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Towards a Model for the Integration of Time into a Graph-based Key Performance Indicator Analysis

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Abstract

The analysis of relationships between key performance indicators is one of the challenging tasks in modern business applications. On the one hand, a complex network of key performance indicators, based on sensor data and calculations, is obviously available in technical systems, but on the other hand, the final human decision is based on the information provided by visualization types like dashboards. But in most cases dashboards only cover static information and neglects temporal dependencies. In this paper, we present an approach for the integration of a temporal perspective into a graph-based visualization for the analysis of key performance indicators using multi-level graphs.

Categories and Subject Descriptors (according to ACM CCS): H.1.1 [Systems and Information Theory]: Information theory—H.1.2 [User/Machine Systems]: Human factors—

1. Introduction

Analysts and decision makers are facing continuous changing dashboards displaying information about multiple individual key performance indicators (KPIs) in each level of the enterprise hierarchy in a global distributed enterprise. KPIs are information sources, which provide a quick overview about status and changes of e.g. business or production processes and their results [FG90]. They are significant predefined measures that provide businesses with the information they need to assess previous performance and to create profound decisions. KPIs define targets and provide individuals with the ability to assess past information [Wu02]. KPIs can be used to control systems, to observe the quality of services, notice issues and start properly actions. For example, KPIs in a production site might help to support the goal of the improvement of the product quality. With the definition based in business analysis and controlling, business KPIs can be standardized, e.g. in [ISO14] or proposed by organizations like VDMA, while others are created for special adapted scenarios. The dependencies and influences between them may be derived from a proposed key performance indicator system, such as the Balanced Scorecard [KN92] for business related KPIs. Other approaches try to derivative relationships for entire key performance indicator systems by statistical analysis [RSB09].

The interconnected and integrated source systems, e.g. sensor-actuator-systems, production lines or logistic areas, are often connected to few common dashboards for the final analysis . In addition to that, daily or weekly KPI reports are generated for the users. Using this setting, the user normally accesses the dashboard for his analysis and view tables, pie charts, line charts or bar charts of a set of individual KPIs. For example, the user might see KPIs such as 'Overall Equipment Effectiveness (OEE)', 'Throughput time', 'Re-Work time count' or 'Direct Run Ratio'. While the calculation of such KPIs become increasingly complex and interconnected, the current way of presenting the information as single KPIs on a dashboard is not sufficient for the analysis of inter-dependencies. Furthermore dashboards might not satisfy the emerging need for the visualization to display temporal inter-dependencies between KPI data objects.

The mere display of individual, unconnected KPIs in dashboards does not reflect entirely the dependent and temporal nature of data during the analysis. We observed that the missing visibility of relationships between KPIs in the dashboard leads to personal interpretation of the relationship by the user based on individual knowledge and observation. For example, events (and therefore KPI results) from an earlier date in time may influence the KPI results with mathematical and logical relationships to each other, but this influence is not visible in current production dashboards. This means, if some issue is visible in a KPI result from the assembly line of an automotive production site, the root cause for this might be caused in an issue some days before in the body shop.

While decision makers must explore causality, the implementation shows that an analysis task for KPIs might be more focused with a graph-based visualization. A graph can provide a clear hierarchy and direction information as a common ground for the interpretation. Thus, Keim states that a new kind of visualization is required to face the challenges on complexity and interaction [KKS*09]. Typical graph-based visualizations are able to present information objects of key performance indicators, such as names, values, units like dashboards before and additionally their relationship to other KPIs using the edges. But while the data source, like a business data warehouse or an in-memory database system, can provide multidimensional data sets for every time period required, only few information items out of these sets can be finally visualized without overloading the user. The contributions of this paper are twofold. Building on the ideas of [HVRH13] and [HVNK13] for static graph-based visualizations, we propose a model for integrating temporal information on top of a KPI dependency graph. Whereas in our previous work we did not include temporal information between KPIs, this work enriches the graph-based approach by defining a model how to provide a variability of temporal information.

The following section 2 will provide a sketch view into the most important related work before presenting our idea of multi-level graphs in section 3 including some detailed description of the informational and temporal characteristic of the concept. We conclude the paper in section 4 with a brief outlook to our future work.

2. Related work

The section of related work is split into two areas. First, we will take a look into the current approaches for visualization of KPIs, second, we will summarize the work in regard of integrating temporal information into graphs.

The analysis concentrated visualization of KPIs is one noticeable topic in terms of business intelligence. The main research focus is based on the improvement of dashboards and the optimization in terms of usability or style of common data visualization elements, such as tables, pie charts, line charts or bar charts [EB12, GRC04, Hil12] and [RC13] whereas the request for a more coherent visualization was been postulated long before [DeS84]. Only few authors have investigated the content that is relevant for business analysis. Most recommendations are geared towards typical information items of individual KPIs without any consideration about dependencies, which are regarded as obsolete in this way by [Kei02]. In the same context, some researchers seem to shift to a plain graph-based visualization for dependencies between business information objects [BHPS12, DT11] and key performance indicators [ALA07, WLR*11, HTB*11].

For the integration of temporal information into general graph-based visualization we have identified several approaches, which can be mapped partly to four categories of dynamic graphs. These four categories, highlighted by [BdMM08] are: 1) all nodes and edges remain fixed, but the values of attached attributes vary, 2) the sole visualization of the additions or deletions of edges over time, 3) the variation of the edge and their visualization attributes over time and 4) the visualization of additions or deletions of nodes over time. The first set of approaches proposes the generation of one unique graph for the entire time period and the visualization of the entire temporal data (e.g. using a time series visualization) within each node entirely [SKM06, BBD08, SLN05]. A quite similar approach can be seen in the works of [APP11, PS06] where a unique graph contains all temporal information for all time steps but nodes or edges are visualized in a different way for the single time step. The second area of related work covers the integration of temporal information by visualizing an individual graph for each step in time and the combination of these single graphs into one unique display whereas each graph is displayed simultaneously and applies visual differences [KNC*11, The06]. The third set of research activities focuses on the generation of dedicated graphs for each step in time [SDM12,LBD07] and the visualization of changes of values and attributes for the nodes and edges between each step in time [DGK01, FSC99, EHK*04, GBD09, FWSL12]. Following the description in the previous section none of these approaches is fully applicable for the analysis of key performance indicators, where we face the observation of the separation between large set of theoretic but enterprise wide valid KPIs as well as the application and specification of few KPIs out of this set for a dedicated use case and the analysis within a dedicated time span. We will specify this observation in the following chapter.

The proposal presented in this paper solves this challenge by formulating a general model for the graph-based visualization of time-dependent key performance indicators.

3. The concept of the multi-level graphs

3.1. Model-graph, view-graphs and nodes

While we researched the temporal setup of the different KPI dashboards used by our industrial partners, we gained insight into the composition and usage of these dashboards. First we noticed that every KPI dashboard displayed an inherited and modified subset of KPIs from a larger, but unique set of KPIs. The larger set of KPIs provided specifications, such as calculation formulas, units of measures, descriptions or identifier. While an applied subset of the KPIs was only valid for a dedicated time span, the underlying KPI specification didn't specify any temporal parameters or maturity. Furthermore, we saw that every inherited KPI value on the dashboard represented information for a dedicated step in time. This observation of the structure, composition and temporal nature of KPI dashboards for the transformation into a graph-based visualization of KPIs leads to the necessity of a concept as described as follows.

First we assume one or more graphs representing KPI networks as a 'model-graph', where all necessary specification of KPIs and their dependencies are stored. This 'model-graph' can include multiple graphs or just individual nodes, if dependencies between some KPIs are not described or not included. Using this 'model-graph' one or multiple sub-graphs can be inherited for a dedicated analysis, monitoring or measuring purpose. Each sub-graph is called 'view-graph'. Within every 'view-graph', single 'nodes' represent the information, such as value, identifier or semantic context for a single KPI. While the analysis, monitoring or measuring task of the responsible user might overlap, multiple 'view-graphs' may contain identical 'nodes'. The following figure 1 illustrates this approach as multi-level graphs. In figure 3 an example can be seen. This figure contains one 'model-graph' with 22 nodes, where the selected nodes for the 'view-graph' are selected for illustrative purpose. The figure also contains a 'view-graph' view A with six nodes, where value of the nodes change from time step t to time step t+1.

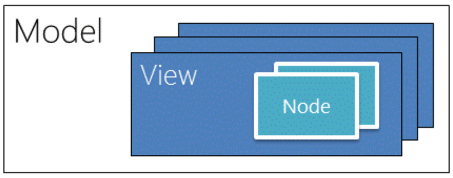

Figure 1: *The concept of multi-level graphs describes one single 'model-graph' for the generation of multiple 'view-graphs'.*

3.2. Information perspective within the multi-level graphs

The separation between 'model-graph', 'view-graph' and 'nodes' facilitates the partitioning of graph related information, graph drawing behavior and interaction. The 'model-graph', in regards to the data structure, might contain three types of information: a generic KPI specification such as formulas, a description, related business areas, all applicable units of measurement (e.g. kilowatt hour, megawatt hour, kWh/yr), the dependencies between the KPIs and information about default graph drawing algorithm or default graph aesthetic rules. In addition to that general specification from the 'model-graph', the 'view-graph' might include information about the subset of the KPIs, the maturity and the granularity of the 'view-graph' and interaction information, which is applied to the entire 'view-graph' and for the time span. This may include filters, search parameters or sub-graph folding information. Each 'node' within the 'view-graph' contains one dedicated information item, which is inherited and refined from the information provided in the 'model-graph'. The refinement can include the specific unit of measurement (kilowatt hour) or some intra-production site responsible person. The data for each time step, allocated to each node includes the value of the KPI for this time step, the identifier, the thresholds and pre-calculated state information.

3.3. Temporal characteristic of the multi-level graphs

Beside the information perspective and the separation (and inheritance) of information within the multi-level graphs, the approach permits the integration of time into each level. In our approach, the 'model-graph' is time-independent. The KPI nodes and the description of dependencies between the KPIs within the 'model-graph' are valid until modifications to the 'model-graph' occur, such as addition or deletion of nodes or edges. The 'view-graph' indicates a defined time span and the granularity of the time steps for the containing nodes. This means multiple 'view-graphs' can exist in parallel describing different time spans and time steps. The time granularity and period is selected up on creation of the 'view-graph', but might be also bound to the time steps of the underlying data source. Inside each 'view-graph', a set of information per 'node' is valid for one dedicated step in time. Hence, while the graph of the 'view-graph' (in regards to the position of nodes and composition of edges) is stable during the entire time span, the only values and states of each individual node per time step change from time step to time step. In our approach, the dependencies between the KPIs are not time dependent to avoid a destruction of the users mental map from the relationships between KPIs as described in [ELS91, MELS95]. The position of nodes and the composition of edges will not change due the life span of the 'view-graph'. This temporal characteristic is illustrated in the following figure 2. In this figure the 'model-graph' is valid between time t and t+1. The view A defines a different time span and time steps for the nodes as view B with some overlap in the time span. The cyan boxes between view A and nodes A (as well as view B and nodes B) are introduced for an illustrative purpose to link the presentation of the nodes clearly to the view.

4. Application

The approach of multi-level graphs has been implemented successful in a .NET/WPF based prototype. The prototype is connected to an enterprise service bus (ESB) for retrieving and transforming data. We refer for more information

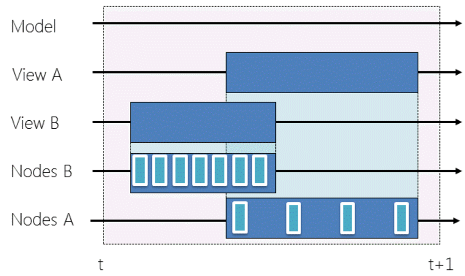

Figure 2: *The temporal characteristics of the multi-level graphs.*

about the distributed architecture to the work proposed in [VHM*12] and extended in [DKM*13]. Both provide detail to the underlying architecture in regards to the back-end implementation. The ESB extends the framework of Apache ServiceMix and integrates heterogeneous components as adapters e.g. for the access machine sensors, to web services, business data warehouses and in-memory database systems. The ESB gathers the external data using these adapters, processes this data and transforms it into a unified JMS based message exchange format for consumption by our prototype. For this paper we generated a 'model-graph' with 150 nodes. The amount of nodes represents the number of supervised KPIs within a medium scale enterprise in the manufacturing area. We know that the creation of such KPI network represents the most intellectual effort since the knowledge of dependencies between KPIs is highly distributed and available in most cases only on individual level by experts. A common expert might be the responsible users for the analysis at the production site. This means, the responsible user knows from experience about three or four dependencies between KPIs in his local work area. But often there is no enterprise wide KPI network defined. We see the non-formalized knowledge of dependencies by KPIs as one major outcome of the usage of KPI dashboards. The figure 3 illustrates this 'model-graph' with 150 nodes. The nodes in the 'model-graph' provide information about the related business-id, business-units, the formalized description of the KPI, an identifier, a data source template, the list of responsible persons for the technical implementation and possible units of measurement. Furthermore the node includes information about the relationship to other KPIs. These information can be seen as basic information per KPI for inheritance to the 'view-graphs'. Beside the KPI relevant information, the 'model-graph' provides default settings for the graph-drawing algorithm and a pre-defined set of graph-aesthetics rules per graph-drawing algorithm.

Each 'view-graph' inherits and specifies this information. For example the data source template is replaced by a data source query entry for accessing the values and the list of technical responsible persons is extended to responsible per-

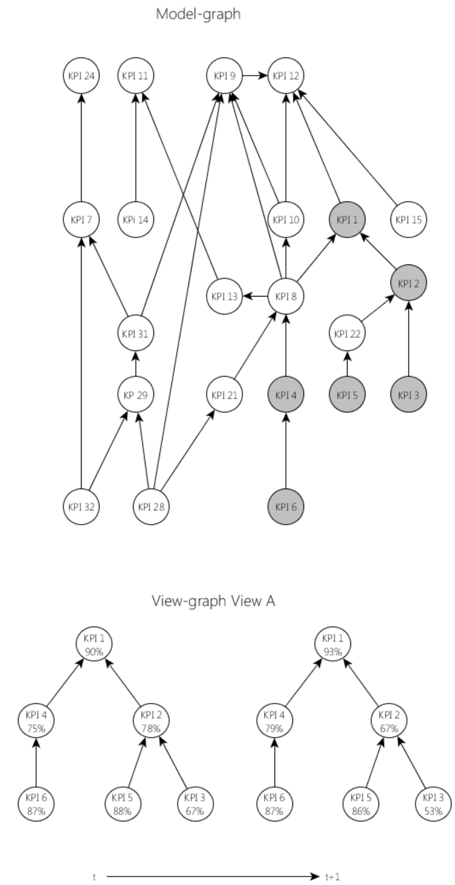

Figure 3: *Example illustration: a) on the left side a 'model-graph' with 22 nodes. nodes which have been selected for the 'view-graph' are highlighted. b) a 'view-graph' view A six nodes. The values of the nodes change between time step t and t+1.*

sons for execution of the associated business process. Typical tasks for the user using the 'view-graph' might be:

- the analysis of previous states and values of the KPIs,
- a drill down into related KPIs to detect root causes,
- an early detection of present issues which might affect other departments in the coming time period,
- and training on relationships and influences between business processes.

The selection of the KPI nodes per 'view-graph' is bound to the tasks of the user. The user can compose each view by himself using drag and drop functionality. The creation of the 'view-graphs' starts with an empty 'view-graph', where the user defines time span and period, and proceeds with drag and drop of the necessary KPIs from a list of KPI models. This means, a specialist for product quality analysis will include all daily KPIs in regard to the quality audit to his

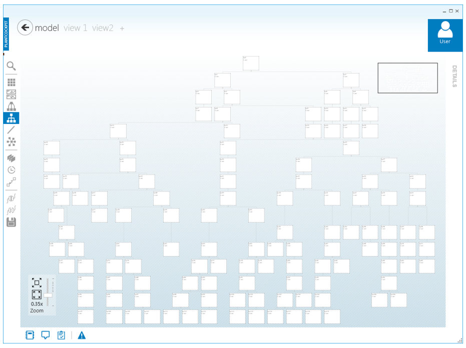

Figure 4: *The implementation of the 'model-graph'.*

'view-graphs', while an executive from the senior management may want to visualize quarterly KPIs related to budget, performance or effectiveness from distributed sources (e.g. all production sites of the enterprise) . We propose an average amount of nodes per 'view-graph' of 15 to 20 nodes, according to cite{Brown1997.

While figure 4 presents a 'view-graph' containing 16 nodes in the time span 01. July 2013 to 31. August 2013 (as view 1), the figure 5 illustrates a second 'view-graph' with four nodes for the time span between 22. October 2013 and 30. October 2013. Both 'view-graphs' inherits the dependency information from the same 'model-graph' as presented in figure 3. The user can access the single time steps for each 'view-graph' individually by using a slider control. On the left side of the screen the start of the time span is controlled, on the right side of the screen the user can control the end of the time span. We extracted one 'node' and two time

Figure 5: *A 'view-graph' named as "view 1", containing 16 nodes from the 'model-graph'; Time span: 01. July 2013 to 31. August 2013.*

steps as figure 6 for illustration. This 'node' is included into 'view-graph' named 'view 1'. For part a of the figure 6 the value is 15.17 for the 06. July 2013 and for part b the value is 23.80 for the 31. July 2013.

Figure 6: *A 'view-graph' named as "view 2", containing 4 nodes from the 'model-graph'; Time span: 22. October 2013 to 30. October 2013.*

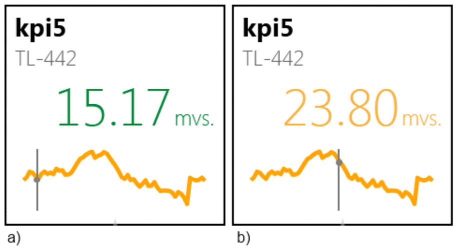

Figure 7: *Comparison of two time steps from one 'node' out of "view 1". time step for part a) 06. July 2013, time step for part b) 31. July 2013*

5. Conclusion and outlook

This work presented a novel approach for integrating multiple temporal aspects into a single graph-based visualization using multi-level graphs. This idea can be used (but is not limited to) for the complex graph-based visualization for KPI analysis where multiple time spans per analysis task and time steps between KPIs information have to be considered. Our proposal provides deep insight in temporal and non-local dependency information between KPIs assuming a valid model-graph in the back-end. The future work will include further research on the specification of common characteristics of all 'view-graphs' for proposing a minimal set of valid criteria for efficient processing of graph-based KPI analysis tasks.

Currently a validation of the concept, using a focus group with six experts from automotive industry, has been finished as a first part of a combined qualitative and quantitative research approach. First insights point to the necessity of an enterprise wide valid KPI model for the creation of time-dependent 'view-graphs' as described in the paper to provide a common ground for the interpretation of dependencies between KPIs. The second part, a quantitative usability study is 'work-in-progress'. The study is part of a thesis and results will be expected soon.

Two questions concerning update mechanism and the granularity of time remain to be addressed: We waived the consideration about the handling of modifications to the 'model-graph' during run-time and the effects to the 'view-graphs'. In the scope of this issue, we will focus on a notification and modification inheritance concept, which can be integrated into the multi-level graphs. Furthermore our approach doesn't consider different granularity in time for each node yet. For the current state, we have implemented a uniform time-line per 'view-graph' because a secondary 'view-graph' with a different time-line might solve this issue. Nevertheless, multiple changes in the granularity of the time-line within the 'view-graph' are imaginable. For this matter we have to focus on a further refinement of the currently temporal uniformity of the 'view-graphs'.

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