

3. $\mathcal{E}(w)$
 Let \mathcal{E} be the cost function for 'w' weights

We know that if w^* is the final solution then

$$\mathcal{E}(w^*) \leq \mathcal{E}(w)$$

$$\mathcal{E}(w) = \sum_{n=1}^K (d(n) - y(n))^2 + \beta \sum_{i=1}^K w_i^2$$

With a learning rate η , we get the steepest descent update rule to be

$$\hat{w}(n+1) = \hat{w}(n) - \eta g(n)$$

where $g(n) = \nabla \mathcal{E}(w)$

$$= \nabla [\mathcal{E}(w)]$$

$$= -e(n)x(n) + 2\beta w(n) \quad \left[\begin{array}{l} \text{From LMS} \\ \text{and } \frac{d}{dw} w^2 = 2w \end{array} \right]$$

$$\Rightarrow \cancel{w_k(n+1)} = \cancel{\eta(-x_k(n) + 2\beta w_k(n))} + \cancel{w_k(n)}$$

$$\Rightarrow w_k(n+1) = w_k(n) - \eta (x_k(n) e(n) - 2\beta w_k(n))$$

Ans.