figure 12: *(3-layer ogive radome optimization)* – Polar plot of the power pattern of the antenna in free space and in presence of the radome (Gaussian and Exponential Correlation solutions): (a) $\phi = 0$ $[deg]$ plane, (b) $\phi = 90$ $[deg]$ plane and (c) $\theta = 0$ $[deg]$ plane.

2 Synthesis of a 3-Layer Ogive Radome (high density core)

2.0.1 Selecting the proper correlation model

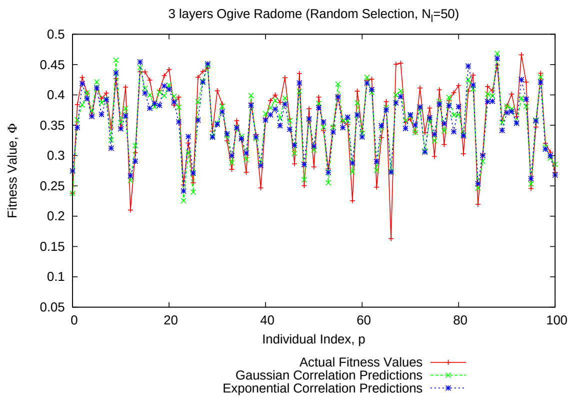
Kriging (Gaussian Process Regressor) parameters

- Regression model: constant (Ordinary Kriging);
- Correlation models:
  - Exponential ($p = 1$);
  - Gaussian ($p = 2$);
- Initial guess for hyper-parameters θ_h: $\theta_{h,0} = 0.5$, for $h = 1, ..., K$;
- Lower bound for hyper-parameters θ_h: $min\,\{\theta_h\} = 0.1$, for $h = 1, ..., K$;
- Upper bound for hyper-parameters θ_h: $max\,\{\theta_h\} = 20.0$, for $h = 1, ..., K$;

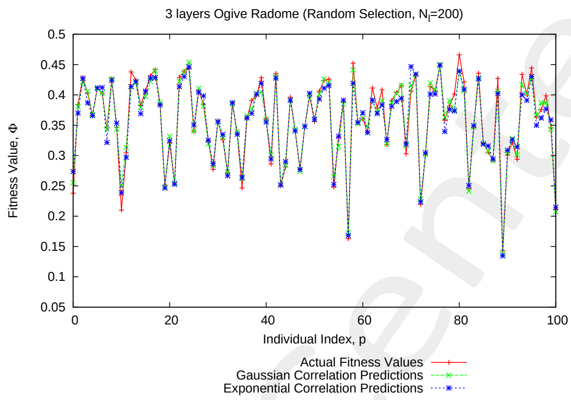
Incremental training parameters

- Number of available simulations: $S = 2000$ (LHS sampling);
- Dimension of the training sets: $N_1 = 50$, $N_{max} = N_L = 1500$, step $\Delta N = 50$;

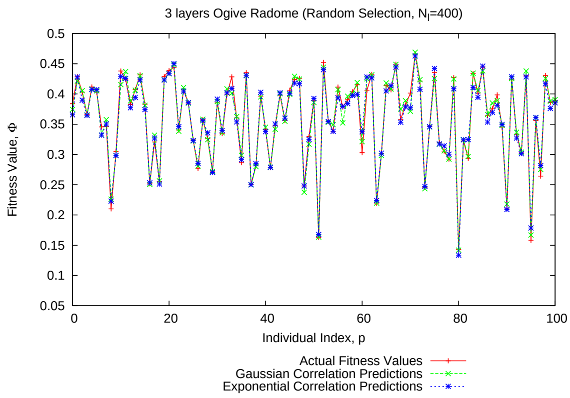
Predicted Fitness Values



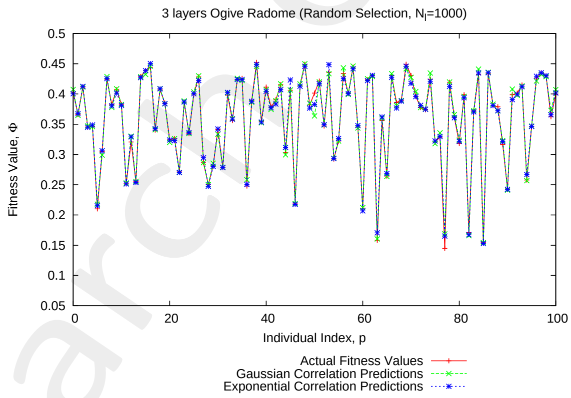
(a) $N = 50$



(b) $N = 200$



(c) $N = 400$



(d) $N = 1000$

Figure 13: *(3-layer ogive radome optimization)* – Actual and predicted functional values of 100 random individuals for different training sizes (N): (a) $N = 50$, (b) $N = 200$, (c) $N = 400$ and (d) $N = 1000$.

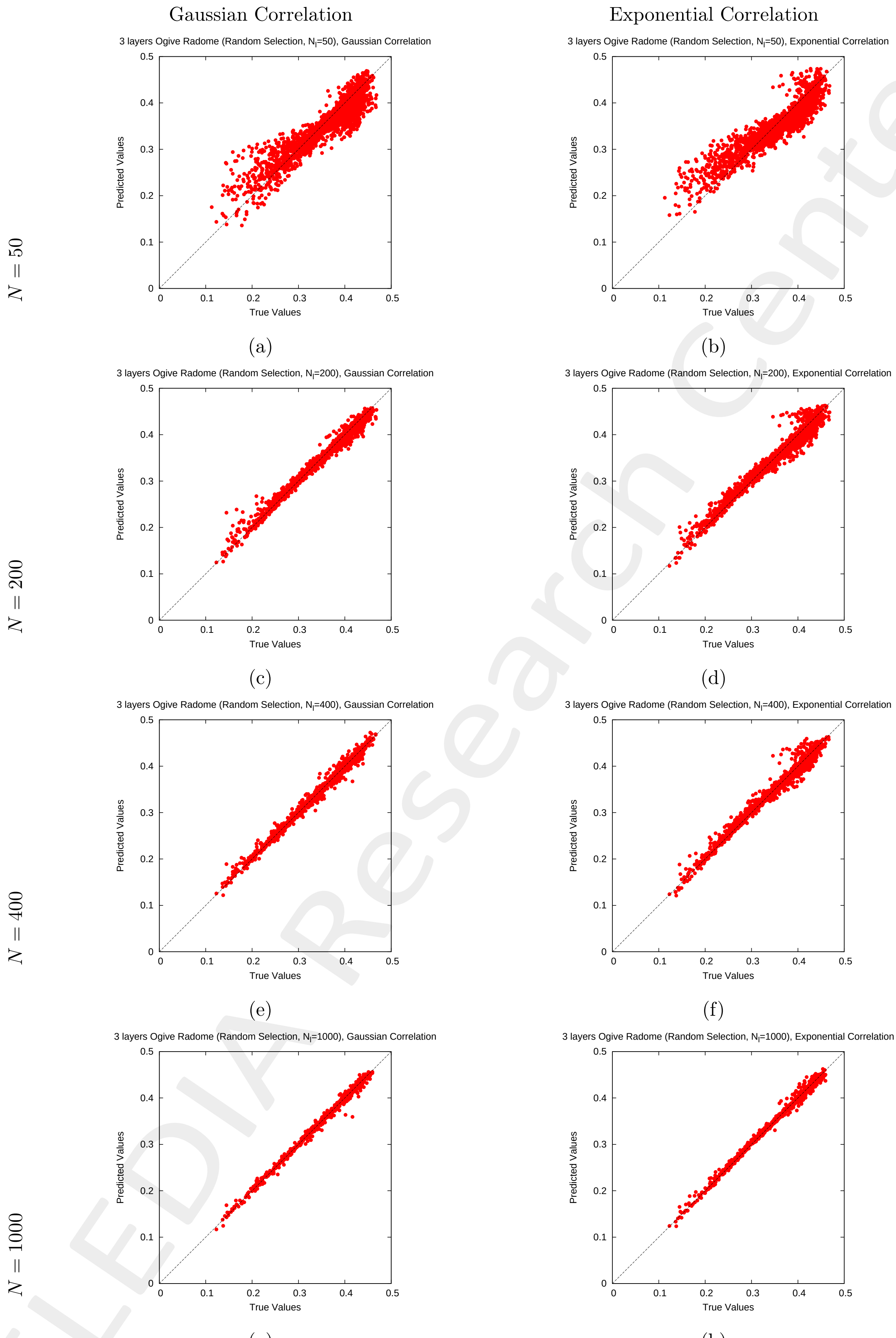
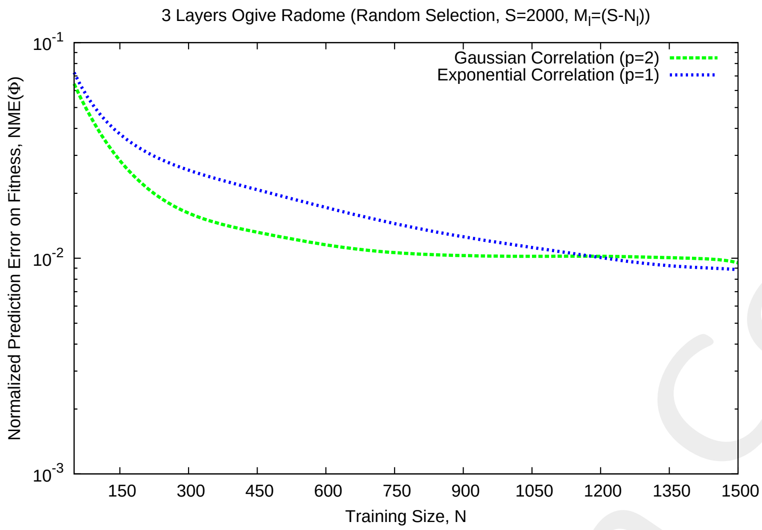
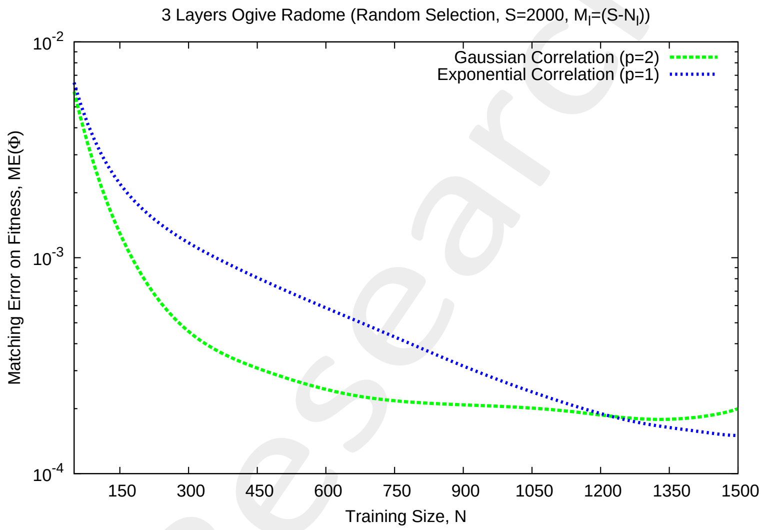


Figure 14: *(3-layer ogive radome optimization)* – Plot of predicted vs actual values for (a), (c), (e), (g) Gaussian Correlation Model and (b), (d), (f), (h) Exponential Correlation Model for different training sizes (N): (a),(b) $N = 50$, (c),(d) $N = 200$, (e),(f) $N = 400$ and (g),(h) $N = 1000$.

Prediction Error vs Training Size



(a)



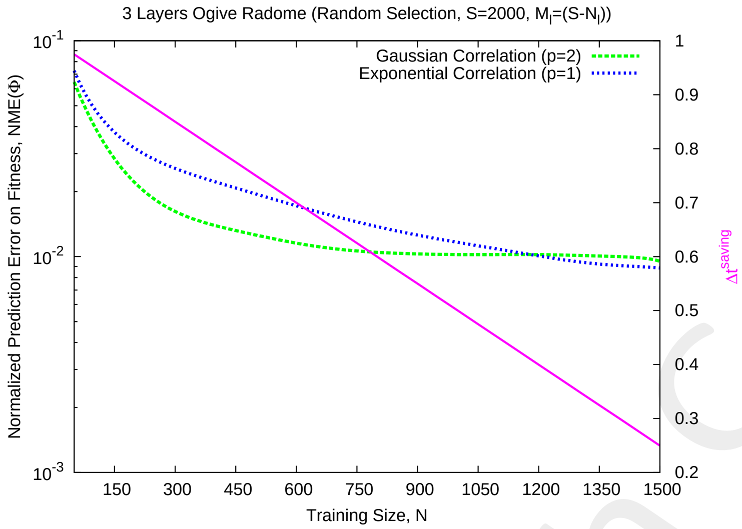
(b)

Figure 15: *(3-layer ogive radome optimization)* – (a) Normalized Mean Error (NME) and (b) Matching Error (ME) vs training size (N) when considering an incremental training with random selection of N_l training samples form a set of S available simulations and testing the corresponding Kriging model on a test set made by the remaining $M_l = (S - N_l)$ simulations.

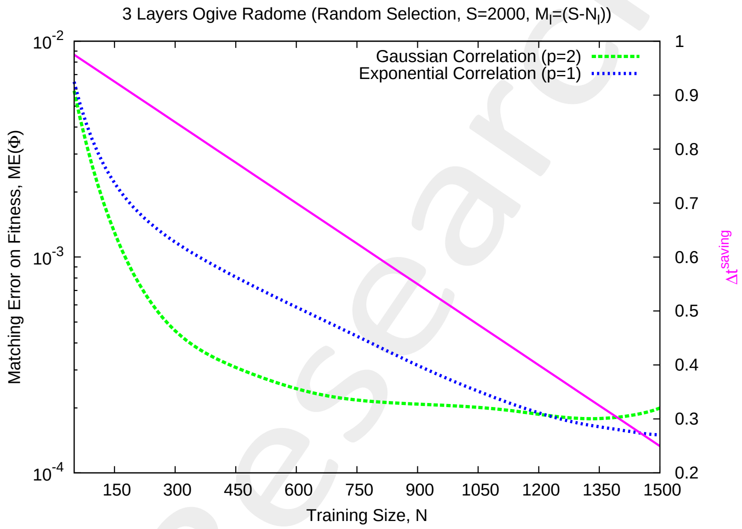
	Gaussian Correlation		Exponential Correlation	
N	NME	ME	NME	ME
50	6.44×10^{-2}	5.89×10^{-3}	7.27×10^{-2}	6.48×10^{-3}
200	1.95×10^{-2}	6.78×10^{-4}	2.91×10^{-2}	1.47×10^{-3}
400	1.41×10^{-2}	3.52×10^{-4}	2.24×10^{-2}	9.22×10^{-4}
1000	9.98×10^{-3}	2.02×10^{-4}	1.15×10^{-2}	2.51×10^{-4}

Table IV: *(3 layer ogive radome optimization)* – Normalized Mean Error (NME) and Matching Error (ME) vs training size (N).

Time Saving Analysis

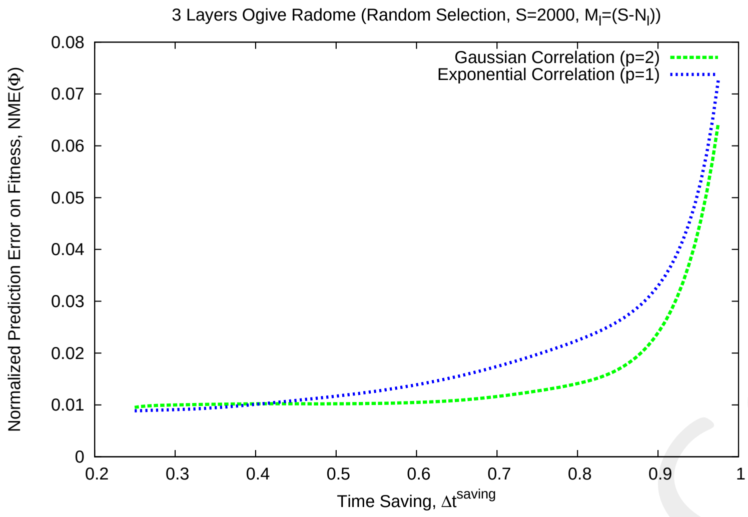


(a) NME

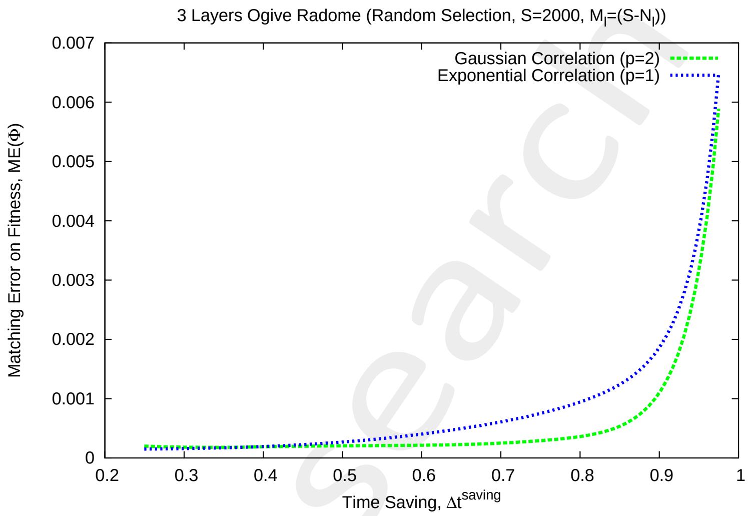


(b) ME

Figure 16: *(3-layer ogive radome optimization)* – Plot of Time Saving (Δt^{saving}) with (a) Normalized Mean Error (NME) and (b) Matching Error (ME) vs training size (N) when considering an incremental training with random selection of N_l training samples form a set of S available simulations and testing the corresponding Kriging model on a test set made by the remaining $M_l = (S - N_l)$ simulations.



(a) NME



(b) ME

Figure 17: *(3-layer ogive radome optimization)* – Plot of (a) Normalized Mean Error (NME) and (b) Matching Error (ME) vs Time Saving (Δt^{saving}).

2.0.2 Optimization

Parameters

Optimization targets

- Functional dimension: $J = 1$;
- Target frequencies:
    1. $f_1 = 200.0$ [MHz];

$SADE$ **parameters**

- Number of variables: $K = 6$;
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Optimized parameters boundaries

Parameter	Description	Min	Max	Measure unit
ε_1	Relative permittivity of the layer 1	3.00	6.00	//
ε_2	Relative permittivity of the layer 2	1.10	3.00	//
ε_3	Relative permittivity of the layer 3	3.00	6.00	//
t_1	Thickness of the layer 1	1.00×10^{-2}	5.00×10^{-2}	[m]
t_2	Thickness of the layer 2	1.00×10^{-2}	5.00×10^{-2}	[m]
t_2	Thickness of the layer 3	1.00×10^{-2}	5.00×10^{-2}	[m]

Table V: *(3-layer ogive radome optimization)* – List of all considered boundaries for the optimized radome descriptors.

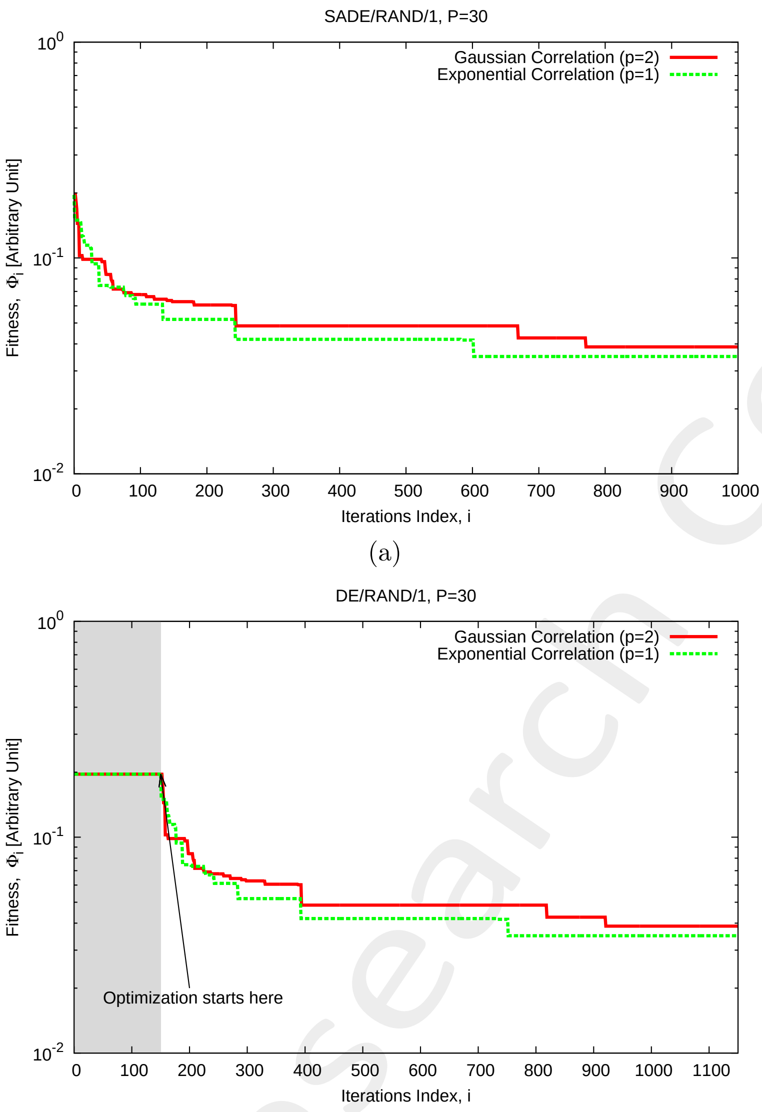
Results of the optimization

- Number of performed $SADE$ iterations: $I_{tot} = I = 1000$;
- Final value of the fitness:
  - Gaussian correlation: $\Phi^{(i=I_{tot})} = 3.88 \times 10^{-2}$;
  - Exponential correlation: $\Phi^{(i=I_{tot})} = 3.50 \times 10^{-2}$;
- Total number of $FEKO$ simulations: $E = (\tau + I_{tot}) = 150 + 1000 = 1150$;

Computational time (@eledialab22-Intel(R) Core(TM) i5 CPU 650 @ 3.20GHz, 4-GB-Ram)

- Average time to compute the fitness associated to a trial solution (**1 core-simulation**): $\Delta t_{avg}^{sim} \simeq 170$ [sec];
- Time for training a Kriging surrogate model with $\tau = 150$ $K = 6$-dimensional training samples: $\Delta t^{train}\big|_{N=\tau=100} \simeq 0.3$ [sec];
- Time for testing $P = 30$ $K = 6$-dimensional trial solutions using a Kriging surrogate model (built on $\tau = 150$ training samples): $\Delta t^{test}|_{M=P=20} \simeq 0.04$ [sec];
- Real total duration of the optimization: $\Delta t^{tot} \simeq 55$ [hours].

Fitness



(a)

(b)

Figure 18: *(3-layer ogive radome optimization)* – Total fitness evolution; (a) evolution vs iteration index during the SADE optimization; (b) evolution vs number of exact function evaluations.

Comparison: $SADE/RAND/1$ **vs** $DE/RAND/1$

The same optimization (i.e., by using the same parameters, such as the random seed and, thus, forcing the same initial population) has been executed using a classic Differential Evolution (DE) algorithm. In particular, the following parameters have been set for DE:

- Population dimension: $P = 30$;
- Scaling factor: $Q = 0.6$;
- Crossover probability: $P_c = 0.8$;
- Primary parent selection mode: $DE/RAND/1$;
- Maximum number of iterations: $I = 1000$;
- Fitness threshold: $\Phi^{th} = 10^{-20}$;
- Random seed: $S = 1$ (same initial population).

Fitness

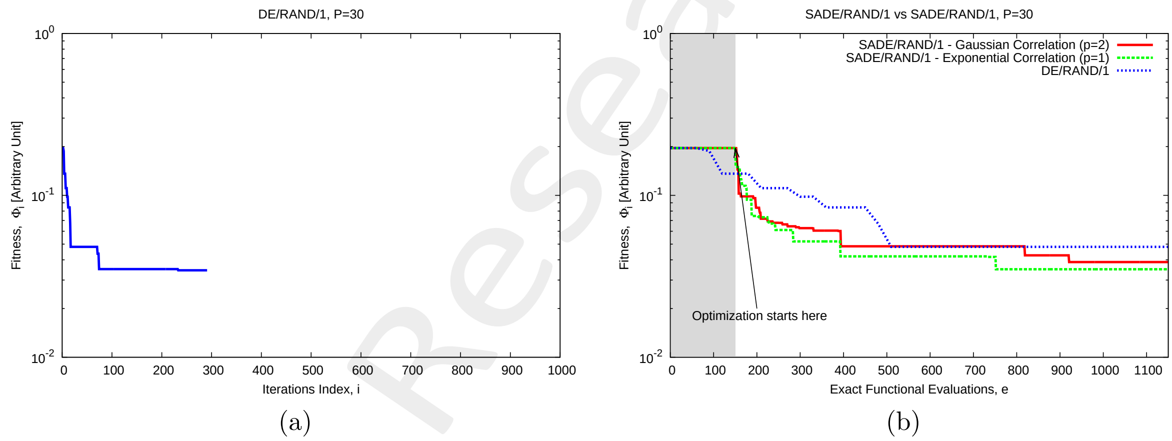


Figure 19: Total fitness evolution; (a) evolution vs iteration index during the DE optimization; (b) evolution vs number of exact function evaluations (simulations with $FEKO$) for both $SADE/RAND/1$ and $DE/RAND/1$ executions.

Computational time

- Theoretical total duration of the optimization:
  - $SADE$ algorithm ($\tau = 150,\ I_{tot} = 1000$):

    $\Delta t^{tot}_{SADE} \simeq \tau \times \Delta t^{\Phi}_{avg} + I_{tot} \times \left(\Delta t^{train}\big|_{N=\tau=200} + \Delta t^{test}\big|_{M=P=50} + \Delta t^{\Phi}_{avg}\right) \simeq 55$ [hours];
  - DE algorithm ($I_{tot} = 1000,\ P = 30$):

    $\Delta t^{tot}_{DE} \simeq I_{tot} \times P \times \Delta t^{\Phi}_{avg} \simeq 1416$ [hours] ($\simeq 59$ [days]);

Evolution of the simulated individuals stored inside the database

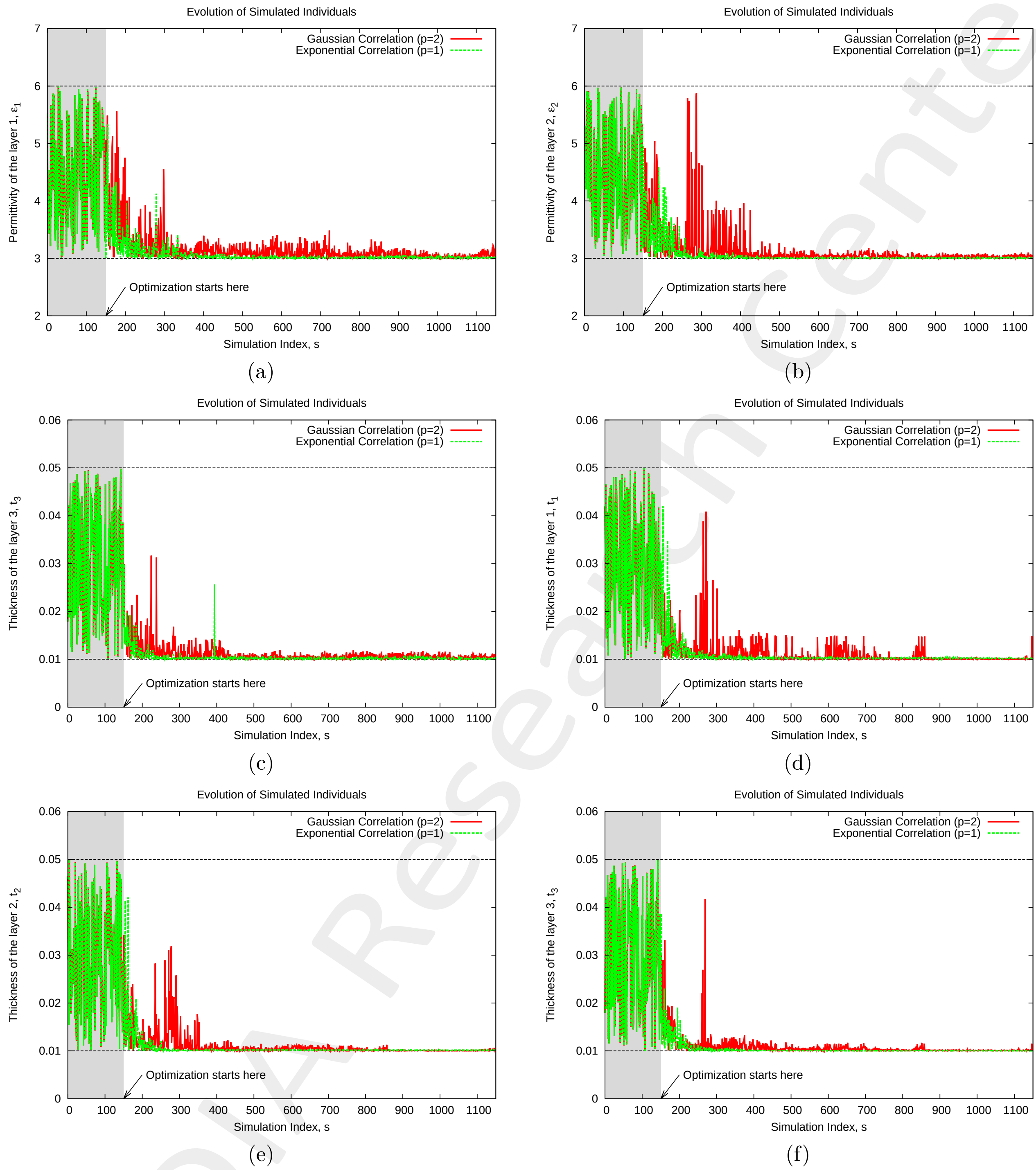


Figure 20: *(3-layer ogive radome optimization)* – Evolution of simulated individuals stored inside the database: parameter (a) ε_1, (b) ε_2, (c) ε_3, (d) t_1, (e) t_2 and (f) t_3.

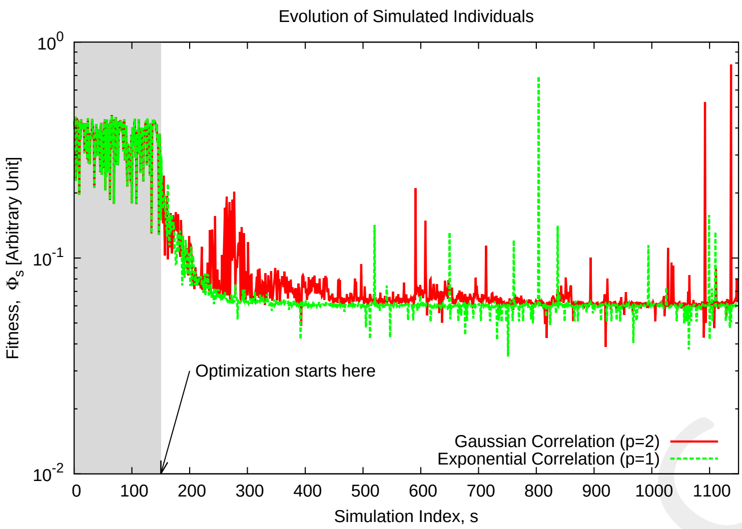
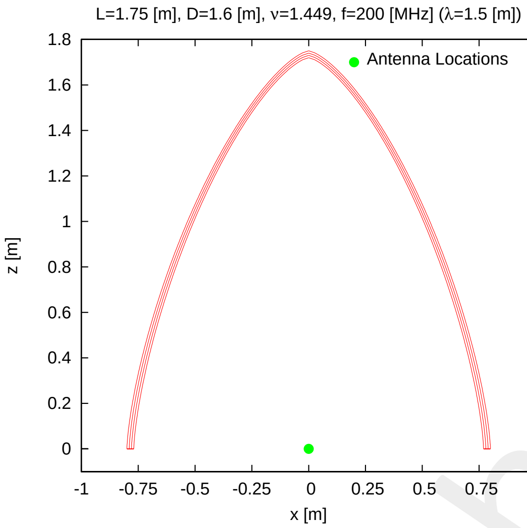


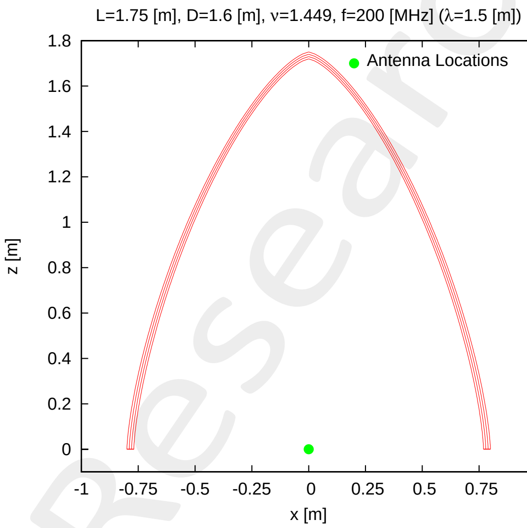
Figure 21: *(3-layer ogive radome optimization)* – Evolution of the fitness of the individuals stored inside the database.

Analysis of the optimal individual

Optimized Model



(a)



(b)

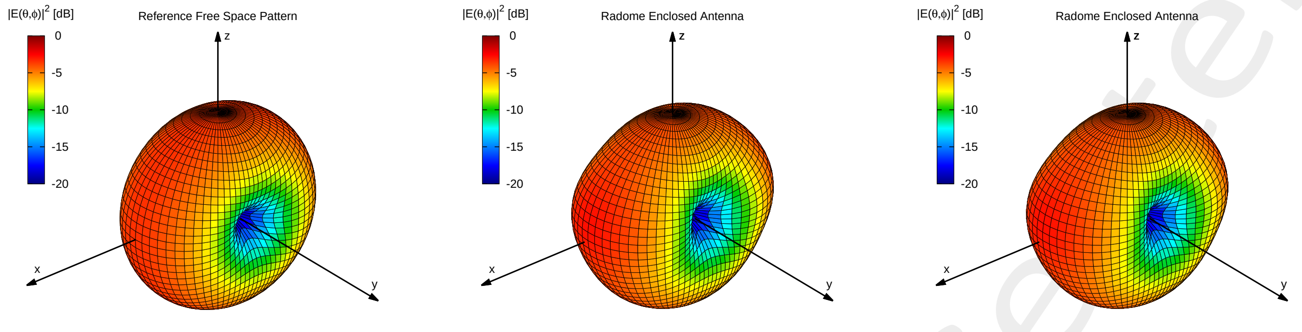
Figure 22: *(3-layer ogive radome optimization)* – Geometry of the optimized radome: (a) Gaussian correlation solution and (b) Exponential correlation solution.

- Total thickness of the structure:
  - Gaussian Correlation: $t = t_1 + t_2 + t_3 \simeq 3.01 \times 10^{-2}$ $[m]$
  - Exponential Correlation: $t = t_1 + t_2 + t_3 \simeq 3.05 \times 10^{-2}$ $[m]$

Parameter	Description	Value - Gauss. Corr. ($p = 2$)	Value - Exp. Corr. ($p = 1$)
ε_1	Relative permittivity of the layer 1	3.00	3.01
ε_2	Relative permittivity of the layer 2	3.04	3.00
ε_3	Relative permittivity of the layer 3	3.06	3.01
t_1	Thickness of the layer 1	1.00×10^{-2} [m]	1.03×10^{-2} [m]
t_2	Thickness of the layer 2	1.00×10^{-2} [m]	1.02×10^{-2} [m]
t_3	Thickness of the layer 3	1.01×10^{-2} [m]	1.00×10^{-2} [m]

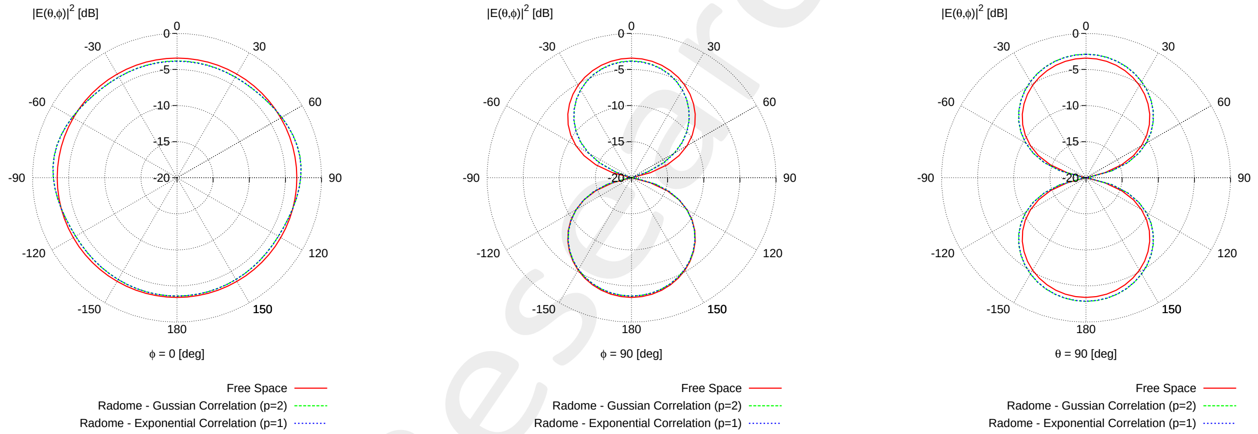
Table VI: *(3-layer ogive radome optimization)* – Optimized values for all considered radome descriptors.

Radiation Diagrams



(a) (b) (c)

Figure 23: *(3-layer ogive radome optimization)* – 3D plot of the power pattern of (a) the antenna in free-space, (b) the antenna enclosed in the optimized radome (Gaussian Correlation solution) and (c) the antenna enclosed in the optimized radome (Exponential Correlation solution).



(a) (b) (c)

Figure 24: *(3-layer ogive radome optimization)* – Polar plot of the power pattern of the antenna in free space and in presence of the radome (Gaussian and Exponential Correlation solutions): (a) $\phi = 0$ $[deg]$ plane, (b) $\phi = 90$ $[deg]$ plane and (c) $\theta = 0$ $[deg]$ plane.

More information on the topics of this document can be found in the following list of references.

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