

# **Next-Generation Multiparameter Fiber Optic Photonic Nose for Energy Infrastructure Sensing**

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The concept of an optical fiber based "photonic nose" via multiple interrogation wavelengths and/or sensor nodes offers a compelling platform technology to realize multiparameter speciation of chemical analytes within complex gas mixtures. We further generalize the notion of multiparameter sensing through the novel "photonic nervous system" concept based upon low-cost, functionalized optical fiber sensor probes monitoring a variety of distinct analyte classes (physical, chemical, electromagnetic, etc.) simultaneously to provide broad situational awareness via integrated sensors. (Y-D Su et al., APL Photonics, Under Review)



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Combined with multivariate analytics, various multiparameter approaches can be demonstrated at the sensing layer device level. One unique way to introduce spectral dependences and selective responses of each contributing layer is to leverage the multilayered structure itself, imposing a leaky engineered waveguide. By leveraging the nature of optical penetration depth difference between light at different wavelengths within each layer, a particular bandwidth for each sensing layer can be sensitized and detected, thus presenting a potential wavelength multiplexing scheme using multi-sensing layer structure. (Y-D Su et al., APL Photonics, Under Review)

### Physics-Informed Sensor Response Calibration and Edge -Inference Analytics

$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$							
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $				Category	Description	Equation	Application
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Offline		Online Edge Inference Engine		Electron-electron $(\omega_{ce})$ and electron- phonon $(\omega_{cp})$ scattering of plasmonic metals	$\begin{split} \omega_{ce}(T) &= \frac{1}{6} \pi^4 \frac{G \Delta}{h  E_F} \left[ (k_B T)^2 + \left( \frac{h \omega}{4 \pi^2} \right)^2 \right]; \\ \omega_{cp}(T) &= \omega^0 \left[ \frac{2}{5} + 4 \left( \frac{T}{T_D} \right)^5 \int_0^{T_D / T} \frac{z^4  dz}{e^z - 1} \right] \end{split}$	Temperature response modeling
$ \begin{array}{c} \hline \textbf{Experimental Spectral Data} \\ \hline free Security to the security to$	Synthetic Data Emulator		Compilation Time I Runtime • Quantization • Sparse Update • Operator Reordering		Defect chemistry equilibrium of metal oxide layers (ex. LSTO)	$\begin{array}{l} O_{0} \rightleftharpoons V_{0}^{"} + 2e + \frac{1}{2}O_{2(g)}, \\ K_{o}(T) = [V_{0}^{"}] \cdot \rho^{2} \cdot \sqrt{pO_{2}}, \\ Sr_{Sr} + O_{0} \rightleftharpoons V_{Sr}^{"} + V_{0}^{"} + (SrO), \\ K_{S}(T) = [V_{0}^{"}] \cdot [V_{Sr}^{"}], \\ 2[V_{0}^{"}] + [La'] - 2[V_{Sr}^{"}] - \rho = 0 \end{array}$	High temperature gas sensing response dominated by equilibration mechanism
$\frac{\theta_{\text{der}}}{\theta_{\text{wavegange}(m)}} = \frac{\theta_{\text{fer}}}{\theta_{\text{wavegange}(m)}} = \frac{\theta_{\text{fer}}}{\theta_{\text{fer}}} = \frac{\theta_{\text{fe}$	Experimental Spectral Data Physics-Simulated Data Optical Waveguide Model Analyte-Dependent Optical Constant Models Data Output	Response Calibration Model Drift Compensator Layer	Transfer Model to MCU Flash	Example Free Carrier Behaviors	1-D approximation of Poisson-Boltzmanr equation for infinite interface	$\int_{0}^{\frac{d^{2}\phi}{dx^{2}}} = \frac{e}{\varepsilon_{s}} \left( N_{d} - N_{e}(\infty) \exp\left[\frac{e}{k_{B}T}\phi(x)\right] - 2N_{v}(\infty) \exp\left[\frac{2e}{k_{B}T}\phi(x)\right] \right)$	Sensing response due to electronic exchange at metal NP - oxide interface
Feature Extraction ModelMode propagation model for step-index $\frac{\partial^2 P(\theta, z)}{\partial \theta^2} + \frac{1}{\theta} \frac{\partial P(\theta, z)}{\partial \theta} + \frac{1}{\theta} \frac$	Feature Extraction Model			pH-dependent surface charge density $(\sigma_0)$ from modified Gouy-Chapman theory	$\begin{aligned} \sigma_0(pH) &= \frac{D_M}{1 + 10^{pK_a} [\mathrm{H}^+]_s} e + D_0 ,\\ [\mathrm{H}^+]_s &= 10^{-pH} \mathrm{exp}_{\mathrm{ind}} \left( -\frac{e\phi_0}{k_b T} \right) \end{aligned}$	pH sensing response based on surface refractive index change	
$\frac{d_{a_{b}}}{d_{b_{c}}} = \begin{pmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{pmatrix} \begin{pmatrix} M_{21} & M_{22} \\ M_{21} & M_{22} \end{pmatrix} \begin{pmatrix} M_{21} & M_{22} \\ M_{21} & M_{22} \end{pmatrix} \begin{pmatrix} M_{21} & M_{22} \\ M_{21} & M_{22} \end{pmatrix} \begin{pmatrix} M_{21} & M_{22} \\ M_{21} & M_{22} \end{pmatrix} = D_{0}^{-1} [\prod_{l=1}^{l} D_{l} P_{l} D_{l}^{-1}] D_{s} ,$ $R_{film} = \frac{1}{2} (\frac{M_{21}}{M_{11}} \int_{s}^{2} +  \frac{M_{21}}{M_{11}} _{p}^{2} ),$ $T_{film} = \frac{n_{s} \cos \theta_{0}}{1} (\frac{1}{M_{11}} \int_{s}^{2} +  \frac{1}{M_{11}} _{p}^{2} )$		Compensation gle-Layer NN Model	GATEWAYS	Optical Waveguide Models	Mode propagation model for step-index multimode fibers	$ \begin{vmatrix} \frac{\partial^2 P(\theta, z)}{\partial \theta^2} + \frac{1}{\theta} \frac{\partial P(\theta, z)}{\partial \theta} \\ - \frac{1}{C_0(\Delta \theta)^2} \frac{\partial P(\theta, z)}{\partial z} - \frac{\alpha(\theta)}{C_0(\Delta \theta)^2} P(\theta, z) \\ = 0 \end{vmatrix} $	Ray tracing of propagating θ- modes through cladded lead fibers
$m_{111} = 2$			loT Network Cloud		Matrix formulation for layered media		Deriving total transmittance / reflectance of isotropic sensing (multi)layers

To address the challenges in (1) acquiring calibration data in "beyond lab" conditions and (2) avoiding overfitting model to the bias of a subset of calibration data, we incorporate the concepts in recent trends of synthetic training dataset that combines simulated data with empirical data, and physics-informed learning method. The importance, of integrating data analytic algorithms with edge-compatible hardware/firmware for grid-tied energy applications, necessitates the approaches of compile-time and runtime separation and model quantization that make edge inference or even training possible. (Y-D Su et al., APL Photonics, Under Review)







