same routes on a daily basis. Controllers know which aircraft related to individual airlines are *good climbers* beyond the data considered in the trajectory model. Ground automation is continually improving — often based on controller input. These issues regarding current automation processes have been addressed in several recent studies, including [15], [16], [17] and [18].

They show that there is a large variation in performance, especially concerning climb and descent flight phases. For that matter, we would like to point out the most significant results in *Aircraft Performance Modelling for Air Traffic Management Applications* by Suchkov, Swierstra and Nuic, [17], where it is shown that there is a dramatic dependency of climb rate with respect to aircraft mass — a parameter, that is not and will (most probably) not be known in the future.

All these factors are based on the unavailability and inaccuracy of data regarding the airspace user as well as environmental factors, and lead to uncertainty in the trajectory prediction within current automation systems. As stated previously, data comm, ADS-B and a system-wide information exchange (SWIM) will improve the performance of ground automation. In [19], it was shown how FANS can improve aircraft derived data for better trajectory prediction. A desired complexity metric will therefore incorperate expected changes to these aspects and relate perceived complexity to data quality.

Note that the authors are aware that some system characteristics fit both to data and model quality. This is the case for e.g. wind and weather information. The authors have discussed that the division is made so that all information that is used as input is considered to be relevant to data quality. If there is no weather model included in the algorithms, it is an issue of model quality — if it is indeed part of the algorithms but the input is only an estimate — it becomes an issue of data quality.

B. Model Quality

This group of issues regarding uncertainty addresses the quality of models and their validation. Even with perfect data quality concerning all involved parameters, most models will not achieve perfect predictions. This is due to the fact that for deriving dynamic models, certain assumptions and approximations have to be made. Furthermore, there are many environmental features that are very hard to model. While some of them might be incorporated into very sophisticated models once computational power has improved (e.g. aerodynamics), others will most probably never be fully modelled, e.g. weather and wind. This is due to the literal nature of the environment.

Nevertheless these factors highly contribute to unpredictable aircraft states ahead in time. In the foreseeable future we will not be able to predict these wind events — especially when looking out an hour or more ahead. Hence, we will always have a level of uncertainty in trajectories moving forward. The nearer term goal is with technologies like data link to be able to bring the accuracy of the FMS to the ground automation.

Current automation systems use sophisticated models like the BADA model trying to incorporate as many information as possible in order to obtain a more accurate trajectory prediction. Nevertheless data on weight, thrust, etc. are not passed on to the ground automation. Analysis as in *Advanced Aircraft Performance Modelling for ATM: Analysis of BADA Model Capabilities*, [16], or in a DFS study regarding VAFORIT performance, have shown that the capability of current automation systems has its limits.

Experiences with the DFS VAFORIT system show that even with carefully designed algorithms, errors and inaccuracies in the model will cause uncertainties in trajectory prediction. Figure (2) shows an inaccurate trajectory prediction from the original VAFORIT Trajectory Predictor. This is also

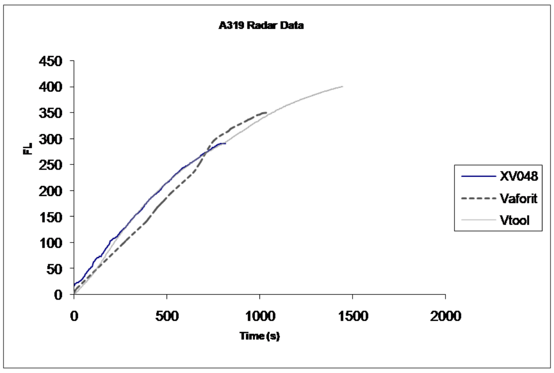

Fig. 2. Previous and current trajectory prediction by the VAFORIT system.

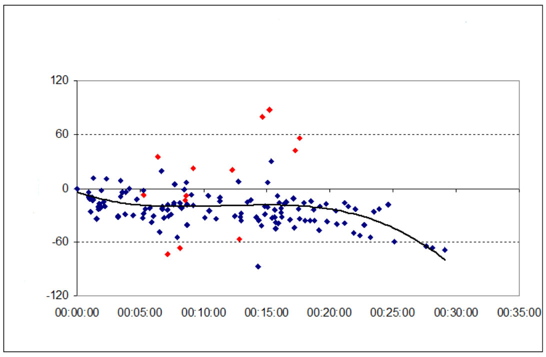

Fig. 3. Relative deviation of actual flights to VAFORIT prediction.

demonstrated by figure (3). It shows the relative deviation of real aircraft data (B737-800) compared to VAFORIT prediction. The straight line is a data fitting curve, while the red points indicate Top of Climb.

As a consequence controllers had to turn off the conflict detection based on altitude feature in the previous VAFORIT release. Before shut-down, this feature did actually increase controller workload as they were questioning the automation system.

Even though the problem is now considered to be solved (observe the new VTool trajectory in figure (2)), the necessary process of updating VAFORIT still shows evidence of typical drivers of unpredictability based on the quality of models used in automated systems.

Additionally, airline practices, individual flight goals and pilot behaviour are not captured. Both NextGen and SESAR will include more information in flight planning related to business goals (CDM) for each flight — data that could be possibly used to improve trajectory prediction.

C. Operational Procedures

An additional area or trajectory uncertainty comes from the execution of operational instructions (*clearances*). One of the majors factors in this group is the timing of execution of controller requested changes in heading or flight level. As of current procedural regulations, a controller will not know when exactly an aircraft will start its climb to a new altitude or its turn towards a new heading. Both aspects are increasing the perceived complexity dramatically, since in both cases, a huge area of possible aircraft positions at a given instant of time ahead is created. Currently, controllers try to compensate for this by assigning boundaries to instructions (*climb before*) in order to achieve a higher level of trajectory certainty.

Figure (4) shows three different climb profiles, exaggerated for the purpose of visibility. It is easily observed that by not knowing when an aircraft will start its climb, and how quickly it will climb, a controller has to reserve and to monitor much more space than actually necessary. An actual

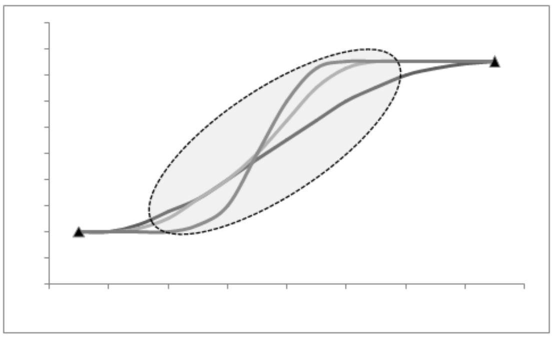

Fig. 4. Various climb trajectories (flight level to time). Ellipse shows the area of uncertainty.

climb profile is shown in (5). Investigating this figure shows evidence of the significant difference between predicted trajectory and actual position at 09:43:12 of more than 1000ft. Possible improvements in trajectory prediction with regard to operational procedures and the soundness of how instructions are followed are addressed in *Controller and Pilot Evaluation of a Datalink-enabled Trajectory-based Operations Concept*, [20].

Figure (6) shows an additional problem with ground

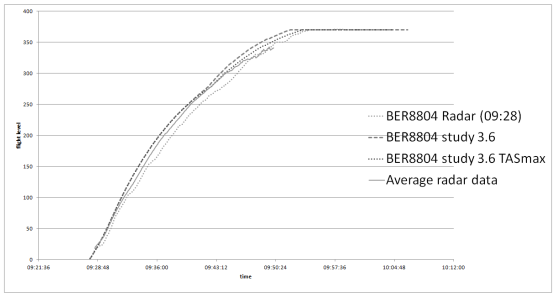

Fig. 5. Actual flight profile of flight BER8804, A320 aircraft.

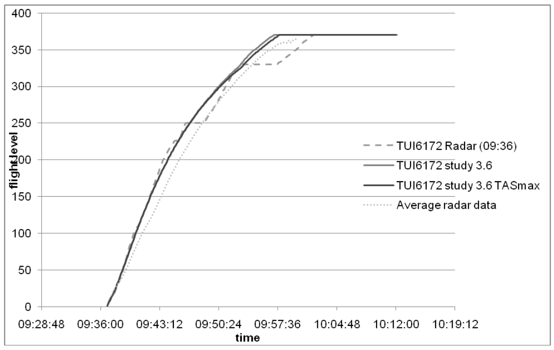

Fig. 6. Actual flight profile of flight TUI6172, B737-800 aircraft.

automation systems predicting trajectories. Here the flight profile for an actual B737-800 flight is mapped. One may observe that the trajectory did meet the prediction very well - untill operational procedures (step climb) took place that resulted in a deviation of approximately five minutes for flight level FL400. If trajectories are built on the average of actual trajectories (or a well-educated estimate) they may do better at the end of the climb, but they will miss early sections of the climb profile.

Figures (7) and (8) show the large variation of flight profiles and rate of climb and descend related to all three aspects above: trajectory data quality, model quality and operational procedures. These figures indicate possible results of inaccurate trajectory prediction and how they will affect sector complexity and workload to controllers.

IV. Proposed Complexity Metric Framework

The 4D trajectory concept of both NextGen and SESAR ([9], [10]) is clearly relying on increased trajectory certainty. In this future framework, controllers will manage non-conforming trajectories by exception. Assuming that the

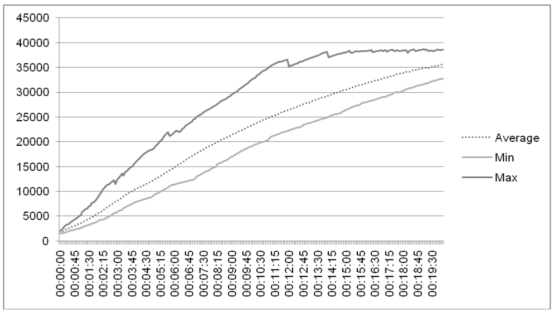

Fig. 7. Flight profile variation for B737-800 aircraft.

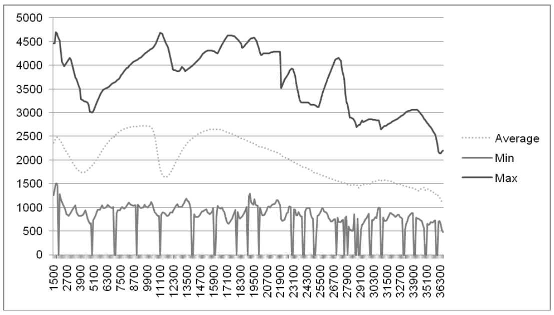

Fig. 8. ROCD with respect to flight level, variation for B737-800 aircraft.

controllers had perfect information about the aircrafts position on the considered time horizon, the same traffic situation would be perceived as much less complex as with uncertain information. In order to enhance the rationale for the deployment of data link technologies, this decrease in perceived complexity must be quantified.

Uncertainty can be captured with 3-dimensional ellipsoids, covering all possible aircraft positions at a specific instant of time ahead. The less uncertainty the smaller the ellipsoid needed when checking trajectories in MTCD. Large ellipsoids produce conflicts that do not need to be solved, hence occupying airspace that could be used by other traffic with the same amount of workload for the controller. Accurate trajectories and conflict detection is key to reducing controller workload.

When uncertainty is included, it becomes clear that the conflict counts will change depending on the predictability of the trajectory. Decreasing the volumes of individual ellipsoids will certainly decrease the number of overlapping ellipsoids, thus reducing the number of potential conflict counts.

Here we propose to assess trajectory uncertainty and its impact on sector complexity by using ellipsoids around predicted aircraft positions that are based on real statistical aircraft data. These ellipsoids can be obtained for any specific instant of time, by using the three-dimensional variance of previously tracked trajectories as the size of all three axes. The volume V of an ellipoid is given by the size of his axes, i.e.

$$V = \frac{4}{3}\pi abc, \quad (1)$$

where we choose a to be the variance in altitude and b, c to be the variance in longitudinal and lateral dimension respectively.

This ellipsoid would represent a possible position of the aircraft for a future instant of time, indicating the uncertainty of a particular trajectory. This approach is demonstrated in figure (9) as a 2-dimensional simplification, where complexity is driven up more severely by crossing or overlapping ellipses.

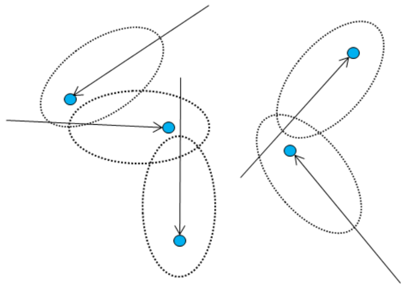

Fig. 9. Top view on 2D ellipsoids for individual trajectories.

The total volume consumed by aircraft in a sector could then be used as a complexity indicator that assesses not only conventional complexity drivers (i.e. traffic geometry), but also the impact of trajectory uncertainty on controller workload. More importantly, the volume of overlapping ellipsoids can be used as a further complexity indicator to assess the possibility of a conflict. When both indicators are combined to obtain a single factor for complexity based on trajectory uncertainty, the volume of overlapping ellipsoids must be indeed assigned to a much higher weight in correspondance to its signifiance.

Regarding conflict detection, the main difference to conventional assessment is achieved by using ellipsoids that are based on real statistical trajectory information that directly depend on the certainty of trajectories. Therefore, the uncertainty is inherently incorperated in the metric function instead of being accounted for by overly sensitive proximity measures. By using our approach, we will be able to quantify how data comm technologies will decrease the possibility of conflicts and increase the feasibility of conflict situations.

A related approach was proposed by Meckiff et all [7], by considering overlaps in 3-D control tubes. This approach could also be appropriate for the calculation above. Our focus is to show the strong relationship to complexity reduction as the sizes of uncertainty zones are decreased with better trajectory information in the ground automation.

Initially, the key element in trajectory uncertainty will be the ability to uplink trajectories from the ground system to the aircraft. A similar and possibly larger improvement will occur when we have enabled the transmission of data in the other direction — i.e. from the aircraft to the ground.

Once we have achieved the transition to an exchange of 4D trajectory constraints, see [21], aircraft flight paths will become more predictable and controller will be able to rely on the automation to predict and resolve conflicts with higher conflidence. Figure (10) gives a visualization of improvements

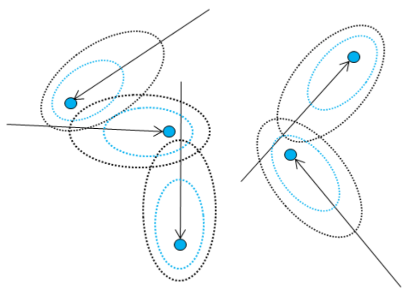

Fig. 10. Improvements in trajectory uncertainty visualized by ellipsoids.

in regard of trajectory uncertainty and corresponding ellipse size. The dotted line represents uncertainty of trajectory prediction with current data synchronization and prediction algorithms. One may observe that there are several possible conflicts between aircraft on the left side. The blue dashed line represents possible improvements in trajectory prediction that will yield much smaller ellipses — no conflicts are indicated, hence reducing perception of complexity and workload.

Interviews with controllers (and trials performed by the MITRE Corporation, see [8]) have shown that this will greatly decrease task load. More detailed information about wind and weather will also further increase the accuracy of trajectory prediction.

As we have mentioned above the emphasis here is on quantifying the impact of increased trajectory prediction on sector complexity and workload. The actual implementation of that new complexity model could be performed as follows. Assume that $F(\mathscr{T})$ is the conservative complexity score of a certain traffic situation $\mathscr{T}$ today, obtained by applying a conventional metric as it is used in Crystal or a comparable tool. Let $V(\mathscr{T})$ be the total volume of all ellipsoids within a sector. Now we may define a new complexity function

$$C(\mathscr{T}) := F(\mathscr{T}) + V(\mathscr{T}) - K, \tag{2}$$

where K is constant that must be calibrated, so that $V(\mathscr{T}_0) = K$, for $\mathscr{T}_0 = \mathscr{T}(t_0)$, where t_0 is today. Applying function (2) to the same traffic situation $\mathscr{T}_*$ with enhanced data link technologies deployed, we will observe a smaller volume of ellipsoids, i.e.

$$V(\mathscr{T}_*) < V(\mathscr{T}_0),$$

hence we obtain

$$C(\mathscr{T}_*) < C(\mathscr{T}_0), \tag{3}$$

even though $F(\mathscr{T}_*) = F(\mathscr{T}_0)$ still holds. This way we obtain a measure that quantifies the improvement made by data link to show its improvements in terms of sector complexity and ultimately sector capacity.

V. Outlook & Applications

In the previous sections we have pointed out how uncertainty of trajectory prediction impacts the perceived sector complexity and controller workload. Therefore, a metric incorperating information about trajectory predictability will yield a better understanding of complexity in a particular sector, hence enabling more efficient resolution strategies.

The main point of this paper however is to highlight that additional benefits for data comm can be captured through improvements in uncertainty. This improvement may be quantified by assessing the volume saved by reducing the size of ellipsoids. Smaller ellipsoids represent one major aspect of workload improved by data comm. Other improvements by data comm include workload reduction for transferring controller functions away from voice, [22]. These have been the primary focus of data comm benefit cases like [23] or [24].

Note that both these workload reductions associated with data comm are not addressable in current complexity measures — and to be fair, they were most likely not intending to work with transforming technologies and procedures.

Furthermore, our framework focuses and for the first time enables two more interesting applications: first the architecture of this approach enables the identification of the individual complexity contribution by single aircraft a_i. By inspecting the array of aircraft

$$A = [a_i, V_i]_{i=1,\ldots,N},$$

where V_i is the volume of a single aircrafts ellipsoid overlapping the ones of other aircraft, and using a simple sorting algorithm, one obtains a sequence of aircraft

$$a_{i_1}, a_{i_2}, \ldots, a_{i_N},$$

ordered by their corresponding ellipsoid size and, possibly, the volume of intersections with other ellipsoids. Interpretating the size of these individual volumes as a measure of individual complexity then gives us information about which aircraft contributes most to perceived sector complexity. This aircraft may then be re-directed, depending on its course and destination, so that sector complexity is decreased.

Therefore, this approach not only helps to detect sector complexity by summing up the total volume of all involved ellipsoids, it also helps to identify single or multiple aircraft that contribute most to sector complexity. This not only enables a better understanding of complexity, but also offers a better way of complexity resolution as certain aircraft may be addressed individually for a better overall performance.

A second application is to investigate the relation between sector complexity and the number of aircraft that are equipped with a more advanced level of data comm technology. The question is how controllers perception of complexity change with the implementation of future data comm technologies? In figure 11, three possible mappings for this relation are displayed (percentage of equipped aircraft to complexity score). It is considered to be an interesting application of our proposed metric to further investigate this relation and determine an actual coherence between complexity and equipage of aircraft.

More specific insight into this relationship would stress the importance of data link technologies and would help to understand the benefits of it. As conventional metrics do not assess the effect of trajectory predictability to complexity, this is certainly a unique feature of our approach.

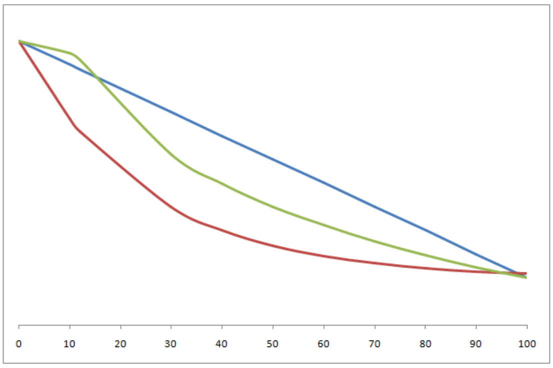

Fig. 11. Some possible functions describing the benefit of data link to sector complexity. Mapping is complexity on % of equipped aircraft.

Further research and real-time simulations are needed for specific calculations of the impact on uncertainty driving workload compared to controller functions like transferring communications voice to data. A focus on complexity driven by trajectory uncertainty addresses the cognitive thinking needed to process the traffic situation. This paper offers a potential framework for future work.

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