In the case of a fully-connected neural network with 2 hidden layers (N1), the output layer would be:

$$\vec{a}^{(3)}_{N1} = W^{(3)}\vec{a}^{(2)} + \vec{b}^{(3)} \quad ①$$

where $\vec{a}^{(2)} = W^{(2)}\vec{a}^{(1)} + \vec{b}^{(2)}$ ② & $\vec{a}^{(1)} = W^{(1)}\vec{a}^{(0)} + \vec{b}^{(1)}$ ③

After fully expanding formula ①,

$$\vec{a}^{(3)}_{N1} = W^{(3)}\left(W^{(2)}\left(W^{(1)}\vec{a}^{(0)} + \vec{b}^{(1)}\right) + \vec{b}^{(2)}\right) + \vec{b}^{(3)}$$

$$= W^{(3)}W^{(2)}W^{(1)}\vec{a}^{(0)}_{N1} + W^{(3)}W^{(2)}\vec{b}^{(1)} + \cancel{\vec{b}^{(3)}}\, W^{(3)}\vec{b}^{(2)} + \vec{b}^{(3)} \quad ④$$

In case where output & input are the same in another fully-connected NN with no hidden layers (N2):

$$\vec{a}^{(3)}_{N1} = \tilde{W}\vec{a}^{(0)}_{N2} + \vec{b}^{(1)}_{N2} \quad ⑤$$

$$\therefore \boxed{\tilde{W}\vec{a}^{(0)}_{N2}} + \boxed{\vec{b}^{(1)}_{N2}} = \boxed{W^{(3)}W^{(2)}W^{(1)}\vec{a}^{(0)}_{N1}} + \boxed{W^{(3)}W^{(2)}\vec{b}^{(1)} + W^{(3)}\vec{b}^{(2)} + \vec{b}^{(3)}}$$

after subbing ⑤ into ④.

By symmetry: $\tilde{W}\vec{a}^{(0)}_{N2} = W^{(3)}W^{(2)}W^{(1)}\vec{a}^{(0)}_{N1}$ & because $\vec{a}^{(0)}_{N2} = \vec{a}^{(0)}_{N1}$

$\therefore \tilde{W} = W^{(3)}W^{(2)}W^{(1)}$ [All 6x6 matrix, lin txf^n] #

(weights of N2)

& $\vec{b}^{(1)}_{N2} = W^{(3)}W^{(2)}\vec{b}^{(1)} + W^{(3)}\vec{b}^{(2)} + \vec{b}^{(3)}$ [All 1x6 vector] #

(weights of N2)

* After matrix transformation of vectors.