

ASP HW1

Problem 1

\mathbf{Z} is circularly symmetric Gaussian $\rightarrow \mathbb{E}[\mathbf{Z}\mathbf{Z}^T] = 0$

Zero mean $\rightarrow \mathbb{E}[\mathbf{Z}] = 0$

$$\text{Covariance } \mathbf{R}_Z = \mathbb{E}[\mathbf{Z}\mathbf{Z}^H] = \begin{bmatrix} 2 & 1+2j & 0.1 \\ \times & 3 & -1+j \\ \times & \times & 5 \end{bmatrix}$$

a.

Since covariance matrix is Hermitian,

$$\mathbf{R}_Z = \mathbb{E}[\mathbf{Z}\mathbf{Z}^H] = \begin{bmatrix} 2 & 1+2j & 0.1 \\ 1-2j & 3 & -1+j \\ 0.1 & -1-j & 5 \end{bmatrix}$$

b.

$$\mu_W = \mathbb{E}[\mathbf{A}\mathbf{Z}] = \mathbf{A}\mathbb{E}[\mathbf{Z}] = \mathbf{0}$$

($\because \mu_Z = 0$)

$$\mathbf{R}_W = \mathbb{E}[\mathbf{W}\mathbf{W}^H] = \mathbb{E}[\mathbf{A}\mathbf{Z}\mathbf{Z}^H\mathbf{A}^H] = \mathbf{A}\mathbb{E}[\mathbf{Z}\mathbf{Z}^H]\mathbf{A}^H$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 2 & 0 & 2 \\ 2 & 0 & 3 \end{bmatrix} \begin{bmatrix} 2 & 1+2j & 0.1 \\ 1-2j & 3 & -1+j \\ 0.1 & -1-j & 5 \end{bmatrix} \begin{bmatrix} 1 & 0 & 2 & 2 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 2 & 3 \end{bmatrix}$$

$$= \begin{bmatrix} 2 & 1.1+2j & 4.2 & 4.3 \\ 1.1-2j & 6 & 10.2-2j & 14.2-j \\ 4.2 & 10.2+j & 28.8 & 39 \\ 4.3 & 14.2+j & 39 & 54.2 \end{bmatrix}$$

c.

Let $\mathbf{u} = [\sqrt{3} \frac{-1}{\sqrt{5}} 2]^T$, then

$$\mathbb{E}[\cdot] = \mathbb{E}[(\mathbf{u}^T \mathbf{Z} + 2)^2] = \mathbb{E}[\mathbf{u}^T \mathbf{Z} \mathbf{u}^T \mathbf{Z} + 4\mathbf{u}^T \mathbf{Z} + 4] = \mathbb{E}[\mathbf{u}^T \mathbf{Z} \mathbf{Z}^T \mathbf{u} + 4\mathbf{u}^T \mathbf{Z} + 4]$$

$$= \mathbf{u}^T \mathbb{E}[\mathbf{Z}\mathbf{Z}^T] \mathbf{u} + 4\mathbf{u}^T \mathbb{E}[\mathbf{Z}] + 4 = 4$$

($\because \mu_Z = 0, \mathbb{E}[\mathbf{Z}\mathbf{Z}^T] = 0$)

Problem 2

a.

By the definition:

$$\mathbb{E}[v(n)v^*(n-k)] = \sigma_v^2 \delta(k)$$

b.

First, we calculate the impulse response function.

$$S_v(z) = \sum_{k=-\infty}^{\infty} r_v(k)z^{-k} = \sum_{k=-\infty}^{\infty} \sigma_v^2 \delta(k)z^{-k} = \sigma_v^2$$

Z-transform the difference equation:

$$(1 - \alpha z^{-1})S_s(z) = S_v(z)$$

$$\Rightarrow H(z) = \frac{S_s(z)}{S_v(z)} = \frac{\sigma_v^2}{1 - \alpha z^{-1}}$$

$$\Rightarrow h(n) = \alpha^n u(n)$$

where $u(n)$ is the unit step function.

Then, we prove a lemma [1]:

When $k > 0$,

$$\begin{aligned} \mathbb{E}[v(n)s^*(n-k)] &= \mathbb{E}[v(n) \sum_t h^*(t)v^*(n-t-k)] \\ &= \sum_t h^*(t) \mathbb{E}[v(n)v^*(n-t-k)] = h^*(-k)\sigma_v^2 = 0 \end{aligned}$$

By the above lemma we then calculate the autocorrelation function:

$$\begin{aligned} r_s(0) &= \mathbb{E}[s(n)s^*(n)] = |\alpha|^2 r_s(0) + r_v(0) + 2\mathbb{E}[\Re\{v(n)\alpha s^*(n-1)\}] \\ &= |\alpha|^2 r_s(0) + r_v(0) \text{ (by lemma [1])} \\ \Rightarrow r_s(0) &= \frac{\sigma_v^2}{1-|\alpha|^2} \text{ ([2])} \end{aligned}$$

Multiply $s^*(n-k)$ and take expectation on both side of the difference equation, we get:

$$\begin{aligned} \mathbb{E}[s(n)s^*(n-k)] &= \alpha \mathbb{E}[s(n-1)s^*(n-k)] + \mathbb{E}[v(n)s^*(n-k)] \\ \Rightarrow r_s(k) &= \alpha r_s(k-1) \text{ (by lemma [1]), when } k > 0 \text{ ([3])} \end{aligned}$$

By [2] and [3], we have:

$$r_s(k) = \alpha^k r_s(0) = \alpha^k \frac{\sigma_v^2}{1-|\alpha|^2}, \quad k > 0$$

Finally, by the Hermitian symmetric property of autocorrelation function, we have:

$$r_s(k) = \begin{cases} (\alpha^*)^{-k} \frac{\sigma_v^2}{1-|\alpha|^2}, & k < 0 \\ \alpha^k \frac{\sigma_v^2}{1-|\alpha|^2}, & k \geq 0 \end{cases}$$

c.

By substituting the difference equation into the expectation formula we get:

$$\begin{aligned} \mu_s &= \mathbb{E}[s(n)] = \mathbb{E}[\alpha s(n-1) + v(n)] = \alpha \mathbb{E}[s(n-1)] + \mathbb{E}[v(n)] = \alpha \mu_s + 0 = \alpha \mu_s \\ \Rightarrow \mu_s &= 0 \end{aligned}$$

d.

$$S_s(z) = H(z)H^*(1/z^*)S_v(z) = \frac{1}{1-\alpha z^{-1}} \frac{1}{1-\alpha^* z} \sigma_v^2$$
$$\Rightarrow S_s(e^{j2\pi ft}) = \frac{\sigma_v^2}{1-2\Re\{\alpha e^{-j2\pi ft}\}+|\alpha|^2}$$

Problem 3

a.

Since,

$$r_x(k) = \mathbb{E}[x(n)x^*(n-k)] = \mathbb{E}[(s(n) + v(n))(s^*(n-k) + v^*(n-k))]$$
$$= r_s(k) + r_v(k) + h(k)\sigma_v^2 + h^*(-k)\sigma_v^2 = (r_s(k) + \delta(k) + h(k) + h^*(-k))\sigma_v^2$$

The correlation matrix is:

$$\mathbf{R} = \mathbb{E}[\mathbf{x}(n)\mathbf{x}(n)^H] = \begin{bmatrix} \mathbb{E}[x(n)x(n)] & \mathbb{E}[x(n)x^*(n-1)] \\ \mathbb{E}[x(n-1)x^*(n)] & \mathbb{E}[x(n-1)x^*(n-1)] \end{bmatrix} = \begin{bmatrix} r_x(0) & r_x(1) \\ r_x^*(1) & r_x(0) \end{bmatrix}$$
$$= \sigma_v^2 \begin{bmatrix} 3 + \frac{1}{1-|\alpha|^2} & \alpha + \frac{\alpha}{1-|\alpha|^2} \\ \alpha^* + \frac{\alpha^*}{1-|\alpha|^2} & 3 + \frac{1}{1-|\alpha|^2} \end{bmatrix} = \frac{\sigma_v^2}{1-|\alpha|^2} \begin{bmatrix} 4 - 3|\alpha|^2 & 2\alpha - \alpha|\alpha|^2 \\ 2\alpha^* - \alpha^*|\alpha|^2 & 4 - 3|\alpha|^2 \end{bmatrix}$$

Also, since

$$\mathbb{E}[x(n-k)d^*(n)] = \mathbb{E}[(s(n-k) + v(n-k))(v^*(n) + v^*(n-1))]$$
$$= (h(-k) + h(-k+1) + \delta(k) + \delta(k-1))\sigma_v^2$$

The cross correlation vector is:

$$\mathbf{p} = \mathbb{E}[\mathbf{x}(n)d^*(n)] = \mathbb{E} \begin{bmatrix} x(n)d^*(n) \\ x(n-1)d^*(n) \end{bmatrix} = \sigma_v^2 \begin{bmatrix} \alpha + 2 \\ 2 \end{bmatrix}$$

b.

$$\mathbb{E}[d(n)d^*(n)] = \mathbb{E}[(v(n) + v(n-1))(v^*(n) + v^*(n-1))] = 2\sigma_v^2$$

c.

By a, b and the Wiener-Hopf equation we have:

$$\frac{\sigma_v^2}{1-|\alpha|^2} \begin{bmatrix} 4 - 3|\alpha|^2 & 2\alpha - \alpha|\alpha|^2 \\ 2\alpha^* - \alpha^*|\alpha|^2 & 4 - 3|\alpha|^2 \end{bmatrix} = \sigma_v^2 \begin{bmatrix} \alpha + 2 \\ 2 \end{bmatrix}$$

$$\text{Let matrix } \mathbf{B} = \begin{bmatrix} 4 - 3|\alpha|^2 & 2\alpha - \alpha|\alpha|^2 \\ 2\alpha^* - \alpha^*|\alpha|^2 & 4 - 3|\alpha|^2 \end{bmatrix}$$

Since $\det(\mathbf{B}) = 16 - 28|\alpha|^2 + 13|\alpha|^4 - |\alpha|^6$ is always positive for all $|\alpha| < 1$, the above linear system always has a solution:

$$\begin{aligned}\mathbf{w}_{opt} &= (1 - |\alpha|^2)\mathbf{B}^{-1}\mathbf{p} = \frac{1-|\alpha|^2}{\det(\mathbf{B})} \begin{bmatrix} 4 - 3|\alpha|^2 & -2\alpha + \alpha|\alpha|^2 \\ -2\alpha^* + \alpha^*|\alpha|^2 & 4 - 3|\alpha|^2 \end{bmatrix} \begin{bmatrix} \alpha + 2 \\ 2 \end{bmatrix} \\ &= \frac{1-|\alpha|^2}{16-28|\alpha|^2+13|\alpha|^4-|\alpha|^6} \begin{bmatrix} 8 - \alpha|\alpha|^2 - 6|\alpha|^2 \\ 8 - 4\alpha^* - 8|\alpha|^2 + 2\alpha^*|\alpha|^2 + |\alpha|^4 \end{bmatrix} \\ &= \frac{1}{|\alpha|^4-12|\alpha|^2+16} \begin{bmatrix} 8 - \alpha|\alpha|^2 - 6|\alpha|^2 \\ 8 - 4\alpha^* - 8|\alpha|^2 + 2\alpha^*|\alpha|^2 + |\alpha|^4 \end{bmatrix}\end{aligned}$$

d.

$$\begin{aligned}h_{wiener}(n) &= \mathbf{w}_{opt}^H \begin{bmatrix} \delta(n) \\ \delta(n-1) \end{bmatrix} \\ &= \frac{8-\alpha^*|\alpha|^2-6|\alpha|^2}{|\alpha|^4-12|\alpha|^2+16}\delta(n) + \frac{8-4\alpha-8|\alpha|^2+2\alpha|\alpha|^2+|\alpha|^4}{|\alpha|^4-12|\alpha|^2+16}\delta(n-1)\end{aligned}$$

e.

$$\begin{aligned}r_y(k) &= \mathbb{E}[y(n)y^*(n-k)] = \mathbb{E}[(w_0^*x(n) + w_1^*x(n-1)][w_0^*x(n-k) + w_1^*x(n-k-1)]^*] \\ &= |w_0|^2 r_x(k) + |w_1|^2 r_x(k) + w_0 w_1^* r_x(k+1) + w_1 w_0^* r_x(k-1) \\ &= (|w_0|^2 + |w_1|^2) r_x(k) + w_0^* w_1 r_x(k+1) + w_1^* w_0 r_x(k-1)\end{aligned}$$

Where

$$\begin{aligned}w_0 &= \frac{8-\alpha|\alpha|^2-6|\alpha|^2}{|\alpha|^4-12|\alpha|^2+16} \\ w_1 &= \frac{8-4\alpha^*-8|\alpha|^2+2\alpha^*|\alpha|^2+|\alpha|^4}{|\alpha|^4-12|\alpha|^2+16} \\ r_x(k) &= (r_s(k) + \delta(k) + h(k) + h^*(-k))\sigma_v^2 \\ r_s(k) &= \begin{cases} (\alpha^*)^{-k} \frac{\sigma_v^2}{1-|\alpha|^2}, k < 0 \\ \alpha^k \frac{\sigma_v^2}{1-|\alpha|^2}, k \geq 0 \end{cases}\end{aligned}$$

$$h(n) = \alpha^n u(n)$$

$u(n)$ is the unit step function

f.

Since

$$\begin{aligned}w_0|_{\alpha=0.1, \sigma_v^2=1} &= 7.939/15.8801 \\ w_1|_{\alpha=0.1, \sigma_v^2=1} &= 7.5221/15.8801 \\ h(n)|_{\alpha=0.1, \sigma_v^2=1} &= 0.1^n u(n) \\ r_s(k)|_{\alpha=0.1, \sigma_v^2=1} &= 0.1^{|k|}/0.99 \\ r_x(k)|_{\alpha=0.1, \sigma_v^2=1} &= 0.1^{|k|}/0.99 + \delta(k) + 0.1^k u(k) + 0.1^{-k} u(-k)\end{aligned}$$

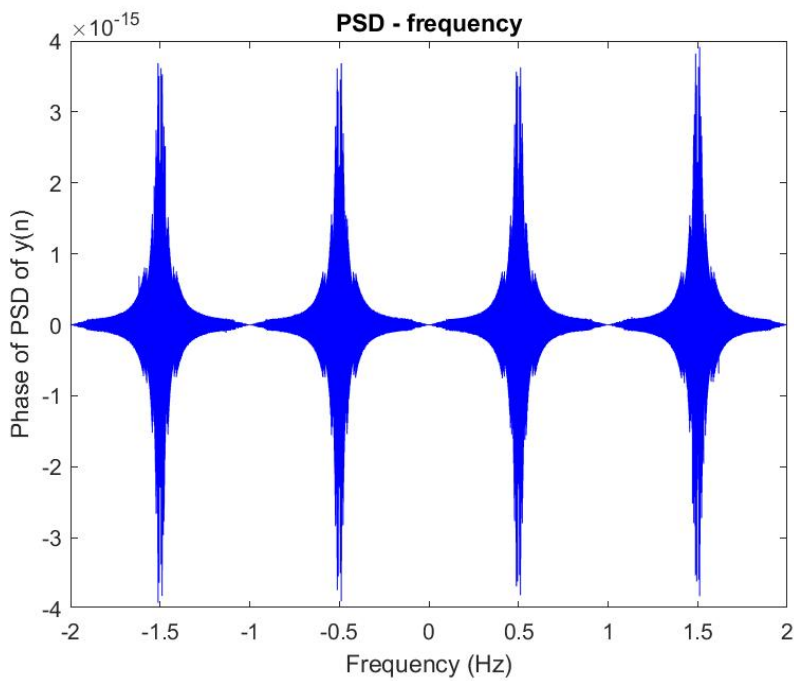
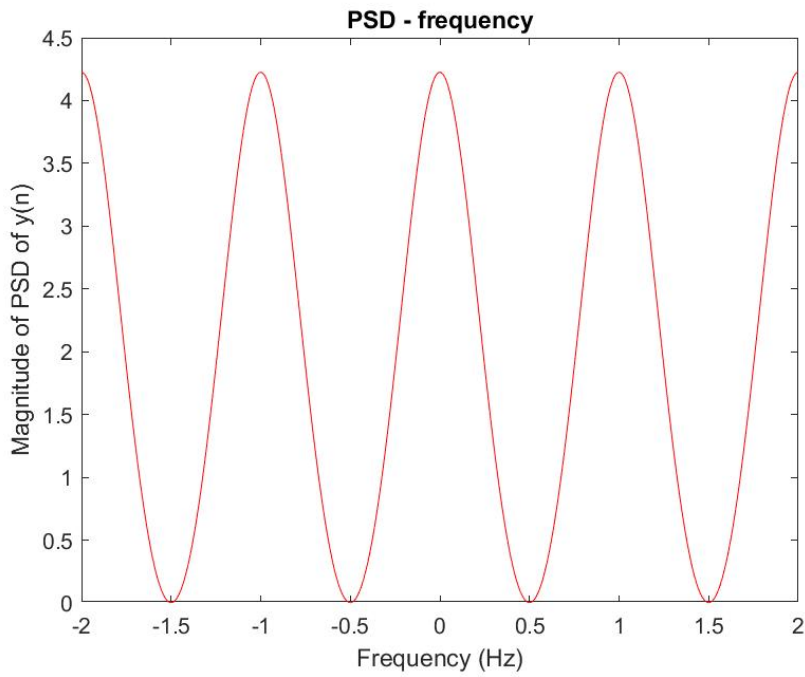
We have

$$\begin{aligned}
S_x(z)|_{\alpha=0.1, \sigma_b^2=1} &= \sum_k r_x(k) z^{-k} |_{\alpha=0.1, \sigma_b^2=1} = \sum_k \{r_x(k)|_{\alpha=0.1, \sigma_b^2=1}\} z^{-k} \\
&= \sum_k \{0.1^{|k|}/0.99 + \delta(k) + 0.1^k u(k) + 0.1^{-k} u(-k)\} z^{-k} \\
&= \sum_{k=1 \sim \infty} \{0.1^k/0.99 + 0.1^k\} z^{-k} \\
&+ \sum_{k=-\infty \sim -1} \{0.1^{-k}/0.99 + 0.1^{-k}\} z^{-k} \\
&+ 3.97/0.99 \\
&= \sum_{k=1 \sim \infty} \{1.99(0.1z^{-1})^k/0.99\} \\
&+ \sum_{k=1 \sim \infty} \{1.99(0.1z)^k/0.99\} \\
&+ 3.97/0.99 \\
&= (1.99/0.99)0.1z^{-1}/(1 - 0.1z^{-1}) \\
&+ (1.99/0.99)0.1z/(1 - 0.1z) + 3.97/0.99 \\
&= \frac{0.199}{0.99(z-0.1)} + \frac{0.199z}{0.99(1-0.1z)} + \frac{3.97}{0.99}
\end{aligned}$$

Hence,

$$\begin{aligned}
S_y(z) &= Z\{(|w_0|^2 + |w_1|^2)r_x(k) + w_0 w_1^* r_x(k+1) + w_1 w_0^* r_x(k-1)\} \\
&= (|w_0|^2 + |w_1|^2)S_x(k) + w_0 w_1^* S_x(k)z + w_1 w_0^* S_x(k)z^{-1} \\
&= \frac{7.939^2 + 7.5221^2 + 7.939(7.5221)z + 7.5221(7.939)z^{-1}}{15.8801^2} S_x(z)
\end{aligned}$$

The following figure shows the plot of PSD to frequency under this condition (take 1e6 samples from -2 to 2):



g.

$$\begin{aligned}
 J_{min} &= \sigma_d^2 - \mathbf{p}^H \mathbf{w}_{opt} \\
 &= 2\sigma_v^2 - \begin{bmatrix} \alpha + 2 \\ 2 \end{bmatrix}^H \frac{\sigma_v^2}{|\alpha|^4 - 12|\alpha|^2 + 16} \begin{bmatrix} 8 - \alpha|\alpha|^2 - 6|\alpha|^2 \\ 8 - 4\alpha^* - 8|\alpha|^2 + 2\alpha^*|\alpha|^2 + |\alpha|^4 \end{bmatrix} \\
 &= \frac{|\alpha|^2(4 + |\alpha|^2 + 2\alpha^* + 2\alpha)}{|\alpha|^4 - 12|\alpha|^2 + 16} \sigma_v^2
 \end{aligned}$$

Problem 4

a.

$$\begin{aligned}
 \left(\frac{\partial(\mathbf{a}^T \mathbf{X} \mathbf{b})}{\partial \mathbf{X}} \right)_{i,j} &= \frac{\partial(\mathbf{a}^T \mathbf{X} \mathbf{b})}{\partial x_{i,j}} = a_i b_j \\
 \Rightarrow \frac{\partial(\mathbf{a}^T \mathbf{X} \mathbf{b})}{\partial \mathbf{X}} &= \mathbf{a} \mathbf{b}^T
 \end{aligned}$$

b.

For $\mathbf{X} = \begin{bmatrix} x_{1,1} & x_{1,2} \\ x_{2,1} & x_{2,2} \end{bmatrix}$, from the characteristic polynomial we get:

$$(x_{1,1} - \lambda)(x_{2,2} - \lambda) - x_{1,2}x_{2,1} = 0$$

$$\Rightarrow \lambda^2 - \text{Tr}(\mathbf{X})\lambda + \det(\mathbf{X}) = 0$$

$$\Rightarrow \lambda_1(\mathbf{X}) + \lambda_2(\mathbf{X}) = \text{Tr}(\mathbf{X})$$

Hence,

$$\frac{\partial(\lambda_1(\mathbf{X}) + \lambda_2(\mathbf{X}))}{\partial \mathbf{X}} = I_2$$

where I_k denotes the identity matrix

c.

By the characteristic polynomial, we can easily verify that $\prod \lambda_i(\mathbf{X}) = \det(\mathbf{X})$

Then,

$$\frac{\partial(\prod \lambda_i(\mathbf{X}))}{\partial \mathbf{X}} = \frac{\det(\mathbf{X})}{\partial \mathbf{X}} = \text{adj}(\mathbf{X})^T$$

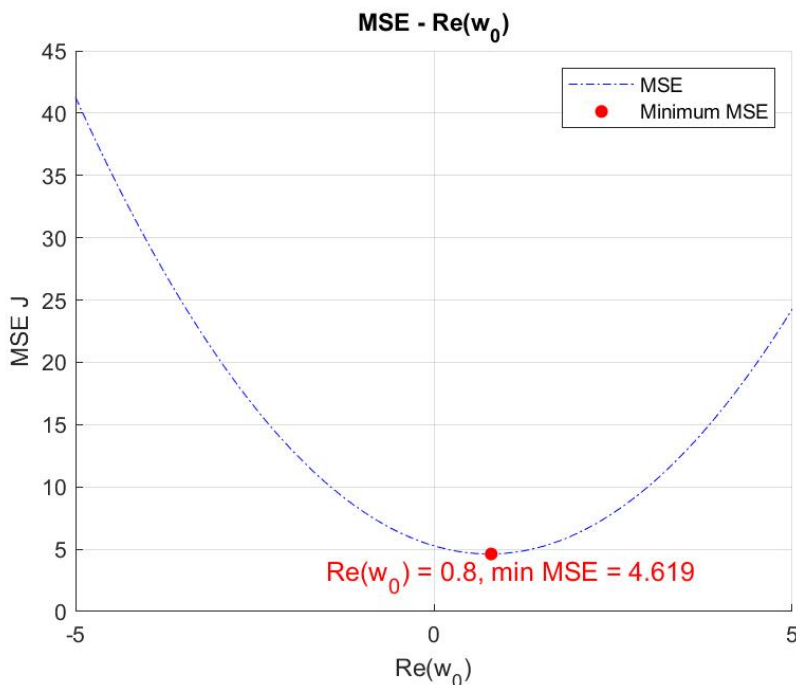
where $\text{adj}(\mathbf{X})$ denotes the adjugate matrix.

Problem 5

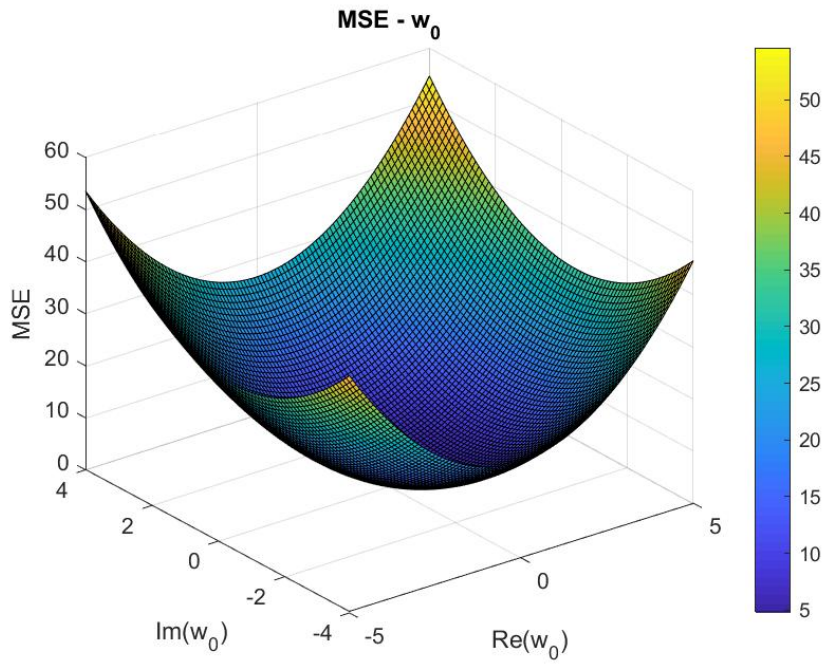
b.

The MSE of the optimal weight vector is: 0.31415

c.



d.



e.

