

Machine Learning in Microwave Sensing: Data Analysis and Applications

From electromagnetic measurements to data-driven decision making

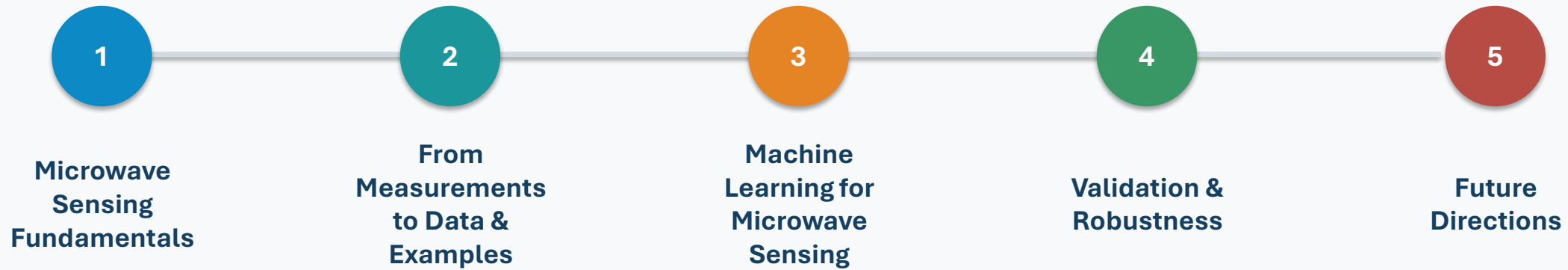


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Talk Roadmap

From sensing physics to robust, data-driven microwave sensing



Microwave measurement → meaningful representation → ML inference → robust validation → practical sensing

Why Machine Learning in Microwave Sensing?

The instrument measures a spectrum

A VNA samples complex electromagnetic response across many frequencies — magnitude, phase and spectral shape.

Classical analysis compresses it

Many sensing studies finally use only resonance frequency, dip/peak magnitude or Q for calibration and decision making.

ML can use complementary cues

When simple shifts are insufficient, multivariate models can exploit several weak but informative signal characteristics together.

Central question: how much useful information are we leaving inside the measured spectrum?

Microwave Sensing Fundamentals

Material response begins with complex permittivity

$$\epsilon^* = \epsilon' - j\epsilon''$$

ϵ' · dielectric constant

Represents electric-energy storage. Changes in ϵ' modify effective electromagnetic loading and often shift resonance position.

ϵ'' · dielectric loss

Represents dissipative behavior. Loss and coupling affect resonance depth, bandwidth and Q.

Composition, moisture and molecular dynamics therefore leave a frequency-dependent electromagnetic fingerprint.

What can be the Material Under Test (MUT)?

For this talk, the MUT is mainly a liquid whose composition changes its dielectric response.

Water-ethanol mixtures



- controlled mixtures
- concentration / adulteration

Edible oils



- pure vs mixed oils
- quality / adulteration

Fuels



- diesel / gasoline
- liquid discrimination

Industrial liquids



- transformer oil / solvents
- composition / condition

Different composition → different dielectric properties → different microwave response

What changes when the liquid composition changes?

The sensor does not directly “see” ethanol, oil or adulteration — it sees an electromagnetic consequence.

1 • Material composition



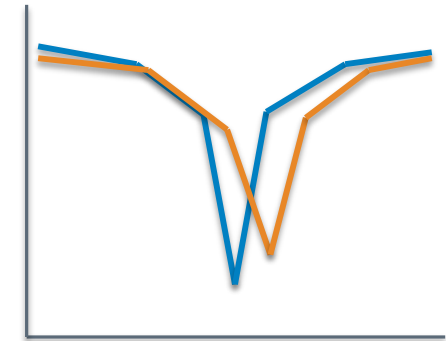
pure ↔ mixture

2 • Dielectric response

ϵ' ϵ''

storage · loss
frequency-dependent
fingerprint

3 • Measured response

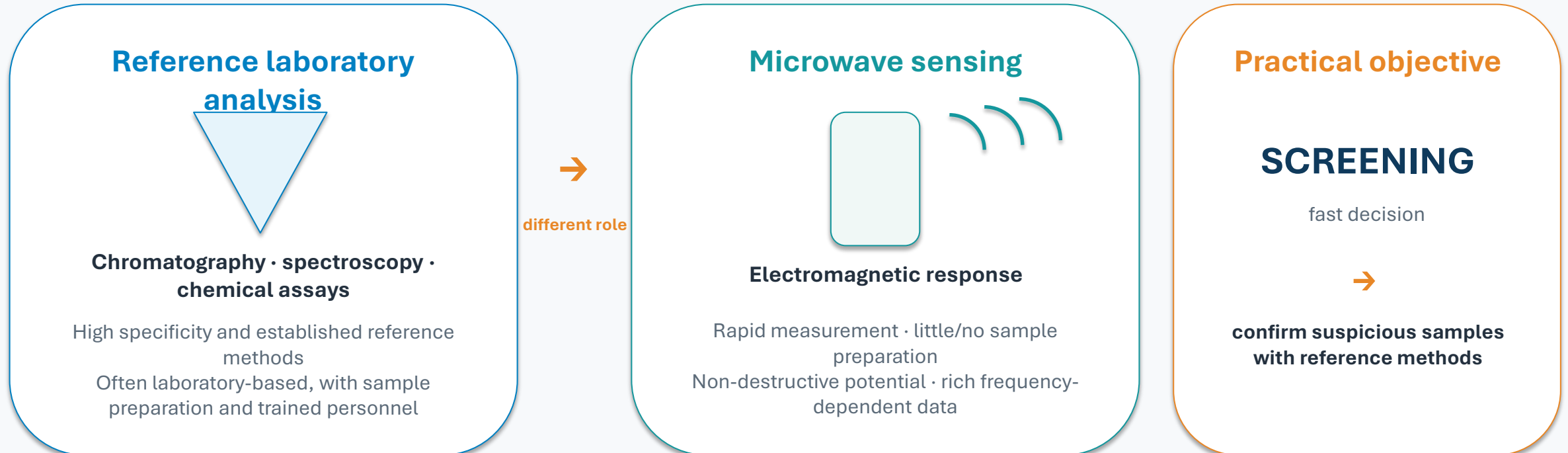


S11 / S21

ML learns the mapping from this electromagnetic fingerprint to concentration, identity or adulteration level.

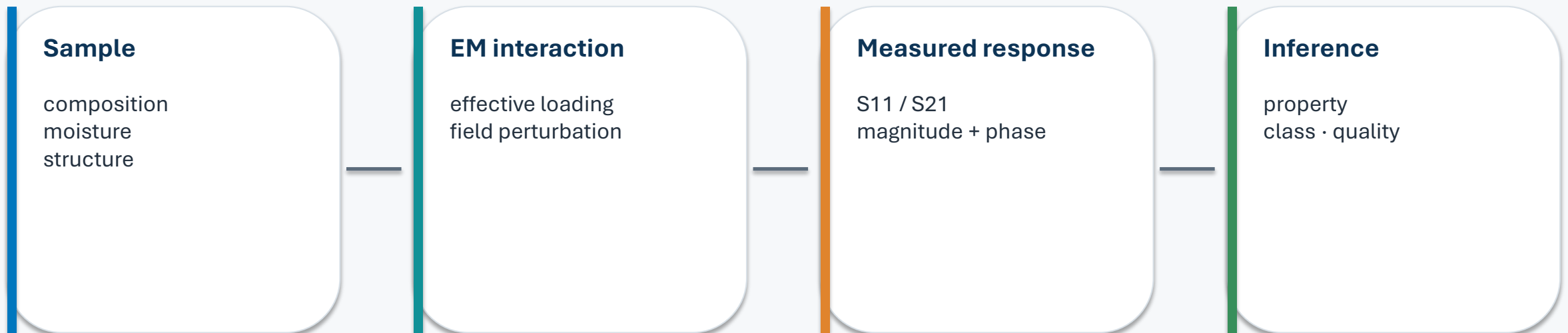
Adulteration is already tested in laboratories. Why microwaves?

Microwave sensing is not proposed as a universal replacement for reference laboratory analysis.



The goal: rapid screening and data-driven decision support — not necessarily replacing the reference laboratory.

How does a material become a microwave signal?



The sensing problem is a mapping from material-dependent electromagnetic perturbation to a useful decision.

Common microwave sensing architectures

There is no single best sensor architecture

Cavity / waveguide

High field interaction and high accuracy potential.

Trade-off: volume, connectors and often VNA / waveguide hardware.

Planar resonators

SRR / CSRR / LC structures are compact and compatible with small-volume or microfluidic sensing.

Trade-off: Q and field interaction vary strongly with design.

Antenna / broadband sensing

Potential for portable or passive readout and richer spectral analysis.

Trade-off: environment, contamination, stability and repeatability.

From Measurements to Data

What should we preserve, extract and feed to the model?

S-parameters → preprocessing → representation → dataset

If the final goal is simple sensing, why start with a VNA?

1 • Explore broadly

Sweep frequency
Measure complex response
S11 / S21 • magnitude • phase

2 • Learn what matters

Identify f_r , Δf_r , Q, bandwidth,
dip/peak, spectral shape
and useful frequency regions

3 • Simplify later

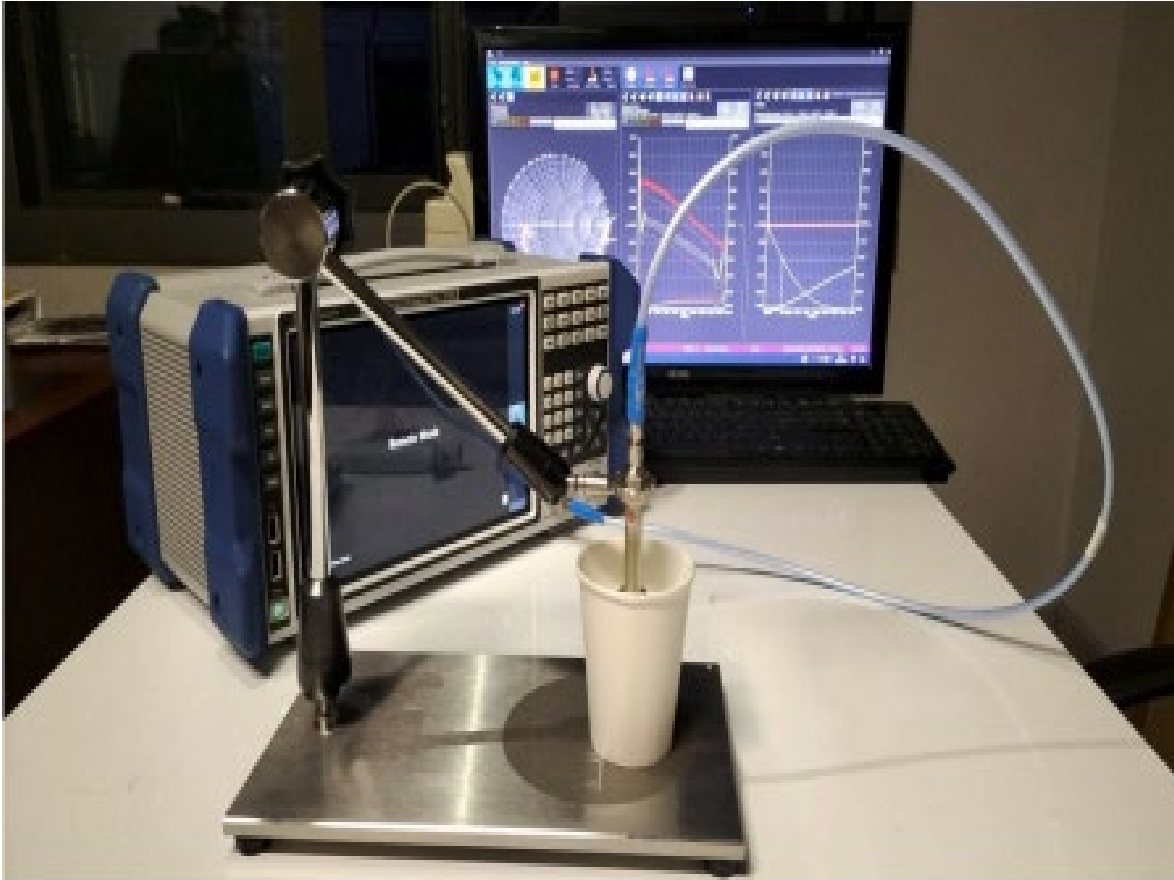
Keep only the information
needed for the decision
→ compact reader / DC output

VNA = research/reference instrument, not necessarily the final product.

Later in the talk: Do we really need a VNA?

Example measurement setup: broadband dielectric characterization

A VNA and an open-ended dielectric probe convert material response into frequency-dependent data.



1 • Excitation and measurement

The VNA sweeps frequency and measures the complex microwave response at the probe reference plane.

2 • Material interaction

The probe is brought into contact with the liquid sample. The measured response changes with its dielectric properties.

3 • Data for analysis

After calibration and conversion, the setup provides frequency-dependent ϵ' , ϵ'' and conductivity — a rich material fingerprint.

**Measurement hardware → electromagnetic response
→ material data**

Scope of the case studies

A deliberately narrow application scope: liquids, their dielectric signatures and quality-related decisions.

Liquid characterization

- complex permittivity
- liquid identification
- composition / concentration
- water–ethanol mixtures

Quality & adulteration

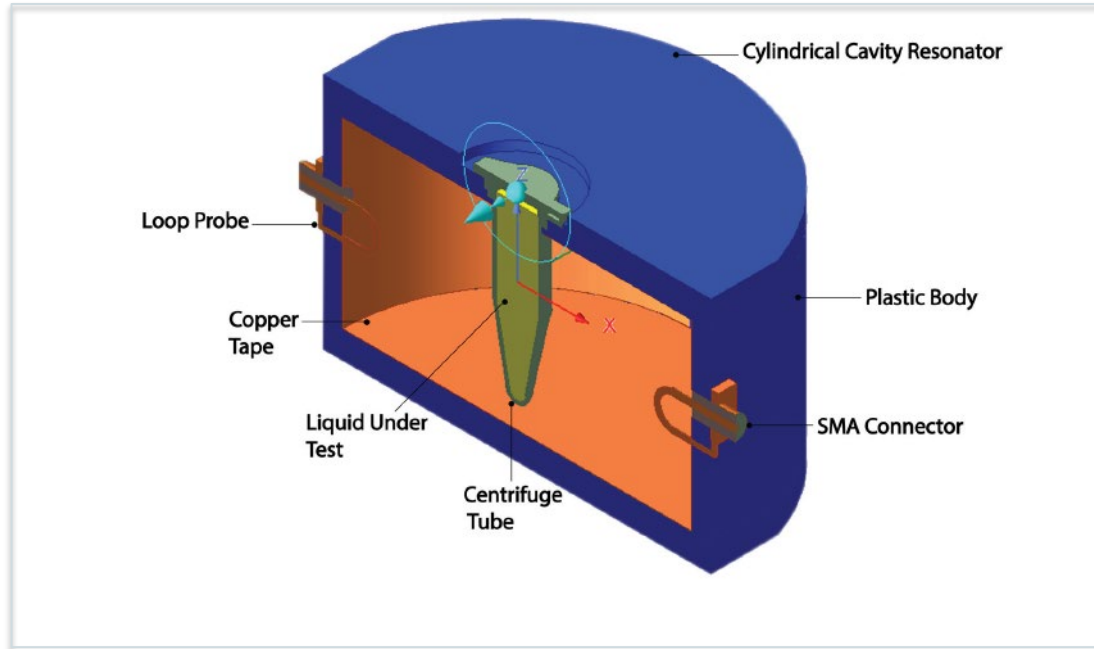
- edible oils
- purity / adulterant ratio
- freshness / degradation
- comparison with reference samples

Portable liquid sensing

- fuel / transformer oil examples
- compact resonant sensors
- low-cost readers
- VNA-free readout

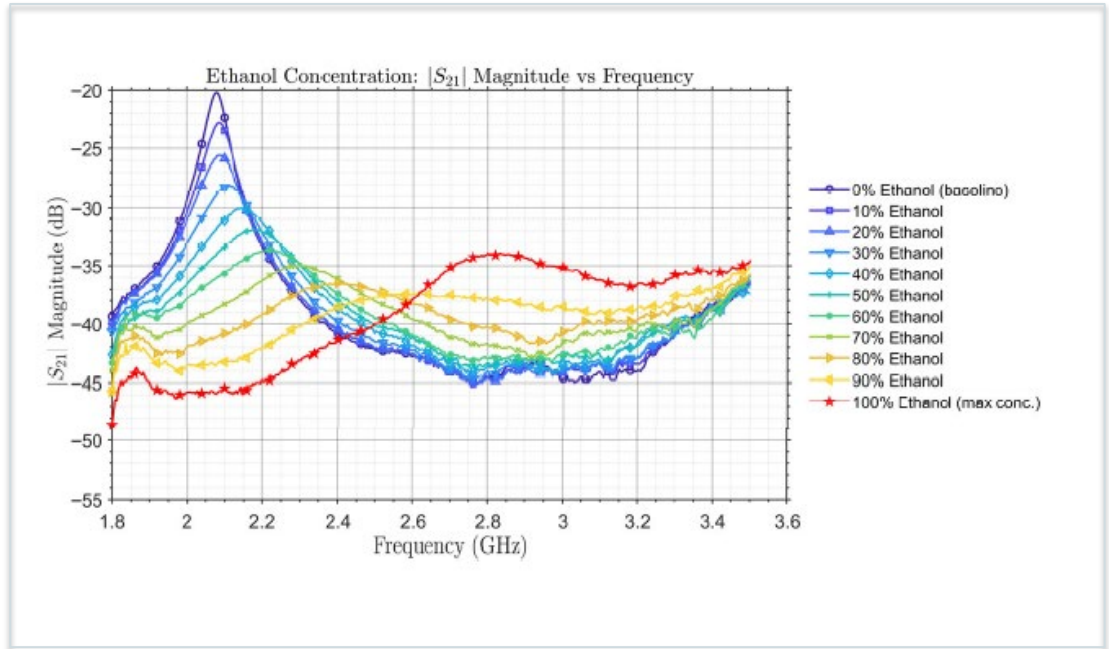
Biomedical and other application domains exist, but they are intentionally outside today's scope.

3D-printed cavity resonator



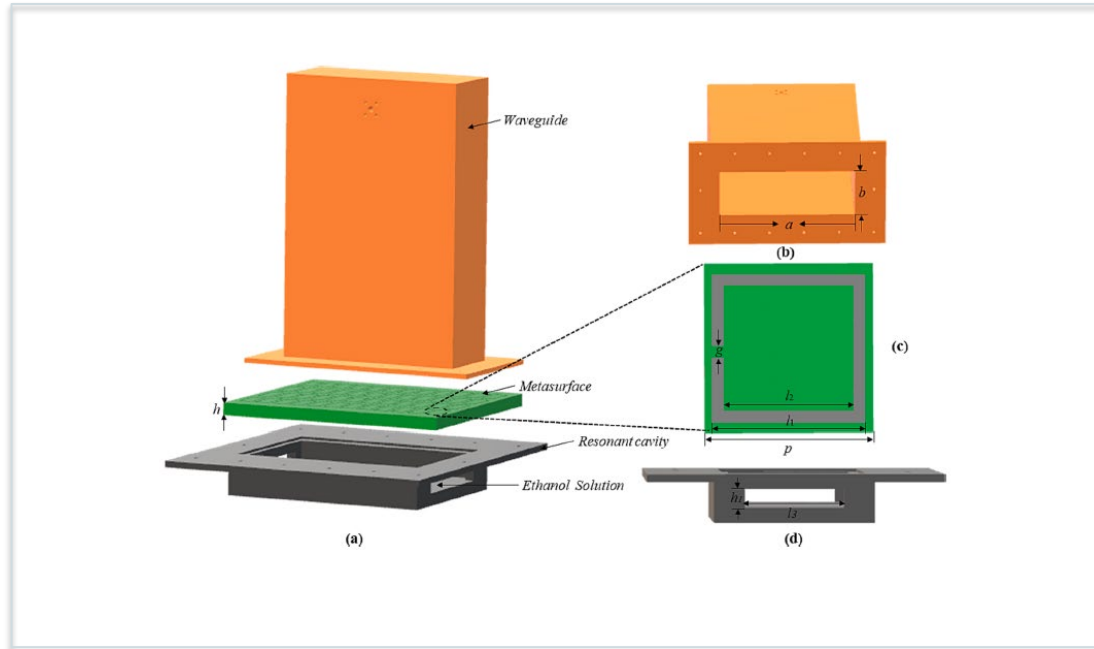
Cross-section of the 3D-printed cylindrical cavity

The PLA body is metallized internally with copper tape, while a standard 1.5 mL centrifuge tube is positioned in the strong-electric-field region at the cavity center. Two loop probes excite the cavity through SMA connectors and measure S_{21} . As ethanol concentration increases, both resonance frequency and magnitude change systematically.



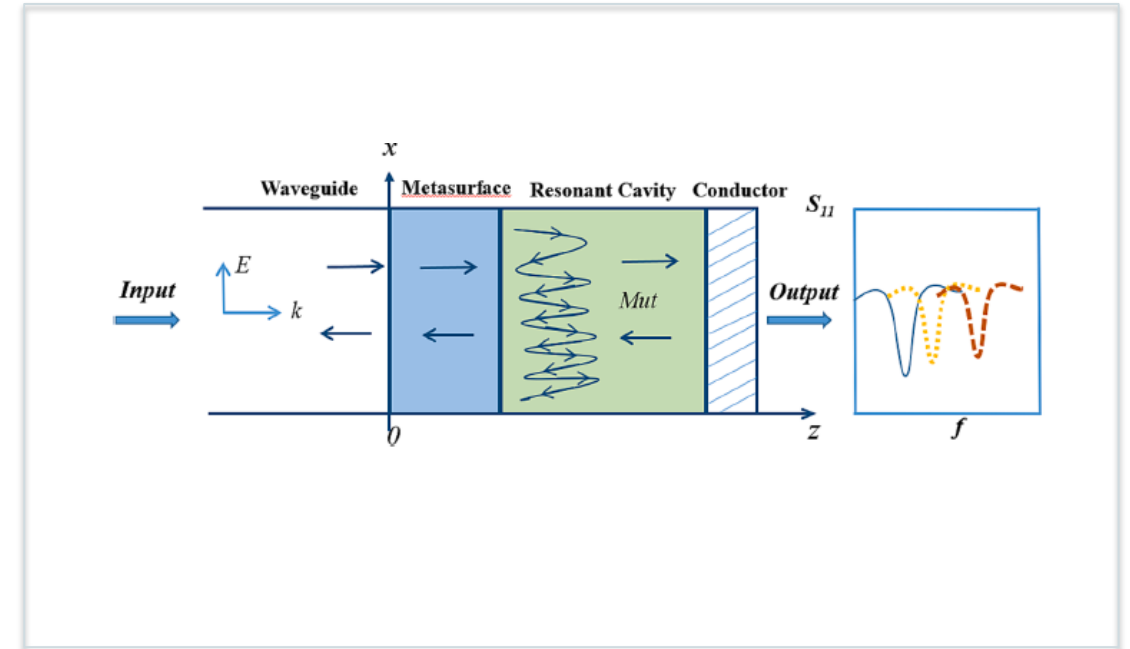
Measured $|S_{21}|$ versus ethanol concentration

SRR + waveguide resonant cavity



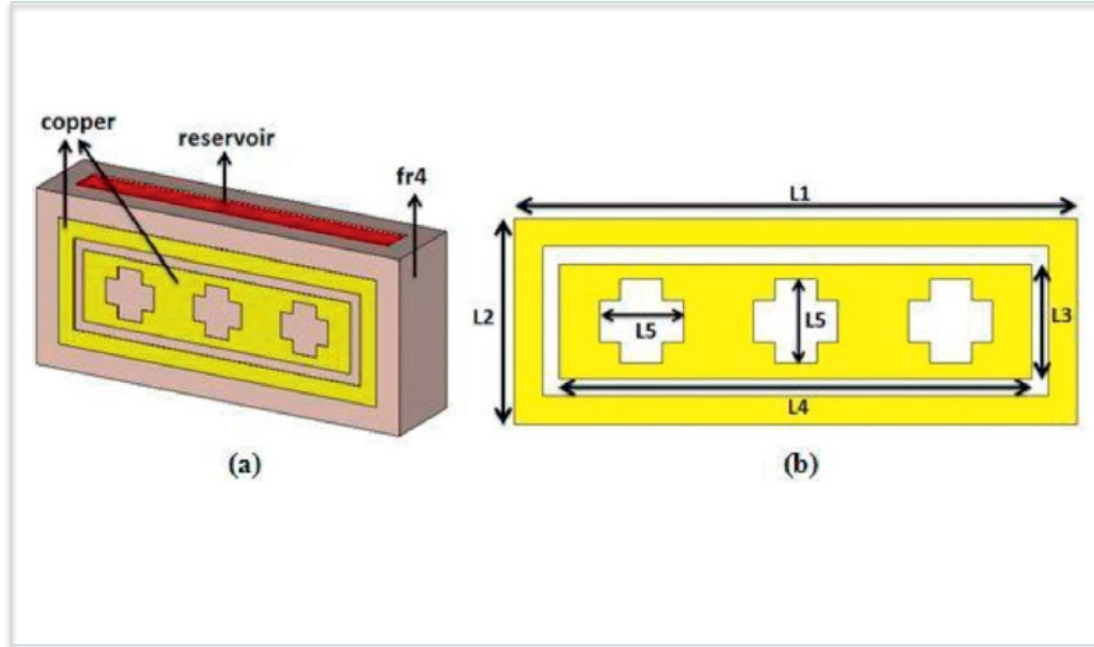
Mechanical / EM structure of the sensor

The first figure shows the waveguide–metasurface–resonant-cavity layers and the position of the ethanol solution. The second summarizes field coupling to the metasurface/cavity and the S_{11} resonance shift caused by changing dielectric loading.



Operating principle and resonance shift

X-band fuel sensor



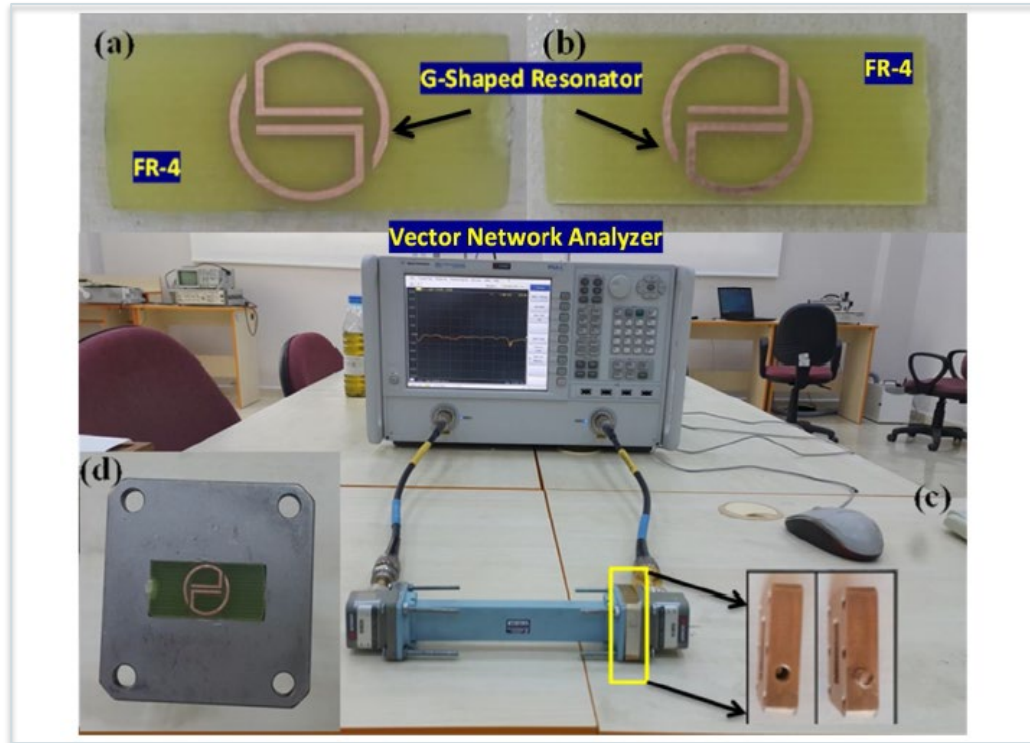
Sensor and waveguide measurement setup

The study operates in the 8–12 GHz X-band. Fuel dielectric properties are first measured with an open-ended probe and used in the CST-based design. The fabricated metamaterial element is then measured inside an X-band waveguide while resonance frequency and reflection magnitude are monitored together.



Resonance response of fuel samples

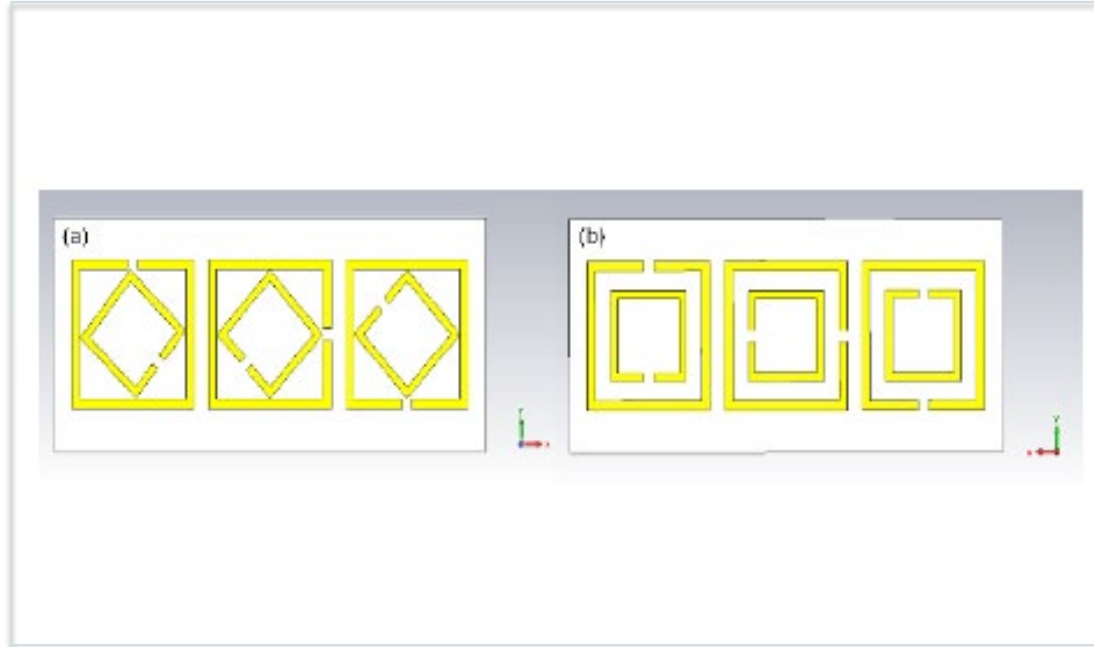
Multi-application X-band chemical sensor



Metamaterial resonator + X-band waveguide measurement

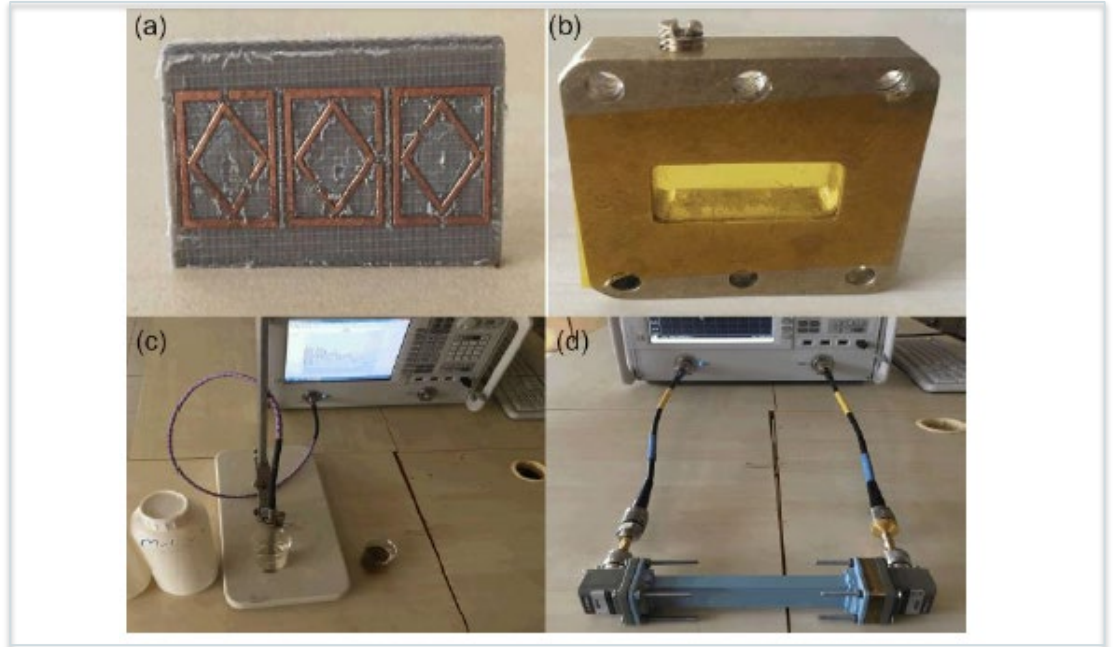
The upper part of the figure shows the FR4-based resonator and liquid reservoir; the lower part shows the experimental waveguide adapters and VNA setup. Dielectric loading changes the effective L-C behavior of the resonator and shifts its resonance.

Split-square-ring X-band sensor



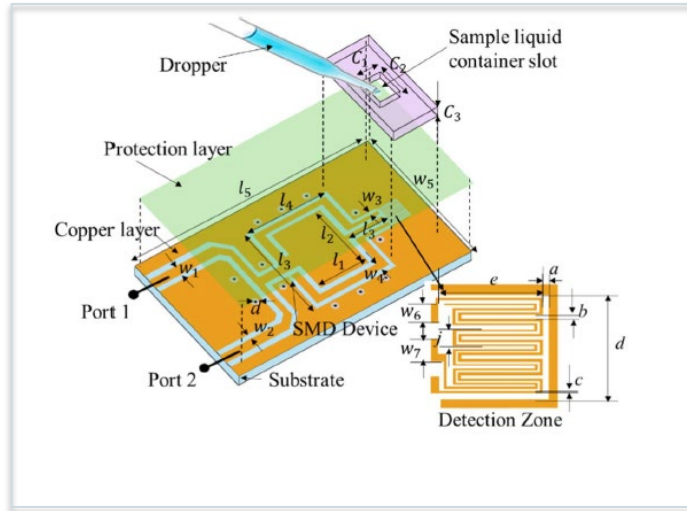
Split-square-ring design and fabrication

Split-square-ring cells are arranged to fit X-band waveguide dimensions. The fabricated structure is inserted into the waveguide measurement line; the complex permittivity of each liquid changes the electrical loading of the resonator. The effect is read from S-parameters through resonance frequency and Q.

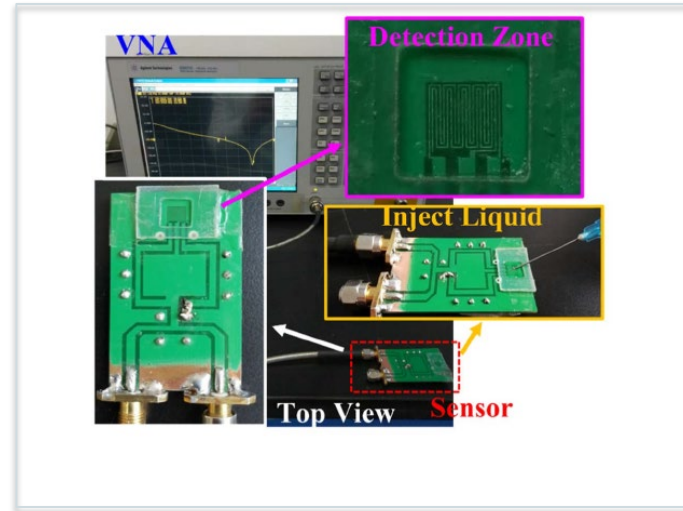


Sensor / waveguide experimental setup

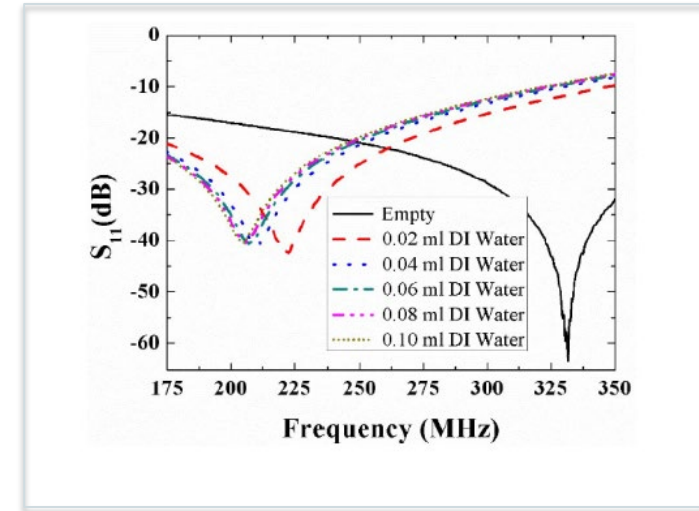
MOCSRR drop-loaded liquid sensor



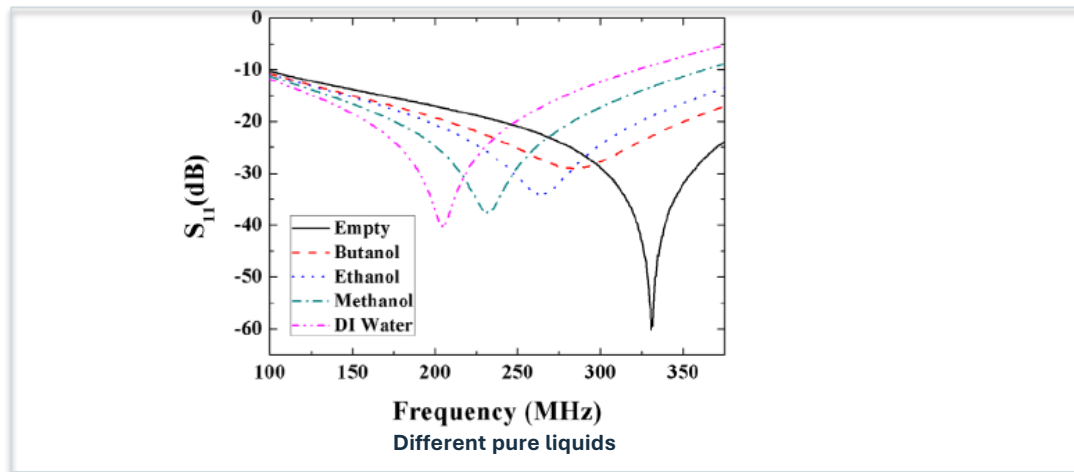
3D sensor geometry



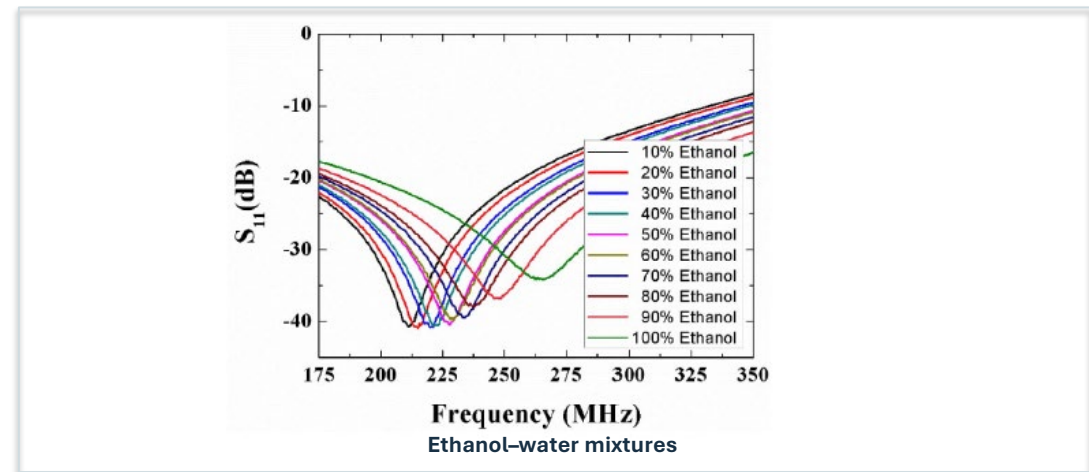
Fabricated sensor + VNA setup



Effect of sample volume



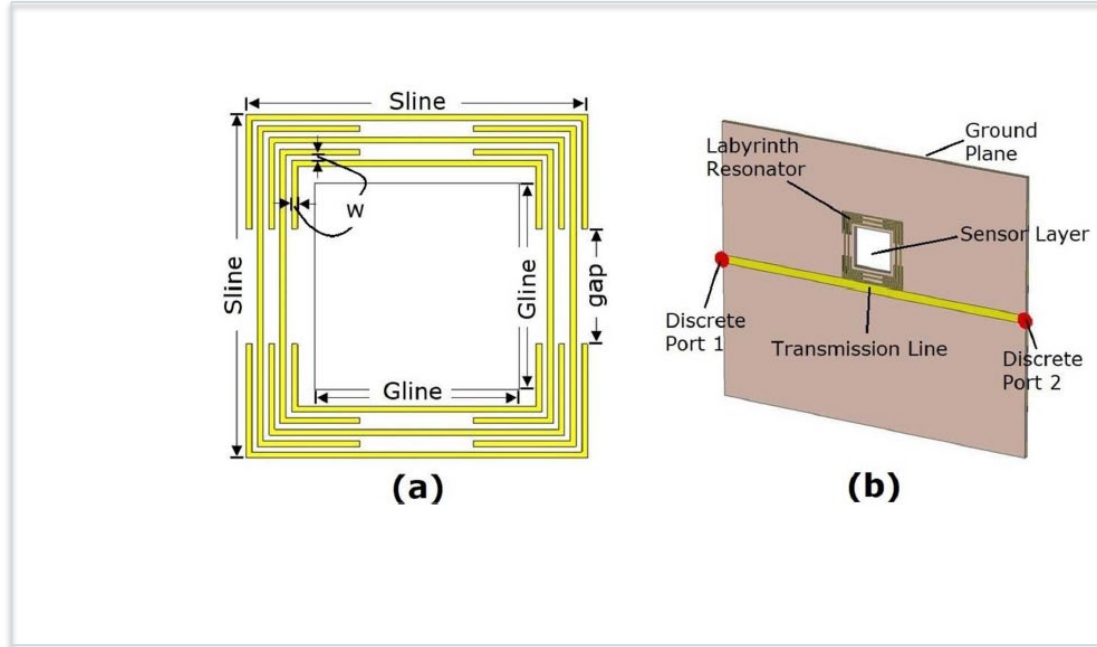
Different pure liquids



Ethanol-water mixtures

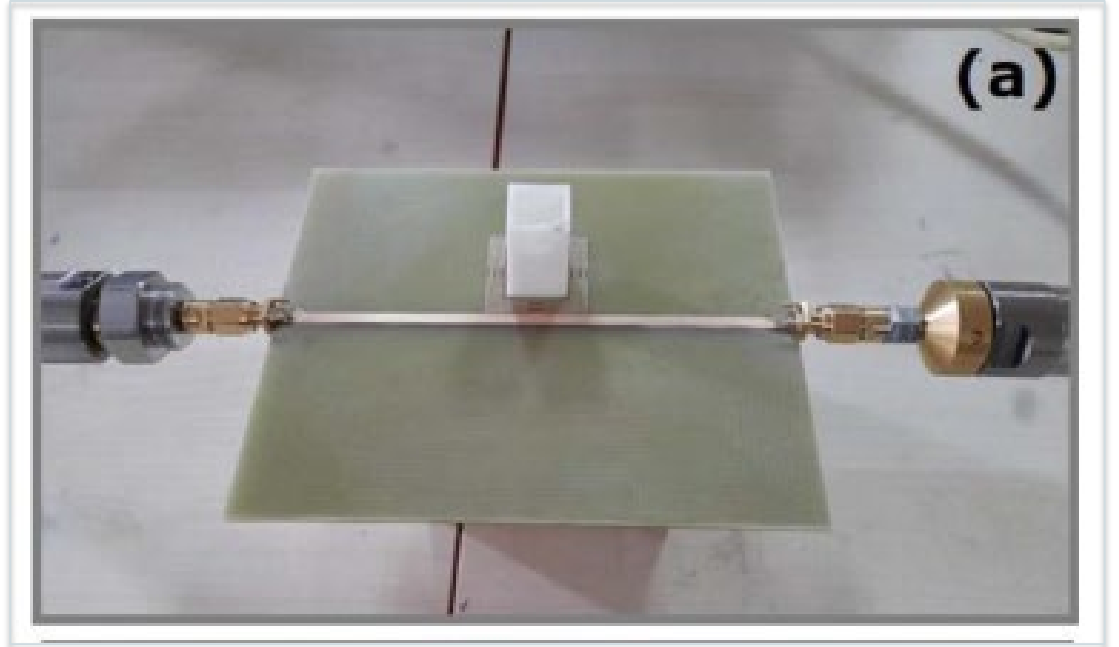
The geometry shows the MOCSRR sensing region and liquid holder. In the experiment, the sample is injected directly onto the detection zone. The volume plot shows resonance stabilization above about 0.08 mL. Other plots show that pure liquids and ethanol-water mixtures in 10% steps shift the S_{11} resonance to different frequencies.

Labyrinth resonator



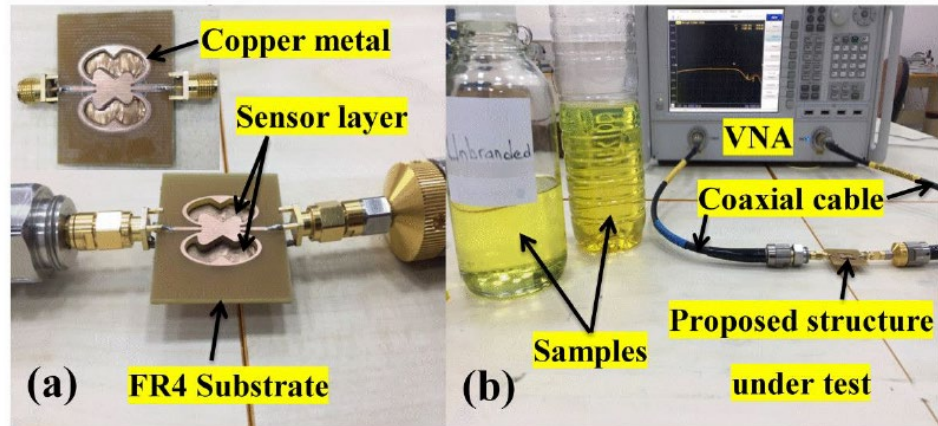
Labyrinth resonator and transmission-line model

The labyrinth geometry compresses a long current path into a compact area to produce a strong resonance. In CST, the resonator is coupled to a transmission line; experimentally, the sample is applied to the sensor layer and measured with a two-port VNA. Before sensor testing, ϵ' and loss information are measured with an Agilent 85070E open-ended probe and transferred to simulation.



Fabricated sensor / experimental connection

Oval-wing metamaterial sensor | An example where magnitude becomes important



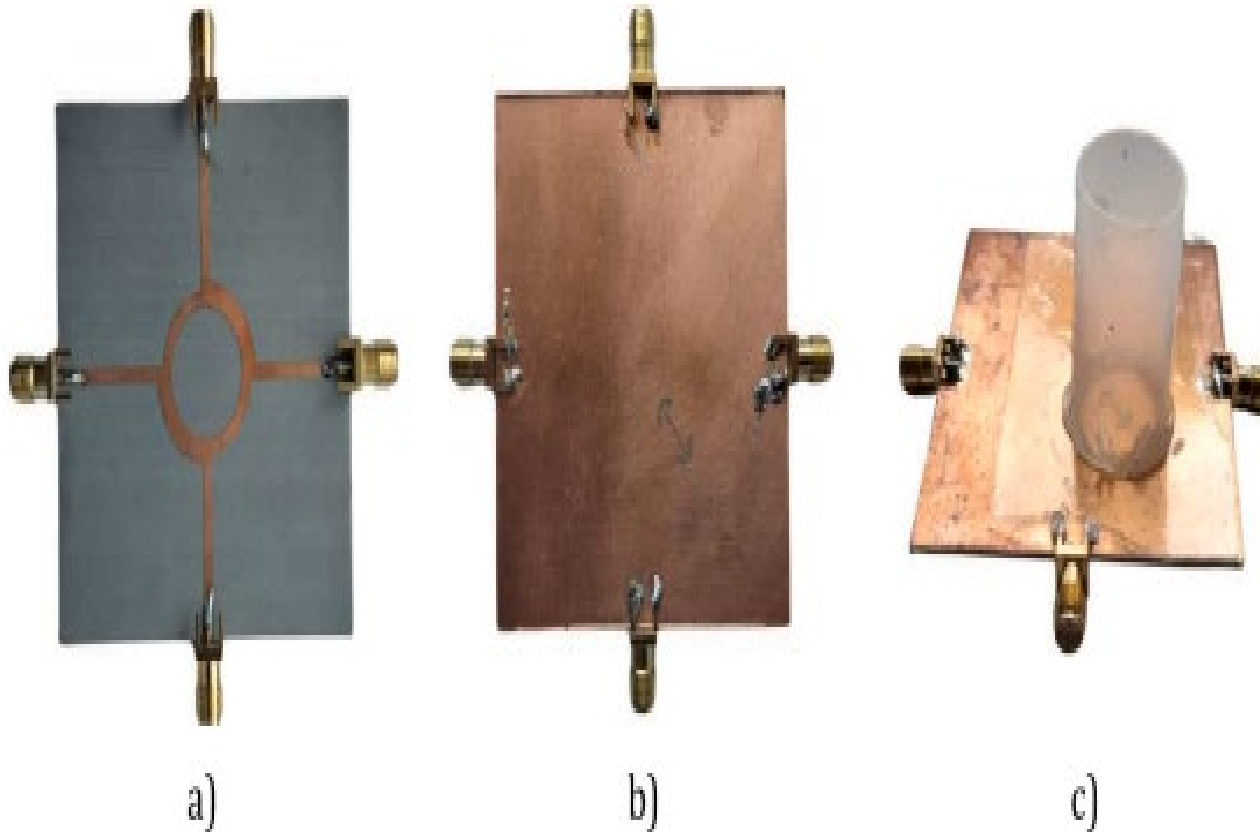
Oval-wing sensor and experimental setup

Technical reading

Two oval-wing resonators are used with a transmission line, and their dimensions are optimized through a parametric/genetic-algorithm approach in CST. The sample is applied to the active region and the S_{21} response is monitored over 8–12 GHz.

From microwave circuit to a repeatable sensing region

The example shows how the resonator is integrated and how the liquid sample is positioned.



Front side • branch-line coupler

The four-port microstrip circuit provides the RF signal paths used by the sensing architecture.

Back side • resonator region

The CEE-LC resonator is placed on the ground side to perturb S21 and create a strong sensing response.

Sample holder • controlled loading

A fixed container defines sample geometry and volume, improves repeatability, and prevents direct milk contact with the resonator surface.

Sensor geometry and sample placement are part of the measurement methodology.

Do we really need a VNA?

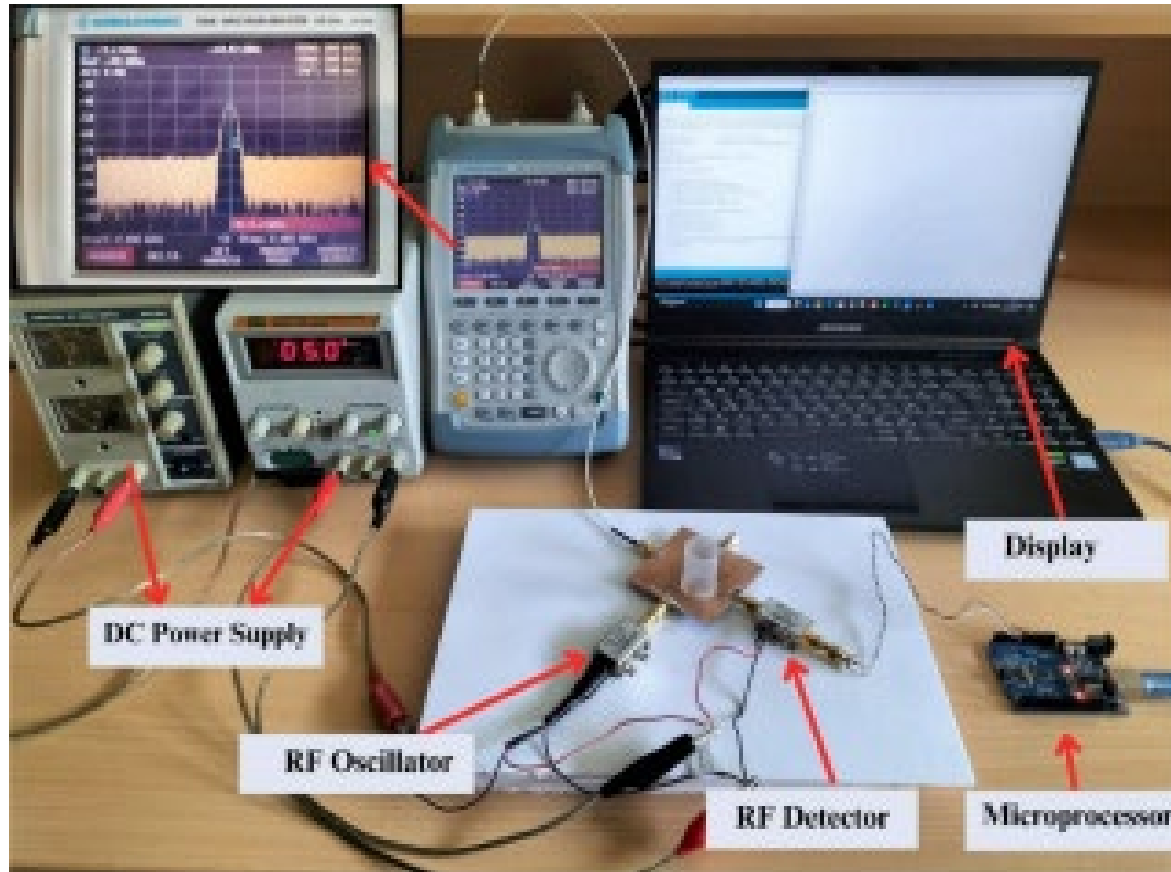
A network analyzer is an excellent reference instrument — but not always the final product.



The next figure shows how the sensing response can be converted directly into a DC voltage.

A different perspective: VNA-free sensor readout

Instead of sweeping S-parameters with a network analyzer, the sensing response can be converted directly into a DC voltage.



Oscillator → Sensor → RF detector → DC voltage

RF oscillator

Generates the excitation signal and feeds the sensor.

Microwave sensor

The sample changes the transmitted RF signal through its dielectric loading.

RF detector → DC voltage

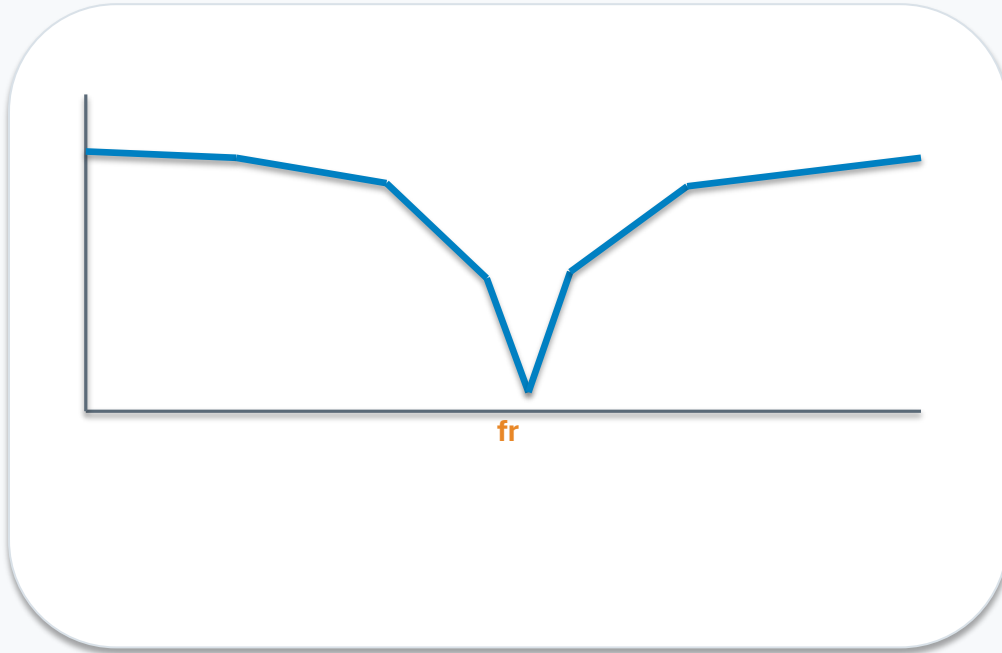
The detector converts the received RF level into a DC output that can be digitized by a microcontroller.

Field-oriented decision

The result can be read as voltage rather than a full VNA spectrum — simpler hardware for practical deployment.

Are we throwing useful information away?

A resonance curve is not only one frequency value.



Classical: compress the curve



?

magnitude

phase

Q

bandwidth

shape

Data-driven: preserve complementary cues

This question motivates the transition from feature extraction to machine learning.

Before ML: build a trustworthy dataset

1

Calibration

Reference-plane and instrument calibration; preserve traceability.

2

Signal handling

Noise treatment, phase handling, baseline / normalization decisions.

3

Repeatability

Control sample placement, temperature and repeated measurements.

4

Data organization

Keep sample, batch, day and condition identifiers for later validation.

A sophisticated model cannot rescue an ambiguous experimental protocol.

Feature engineering: three levels of representation

Level 1 • Classical

fr
peak / dip magnitude
Q factor
bandwidth

+ interpretable
+ low dimensionality

Level 2 • Multi-feature

fr + Q + magnitude + phase
selected frequency samples
shape descriptors

+ preserves complementary information

Level 3 • Broadband

full / reduced complex spectrum
spectral sequence

+ highest information content
– higher data and validation demands

Machine Learning for Microwave Sensing

Choose the model according to the scientific task — not the other way around.

Regression · Classification · Deep / spectral learning

Two common ML tasks in microwave sensing

The same measurement chain can support either numerical estimation or sample-level decisions.

Regression

Estimate a continuous quantity

Typical outputs

- concentration / adulterant ratio
- ϵ' , ϵ'' or other dielectric quantities
- quality or degradation index

Evaluation

MAE · RMSE · R^2 · residual analysis

Classification

Decide what the sample is

Typical outputs

- pure vs adulterated
- material / liquid identity
- acceptable · suspicious · adulterated

Evaluation

accuracy is not enough: precision · recall · F1 ·
confusion matrix

Important: always compare ML against a simple calibration or rule-based baseline.

When does deep learning become interesting?

Broadband sequences

CNN / 1D-CNN or sequence models can learn local and global spectral patterns directly from many frequency samples.

Image-like representations

Time–frequency maps, spatial microwave images or multiplexed responses can justify convolutional architectures.

The caution

High-capacity models need enough independent data. More parameters do not automatically mean more physical insight or better field performance.

What do the case studies tell us?

The examples point to a progression from single-feature sensing toward richer data-driven inference.

1 • Resonance frequency is powerful

When the shift is large and monotonic, fr alone can provide a simple, interpretable calibration. It remains an essential baseline.

2 • But the curve contains more

Magnitude, phase, resonance depth, Q and bandwidth can add discrimination when frequency shifts become small or overlap.

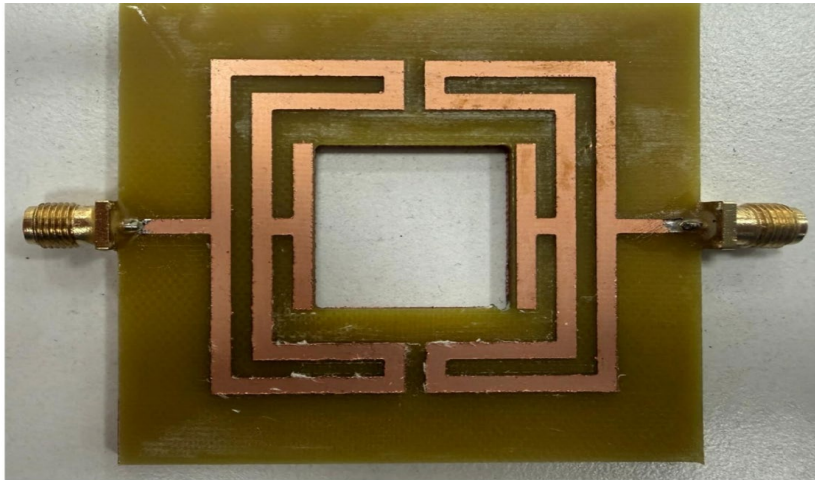
3 • ML can combine weak cues

Instead of forcing the entire decision through one scalar feature, multivariate models can learn from several complementary electromagnetic descriptors.

The key transition: one resonance metric → multi-feature sensing → broadband / data-driven sensing

A compact microwave-sensing example

A quick example: a compact liquid sensor can provide RF measurements that are mapped to material properties.



Fabricated liquid sensor

The exposed sensing region is loaded by the liquid sample; the measured RF response changes with dielectric properties.

1 • Interrogate

operate the sensor at selected frequencies or conditions

2 • Measure response

collect a compact RF fingerprint

3 • Learn the mapping

estimate concentration, identity or dielectric properties

Main point for this talk

The key idea is not the specific readout protocol. It is the use of a compact RF response as input to an ML model.

Two routes from microwave measurements to ML inputs

The representation depends on whether we measure the material directly or through a designed sensor.

Direct material characterization

Example: VNA + open-ended probe

Possible inputs

- reflection coefficient Γ
- Re/Im or magnitude/phase
- ϵ' , ϵ'' , $\tan\delta$, conductivity σ
- selected frequencies or broadband response

Typical outputs

concentration · composition · dielectric properties

Sensor-based measurement

Example: resonator / antenna / cavity sensor

Possible inputs

- S11 / S21 spectra
- resonance frequency f_r and Δf_r
- dip / peak magnitude
- phase, Q factor, bandwidth
- selected frequency-point vectors

Typical outputs

liquid identity · adulteration decision · quality class

Both routes can provide inputs for machine-learning models; the key choice is what information we preserve before training.

Path A • Direct dielectric measurement → ML

No dedicated resonant sensor is required: the measurement itself can become the dataset.

Raw reflection information

A VNA + dielectric probe measures the complex reflection response across frequency.

Possible inputs:

- $\text{Re}\{\Gamma\}$, $\text{Im}\{\Gamma\}$
- $|\Gamma|$ and phase
- selected frequency points
- broadband reflection sequence

Derived dielectric information

Calibration / inversion yields material quantities such as:

- ϵ'
- ϵ''
- $\tan\delta$
- conductivity σ

These can be used individually or together.

What can ML learn?

Regression

- concentration / composition
- dielectric property
- quality index

Classification

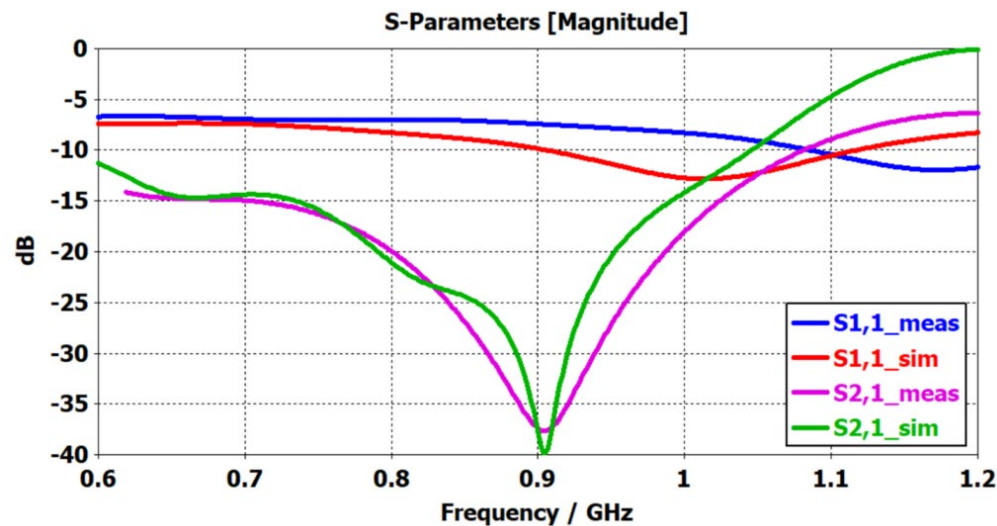
- material identity
- pure vs adulterated

A useful comparison is raw reflection coefficients versus derived ϵ -based features.

This path separates the question of material characterization from the question of sensor design.

Path B · Turning an S-parameter curve into an ML dataset

A resonant sensor does not have to be reduced to only one resonance frequency.



Point-based representation

Sample the curve at selected frequencies:

$S_{11}(f_1) \dots S_{11}(f_n)$
 $S_{21}(f_1) \dots S_{21}(f_n)$

Use magnitude, phase, real and imaginary components as features.

Physics-based features

Extract compact descriptors:

- dip / peak value
- resonance fr
- frequency shift Δf_r
- Q factor
- bandwidth
- slope / shape descriptors

Point-wise and engineered features can also be combined in one model.

Beyond engineered features · learning from the full response

Deep learning becomes relevant when the dataset is large enough and the representation justifies the model complexity.

1D-CNN / sequence models

A broadband S11/S21 sequence can be treated as an ordered spectral signal.

Potential advantage:
learn local resonance structure and broader spectral context without manually selecting every descriptor.

CNN on graphical representations

Spectra can also be represented as images or multi-channel maps.

This can be explored, but it should be compared against simpler vector/sequence representations to verify that image conversion really adds value.

Where does GNN fit?

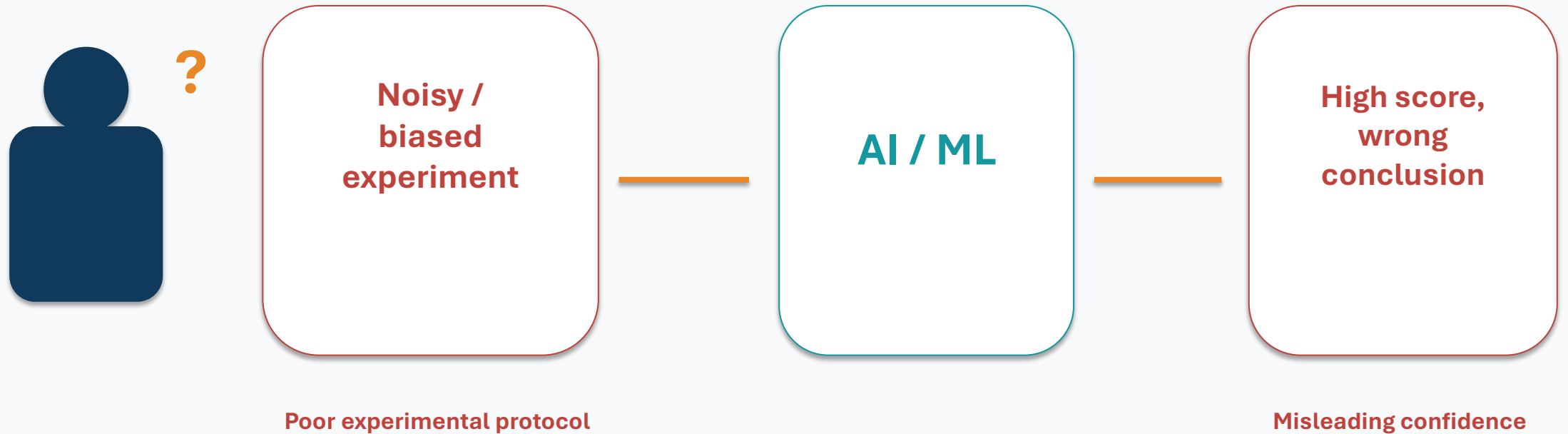
GNNs are attractive when the data have an explicit graph structure—e.g., coupled sensing nodes, spatial networks or topology-aware representations.

A plotted spectrum is not automatically a graph-learning problem.

Deep learning is an option, not a requirement: the right representation and independent validation matter more than model complexity.

Can AI fix a bad experiment?

A powerful model can fit systematic errors just as easily as useful physics.



Good sensing physics and trustworthy data come first; AI comes after.

Validation is part of the sensing methodology

A high score is meaningful only if the model survives genuinely new samples and conditions.

Split correctly

Do not place near-duplicate repeated measurements of the same physical sample in both training and test sets.

Group by sample / batch / day where appropriate.

Challenge the model

Validate across new days, temperatures, product batches, repositioning and — eventually — reader or laboratory changes.

Report uncertainty

Do not rely on one headline metric.

Show residuals, error distributions, confusion, repeatability and confidence / uncertainty where possible.

Where AI can help — and where it cannot

Sensitivity vs. selectivity

Overlapping signatures

Multivariate nonlinear discrimination

Calibration burden

Thermal / system drift

Algorithmic correction or virtual calibration

High-frequency metrology

Noise and phase error

Denoising / spectral reconstruction

Domain shift

New day, batch, reader or lab

External validation and adaptation

AI does not replace good sensor design, controlled sampling or traceable measurement.

Future Directions

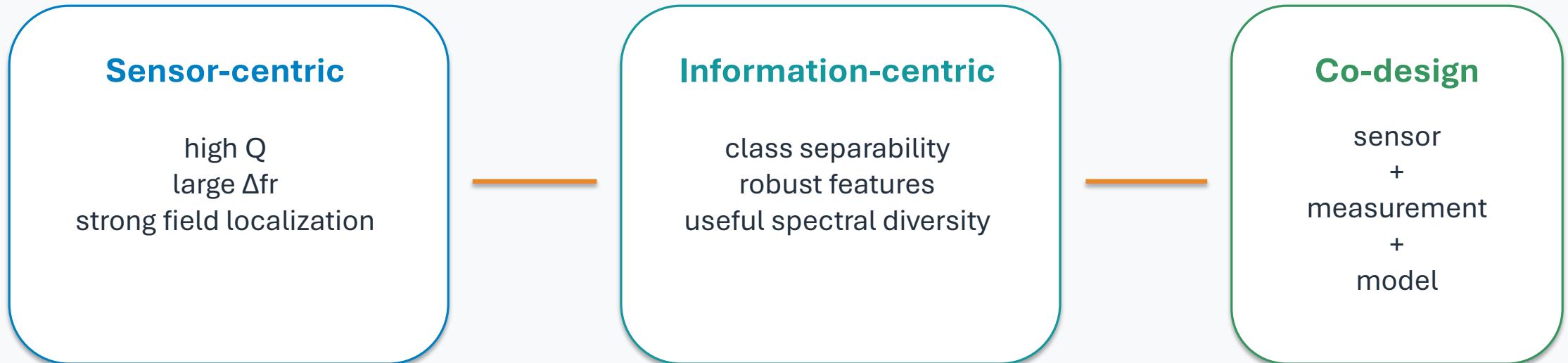
Five questions for the next generation of intelligent microwave sensing



The next slides frame future work as research questions rather than a technology wish-list.

What should we optimize: the strongest resonance — or the most informative data?

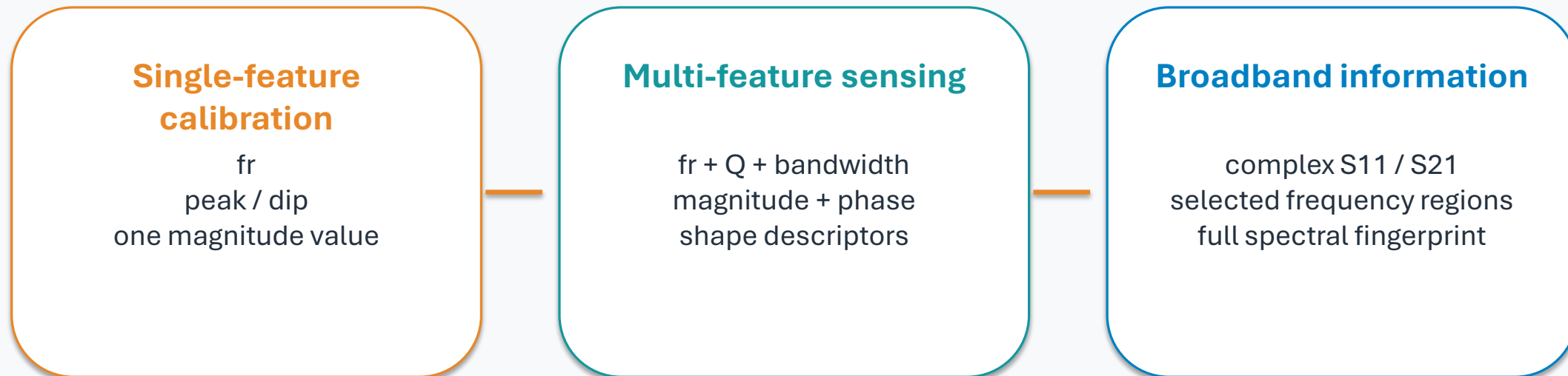
Traditional sensor design often maximizes an electromagnetic figure of merit. Data-driven sensing adds another objective: separability, robustness and information content.



Future objective: maximize useful and transferable information — not only resonance performance.

1 • From single features to information-rich sensing

How much of the measured response should a sensing system actually use?



Research questions Which features add independent information? • Which are redundant? • Which remain stable across days, batches and sensor conditions?

Methods to examine: feature selection • feature importance • dimensionality reduction • ablation studies

2 · From engineered features to full-spectrum learning

The key question is representation — not simply whether to use deep learning.

Engineered features

fr · Q · BW · magnitude · phase

Classical ML

interpretable · data-efficient

Frequency vectors

S11(f1)...S11(fn)
real / imaginary / phase

ML / MLP

preserves selected spectral detail

Full spectrum

ordered broadband S11/S21

1D-CNN / sequence models

learns local + global spectral patterns

Structured response

multi-port / array / meaningful graph

GNN — when structure justifies it

not because a plotted curve looks like a graph

Future comparison: Which representation gives the best balance of accuracy, physical interpretability, data demand and generalization?

3 • From rich laboratory measurements to simpler sensing

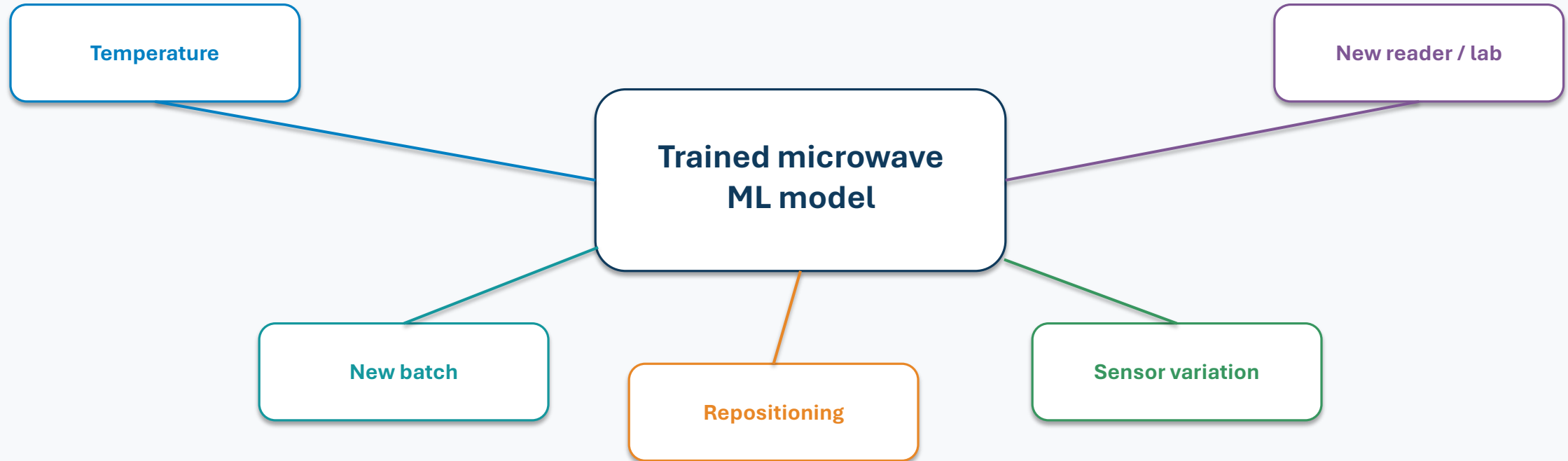
Can we reduce measurement complexity without losing decision-relevant information?



AI may not only interpret sensor data — it can help decide what the future sensor actually needs to measure.

4 · Robustness, calibration transfer and real-world generalization

A model that works on one measurement day is not yet a practical sensing system.



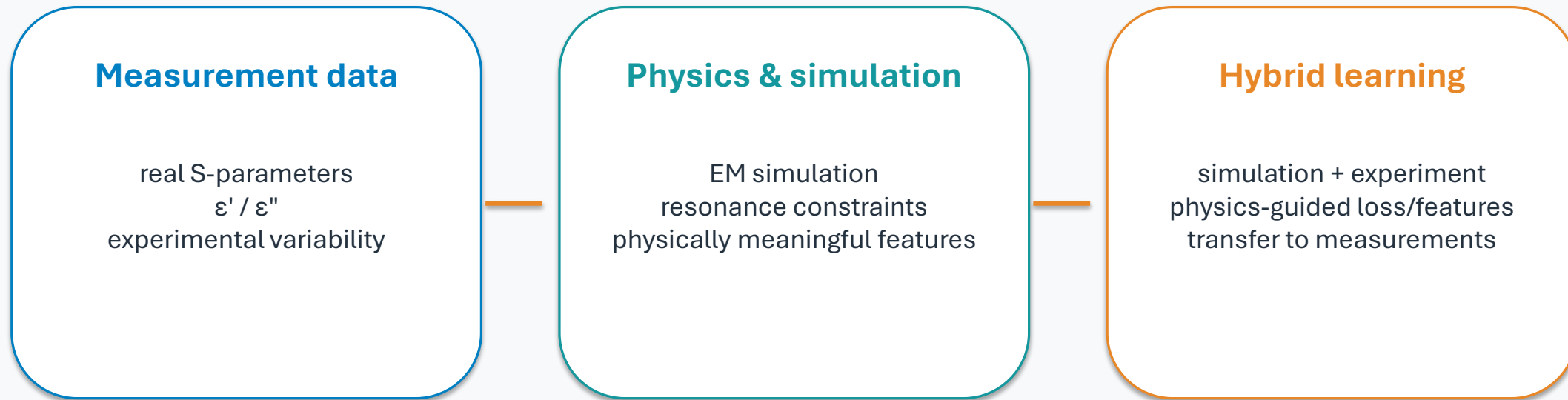
Methods to investigate

grouped / external validation · calibration transfer · domain adaptation · transfer learning · drift compensation · uncertainty estimation

Future benchmark: performance under controlled domain shift, not only random train/test splits.

5 • Physics-guided and hybrid microwave AI

Can electromagnetic knowledge reduce the amount of experimental data required by AI?



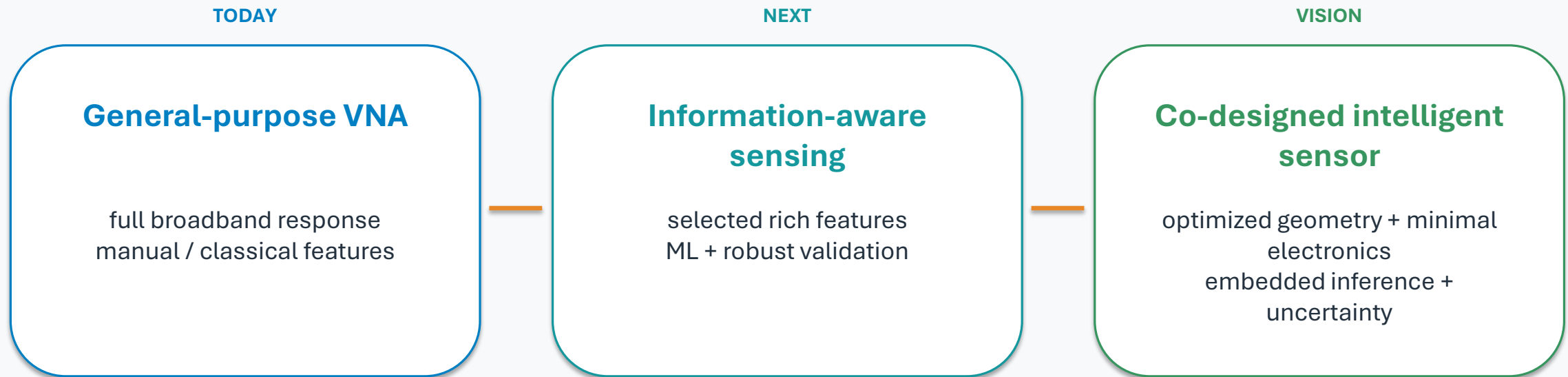
Questions worth studying

Can simulation pretraining reduce measurements? • Can physical constraints improve extrapolation? • Which physics-derived features remain useful when conditions change?

Goal: less data, better interpretability and more physically plausible predictions.

Toward intelligent microwave sensing

The research direction is a progression from measurement-rich laboratories to purpose-designed sensing systems.

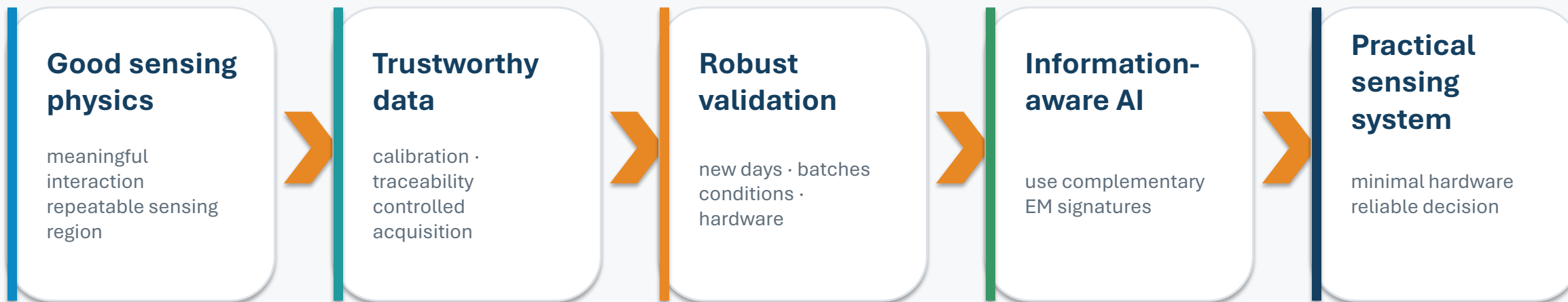


Sensor + measurement strategy + data representation + learning model

The future is not simply a smarter algorithm or a more sensitive sensor — it is their co-design.

From promising AI to robust microwave sensing

Robustness emerges from the complete sensing chain — not from the learning algorithm alone.



For microwave sensing, robustness is a property of the sensor–data–model system.

Reliable AI begins with reliable measurement — and must remain reliable beyond the laboratory.

Take-Home Messages

01

Microwave measurements contain more information than resonance frequency alone.

02

ML is most useful when it exploits complementary electromagnetic information for a clear sensing task.

03

Independent validation is essential: accuracy without generalization is not a practical sensor.

04

The future is joint design of microwave hardware, data representation and inference algorithms.

Microwave sensing + physically meaningful data + rigorous ML → intelligent sensing

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Thank you

Questions & Discussion

