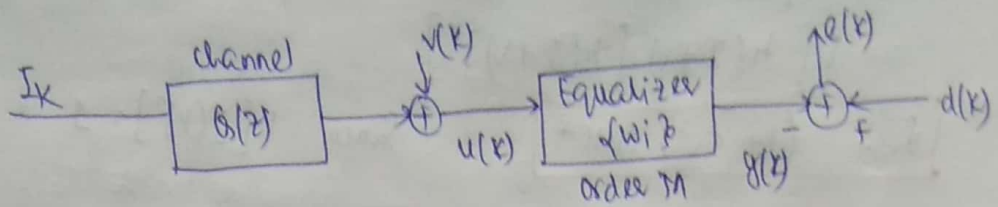


Tutorial 4

Q.1)



Given, $\forall k$ $\{I_k\}$ is iid with $E[I_k] = 1$

and $P[I_k = +1] = P[I_k = -1] = \frac{1}{2}$ $v(k) \rightarrow$ AWGN, $\sigma_v^2 = 0.2$

and $E[I_k v(i)] = 0$ for $\forall k, i$

$$G(z) = 1 - z^{-1} + 0.5z^{-2}, \text{ equalizer order} = M$$

(a) $M=2$, $d(k) = I(k)$. $G(z) = 1 - z^{-1} + 0.5z^{-2}$, $\sigma_v^2 = 0.2$, $E[I(k)^2] =$

$$\therefore u(k) = \begin{bmatrix} 1 & -1 & 0.5 \end{bmatrix} \begin{bmatrix} I(k) \\ I(k-1) \\ I(k-2) \end{bmatrix} + v(k)$$

$$\text{or, } u(k) = (1 - z^{-1} + 0.5z^{-2}) I(k) + v(k)$$

$$\text{or, } u(k) = I(k) - I(k-1) + 0.5 I(k-2) + v(k)$$

$$\text{and, } u(k-1) = I(k-1) - I(k-2) + 0.5 I(k-3) + v(k-1)$$

Since, $M=2$

$$\underbrace{\begin{bmatrix} u(k) \\ u(k-1) \end{bmatrix}}_U = \underbrace{\begin{bmatrix} 1 & -1 & 0.5 & 0 \\ 0 & 1 & -1 & 0.5 \end{bmatrix}}_H \underbrace{\begin{bmatrix} I(k) \\ I(k-1) \\ I(k-2) \\ I(k-3) \end{bmatrix}}_I + \underbrace{\begin{bmatrix} v(k) \\ v(k-1) \end{bmatrix}}_V$$

$$\therefore U = HI + V$$

$$\text{Now, } R = E[UU^*] = E[(HI + V)(HI + V)^*]$$

$$= E[HI I^* H^* + H I V^* + V I^* H^* + V V^*]$$

$$= H E[II^*] H^* + 0 + 0 + E[VV^*]$$

$$= H H^* + \sigma_v^2 I_{2 \times 2}$$

$$= \begin{bmatrix} 2.45 & -1.5 \\ -1.5 & 2.45 \end{bmatrix}$$

$$\therefore E[I_k v(i)] = 0$$

$$\& E[I_k^2] = 1$$

$$\sigma_v^2 = 0.2$$

Now,

$$P_1 = E[d(k)U] = E[d(k)(HI + V)]$$

$$= E[I(k)(HI + V)] \quad (\because d(k) = I(k))$$

$$= E[I(k)HI + I(k)V]$$

$$= H E[I(k)I] + 0$$

$$= H \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\therefore w_{opt1} = R^{-1} P_1 = \begin{bmatrix} 0.6529 \\ 0.3997 \end{bmatrix}$$

$$\text{and, } J_{min1} = \sigma_I^2 - P_1^H w_{opt1} = \underline{0.3471} \quad \text{Ans.}$$

(b) $M=2$, $d(k) = I(k-1)$

$$P_2 = E[d(k)U] = E[I(k-1)(HI+V)] = H E[I(k-1)I] + 0 \\ = H \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

$$\therefore w_{opt2} = R^{-1} P_2 = \begin{bmatrix} -0.2532 \\ 0.2532 \end{bmatrix}$$

$$\text{and, } J_{min2} = \sigma_I^2 - P_2^H w_{opt2} = \underline{0.4937} \quad \text{Ans.}$$

(c) $M=2$, $d(k) = I(k-2)$

$$P_3 = E[d(k)U] = E[I(k-2)(HI+V)] = H \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.5 \\ -1 \end{bmatrix}$$

$$\therefore w_{opt3} = R^{-1} P_3 = \begin{bmatrix} -0.0733 \\ -0.4530 \end{bmatrix}$$

$$\text{and, } J_{min3} = \sigma_I^2 - P_3^H w_{opt3} = \underline{0.5836} \quad \text{Ans.}$$

(d) DFE with $M=2$ (feedback taps), $L=2$ (feed forward taps)

(i) $\Delta=0$

$$a_1 = \begin{bmatrix} U(k) \\ U(k-1) \\ I(k-1) \\ I(k-2) \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & -1 & 0.5 & 0 \\ 0 & 1 & -1 & 0.5 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}}_{H_1} \underbrace{\begin{bmatrix} I(k) \\ I(k-1) \\ I(k-2) \\ I(k-3) \end{bmatrix}}_{I_1} + \underbrace{\begin{bmatrix} V(k) \\ V(k-1) \\ 0 \\ 0 \end{bmatrix}}_{V_1}$$

$$\therefore a_1 = H_1 I_1 + V_1$$

Now $R_1 = E[a_1 a_1^*] = E[(H_1 I_1 + V_1)(H_1 I_1 + V_1)^*] \\ = H_1 E[I_1 I_1^*] H_1^* + E[V_1 V_1^*] \\ = H_1 H_1^* + 0.2 I_{4 \times 4}$

$$R_1 = \begin{bmatrix} 2.45 & -1.5 & -1 & 0.5 \\ -1.5 & 2.45 & 1 & -1 \\ -1 & 1 & 1.2 & 0 \\ 0.5 & -1 & 0 & 1.2 \end{bmatrix}$$

$$\text{and, } p_1 = E[I(x) \underline{a}_1] = E[I(x)(H_1 I_1 + V_1)] \\ = H_1 E[I(x) I_1] \\ = H_1 \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad \checkmark$$

(ii) $\Delta = 1$,

$$\underline{a}_2 = \begin{bmatrix} V(x) \\ V(x-1) \\ I(x-2) \\ I(x-3) \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & -1 & 0.5 & 0 \\ 0 & 1 & -1 & 0.5 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{H_2} \underbrace{\begin{bmatrix} I(x) \\ I(x-1) \\ I(x-2) \\ I(x-3) \end{bmatrix}}_{I_2} + \underbrace{\begin{bmatrix} V(x) \\ V(x-1) \\ 0 \\ 0 \end{bmatrix}}_{V_2}$$

$$\therefore \underline{a}_2 = H_2 I_2 + V_2$$

$$\text{Now, } R_2 = E[\underline{a}_2 \underline{a}_2^*] = H_2 H_2^* + 0.2 I_{4 \times 4} = \begin{bmatrix} 2.45 & -1.5 & 0.5 & 0 \\ -1.5 & 2.45 & -1 & 0.5 \\ 0.5 & -1 & 1.2 & 0 \\ 0 & 0.5 & 0 & 1.2 \end{bmatrix}$$

$$\text{and, } p_2 = E[I(x-1) \underline{a}_2] = H_2 E[I(x-1) I_2] = H_2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

$$\therefore p_2 = \begin{bmatrix} -1 \\ 1 \\ 0 \\ 0 \end{bmatrix} \quad \checkmark$$

(iii) $\Delta = 2$

$$\underline{a}_3 = \begin{bmatrix} V(x) \\ V(x-1) \\ I(x-3) \\ I(x-4) \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & -1 & 0.5 & 0 & 0 \\ 0 & 1 & -1 & 0.5 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{H_3} \underbrace{\begin{bmatrix} I(x) \\ I(x-1) \\ I(x-2) \\ I(x-3) \\ I(x-4) \end{bmatrix}}_{I_3} + \underbrace{\begin{bmatrix} V(x) \\ V(x-1) \\ 0 \\ 0 \end{bmatrix}}_{V_3}$$

$$\therefore \underline{a}_3 = H_3 I_3 + V_3$$

$$\therefore R_3 = E[\underline{a}_3 \underline{a}_3^*] = H_3 H_3^* + 0.2 I_{4 \times 4} = \begin{bmatrix} 2.45 & -1.5 & 0 & 0 \\ -1.5 & 2.45 & 0.5 & 0 \\ 0 & 0.5 & 1.2 & 0 \\ 0 & 0 & 0 & 1.2 \end{bmatrix}$$

$$\text{and, } p_3 = E[I(x-2) \underline{a}_3] = H_3 E[I(x-2) I_3] \\ = H_3 \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.5 \\ -1 \\ 0 \\ 0 \end{bmatrix} \quad \checkmark$$

2.

(a)

$$I(n) \in \{-1, 1\}.$$

$$H(z) = 1 - 2z^{-1} + 0.5z^{-2}$$

$$\sigma_u^2 = 0.3.$$

Given $\bar{\mathbf{w}}$ is 2-tap, so \mathbf{R}_{zz} is a 2x2 matrix and $\bar{\mathbf{p}}$ is a 2x1 vector.

$$\text{Denote } \bar{\mathbf{z}} = \begin{bmatrix} z(n) \\ z(n-1) \end{bmatrix}$$

$$z(n) = I(n) - 2I(n-1) + 0.5I(n-2) + u(n)$$

$$z(n-1) = I(n-1) - 2I(n-2) + 0.5I(n-3) + u(n-1)$$

Here $\sigma_I^2 = \frac{2^2}{12} = 0.33$ as it originates from a uniform distribution.

$$\mathbf{R}_{zz} = E[\bar{\mathbf{z}}\bar{\mathbf{z}}^T] = \begin{bmatrix} (1+4+0.25) \times 0.33 + 0.3 & (-2-1) \times 0.33 + 0.3 \\ (-2-1) \times 0.33 + 0.3 & (1+4+0.25) \times 0.33 + 0.3 \end{bmatrix}$$

$$\mathbf{R}_{zz} = \begin{bmatrix} 2.05 & -0.7 \\ -0.7 & 2.05 \end{bmatrix} \text{ is the autocorrelation matrix.}$$

(b)

We know, $J_{min} = \sigma_I^2 - \bar{\mathbf{w}}_{opt}^T \bar{\mathbf{p}}_\Delta$ for each value of Δ . That is,

$J_{min} = \sigma_I^2 - \bar{\mathbf{p}}_{\Delta*}^T \mathbf{R}_{zz}^{-1} \bar{\mathbf{p}}_{\Delta*}$. We only need to calculate the cross correlation vector for different values of Δ to find the optimum Δ^* .

$$\bar{\mathbf{p}}_0 = E \left[I(n) \begin{bmatrix} z(n) \\ z(n-1) \end{bmatrix} \right] = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \sigma_I^2$$

$$\bar{\mathbf{p}}_1 = E \left[I(n-1) \begin{bmatrix} z(n) \\ z(n-1) \end{bmatrix} \right] = \begin{bmatrix} -2 \\ 1 \end{bmatrix} \sigma_I^2$$

$$\bar{\mathbf{p}}_2 = E \left[I(n-2) \begin{bmatrix} z(n) \\ z(n-1) \end{bmatrix} \right] = \begin{bmatrix} 0.5 \\ -2 \end{bmatrix} \sigma_I^2$$

$$\bar{\mathbf{p}}_3 = E \left[I(n-3) \begin{bmatrix} z(n) \\ z(n-1) \end{bmatrix} \right] = \begin{bmatrix} 0 \\ 0.5 \end{bmatrix} \sigma_I^2$$

$$\mathbf{R}_{zz}^{-1} = \begin{bmatrix} 0.5522 & 0.1886 \\ 0.1886 & 0.5522 \end{bmatrix}$$

$$J_0 = \sigma_I^2 - \bar{\mathbf{p}}_0^T \mathbf{R}_{zz}^{-1} \bar{\mathbf{p}}_0 = 0.2720$$

$$J_1 = 0.1104$$

$$J_2 = 0.1145$$

$$J_3 = 0.3180$$

It is clear that $J_{min} = 0.1104$, which is attained for $\Delta = 1$.

(c)

$$J_{min} = 0.1104$$

(d)

The minimum MSE at the optimum Δ is 0.1104. This includes noise contribution as well as that purely due to ISI. The residual noise contribution is given by $\sigma_u^2(\sum w_i^2)$ because variance of filtered white noise is the variance of the unfiltered noise multiplied by the sum of squares of filter's impulse response coefficients.

$\bar{\mathbf{w}}_{opt} = \bar{\mathbf{p}}_{\Delta*}^T \mathbf{R}_{zz}^{-1} = [-0.3053, 0.0584]^T$. Thus, noise after Wiener filter is $(0.3053^2 + 0.0584^2) \times 0.3 = 0.0290$. Thus, the variance of the residual ISI is $J_{min} - \sigma_{u,residual}^2 = 0.1104 - 0.0290 = 0.0814$.

The expression of average probability of error will now be modified as

$$Q\left(\frac{d}{\sqrt{J_{min}}}\right) = Q\left(\frac{d}{\sqrt{\frac{N_0}{2}}} \sqrt{\frac{N_0/2}{J_{min}}}\right) = q\left(d \sqrt{\frac{N_0/2}{J_{min}}}\right)$$

Q.2) Given, a uniform real iid sequence $\{d[k]\}$ with $E\{|d[k]|\}^2 = 1$
 At receiver,

$$u[k] = (1 - 0.5z^{-1} + \frac{1}{3}z^{-3})d[k] + (1 + 0.8z^{-1})v[k]$$

where, $v[k]$: AWGN with variance = 0.25

$$\therefore u[k] = \begin{bmatrix} 1 & -0.5 & \frac{1}{3} \end{bmatrix} \begin{bmatrix} d[k] \\ d[k-1] \\ d[k-2] \end{bmatrix} + \begin{bmatrix} 1 & 0.8 \end{bmatrix} \begin{bmatrix} v[k] \\ v[k-1] \end{bmatrix}$$

(a). Given, R_{uu} of size 3×3

$$\therefore \underbrace{\begin{bmatrix} u[k] \\ u[k-1] \\ u[k-2] \end{bmatrix}}_v = \underbrace{\begin{bmatrix} 1 & -0.5 & \frac{1}{3} & 0 & 0 \\ 0 & 1 & -0.5 & \frac{1}{3} & 0 \\ 0 & 0 & 1 & -0.5 & \frac{1}{3} \end{bmatrix}}_H \underbrace{\begin{bmatrix} d[k] \\ d[k-1] \\ d[k-2] \\ d[k-3] \\ d[k-4] \end{bmatrix}}_d + \underbrace{\begin{bmatrix} 1 & 0.8 & 0 & 0 \\ 0 & 1 & 0.8 & 0 \\ 0 & 0 & 1 & 0.8 \end{bmatrix}}_{H'} \underbrace{\begin{bmatrix} v[k] \\ v[k-1] \\ v[k-2] \\ v[k-3] \end{bmatrix}}_v$$

$$v = Hd + H'v$$

$$\begin{aligned} R_{vv} &= E[vv^*] = E[(Hd + H'v)(Hd + H'v)^*] \\ &= HE[dd^*]H^* + H'E[vv^*]H'^* \\ &= HH^* + 0.25H'H'^* \\ &= \begin{bmatrix} 1.77 & -0.46 & 0.33 \\ -0.46 & 1.77 & -0.46 \\ 0.33 & -0.46 & 1.77 \end{bmatrix} \end{aligned}$$

Ans.

(b). $P = E[v(k)d(k-\Delta)]$

(i) $\Delta = 1$ $P = E[d(k-1)(Hd + H'v)]$

or, $P = HE[d(k-1)d] + 0$

or, $P = H \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} -0.5 \\ 1 \\ 0 \end{bmatrix}$ ✓

(ii) $\Delta = 4$ $P = E[d(k-4)(Hd + H'v)]$

= $HE[d(k-4)d] + 0$

= $H \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{3} \end{bmatrix}$ ✓

4)

Given that

$$\begin{aligned} U(z) = G(z)I(Z) + V(z) &\implies (1 - 0.8z^{-1})U(z) = I(z) + (1 - 0.8z^{-1})V(z) \\ &\implies u(k) = I(k) + v(k) - 0.8v(k-1) + 0.8u(k-1) \end{aligned}$$

Let $z(k) = I(k) + v(k) - 0.8v(k-1) \implies u(k) = z(k) + 0.8u(k-1)$. Expanding $u(k-1)$,

$$u(k) = z(k) + 0.8z(k-1) + (0.8)^2u(k-2)$$

Through recursive expansion, we can get

$$u(k) = \sum_{p=0}^{\infty} (0.8)^p z(k-p)$$

$$\mathbf{u} \triangleq \begin{pmatrix} u(k) \\ u(k-1) \end{pmatrix}. \text{ Then, } \mathbf{R} = \mathbb{E}[\mathbf{u}\mathbf{u}^H] = \begin{pmatrix} \mathbb{E}[u^2(k)] & \mathbb{E}[u(k)u(k-1)] \\ \mathbb{E}[u(k)u(k-1)] & \mathbb{E}[u^2(k-1)] \end{pmatrix}. \text{ For lag } l,$$

$$\begin{aligned} \mathbb{E}[u(k)u(k-l)] &= \mathbb{E}\left[\left\{\sum_{p=0}^{\infty} (0.8)^p z(k-p)\right\}\left\{\sum_{q=0}^{\infty} (0.8)^q z(k-l-q)\right\}\right] \\ &= \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} (0.8)^{p+q} \mathbb{E}[z(k-p)z(k-l-q)] \end{aligned}$$

Given that $\mathbb{E}[I(k)v(i)] = 0 \forall k, i$, $\mathbb{E}[I(k)I(k-m)] = \delta(m)$ and $\mathbb{E}[v(k)v(k-m)] = \delta(m)$. Hence,

$$\begin{aligned} \mathbb{E}[z(k-p)z(k-l-q)] &= \mathbb{E}[I(k-p)I(k-l-q)] + \mathbb{E}[v(k-p)I(k-l-q)] \\ &\quad - 0.8 \mathbb{E}[v(k-p-1)I(k-l-q)] + \mathbb{E}[I(k-p)v(k-l-q)] \\ &\quad + \mathbb{E}[v(k-p)v(k-l-q)] - 0.8 \mathbb{E}[v(k-p-1)v(k-l-q)] \\ &\quad - 0.8 \mathbb{E}[I(k-p)v(k-l-q-1)] - 0.8 \mathbb{E}[v(k-p)v(k-l-q-1)] \\ &\quad + 0.64 \mathbb{E}[v(k-p-1)v(k-l-q-1)] \\ &= \delta(q-p+l) + 0 - 0 + 0 + \sigma_v^2 \delta(q-p+l) - 0.8 \sigma_v^2 \delta(q-p+l-1) - 0 \\ &\quad - 0.8 \sigma_v^2 \delta(q-p+l+1) + 0.64 \sigma_v^2 \delta(q-p+l) \\ &= (1 + 1.64 \sigma_v^2) \delta(q-p+l) - 0.8 \sigma_v^2 \delta(q-p+l-1) - 0.8 \sigma_v^2 \delta(q-p+l+1) \end{aligned}$$

Thus,

$$\begin{aligned}\mathbb{E}[u(k)u(k-l)] &= (1 + 1.64\sigma_v^2) \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} (0.8)^{p+q} \delta(q-p+l) \\ &\quad - 0.8\sigma_v^2 \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} (0.8)^{p+q} \delta(q-p+l-1) \\ &\quad - 0.8\sigma_v^2 \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} (0.8)^{p+q} \delta(q-p+l+1)\end{aligned}$$

But,

$$\begin{aligned}\sum_{p=0}^{\infty} \sum_{q=0}^{\infty} (0.8)^{p+q} \delta(q-p+m) &= \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} (0.8)^{2p-m} \delta(q-p+m) && [\because f(k)\delta(k-j) = f(j)\delta(k-j)] \\ &= \sum_{p=0}^{\infty} (0.8)^{2p-m} \sum_{q=0}^{\infty} \delta(p-m-q) && [\because \delta(m) = \delta(-m)] \\ &= \sum_{p=0}^{\infty} (0.8)^{2p-m} \mathcal{U}(p-m) && [\because \sum_{j=0}^{\infty} \delta(k-j) = \mathcal{U}(k), \text{ unit-step function}] \\ &= \begin{cases} \sum_{p=0}^{\infty} (0.8)^{2p-m}, & m < 0 \\ \sum_{p=m}^{\infty} (0.8)^{2p-m}, & m \geq 0 \end{cases} = \begin{cases} \frac{(0.8)^{-m}}{1 - (0.8)^2}, & m < 0 \\ \frac{(0.8)^m}{1 - (0.8)^2}, & m \geq 0 \end{cases} \\ &= \frac{(0.8)^{|m|}}{1 - (0.8)^2} = \frac{(0.8)^{|m|}}{0.36}\end{aligned}$$

Thus,

$$\begin{aligned}\mathbb{E}[u(k)u(k-l)] &= \frac{1}{0.36} \left[(1 + 1.64\sigma_v^2) (0.8)^{|l|} - 0.8\sigma_v^2 (0.8)^{|l-1|} - 0.8\sigma_v^2 (0.8)^{|l+1|} \right] \\ &= \frac{1}{0.36} \left\{ (0.8)^{|l|} + \sigma_v^2 \left[1.64(0.8)^{|l|} - (0.8)^{|l-1|+1} - (0.8)^{|l+1|+1} \right] \right\}\end{aligned}$$

Hence,

$$\mathbb{E}[u^2(k)] = \frac{1}{0.36} [1 + 0.36\sigma_v^2] = \frac{25}{9} + \sigma_v^2 \quad \text{and} \quad \mathbb{E}[u(k)u(k-1)] = \frac{0.8}{0.36} = \frac{20}{9}$$

$$\Rightarrow \mathbf{R} = \frac{1}{9} \begin{pmatrix} 25 + 9\sigma_v^2 & 20 \\ 20 & 25 + 9\sigma_v^2 \end{pmatrix}$$

$$\text{Also, } \mathbf{p} = \mathbb{E}[I(k - \Delta)\mathbf{u}] = \begin{pmatrix} \mathbb{E}[I(k - \Delta)u(k)] \\ \mathbb{E}[I(k - \Delta)u(k - 1)] \end{pmatrix}$$

$$\begin{aligned} \mathbb{E}[I(k - \Delta)u(k - l)] &= \mathbb{E}\left[I(k - \Delta) \left\{ \sum_{p=0}^{\infty} (0.8)^p [I(k - l - p) + v(k - l - p) - 0.8v(k - l - p - 1)] \right\}\right] \\ &= \sum_{p=0}^{\infty} (0.8)^p \mathbb{E}[I(k - \Delta)I(k - l - p)] + 0 + 0 \\ &= \sum_{p=0}^{\infty} (0.8)^p \delta(p - \Delta + l) = (0.8)^{\Delta - l} \mathcal{U}(\Delta - l) \end{aligned}$$

$$\text{Let } \Delta = 0. \text{ Hence, } \mathbf{p} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}. \text{ Also, } \mathbf{R}^{-1} = \frac{9}{(25 + 9\sigma_v^2)^2 - 400} \begin{pmatrix} 25 + 9\sigma_v^2 & -20 \\ -20 & 25 + 9\sigma_v^2 \end{pmatrix}$$

$$\implies \mathbf{w}_0 = \mathbf{R}^{-1}\mathbf{p} = \frac{9}{(25 + 9\sigma_v^2)^2 - 400} \begin{pmatrix} 25 + 9\sigma_v^2 \\ -20 \end{pmatrix}$$

$$\text{(a) } \sigma_v^2 = 1, \implies \mathbf{w}_0 = \begin{pmatrix} 0.4048 \\ -0.2381 \end{pmatrix}$$

$$\text{(b) } \sigma_v^2 = 0.3, \implies \mathbf{w}_0 = \begin{pmatrix} 0.6788 \\ -0.4901 \end{pmatrix}$$

$$\text{(c) } \sigma_v^2 = 0, \implies \mathbf{w}_0 = \begin{pmatrix} 1 \\ -0.8 \end{pmatrix}$$

Note:

It can be observed that as $SNR \rightarrow \infty$, (i.e., $\sigma_v^2 \rightarrow 0$), \mathbf{w}_0 approaches $[1 \ -0.8]^T$. The corresponding transfer function $W(z) = 1 - 0.8z^{-1}$ is the inverse of channel function (i.e., $W(z) = G^{-1}(z)$). Thus, LMSE filter completely cancels the Inter-Symbol-Interference (ISI) in this scenario. But, such a perfect ISI cancellation is not achievable even at infinite SNR when both L and M are finite. However, LMSE filter will be the same as that of zero-forcing filter at infinite SNR irrespective of L and M .

5)

Given that

$$U(z) = \frac{0.36}{1 - 0.8z^{-1}} I(z) \quad \text{and} \quad D(z) = (1 + 2z^{-1})U(z) + V(z)$$

Hence,

$$u(n) = 0.36 \sum_{p=0}^{\infty} (0.8)^p i(n-p) \quad \text{and} \quad d(n) = u(n) + 2u(n-1) + v(n)$$

(a)

$$\begin{aligned} \mathbb{E}[u(n)u(n-l)] &= \mathbb{E} \left[\left\{ 0.36 \sum_{p=0}^{\infty} (0.8)^p i(n-p) \right\} \left\{ 0.36 \sum_{q=0}^{\infty} (0.8)^q i(n-l-q) \right\} \right] \\ &= (0.36)^2 \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} (0.8)^{p+q} \mathbb{E}[i(n-p)i(n-l-q)] \\ &= (0.36)^2 \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} (0.8)^{p+q} \delta(q-p+l) \quad [\because \mathbb{E}[i(n)i(n-j)] = \delta(j)] \\ &= (0.36)^2 \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} (0.8)^{2p-l} \delta(p-l-q) \\ &= (0.36)^2 \sum_{p=0}^{\infty} (0.8)^{2p-l} \mathcal{U}(p-l) \end{aligned}$$

Hence,

$$\begin{aligned} \mathbb{E}[u^2(n)] &= (0.36)^2 \times \frac{1}{1 - (0.8)^2} = 0.36 \\ \mathbb{E}[u(n)u(n-1)] &= (0.36)^2 \times \frac{0.8}{1 - (0.8)^2} = 0.36 \times 0.8 \end{aligned}$$

Thus,

$$\mathbf{R} = 0.36 \begin{pmatrix} 1 & 0.8 \\ 0.8 & 1 \end{pmatrix}$$

$$\begin{aligned} \mathbb{E}[d(n)u(n)] &= \mathbb{E}[u^2(n)] + 2\mathbb{E}[u(n)u(n-1)] + \mathbb{E}[u(n)v(n)] \\ &= 0.36 + 2 \times 0.36 \times 0.8 + 0 \\ &= 0.936 \end{aligned}$$

$$\begin{aligned}
\mathbb{E}[d(n)u(n-1)] &= \mathbb{E}[u(n)u(n-1)] + 2\mathbb{E}[u^2(n-1)] + \mathbb{E}[u(n-1)v(n)] \\
&= 0.36 \times 0.8 + 2 \times 0.36 + 0 \\
&= 1.008
\end{aligned}$$

Hence,

$$\mathbf{p} = \begin{pmatrix} 0.936 \\ 1.008 \end{pmatrix}$$

(b)

$$\mathbf{R}^{-1} = \frac{1}{(0.36)^2} \begin{pmatrix} 1 & -0.8 \\ -0.8 & 1 \end{pmatrix}$$

Thus,

$$\mathbf{w}_{opt} = \mathbf{R}^{-1}\mathbf{p} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$

(c)

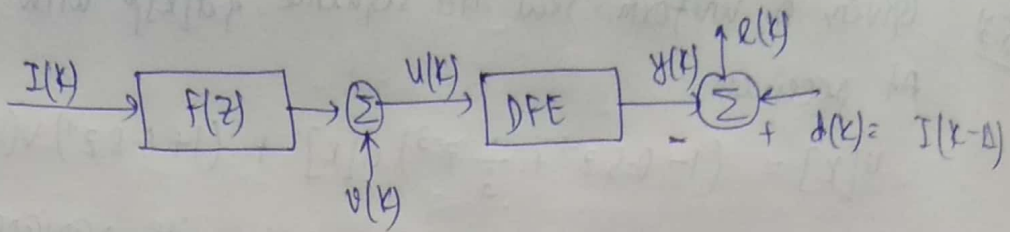
$$\begin{aligned}
\mathbb{E}[d^2(n)] &= \mathbb{E}[(u(n) + 2u(n-1) + v(n))^2] \\
&= \mathbb{E}[u^2(n)] + 4\mathbb{E}[u^2(n-1)] + \mathbb{E}[v^2(n)] \\
&\quad + 4\mathbb{E}[u(n)u(n-1)] + 2\mathbb{E}[u(n)v(n)] + 4\mathbb{E}[u(n-1)v(n)] \\
&= 0.36 + 4 \times 0.36 + 0.1 + 4 \times 0.36 \times 0.8 + 0 + 0 \\
&= 3.052
\end{aligned}$$

Hence,

$$\begin{aligned}
J_{min} &= \mathbb{E}[d^2(n)] - \mathbf{p}^H \mathbf{w}_{opt} \\
&= 3.052 - 2.952
\end{aligned}$$

$$J_{min} = 0.1$$

Q.6)



Given: $F(z) = 1 + 2z^{-1} - z^{-3}$ and additive noise variance, $\sigma_v^2 = 0.1$

$\Delta = 1$, no. of feed forward taps $L = 3$

no. of feed back taps $M = 2$.

Let,

$$g(k) = \begin{bmatrix} u(k) \\ u(k-1) \\ u(k-L+1) \\ I(k-\Delta-1) \\ I(k-\Delta-M) \end{bmatrix}$$

and $R = E[g(k)g^*(k)]$,

$$p = E[d(k)g(k)]$$

At receiver,

$$u(k) = [1 \ 2 \ 0 \ -1] \begin{bmatrix} I(k) \\ I(k-1) \\ I(k-2) \\ I(k-3) \end{bmatrix} + v(k)$$

Hence

$$g(k) = \begin{bmatrix} u(k) \\ u(k-1) \\ u(k-2) \\ I(k-2) \\ I(k-3) \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 2 & 0 & -1 & 0 & 0 \\ 0 & 1 & 2 & 0 & -1 & 0 \\ 0 & 0 & 1 & 2 & 0 & -1 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}}_H \underbrace{\begin{bmatrix} I(k) \\ I(k-1) \\ I(k-2) \\ I(k-3) \\ I(k-4) \\ I(k-5) \end{bmatrix}}_I + \underbrace{\begin{bmatrix} v(k) \\ v(k-1) \\ v(k-2) \\ 0 \\ 0 \end{bmatrix}}_V$$

$$R = E[(HI + V)(HI + V)^*]^H$$

$$= E[(HI + V)(I^*H^* + V^*)]$$

$$= E[HI I^*H^* + HI V^* + VI I^*H^* + VV^*]$$

$$= HH^* + VV^* \quad (\text{cross terms' expectation will be zero})$$

($E[II^*] = 1$)

$\therefore R = HH^* + \sigma_v^2 I_{5 \times 5} \rightarrow$ (identity matrix)

$$R = \begin{bmatrix} 1 & 2 & 0 & -1 & 0 & 0 \\ 0 & 1 & 2 & 0 & -1 & 0 \\ 0 & 0 & 1 & 2 & 0 & -1 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 2 & 1 & 0 & 0 & 0 \\ 0 & 2 & 1 & 1 & 0 \\ -1 & 0 & 2 & 0 & 1 \\ 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 \end{bmatrix} + 0.1 \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$R = \begin{bmatrix} 6 & 2 & -2 & 0 & -1 \\ 2 & 6 & 2 & 2 & 0 \\ -2 & 2 & 6 & 1 & 2 \\ 0 & 2 & 1 & 1 & 0 \\ -1 & 0 & 2 & 0 & 1 \end{bmatrix} + \begin{bmatrix} 0.1 & 0 & 0 & 0 & 0 \\ 0 & 0.1 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0 & 0.1 & 0 \\ 0 & 0 & 0 & 0 & 0.1 \end{bmatrix}$$

$$R = \begin{bmatrix} 6.1 & 2 & -2 & 0 & -1 \\ 2 & 6.1 & 2 & 2 & 0 \\ -2 & 2 & 6.1 & 1 & 2 \\ 0 & 2 & 1 & 1.1 & 0 \\ -1 & 0 & 2 & 0 & 1.1 \end{bmatrix} \checkmark$$

And, $P = E[I(k-1)(HI + V)] = H E[I(k-1)I] + 0$

$$= H \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

since $E[I(n)I(m)] = \begin{cases} 0, & \text{if } n \neq m \\ 1, & \text{if } n = m \end{cases}$

$$\therefore P = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \checkmark$$