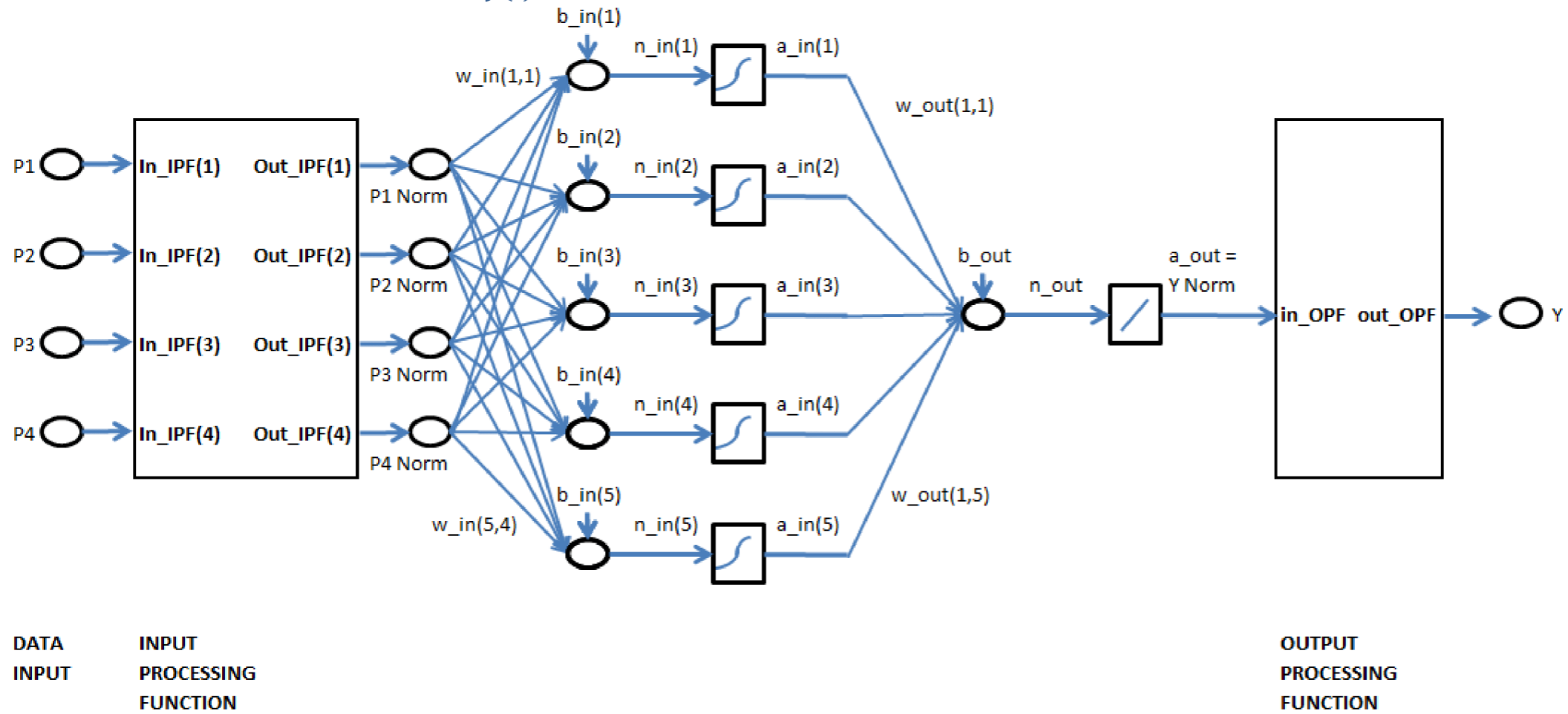


1. NEURAL NETWORK ARCHITECTURE $f(\cdot)$



2. Input and Output Processing Functions.

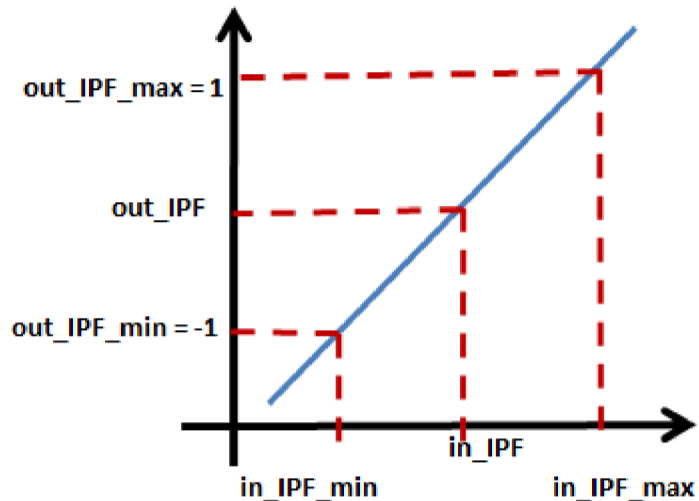
“Input Processing Functions” transforms input data so that all values fall into the interval [-1,1], or normalizes the input values. Training is often faster when values are normalized.

And if “Input Processing Functions” is used to scale the targets, then the output of the network will be trained to produce outputs in the range [-1,1]. To convert these output back into the original units, we use “Output Processing Function”.

Example illustration of “Input and Output Processing Functions” with the function.

INPUT PROCESSING FUNCTIONS :

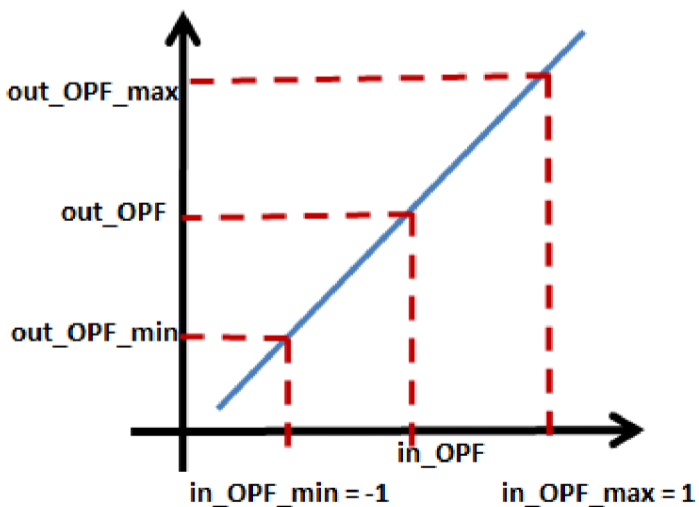
“Input Processing Functions” transforms input data so that all values fall into the interval [-1,1], or normalizes the input values.



$$\begin{aligned}
 P_{Norm} &= \frac{(P - in_IPF_min) \cdot (out_IPF_max - out_IPF_min)}{(in_IPF_max - in_IPF_min)} + out_IPF_min \\
 &= \frac{(in_IPF - in_IPF_min) \cdot (2)}{(in_IPF_max - in_IPF_min)} - 1
 \end{aligned}$$

OUTPUT PROCESSING FUNCTIONS :

If “Input Processing Functions” is used to scale the targets, then the output of the network will be trained to produce outputs in the range [-1,1]. To convert these output back into the original units, we use “Output Processing Function”.



$$\begin{aligned}
 out_OPF &= \frac{(in_OPF - in_OPF_min) \cdot (out_OPF_max - out_OPF_min)}{(in_OPF_max - in_OPF_min)} + out_OPF_min \\
 &= \frac{(in_OPF + 1) \cdot (out_OPF_max - out_OPF_min)}{2} + out_OPF_min
 \end{aligned}$$

3. EXAMPLE CALCULATION

From the above architecture :

<p>Input Processing Function Parameter :</p> <p>In1_max=7.9 In1_min=4.3 In2_max=4.4 In2_min=2 In3_max=6.9 In3_min=1 In4_max=2.5 In4_min=0.1</p>	<p>w_in(1,1)= -0.743495 w_in(1,2)= 0.449171 w_in(1,3)= -0.585676 w_in(1,4)= -0.309007 w_in(2,1)= 0.437339 w_in(2,2)= 0.21939 w_in(2,3)= -0.869233 w_in(2,4)= 0.774321 w_in(3,1)= -0.556053 w_in(3,2)= 0.387743 w_in(3,3)= 0.791078 w_in(3,4)= 0.212789 w_in(4,1)= 0.546645 w_in(4,2)= -0.274682 w_in(4,3)= -0.857102 w_in(4,4)= 0.181313 w_in(5,1)= -0.43569 w_in(5,2)= -0.170569 w_in(5,3)= 0.301563 w_in(5,4)= 0.971447</p>	<p>b_in(1) = 0.537452 b_in(2) = -0.901691 b_in(3) = -0.55688 b_in(4) = -0.860293 b_in(5) = -0.212749</p> <p>w_out(1,1) = -0.597222 w_out(1,2) = -0.67192 w_out(1,3) = 0.496553 w_out(1,4) = -0.400212 w_out(1,5) = 0.801744</p> <p>b_out = -0.187959</p>	<p>Output Processing Function Parameter :</p> <p>Out_max = 3 Out_min = 1</p>
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If we choose

P1=5.9

P2=3

P3=5.1

P4=1.8

$$P \text{ Norm} = \frac{(P1 - in1_min) \cdot (2)}{(in1_max - in1_min)} - 1$$

P1 Norm = -0.111111

P2 Norm = -0.166667

P3 Norm = 0.38983

P4 Norm = 0.416667

$$n_in(i) = w_in(i, 1) \cdot P1Norm + w_in(i, 2) \cdot P2Norm + w_in(i, 3) \cdot P3Norm + w_in(i, 4) \cdot P4Norm + b_in(i)$$

n_in(1) = 0.188133

n_in(2) = -1.00307

n_in(3) = -0.162672

n_in(4) = -1.13383

n_in(5) = 0.386417

$$a_in(j) = f(n_in(j))$$

$$a_{in(i)} = \frac{2}{1 + \exp(-2 \cdot n_{in(i)})} - 1$$

a_in(1) = 0.185945

a_in(2) = -0.76288

a_in(3) = -0.161252

a_in(4) = -0.812326

a_in(5) = 0.368267

$$n_out(k) = a_in(1) \cdot w_out(k, 1) + a_in(2) \cdot w_out(k, 2) + a_in(3) \cdot w_out(k, 3) + a_in(4) \cdot w_out(k, 4) + a_in(5) \cdot w_out(k, 5) + b_out(k)$$

$$a_out(k) = f(n_out(k))$$

n_out = 0.753875

Y Norm = n_out (activation function : linear)

Y Norm = 0.753875

$$Y = \frac{(Y_Norm + 1) \cdot (out_max - out_min)}{(2)} + out_min$$

Y = 2.75387

4. Learning Equation

Backpropagation Algorithm

1. Initialization: Randomize the weights to small values.
2. Presentation: Apply a pattern to the input and calculate the network output.
3. Error Computation: Compare the output with the desired output and compute the error (difference).
4. Backward Computation: Backpropagate the error through the network and adjust the weights to minimize the error.
5. Iteration: Repeat steps 2-4 until a desired error goal is reached.

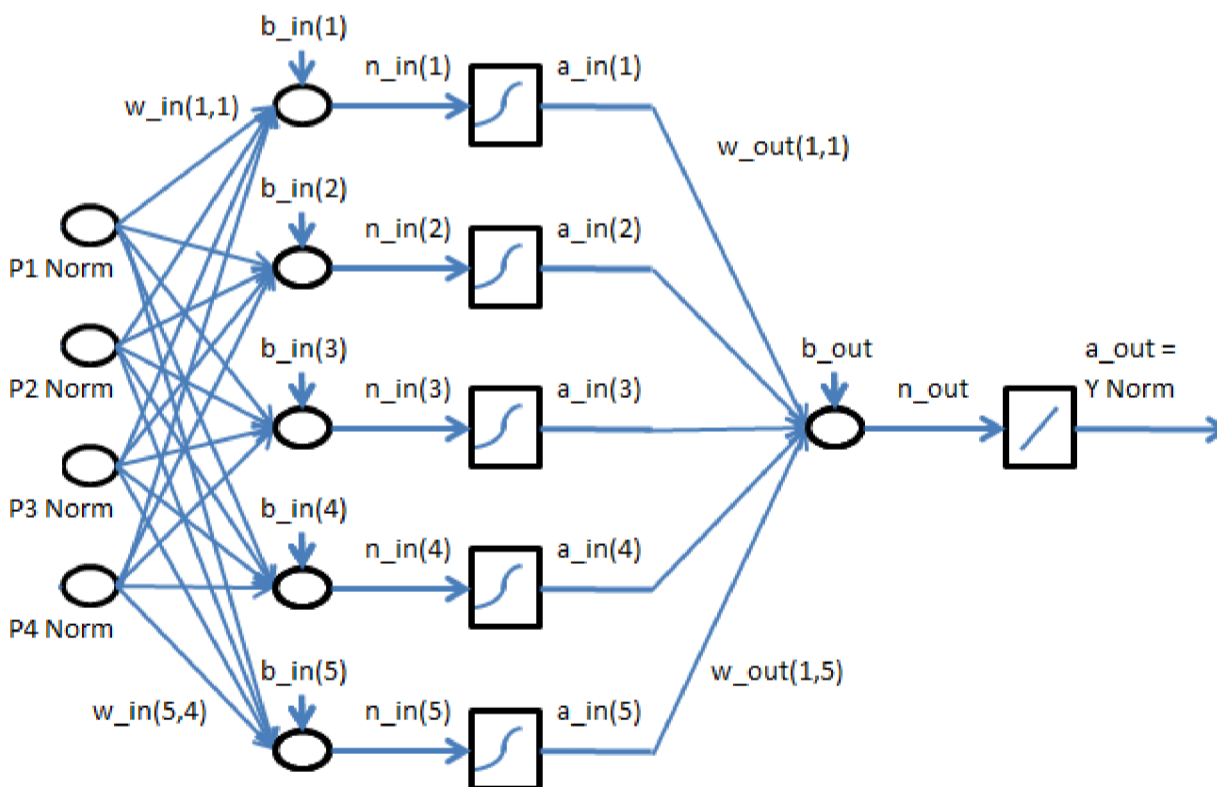
- Total Error Energy : $E = \frac{1}{2} e^2$
- Error Signal at iteration (n) = $e(n) = TNorm(n) - YNorm(n)$
 YNorm : keluaran NN yang masih ternormalisasi (rentang nilai antara -1 s.d. 1)
 Tnorm : target keluaran NN
- Backward Computation :

$$W^{new} = W^{old} + \Delta W$$

$$W^{new} = W^{old} - \eta \frac{dE}{dW}$$

$$W^{new} = W^{old} - \eta \left(\frac{dE}{de} \right) \cdot \left(\frac{de}{dYNorm} \right) \cdot \left(\frac{dYNorm}{dn_{out}} \right) \cdot \left(\frac{dn_{out}}{dW} \right)$$

$$W^{new} = W^{old} - \eta \cdot e \cdot (-1) \cdot (1) \cdot \left(\frac{dn_{out}}{dW} \right)$$



PERSAMAAN NN YANG DIGUNAKAN

$$n_{in}(i) = w_{in}(i,1) \cdot P1Norm + w_{in}(i,2) \cdot P2Norm + w_{in}(i,3) \cdot P3Norm + w_{in}(i,4) \cdot P4Norm + b_{in}(i)$$

$$a_{in}(i) = \frac{2}{1 + \exp(-2 \cdot n_{in}(i))} - 1$$

$$n_{out} = a_{in}(1) \cdot w_{out}(1,1) + a_{in}(2) \cdot w_{out}(1,2) + a_{in}(3) \cdot w_{out}(1,3) + a_{in}(4) \cdot w_{out}(1,4) + a_{in}(5) \cdot w_{out}(1,5) + b_{out}$$

$$Y Norm = n_{out}$$

MAKA PENURUNAN PERSAMAAN BACKWARD COMPUTATION :

$$b_{out}^{new} = b_{out}^{old} + \eta \cdot e$$

$$w_{out}(1,j)^{new} = w_{out}(1,j)^{old} + \eta \cdot e \cdot a_{in}(j)$$

$$\begin{aligned} b_{in}(j)^{new} &= b_{in}(j)^{old} + \eta \cdot e \cdot \left(\frac{dn_{out}}{da_{in}(j)} \right) \cdot \left(\frac{da_{in}(j)}{dn_{in}(j)} \right) \cdot \left(\frac{dn_{in}(j)}{db_{in}(j)} \right) \\ &= b_{in}(j)^{old} + \eta \cdot e \cdot (w_{out}(1,j)) \cdot \left(\frac{4 \cdot \exp(-2 \cdot n_{in}(j))}{(1 + \exp(-2 \cdot n_{in}(j)))^2} \right) \cdot (1) \end{aligned}$$

$$\begin{aligned} w_{in}(j,i)^{new} &= w_{in}(j,i)^{old} + \eta \cdot e \cdot \left(\frac{dn_{out}}{da_{in}(j)} \right) \cdot \left(\frac{da_{in}(j)}{dn_{in}(j)} \right) \cdot \left(\frac{dn_{in}(j)}{dw_{in}(j,i)} \right) \\ &= w_{in}(j,i)^{old} + \eta \cdot e \cdot (w_{out}(1,j)) \cdot \left(\frac{4 \cdot \exp(-2 \cdot n_{in}(j))}{(1 + \exp(-2 \cdot n_{in}(j)))^2} \right) \cdot PiNorm \end{aligned}$$