Performance Benchmarking in Interdependent ATM Systems

Integration of Analytical and Process Oriented Performance Benchmarking Schemes in Complex ATM Systems

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***Abstract*—Understanding and quantifying aviation as a whole system of coupled and interdependent sub-systems is a challenging task. To overcome resulting complexities and dynamic effects we approach the problem from an analytical and operational point of view. Both differ in their required data inputs as well as their methods to analyze and identify interdependencies in the system. Interdependencies are central elements for holistic optimizations as they take into account propagation of data and decisions; i.e. how a local system affects other systems and vice-versa. In this paper we discuss our approach to leverage the potential of both measurement methods. We discuss how they solve specific problems and how they differ. Finally we offer a concept on how to integrate both methods which offers the possibility to compare and complement each other. This allows to cross-validate results and the partial mitigation of weaknesses of the other. Also it opens new ways to identify potential for improvements, which will be discussed.**

Performance Analysis; Dynamical Systems; Interdependencies; Machine Learning; Key Performance Indicators

I. INTRODUCTION

A. *Problem Statement and Paper Contribution*

Understanding the inner workings of a complex system (of systems) like aviation also requires to understand the relationships and interactions between them. These also introduce interdependencies which basically states that no single system operates without affecting other, exogenous systems and vice versa. Because of these bi-directional relationships local decisions or performance measurements are often problematic. To achieve a global optimum or quantification of a system one has also to account for the local system's influence on other parts of the whole. In light of an increasing interest in research on performance based airport management (PBAM) [1] and todays importance of Key Performance Indicators (KPI) in decision support systems (DSS) [2] this paper focuses on the role of interdependencies on KPI and operational levels.

To analyze such interdependencies we follow two general approaches: a) applying analytical models on a KPI level and b) modeling the underlying architecture from a process oriented point of view. In the following chapters we will discuss each approach in regard to its capability to identify and model system interdependencies. We then discuss our idea to integrate both approaches and how this will complement strengths and weaknesses of the other approach.

In summary our paper makes the following contributions:

- Discussion of system interdependencies and their criticality for future improvements of the aviation system
- Introduction of two approaches to analyze interdependencies
- Proposition of a concept to integrate both approaches into a unified systems-interdependency metric

We address this by first discussing performance measurement in aviation and the special role of interdependencies in chapter 2 and putting our paper in context of existing research. We then introduce our two approaches for performance measurements in chapter 3. Finally we propose an integration scheme and discuss how they differ and complement each other in chapter 4. Chapter 5 provides an outlook on the next research steps required to implement such a system.

B. *Aviation Performance Measurement*

Performance measurement is a process involving the collection, analysis and representation of information of a system. It is mainly focused on the identification of the gap between target and actual states to optimize a system's behavior and control it in an appropriate way. There are several definitions of performance frameworks for the benchmarking process in the field of aviation created by different committees; for example from the European

Commission [3], SESAR [4] or ICAO [5]. They differ in their way of defining measurable areas and collecting emitted data of the system, but they agree in their general concept of analyzing systems: the definition of Key Performance Areas (KPAs) and their segmentation in Key Performance Indicators (KPIs). A KPI is a quantification of one specific area of interest representing its performance or workload [6]. All KPIs represent a transparent, valid and comprehensive way of depicting the system status and monitoring process behavior. But none considers intrinsic interdependencies which are essential for a consistent evaluation.

This necessity is known in general and simplified in [5], implemented as a trade-off-operation to balance performance in regard to different target values within the system. This balancing is done after the determination if such conflicting objectives exists and involves different types of multi-criteria decision-making techniques (MCDM). The process takes place after determining if there are conflicting objectives that need to be balanced and involves several types of MCDM. To avoid such a downstream adaptation of interdependencies via trade-offs the here described pattern recognition model for KPI interdependencies is executed within the analysis. A similar approach is introduced in [7], where so called "core-KPIs" are identified, which have an assumed relation to a set of exogenous KPIs. Nevertheless, this connection is not proven mathematically.

C. Role of Interdependencies

The idea of analyzing interdependencies within a complex system as aviation is to uncover relationships between (sub-)systems and their components which influence each other as a result of actions taken by another, related system. This leads to complex effects which depend on the actions of the exogenous system; therefore creating an interdependent relationship. While such a relationship can be directly between two systems it can also be indirect via a third (fourth, ...) system as depicted in the figure 1 below. The circles represent systems and the arrows effects, propagating from one system to the other leading to an indirect relationship.

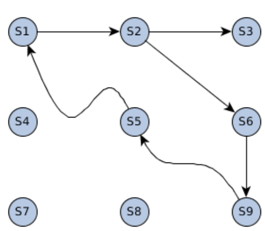

Figure 1: Propagation of effects through interrelated systems

Because effects may propagate on a complex path through the whole systems network, relationships are often not trivial to identify. To help research, structured methods are required to identify and quantify those interdependent relationships.

In the context of aviation, the reactional delay during aircraft rotations [8], turnaround management [9] [10] or the dynamic passenger behavior [11] demonstrates the effect of interdependencies of (dynamically) coupled systems. Analyzing interdependencies therefore helps to improve the systematical benchmarking process in the ATM sector through a better understanding of patterns and correlations between KPAs & KPIs [12]. This creates new usage opportunities of performance frameworks as decision support systems (DSS), as they generate a deeper systems understanding and the generation of a benchmarking metric without contradictions.

As stakeholders work simultaneously on a common problem set from different perspectives, with such metrics as a DSS tool, their optimization strategies mostly work in a diametrical way or fail to influence each other in a positive way through using interaction potentials by affecting the same KPAs/KPIs and the exploitation of a common achievement of objectives. Knowing about inner-system links helps to balance a multi user system control and may represent system behavior in a nearly complete way.

II. Measurement Methods

This chapter covers two approaches we are pursuing to identify interdependencies in a given system. The first focuses on an analytical level of KPIs which represent specific performance characteristics of the systems. Through statistical analysis on large datasets, correlations between two or more KPIs are identified. After the validation of identified interdependencies their specific functional relation is derived.

The second is focused on the operational relations and processes of the constituting systems and therefore relies on the implied systems architecture which has been discussed from an hierarchical perspective of transportation systems in [13]. Such architecture has to be modeled with a bottom-up approach. Interdependencies are then an emergent property of the whole system and can be identified by static analysis of the architecture or dynamically by simulation.

A. Analytical Approach

Often the analysis by application of expert knowledge is not sufficient; hidden patterns, (ir)regularities and predictive information are missed out because of their abstract and unexpected character resulting from interdependencies. To extract useful information from large data bases, data mining is a useful pool of methods. Data mining is segmented in different tools which allow to predict system behavior and users to make knowledge-based decisions.

KPIs as output devices of a system, are characterized by an inhomogeneous and incomplete nature. For some, a huge amount of data is available while others are non-measurable.

All refer to single objects or processes at airports, airlines, ANSPs, etc., describing individual properties in different units and time scales. Correlations and relations are hard to identify on this level of abstraction, so it is nearly impossible to make correct predictions. By extracting knowledge, KPI outputs can be separated into classes from which general rules and structures may be derivable.

TABLE I. RELEVANT IN- AND OUTPUTS

Input	• Emitted performance data which is quantified via benchmarking structure ○ inhomogeneous data base ○ lack of data ○ different scales in time and unit
Output	• Functional correlations between performance indicators • System behavior approximation

Table I shows the characterization of in- and outputs of a KPI driven benchmarking scheme. Any selected statistical algorithm or method must also be able to deal with these constraints to be applicable for pattern recognition in performance benchmarking schemes. Especially when working with fragmented and incomplete data bases, the applied method should be able to produce consistent results. Because of system complexities and the high number of inner-system effects it is difficult to make conclusions about the type of correlations between performance indicators and to attest them an analytical resolvable character.

As a useful method out of the field of multivariate data mining technologies, *Artificial Neural Networks (ANN)* meet those requirements and are able to extract information about the relationships between variables in complex system networks. ANN can be parameterized in different ways (in form of the chosen initial values which directly affect learning behavior and the results) to adapt them to specific scenarios. They are a promising candidate to adequately complement standard data mining methods like regression analysis. Implemented as adaptive computer programs, ANN allow for highly complex pattern detection and machine learning algorithms in intelligent data analysis. This is because correlations are autonomously discovered (learned) by the ANN and not only detected.

As ANN do not describe or formalize their self-learned solving algorithms externally, they are extended by *fuzzy logic* to *neuro-fuzzy-algorithms* to avoid black box properties. Fuzzy logic is an extension of the classical binary logic (0 and 1) of sharp sets and allows a mathematical description of noise-datasets by adding an affiliation function $\mu(x)$ between the hard defined borders 0 and 1. A combination of ANN and fuzzy systems creates adaptive, comprehensible and interpretable procedures, where a) fuzzy logic represents the mathematical foundation to detected data interdependencies and b) ANN supplies fuzzy rules through learning from historical data. Integration of prior knowledge is possible by manually adding additional fuzzy rules [14].

Effects of dynamic behavior also need to be identified by the benchmarking scheme. Given a comprehensive network NET_{KPI} with *n* output devices (KPIs), identifying correlations between them is not sufficient to represent their inner-system dynamics in light of bi-directional influences. Consider figure 2: The relationship f: X → Y between KPI_x and $KPI_y \in NET_{KPI}$ (with X and Y are state spaces for all recorded outputs of KPI_x and KPI_y) in a performance framework is (with exceptions) not invertible, which means the correlation depends on the source of a released signal (KPI_x affected by variations of KPI_y and vice-versa). This phenomenon is based on different underlying process structures.

In case of the given example figure 2, f(x) is injective (distinct elements of its domain are never mapped to the same element of its co-domain), but not surjective (not every element of the co-domain is mapped to by at least one element of the domain), because event/KPI_y output D is matched by another correlation/another process. In conclusion variations in KPI_x affect KPI_y anyway, but variations in KPI_y are not forcibly conditioned by KPI_x.

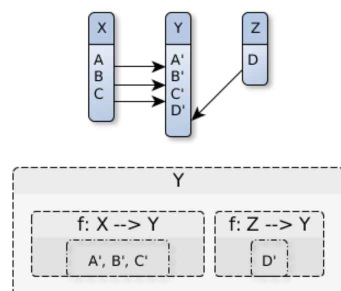

Figure 2: Visualization of multi-dimensional KPI influences

Considering the complexity of a system (a huge amount of variations in single time steps) and the abstract character of the observation layer (just receiving system emissions) a direct linking to the underlying processes without structural knowledge is difficult, because one can only hypothesize in a heuristic way. The application of neuro-fuzzy-models allows to specify a noise-, but system-connecting affiliation function, for every output device (KPI). A fuzzy set is clearly depicted by its type of affiliation function $\mu(x)$. In our example: by representing all possible values between 0 and 1 it is possible to match the output of KPI_y to its sources in X and Z by describing the links in a fuzzy format (figure 3) resulting in a clear two-set division and a noise interference set depending on the value of changes in Y. This way of backtracking a KPI output to its sources leads to a heuristic implementation of fictional underlying process structures. In the given example KPI_y is definitely affected by at least two different processes.

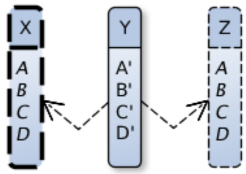

Figure 3: Backtracking of KPI outputs to their sources via FUZZY

In addition to a view on the cross section of the system at the time of t_0 a view at the longitudinal section representing the system behavior over time $t \rightarrow \pm\infty$ is now presentable. System effects like bifurcation (describing a qualitative change of state) or stability dependent on a variation in the input data by a user enabled differentiated choices of changing a systems parameter set. A simple example the increase of flight movements in combination with reduced turnaround durations.

In summary, the complete network of KPIs and studying their behavior in an autonomous, dynamical system leads to the possibility of understanding and exploiting interdependencies. An appropriate visualization and mathematical description through fuzzy logic describes inner-system connections to the users working with performance frameworks as DSS.

B. *Operational Approach*

Large scale systems like todays aviation are comprised of many, (semi-)independently operating sub-systems working together to achieve a common goal [12]. The operational approach in context of performance benchmarking analyzes interdependencies with focus on the involved processes, necessary to reach that goal.

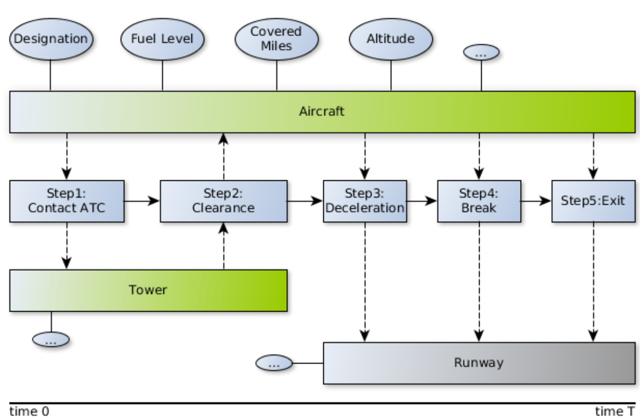

Figure 4: Example model showing single process steps, entities, relations and attributes

A process is a chain of multiple actions of systems while each step transforms inputs into outputs. To model a process, the constituting systems have to be identified as well as the relationships among them. Associated with each system and relation are different attributes which either define their structure or describe their current state. A process again may be composed of sub-processes which are not part of the current perspective; modeling therefore is done on different levels of abstraction depending on what focus the researcher has. The resulting model is a simplified abstraction of the real-world process, creating a network of systems having input-output relationships to each other.

Consider the given example process in figure 4: depicted is a simplified model of the process “segment of final approach of an aircraft”. The boxes in the center are the actual process steps, ordered chronologically alongside the time axis from left to right. Aircraft, Tower and Runway are systems directly involved in the actions (steps) of the process. Associated with each entity is a set of attributes. For the entity “Aircraft” the “Designation”-attribute is static – since it seldom changes. The other attributes are dynamic and change over time. The dashed arrows illustrate the systems involved in each process step and from which direction the step is initiated.

The given process is part of another, higher level process 'flight'. From that we observe that the modeled process is on a specific level of abstraction resulting in the statement, that all described process steps can be decomposed into more detailed sub-processes, until further breakdowns are not possible. This is illustrated in figure 5.

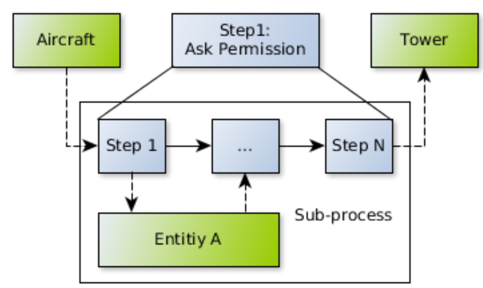

Figure 5: Example breakdown into sub-process

Performance characteristics are therefore directly dependable from the constituting sub-processes. If assessing the performance of this given process we need to quantify each step with a valid KPI (see chapter 5). From a higher abstraction level this might be as simple as “time for each process step”, “time taken to touch-down” or more specific ones like “miles covered till touchdown” or “fuel consumed till exit from runway”. On the other hand, if we were assessing the overall performance of a "flight process" those local performance indicators will have to be used as input for the higher-level process measurement.

How do interdependencies play into this process oriented view? The following relationships within performance measurements can be observed:

- A single process step might be dependent on steps prior or after itself
- A process step might be dependent on an exogenous system
- A higher level process, integrating sub-processes, is directly measured and defined over the performance of that sub-processes

The example shows that measurements are not always independent. The key performance indicator (KPI) "fuel consumption" is clearly dependent on exogenous factors (from the aircraft perspective), not taken care of in this example (aircraft type, weather conditions, current airport capacity, etc.) and the performance of other process steps of exogenous system (eg. within the tower). Fuel consumption directly depends on the separation process, which influences the duration of the approach and with it the required fuel. In critical situations the fuel level of a given aircraft again influences the separation process: is the fuel level too low, the aircraft needs priority clearance, so the separation has to be changed. This in turn affects other aircraft, indirectly creating a complex set of interdependencies, which exist especially at busy airports.

Those interdependencies will be modeled or made visible in the way the system-relations are modeled and by their corresponding input-output relationships. However, they might not be visible to the researcher since the functional chain might be complex or hidden within a sub-process not modeled at the given level of abstraction. Or it might be hidden inside another systems process, exogenous to the local process at hand.

To analyze the performance of a system or overall process, measurements of tokens of interest have to be done. Those are directly attributable quantifications to a local level and are taken from an *actual process instance.* That means, that there is the formal process description on the one hand and a concrete real-world process (or a simulation of it) on the other. Only on this level measurements are taken. The overall performance of such a process is then derived from a series these process measurements. These measurements, without the underlying process structure are the input for any KPI-level analysis. Doing this on the global scale leads to a holistic structure and process model, describing the overall system.

III. COMPARISON AND INTEGRATION

The goal is to gain a deeper understanding of the interdependencies between different systems used in performance benchmarking schemes. This is either done on data which has been extracted from real-life measurements or from simulation experiments. Or it is done from a formal model of the underlying processes which form a network of interrelated systems.

A. Relation and Integration

Both discussed methods exist for themselves, yet they have an underlying relation to each other. In this chapter we discuss the nature of this and how both methods can be integrated into a common benchmarking scheme. For this we first discuss how they complement each other and what their differences are.

An analytical (data-based) approach allows to employ different methods from the field of data mining and statistics as we have discussed in II.A. The result is a structured graph of interrelated KPIs, while for each a mathematical functional relationship can be calculated. That is, we can quantify how much a modification of one specific KPI_a affects an KPI_b. Since we also have identified the relations KPI_b has to other KPIs, we can also formalize their functional influence on these KPIs. In case of a bi-directional relation between KPI_a and KPI_b we speak of interdependent KPIs. Note that this bi-directional influence can also be indirect, meaning that a change on KPI_b, origination from KPI_a affects KPI_c, while the change there leads to a change in $KPI_{a.}$
A process oriented approach on the other hand works from the bottom-up; systems are modeled in regard to their relations to other systems. A process describes all the steps in their time-discrete sequence needed, to achieve its specified goal. Associated with each system and relation are different attributes, either statically describing their inherent properties or dynamically reflecting their state at a point in time *t*. Measurements and therefore KPIs can directly be attributed to specific systems and process steps, this is only partially true for a data based method. It is true that a KPI is merely a measurement point, a quantification of an aspect of interest within a process model. But this is an static attribution and misses the relations to others systems as part of an integrated process. This again is the core of a process model where system relations are modeled as input-output relations between single process steps. The structure of interdependencies therefore is inside the models structure in comparison to it being in the data.

TABLE II. COMPARISON OF METHODS

Data Level Analysis	Process Level Analysis
Identifies interdependencies between specific KPIs through statistical analysis	Can identify interdependencies through the modeled systems, relationships and associated attributes
Is able to derive a functional relationship to quantify interdependent effects	Performance is derived from direct measurements of involved processes
Cannot explain the underlying structure of this high-level observations	Performance indicators are directly attributable to specific systems and processes.
	Cannot formalize the functional relationship

An integration of both methods would allow to generate a better understanding of interdependencies and relations between KPIs and systems involved. It also enables both methods to leverage the potential of the other. From a KPI oriented viewpoint, the understanding of the underlying structure of processes gets more precise and effects can be attributed to specific systems and areas of real-world processes instead of being simple measurement points. This is an important aspect since a process model holds causal relations between system (because they are derived from real-world observations) which can used to validate correlations identified from data analytics. From a process oriented view additional tools for the identification of interdependencies and relations become available helping to identify weaknesses in the process model. Also "what-if" analyses on a process become easier since the effect a change would have can directly be quantified on the KPI level.

An integration would then require the following major steps:

1. A process model as the starting point
2. A KPI benchmarking scheme has to be defined
3. KPIs have to be mapped to the process model

Performance measurements must be based on real systems and processes of interest. Therefore a process model is required. This model then helps to actually determine what could be and what is measured. It also states against what measurements are done and therefore gives meaning to it. The associated KPI scheme defines what is actually measured and how it is measured. Here high level KPIs can be defined and measurements can be grouped into complex KPIs. The last step is the actual integration of both methods. A high-level KPI has to be mapped onto the process model in such a way, that it is clearly visible to which parts in the process model it is connected. Figure 6 illustrates this. To associate a KPI with a specific set of systems and attributes in relation to some other measurable. The KPI "Fuel Consumption" then would be associated with the system "Aircraft", its attribute "Fuel level" measured against "Time.

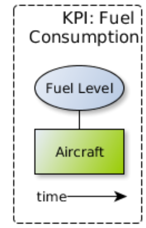

Figure 6: Example KPI definition from process model

B. *Application Example in Aviation*

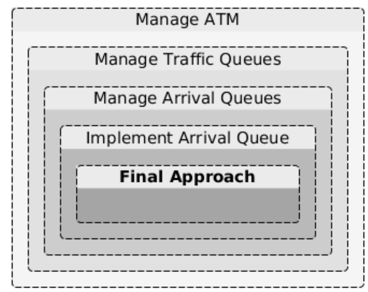

Figure 7: Hierarchy of systems and processes within ATM

Figure 7 shows a hierarchy of (sub-)processes based on [15]. The top system with the highest level of abstraction is the "Manage ATM" system. The lowest level system is the sub-system "Final Approach". It is possible to map KPIs from a higher level system to a lower levels of comprising systems. In the example all emitted data of the Final *Approach* sub-system in the superior system *Implement Arrival Queue* – not in their original form as absolute process parameters, but as relative parameters representing the average behavior of an approach.

In this way it is possible to analyze the system at several levels of abstraction, whether a more micro- or macroscopic view is needed. Tracking specific outputs to their source from a starting process is possible by linking all sub-processes throughout the abstraction layers.

In the following we apply the scheme outlined in the previous chapter to create a simple benchmarking based on the simplified example process "Aircraft Final Approach".

Step 1: Process Model - Final Approach of Aircraft

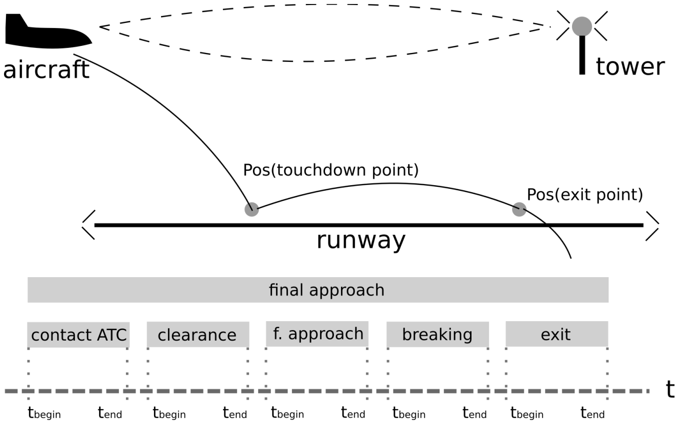

Figure 8: Process model of the final approach

The figure 8 above shows a simplified process model of an aircraft's final approach while flying from airport A to B. This sub-system is represented by entities (aircraft, tower) and the general structure (runway, terminal maneuvering area (TMA)/airspace). The process begins when the aircraft comes into reach of the tower and ends with it exiting onto the taxiway. This is the starting point from our performance analysis. Benchmarking results from this abstraction level would then be the input for a higher level in the process hierarchy.

Step 2: KPI Benchmarking Scheme

This step defines what is to be measured and defines KPIs which will reflect the performance of the process.

TABLE I. KPIS OF INTEREST

KPI	Description
$KPI_{TotalTime}$	Total time taken to complete the final approach phase which will end with the exit of the aircraft from the runway.
$KPI_{FuelConsumed}$	Total amount of fuel consumed during process.
$KPI_{FuelConsumptionTime}$	Fuel consumed during final approach per unit of time.
$KPI_{FuelConsumptionDistance}$	Fuel consumed during final approach per unit of distance covered.

We choose the KPIs defined in table I. Those higher level KPIs are defined from sub-KPIs. Especially $KPI_{FuelConsumption*}$ needs to be measured in relation to some other measurable. In our example this will be "fuel consumed over time" and "fuel consumed over distance covered". Sub-KPIs are defined in the table II below.

TABLE II. SUB-KPIS

KPI	Description
KPI_A: Time for final approach	t_{begin} t_{end}
KPI_B: Time for rolling	t_{begin} t_{end}
KPI_C: Absolute distance for final approach	Pos(Aircraft) Pos(touchdown point)
KPI_D: Absolute distance for rolling	Pos(touchdown point) Pos(exit point)

The KPIs are separated in the phases "flying" and "rolling" which is more precise within benchmarking. KPI_a and KPI_b reflect the time component of the approach while KPI_c and KPI_d reflect the distance component.

Step 3: KPI Mappig to Process Steps

Table II shows the sub-processes of the final approach example with associated, possible measurement points and its corresponding entity. The "t"-parameters define the time slot of each sub-process, so the total of all sub-processes equals the overall process time $KPI_{TotalTime}$. The "pos"-parameters cover the entity positions in a defined coordinate system. For example the sub-process "Contact ATC (Tower)" is initiated by the entity "Aircraft". Based on the previously defined KPIs we measure the time the process takes until completion: we record the beginning time of the process t_{begin} and the end time t_{end} with the overall time = $t_{end} - t_{begin}$. Also we measure the absolute position of the entity aircraft at the beginning and end of the process with the total distance covered = Pos(Aircraft, t_{end}) - Pos(Aircraft, t_{begin}).

TABLE III. SUB-PROCESSES, ENTITIES AND PARAMETERS

Subprocess	Entity	Parameters
Contact ATC (Tower)	Aircraft	t_{begin} tend Pos(t_{begin}) Pos(t_{end})
Landing Clearance	Tower	t_{begin} t_{end} Pos(t_{begin}) Pos(t_{end})
Final Approach	Aircraft	t_{begin} t_{end} Pos(t_{begin}) Pos(t_{end})

Touchdown / Deceleration	Aircraft	t_{begin} t_{end} $Pos(t_{begin})$ $Pos(t_{end})$
Exit to Taxiway	Aircraft	t_{begin} $Pos(t_{end})$ $Pos(t_{end})$
-	Aircraft	FuelLevel(ProcessStep)

t = time | pos() = position of aircraft at given time

Putting all the previous definitions together, the following shows how the KPIs are measured from the associated process steps and entities. References are given in the form:

Entity.Sub-Process.Parameter(Entity.$_{Attribute}$)

Measuring the Sub-KPIs:

$$KPI_A = Aircraft.FinalApproach.t_{end} - Aircraft.FinalApproach.t_{begin}$$

$$KPI_B = Aircraft.Breaking.t_{begin} - Aircraft.ExitTaxiway.t_{begin}$$

$$KPI_C = |\ Aircraft.ContactATC.Pos(Aircraft) - Aircraft.Touchdown.Pos(Aircraft)\ |$$

$$KPI_D = |\ Aircraft.Exit.Pos(exit\ point) - Aircraft.FinalApproach.Pos(touchdown\ point)\ |$$

Measuring the top-level KPIs:

$$KPI_{TotalTime} = KPI_{a} + KPI_{b}$$

$$KPI_{FuelConsumed} = Aircraft.FuelLevel(ContactATC.t_{begin}) - Aircraft.FuelLevel(ExitTaxiwayt_{begin})$$

$$KPI_{FuelConsumptionTime} = KPI_{FuelConsumed} / KPI_{TotalTime}$$

$$KPI_{FuelConsumptionDistance} = KPI_{FuelConsumed} / (KPI_C + KPI_D)$$

Applying the KPI - Process integration model to the system structure enables the user to analyze inner-system effects through interdependencies between the given KPIs above. The analysis is focused on the identification of relations between the sub-processes descent and breaking. As shown in this example, it is possible to track the event chain of effects to its source and directly address the relevant (sub-)process or systems.

IV. Conclusion and Outlook

Both discussed methods enable a deeper understanding of the inner workings of the system especially in regard to interdependencies. Going forward from a local analysis we proposed a scheme which aims to integrate both methods. This creates new potential for the analysis of system performance. A researcher now not only has the view on abstract KPIs which are based on the analysis of measured data. But he can also attribute each measurement to a local process and system which is responsible for a specific effect observed in measurements. This contribution is part of ongoing research activities in the Department of Air Transportation at DLR in the area of performance based airport management and complex systems analysis. The next research steps are focused on data analysis/-mining, the application of ANN and methods for complex systems modeling based on a system-of-systems approach. This aims at an integrated airport management, unifying systems architectures and performance benchmarking to create advanced decision support systems for the aviation domain.

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