

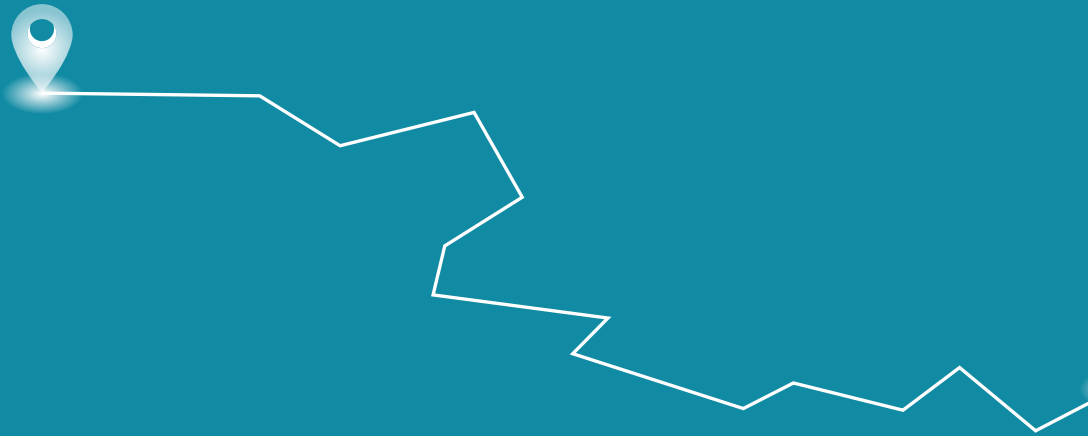
A stylized map background in shades of teal and green. It features a blue location pin at the top left, a light blue line representing a path or route, and a yellow car icon inside a location pin at the bottom right. The map is overlaid on a background of faint, light-colored grid lines.

# JOINT EMBEDDING PREDICTIVE ARCHITECTURE (JEPA) FOR 5G NETWORK-BASED LOCATION

Moving the LMF Beyond Measurement Aggregation

A TECHNICAL POSITION PAPER BY ALLERIUM





Network-based positioning in 5G has reached a paradoxical moment.

Operators have deployed standards-compliant Location Management Functions (LMFs). Regulatory requirements are being met. Reference signals are configured. Measurements are aggregated. Coordinates are produced.

And yet, in the environments where positioning matters most — dense urban corridors, indoor transitions, handover boundaries, non-line-of-sight conditions — performance remains fragile.

The issue is not measurement volume. It is architectural posture.

Today's LMF implementations are fundamentally reactive. They ingest measurements, apply geometric solvers, and output coordinates. Each session is treated largely in isolation. When measurement quality degrades, positioning degrades.

This stateless design satisfies standards. But it constrains intelligence.

The next phase of network-based positioning will not be unlocked by denser signal grids or incremental solver refinement. It will require a structural shift: from measurement aggregation to contextual prediction.

This paper explores that shift.

## The Architectural Constraint

The 5G LMF is architecturally sophisticated. It orchestrates UE measurements, manages reference signal configurations, and aggregates UL-AoA, UL-TDOA, NR E-CID, and multi-cell RTT position estimates delivering them in strict alignment with 3GPP specifications.

“ Operators with comparable signal infrastructure will achieve different positioning accuracy. The difference will not be signal density, but accumulated network intelligence.”

It does everything the standards mandate.

And therein lies the limitation.

The LMF is measurement-bound and fundamentally stateless. Each positioning session is solved largely in isolation. When measurement geometry is favorable, performance is strong. When geometry degrades — urban canyons NLoS multipath, indoor transitions — performance degrades proportionally.

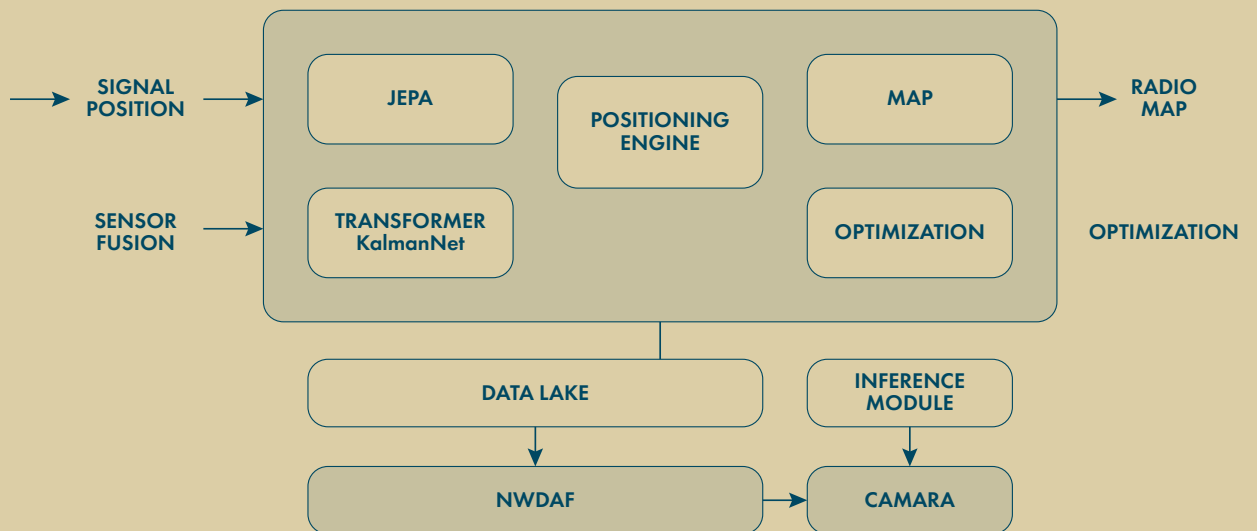
This is not an implementation flaw. It is an architectural posture.

The question is not whether more reference signals can be configured.

The question is whether a positioning system that lacks memory can ever be robust in environments defined by dynamic context.



## AI-Assisted 5G Location Management with JEPA



## Beyond Geometric Solvers: Representation Learning for Positioning

A growing body of AI research has explored an alternative paradigm: representation learning. Instead of reconstructing raw signals, these systems learn structured embeddings of the underlying world.

One particularly relevant architecture is Joint Embedding Predictive Architecture (JEPA), introduced by research teams at Meta AI.

Traditional generative models learn by reconstructing raw inputs - tokens, pixels, or signals. In contrast, JEPA learns to predict abstract representations in a latent embedding space. It asks:

- What structural properties of an environment persist across observation conditions?
- Which aspects of measurement noise are incidental rather than essential?

This distinction is critical for 5G positioning.

An LMF observes:

- Angle-of-arrival
- Beam indices
- RSRP
- RSRQ
- Timing advance
- UL-RTOA
- UE/gNB Rx-Tx Time Difference

These are high-dimensional, noisy signals shaped by instantaneous RF conditions. A model trained to reconstruct them learns noise alongside structure.

A representation-based model learns something different: it maps measurements from the same physical location - captured under different channel conditions - into a shared latent representation.

In other words, it learns the geometry of the environment rather than the volatility of the channel.

JEPA is one concrete implementation of this broader representational approach. It is not the only possible architecture, but it provides a rigorous and implementable framework for contextual prediction.



## A JEPA-Augmented LMF Architecture

In a JEPA-augmented positioning stack, the LMF is extended - not replaced.

Three components operate in coordination:

# 1

### Context Encoder

Processes the current measurement state: serving cell, neighbor deltas, beam history, timing trajectory, and UE profile. It maps these to a latent embedding representing probable spatial context within the operator's learned RF manifold.

This embedding is not a coordinate. It is a structured representation of position probability conditioned on learned environmental geometry.

# 2

### Predictor Network

Operates entirely in latent space. It projects future embeddings based on trajectory history, mobility priors, and network event signals such as handover triggers or RSRP drops.

Because prediction occurs in representation space rather than raw signal space, NLoS contamination and instantaneous fading effects are suppressed rather than amplified.

# 3

### Target Encoder

Provides the stable future embedding used for training. It leverages high-confidence geometric fixes, GNSS-corroborated sessions, or multi-source validated positioning events. Critically, it runs without gradient backpropagation, stabilizing training in a self-supervised manner.

This architecture transforms the LMF from a measurement consumer into a context-aware inference system.

“ A stateless LMF measures each session in isolation. A learning LMF models the physical world, and improves with every session.”

## Transformative Use Cases

### Handover-Resilient Position Continuity



During inter-cell handover, conventional LMF pipelines experience measurement gaps. Position continuity breaks.

A representation-based predictor trained across historical handover sequences can propagate a stable latent trajectory through this interval. The output coordinate remains continuous even when instantaneous measurement geometry is temporarily insufficient.

Emergency positioning does not collapse at cell boundaries. Fleet applications avoid abrupt spatial discontinuities.

The LMF transitions from reactive solver to trajectory-aware agent.

### Implicit NLoS Detection



Non-line-of-sight conditions introduce the largest ranging errors in urban deployments.

Rather than relying on labeled NLoS classifiers or measurement redundancy, a representation model learns that measurements inconsistent with latent spatial embeddings are statistically improbable. Outliers become detectable as violations of learned environmental structure.

NLoS classification becomes emergent - not explicitly supervised.

This reduces reliance on costly labeled datasets while improving robustness.

### Indoor-Outdoor Transition Prediction



Indoor transitions represent both regulatory risk and commercial opportunity.

A JEPA-style model trained across macro cells, indoor small cells, and DAS deployments learns the manifold boundaries between environmental regimes. When RF signatures indicating indoor transition emerge, the model activates appropriate latent priors before GNSS degradation.

Positioning does not fail at the threshold of a building. It transitions.



## Practical Implementation Path

Adoption does not require replacing 3GPP-compliant positioning engines.

- JEPA operates as an additive inference module alongside the geometric stack. Outputs are fused using confidence-weighted combination logic:
- High-confidence geometry dominates when measurement conditions are favorable.
- Representation prediction dominates when geometry degrades.

Training is conducted offline using historical session data already present in operator networks. No additional measurement infrastructure is required.

Importantly, the model is network-specific. It learns the RF topology, building density, and mobility patterns unique to that operator's deployment. This specificity creates defensible performance differentiation.

JEPA does not compete with 3GPP positioning standards. It intervenes precisely where geometric solvers reach their limits - which, in dense urban deployments, is often the operational norm rather than the exception.



## Strategic Implications

The positioning ecosystem is approaching structural inflection.

For the past decade, advancement has focused on signal expansion - more beams, denser cells, improved synchronization, refined solvers. These improvements matter, but they remain bounded by measurement geometry.

A stateless LMF will always be constrained by the quality of the present moment.

A learning LMF is constrained by accumulated experience.

This distinction is structural.

- When positioning becomes representation-driven:
- Accuracy improves as deployment history grows.
- Network topology becomes an asset.
- Competitive differentiation compounds over time.
- Compliance is achieved with margin rather than fragility.
- Commercial positioning evolves from reactive estimation to predictive intelligence.

Standards-compliant-but-stateless systems cannot match this compounding effect.

Positioning infrastructure ceases to be a passive measurement engine. It becomes a learning layer of the network - modeling the physical world and refining its understanding with every session processed.

The architecture is necessary, but not sufficient. A positioning system is only as intelligent as the spatial world it has learned to represent.

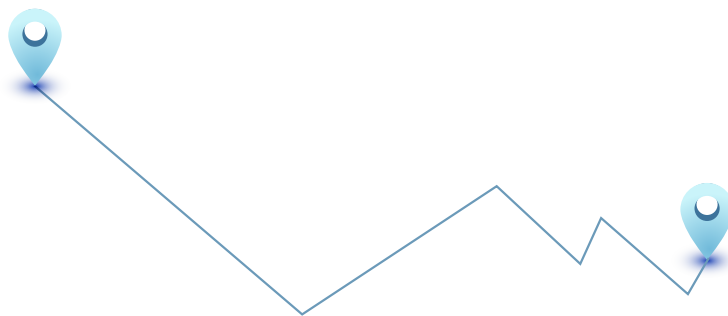
The transition from geometric aggregation to contextual prediction will define the next era of network-based location.

The remaining question is not technical feasibility.

It is architectural ambition.

## Glossary of Terms

<b>DAS</b>	Distributed Antenna System.
<b>JEPA</b>	Joint Embedding Predictive Architecture – AI architecture that learns latent representations and predicts future embeddings without reconstructing raw input signals.
<b>GMLC</b>	Gateway Mobile Location Centre – Interfaces between positioning services and external clients.
<b>GNSS</b>	Global Navigation Satellite System.
<b>LMF</b>	Location Management Function – 5G network entity responsible for calculating UE position using radio measurements.
<b>NLoS</b>	Non-Line-of-Sight signal reception.
<b>NR E-CID</b>	New Radio Enhanced Cell ID positioning.
<b>RSRP/RSRQ</b>	Reference Signal Received Power / Quality metrics.
<b>RTT</b>	Round Trip Time measurement.
<b>UL-TDOA</b>	Uplink Time Difference of Arrival positioning methods.
<b>UL-RTOA</b>	Uplink Relative Time of Arrival.



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