Optimization of Airport Processes

Support system for human decision making in total airport management

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***Abstract* — this paper describes a planning and optimizing system (TOP), generating sample airport operations plans (AOP) - the foundation for common decision making (CDM) process. Diverse 'state-of-the-art' algorithms of optimization combined on two levels of abstraction made it possible to provide the human decision makers with reliable and possible best solutions of operations planning satisfying requested preferences subject to predefined or negotiated constraints and objectives, given the continually changing input data.**

Keywords – TAM, APOC, CDM, planning, TOP, AOP, heuristic optimization, traffic flow, scheduling

I. Introduction

Creating an optimal plan of operations for even a middle sized airport is not a trivial problem. Due to uncertainties and dependencies on factors beyond control it is generally not possible to optimize such solutions analytically. Nowadays extensive sophisticated algorithms are used to solve optimizing of short term delimited dedicated problems e.g. of sequencing arrivals or departures on runway or associating ground handling resources with planes at gate. However the main goal for our efforts was to support human decision makers in the time frame of pre tactical phase (time horizon of 24 hours) of operations planning [1,2]. Besides, because of this being a support for live interactive human communication, alternative solutions depending on individual preferences are expected within seconds, to not break fluency of negotiation. Fulfilling these contradictory goals, namely producing of possible exact prediction of events with optimized control suggestion within a very short time was a challenge to be solved aiming the main target a human centered decision system. Since the resolutions are not safety relevant and there is always still enough time to correct infelicitous suggestions (especially because of humans involved in the decision loop) one can slightly sacrifice exactness to meet the most important requirements.

In our TOP we solve this problem on two separate levels of abstraction. First, using a simplified model of an airport operating system, defined as a set of interacting traffic flows of abstract entities, resources and control parameters, a prediction of future state will be calculated and optimized towards individual objectives under constraints predefined in contract of quality of service using a 'temporal greedy' algorithm of partially linear solutions. Based on predicted abstract results the detailed plan of operations for all participants will be generated using diverse meta-heuristic probabilistic methods such as ‘simulated annealing’ (SA), ‘stochastic tunneling’ (ST) etc. taking into account all individual constraints for events and resources being skipped on traffic flow abstraction level..

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II. Problem Definition

A. The Generic AOP definition

Given finite sets $\{p_k \in P\}$, $\{r_l \in R\}$ of planes and resources (or milestones describing plane status, as in [4]), a time interval $\{t \in T_H : t_{HS} \le t < t_{HE}\}$ and $T = T_H \cup \{t_{N/A}\}$ let an AOP be:

$$AOP : P \times R \to T \qquad \mathrm{AOP}(p,r) = \begin{cases} t_p^r \in T_H & for\ \mathrm{r} \in R_p \\ t_{N/A} & \text{otherwise} \end{cases} \tag{1.1}$$

under following constraints:

$$\forall_r \forall_t card\left\{p : r \in R_p, t_p^r \in \left[t - D^r(p), t\right)\right\} \le C_U^r(t) \le C^r(t) \le C^r \tag{1.2}$$

$$\forall_r \forall_{i,j:r \in R_{p_i} \cap R_{p_j}} dist\left(t_{p_i}^r, t_{p_j}^r\right) \ge S^r\left(p_i, p_j\right) \ge S^r \tag{1.3}$$

$$\exists_{r_i, r_j} \forall_{p_l, p_k} dist\left(t_{p_l}^{r_i}, t_{p_k}^{r_j}\right) \ge S\left(r_i, r_j, p_l, p_k\right) \tag{1.4}$$

$$\forall_p \forall_{r_i \le r_j \in R_p} t_p^{r_j} - t_p^{r_i} \ge L_p\left(r_i, r_j\right) \tag{1.5}$$

$C_U^r(t), C^r(t), C^r$ - physical resource capacities (user defined, environment, maximal)

$S^r\left(p_i, p_j\right), S^r, S\left(r_i, r_j, p_l, p_k\right)$ - separation of events (single resource, dependant resources or milestones)

$R_p, L_p\left(r_i, r_j\right), D_p^r$ - event processing restrictions (subset of partially preordered resources, event lag matrix, duration of processing)

B. *The quality measurment and optimizing target*

Let a presumed set of functional assign values of key performance indicators (KPI) [3, 4, 5] for each AOP:

$$KPI_i : AOP \times T_H \rightarrow \mathbb{R} \tag{2.1}$$

which are usually quality measure functions of different partial distances between desired AOP and actual one. The final goal is to minimize Costs defined as,

$$C\left(AOP\right) = \sum_i \int_t^{T_H} \alpha_i\left(t\right) * KPI_i(t, AOP) dt \tag{2.2}$$

or more often used in a discrete form as,

$$C\left(AOP\right) = \sum_i \sum_{t_k = t_{HS}, \Delta t}^{t_{HE}} \alpha_i\left(t_k\right) * KPI_i(t_k, AOP) \tag{2.3}$$

weighted linear combination of KPIs, given the set of weights defining user preferences $a(t) = \begin{bmatrix} \alpha_0(t) \\ \dots \\ \alpha_N(t) \end{bmatrix}$.

Due to nonlinear and non differentiable dependencies between partial costs and distance between AOPs such problems cannot be solved analytically. The amount of input data (from 300 airplanes for a middle sized airport to 1000 for main traffic nodes, over 10-15 resources) makes complete numerical solutions non practicable using common desktop computers. Formerly mentioned methods to solve delimited sub problems concentrate on a limitation of the space of resources (mostly down to one) and number of planes taken into account. Even for the large airports within a time horizon of half an hour no more then 50-60 events are expected to take place. Besides such short period allow to neglect temporal causalities between solutions for the same plane (arrival – turn around – departure). On the other hand, the necessity to provide data to direct control of flights in safety relevant space of tactical control phase, demands for exactness, reliability and stability of solutions are much higher than for pre tactical planning phase. So the solutions are searched in continuous time space, with a lot of sharp restrictions but often simple and monotonic partial cost functions.

C. *Splitting of the problem*

One of the most effective methods to solve multidimensional complex optimization problems is splitting them into a set of solvable sub problems of significantly reduced complexity, where the sum of partial efforts is clearly smaller than an attempt to search solution globally. The challenge is to accomplish this not changing the results, or at least to deliver a result which is quite sure not far away from the global optimum [6, 7]. There are no recipes for that - an educated guess, an intuitive judgment, and common sense are the only signposts for design. Assuming that the exact time definition for events for which even the source data are burdened with uncertainties of more than 5 minutes and the realization of suggested solution alike, we decide to transform the final stage of the original problem to:

Events and Resources Level

- assuming a given table of possible times (event independent) for each resource (fulfilling capacity and temporal causality restrictions of original) find the solution, as a simple scheduling of events (projection from continuous time space into discrete domain)
- search for a solution in a subset of key resources followed by simple chained resource assignment for intermediate ones
- the original functional C can be used for the assessment of resulting AOP quality

The necessary set of possible times for resources can be generated with a feasible accuracy using a system simulation, this leads to:

Traffic Flow Level

- based on given operational procedures at an airport [3, 4] a deterministic traffic flow model of resource usage has been constructed, where individual input events are transformed into abstract flow streams traversing the process model according to predefined restrictions
- changes of model states take place at evenly distributed time stamps
- selected tapped flows correspond to usage of certain resource and therefore founds a source for counterpart time series
- selected flows of control (settings and restrictions) are used to optimize the total system performance towards a set of derived cost functions (defined on another subset of tapped flows, additionally expanded in the discrete space of model time intervals)

Gain of cascade optimal solutions for both problems results with one for the originally formulated. Given a very simple algorithm First Come First Serve, which generates a valid AOP we have a limiting worst solution, on the other side, using all the settings but neglecting capacity restrictions, we have a possibly invalid AOP, but a limes value for the best possible solution. However, due to the very high variance of the preferences (cost function factors) and restrictions or configuration - which is one of the most important features of the presented system [2] - it is very difficult to compare single results. The only real assessment of its quality is the opinion of human user and judgment of experts. Comparison of results towards limiting values supplemented with expert knowledge founds a base for continuous system tuning - selection and parameter for cost functions, model structure and projection of cost functions from event level into traffic flow (following the original are the functions of distances between AOP instances, what means differences of times for specified events, being unknown on the traffic level). Being a part of a long term efforts to reduce rapidly increasing cost of air transportation and especially its impact on environmental resources, the constant improvements of the system are the main target for the next time.

III. TOP IMPLEMETATION DETAILS

According to the presented problem splitting strategy the architecture of the implemented software system can be divided into two separated sub planners. Both parts work separately with supervising instance responsible for their configuration, parameterization and data exchange. Thus diverse algorithm could be tested at each level independently.

A. Traffic Flow Level

The first part of the planning system is both, airport operational state predictor combined with control parameter optimizer. Constructed discrete model of interactions between traffic flow streams (Fig.1),

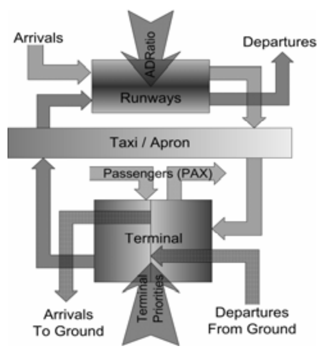

Figure 1. Simplified Traffic Flow Diagram

resource capacities and processing lags simulates handling of real objects on synchronized time slots of constant length (compare [11]). At this level, the individual characteristics and restrictions between particular planes (1.5) are neglected, solely capacity and separation constraints are considered. Expected events, such as 'Estimated LanDing Time' (ELDT), 'Scheduled In Block Time' (SIBT) of single planes, aggregated into continuous stream density function of input or reference traffic flows (3.1), discretized on selected time slots, are fed into the model.

$$F_S(t) = \sum_P f_p^t\left(t - t_p^S\right) \tag{3.1}$$

Simple triangle density functions are used for approximation of single events. The exact shape depends on the type of event as well as on remoteness to the calculation time, the more accurate data source the slimmer and higher the triangle, and with increasing distance widen the triangles and are more and more symmetric due to increasing probability of equal chance for changing in both directions.

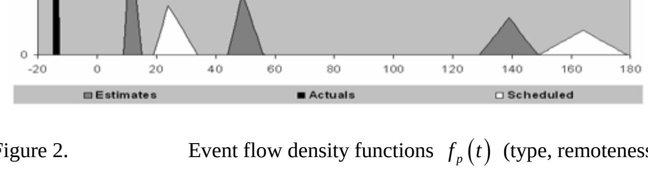

Figure 2. Event flow density functions $f_p(t)$ (type, remoteness)

Of course, the integral area stays constant in all these cases as shown on Fig.2, and the example of aggregated flow stream density for the near future estimated events on Fig.3.

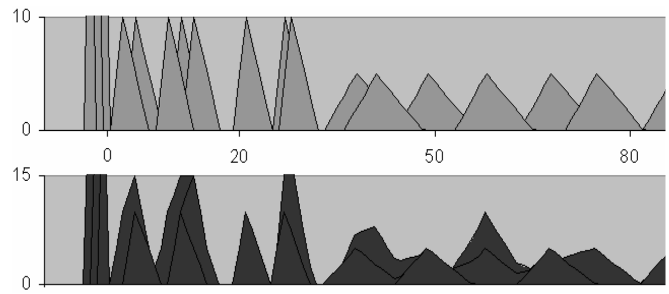

Figure 3. Example of $\boldsymbol{F_S(t)}$ - stream estimates

The best settings for controls are determined in an iterative process of multi dimensional (both in space of variables as well as in time) greedy algorithm. Although the described process generally does not always exhibit the optimal substructure, the separation and limited interference of influence between controls within one time interval, subsequently time limited control independence justifies usage of this simple and very effective method. Breaking criterion for temporal iterations, whereas the model flow calculation will be done for all consecutive following intervals together with final outcome cost, is its negligible decrease. Since the cost calculation effort at this stage is very high (necessity to run the model for rest of evaluation period), it was very important to choose a very effective method of finding minimum for the one dimension case. The Brent's algorithm seemed to be a good choice for this task due to its simplicity. The results of first optimizations confirmed this assumption. Although the cost function cannot generally be approximated with parabolic function, those approximations make good instrument for graduated approach to limiting interval, within which the function converges to such. The risk of being stuck on local minimum has been banished through multiple iterations using variable start points (necessary anyway, due to multidimensional character of the search).

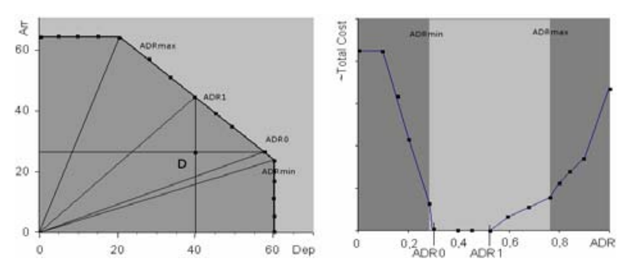

Figure 4. ADR Pareto curve of a runway [12], interval of controllability and 'no influence' window for demand $D_t(40_{Dep},27_{Arr})$

The only problematic (but well separated case) and one which lead to completely erroneous solutions using the classic form of the algorithm, was the case where for some parts or even for the whole interval of controllability the responsible variable has no influence on the outcome. Unfortunately, this is very often the case, occurring for all time intervals, where the working point of demands lies below the Pareto curve [12] of Arrival/Departure Ratio (ADR) for typical runway system (1.3) describing the limitation of mixed operation of resource (Fig.4). These regions of input variable can be simply recognized and isolated and then the search restarted on remains of the original interval. Presented on Fig.4 Pareto curve represents typical characteristics of a control block in the model. Through changes of capacity assignment within its physical or operational limits, traffic flow streams will be passed into corresponding model part with diverse delay and magnitude changing momentary demands for adjacent resource. Thus, according to capacity and delay restrictions, a self-consistent optimized traffic flow will be established. The outcome of the traffic level comprises then tables of separated time events for each modeled resource of the airport.

B. Events and Resources Level

The main performance gain on this level could be achieved through reduction of number of resources taking into account for the global optimization task. Since normally the most 'expensive' and restricted resource is the runway, being simultaneously used by two streams of event flows, so appearing as two dependent resources in the original problem formula, it makes the low limit of reduction. The possibility of a projection of dependence costs onto the stream of precedence will allow, in the future version of the system, to solve these parts consecutively – currently, the search algorithm works on the whole set of events. However the neighbors for iterations are restricted to disjoint subsets of arrival and departure times.

Such problem can be defined for $\{r_0, r_1\}$ (or $\{r_0, r_1, r_2, r_3\}$), and for each r_k given $\{p_i \in P^{r_k} : r_k \in R_{p_i}\}$ and $\{t_j^{r_k} \in T_H\}$ as: finding permutations $\pi^r = \begin{pmatrix} 1 & 2 & \dots & M \\ p_1 & p_2 & \cdots & p_M \end{pmatrix}$ such, that $C\left(AOP_0\right)$ achieves minimum, where: $\underset{i,r}{\forall} AOP_0(\pi^r(i), r) = t_i^r$.

Formulated in this way, the scheduling problem is a typical case for iterative stochastic algorithms as SA [8] or its derivative – ST [10]. It is obvious, that practically it would not be possible to recalculate the total cost on each iteration step. However, substituting

$$KPI_i(t, AOP) \doteq \sum_{r_k} f_k^i(t, AOP) + \sum_{(r_k, p_j)(r_l, p_i)} h_{kj,li}^i \left(t_{p_j}^{r_k}, t_{p_i}^{r_l}\right) \qquad (4.1)$$

where $f_k^i(t, AOP) = \sum_{p_j \in P^{r_k}} g_{jk}^i(t, t_{p_j}^{r_k})$, we get (comp. (2.3)):

$$C\left(AOP\right) = \sum_r C^r\left(AOP\right) + \mathrm{C}^D\left(AOP\right) \text{ with} \qquad (4.2)$$

$\mathrm{C}^D\left(AOP\right) = \sum_P f^D\left(p, AOP\right)$ and $C^r\left(AOP\right) = \sum_{p_j \in P^{r_k}} \sum_i \sum_{t_k = t_{HS}, \Delta t}^{t_{HE}} \alpha_i\left(t_k\right) * g_{jk}^i(t, t_{p_j}^r)$,

setting $\underset{r}{\forall}\underset{m,n}{\forall} f_r^C\left(m,n\right) = \sum_i \sum_{t_k = t_{HS}, \Delta t}^{t_{HE}} \alpha_i\left(t_k\right) * g_{jk}^i(t, t_n^r)$ we obtain a final formula for total AOP cost:

$$C(AOP) = \sum_i f_r^C\left(i, \pi^r(i)\right) + C^D\left(AOP\right) \qquad (4.3)$$

Limiting neighboring solutions to simple swap of two events, keeping already calculated values of independent components in an adaptive sparse matrix and caching recent dependent cost (4.3) for each event - the calculation effort has been reduced to maximum two new values for independent and two new values for dependent costs. Since the former can oftener be reused and complexity of the latter is limited to a small set of predefined dependencies, the total optimization time could be kept within 10-30sec for 600-1000 events of daily operations. Cumulative total cost (additionally transformed for ST algorithm [10]) compared with decreasing 'temperature' controls search devolution. The exact parameterization, used 'temperature' trends and restrictions for neighborhood are elaborately discussed in [9] together with some alternatives e.g. genetic algorithms.

IV. RESULTS

Presented system has been realized as part of internal DLR project, whose main target is to study the CDM process in operational environment of an airport. The results of simulation and optimization for both the actual data (thus the prediction of upcoming situation), and individual What-If probing of CDM actors with changed parameter under control of human decision maker, can be compared and used as reasoning in the discussion of needed actions. The main focus on this side is therefore the best possible prediction of events and the best suggestion of possible action to undertake, to improve performance according to agreed constraints, or at least to increase the awareness of possible traffic bottlenecks or expected resource shortfall. Results below are limited to one day real scenario at airport Frankfurt (FRA) with modified restrictions, simulated environmental influence and changing human parameter settings.

On the following two diagrams we present couple trends of cost functions improvement for randomly selected optimization processes; traffic flow level costs Fig.5 and event level solutions on Fig.6. On the former there are characteristic inflection points, which correspond to begin of temporal iterations – the obvious consequence of greater influence of control settings at the beginning of the causality chain. Real simulation results often (in case of sufficient degree of freedom) outperform the expected final gain of 40-50% of start value.

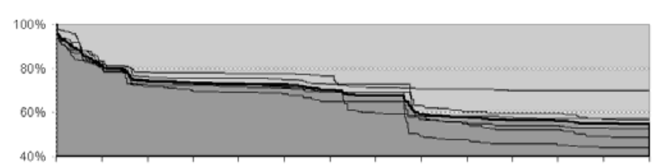

Figure 5. Trend of cost for traffic flow model (fett line/dark grey area) with six randomly selected instances of optimization process (variance)

For the latter one, each data series has been divided into two regions: improvement in the first phase of optimization (logarithmic trend due to ceasing restriction violations) and the actual search for optimal event schedule. As for these results, there is still a lot of space for improvement, for example by the automatic adjustment of parameter for this process. In difficult cases, the improvement against start value achieves ~70%, but shows that limitation to maximal 1000000 iterations breaks the process still having potential of further ca. 10%.

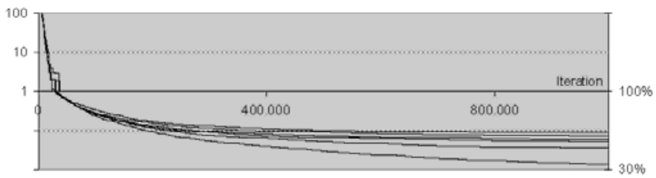

Figure 6. Trends of event level solutions (SA optimization).

On the other hand, lack of not changing regions of best cost, followed by heavy decrease of value suggests, that ‘temperature’ declines too fast, or that the neighborhood variations are possibly too weak. These, along with apply of ST modification of the algorithm, will guide future investigation.

Finally, using two example scenarios of daily operations, we want to present the effects of the system for event scheduling and resulting KPIs.

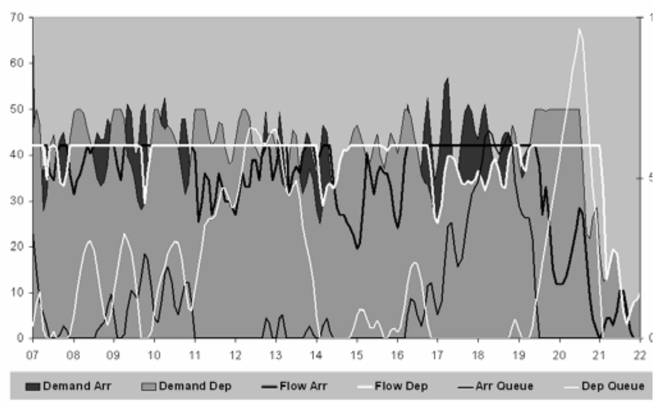

Figure 7. Flow trends of arrivals and departures relative to respective demands for simulated not optimized operations (left axis), together with resulting holding queues (right axis).

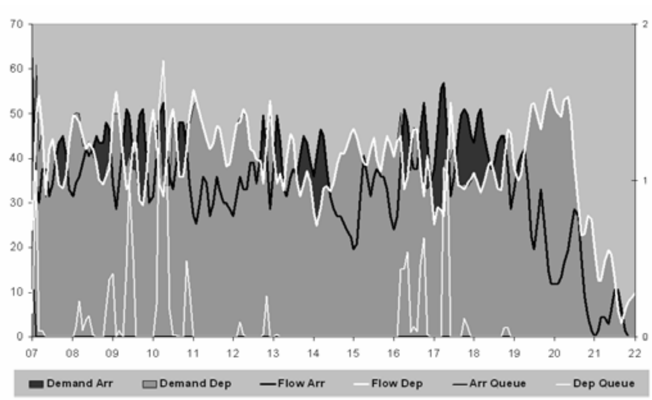

Figure 8. Flow trends (as Fig.7) – after optimization.

The first use case is a non complicated, undisturbed ‘quiet’ traffic, however quite close to the capacity limits of the airport runway system. Total number of planes 850, thereof 464 after landing and turn around will start at the same day of operation, 184 arrivals to stay at airport for the night and 202 waiting for departure at the beginning of the day. A dark scenario with a lot of airplanes waiting for runway access could be expected based on the simulation results of non optimized procedures Fig.7. Even very expensive queues of landing ‘holds up’ attain the level of 5 planes per hour and this for over one hour. As a result of optimized plan Fig.8, all landing queues disappear and number of departing planes waiting for runway clearance reduces to maximum 1, which anyway is a non realistic good number, due to variations in taxiway and apron traffic. Appropriate calculated KPIs are shown on following diagrams (Fig.9-10). Expected delays after optimization stay below 15 minutes limitation (normal limit for punctual event) and appear only in ‘rush-hour’ times, and total punctuality does not fall below 90%, which marks would be constantly underperformed in former situation.

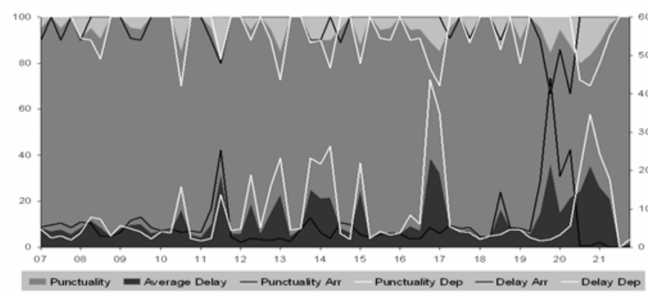

Figure 9. Predicted trends of calculated KPIs for non optimized case of undisturbed operations.

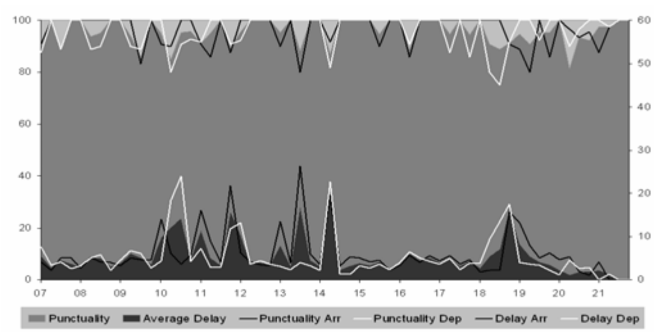

Figure 10. Final prediction of KPIs for optimized schedule.

As a second example exposing performance of applied algorithms we have chosen the same day, but with simulated necessity of complete inhibition of runway operation for only 15 minutes between 10:30–10:45 – typical snow removal proceeding in case of heavy snowfalls. The model simulation can in such situation help to find the best time to accomplish this task in the face of variable and changing demands. Once more, on modeling results we observe a disastrous impact of this action for next 8 hours of operation (Fig.11) which in optimized case could be limited to approx. 1 hour, so from 12:00 the undisturbed, however modified process might proceed (Fig.12). As for original case the impact for individual events propagates until late afternoon, the average airport performance could possibly be kept at high quality level of service (Fig.14, compare Fig.13).

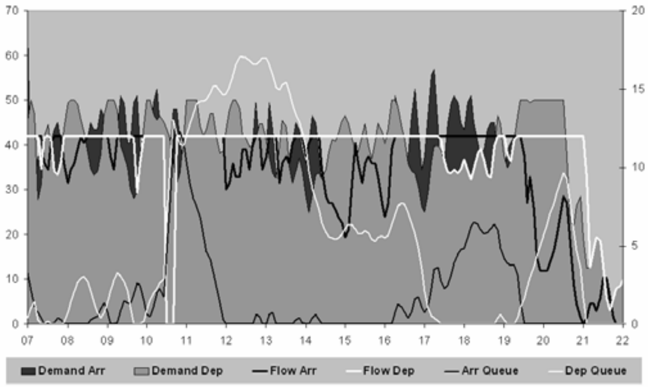

Figure 11. Flow trends (as Fig.7) – for case of runway system ihibition for 15 minutes (10:30–10:45) (non optimized reference).

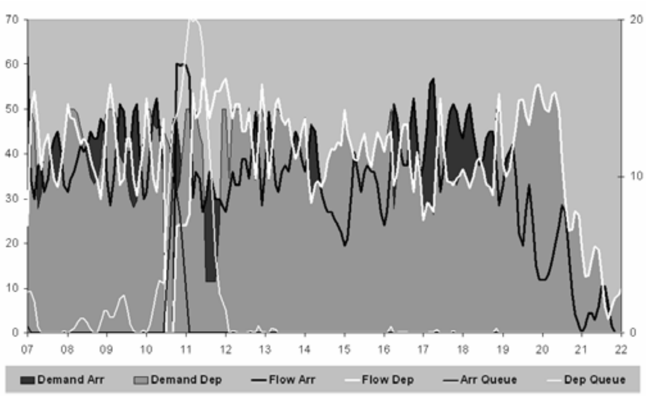

Figure 12. Optimized flow trends for the second use case.

V. OUTLOOK AND FUTURE TASKS

The complex decision processes and their support possibilities still have to be investigated. More operational constraints have to be analyzed to specify the underlying model and its optimization. Some problems in modeling of complex dependencies between operational entities of an airport were drafted and the ways to better approximation were signed, both needing further exploration.

Besides, solving more problems, like the integration of runway assignment with target time optimization or embracing of the traffic within airport approach airspace into simulation model, will improve reliability of simulation and would boost confidence of CDM actors for suggested solutions. A description of situation based target function weights shall be discussed and verified against current expert knowledge and practice. The next step – installation and probing of the system in shadow mode in operational environment shall lead to smooth translation into its full operational status.

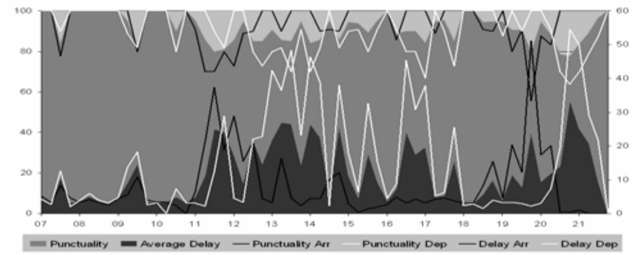

Figure 13. Predicted trends of calculated KPIs for non optimized case of operations in the face of runways system ihibition (second use case)

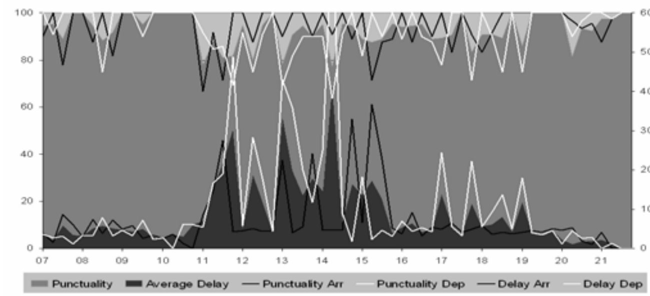

Figure 14. Final prediction results for KPIs in the second use case.

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