IEEE COGNITIVE COMMUNICATIONS FOR AEROSPACE APPLICATIONS WORKSHOP

Machine Learning based Adaptive Predistorter for High Power Amplifier Linearization

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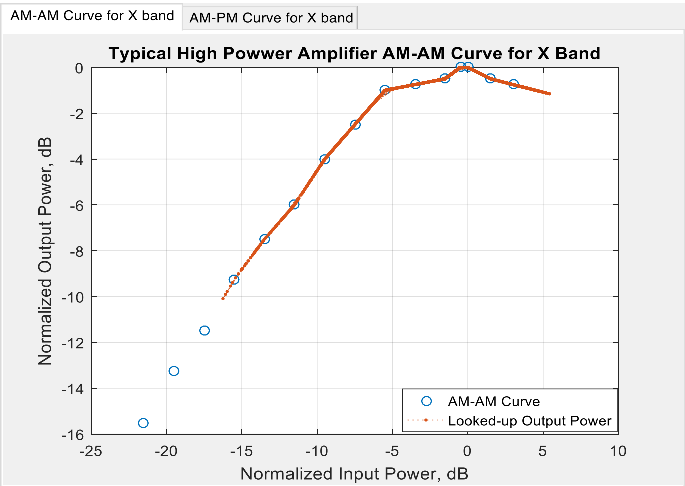
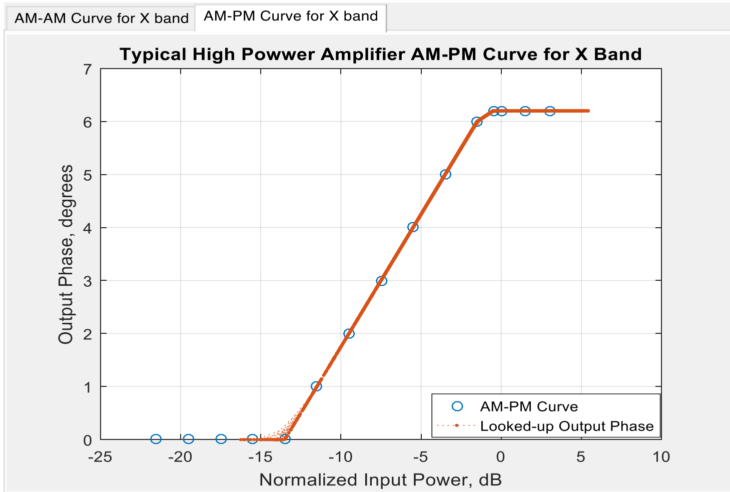
Outline

- Introduction
- CONOPS and System Model
- Extended Saleh's Model
- Reinforcement Learning based PD Design
- Conclusion and Future Work

Introduction

- The transponders are equipped with high power amplifiers (HPAs), which, unfortunately, cause nonlinear distortions to the transmitted signal, since HPAs normally operate close to or at saturation, so as to maximize power efficiency.
- This nonlinear distortion can be characterized as amplitude modulation-to-amplitude modulation (AM-AM), and amplitude modulation-to-phase modulation (AM-PM) effects.
- AM-AM and AM-PM distortions cause interference signal non-recognizable.
- The conventional predistortion (PD) method cannot handle the non-linearization problem in the presence of interferences.





Simulated HPA AM-AM and AM-PM curves for X band Signal

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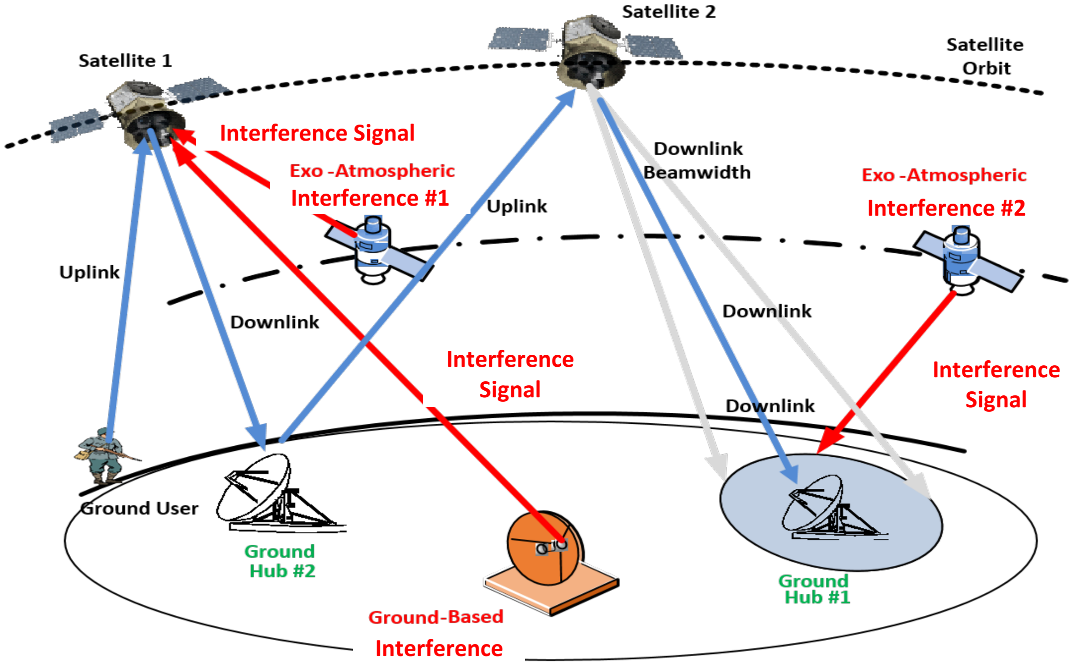
CONOPS Description

Satellite 1:
- interference attacks the uplink (U/L) - This is the case of our interest
- Case 1: The interference signal does not cause AM-AM and AM-PM distortion effects
- Case 2: The interference signal power causes the HPA to operate at saturation.

Satellite 2:
- interference attacks the downlink (D/L) signal
- interference signal on the D/L does not cause AM-AM and AM-PM distortions and hence it is not of our interest

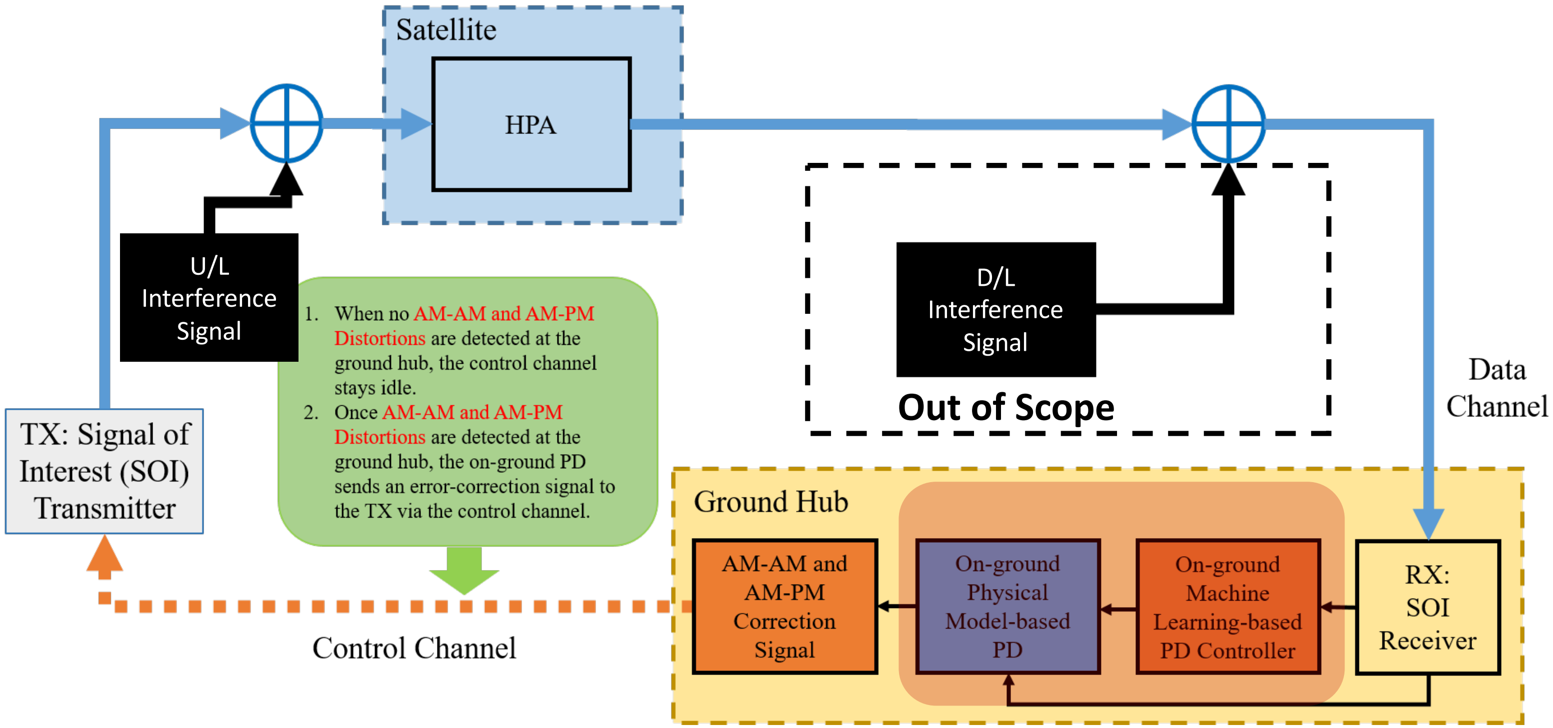


System CONOPS in the presence of interferences

To linearize satellite transponder in the presence of interferences

System Model

- The on-ground PD is able to correct the AM-AM and AM-PM nonlinear distortions by itself when the nonlinearity is not caused by interference signals.
- When interference causes nonlinear distortion to the HPA, the PD controller uses machine learning technique to adjust the parameters of the PD, and send the correction signal to the transmitter.



Proposed on-ground solution for near-term implementation

This solution only requires us to modify the configurations of the hub and user terminals, which can achieve the goal of low cost.

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Extended Saleh's Model: HPA Modeling

Normal Ambient Temperature

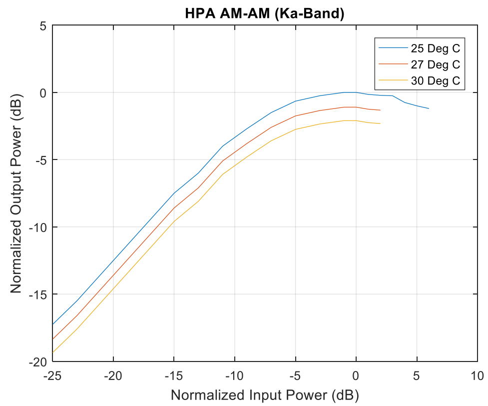
at Room Temperature (25 deg C)

Pin(dB) $P0\_in_i :=$	Pout(dB) $P0\_25degC\_out_i :=$	Phase-out(deg.) $\Phi\_25degC\_out_i :=$
−25	−17.25	0.1
−23	−15.5	0.1
−21	−13.5	0.1
−19	−11.5	0.8
−17	−9.5	1.25
−15	−7.5	2.55
−13	−6	6.1
−11	−4	8.55
−9	−2.7	13.1
−7	−1.5	17.71
−5	−0.65	23.82
−3	−0.25	30
−1	0	36.3
0	0.002	40
1	−0.15	43
2	−0.22	45
3	−0.25	47.5
4	−0.75	50
5	−1	53.5
6	−1.2	56

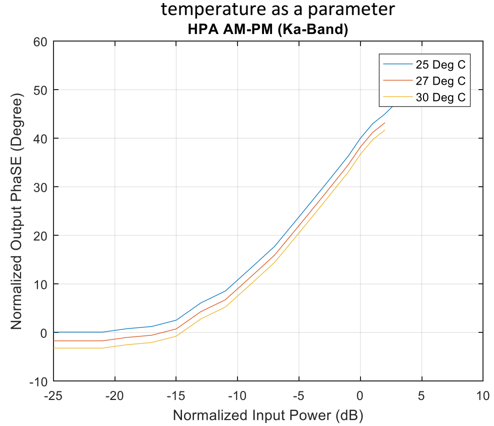
Non-Normal Ambient Temperature

$P0\_in_i :=$	at 27 Deg C: Pout(dB) $P0\_27degC\_out_i =$	at 27 Deg C: Phase-out(deg.) $\Phi\_27degC\_out_i$	at 30 Deg C: Pout(dB) $P0\_30degC\_out_i =$	at 30 Deg C: Phase-out(deg.) $\Phi\_30degC\_out_i$
−25	-18.35	-1.7	-19.35	-3.2
−23	-16.6	-1.7	-17.6	-3.2
−21	-14.6	-1.7	-15.6	-3.2
−19	-12.6	-1	-13.6	-2.5
−17	-10.6	-0.55	-11.6	-2.05
−15	-8.6	0.75	-9.6	-0.75
−13	-7.1	4.3	-8.1	2.8
−11	-5.1	6.75	-6.1	5.25
−9	-3.8	11.3	-4.8	9.8
−7	-2.6	15.91	-3.6	14.41
−5	-1.75	22.02	-2.75	20.52
−3	-1.35	28.2	-2.35	26.7
−1	-1.1	34.5	-2.1	33
0	-1.098	38.2	-2.098	36.7
1	-1.25	41.2	-2.25	39.7
2	-1.32	43.2	-2.32	41.7
3				
4				
5				
6				

T. M. Nguyen, J. Yoh, C. H. Lee, H. T. Tran, and D. M. Johnson, "Modeling of HPA and HPA Linearization Through a Predistorter: Global Broadcasting Service Applications", *IEEE Trans. on Broadcasting, Vol. 49, No.2*, 2003.

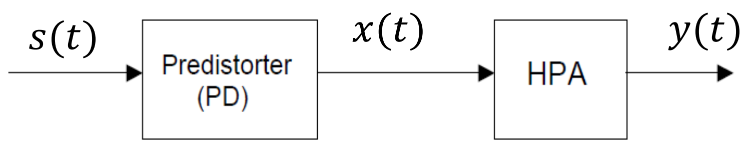


Measured AM-AM characteristics of Ka-Band HPA with temperature as a parameter



Measured AM-PM characteristics of Ka-Band HPA with temperature as a parameter

Extended Saleh's Model: HPA Modeling



Saleh's model has been proposed for characterizing an HPA's AM-AM and AM-PM distortions accurately. The extended model is designed especially for travelling wave tube (TWT) and /or solid high power amplifiers.

The complex signals $s(t)$, $x(t)$, and $y(t)$ can be written as follows.

$$s(t) = \rho_{s(t)} e^{j\theta_{s(t)}}$$
$$x(t) = \rho_{x(t)} e^{j\theta_{x(t)}}$$
$$y(t) = \rho_{y(t)} e^{j\theta_{y(t)}}$$

where $\rho_{s(t)}, \rho_{x(t)}, \rho_{y(t)}$, and $\theta_{s(t)}, \theta_{x(t)}, \theta_{y(t)}$ are the amplitude and phase of the complex signals $s(t)$, $x(t)$, and $y(t)$, respectively. We let $M(\rho_{x(t)})$ and $\Phi(\rho_{x(t)})$ be the normalized AM-AM and AM-PM responses of the HPA due to the input signal $x(t)$, then we have

$$y(t) = M(\rho_{x(t)}) e^{j(\theta_{x(t)} + \Phi(\rho_{x(t)}))}$$

Then, the original Saleh's model is extended for HPA by including eight extra parameters $(a_0, a_1, b_0$, and $b_1, \alpha_0, \alpha_1, \beta_0$ *and* $\beta_1)$, resulting in the following generalized equations for $M(\rho_{x(t)})$ and $\Phi(\rho_{x(t)})$ as follows.

$$M(\rho_{x(t)}) \equiv \rho_{y(t)} = \frac{\alpha_0 \rho_{x(t)}}{a_0 + \beta_0 (\rho_{x(t)} + b_0)^2}$$

$$\Phi(\rho_{x(t)}) = \frac{\alpha_1 \rho_{x(t)}^2}{a_1 + \beta_1 (\rho_{x(t)} + b_1)^2}$$

We can write $\exp(j\theta_{x(t)})$ as

$$e^{j\theta_{x(t)}} = \frac{x(t)}{\rho_{x(t)}}$$

$y(t)$ can be further obtained as

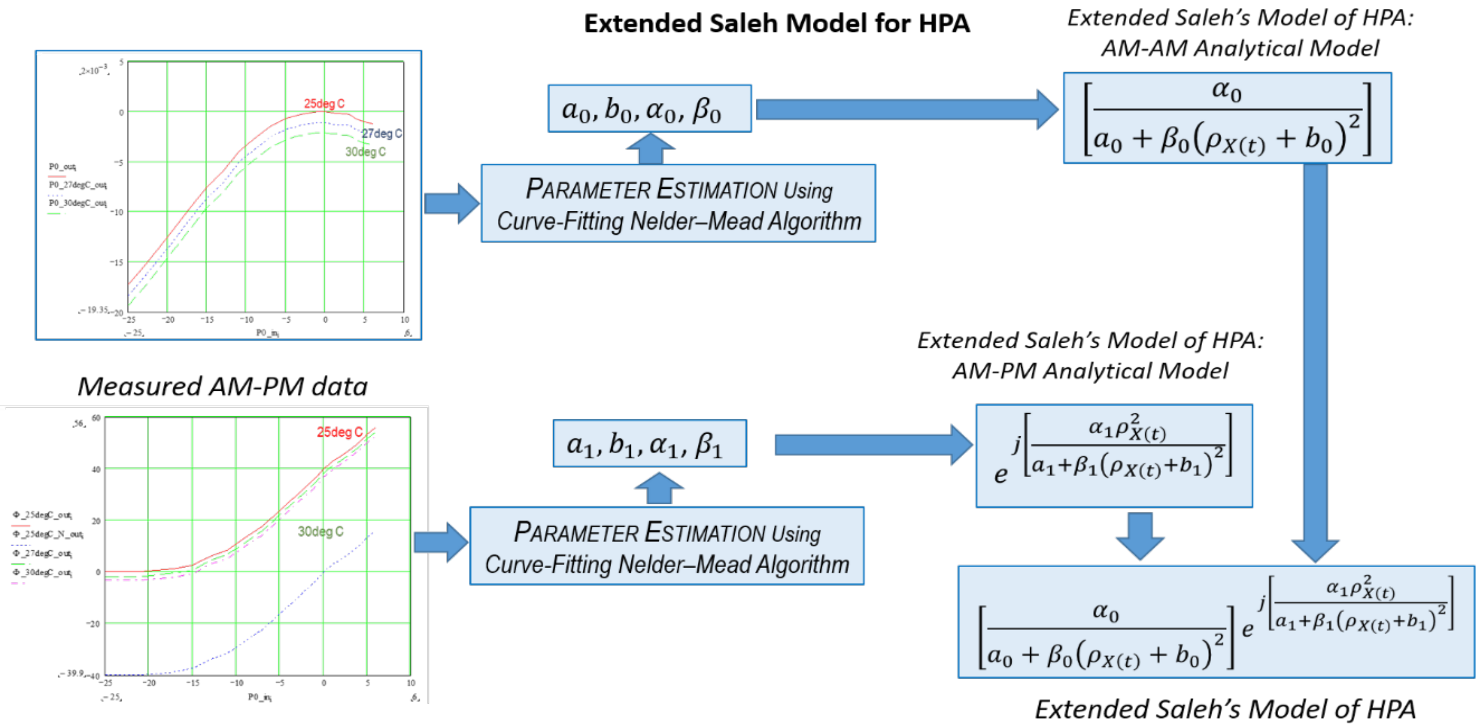
$$y(t) = \left[\frac{\alpha_0 x(t)}{a_0 + \beta_0 (\rho_{x(t)} + b_0)^2}\right] e^{j\left[\frac{\alpha_1 \rho_{x(t)}^2}{a_1 + \beta_1 (\rho_{x(t)} + b_1)^2}\right]}$$

It is obvious that the ideal PD output for a given input $s(t)$ is:

$$x(t) = s(t) \left[\frac{a_0 + \beta_0 (\rho_{x(t)} + b_0)^2}{\alpha_0}\right] e^{-j\left[\frac{\alpha_1 \rho_{x(t)}^2}{a_1 + \beta_1 (\rho_{x(t)} + b_1)^2}\right]}$$

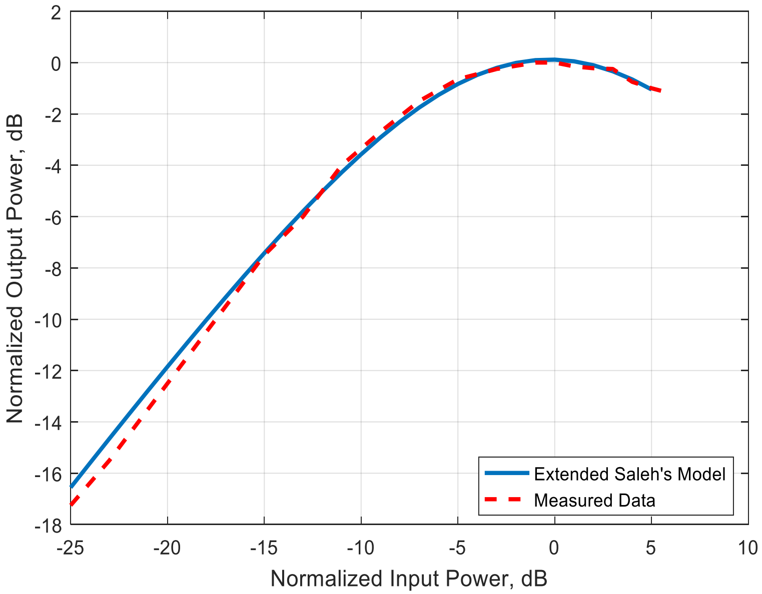
Extended Saleh's Model was developed in order to accurately characterize a wide range of HPAs, including, L-/S-/X-/Ku-/Ka-band HPAs. The Eight-parameter Model was selected to provide the required accuracy and minimum processing time.

Extended Saleh's Model: HPA Modeling

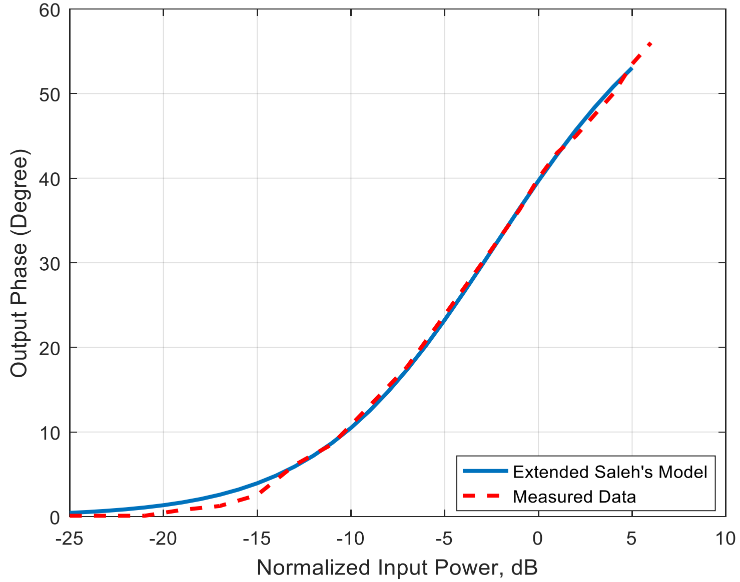


Work flow of achieving unknown parameters using curve-fitting algorithm

Extended Saleh's Model: HPA Modeling



Normalized output power vs. normalized input power for the GBS HPA



Output phase vs. normalized input power for the GBS HPA

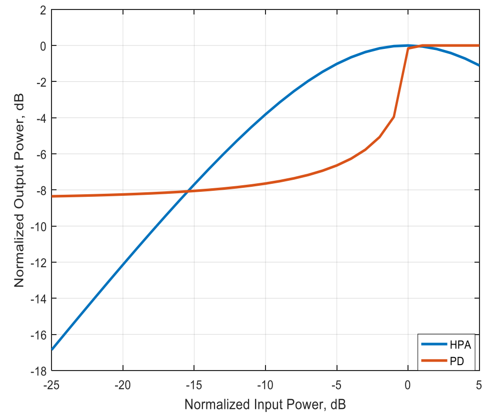
$$\boldsymbol{q_{AM}} = \{a_0, b_0, \alpha_0, \beta_0\} = \{3.6407, 0.3063, 11.1163, 4.2947\};$$
$$\boldsymbol{q_{PM}} = \{a_1, b_1, \alpha_1, \beta_1\} = \{0.4978, 0.1273, 74.6172, 1.0879\}.$$

Extended Saleh's Model: PD Modeling

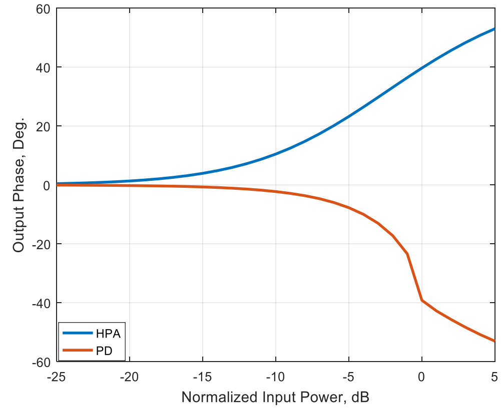
$$\rho_{PD} = \begin{cases} \dfrac{(\alpha_0 - 2b_0\beta_0\rho_{x(t)}) - \sqrt{\alpha_0^2 - 4\beta_0\rho_{x(t)}(a_0\rho_{x(t)} + b_0\alpha_0)}}{2\beta_0\rho_{x(t)}^2} & \rho_{x(t)} \leq 1 \\ 1 & \rho_{x(t)} > 1 \end{cases}$$

$$\rho_{y(t)} = \rho_{PD} \cdot \rho_{x(t)}$$

$$\theta_{PD} = -\frac{\alpha_1 \rho_{y(t)}^2}{a_1 + \beta_1 (\rho_{y(t)} + b_1)^2}$$



Input and output power relationship of the PD model using extension of Saleh's model for the GBS HPA

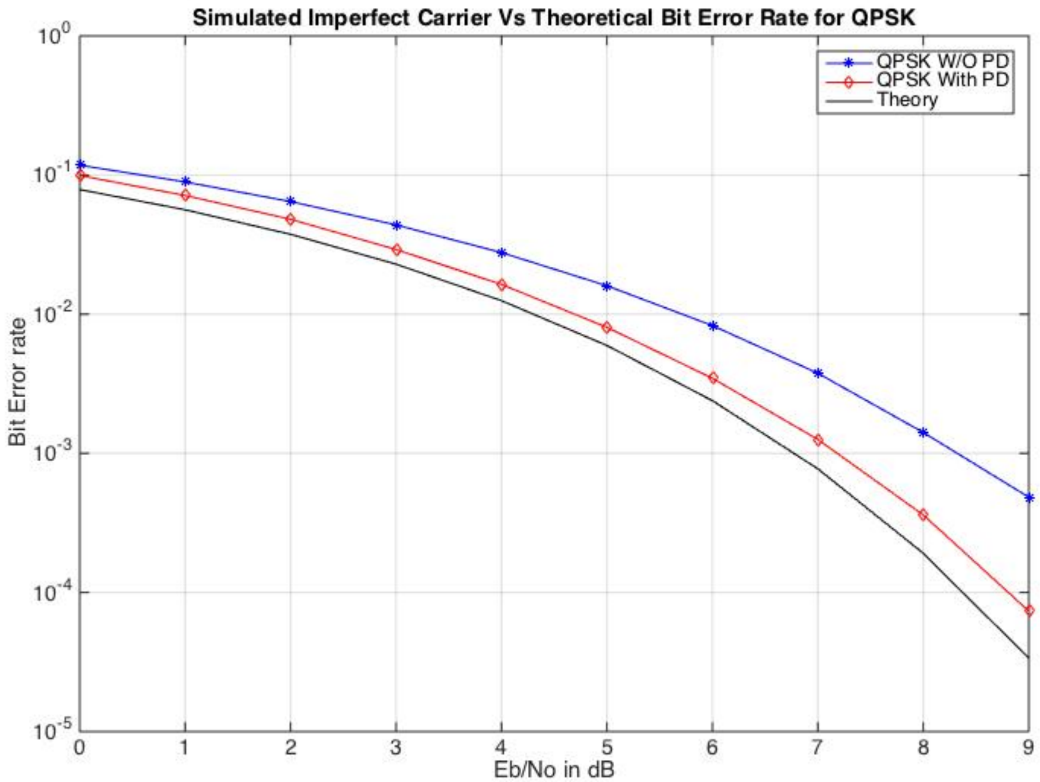


Input and output phase relationship of the PD model using extension of Saleh's model for the GBS HPA

Extended Saleh's Model of PD, on which the machine learning based PD designed is developed.

BER Performance Evaluation

❑ Unfiltered QPSK for assessing the PD's impacts on the waveform at saturation



BER performance for unfiltered QPSK signal passing through a transponder with and without PD at Ka-band

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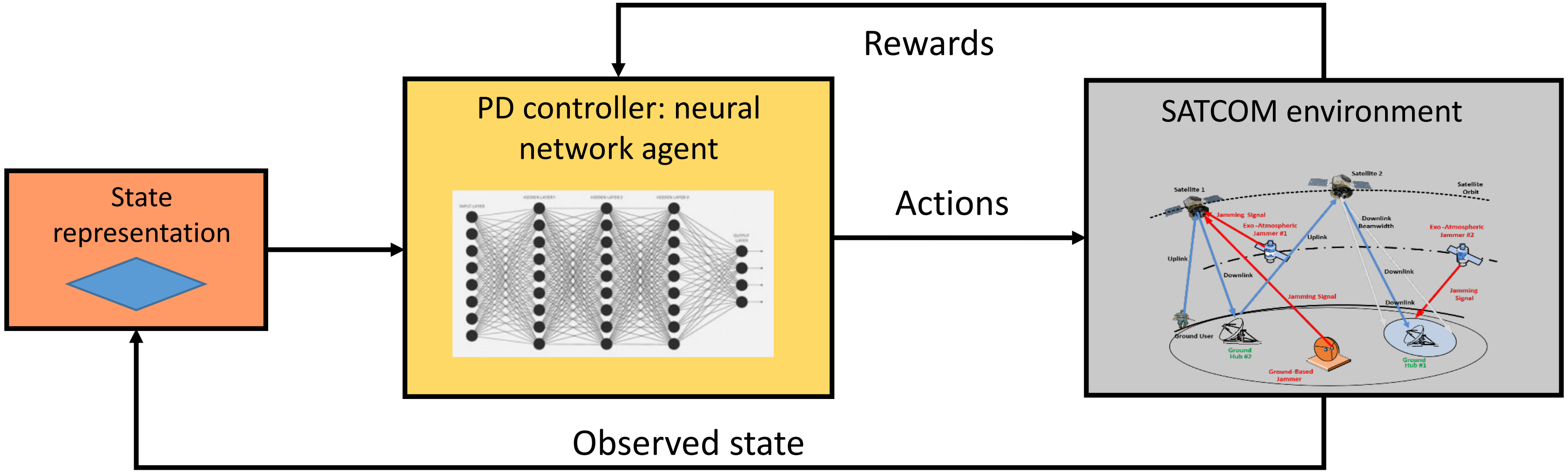
Machine Learning-based PD Controller

Reinforcement learning (RL) is the subfield of machine learning concerned with decision making and optimized control. It studies how an agent can learn and adapt to achieve desired goals in a complex and uncertain environments.



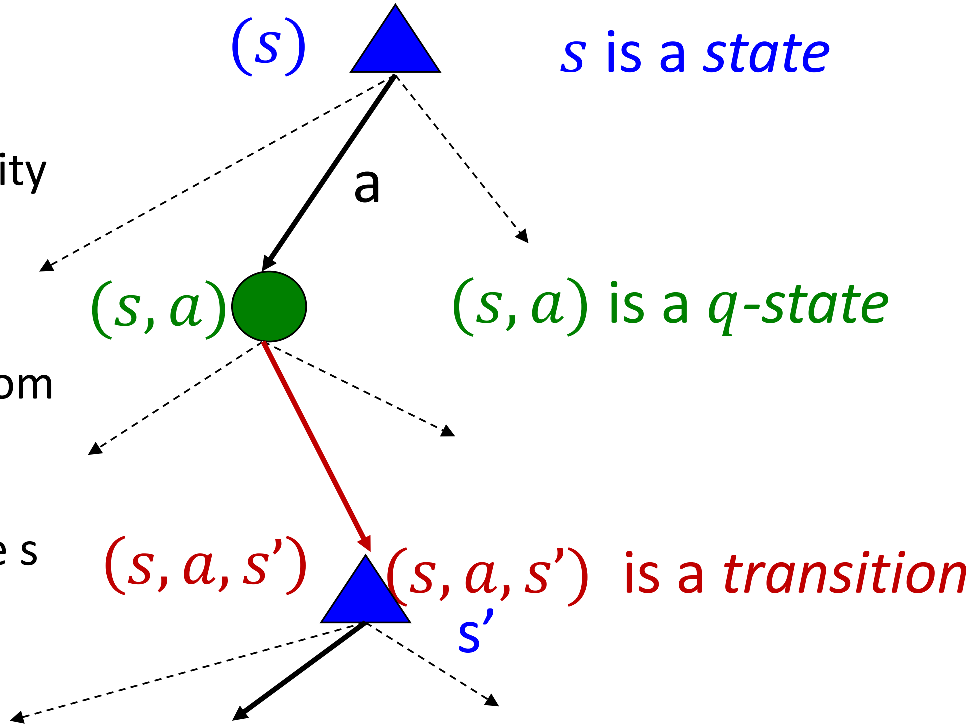
To develop an effective PD controller, we need to accurately characterize the environment states (Pout, Phout) by differentiating the effects of HPA imperfections and interference signals.

Reinforcement Learning Approach

- The value (utility) of a state $s - V^*(s)$: expected utility starting in s and acting optimally

- The value (utility) of a q-state$(s, a) - Q^*(s, a)$: expected utility starting out having taken action a from state s and (thereafter) acting optimally

- The optimal policy$-\pi^*(s)$: optimal action from state s

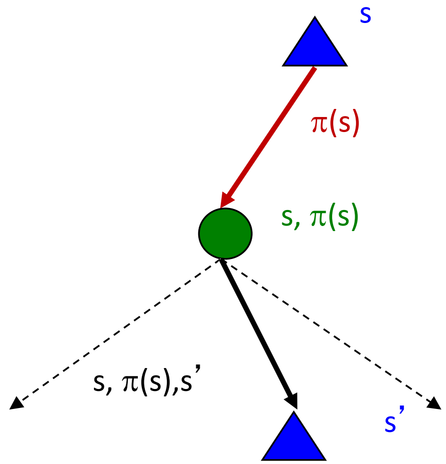


Reinforcement Learning Approach

$$V^*(s) = \max_a Q^*(s,a)$$

$$Q^*(s,a) = \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V^*(s')]$$

$$V^*(s) = \max_a \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V^*(s')]$$



- Simplified Bellman updates calculate V for a fixed policy,

$$V_0^\pi(s) = 0$$

$$V_{k+1}^\pi(s) \leftarrow \sum_{s'} T(s,\pi(s),s')\,[R(s,\pi(s),s') + \gamma V^*(s')]$$

  - This approach fully exploited the connections between the states
  - We need transition T and reward R

- Q-Learning: sample-based Q-value iteration

$$Q_{k+1}(s,a) \leftarrow \sum_{s'} T(s,\pi(s),s')\left[R(s,\pi(s),s') + \gamma \max_{a'} Q_k(s',a')\right]$$

- Learn Q(s,a) values as iterations continue,
  - Receive a sample (s,a,s')
  - Consider your old estimate: $Q(s,a)$
  - Consider your new sample estimate:

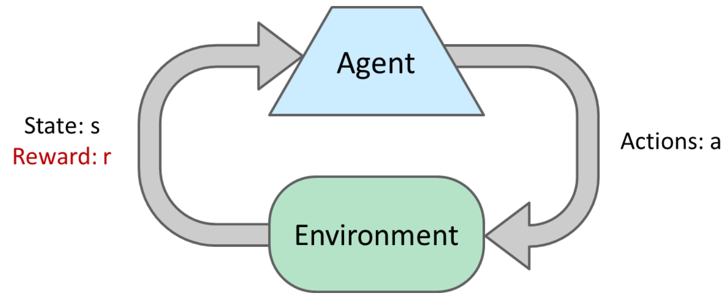
$$sample = R(s,a,s') + \gamma \max_{a'} Q(s,a')$$

  - Incorporate the new estimate into a running average:

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha[sample]$$

Reinforcement Learning Approach

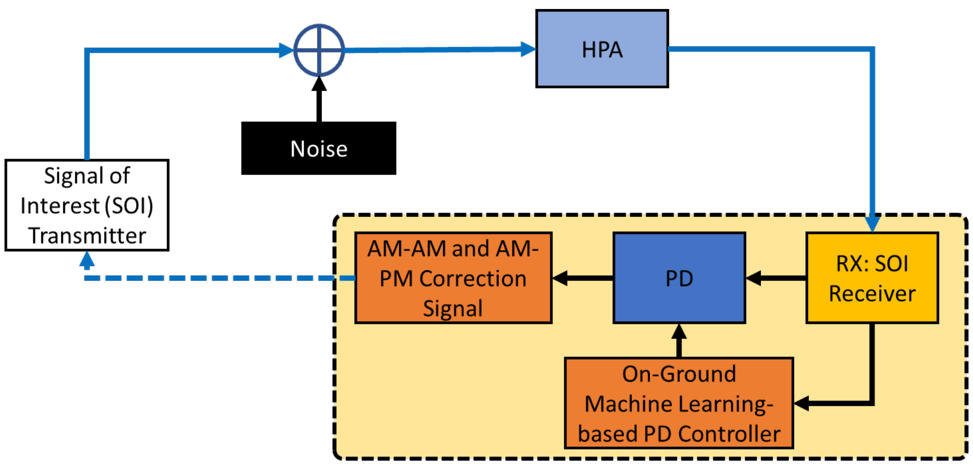
- *Action* ***a***: the actions the PD takes is to adjust (increase or decrease by certain range) of the 8 parameters of the extended Saleh's model, namely $(a_0, b_0, \alpha_0, \beta_0)$ and $(a_1, b_1, \alpha_1, \beta_1)$.
  - The first four parameters directly correspond to the AM-AM relations, the AM-PM are characterized based on these 8 parameters together.
- *States* ***s***: the observable (at least partially) status of the PD Controller's relation with the environment, defined as 2-dimensional continuous states.
  - The feasible set of each parameter is discretized for the algorithm implementation.
- *Rewards* ***r****: Given "Input Power" (or Pin) and "Input Phase" (or Phasein), we use the distance between estimated and measured output power and phase of the HPA as the rewards function.*



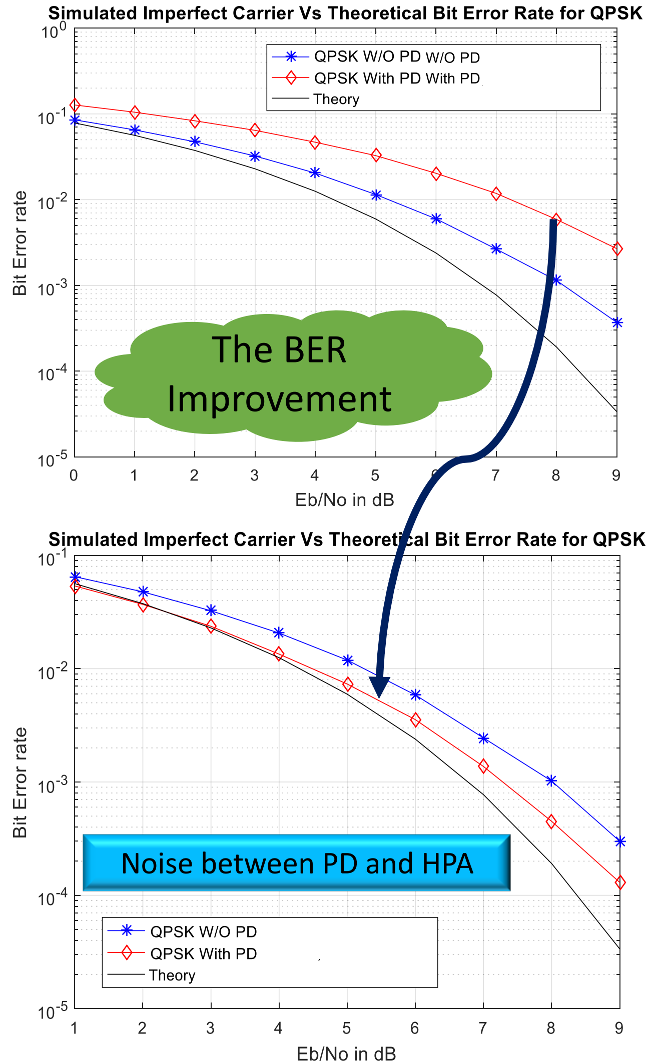
  - $\Delta_p = \sqrt{\left(P_{out_{obj}} - P_{out_{mea}}\right)^2}$
  - $\Delta_{phase} = \sqrt{\left(Phase_{out_{obj}} - Phase_{out_{mea}}\right)^2}$.
  - Regarding the reward function definition, it can be further simplified by analyzing the characteristics of PD and HPA.

PD-Scenario 1: Noise Exists between the PD and HPA

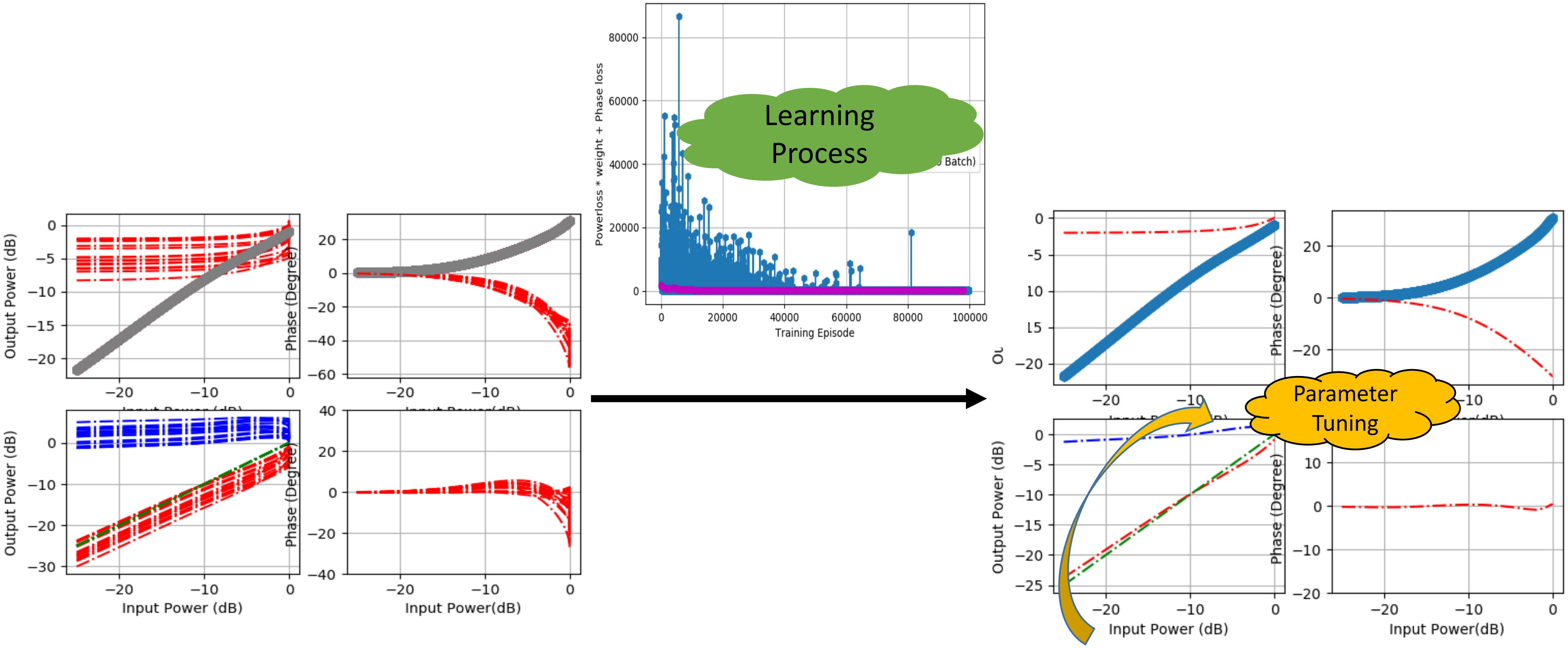
- Noise exists between the PD and HPA
- The Noise is characterized based on E_b/N_0
- Machine learning approach is deployed to update the PD parameter set $(a_0, b_0, \alpha_0, \beta_0, a_1, b_1, \alpha_1, \beta_1)$



$a_0 = 10.956\ b_0 = 0.1930\ \alpha_0 = 15.2576\ \beta_0 = 3.4007$
$a_1 = 0.2261\ b1 = 0.2354\ \alpha_1 = 61.4107\ \beta_1 = 1.0755$



PD-Scenario 1: PD Parameter Set Learning Process

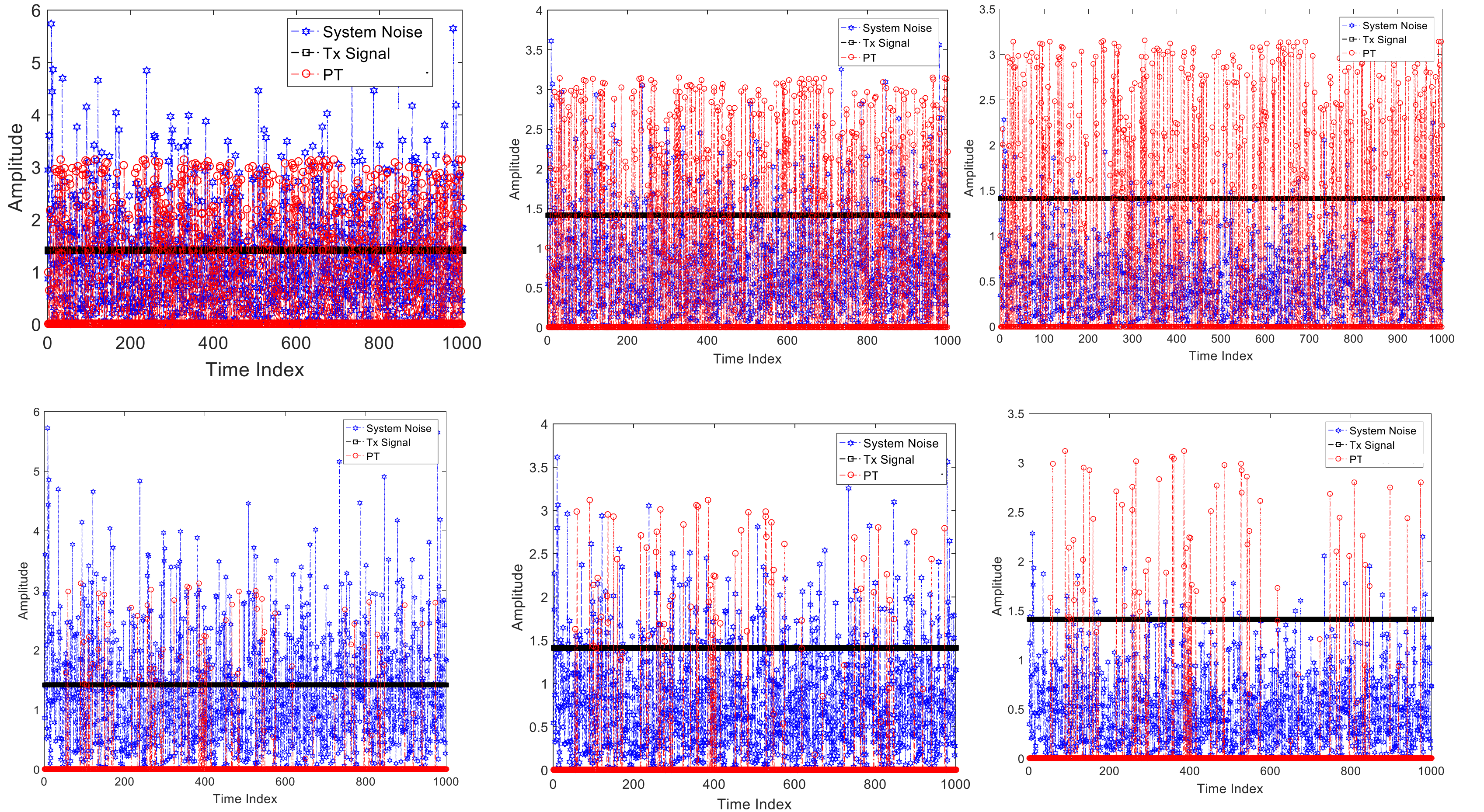


$$a_0 = 10.956\ b_0 = 0.1930\ \alpha_0 = 15.2576\ \beta_0 = 3.4007$$
$$a_1 = 0.2261\ b1 = 0.2354\ \alpha_1 = 61.4107\ \beta_1 = 1.0755$$

PD-Scenario 2: Partial Time interference

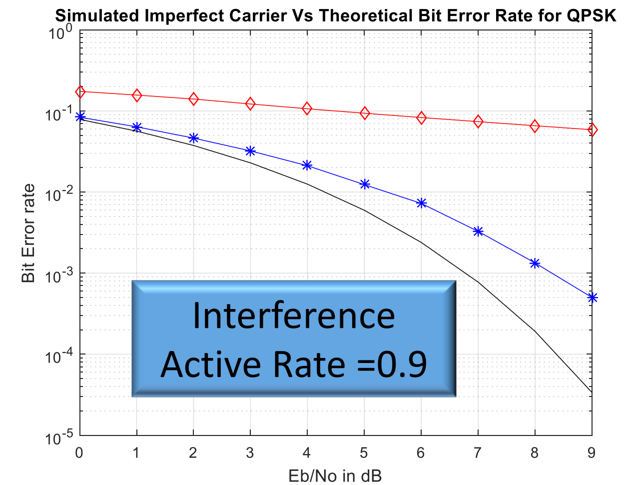
Active Rate=0.9

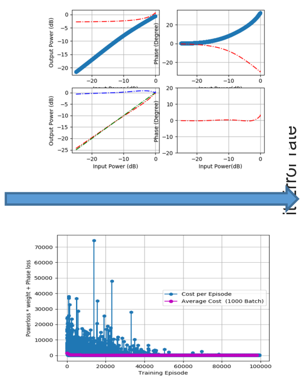
Active Rate=0.2

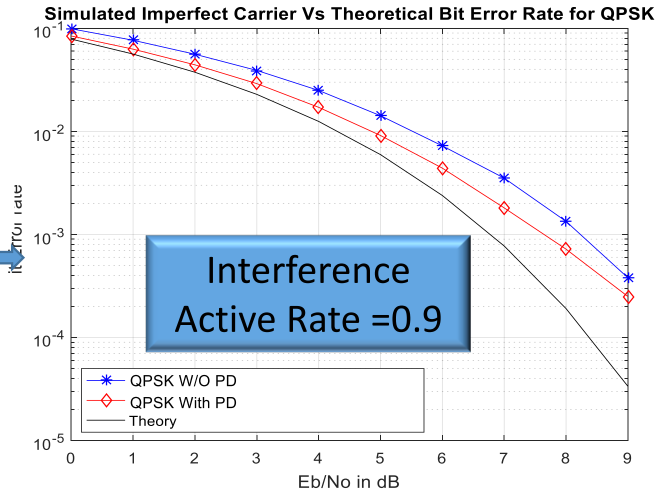


$$\frac{E_b}{N_0} = 1 \qquad \frac{E_b}{N_0} = 5 \qquad \frac{E_b}{N_0} = 9$$

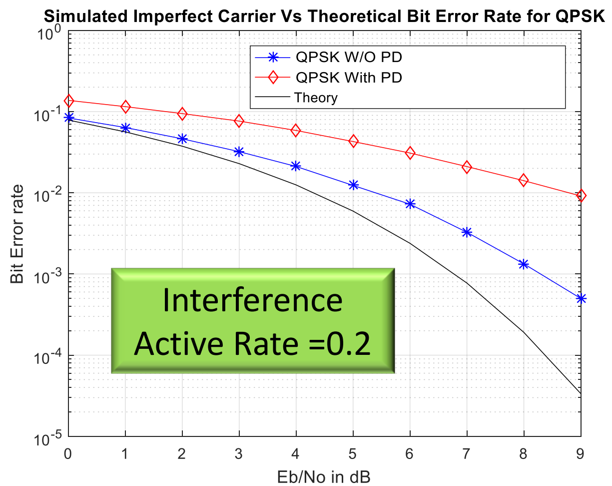
PD-Scenario 2: Partial Time interference

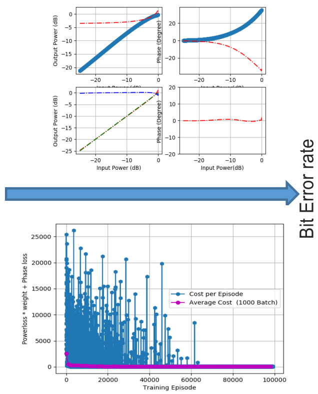


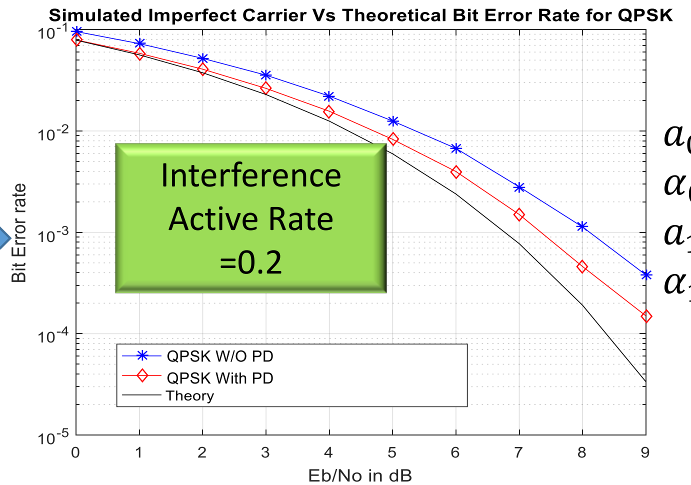




$$\alpha_0 = 3.5188 \; b_0 = 0.2621$$
$$\alpha_0 = 4.9642 \; \beta_0 = 1.0252$$
$$a_1 = 0.8371 \; b1 = 0.8371$$
$$\alpha_1 = 201.77 \; \beta_1 = 4.7948$$







$$a_0 = 12.5052 \; b_0 = 0.3661$$
$$\alpha_0 = 19.9163 \; \beta_0 = 4.6128$$
$$a_1 = 0.7536 \; b1 = 0.0570$$
$$\alpha_1 = 154.5747 \; \beta_1 = 3.5663$$

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Conclusions and Future Work

- *<u>Summaries/Conclusions</u>*:
  - Designed a complete SATCOM PD solution with on-ground system modifications to satisfy low-cost demand.
  - Mathematically modelled HPA to achieve an excellent agreement with actual AM-AM and AM-PM data, and developed an effective physics-based PD model accordingly.
  - Successfully develop a machine-learning based PD controller, which is able to intelligently adjust PD's parameters in the presence of interference signals.
  - Assessed BER and spectral regrowth performance of the developed PD by adopting a simplified NPR transponder simulation model.
  - The system performance is significantly improved based on our simulation results.
- *<u>Future Work</u>*:
  - Develop a database to capture all possible HPA distortions in different operating conditions and associated MODCOD performance.
  - Implement the PD design on the hardware.


thank you
danke
謝謝
ngiyabonga
teşekkür ederim
gracias
merci
obrigado
bedankt
dziękuję
go raibh maith agat
sukriya
kop khun krap
terima kasih
mochchakkeram
tapadh leat
спасибо
Баярлалаа
рахмат
dank je
arigatô
dakujem
grazie
takk
taiku
sagolun
hvala
mauruuru
감사합니다
ありがとう
ευχαριστώ
мерси
хвала
blagodaram
misaotra
matondo
paldies
grazzi
mahalo
asante
manana
obrigada
tenki
murakoze
chokrane
mamnun
trugarez
shukriya
merce
dhanyavadagalu
diolch
tanemirt
rahmet
xiexie
najis tuke
kam sah hamnida
rahmat
didi madloba
mèsi
dekuji
sobodi
enkosi
bayarlalaa
gracie
koszonom
dankon
aciu
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djiere dieuf
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gratias ago
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vinaka
спасибі
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kiitos
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nanni
nandri
dhanyavad