INTENT-BASED DEPLOYMENT FOR ROBOT APPLICATIONS IN 5G-ENABLED NON-PUBLIC NETWORKS

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Abstract *– Cloud and edge computing, distributed AI, and most recently 5G/6G communications are coming together and changing the way we collaborate, connect and interact. A new generation of AI-powered robots are also expected to be facilitated by these digital technological breakthroughs. Robots are supposed to tackle unknown situations and adapt in the long term by collaborating, connecting and interacting with the digital world. Such applications generate versatile, perpetuated and rapidly changing transmission demands to the network. Traditional network resource management is insufficient in supporting such traffic to meet the QoS. In this paper, we go a step further, in addition to the effort on the network side for traffic engineering; we also work on the application side to shape the traffic within non-public networks. We present an initial development for the proposed intent-based deployment for robotic applications.*

Keywords – 5G vertical applications, intent-based development, robot deployment, robot learning

1. INTRODUCTION

5G and beyond is recognized as instrumental for industrial communications that help digitize the economy. The networking will shift from supporting the end users, to supporting the so-called vertical applications. 5G is in its early stages of development. The new architecture of 5G introduces Software Defined Networks (SDNs) and Network Functions Virtualization (NFV) will certainly help, however, the foreseeable challenges of supporting vertical applications is also obvious: the demand on networks to efficiently manage its resources (even if it is software defined) in order to cope with the potentially bandwidth-hungry applications with uncertain and ever-changing transmission demands. The paper focuses mainly on the impact of the SDN and NFV towards the QoE of robotics. The intent-based networking for 5G-enabled Non-Public Networks (NPNs) is realized through a middleware via the Platform as a Service (PaaS) paradigm. It enables virtual network platforms to be tailored for individual vertical applications rather than the vertical applications to be customized for the network infrastructure. The approach could further improve network applications on resource management and improving the Quality of Experience (QoE), for example enabling 5G-Enhanced Robot Autonomy (5G-ERA) by offload learning under a multi-domain multi-administration environment. The vertical-oriented approach could further improve 5G's support to intent-based deployment for future robotic applications.

The robotic applications are one of the most promising vertical applications, which are used in many sectors. The deployment of robots can benefit from 5G's SDN and NFV to scale up robot learning and knowledge sharing that was impossible in the past. The robotic application we propose and discuss in this paper requires intensive data transmission and processing, which is different from those currently demonstrated by other projects as initial proofs-of-concept of robotic vertical applications, such as: the H2020 SliceNet framework [1] 5G-Tours [2] and 5G-HEART project [3] demonstrated robotic services in smart/ connected ambulance, museum tour and healthcare with virtual network slices.

In reality, the ability to deploy robotic applications, on a large scale or most importantly, a robust application that robots can react to the real-world scenario after deployment is still challenging. Deployable robotics is about enabling robot deployment capacity in a real-world environment. Currently, the capacity is limited by fragmented intelligence and poor scalability. By formularizing a paradigm of transparent knowledge, connected intelligence and scalable skills, the key character of the deployable robotics is autonomous with the ability to tackle unexpected situations.

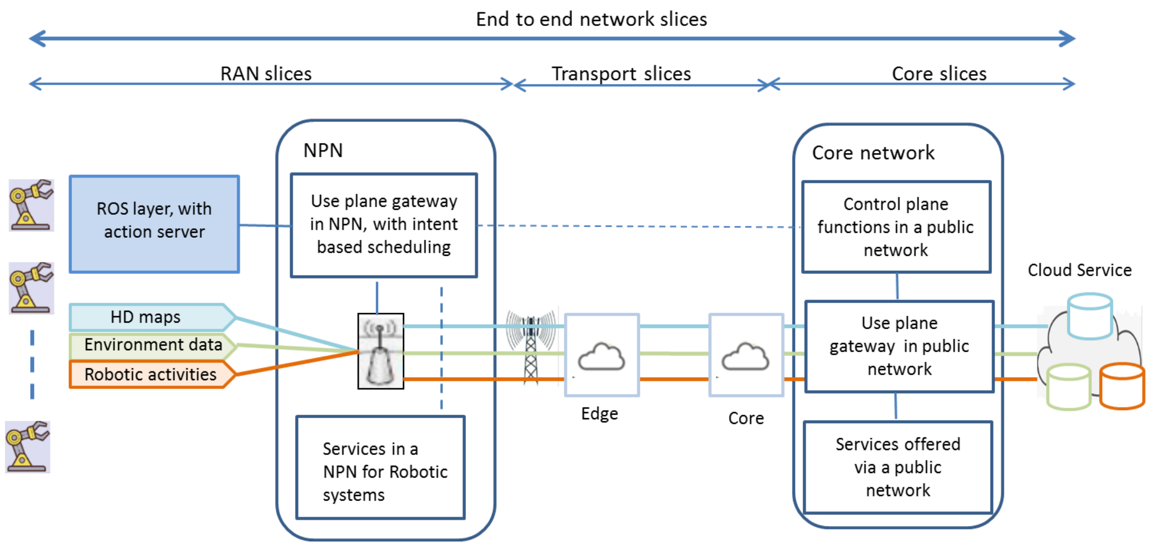

Fig. 1 – Scenario of 5G robotic application deployment with edge gateway and core gateway delimiting the transport network/slice

From a robotics perspective, an autonomous robot is essential for many 5G vertical sectors and has significance in automated mobility, Industry 4.0 and healthcare. 5G, on the other hand, has great potential for robot autonomy enhancement. It is truly enabling with respect to the shift of knowledge and learning from the individual to the collective that robot autonomy enhancement needs.

To use the potential of allowing third parties to develop autonomous robotic applications across vertical sectors, it is important and urgently needed to further develop and standardize experimentation facilities.

Our work in the EU 5G-ERA project is to tackle the challenge on the application side as well as the network side in developing middleware to facilitate the vertical application. The rest of the paper is arranged as follows: In Section 2 we explain the background and the state of the art of the research. In Section 3 the 5G-ERA overall solution is presented and in Section 4, a high-level intent-based solution is explained.

2. PROBLEM STATEMENT AND THE STATE OF THE ART

2.1 Autonomous robotic applications

5G robotic applications have received considerable attentions in recent years. While most of the research has been focused on closed-loop control, the usefulness of this approach alone is questionable in the robotics community as it overlooks a key experience of robotics, the need for robot autonomy, particularly in real-world robotic applications. By shifting knowledge and learning from individual robots to the edges and the central cloud, 5G is able to establish collective robotic intelligence, to realize and to enhance robot autonomy with the collective intelligence. For an optimized experience on individual 5G-based robot applications, 5G needs to specify and optimally allocate the collective robotic intelligence. Intent-based networking predicts the need for the intelligence from the intents and specifies policy on individual applications to deliver management, topology, placement and resource optimization within 5G cloud environments.

Existing and well-established training processes in robotics rely on complete knowledge and complete control of the environment. However, for post-deployment training, a robot most likely works in an unstructured environment (the environment is only partially known), thus, the robot cannot rely on prior knowledge about its environment; and do not have the needed skills for suitable interactions. The widely used training process to improve robot autonomy is collaboratively done by the robot with help from a remote control centre: the robot collects information from the environment and transfers it to the control centre.

The term "unstructured" means the environment is only partially known. This is a most common scenario in real-world applications.

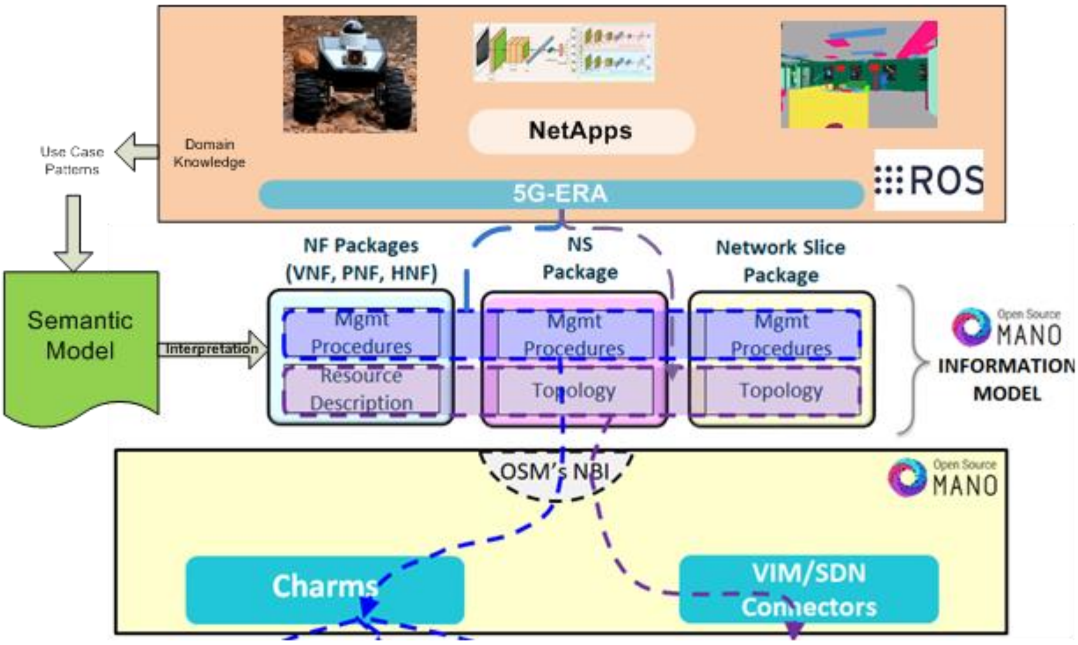

Fig. 2 – Semantic and information model used in the 5G-ERA to support Virtual Network Function (VNF), Physical Network Function (PNF), Hybrid Network Function (HNF), Network Service (NS) and network slice package

To be autonomous, the robot has to learn during its operational process. As mentioned in Section 1, due to: 1) limited computing resources, 2) safety constraints and 3) biased training data [11], the learning needs to be shifted to the cloud using 5G technologies.

The applications present perpetuated demand on network support, when the robot is in the structured condition, the need for network support (in terms of uploading data and training) is limited, but in the case of an unstructured condition, the robot needs to upload environmental data and reply on the edge or cloud to conduct training in order to cope with the unstructured scenario.

2.2 Non-public network

In the case of deploying robotic applications in the industrial environment, it is likely to be deployed within a private network, where a certain level of isolation is required for security and privacy reasons. In fact, 5G Alliance for Connected Industries and Automation (5GACIA) defined non-public networks for industrial scenarios [4]. 5G services, for vertical industries are categorized based on (i) Standalone NPN (S-NPN) and (ii) Public Network Integrated NPN (PNI-NPN). In the case of shared RAN and shared CN control plane, the only part of the NPN that remains entirely separate from the Public Land Mobile Network (PLMN) is the CN user plane. The CN control plane is provided by the PLMN, which means the: i) network control tasks in the NPN are performed in the MNO's administrative domain, and ii) NPN devices are by definition public network subscribers. In this scenario, segregation of non-public and public traffic portions can be achieved by means of 3GPP-defined mechanisms, including network slicing.

PNI-NPN enables the public and private network services to verticals by allowing E2E (isolated) networks, e.g., using a network slicing feature. In the PNI-NPN framework, provisioning of private 5G networks is enabled by network slicing to facilitate various use cases of private networks ranging from enterprise to military applications.

In the PNI-NPN, basically the operations of network, network services and resources can be governed by a PLMN operator. However, it is essential to study the end-to-end operational capabilities required or supported by the NPN. How the sensitive NPN devices or subscriber's data/data traffic can be managed and controlled in PNI-NPN taking into consideration deployment options, architectural aspects and isolation requirements. Fig. 1 illustrates the deployment scenario of the 5G robots under an NPN.

2.3 Network resources allocation

Vertical application requirements are versatile and changing, maybe rapidly over time. In addition, some requirements are new to the network.

For example, in the case of deterministic end-to-end delay, the delay has precise requirements and it may be task-based. The network normally deals with delay based on traffic type, and guarantees the Quality of Service (QoS) for the type of traffic. Traditionally, network resource allocation is achieved by the network providers (e.g., operators) via techniques, such as access control, traffic shaping and traffic scheduling on the network side. Finer control over the scheduling needs precise knowledge of the available and needed resource. The Network Data Analytics Function (NWDAF) [5] are added as an additional standard in 5G for supporting resources allocations, powered by AI-based data analysis [9-10].

In this paper, we go a step further, in addition to the effort on the network side for traffic engineering, with AI-based prediction, we also work on shaping the traffic within the non-public network. Imagine there are 100 robots in an industrial site, the tasks for each robot are different, and in order for each robot to work properly, some need extra help, such as training, which may involve communication with the cloud. A balancing and shaping within NPN can only be done by the application and within the NPN.

3. THE OVERALL 5G-ERA PROJECT IDEA

As shown in Fig. 2, a reference cloud native NetApp will be implemented in the project to: 1) demonstrate the services composition in 5G-enhanced robot autonomy; and 2) support continuous deployment and integration offered by a cloud-native application. To realize the cloud-native design, generic vertical services will be implemented using microservices. The service definition can be obtained using the reference catalogue service. The service can be ordered and replicated using the reference order service. The applications within the library of generic vertical services can be developed using a Robot Operating System (ROS) directly. Low-level events obtained from testbeds will be propagated on the event bus and translated by a semantic interpretation engine for high-level meanings. The capability ensures interpretability. Third party vertical developers can reuse VNFs and KNFs of the generic vertical services which have guaranteed compatibility from the testbeds. Therefore, the experimental facilities are encapsulated to the developer. They are ready to be expanded for use case-specific functions in the project, such as 5G-enhanced perceptions, detection and planning in vertical sectors.

Without a loss of generality, a simple scenario of the autonomous robot deployed in an unstructured workspace is illustrated in Fig. 3. The term “unstructured” means the environment is only partially known. This is a most common scenario in real-world applications. To be autonomous, the robot has to learn during its operational process. As mentioned in Section 2.1, due to: 1) limited computing resources, 2) safety constraints, and 3) biased training data [6], the learning needs are to be shifted to the cloud using 5G technologies. The workflow of 5G-enhanced robot autonomy follows a Plan–Do–Check–Act (PDCAt) model, where “plan”, “do” and “check” are carried out virtually in clouds, and the “act” is performed in a real workspace by a robot. The mechanism could take the best advantage of the computing resources on the cloud. By trialling virtually, it avoids safety constraints. Moreover, the virtual environments are always updated with data coming from the real workspace enabling the so-called “Digital Twin” (of the robot, of workspace and operators) that can be used, not only for online real-time warnings and feedback, but also to carry out what-if analysis and support the decision process and/or the optimization of the robot operational environment. Thanks to the 5G technologies, cloud and robots can be linked closely together for a collective intelligence. The robot sends its sensing data to the cloud, and updates the local decision model via the cloud. It has to be noted that real-time communication is not always essential for autonomous robots in this workflow due to local intelligence. The autonomous leads to a high tolerance on the placement of the service components, which is important for resilience of the applications.

Referring to Fig. 3, a typical workflow is listed as follows:

- A robot is placed in an unfamiliar environment, it checks with MEC for more up-to-date information for the environment.
- The information is not available; the robot connects to the cloud for help.
- The robot sends a large volume of dense data (of point cloud) to the cloud continuously, as illustrated in steps 1 and 2 on the right-hand side of Fig. 3.

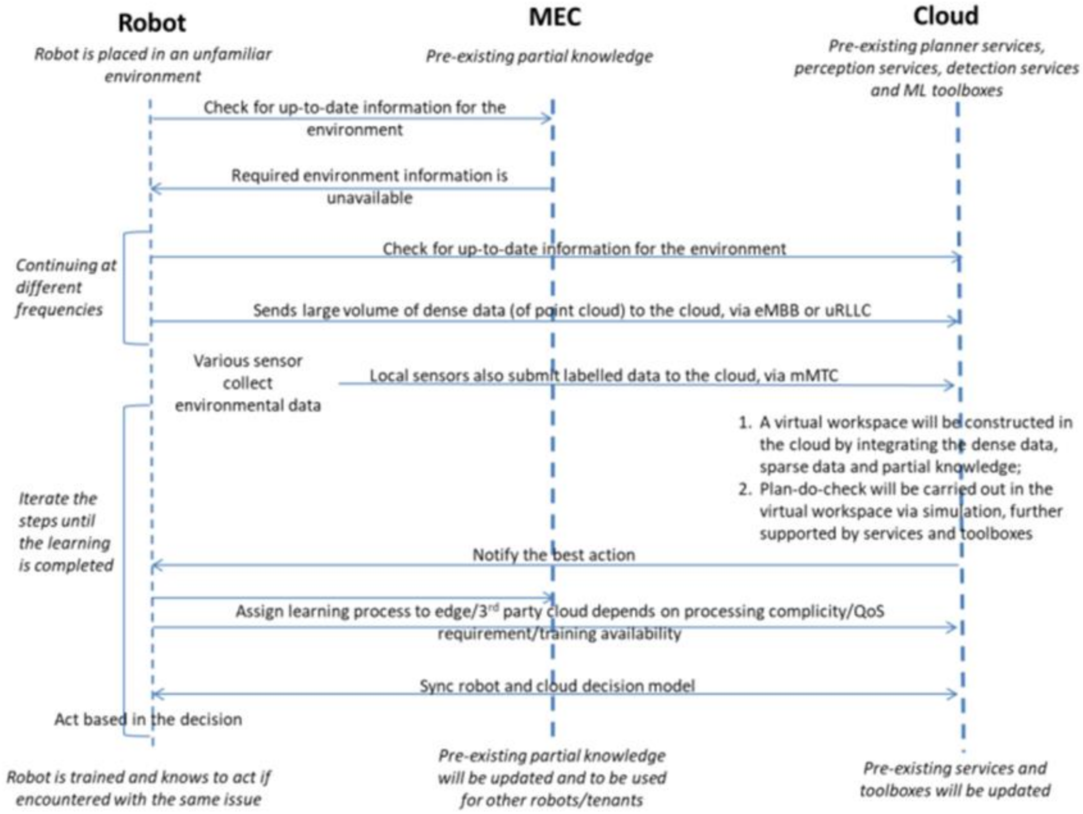

Fig. 3 – Workflow of multi-domain learning process

- Local sensors and IOTs also submit labelled data to the cloud, however in different frequencies with much less volume.
- Pre-existing partial knowledge is available and stored in the edge.
- A virtual workspace will be constructed in the cloud by integrating the dense data, sparse data and partial knowledge together.
- To identify the best action; the “plan”, “do” and the “check” are carried out in the virtual workspace via simulation. “While the virtual workspace will provide a real-time updated view of the robot and its workspace (through its digital twin), the plan, do and check are executed thanks to a dedicated simulation layer (where simulation is executed in a fast time to provide quick results). This is further supported by planner services, perception services, detection services and ML toolboxes in the cloud.
- Depending on the problem complexity and the QoS requirements, the learning process can also be transferred to third party cloud services (such as AWS RobotMaker and Google Cloud AI) in different domains.
- A robot’s local decision model is synchronized with the cloud model; the robot “acts” in the workspace based on its local decision model.
- After a few iterations, the learning will be completed. The result will be stored in data centres for future knowledge discovery and reuse. The pre-existing partial knowledge on the edge will also be updated in case it is required by other robots or tenants visiting the same site.

The cloud side of the training is focused on experience replay rather than knowledge generalization. The difference between the experience replays and the generalization is that the replayed experiences are propositions only. They are highly likely to be fake. Therefore, multiple predictions should be generated at the same time, and further verified by robots during the “plan”, “do” and the “check” processes.

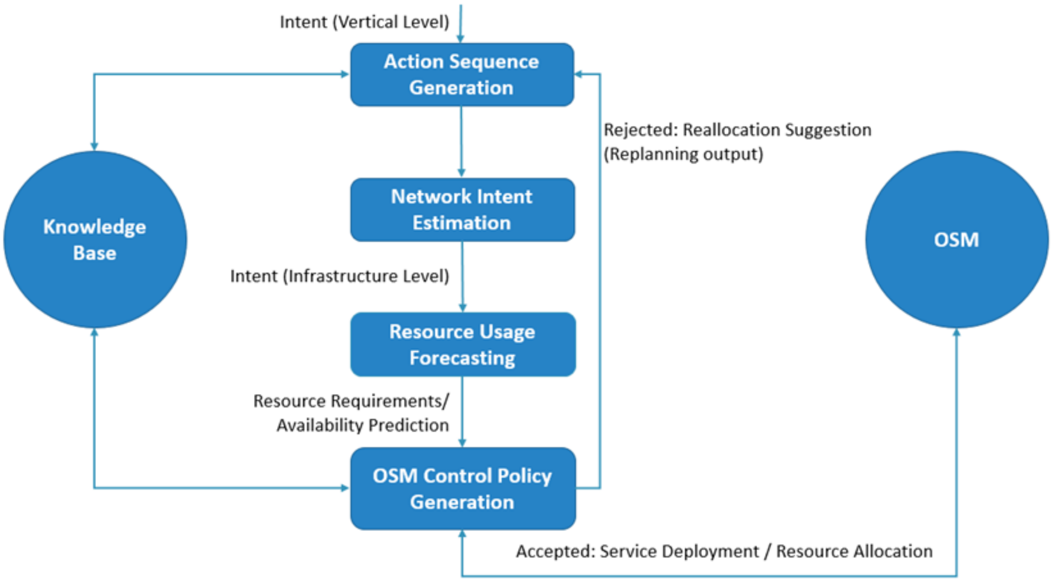

Fig. 4 – Workflow of developed tools for intent-based management

To enable faster learning, there are two possible approaches for cloud-based experience replay:

1) Replay the experience through meta-learning: meta-learning has been developed for connecting previous observations with new evidence. It produces meta-models which replay previous observations. The paradigm enables knowledge to be connected among situations without predefined symbols. With meta-models in hand, the cloud side of the training could recognize new situations in another word, making hypotheses with very little evidence (small samples) based on the old observations.

2) Replay the experience through meta-reasoning: by projecting experiences from complicated action space into a limited reward space, meta-reasoning can be used for evaluating existing policies stored in the cloud. The policies are originally generated by robots in other environments.

Due to the scope of this paper, the approaches are not further elaborated.

5G-ERA uses domain-driven design to address the challenges through the following steps:

- Translate the unstructured vertical intents at the task level into the structured vertical intents of robot actions.
- Map the structured vertical intents of robot actions into placement and instantiation of containers, which shapes the resource requirements on the network level.
- Align the networking requirements based on the vertical intents to procedures on the testbed level with 5G-ERA Machine Learning (ML) toolboxes.
- Integrate the intents with an existing orchestrator such as Open Source MANO (OSM).

The main purpose of this paper is to present our initial work on managing the intention of the individual customer, in order to manage traffic within the non-public network, and shaping traffic before it leaves the non-public network.

4. INTENT-BASED – THE CONCEPT

Intent-based networking captures users' (vertical customers) intents and aligns continuously the E2E networking to the recognized intents. It is the solution of optimizing the QoE of 5G orchestrators for vertical applications and essential for improving QoE in the targeted verticals.

The 5G-ERA project is on the user-centric paradigm of integrating vertical knowledge into the existing standardized 5G testing framework to improve the Quality of Experience (QoE) for vertical customers.

Fig. 4 shows the workflow of the intent-based process. Action sequence generation and network intent estimation are undertaken on the application side. Resource usage forecasting and OSM control policy generation are the tasks embedding in the OSM and is managed by the slice provider. The network side of tasks are out of scope of this paper.

Here is a list of definitions used in the paper:

1) *Actions* represent the capability of the robot on solving specific and predefined problems. They are structured intents to be used for interpreting the vertical intent of robots.

The capability of a robot such as move base, SLAM and detection, are stored as containerized functions with respective preconditions, and post-conditions for orchestration. They are the vertical level of the Virtual Network Function (VNF) or the Physical Network Function (PNF). Examples are: move base (PNF), and door detection (VNF).

2) *Resource configuration of an action*: Placement of the VNFs, expected QoS, expected QoE move base (on robot platform) SLAM (on edge) door detection (on cloud).

For recognising and interpreting the intent of vertical applications, 5G-ERA uses Knowledge Base (KB) to store structured and unstructured data regarding the autonomous robots. To better understand the data, semantic technology is integrated into the KB for mapping unstructured semantic relationships into structured logical relationships. In particular, the knowledge graph [7] is applied in the 5G-ERA semantic KB to encode the semantics within the data.

3) *Quality of Experience (QoE)*: QoS has been widely used in networking in order to distinguish the different types of traffic, and to deliver the relevant traffic to meet the requirements. To ensure this, network operators are making continous effort in ensuring an appropriate environment that all traffic will be delivered, based on its characteristics under the availability of the network resources. However, from the use perspective, the effort made by networking may not fully benefit the end users. That is, the user experienced delay, bandwidth may not actually meet the requirement even though from the network perspective the QoS is met. QoEs could be determined by a single QoS, the decreased satisfaction and the loss of performance due to experience blocking.

To quantify the vertical experience with a network service (VNF/PNF): For QoEs that need to be determined by multiple QoS, a cookbook is defined using a domain-driven design. A cookbook contains many recipes as templates. They are prepared for the vertical with multiple concurrent applications. A 5G-ERA semantic KB has created a schema to describe possible building blocks (such as a 'Robot_Edge' node type, an 'Edge' node type or 'Cloud' node type) of applications. They will be used in the model for constructing a behaviour template together with QoE models. The type system is then used to define service templates (robot service, edge service, and cloud service) to improve the QoE.

4) *Actor*: A place to hold the VNF or PNF. Examples of actors are cloud, edge and robot platform. A robot platform is different from the robot in this document. It is the computing platform, which holds the corresponding VNF and PNF.

5) *Predefined semantics*: Predefined semantic relation to realize a specific reasoning process. For making decision and queries, RedisGraph could be a good candidate to support the inference.

6) *Semantic graph for task planning*: Map the given task into a list of actions.

7) *Semantic graph for resource planning*: Map QoE of actions into a configuration of the actions (Placement, QoS of VNFs/PNFs etc.).

5. INTENT-BASED – THE DEVELOPMENT

Given a task, action sequences chained by VNFs and PNFs need to be instantiated and placed according to a logical relationship between containers and images. The 5G-ERA knowledge base manages the semantic relationships dynamically in the forms of planning graphs, predefined state machines and user-specified policies, and realizes the corresponding logical relationship. This process will be further optimized by machine learning tools via intelligent resource prediction and planning. The intent-based networking is realized by a 5G-ERA[1] middleware using microservice architecture. The main components of the middleware are:

Gateway: It redirects the traffic across the middleware system meaning rerouting to the microservices within the system. It also handles the authentication and authorisation process.

Action planner: It integrates the semantic knowledge (predefined as planning graphs) of the vertical into resource planning. It is part of the vertical level lifecycle management implemented by the middleware.

Resource planner: It is responsible for assigning the placement example (again predefined as planning graphs), on the cloud, edge to the tasks.

[1] https://github.com/5G-ERA

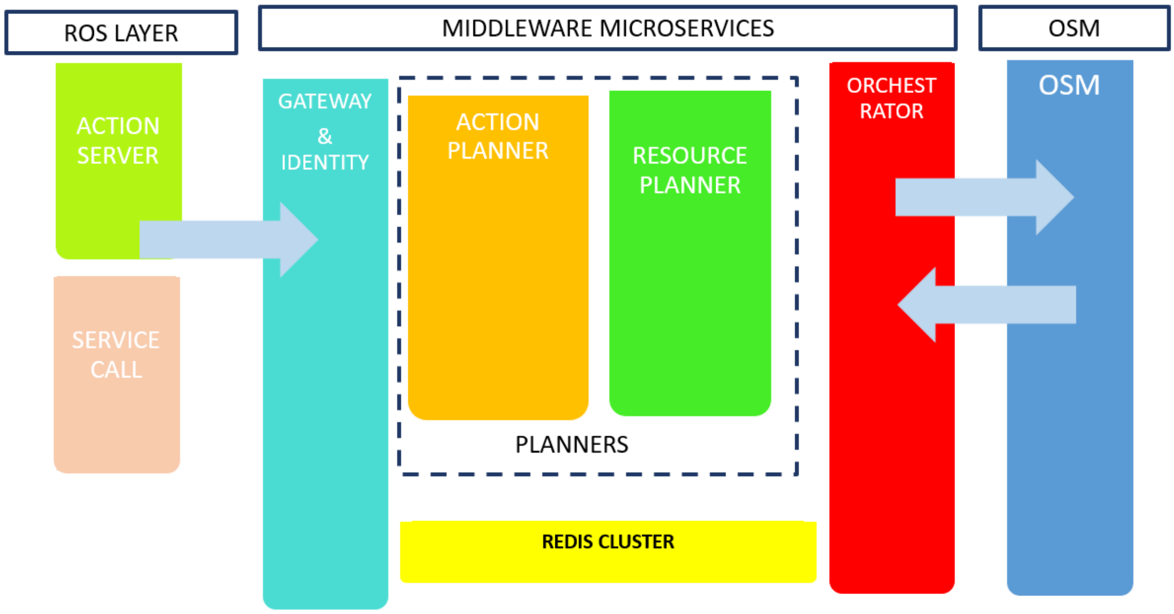

Fig. 5 – Realization of QoE by translating vertical intents into QoS network requirements

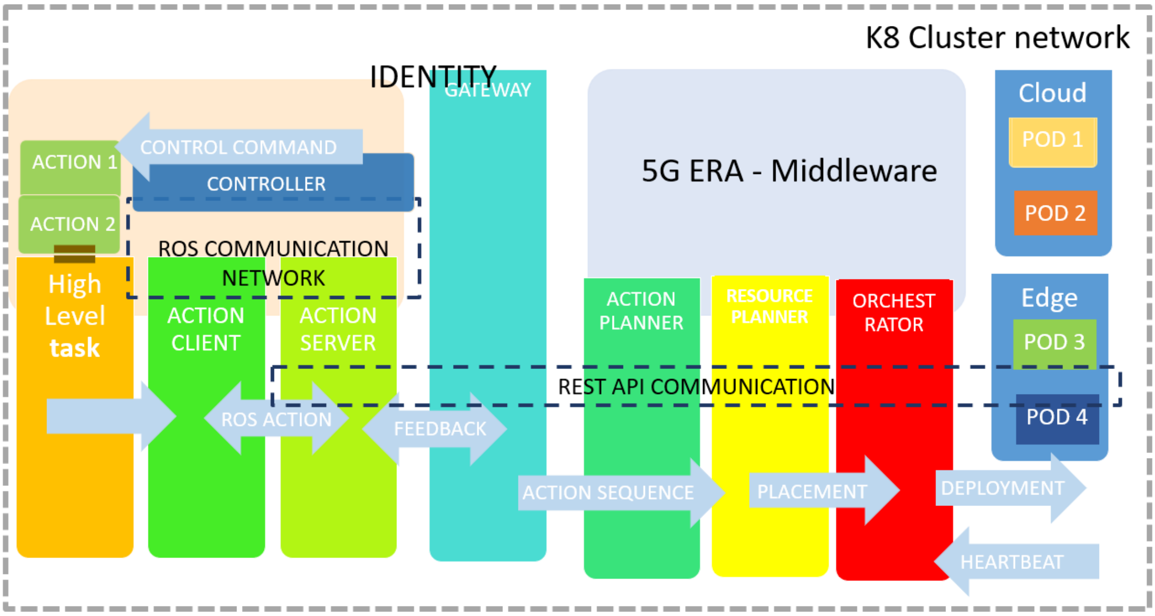

Fig. 6 – QoE transformation pipeline from high-level vertical tasks to resource management

Orchestrator: It orchestrates the process of the deployment of resources. It is responsible for the vertical level lifecycle management of the deployed services.

Redis interface: It allows the users to retrieve, insert and update data from/into the Redis-Server.

Fig. 5 illustrates the interaction of the microservices to realize the intent network structure developed in 5G-ERA. A typical workflow of the intended-based deployment which translates QoS features into QoE of the robot is illustrated in Fig. 6. High-level tasks on the left-hand side are converted into ROS action goals and linked to the gateway for registration and the security token. The action planner and resource planner decompose the tasks into a structured resource plan and realize the corresponding virtual service platform according to the plan using the orchestrator. The virtual platform enables the on-demand instantiation and the placement of the VNFs and PNFs during the task execution.

5.1 Network deployment scenario

The development of the semantic tool is technically complex. The major challenges include:

- A robust reasoning mechanism is needed for unstructured information. 5G-ERA needs an information model to properly accommodate the unstructured data produced by the scenario actors. This data needs to be sorted according to a model that will translate the unstructured data into structured information for future processing.
- 5G-ERA faces multi-objective optimization problems. The semantic reasoning will help us to optimize vertical actions by ranking the possible actions' sequence in a sorted array by a predefined policy. The action sequence will be further optimized to accomplish resource requirements and placement.
- A flexible reasoning mechanism for dynamic and sophisticated relationships. Relationships in 5G-ERA environments are expected to be complicated and highly dynamic. A robot might switch from one edge to another; the expected relationship in a given environment might be dynamically changed to an unexpected case. The action planner needs to handle the sophisticated cases.

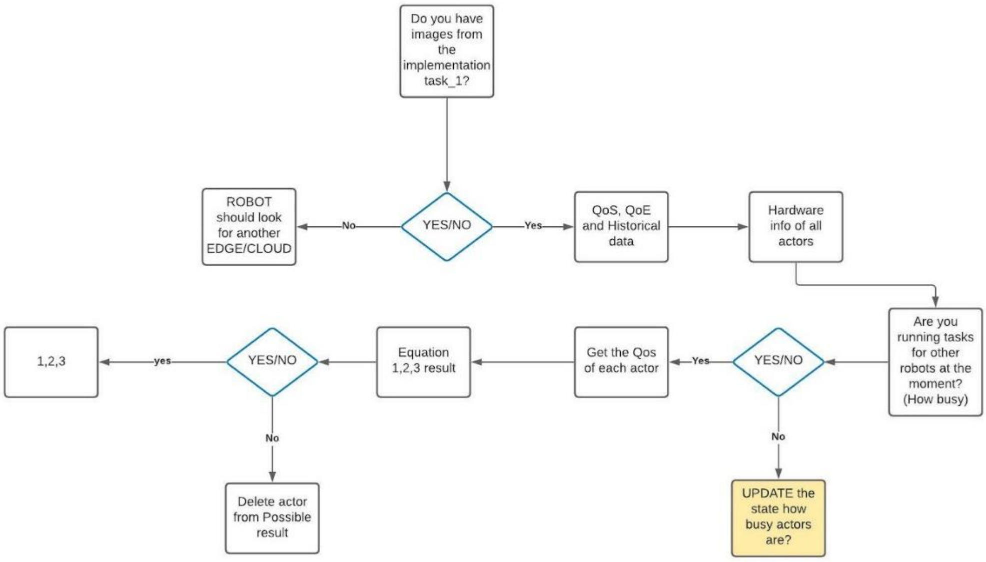

Fig. 7 – State machine behind the resource planning

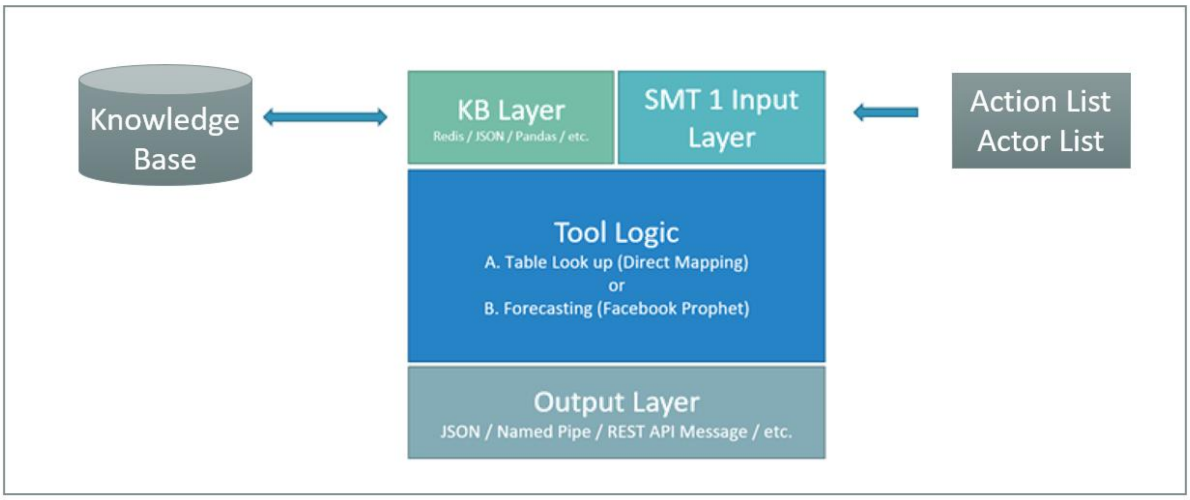

Fig. 8 – Modular design of the toolbox for mapping intent to resource usage

5.2 The action planner example

The action planner will divide the high-level tasks into a low-level algorithmic actions sequence that will be fetched to the resource planner allocation system later on. We illustrate with an example task: go-to-kitchen. In particular, we use an action planner.

An abstract model defines all possible states that the system can be. Transactions are defined to specify how and by which conditions one state of the system can change to another. By this, tracking of all states is performed and simple logical operations can be done. The following are some states of a 5G-ERA state machine, as shown in Fig. 7, for the task of the go-to-kitchen:

- Robot does not know position [state 1].
- Robot knows position [state 2].
- Robot is localized in a map within a cartesian space [state 3].
- Robot knows map but not the position [state 4].
- Robot is located but not in the kitchen [state 5].
- Robot is located and in kitchen [state 6].
- Robot needs to create a map because 5G-ERA does not have one [state 7].

5.3 Semantically define the tasks

Mapping intent from vertical applications to individual Quality of Service (QoS) requirements through action sequence generation is essential to network management and resource planning. Every provided robotic service has its own QoS requirements with respect to its purpose and implementation. The QoS demands may differ based on the location (ROBOT / EDGE / CLOUD) of this service, and even based on the requesting actor. Each actor (robot) may have a different set of sensors, and QoS may vary due to different resolutions of the camera, bit rate, frame per second, etc. This set of QoS indicators creates a Knowledge Base (KB), and is source information for mapping intent to resource usage.

For intent-based networking in the context of 5G-enhanced robot autonomy, the goal of this tool introduced in the section is to predict expected QoS and placement of the Kubernetes Network Functions （KNFs) / Virtual Network Functions (VNFs) according to recognized robot intent.

5.4 Mapping the intents

The main idea of this tool is to translate robot intent to resource requirements using provided knowledge base and historical data optionally. The semantic and machine learning tool performs individual resource planning through two independent mechanisms.

Static mapping is the default variant, which is based on deterministic table lookup according to predefined information in the KB. Lookup is performed with respect to a requested service and actor, if available. In a case where there are multiple records, the mean value of each metric is reported as part of the expected QoS. The same applies in case that historical records are provided.

Forecasted QoS exploits multiple records for each service with respect to the timeline order of these records (time-series), their seasonality, influence of holidays and forecast uncertainty. Authors in [8] presented a framework called Facebook Prophet for forecasting at scale.

Fig. 8 illustrates the modular design of the toolbox for mapping intent to resource usage. The core part (tool logic) implements both planning mechanisms. The Knowledge Base Layer (KB Layer) is designed to handle multiple data sources, as well as the Output Layer which may report results in multiple ways. Semantic Tool 1 Input Layer (SMT 1 Input Layer) takes a list of actions and a list of actors produced by the tool described in Section 3. In its current form of toolbox, inputs and outputs are handled through the REST API.

6. CONCLUSION AND FUTURE WORK

This paper presents our initial attempt in intent-based deployment for robot applications in the 5G-enabled non-public network with the aim of managing and shaping traffic before it leaves the private network. This approach is generic, but the intentions need to be defined with domain knowledge. This is additional to network resource management approaches that are used at the network side.

In the future, the approach will be tested and evaluated under various scenarios in order to provide further recommendations.

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