On Advanced Business Simulations
Converging Operational and Strategic Levels

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Keywords: KPI predictions, Business Dynamics, Business Process Simulation, Process Performance Parameters, Business Simulations, Semantic Knowledge, Ontologies.

Abstract: Business Dynamics (BD) enables strategic Key Performance Indicator (KPI) predictions to monitor the health status of companies and support the decision making process. Nevertheless, a very important factor, which is generally overlooked, is that the top level strategic KPIs are highly influenced by the operational level business processes. These two domains are, however, mostly segregated and examined as silos with different solutions. In this paper, we are proposing a framework for advanced business simulations, which converges the two domains by utilising Ontologies and process execution data. Establishing this connection enables drilling down from a high level KPI perspective into the underlying operational level details to discover hidden bottlenecks and pre-emptively apply corrective actions.

1 INTRODUCTION

Managing global companies is an extremely challenging task, which needs a lot of expertise and experience. These companies are highly complex ecosystems, with millions of customers and thousands of employees organised in various departments in different geographical locations. Like every other complex ecosystem, these need to be managed carefully and with huge responsibility to keep them flourish and stimulate growth. KPI monitoring and prediction solutions, based on multiple concepts (for example, database reporting tools, time series analyses or Business Dynamics (BD) (Sterman, 2000)), are generally employed to keep a check on the company's performance, foresee future development and make critical decisions. Examples of conventional strategic KPIs, which are generally monitored, are revenue, profit, number of orders, employee turnover rate, customer satisfaction, etc. These KPIs mainly relate to business objects, (e.g. Sales Order, Customer, Employee, etc.) and in most cases are computed based on the actual data contained in the business objects (e.g. sales orders in case of sales revenue). A very important factor, which is generally overlooked, is that these strategic KPIs are highly influenced by the operational level business processes, which are the foundation pillars of any company, and are orchestrated to offer the services or products that the company deals with. An efficient execution of these processes is therefore vital for company's success. Huge amount of event data (process logs), is generated during process execution, which has only recently received attention by the business world and research community. The performance indicators computed from execution data, called Process Performance Indicators (PPIs), are used to evaluate the performance of business processes (Ann et al., 2011; Del-Rio-Ortega et al., 2010). Such PPIs are, for instance, process queue length, throughput, resource utilisation, instance occurrence, etc. This process execution data, therefore, holds the key to uncover problems and bottlenecks at the business process execution level. Significant research work has been carried out in the area of PPI extractions, for instance, in the context of Process Performance Mining and Business Process Performance Management (Redlich and Gilani, 2011; Fritzsche et al., 2009; Heilig and Möller, 2014).

However, so far KPIs and PPIs have mostly been dealt with and consumed in isolation at different levels (strategic and operational). For example, if one looks into the widely adopted commercial solutions in the Business Intelligence domain, such as Business Objects, Aris WebMethods, Oracle BAM, SAP Process Observer, they all deal exclusively either with

Drobek M., Gilani W., Redlich D., Molka T. and Soban D.
On Advanced Business SimulationsConverging Operational and Strategic Levels.
DOI: 10.5220/0005425601660171
In *Proceedings of the Fourth International Symposium on Business Modeling and Software Design (BMSD 2014)*, pages 166-171
ISBN: 978-989-758-032-1

PPIs or KPIs (Howson and Newbould, 2012; Hecking and Schroder, 2013). The authors have not come across any work that connects the PPIs and KPIs, except a commercial solution by Software AG that offers a manual mapping approach to connect these two levels (SoftwareAG, 2014). But clearly, there is a connection between the two levels, as inefficient execution of BPs eventually leads to KPI deviations, which might cause financial collapse of the company. Simple examples highlighting this deep connection between PPIs and KPIs are:

- An inefficient execution of Sales Opportunity Management process in a sales office leads to decreased revenue.
- A delayed Consignment Fill-up process leads to lost sales.
- An imperfect execution of the Idea to Market (I2M) process leads to companies failing to introduce novel competitive solutions, thus loosing market share (e.g. Kodak and Blackberry).

In this paper, we propose a systematic framework for BD simulations which utilises semantic knowledge sources, simulations and PPI analyses, to explore and enhance KPI predictions. This paper is therefore split into the following sections: Section 2 describes the available operational data and the two approaches that are generally used for PPI predictions. Section 3 gives an explanation of KPI predictions with BD simulations and highlights the need of semantic knowledge to generate such predictions. Section 4 introduces our advanced business simulation framework and design decisions that have been made, to incorporate PPI predictions in BD models with the goal of enhanced KPI predictions. We further outline the need for additional semantic knowledge sources, necessary to describe the dependencies between KPI-KPI and KPI-PPI to create KPI predictions. Finally, in Section 5, we conclude the paper and list further research challenges, which need to be tackled in future work.

2 BUSINESS PROCESS ANALYSES

Software systems supporting the execution and management of operational BPs are called Business Process Management Systems or Business Process Management Suites (BPMSs) (Ko et al., 2009). Examples of BPMSs are SAP Netweaver BPM (Woods and Word, 2004) or Intalio BPMS Designer (Intalio, 2013). When BPs are executed they produce events each representing a transition in the system's state.

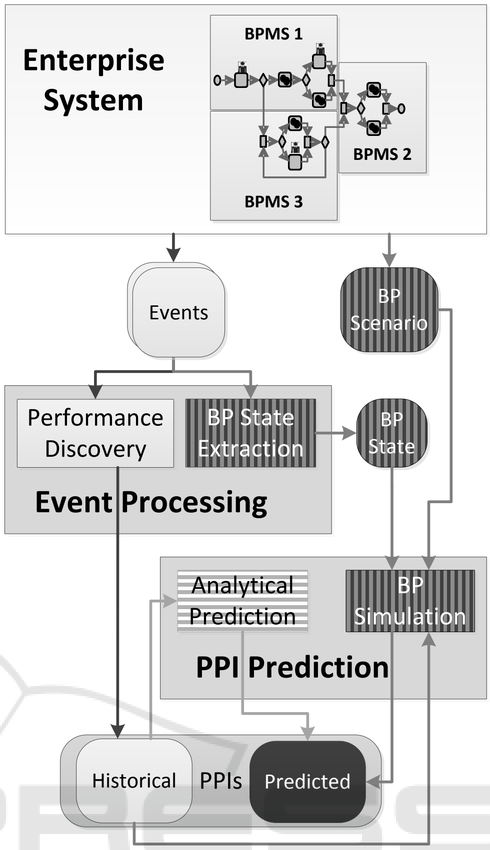

Figure 1: Information flow for PPI Extraction and Prediction: (1) Analytical Prediction (horizontally striped); (2) Prediction via Simulation (vertically striped).

These events are usually of a simple nature and often only comprise raw information, like process instance id, timestamp, and type of the state transition but not the state of the whole system (Van Der Aalst, 2011). One example of such an event is:

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2013-05-26 T 13:45 CET: Activity "Check
  availability" completed, pi-id:  253
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The performance of the BPs is measured with PPIs, e.g. *activity net working time* - the elapsed time of an execution of a single activity, or *activity throughput* - number of executions of a single activity per time period, or *process instance occurrence* - how often the process has been initiated. The historical PPIs are computed by capturing, selecting, aggregating, and eventually abstracting raw events from process logs to generate high-level performance information about the system (Performance Discovery).

The prediction of PPIs is generally carried out with two different approaches: The first approach is to utilise existing data-centric Business Intelligence tools to predict each PPI individually based on its history, i.e. *Analytical Prediction*. These numerical and/or statistical methods do, however, not take the workflow information that is readily available in many BPMSs into account (Redlich and Gilani, 2011). The second approach, which includes workflow information to create more meaningful prediction results, is *Prediction via Simulation*. In this second approach, in addition to the extracted historical performance data, *BP Scenario* information about control workflow, involved roles and resources are utilised in a discrete event simulation (Robinson, 1964). The beneficial effect of using simulation over analytical methods for predicting PPIs is discussed in (Redlich and Gilani, 2011) and (Porzucek et al., 2010). Figure 1 shows the general concept for extracting *Historical* (and current) PPI data plus the two approaches of how to compute the *Predicted* PPI data via Analytical Prediction (horizontally striped) and Prediction via Simulation (vertically striped).

3 BUSINESS DYNAMICS

Predicting KPIs in enterprises is a commonly used method to support the decision making process to line up the future business strategy. These predictions are usually carried out with time series analyses of historical KPI data (Brockwell and Davis, 2006). However, in large businesses, KPIs appear to be high-dimensional, non-linear, are part of feedback loops and not isolated. Especially the fact, that KPIs are no silos, thus are being influenced by a variety of other KPIs and variables, raises the level of mathematical expertise needed to perform time series analyses. In such cases, when the system under study is highly non-linear and contains feedback, Forrester's System Dynamics concept is in general well suited (Forrester, 1961). Sterman already showed the applicability of Business Dynamics (BD) in the business domain (Sterman, 2000). Since BD is essentially a specialised SD concept, it adopts the same traditional SD steps to support the modeller in understanding the business and creating predictions. SD itself is, however, already a well established concept and various steps involved in SD have been debated for decades (Burns, 1977; Ford, 1999; Binder et al., 2004). We have summarised these traditional steps in the lifecycle figure 2, using Burns and other sources.

The process usually starts with eliciting knowledge from the business domain experts (company employees, BP owners, managers, directors and so on) and formalise it into *Causal Loop Diagrams*. CLDs capture the most important business variables (revenue, sales, orders, customer satisfaction) and their inter-connections (Burns, 1977). The next phase is

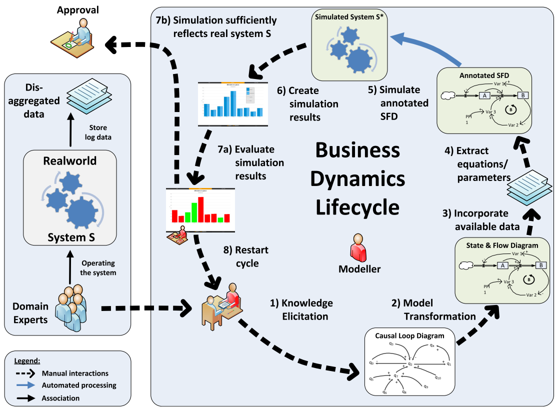

Figure 2: The traditional BD life cycle.

the transformation of CLDs into *State/Flow Diagrams* (SFDs), which capture the resources/material flowing through the business (Forrester, 1961). In the next step, the SFDs are annotated with parameters and equations, which embodies a variety of different limitations (Drobek et al., 2013), and then fed into the simulation engine (e.g. Vensim, Stella (Richmond and isee systems (Firm), 2008)) to finally carry out simulations. Once first simulation results have been produced, the modeller has to evaluate, whether the output matches the real-world behaviour. Further iterations are executed to improve simulation results.

The BD modelling process is, however, not trivial, since it is mostly based on the modellers understanding and knowledge of the target business. For instance, the modeller is expected to:

- semantically link together the KPIs and their influencing variables in the CLD (e.g., profit is influenced by monthly expenses)
- detect and model feedback loops
- determine the resources/material flowing through the system to create SFDs (e.g., money, customers, satisfaction)

To find these connections, the modeller usually relies on the business domain experts (Forrester, 1991). Mostly, this knowledge is a mental model and needs to be manually extracted by the modeller, which gives room for misinterpretation and failure (Ford and Sterman, 1998). Additionally, the modeller has access to the historical business data (KPIs, documentation, reports), which she uses to extract the dependencies and relations of the target KPI. But even with this knowledge, modelling CLDs and SFDs is still a very challenging task, since the identification of the important variables, which influence the target KPI and main feedback loops, requires a lot of experience, expertise and imagination.

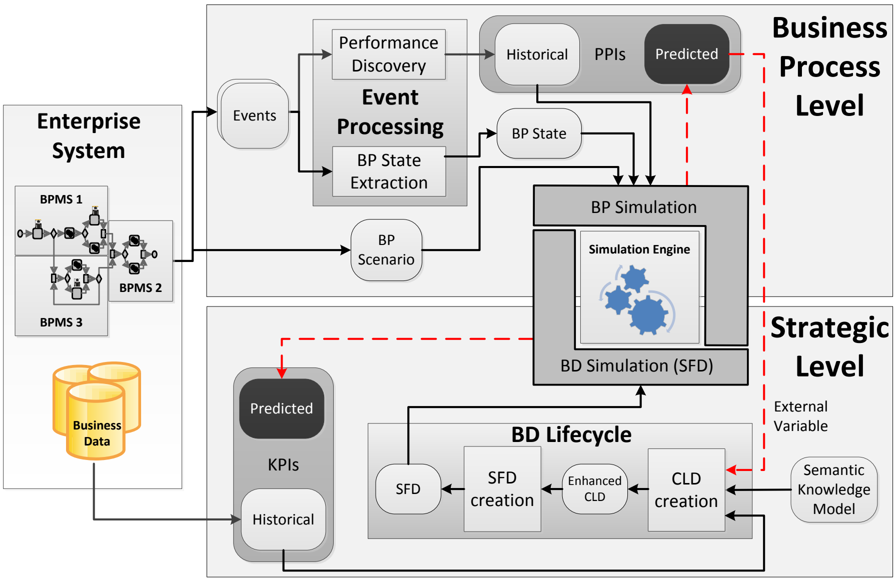

Figure 3: Framework for linking strategic KPIs with operational PPIs.

4 AN ADVANCED BUSINESS SIMULATION FRAMEWORK

As stated earlier in the introductory section, and highlighted with examples, the strategic KPIs are highly influenced by the execution of BPs at the operational level. However, the strategic level decision makers (head of sales, board members, etc.) lack the process level visibility to make informed decisions. Establishing a link between the PPIs and KPIs will enable this process visibility. Our proposed framework solution, in addition to the strategic KPIs, also incorporates the predicted PPIs in the BD life cycle, thus establishing a link between the operational and strategic level. With these links, our framework enables identifying and addressing issues and bottlenecks pro-actively at the operational level before they start impacting the strategic KPIs. Figure 3 shows a schematic description of our advanced business simulation framework. The two main approaches to compute PPI predictions are described in Section 2. Our framework employs the second approach, *Prediction via Simulation*, because it preserves the control flow information of the targeted BPs and thereby helps to exploit the benefits of behavioural simulations (Porzucek et al., 2010). Additionally, the KPI prediction process via BD simulation is orchestrated following the BD life cycle provided in Section 3 (shown in figure 2). The connection between the operational and strategic level is established by including the PPIs in the CLD creation process. This is done by applying causal indicators, such as correlations and Granger causality (Granger, 1969), among the KPIs and PPIs and further extracting their semantic dependencies from available enterprise ontologies, as described later. The precomputed PPIs are an additional input data source, when designing these *enhanced CLDs* in our framework. Once an enhanced CLD is transformed into an SFD, it is simulated and finally KPI predictions are generated. In a standard BD simulation run, each element apart from static parameters or converters is simulated. Since the PPIs are more accurately calculated via event processing and BP simulations (as shown in figure 1), they are not recomputed again in the BD simulation. The reason behind this accuracy is the availability of highly formalised and well structured behavioural models and event data that enables an automated prediction process. The PPIs are therefore, by definition, considered to be parameters or converters in a BD simulation run, even though, they also change over time. Our solution introduces a new BD element type called *"external variable"*, which maps to a precomputed PPI. Such an external variable is not influenced by any of the other BD elements, but is still continuously updated with each simulation run at the operational level.

The creation of CLDs has always been a non-trivial task, as discussed in Section 3. By introducing an additional operational PPI input, this problem becomes even more challenging. This raises the need for a definition of some sort of a *"dependency model"* to provide a guideline on how to link together operational data to the KPIs. Such a model needs to describe the relations and dependencies be-

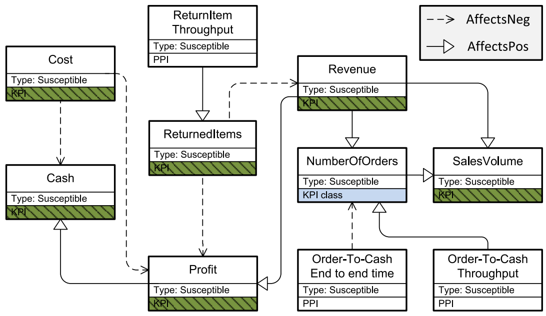

Figure 4: Visual representation of a business ontology to describe the relation between KPIs and PPIs.

tween KPI-KPI and KPI-PPI, thus reflecting the semantic knowledge that usually resides in the mental models of the domain experts. Ontologies and knowledge graphs are two examples for formal ”semantic knowledge models” (SKM) (Zhang, 2002). Companies, such as Google, are using knowledge graphs to *”... understand real-world entities and their relationships to one another”*, which are either automatically harvested from the web or are once manually created by the domain experts and then reused (Steiner et al., 2012). We find Ontologies to be well suited to describe this kind of semantic information and have included such ”semantic knowledge models” into the framework, as shown in figure 3. A snapshot of an example retailer business ontology is shown in figure 4. This picture visualises the connection between some high-level KPIs, for instance, Revenue, NumberOfOrders, ReturnedItems, and three PPIs, namely *ReturnItem_Throughput*, *OrderProcess_Throughput* and *OrderProcess_EndToEndTime*. These three PPIs are reflecting the throughput of the ReturnItem and Order-To-Cash BP, as well as the average execution time for one Order-To-Cash BP instance. Additionally, the KPIs and PPIs are connected via two relations: *affectsPos* and *affectsNeg*. Whilst the affectsPos relation suggests a positive influence from source to target element (e.g. directly proportional), the affectsNeg relation negates this dependence (e.g. inversely proportional). In this given case, we know that the Order-To-Cash BP drives the high-level KPI NumberOfOrders, which then impacts the sales volume and finally the overall revenue of the company. If a modeller was to predict the company’s revenue, she should consider the impact of the Order-To-Cash PPIs and incorporate those into the simulation.

A valid question at this point is the expected number of KPIs and PPIs, which have to be considered to create such ontologies. Mostly, BPs are standardized, but are still sometimes customised to cater specific requirements of particular companies, for instance, introduction of additional activities in the standard Order-To-Cash BP. The fundamental PPIs, such as end-to-end execution time or instance occurrence, still remain valid. The same holds for universal KPIs (revenue, sales volume, cost), which are employed in all companies to check the health status of the business. On the other hand, there are also KPIs, which are unique for each different company, e.g., ”number of orders for product X” or ”current stock of product Y”. Because companies are selling so many different products and services, one can not simply map each single product into one universal ontology. In our framework, we have introduced the notion of KPI/PPI classes. These classes are used as templates in the ontology. A good example for such a class in our ontology is *NumberOfOrders*, which acts as parent for each single ”number of orders for specific product” KPI. With this available ontology, all that is left for the modeller to create CLDs, is: Classify the current KPI/PPI and query the relationships of its parent class to other KPIs/PPIs from the ontology.

The introduction of a link between the operational and strategical level within our framework offers one huge benefit: It enables the modeller to drill-down from a high-level strategic view to the low-level operational view. Since an enhanced CLD now contains both, the KPIs and PPIs, possible strategic KPI bottlenecks can be tracked all way down to the operational level, thus showing the root cause of deviations. This KPI-PPI connection is established with the help of ontologies within our framework. Additional benefits of having such an ontology is, that these are highly extensible and reusable for the targeted domains, for instance, any newly observed domain specific dependencies can be included into the ontology. On top of that, ontologies are well suited for automated processing and can easily be queried with SPARQL to retrieve the KPI/PPI relationships (The W3C SPARQL Working Group, 2013).

5 CONCLUSION AND FUTURE WORK

In this paper, we have proposed an advanced business simulation framework that addresses the missing connection between the strategic and operational level in businesses, thereby converging the two domains. Within our framework, the operational level PPIs are included as a part of BD simulation for KPI predictions and enabling operational level visibility. This means any KPI violation at the strategic level can be tracked down to the operational level to carry out corrective actions. Furthermore, in order to address the increased complexity resulting from the introduction of PPIs into BD simulations, we have designed and implemented additional SKMs. These SKMs (ontologies) provide knowledge about relations and dependencies of KPIs and PPIs, and can be used as *business dictionaries* to look up relationships of KPIs and PPIs either manually or automatically. An automated consumption of SKMs can further be used to automate the BD simulation process for continuous KPI predictions in real-time. So far this approach is unidirectional, because we have only incorporated PPIs as main influencing factor towards KPIs. For future work, it would be interesting to analyse the KPI influence towards PPIs as well. We believe, that the prediction of PPIs could also be beneficially impacted by incorporating the simulated KPIs. The next step would be, to evaluate the framework in the context of an industrial use-case, to demonstrate improved KPI predictions.

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