Sharing Performance Measurement Events Across Domains

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***Abstract*—Network management activities, such as fault analysis and configuration management, are eventually related to changes in network measurements. Some measurement event might be either a trigger or objective of a management activity. We argue that sharing the semantics of performance data across networks provides a basis for more advanced automation. This paper presents an ontology-based system for sharing information about network measurements across network domains. The represented information contains correlations and human-defined mappings between network measurements and the system is based on semantic reasoning that identifies dependencies which arise by combining local and shared information. We demonstrate the usage of the system in a Long Term Evolution (LTE) network domain. Our experiments from an LTE simulator and LTE test network show that a combination of correlations, human-defined mappings, and ontological reasoning produces useful cross-domain information that can be accessed with ontology queries.**

I. Introduction

Making the best use of cellular network infrastructure investment requires the optimization of network parameters in view of changing usage patterns and traffic mix. The target is to achieve the best utilization of capacity while providing the right level of service quality for different applications [1].

The growth in the complexity of mobile networks has necessitated the adoption of automation. The situation has been recognized by Next Generation Mobile Networks (NGMN), and an automation framework has been provided for Long Term Evolution (LTE) networks in the form of Self-Organizing Networks (SON) concept [2]. It provides a closed-loop automation for the classes of operability use cases implemented as SON functions. In a typical realization, fixed rule bases are used for defining the behaviour of SON functions. The definition and governance of rule bases are expensive [3] which puts a price tag on optimizing closed-loop automation on per-cell level. Such needs arise from geographic and temporal variety on a cell level of radio access networks.

In addition to the limitations associated with SON function management, more automation is expected to be needed in many network management tasks such as the fault identification, troubleshooting and continuous optimization of networks [4]. It is expected that adaptive automation is needed in 5G to manage the more complex network.

The use of adaptive automation is not limited to 5G wireless systems. Below, we use the wireless network as a concrete example, but the core idea can be used in any other network management domains.

A. Information exchange

Traditional information sharing needs to take care of network-specific parameters and mappings between networks by means of software. Semantic mappings can be performed using Common Information Models (CIMs) such as TMForum Shared Information/Data (SID) model, but these typically need to be extended for use in mobile domains, not to mention service provider or vendor specific parameters.

We argue that semantic representations of network status together with domain ontologies and reasoning simplifies implementation by facilitating query-based access to knowledge representations [5]. Reasoning can involve both classical and probabilistic aspects [6].

B. Our approach

In this paper, we present Effect Sharing Service (ESS), a framework for sharing performance measurements globally. The motivation behind our approach is enabling effective information exchange across networks which lends itself to automation. Every network operation from anomaly detection to network configuration is eventually related to changes in network measurement values, and thus, these relations could be utilized to connect information about network problems and solutions across domains. For example, a local network might have deployed a SON function with some settings to address an anomaly. Another local network can find this solution via the ESS by querying a solution for its own anomaly. Even though these anomalies have occurred in different networks and might address different metrics, the ESS finds a relation between the metrics in question (e.g. via a statistical correlation and semantic mapping).

The rest of the paper is organized as follows: the next Section II briefly presents an overview of the framework and related use cases. Section III describes technical details and logical axioms for the components of the ESS. Section IV provides statistical experiments from two measurement scenarios (LTE simulator [7] and test LTE network), semantic reasoning

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results, human-defined mappings and a query example. Finally, Section V discusses related work and Section VI concludes the paper and clarifies our future work.

II. Overview of the ESS

A. Architecture

The core concept of the ESS framework is to express context-specific dependencies between metric effects (value changes in metrics) in network management systems (NMS). A network metric can be any measurement that has a scalar value and characterizes some aspect of the network status, such as a low-level counter, a key performance indicator (KPI), or a high-level business objective, such as customer satisfaction. Vector-valued measurements, such as the Channel Quality Indicator (CQI), are converted to a set of scalar measurements. Currently, our model covers only per-cell measurements, but it is expandable to cell-pair measurements or base station-specific metrics.

The ESS contains a knowledge base and a reasoning capability that are used for linking and finding relations between metrics across domains. Figure 1 presents the ESS architecture in the context of virtualized networks and global network applications. The ESS can be utilized directly from a virtualized NMS that provides performance data and context-specific metadata about a network domain. An NMS can query the ESS, obtaining cross-domain relations from the performance measurements of another network domain. Cross-domain relations between metrics can be utilized to find solutions from one network to a problem in another. For example, one network might have an algorithm addressing changes in a particular metric. Due to a cross-domain relation between metrics in the two networks, the algorithm can be found and re-used also in the other network.

The ESS can also be used by global network applications that aggregate heterogeneous data from network domains and provide global NMS-relevant information such as anomalies, configurations, or network planning. These applications share cross-domain information from particular network management activities, such as fault analysis or configuration management. The ESS may serve these applications with a global representation of network status changes (the metadata of activities), along with an automated tool analysing relations between network states.

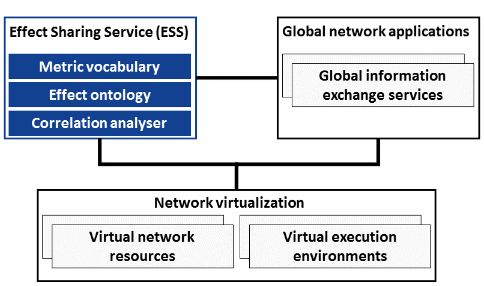

Fig. 1. The ESS architecture and its relation to network virtualization and global network applications.

The ESS consists of a *correlation analyser* that calculates correlations from network domain Performance Management (PM) data, a *metric vocabulary* that maintains a list of metrics used in the ESS, and *effect ontology* that stores and infers semantic metric effects and information about them (Figure 1).

B. The interaction between a local network and the ESS

An NMS have three use cases towards the ESS: mapping of common metrics, sending PM time series, and querying inter-domain effect relations.

1) Mapping of common metrics: Local operators can map some metrics used in their systems to commonly used metrics (described in the ESS). Standard metrics such as those described in 3GPP specifications[1], may be used here. For example, the CQI is specified in the 3GPP specifications and could be defined as common metric in the ESS. A local network operator may measure CQI in its own network and due to the equivalence of the two metrics, the operator can map the local CQI to the CQI instance in the ESS.

2) Sending PM time series: A human operator may send PM time series to the ESS. From this data, correlations are analysed between metrics and the effect ontology is populated with new instances (metrics appeared in the measurement data) and updated with respect to the correlation data. A semantic reasoner can infer new logical implications from the updated ontology. The outcome of the reasoner includes new correlations and contradictions (effects which cannot be achieved simultaneously) between effects. A detailed explanation of the reasoner can be found in the Section III. Information about correlations and contradictions can be used, for example, for automating the governance of closed-loop automation such as SON: correlations and contradictions between metrics clarify which SON functions can operate parallel in the same network without having conflicts.

3) Querying inter-domain effect relations: As a result of the preceding steps, the ESS contains a graph of metric effects and their dependencies. Subsequently, the NMS may now query the ESS to find context-specific effects that are related to queried effects. When the ESS receives a context-specific effect query, the reasoning of effects with similar context is triggered, returning all effects that are satisfying the query via dependency mappings (human-defined mappings or correlations). An example query is demonstrated in the Section IV-E.

III. Description of the Components in the ESS

A. Statistical correlation analysis

A fundamental part of the ESS framework is analysing statistical correlations between metrics. From a statistical point of view a metric is considered as a random variable, whose observed values are values of the metric of a certain cell at a certain point of time. Correlations between metrics are computed within the ESS in order to make results comparable

[1]http://www.3gpp.org/specifications

across domains. We want to detect pairs of metrics with a linear relation, e.g., pairs where a positive change in one metric usually occurs simultaneously with a negative change in the other metric. We use Pearson's product-moment correlation coefficient r_{xy}, which measures the linear correlation between two metrics x and y. The correlation is calculated over all cells included in the context.

The correlation coefficient always lies between -1 and 1. We classify the correlation between two metrics as significant, if $|r_{xy}| > 0.5$. With respect to a transitive correlation between x and z (as a consequence of their correlations to y) the following inequality holds for coefficients r_{xy}, r_{yz}, and r_{xz} [8]:

$$\begin{aligned} r_{xy}r_{yz} - \sqrt{(1-r_{xy}^2)(1-r_{yz}^2)} \leq r_{xz} \\ \leq r_{xy}r_{yz} + \sqrt{(1-r_{xy}^2)(1-r_{yz}^2)} \end{aligned} \tag{1}$$

From Equation (1) we can see that if both r_{xy} and r_{yz} are greater than $\frac{\sqrt{3}}{2}$ or less than $-\frac{\sqrt{3}}{2}$, then the correlation between x and z is significant as $r_{xz} > 0.5$. We can also see that if one of r_{xy} and r_{yz} is less than $-\frac{\sqrt{3}}{2}$ and the other is greater than $\frac{\sqrt{3}}{2}$ then there is significant negative correlation between x and z.

To make use of this information, we further classify the correlation between x and z as strong correlation if $|r_{xy}| > \frac{\sqrt{3}}{2} \approx 0.866$. The transitivity of individual correlations through a pair of strong correlations is an important feature in our semantic model as it is described in following subsections.

B. Effect ontology

We define an effect as an event where a metric value increases or decreases significantly. The limit for "significant" varies across metrics. For this article, we use 5 % change as an arbitrary uniform criterion for significant change by way of demonstration.

The ontology uses the resource description framework[2] (RDF) and web ontology language[3] (OWL 2) to model effects and facts about them. The OWL 2 is compatible with description logic (DL) and semantic web rule language[4] (SWRL). Thus, in addition to the semantic representation of the effects, the ontology facilitates reasoning which we implement with a semantic reasoner, Pellet [9], to infer dependencies between effects.

An effect in the ontology is defined with the following data elements:

- *Metric*: Universal Resource Identifier (URI) as an identifier.
- *Impact direction*: increase or decrease.
- *Context attributes*: describing the environment where the effect has occurred.
- *Dependencies*: Links between effects that may occur at the same time.
- *Contradictions*: Links between effects that are not achievable at the same time.

Every effect metadata contains a metric URI and direction of the value change. The environment where the effect has occurred is expressed with context attributes, such as spatial, temporal or network-related attributes. An effect might have dependencies, such as statistical, subsuming, and human-defined mappings, to other effects.

1) Context attributes: Context attributes describe the measurement scenario the effect is related to. Some context classes and their attributes are described below. These attributes are presented for demonstration purposes and the list of attributes is assumed to expand over time, when measurement scenarios need more sophisticated definitions.

- *Location type:* urban, suburban, rural, highway
- *PM status:* classified attributes of the network performance, such as low/medium/high load and throughput
- *Network Technology:* LTE, UMTS, GSM, Hetnet
- *Overall attribute:* general

Due to the open world assumption of the semantic representation (the absence of an attribute is considered as $unknown$ rather than $false$), new attributes will not violate existing effects. A special context attribute is $general$ that covers all attributes and contexts.

2) Statistical dependencies: Statistical correlations higher than 0.5 or less than -0.5 are represented in the ontology with a general *hasDependency* property. If two metrics have a positive (negative) correlation, then their effects with the same (opposite) impact direction are depended. Effects might also have a *hasStrongDependency* property, which is defined for correlations higher than 0.866 or less than -0.866. A strong dependency has transitive characteristics in a sense that two strong dependencies between effects XY and YZ will produce a general dependency between XZ.

3) Subsumption: A subsumption property, *subsumptionOf*, can be defined in two cases. First, it describes a link from an effect which is part of an aggregated effect to its aggregation, for example from a low-level counter effect to an effect of an aggregated KPI value of several counters, including the linked one. Second, it describes a link from an effect with a limited context (few attributes only) to an effect with a more general context (including all attributes in the other effect). Subsumption is a non-symmetric property; the subsumption relation holds only from the sub-effect to its parent effect.

4) Human-defined mappings: Human experts can share their information about effect dependencies with a *hasLogicalDependency* property. For example, the property can be used to map semantically equal effects between two networks.

5) Transitive dependencies: In order to utilize the transitivity of statistical and human-defined dependencies described above, we define *hasStrongDependency*, *subsumptionOf*, and *hasLogicalDependency* also as subproperties of *hasTransitiveDependency*. Due to this definition, we can utilize an SWRL rule (Equation (2)) for generating dependencies between effects that are transitively connected with two *hasTransitiveDependency* properties. Using the general superproperty,

[2]https://www.w3.org/TR/2014/REC-rdf11-concepts-20140225/

[3]https://www.w3.org/TR/owl2-overview/

[4]https://www.w3.org/Submission/SWRL/

we can identify transitive links whether they are statistical, human-defined, or a mix of them. The resulting property is a general *hasDependency*. The notation of the equation describes an SWRL rule in the ontology. The rule indicates that if the ontology contains a transitive dependency between effects $?x$, $?y$, and between $?y$, $?z$, then a dependency link is generated between $?x$ and $?z$.

$$\begin{aligned} hasTransitiveDependency(?x, ?y) \sqcap \\ hasTransitiveDependency(?y, ?z) \\ \Rightarrow hasDependency(?x, ?z) \end{aligned} \tag{2}$$

6) Contradictions: A contradiction is defined as a symmetric and transitive property between effects that cannot occur at the same time. Equation 3 shows a rule that generates a contradiction between effects $?x$ and $?y$, because they have the same metric $?metric$, but their impact directions $?impX$ and $?impY$ have different types ($Decrease$ and $Increase$).

$$\begin{aligned} hasMetric(?x, ?metric) \sqcap hasMetric(?y, ?metric) \sqcap \\ hasImpact(?x, ?impX) \sqcap hasImpact(?y, ?impY) \sqcap \\ Decrease(?impX) \sqcap Increase(?impY) \\ \Rightarrow hasContradiction(?x, ?y) \end{aligned} \tag{3}$$

With respect to the SWRL rule above and to *hasStrongDependency* property between effect instances, the semantic reasoner can infer new contradictions with a rule defined in Equation 4. The rule defines that if effects $?x$, $?y$ contradict and $?y$, $?z$ have a transitive dependency, then a contradiction link is generated between $?x$ and $?z$.

$$\begin{aligned} hasContradiction(?x, ?y) \sqcap \\ hasTransitiveDependency(?y, ?z) \\ \Rightarrow hasContradiction(?x, ?z) \end{aligned} \tag{4}$$

C. Common metrics

We define common metrics as generally used metrics among stakeholders. For demonstration purposes, Received Signal Strength Indicator (*RSSI*) is defined as common metric in the vocabulary. The list of common metrics will be complemented as new use cases and new data sources are added to the ESS. Generally, these could be extracted from 3GPP specifications, such as [10], or otherwise commonly used metrics in SON function and autonomous network management.

Common metrics provide global links between separate network domains. Once network operators have uploaded network-specific metrics and effects to the ESS, they can map some of the metrics to common metrics. Then, the ESS can be queried for inter-domain effect relations. As an example, if metrics in network domains D_1, D_2, and D_3 have been mapped to a same common metric, then their metric effects are also related (increases in the two metrics correlate). Now, if network D_1 has an algorithm addressing issues related to its metric, network D_2 and D_3 will find information about this algorithm by querying the ESS and finding the link to the network D_1 via the common metric mappings.

IV. Experiments

We analysed the usage of the ESS in two environments: LTE simulator [7] and LTE test network. In the simulator, the measurement scenario consists of a 2 GHz LTE network with 32 macro cells covering an urban area with a diameter of 5 km and 2000 terminals. The test network is a live LTE network for research purposes. The network operates at 2.6 GHz and comprises 20 LTE base stations with 36 LTE cells. The test network can host up to 200 real and simulated LTE users.

A. Context for scenarios

The information about measurement scenarios described above can be expressed with context attributes as shown in the table I. Given the context attributes above, all cells in the simulator are included in correlation analysis. From the test network, we include four cells fulfilling the context criteria.

	Location type	Network tech.	PM status
Simulator	Urban	LTE, 2,0GHz	high thrp, high load
Test network	Urban	LTE, 2,6GHz	medium thrp, medium load

TABLE I
CONTEXT ATTRIBUTES FOR SIMULATION AND TEST NETWORK SCENARIOS.

B. Simulator correlations

We analysed the following metrics in the simulator: individual CQI classes, average CQI (CQI_Avg), Radio Link Failures (RLF), terminals per cell (CUEs), and average RSRP. The table II shows correlation coefficients between the metrics. Strong correlations higher than $|0.87|$ are highlighted in the table. As the table shows, CQI class 1 (CQI_1) has a strong correlation with RLF and the CQI_Avg has a strong negative correlation with the RSRP.

Measurements also revealed that other low CQI classes (1 to 3) correlated with the RLF and that the CQI_Avg correlated with several CQI classes; to classes from 3 to 11 CQI_Avg had coefficients higher than 0.5. For simplicity, the table presents only CQI_1 from the CQI classes.

	CQI_1	CQI_Avg	RLF	CUEs	RSRP
CQI_1	1	0.19	**0.87**	0.69	-0.44
CQI_Avg	0.19	1	0.07	0.46	**-0.93**
RLF	**0.87**	0.07	1	0.78	-0.27
CUEs	0.69	0.46	0.78	1	-0.58
RSRP	-0.44	**-0.93**	-0.27	-0.58	1

TABLE II
CORRELATIONS FOUND IN THE SIMULATOR. SEE TEXT FOR EXPLANATION OF METRICS.

C. Test network correlations

The following per-cell metrics were analyzed in the test network: a signal-to-noise ratio (SINR), RSSI, uplink throughput (U-THR) and downlink throughput (D-THR). All the cells had similar behaviour and correlations for given metrics. Correlations are reported in the table III, which presents coefficients between selected metrics. From these metrics, the RSSI correlated strongly with the SINR and the D-THR with the U-THR.

	RSSI	SINR	D-THR	U-THR
RSSI	1	**0.88**	0.49	0.31
SINR	**0.88**	1	0.66	0.44
D-THR	0.49	0.66	1	**0.90**
U-THR	0.31	0.44	**0.90**	1

TABLE III
CORRELATIONS FOUND IN THE TEST NETWORK. SEE TEXT FOR EXPLANATION OF METRICS.

D. Semantic contradiction analysis

The semantic reasoner infers contradictions between metric effects. The obvious contradictions can be found with respect to the axiomatic rule in Equation 3 (opposite impacts of the same metric cannot occur at the same time). In addition to these, table IV shows which contradictions the semantic reasoner has inferred from the simulator and test network with respect to the ontology rule 4 and earlier presented correlation data (tables II and III). The first column depicts the environment, second contradicting metrics and third the direction of a contradiction (+/–). The direction of the contradiction is opposite to the sign of the correlation coefficient. For example, the first row of the table defines that CQI_1 and RLF contradict negatively meaning that CQI_1 cannot increase when RLF decreases and vice versa.

Environment	Metric pair	Direction of contradiction (+/–)
Simulator	CQI_1, RLF	–
	CQI_Avg, RSRP	+
Test network	SINR, RSSI	–
	U-THR, D-THR	–

TABLE IV
INFERRED CONTRADICTIONS FROM THE SIMULATOR AND TEST NETWORK.

Information about contradictions can be used to validate an action in an NMS. For example, an action that increases CQI_1 in the simulator in the given context is undesirable if RLF should not increase at the same time. Similarly, it is not possible to execute an action that has an objective to increase downlink and decrease uplink throughput in the test network (in the given context), as these effects contradict.

E. Common metric mappings and inter-domain query example

Let us consider a scenario where one network expert has access to the simulator data and another to the test network data. They examine common metrics and look for correspondencies in their networks. If we have an RSSI as a common metric, one obvious mapping in the test network is between the common and local RSSI metrics as they are most likely equal KPIs. With respect to the RSRP metric in the simulator, let us make a hypothesis based on the theory of RSSI and RSRP formulas [11][12], that effects in RSRP are part of effects in RSSI (e.g. when RSRP increase, also RSSI increases). Thus, a one-way *subsumptionOf* link from the simulator RSRP to the common RSSI is created. After the mappings are done, we may assume that if these metrics would be available in the same network environment, there would be correlations between them and for this reason, we may find inter-domain effect relations.

As an example of related inter-domain effects, Figure 2 illustrates them with a graph visualisation. The figure depicts effect relations in the simulator, test network, and global effect vocabulary. Every square node represents an effect with information about its metric, impact direction, and context attributes included. The results of the abovementioned RSSI mappings have produced effect relations to the global vocabulary from the simulator (between nodes 3 and 4) and the test network (4 and 5).

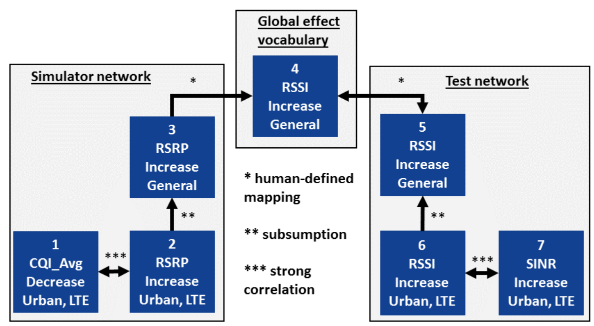

Fig. 2. Query results for decreasing CQI_Avg in simulator with attributes: urban, and LTE.

Now, assuming that during an LTE network simulation, a significant decrease in the average CQI has been identified in cells in an urban area. The operator sends a query to the ESS to find effects related to this anomalous effect (with context attributes urban and LTE). Reasoning over results is initiated with a SPARQL interface and the results for the query are shown in the Figure 2, as a graph. The table shows matched effects: the first match (the node 1) is to an effect having a match in impact, metric, and context attributes (may be general or specific attributes). After that, RSRP_Inc is matched via a strong correlation (2), which is turn has a subsumption relation to its general effect (3). The general RSRP_Inc is matched to RSSI_Inc (4) in the global vocabulary due to the human-defined subsumption mapping. The global RSSI_Inc is in turn matched to the corresponding test network metric effect (5). After the context-specific RSSI_Inc is matched (6), we finally get a match to a context-specific SINR_Inc (7) that is found via strong correlation. From the results, we can conclude that in a context, in which simulator metric CQI_Avg decreases, the test network metric SINR would increase. Further assuming that there would be an algorithm addressing anomalies in SINR in the test network (some link between the algorithm instance and the SINR effect), the example query would provide a path to this algorithm, even though there was no predefined semantics between the CQI in the simulator and SINR in the test network.

The aforementioned query demonstrated the use of the ESS; one can use this information to find related measurements across networks.

V. Related Work

A study in [13] presents a conceptual architecture for cross-domain 5G network management system between cellular and industrial networks. An architecture for shared infrastructure in future cellular networks has also been addressed in [14] which proposes a network configuration platform that would aggregate multi-domain resources and translate requests between several control planes and NMSs.

Context-specific measurements have also been presented in [15] by means of an adaptive SON function management mechanism. Here, the goal is to bind context-specific metric measurements together with SON configurations to enable the dynamic adoption of suitable SON configurations with respect to current network status. [15]

A service management-related research paper has proposed an ontology-based global service management framework that links local systems together [16]. The paper describes a common taxonomy for service management concepts, also for KPIs which are linked to service level agreements SLAs. [16]

Cited studies relate to inter-domain platforms and information exchange mechanisms that react or analyse changes in performance metrics. The ESS instead provides a unified framework for representing these metric value changes in the network status. Thus, this work can be seen as a common ontology and reasoning capability from which network-related global platforms can benefit, for example for linking performance events to the platform and information (in a view of metric effects) across platforms.

Semantic and logical models for performance metrics are researched earlier. In [17] has been presented an ontology for representing the units of measurements. In [18] and [19] ontologies have been defined for the semantic representation of performance metrics and their metadata, such as formulas (including the units of measures), targets, and dimensions (temporal, organizational, etc.). [18][19] These works focus more on describing metric itself, whereas the ESS describes a measurement event (metric value change) and context metadata about it.

In [20] predicate logic has been used to define similar logical relations between performance metrics as in our system. For example, the authors define causality, aggregation (similar to subsumption in our work) and correlation for metric relations. However, the axioms are not directly adaptable, as we define our axioms specifically for context-specific metric effects. In addition to logical differences, our framework provides a semantic representation of metric effects which enables better interoperability between heterogeneous data sources and global usage of effects.

VI. Conclusions and Future Directions

This paper presented a framework, Effect Sharing Service (ESS), for distributing information about context-specific metric effects across virtual networks. We have described the semantic and logical foundation of our system and described its functionality with an architecture, examples, and experiments from two data sources: LTE simulator and test network. The results of our first experiments with the ESS validate the interaction between local networks and the ESS. Both human-defined mappings and experiments from correlation analysis from the data sources have been translated into effects which are linked globally via the effect ontology. In particular, the use case example in the Section IV-E demonstrates the benefit of the ESS, as the operator utilizes new effect information extracted from the measurement scenarios and points out linked effects between the simulator and test network.

Although the first results look promising, some issues still needs to be further analysed. One issue is the level of statistical significance in the correlation analysis. As defined in III-A, the threshold for a normal metric correlation is set to 0.5. This value should be further investigated to find out a probability for metric effects to co-occur, given a certain metric correlation coefficient. Another issue to be considered in statistical analysis is a confidence value indicating the quality of the analysed dataset. The confidence value would express the reliability of analysis. For example, what is the variance in the metric values, what is the time range considered, and how many cells are included.

Instead of analysing metric value correlations, we could directly examine event correlations. For example, classifying value changes into effects, such as ”no change”, ”small change”, and ”significant change”, and comparing the occurrences of these metric effects. This way, we might get deeper insight to effect relations and possibly the statistical analyser would reveal various types of relations, such as subsumptions (e.g. subeffect correlates with the parent effect but not the opposite) and other one-way metric correlations (e.g. the increases of two effects co-occur while decreases do not).

A potentially important aspect for the future work is the exploration of context attributes which produce semantically valuable relations between effects. Current scenarios serve as practical examples of how to use the ESS, but might be too general and different from each other to make further conclusions about the similar behaviour of cells in these contexts. Thus, the ESS would need the analysis of semantically similar metrics in various contexts and with many data sources in order to extract the relevant sets of context attributes.

Altogether, the goal for building the ESS was to enable semantic connections between metric-related data across networks. This paper gives promising results from experiments indicating the need for the semantic representation of metric data in the view of global information exchange.

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