AUTOMATED INTELLIGENT COMMUNICATION SYSTEM CONFIGURATION REGULATOR USING REINFORCEMENT LEARNING ALGORITHM

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AUTOMATED INTELLIGENT COMMUNICATION SYSTEM CONFIGURATION REGULATOR USING REINFORCEMENT LEARNING ALGORITHM

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ABSTRACT

Techniques are described herein for using an intelligent Reinforcement Learning (RL) based model (agent) along with the respective intelligent and adaptive environment to analyze and learn historical monitoring data collected from on-premise collaboration deployments. The usage pattern may be accurately predicted for each specific day of the week as well as for the next day of the week in corresponding collaboration deployments. Based on the prediction, the administrator may be notified of the predicted network requirement for the next specific day(s). Communication system configuration can also be regulated intelligently as per the requirement for the day(s). If required, the output of the prediction system can be fed to the network control layer or communication system configuration management layer to automatically tune the system as per the predicted demand.

DETAILED DESCRIPTION

The pattern of user interaction with Voice Over Internet Protocol (VOIP) deployment can vary over time and can greatly influences the efficiency of the entire system. Customer deployment static rules and configurations may sometimes be insufficient or surplus with respect to the bandwidth requirements for the day. Call failures can occur for various reasons, and one of the major contributing factors is insufficient bandwidth which not only causes call failure but may also be responsible for unsatisfactory call quality. Static configuration/deployment of VOIP components (e.g., Session Initiation Protocol (SIP) trunks, T1/E1 interfaces, border elements, etc.) can also sometimes handicap the scalability and responsiveness of the overall infrastructure.

Accordingly, as described herein, using intelligent and auto-tuned/rectified Reinforcement Learning (RL) based models, historical monitoring data may be processed and analyzed (learnt) to accurately predict the usage pattern for each specific day of the
week as well as for the next day of the week. This mechanism may meticulously introspect the entire data and generate the prediction taking into account all aspects. The same mechanism may also be used to predict the daily load requirement and assess the performance of the main call controlling system along with the edge devices in the collaboration deployment driven by the week of day or day of month paradigm instead of performing the overall prediction at a very high level.

The usage pattern may include the number of calls, type of calls (e.g., audio/video Peer-to-Peer (P2P), audio/video conference, Public Switched Telephone Network (PSTN) / SIP calls, Mobile and Remote Access (MRA) / non-MRA calls, etc.), maximum negotiated codec, desktop sharing pattern, etc. Thus, with the help of this mechanism the administrator may be notified of the predicted network requirement for the next specific day(s). Communication system configuration can also be regulated intelligently as per the requirement for the day(s). If required, the output of the prediction system may be fed to the network control layer or communication system configuration management layer to automatically tune the system as per the predicted demand.

Figure 1 below illustrates an example solution architecture.
Figure 2 below illustrates an example double Deep Q-Learning (DQN) architecture and algorithm.

![Figure 2](image)

Figure 2

Figure 3 below illustrates an example DQN paradigm.

![Figure 3](image)

Figure 3
Figure 4 below illustrates an example data set creation flow (DS flow).

![Figure 4]

Figure 5 below illustrates an example training flow of an environment model and DQN models (TRN flow).

![Figure 5]
Figure 6 below illustrates an example intelligent and proactive continual training flow (C-TRN flow).

![Figure 6](image)

Figure 7 below illustrates an example overall flow.

![Figure 7](image)

A cloud-connected communication system may be used as the hosting platform for the RL-driven network guidance system to operate on the collected metrics from various data sources (e.g., call detail records, call management records, inventory, system performance metrics, etc.) in on-premise devices. The RL based guidance system may suggest the configuration recommendation to the communication system management
system on the cloud which may build and push the final configuration to the on-premise based communication system deployment system and Software-Defined Networking (SDN) controller.

There may be change point detection mechanisms (e.g., online and offline) which may monitor the original analytic dataset and the recommended actions of the RL (Q-Network) model along with the corresponding rewards from the environment. These mechanisms may tune (update) the environment multi-label classification model as well as the Q-Network model on an as-needed basis as part of the continual learning pipeline. Thus, the overall solution may be extremely intelligent and highly accurate based on the recommendation of the appropriate configuration.

There are many different examples of usage in the communication system. One example is call failures due to insufficient bandwidth, which can be identified with termination cause code "125". Location bandwidth manager locations such as "audio bandwidth intra location" and "audio bandwidth inter location" can be automatically fine-tuned according to the number of failures that occurred based on the number of calls expected to happen in the upcoming day and in a particular call admission control location as recommended by the RL model.

Another example is video call failures from telepresence endpoints due to insufficient session bandwidth for video calls. Session bandwidth for immersive video calls can be tuned in the location configuration settings for the upcoming predicted days based on collected historical data. For example, the historical data may fall under the buckets of video call failures and/or video call quality issues determined by the call management records of corresponding failures.

In another example, using the SDN controller, the required bandwidth can be provisioned by utilizing bandwidth reservation according to the needs of the predicted traffic for the following day(s).

Another example involves calls across the SIP trunk to border element failures, which can be determined based on the termination cause codes at the SIP trunk side. The border element dial-peer session maximum concurrent calls can be reconfigured for a specific day based on the predicted number of calls. Similarly, the maximum concurrent sessions can also be reduced if it has been over-subscribed.
In another example, trunk utilization and route group utilization can be monitored in the analytics on an hourly basis for every day. The call failures that occurred due to a trunk busy out can also be identified using the call detail records as well as the data collected from the voice gateways and border elements.

As per the RL data pattern analysis, additional trunks can be added on the fly to the existing route groups for the upcoming predicted busy days in the call controller. Situations involving over- or under-provisioning of trunks can be optimized.

Applying the aforementioned algorithm to different data sources in on-premise communication system applications may enable the techniques described herein. It will be appreciated that the prediction window may be controlled even at the "hour of day" level in this framework in order to offer extreme flexibility and optimal usage of the deployed infrastructure.

A similar solution may be extended in the contact center enterprise context as well. In this example, any suitable parameter(s) may be learned, such as Busy Hour Call Attempts (BHCA), policy suite for contact center router, talk time, Average Holding Time (AHT), Busy Hour Traffic (BHT) (e.g., measured in erlangs), call blocking percentage, queuing, etc. Any number of voice response unit ports, agents, and/or trunks may be controlled/regulated/allocated/de-provisioned based on the RL reward.

This solution may be offered as a cloud service or as an on-premise value-added service on a dedicated node. End customers may obtain a complete insight into the communication system deployment and the administrator may be notified of the appropriate actions. This may reduce the complexity of monitoring and capacity planning, and may be used as an internal regulator tool.

In summary, techniques are described herein for using an intelligent RL based model (agent) along with the respective intelligent and adaptive environment to analyze and learn historical monitoring data collected from on-premise collaboration deployments. The usage pattern may be accurately predicted for each specific day of the week as well as for the next day of the week in corresponding collaboration deployments. Based on the prediction, the administrator may be notified of the predicted network requirement for the next specific day(s). Communication system configuration can also be regulated intelligently as per the requirement for the day(s). If required, the output of the prediction
system can be fed to the network control layer or communication system configuration management layer to automatically tune the system as per the predicted demand.