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| **Title\*:** | MEC036 Use case Mission critical vehicular and mobile node application |
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| from **Source**\*: | InterDigital, Inc., UC3M, NEC |
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| input for **Committee**\***:** | MEC |
|  |  |
| Contribution **For\*:** | Decision | **X** |  |
|  | Discussion |  |  |
|  | Information |  |  |
|  |  |
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| Relevant WI(s), or deliverable(s): |  DGR/MEC-0036ConstrainedDevice |
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**Decision/action requested:** Please approve

**ABSTRACT:***Use case on Mission critical vehicular and mobile node* application. This contribution presents the use case of decentralized and federated learning where resource constrained MEC devices, including some operating in dynamic environments (mobile, wireless), collaborate to collectively train a high-quality centralized learning model in a decentralized manner. This use case is being addressed in the scope of multiple H2020 projects such as 5G-DIVE *“eDge Intelligence for Vertical Experimentation”* ([www.5g-dive.eu](http://www.5g-dive.eu)) and 5GROWTH *“5G-enabled Growth in Vertical Industries”* ([www.5growth.eu](http://www.5growth.eu)).

# 1. Discussion

A new use case on Mission critical vehicular and mobile node application is proposed.

# 2. Proposal

The following changes are proposed.

**First change**

## 5.2 Use case #2: Mission critical vehicular and mobile node application

### 5.2.1 Description

Vehicular applications including remote controlling, self-driving, and platooning demand real-time decision-making under high reliability and low latency, even when network connectivity is lost. For instance, applying breaks in a platoon of vehicles or robots cannot afford millisecond range latencies. Remotely controlled vehicles must stay operational even under temporary losses of connectivity. Increasingly vehicles are being equipped with computing resources, where distributed machine learning (ML) techniques, such as Federated Learning, with minimum signalling overheads are deployed.

Federated learning (FL) is a distributed learning technique where privacy sensitive training data is generated and processed (possibly unevenly) across learning agents, instead of being transported and processed in a centralized edge cloud or distant cloud. Federated Learning allows each agent (e.g. deployed on a far edge constrained device) to compute a set of local learning parameters from the available training data, referred to as local model. Instead of sharing the training data, agents share their local models with a central entity (e.g. Edge cloud), which in turn does model averaging then sharing a global model with the agents (e.g. on the far edge constrained devices). As such, Federated Learning does not require exchanging training data, thus reducing the communication latencies.

Moving nodes, e.g., V2V, Edge Robotics or UAV Swarms, deploy decentralized learning to minimize central control and coordination. Use of low-latency distributed learning for such nodes enables real-time applications with limited battery power. Use of DMTL (Distributed Multi-Task Learning) and Federated Learning on these mobile nodes allows temporary loss of link or node failure to be un-noticeable.

FL and DMTL techniques have different requirements of local computation on the devices (including constrained devices) as well as communication interactions with the central entity. These requirements depend on convergence, accuracy, and robustness of the trained model. The resource constrained moving nodes collectively train a high-quality centralized model in a decentralized manner for different ML architectures. As operating condition changes dynamically, such as mobility, link quality, these nodes adapt and continue providing service with almost no degradation in quality and reliability.

**End of change**