PAA NAME	SERIES-PARALLEL PREDICTOR	EXTENDED LEAST SQUARES(ELS)	PARALLEL PREDICTOR	PARALLEL PREDICTOR WITH FIXED COMPENSATOR	PARALLEL PREDICTOR WITH ADJUSTABLE COMPENSATOR
OTHER NAMES	RECURSIVE LEAST SQUARES (RLS) OR STANDARD EQUATION ERROR METHOD	/	OUTPUT ERROR METHOD	OUTPUT ERROR METHOD WITH FIXED COMPENSATOR (O.E.M.F.C)	OUTPUT ERROR METHOD WITH ADJUSTABLE COMPENSATOR (O.E.M.A.C)
Common Eq C.T.	$\dot{y}(t) = \theta^T\phi(t);\ \dot{\hat{y}}(t) = \hat{\theta}^T(t)\phi(t)$	$\tilde{\theta}(t) = \hat{\theta}(t) - \theta$	$\dot{\hat{\theta}}(t) = F(t)\phi(t)\nu(t)$		
Common Eq D.T.	$y(k+1),\ \hat{y}^o(k+1),\ \hat{y}(k+1)$ see below	$\tilde{\theta}(k) = \hat{\theta}(k) - \theta$	$\hat{\theta}(k+1) = \hat{\theta}(k) + \frac{F(k)\phi(k)}{1+\phi^T(k)F(k)\phi(k)}\nu^o(k+1) = \hat{\theta}(k) + F(k)\phi(k)\nu(k+1)$		$F(k+1) = \frac{1}{\lambda_1(k)}\left[F(k) - \frac{F(k)\phi(k)\phi^T(k)F(k)}{\frac{\lambda_1(k)}{\lambda_2(k)}+\phi^T(k)F(k)\phi(k)}\right]$
PLANT + NOISE MODEL	$y(k+1) = \frac{B(z^{-1})}{A(z^{-1})}u(k) + \frac{1}{A(z^{-1})}w(k+1)$	$y(k+1) = \frac{B(z^{-1})}{A(z^{-1})}u(k) + \frac{C(z^{-1})}{A(z^{-1})}n(k+1)$	$y(k+1) = \frac{B(z^{-1})}{A(z^{-1})}u(k) + \frac{1}{A(z^{-1})}w(k+1)$	$y(k+1) = \frac{B(z^{-1})}{A(z^{-1})}u(k) + n(k+1)$	$y(k+1) = \frac{B(z^{-1})}{A(z^{-1})}u(k) + n(k+1)$
PARAMETER VECTOR	$\theta^T = [a_1 \cdots a_n\, b_0 \cdots b_m]$; [1]	$\theta_e^T = [\theta^T\, c_1 \cdots c_n]$; [2]	$\theta^T = [a_1 \cdots a_n\, b_0 \cdots b_m]$	$\theta^T = [a_1 \cdots a_n\, b_0 \cdots b_m]$	$\theta_e^T = [\theta^T\, a_1 \cdots a_n]$
ESTIMATED PARAMETER VECTOR	$\hat{\theta}^T(k) = \left[\hat{a}_1(k) \cdots \hat{a}_n(k)\, \hat{b}_0(k) \cdots \hat{b}_m(k)\right]$	$\hat{\theta}_e^T(k) = \left[\hat{\theta}(k)\, \hat{c}_1(k) \cdots \hat{c}_n(k)\right]$	$\hat{\theta}^T(k) = \left[\hat{a}_1(k) \cdots \hat{a}_n(k)\, \hat{b}_0(k) \cdots \hat{b}_m(k)\right]$	$\hat{\theta}^T(k) = \left[\hat{a}_1(k) \cdots \hat{a}_n(k)\, \hat{b}_0(k) \cdots \hat{b}_m(k)\right]$	$\hat{\theta}_e^T(k) = \left[\hat{\theta}(k)\, \hat{c}_1(k) \cdots \hat{c}_n(k)\right]$
OBSERVATION VECTOR	$\phi^T(k) = [-y(k) \cdots - y(k+1-n)\, u(k) \cdots u(k-m)]$	$\phi_e^T(k) = [\phi^T(k)\, \varepsilon^o(k) \cdots \varepsilon^o(k+1-n)]$	$\phi^T(k) = [-\hat{y}(k) \cdots - \hat{y}(k+1-n)\, u(k) \cdots u(k-m)]$	$\phi^T(k) = [-\hat{y}(k) \cdots - \hat{y}(k+1-n)\, u(k) \cdots u(k-m)]$	$\phi_e^T(k) = [\phi^T(k), -\varepsilon(k) \cdots - \varepsilon(k+1-n)]$
a priori Predicted Output	$\hat{y}^o(k+1) = \hat{\theta}^T(k)\phi(k)$	$\hat{y}^o(k+1) = \hat{\theta}_e^T(k)\phi_e(k)$	$\hat{y}^o(k+1) = \hat{\theta}^T(k)\phi(k)$	$\hat{y}^o(k+1) = \hat{\theta}^T(k)\phi(k)$	$\hat{y}^o(k+1) = \hat{\theta}^T(k)\phi(k)$
a posteriori Predicted Output	$\hat{y}(k+1) = \hat{\theta}^T(k+1)\phi(k)$	$\hat{y}(k+1) = \hat{\theta}_e^T(k+1)\phi_e(k)$	$\hat{y}(k+1) = \hat{\theta}^T(k+1)\phi(k)$	$\hat{y}(k+1) = \hat{\theta}^T(k+1)\phi(k)$	$\hat{y}(k+1) = \hat{\theta}^T(k+1)\phi(k)$; [3]
a priori Adaptation Error	$\nu^o(k+1) = \varepsilon^o(k+1)$	$\nu^o(k+1) = \varepsilon^o(k+1)$	$\nu^o(k+1) = \varepsilon^o(k+1)$	$\nu^o(k+1) = \varepsilon^o(k+1) + \sum_{i=1}^n c_i\varepsilon(k+1-i)$;[4]	$\nu^o(k+1) = \varepsilon^o(k+1) + \sum_{i=1}^n \hat{c}_i\varepsilon(k+1-i)$
a posteriori Adaptation Error	$\nu(k+1) = \varepsilon(k+1)$	$\nu(k+1) = \varepsilon(k+1)$	$\nu(k+1) = \varepsilon(k+1)$	$\nu(k+1) = C(z^{-1})\varepsilon(k+1) = \varepsilon(k+1) + \sum_{i=1}^n c_i\varepsilon(k+1-i)$	$\nu(k+1) = \varepsilon(k+1) + \sum_{i=1}^n \hat{c}_i\varepsilon(k+1-i)$
Deterministic Stability Cond	Always stable	Not covered	$\frac{1}{A(z^{-1})} - \frac{\lambda}{2}$ is SPR	$\frac{C(z^{-1})}{A(z^{-1})} - \frac{\lambda}{2}$ is SPR	Always stable
Convergence Condition (with 0 mean noise)	1, $u(k)$ rich in frequency 2, $u(k)$ independent from $w(k+1)$ 3, $w(k)$ is white	1, Input rich in frequency 2, $n(k)$ white + $\frac{1}{C(z^{-1})} - \frac{\lambda}{2}$ is SPR	1, Input rich in frequency 2, Input independent from $w(k+1)$ 3, Zero mean noise	Not covered	1, Input rich in frequency 2, $n(k)$ white + $\frac{1}{A(z^{-1})} - \frac{\lambda}{2}$ SPR, <u>or</u> $n(k) = \frac{1}{N(z^{-1})}s(k)$, with $s(k)$ white + $\frac{N(z^{-1})}{A(z^{-1})} - \frac{\lambda}{2}$ SPR
Disadvantage	The whiteness of $w(k)$ is hard to achieve, thus the estimated parameters are usually biased	Deals with only a particular disturbance	Stability is usually not easy to see when poles of plant are unknown	/	/

[1] n: ORDER OF $A(z^{-1})$; m: ORDER OF $B(z^{-1})$
[2] $C(z^{-1}) = 1 + c_1 z^{-1} + \cdots + c_n z^{-n}$
[3] <u>NOT</u> ϕ_e and θ_e!
[4] <u>NOT</u> ε^o