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Automating End-To-End Service Delivery In Telecom Using Infrastructure Orchestration And AI-Powered Policy Engines

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The telecommunications industry undergoes a technological and business-driven evolution, influencing how communication services are delivered and consumed. State-of-the-art service providers leverage virtualization and cloudification technologies to accelerate solution deployment, reduce CAPEX and OPEX, and enable novel services and business models. Network function virtualization and software-defined networking are employed to orchestrate the hybrid deployment of virtual network functions on cloud infrastructure. End-to-end service orchestration processes may span multiple technological domains, such as the OT and IT domains in telecommunications and IT industries, respectively. This is a prerequisite of Edge cloud scenarios, in which application and service functions are distributed across different locations. Moreover, the mere implementation of automation solutions on specific domains may not be sufficient to diminish OPEX and improve service management efficiency. Therefore, the unified management of heterogeneous domains is a must, and several orchestration stacks are proposed with the goal of orchestrating hybrid resources across multiple vendors, technologies, and problem domains.

Telecommunication service delivery is a complex process that spans multiple domains and involves multiple stakeholders and system components. The automation of end-to-end service delivery combines existing automation solutions, adapts them or introduces novel solutions, which enable the automation of technical processes that are currently performed manually. A study is performed on the state-of-the-art of automated end-to-end service delivery solutions and systems in the domain of telecommunications, which assist the transition to a fully automated state. This includes orchestrating and automating the processes of a complex end-to-end service delivery in a real-world telecommunications infrastructure with commercially available solutions. The focus is on critical challenges in current solutions and systems, and suggestions are provided for research opportunities. Ultimately, the goal of telecommunications automation is to enable end-to-end business processes to be automated from the moment the service request is made by the customer until the moment the service is put into operation.

In a fully automated network, the objective is to enable an end-to-end service delivery without human intervention. A human user can interact with the GUI provided by the service portal to create a service request. The service request is typically in the form of a high-level description of the required service (service model). This service model is then transformed into a solution design model via a transformation. A solution design model provides sufficient and complete information to provision the requested service. A high-level solution design model is then refined into a set of provisioning parameters that can be directly used to provision the requested service.

Keywords: Telecom Automation,Service Orchestration,End-to-End Delivery,Infrastructure Orchestration,AI Policy Engines,Network Automation,Service Assurance,Zero-Touch Provisioning,5G Network Management,Intent-Based Networking,Closed-Loop Automation,Machine Learning in Telecom,Operational Efficiency,Dynamic Resource Allocation,Telecom Cloud Infrastructure.

1. Introduction

Once service provisioning has been automated in a telecom operator's networks, an observing AI-powered policy engine needs to assess the situation of a service periodically to identify performance degradation and, based on that, automatically orchestrate actions to fix the situation by applying a sequence of dimensional actions like scaling in/out or modify the topology of the service. This requires a holistic approach, given the need to observe the overall chain of services spread across multiple network and IT domains. With the orchestration of the "ad hoc" chain of connected observability capabilities, this monitoring will comply with performance-level agreements. The output of each extensible observation capability is fed into the AI-based policy engine. It generates a description of the service performance state, a description of any detected problems, and the orchestration of actions to execute against the service: where, when, what and how. The key orchestration process assembles the actions into a workflow and translates them into the appropriate application programming interface calls of each target orchestrator.

Next, the orchestrated actions must be executed. An execution monitor observes the orchestration's progress and logs the outcome of each orchestrated action as they are executed. The observability and AI-powered policy engine orchestrators can be very heterogeneous. Policies and the observability chain generated by the AI-powered policy engine can be made extensible throughout the network, and these platforms can also be interoperable with other products. Timely responses will depend on the execution of the observed actions and measured service performance after its execution. AI-powered policy engines are designed to run in a single network domain. Network and IT cloud orchestrators will need to cooperate in a federated manner to manage orchestrated actions at different network domains.

Service observability, orchestration and remediation capacities need to be in place to ensure an operative predictive and proactive network and IT cloud IoT edge service delivery for high impact use cases like autonomous driving, tele-surgery or real-time industrial process remote supervision . This framework is demonstrated with their hybrid observing AI-powered policy engines, orchestration engine and extensible observability capacities. Full stacks automate all the necessary capabilities across the different network and compute domains for detecting the situation of network and IT cloud services, diagnosing their cause, deciding and orchestrating actions to recover the service if necessary, and executing the actions.

Fig : 1 AI in Telecom Industry

1.1. Background And Significance

End-to-end service delivery in Telecom has become extremely complex with networks evolving, adding a rapidly growing number of network elements and functions, and new modes of service delivery introduced by networks. This has made the traditional, manual service delivery processes untenable. These processes need to become automated end-to-end embracing not only the telecom networks, but the IT, vertical applications, and service orchestration domains as well. For this, effective collaboration of industry players across the value chain is required, which is challenging as stakeholders do not want to share their precious assets. As a workaround, the Telecom and IT domains can collaborate by orchestrating their common infrastructure to deploy the virtualized telecom assets. Such collaboration is useful as it is in the interest of both domains since telcos are interested in automating the end-to-end service delivery of telecom services, and cloud and IT domain players are keen to find new applications for their infrastructure in light of the declining investments, margins and revenues of these domains.

Infrastructure orchestration is a solution that provides a standardized northbound interface to clients to automate the management of the infrastructure resources, isolating them from the heterogeneous underlying low-level equipment. It handles the resource management and processing, and enforces policies that are specified and expressed as rules. It is implemented by the infrastructure abstraction and the API platform, AI-based policy engine component. Collaboration of the orchestration and the policy engine creates a standard-based, AI-enabled, efficient control mechanism to enhance the infrastructure utilization and performance while ensuring the enforcement of the policy rule objectives. With the help of the semantic reasoning capability, complex policies composed of multiple atomic rules can be expressed formally. This collaboration provides an intelligent and extensive means to automate the deployment, evolution, optimization and assurance of network services on the infrastructure resources in an integrated manner [3]. This is beneficial to both domains as automation of a single process can improve the utilization and efficiency of the respective domain resources, shortening their end-to-end process time. The implementation of the control mechanism enhances the event-driven responsive capability of the cloud and telecom infrastructures. This is of significance to the timely assurance of an on-going process where events are threats for SLA violations that could degrade the performance or experience of the end user, and even incur penalties .

Equ : 1 Resource Orchestration Equation

$$\sum_{j=1}^{m} A_{ij} \cdot d_{ij} \leq c_i \quad \forall i \in \{1, ..., n\}$$

Where:

- d_{ij} is the demand of resource r_i by service s_j,
- c_i is the capacity of resource r_i.

2. Overview of Telecom Service Delivery

Automating end-to-end service delivery in telecom using IA-powered policy engines and NFV orchestration can be performed in three consecutive phases. First, with large-scale industries for telecom service delivery where all procurement and installation steps are performed automatically, orchestrated by IA engines, and their policies are optimized. Secondly, services are intelligently learned and are, in turn, leveraged to assist manual service delivery. Evolving from TEC to small office/home office, the automation progress remains in the first phase but with different requirements for infrastructure landscapes and service demand patterns. Commercialization also plays an important role in the evolution, of which the current stage is transforming a vendor-centric market to an open cloud-based market, or internet-based telecommunications where the cloud is promised to be open and equitable with no gate-keeping or constraints from proprietary technology or policy. Hence, dynamic management policies for telecom service delivery are to be automated and standardized involving open and federated infrastructures.

With the rapid development of cloud computing, telecommunications and IT capabilities are converging. Telecom carriers are plunging into data service provision, while data service providers and technology companies have, in turn, been deploying their own networks. As a result, multiple telecom and IT cloud infrastructures from various vendors engage in the automated service delivery process, where hardware and software decisions are hard-coded or opaque to telecom attendants. The closed integrations and heterogeneous systems pose challenges for maintaining stability and mutual interoperability, leading to service downtime, unnecessary outages, wasted resources, and unfavorable advertisement. In such federated infrastructure landscapes, generic telecom and IT service delivery policies are desired to guide the orchestration of automated and intelligent service delivery processes.

Equ 2: AI-Driven Policy Engine Decision Function

$$a_t = \pi(\vec{x}_t) = \arg\max_{a} Q(\vec{x}_t, a)$$

Where:

- $Q(\vec{x}_t, a)$ is the expected reward for action a in state $\vec{x}_t$

3. Challenges in Traditional Telecom Service Delivery

Modern telecom service delivery is complex, involving diverse and heterogeneous technology domains and business processes. As a result, end-to-end delivery of telecom services requires orchestration capabilities across many separate systems and interfaces, belonging to different technology domains and possibly even telecom operators. This heterogeneous nature represents a significant challenge to orchestrate on a coordinator level, with technology and business process fragmentation accounting for the absence of an end-to-end umbrella orchestrator. Additionally, services that span different technology domains often need to comply with strict quality parameters, such as bandwidth and latency compliance, making the required resources costly and scarce. Even if explicit resource constraints are met, intra-domain resource provisioning often relies on coarse and static configurations, making the meeting of final parameters challenging. Finally, orchestrating across technology domains tends to focus on network and platform resources, neglecting system resources for virtualized functions, servers, and storage. As telecom services move toward a model in which a flexible software ecosystem continually adapts to load and topology changes, the scope will expand to include on-the-fly changes to technology domains, load and topology conditions, and underlying business policies. The increasing sophistication will require AI-powered engines to provide a unified view and a robust governing hand, capable of managing the constant change and underlying complexity and keeping the system behavior within the boundaries of network operator goals, resource availability, and regulatory conditions. Recent moves toward software-defined telecom network infrastructure allow for much simpler optimization and adaptation of key functions, enabling a wide range of autonomous behavior. The public swap of software-based, neatly defined technology blocks as services allows for well-defined and structured interfaces, discretizing the modeling complexity of telecom networks. This shift introduces a surfacing awareness of the need for technology independence, as flexible, technology-agnostic orchestration frameworks and policy engines become easier to develop than before. However, much remains to be tackled to further expand the scope toward the desired level of complexity and sophistication.

Fig : 2 Challenges Of Telecom Industry

4. Infrastructure Orchestration

Service delivery automation typically implies dynamic service provisioning that enables dynamic group formation, service resource allocation, and service management across multiple subordinate and external operative domains. The automation of dynamic service delivery is not a task achievable in isolation. To be successful it will require an ecosystem of platforms that can span operator domains as well as third-party domains or services. Much attention has been paid in industry and within standards bodies to the proper automation of constrained end-to-end delivery service provisioning across multiple sub-systems. Automation then focuses mainly on protocol translation, communications, and process coordination. The abstraction of tooling software applications, with their interfaces, protocols, and data formats that exchange information, is relatively simple to conceive and understand.

However, with more freedom and hence increased complexity comes the critical need for well-defined governance, policies, and organization of this tooling ecosystem. Even within operator domains, the ability to harness and configure potentially hundreds of libraries of external systems components and their interface properties to be able to automate and customize operations is non-trivial [4]. Change in the data centers and clouds for example means that many libraries will need to be altered for domains that are very differently operated, and with a range of differing SLAs and their translations. New network technologies and paradigms surfacing in the market such as SDN and Flexgrid will not be able to be temporarily adapted. The specific intent of this part is to address how this large and multifaceted challenge might be approached. Automation well beyond limited process orchestration as has been conceived currently is required in the medium term. Efforts using neural networking and AI like techniques are starting to be applied towards automating the operation of single systems such as applications and networks. Much more needs to be done on the meta-level to allow a diverse set of external systems to be constructed and customized for a given operator network, to allow safety bounded testing.

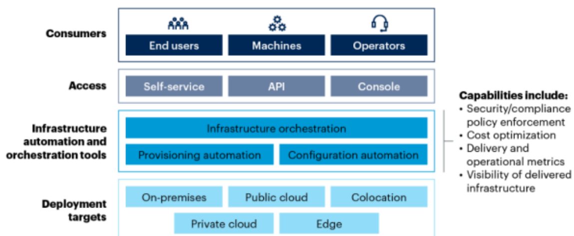

Fig : 3 Infrastructure Automation and Orchestration

4.1. Definition and Importance

A service delivery process refers to the end-to-end set of activities performed by a service provider to deliver a particular service to a customer. These activities usually span multiple organizational units within the service organization leading to a complex multidisciplinary concern that requires full awareness of ICT systems and services proliferation across network, infrastructure, and cloud resources from operation, service, and screening perspectives. Service delivery steps including service orders capturing, designing, approving, provisioning, and delivery and closure altogether is defined as a big service delivery process. Such dynamics of encapsulating several organizational silos and operating at multiple timescales makes the service delivery process ill suited to undergo full automation devoid of human intervention. Nevertheless, many activities of the service delivery process can become automated via IT systems integration, Infrastructure Orchestration and AI powered policy engines. Enabling service delivery process automation solutions based on such technologies is presented. Such a solution constitutes a key component in realizing agile telecoms hence reducing cost base and improving service time to market and quality.

A business process, or business workflow, refers to a collection of related and structured tasks along with the corresponding work procedures and target outputs to achieve a business goal. A business process may exist at operational level performing user duties, at business level involving task delegation and strategic goals definition and at managerial level specifying business metrics to achieve. To be effective, the business process should be based on a representation of the services internally provided and externally provided either on a subscription basis or upon explicit requests.

4.2. Key Technologies in Infrastructure Orchestration

Peer-to-peer architecture paradigm separates service management logic from physical infrastructure management. An application layer supports multi-domain orchestration and AI-enabled auto-resilience capabilities. A transformation layer provides compatibility with legacy systems. Underlying orchestration engine translates high-level policies into machine instructions that operate diverse types of telecom hardware. {This paragraph is reserved to describe how these key technologies block together to provide the entire solution to telecom service orchestration.} {This paragraph is reserved to address various automation use cases for business/operations optimization.} {This paragraph is reserved to summarize main achievements, state-of-the-art and the next step for wider adoption in the telecom industry.}

4.3. Case Studies of Successful Implementations

As 5G deployment is ramping up globally, service providers are gearing up to offer 5G service across their networks. The current service offering market is full of competitive forces in the form of Competitive Local Exchange Carriers (CLEC), New Entrants on Fixed and Mobile, cable operators, private new entrants for verticals, and later entrants for public sector networks. The overwhelming amount of choice is translating into a “Churn Pandemic” where customers have unlimited choice and the lowest of the low-cost providers cannot sustain profits. With market entry players focussing on a ‘low-cost’ model to reduce costs related to Network Deployments and Operations, the market is shifting gears from Capital Expenditure (CapEx)-heavy, Revenue (Rev)-focused low margin telecom operating models of today to a Cost-Effective, Operational Expenditure (OpEx)-heavy model, which results in cheaper per service provisioning margins on net revenue.

Operators have started looking at Network Function Virtualization (NFV) and Software Defined Networks (SDN) as tools capable of tackling the challenges posed by cost-effective and highly dynamic end-to-end provisioning. Europeansans United Network and Seventh Framework Telecom project Beyond 2020 have been experimenting with batch-oriented orchestration for 5 years now. They have dry-runs of end-to-end fixed access provisioning from VHG to edge-to-edge border router siloed within a specific domain using coarse-grained dedicated configuration protocols.

There has been some work showing SDN-driven end-to-end service orchestration, which uses a transport API called Control Orchestration Protocol (COP) which is to be layered on the Northbound interface (NBI) of existing multi-domain controller implementations. Operationally, the state-of-the-art approach for engineers is to work with more than one Multi-Domain Orchestrator (MDO). The SDN-based service orchestrator binds to multiple MDOs using different APIs, and for each individual MDO, it keeps an updated translation module for encoding and decoding requests and states.

Equ : 3 Overall Optimization Objective

$$\max_{A,x,\pi}\left(\sum_{j=1}^{m} U_j(s_j) - \lambda \cdot \sum_{i=1}^{n}\sum_{j=1}^{m} A_{ij} \cdot d_{ij}\right)$$

Where:

- $U_j(s_j)$ is the utility (e.g., QoE) of service s_j,
- λ is a weighting factor for resource cost

5. AI-Powered Policy Engines

The introduction of AI-based policy engines provides a richer set of functionalities than properties packages in orchestrators. These new capabilities allow the ML and AI models to be effectively and efficiently integrated and continuously improved over the infrastructure orchestrators. Such a capability allows the service providers to be relatively light on the completely new features that are evolving. The bake-off of the AI-based policy to the orchestration environment can be considered to be a superior version of the test and trial capability of many orchestrators.

Two implementation patterns of AI-based policy runtime exist: black-box use of AI, and online learning of policy engines. The first pattern requires the orchestration and infrastructure provisioning environment to be fault tolerant with sophisticated mechanisms for architecture probe and monitoring. Black-box AI service quality is heavily dependent on the coverage of training data. Coverage can be enhanced through online pipeline learning. But training is resource-consuming. Another implementation pattern of AI-based policy engines pursues a new service and learning model that is compatible with both black-box use of AI and online learning. The underlay service providers provide essential policies and resource observability and metrics.

Through observation, the infrastructure provisioning environment can extract operating conditions and/or the unknowledge (out-of-control) of the environment so that the AI models can probe actions to update or improve service availability/fault recovery policy.

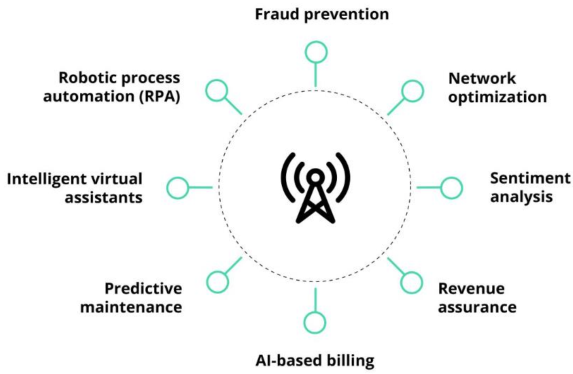

Fig : 4 AI-Powered Policy Engines

5.1. Role of AI in Telecom

Data is becoming increasingly essential as telecom providers rush to automate and monetize. Telecom companies are investing in AI platforms to combat outages, improve customer experience, and boost revenue quickly. The key changes to consider are how and where data, analytics, and intelligence can be leveraged to improve customer experience and business outcomes. AI-native systems are more than just positioning data across an organization; they need to be architected differently than the systems of record that have historically existed in the telecom sector. Emerging generative AI technologies can augment some of the capabilities of existing AI systems, and adaptation/refinement of visionary work is needed to produce AI-native systems that telecom providers will value over third-party solutions. Every layer/horizon of the telecom business has historical systems that can be augmented with new AI capabilities.

Telecom is a regulated business with high legal, security, ethical, and privacy issues related to the granting and use of data. Major incidents have occurred related to the massive compromise of highly sensitive personal data of customers, leading to lawsuits, fines, or changes in the direction of companies. Call Detail Records (CDR) may need to be kept for years and are highly sensitive for privacy clarifications. Also, sensitive company data is in CSP's systems and might also be at risk. Customer-affection models are sensitive and might reveal valuable business secrets. As a result, data are highly siloed with multiple controls for granting access to, and usage of data. Granularity of data can make it hard to obtain the correct form of data for analysis, making many analyses just impossible in telecom. Furthermore, interconnected systems often create blind scenarios when something goes wrong, which is not recoverable with AI/ML technology at any scale. Accidents are not predictable, and KPIs can't be foresighted when human involvements require long planning times and events can't be scaled down for simulations. Finally, as telecom is a multi-pronged business, scheduling issues and mergers make it complex and hard to reduce computationally with any technology.

5.2. Designing Effective Policy Engines

Quality-of-Service (QoS) assurance on virtual network services is an important challenge for telecommunication service providers. The network service providers offer the requested service levels for a recurring subscription fee. Some of these low-level policies determine the resource allocation of Virtual Machines (VMs), while others influence the routing of the packets. Most of them depend on further configurations in order to achieve the expected QoS guarantees, while insignificant deviations from pre-configured values could lead to QoS degradation considering service contracts and user satisfaction levels. However, both the number of service specifications and policies are substantial, which makes manual mapping not advisable or too slow to cover the time constraints when provisioning services. Thus, automated and semi-automated mapping approaches have to be considered. As an initial starting point, the work comprehends several actions based on a detailed survey of existing network services, together with their corresponding performance expectations, possible policy actions, and most commonly preconfigured indicative values. These actions can significantly enhance the results of policy enforcement and satisfy end-user QoS requirements, before further configuration by service/infrastructure provider experts must be applied. Afterward, a novel semi-automatic mapping technique is presented, which estimates the influence of policy parameters on the service performance by implementing Artificial Neural Networks as black boxes. Subsequently, a suggestion mechanism is introduced to provide recommendations on policy parameter values in order to assure QoS levels on a diverse range of input services. The proposed techniques leverage the flexibility and generality of ANNs and outperform alternative approaches concerning several objectives. As such, the network service providers are able to provide effective QoS assurance without exposing sensitive information regarding their infrastructure and operational practices. Exploiting the combination of both ANNs and genetic algorithms can also yield improved results, when enough additional resources are available.

5.3. Integration with Existing Systems

With the emergence of new technologies like SDN and NFV, changes in the service provisioning and delivery chain will occur. This has two effects: usage of a broader set of resources (network infrastructure use) and a more distributed service delivery deployment. As the service component stack is further decomposed and the chain is altered, some service components may execute on a public infrastructure, others on a sub-organizational infrastructure, and others still on an intra-organization infrastructure. From an end-user perspective, resource and service abstractions with good OSI matching across layers (compute, storage, and networking), may be provided. Integration with existing systems through APIs may be done, some of these APIs translatable to Telco Network exposed APIs. Service exposure is necessary for internal service self-provisioning and delivery, and to provide third-party access. This creates a revenue opportunity, since developers would be faced with a more homogeneous interface and model. New API gateways are needed, allowing interaction with different orchestrations. A commitment to develop a minimal offering of APIs, service models, and endpoints will need careful consideration of historical knowledge, smart software used, systems being used, and suppliers involved. Transparent exposure of external system functions would create a targeting opportunity, given access control.

The network management layer should issue policies in TMF 799 style when provisioning the service at the infrastructure layer. Policies recently adopted by the TM Forum are a fundamental block of the automated service delivery approach. A well-defined methodology for transition must be produced, mostly focused on TMF 882 application, endpoints, and even messages pre-elaboration. Pre-elaboration techniques should undergo assessments to determine which could be sustained by orchestration implementations.

6. End-to-End Automation Framework

Telecom Service Providers (TSPs) are dynamically changing their existing applications and actively collaborating through open-source software developments to fulfil their vision of 5G Networking Operations via End-to-End (E2E), Closed-loop, Zero-touch, and Autonomous. Instantiation of new services is made much quicker and bypasses risks due to predictable service behaviours through automated service deliveries with Infrastructure Orchestration over multiple clouds and geographical locations. Rapid and deterministic service deliveries and embedded closed-loop self-healing services are enabled through intelligent policy engines powered with Artificial Intelligence. Major service function implementations – Optical Transport and IP-Routing – are presented with E2E service delivery and closed-loop autonomous operations, alleviating multiple clouds and geo-locations. Multi-domain service orchestration and networking applications over Optical-Control-Data-SD-WAN domain are accelerated in weeks through AI-based analysis of service requirements and optimised placement of service function implementations along paths between Customers and Data-centres.

Multiple threads of technology evolution are combined to achieve the vision of E2E automated service deliveries with Autonomous Networking. Mobile Telecom Service Providers (TSPs) are rapidly changing their existing applications from Legacy Network Management Systems/Operation Support Systems to Advanced NMS/OSS with Infrastructure Orchestrators, Telemetry & Big data lake, and AI engines for Machine Learning / Genome sorting / Optimisation & prediction analytics. These evolved applications are also actively collaborating between multiple TSPs and open-source software developments. For a fully automated service delivery solution that is independent of geographical locations, cloud types, or network domains, that is standardized by E2E TM Forum Information Framework, issues and resolved approaches with technology evolutions are shared with detailed implementations. Multi-domain orchestration and its intelligent policy engines are described as the key implementations for automated service deliveries. TSP recognizes several networking functions as friction points hampering E2E automatic operations including Optical Transport, Core IP-Routing, Streaming-Video-Multi-service-Content-Delivery, and Critical-Edge-Accelerated-Analytics-Edge-Cloud-Gaming. With Federation of multiple InO/VIMs across clouds and geo-locations, TSP also realizes the contest of service delivery and interactions beyond network domains.

6.1. Components of the Framework

As the first component of the new framework, infrastructure orchestration provides the means to automate the stitching, monitoring, and management of the service chains across multi-domain network and cloud infrastructures. There are four orchestration layers: the service orchestrator that connects to the API interfaces of the infrastructure orchestrators, the infrastructure orchestrators, and the infrastructure controllers that connect to the infrastructure resources. The infrastructure orchestrators expose the API to the service orchestrators and invoke configuration and monitoring commands towards the infrastructure controllers on behalf of the service orchestrators [4]. Each infrastructure orchestrator embeds two controllers: the radio access (RAN) controller and the core network (CN) controller. The interfaces of the infrastructure orchestrators are modeled in TOSCA and the substantiations of the TOSCA classes are programmatically implemented in OpenStack Python client library and ONAP RAN controller controller API.

The executed functionalities at the infrastructure controllers include two layers: The southbound interfaces of the infrastructure orchestrators invoke commands to the infrastructure controller situated below them through a controller management protocol. In ONAP, the message routing and content conversion to/from the service orchestrator are completed through enterprise service bus (ESB) before arriving at the infrastructure orchestrators. In ONAP, the actuator initiated and resource impact change-based flows are processed in a workflow engine called activation management function (AMF). Provisioning of the service chain entities (network functions and service forwarding graph) is achieved through the model-driven and standard API interfaces exposed by the application programming interface (API) and microservice management function (MMF) components of the ONAP architecture .

6.2. Workflow Automation Strategies

Workflow automation is a trend that is expected to reshape various industries. For telecom service delivery, automating workflow execution is one of the critical components to achieve end-to-end service delivery automation. A telecom service delivery workflow is a set of prescribed processing operations that need to be executed to deliver a specific telecom service, such as a leased line service. For a service in a telecom domain, a workflow is usually represented as a directed acyclic graph (DAG) where nodes are operations and edges represent the order of execution. These operations may include adding, modifying, or deleting customers or network resources in the operation support system (OSS) and network elements (NE). As customers and resources in this domain are usually represented in different databases, applying an operation requires accessing various databases. When a service is requested, the workflow begins execution and calls processing engines, some of which may be stateful. This will introduce the need for workflow state persistence and recovery. To achieve end-to-end automation, service delivery workflows must be automated.

With the emergence of cloud computing, many telecom companies are migrating their on-premises OSS and NE services to cloud or hybrid environments based on microservice architecture and containers. However, service delivery workflows are still implemented as monolithic systems and embedded into two-stage, specified network element provisioning control systems. A dual control strategy is adopted where control will be switched to another side if the master fails in a specific timeframe. Switching control will reset the control state status and impact the service delivery. Even in cloud services, workflow execution failure cannot be tolerated but requires manual repair, during which the service delivery will be suspended. A complete state recovery process is required on recovery. To address these concerns, it is critical to address the cloud-native, stateful, and heterogeneous execution engines for telecom service delivery workflows, which can be achieved through cloud-native workflow orchestration.

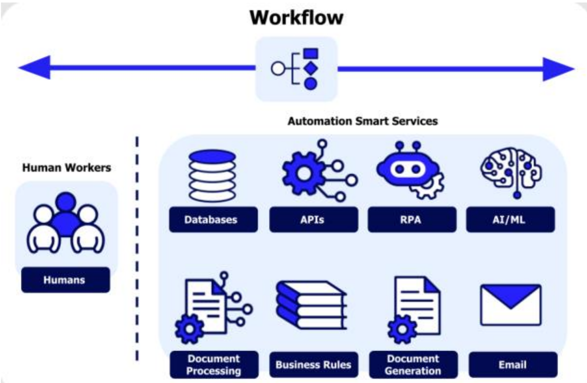

Fig : 5 AI Workflow Automation

7. Conclusion

The telecom sector has been heavily investing in upgrading its traditional network infrastructure, design paradigms, policies, and orchestration of operations so that it can handle the growing demand for advanced and speedier data and voice services. The move towards the cloud in telecommunication systems, called cloudification, is a necessity. In a virtual telecom architecture, software-based virtual network functions (VNFs) integrated into a data plane network can be orchestrated in a dynamically changing manner, independent of the VNFs' ownership across many cities, domains, and vendors for effective optimization of the end-to-end service delivery.

Currently, no operational solutions exist to maximize the automated service delivery in donut-shaped WAN telecoms. Existing orchestration engines cannot dynamically instantiate the system-wide network resource allocation and determine the optimal control parameter settings by considering the non-linear forbidding behaviors coupled with the local-time observables of the service delivery. A two-step solution framework, consisting of an infrastructure orchestration engine that considers dynamic resource allocation across different domains, and AI/ML-empowered policy engines that unexplainably infer the system parametric constraints and globally optimize the resource allocation across domains, is presented.

Network operators allocate their present services and resource functions in preventive to instantaneously responding to demands. This paper proposed a two-step solution framework, consisting of an infrastructure orchestration engine that considers dynamic resource allocation across different domains of telecommunication systems, and a policy engine that enables the F/Ds' explaining actions towards globally optimizing resource allocation across domains of the telecommunication systems. Despite this work being conducted based on a prototype, it is a substantial step toward effective SDN-based automated and proper governance of telecommunication networks. Many compelling future works exist, and feasible implementations in operational systems are being performed.

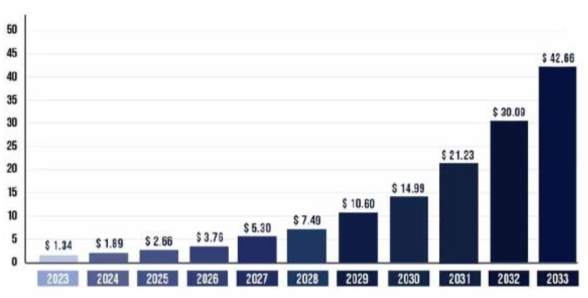

Fig : 6 AI in Telecom industry

7.1. Future Trends

With the advent of Network Function Virtualization (NFV) and Softwarized Networks, the interconnections between datacenters and servers, routers, switches, and other devices are becoming more agile and flexible through their direct orchestration. NFV offers the possibility to move telecom systems from dedicated hardware to virtualized Computing Nodes spread throughout the network. VNFs can reside in either wide-scale resources spread along the network defined as “Clouds”, or disperse resources located at the network edge, categorised as “Fog” or “Edge”. Modern Edge Clouds/NFs must meet the demands of ultra-low latency and guaranteed Symmetric Quality for 4G and 5G-based mobile systems. In parallel with NFV developments, major telecom transport network players are becoming either virtualized or ‘disaggregated’. Configurations originally using one single entity are being segregated into hardware and software disaggregated domains configurable through their corresponding NETCONF/YANG-based new generation Open APIs, enabling a competitive supply of routing, switching, and transport functionality across continents. Combining the latest developments in network architecture with this dizzying evolution in operating systems provides the opportunity to provide agility and flexibility in the telecommunications network as has taken place in the IT domain. One step ahead relies on the capability of orchestrating/distributing the service across both data centers and telecom devices adopting either an iPOX or a ROADM-based approach for the layer 0/1/2/3.

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