linear predictor $\hat{v}(t_i) = \hat{v}_n + \hat{a}_n(t_i - t_n)$

$\hat{a}_n$ and $\hat{v}_n$ are estimated from buffered data sample (past measures over $N^\bullet - 1$ cycles + current sample) according to the least squares fitting method (i.e. by minimizing the sum of squared residuals)

$$Q(\hat{v}_n, \hat{a}_n) = \sum_i e_i^2 = \sum_{i=n}^{n-N^\bullet+1} [v_i - \hat{v}(t_i)]^2 = \sum_{i=n}^{n-N^\bullet+1} [v_i - \hat{v}_n - \hat{a}_n(t_i - t_n)]^2$$

by setting the derivative to zero we obtain

$$\begin{aligned}
\frac{\partial Q(\hat{v}_n, \hat{a}_n)}{\partial \hat{a}_n} &= \sum_{i=n}^{n-N^\bullet+1} -2[v_i - \hat{v}_n - \hat{a}_n(t_i - t_n)](t_i - t_n) = 0 \\
\sum_{i=n}^{n-N^\bullet+1} (v_i - \hat{v}_n)(t_i - t_n) &= \hat{a}_n \sum_{i=n}^{n-N^\bullet+1} (t_i - t_n)^2 \\
\hat{a}_n &= \frac{\frac{1}{N^\bullet} \sum_{i=n}^{n-N^\bullet+1} (v_i - \hat{v}_n)(t_i - t_n)}{\frac{1}{N^\bullet} \sum_{i=n}^{n-N^\bullet+1} (t_i - t_n)^2}
\end{aligned}$$

last step was obtained by dividing by $N^\bullet$ and rearranging the terms: