b). if there is optimal $\delta = 0$, then:

$$y_i(\vec{w}^T \vec{x}_i + \theta) \geq 1, \quad \forall (\vec{x}_i, y_i) \in D$$

Therefore:

$$y(\vec{w}^T \vec{x} + \theta) \geq 1 \geq 0, \quad \forall (\vec{x}, y) \in D, y = 1$$

$$y(\vec{w}^T \vec{x} + \theta) \leq -1 < 0, \quad \forall (\vec{x}, y) \in D, y = -1$$

which satisfy the condition of linear separable.

c) With $\delta > 0$, if $1 - \delta > 0$, we can easily know the data set is linear separable by using same method as b). If $\delta \geq 1$, we cannot make sure it is linear separable. If the minimal $\delta \geq 1$, the data set is not linear separable.

d). The optimal solution is $\vec{w} = 0$, $\theta = 0$, $\delta = 0$. The issue with this formula is that it is not a hyperplane with this optimal solution.

e). (Seems the question should be $\vec{x}_1^T = [1\ 1 \ldots 1]$, $\vec{x}_2^T = [-1\ -1 \ldots -1]$ since $\vec{x}_i$ is n-dimensional vector)

The data set is separable since there are only two samples. Hence the optimal $\delta = 0$, and $\vec{w}$, θ follow the constraints:

$$w_1 + w_2 + \cdots + w_n + \theta \geq 1$$

$$-(-w_1 - w_2 - \ldots - w_n + \theta) \geq 1$$

Therefore $w_1 + w_2 + \ldots + w_n \geq 1 + |\theta|$

Thus, optimal solution would be $(\vec{w}, \theta, \delta)$ with $\delta = 0$, $w_1 + w_2 + \ldots + w_n \geq 1 + |\theta|$.