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Swarm theory applied to air traffic flow management

Sergio Torres*

Lockheed Martin, 9211 Corporate Blvd, Rockville, MD, USA

Abstract

The goal of air Traffic Flow Management (TFM) is to balance demand against capacity in order to reduce inefficiencies. As an optimization problem TFM poses a number of difficult challenges. From the airline perspective the solutions should minimize the aggregate delay time relative to the scheduled time that is used by airlines to drive their operations. TFM must take into account air traffic control restrictions used to maintain aircraft separation and changes in capacity due to weather disruptions. In current operations TFM is done based on a centralized approach that relies on predictions and that does not integrate airline preferences. Combinatorial optimization techniques to solve the multi-objective traffic flow optimization problem are not practical; the vast number of variables and the exceedingly large Pareto front associated with the solution space generates a combinatorial explosion that makes the approach completely intractable. This paper presents a different approach to TFM, inspired in swarm theory, that converts pilots into goal seeking agents that individually find local solutions to the optimization problem and as a whole the collective action of agents creates emergent behavior that naturally tends to converge on its own to a Pareto efficient state.

Keywords: swarm intelligence, particle swarm optimization; air traffic control; traffic flow management; air traffic optimization;

1. Introduction

At a time of peak traffic in the US there could be 6,000 flights that need to be safely guided to their final destination. The airspace available for general aviation and commercial operators for the cruise phase of the flight is vast but because of schedule pressures at large airports and the limited number of runways, congestion and delays in terminal areas ensues. Schedules are driven by airline business considerations that generate tremendous pressure at peak times resulting in frequent periods when demand exceeds capacity. High demand for airspace and air traffic control services, limited capacity, weather events, and safety constraints result in costly and inefficient operations. The objective of Traffic Flow Management (TFM) is to balance air traffic demand against capacity in order to reduce inefficiencies. The air traffic flow problem can be stated as finding the TFM solutions that minimize the

* Corresponding author. Tel.: +1-301-640-4046
E-mail address: sergio.torres@lmco.com

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overall cost.

A key point with respect to the optimization problem is that the overall efficiency of the air traffic system depends on the collective behavior of all players. The events that influence the execution of a flight from origin to destination depend on multiple interactions with other flights. The coordination of arrivals and departures at an airport are operations that involve the entire collection of aircraft in the inflows and outflows. The dependence on collective behavior and the highly complex and tightly linked network of agents that characterizes the air traffic flow optimization problem led Teodorovic [1] to examine the principles of natural *swarm intelligence* (SI) to determine if they can provide ideas aimed at solving complex problems in air traffic.

Swarm intelligence is the emergent behavior that results from the interactions of a group of goal seeking agents competing for resources [2]. In nature it is observed that SI exhibits remarkable efficiency in solving optimization problems: pheromone markings and evaporation during foraging excursions by ants is an example amply studied [3]. There are several common traits between the air traffic system and natural systems made of simple interacting social agents. In this context, are there elements of SI that can be applied in the air traffic realm? The answer is yes. Several aspects of air traffic operations exhibit the level of complexity for which an SI approach seems appropriate. Advancements in airborne technologies [4] make SI even more relevant, specifically cockpit display of traffic information. This capability allows pilots to monitor neighboring traffic and provide separation assurance as delegated by the responsible air traffic controller. Accurate position of neighboring aircraft will be available by the Automatic Dependent Surveillance Broadcast (ADS-B) system and the Traffic Information Service (TIS-B) system. In the former, receivers on board the aircraft will be able to obtain Global Positioning System (GPS) based position information broadcast from other aircraft. In TIS-B, surveillance information derived from ground sensors is broadcast to equipped aircraft. Broadcast position reports could serve as the "electronic pheromones" that pilots can use to monitor traffic and make adjustments to their own flight plans. The Airborne Spacing – Flight deck Interval Management (ASPA-FIM) concept being developed by the Federal Aviation Administration (FAA) [5] establishes a merging and sequencing procedure by aligning one aircraft behind another and maintaining spacing by means of ADS-B position reports broadcast by the leading aircraft. Civilian flight formation, where separation responsibility is delegated to a group of aircraft in close formation, is another concept where SI principles can be advantageous.

Swarm intelligence has inspired the development of global optimization algorithms suitable for complex multidimensional systems. One such algorithm, Particle Swarm Optimization (PSO), emulates swarm behavior to probe the solution space of an objective function and efficiently find the location where the optimal solution resides [6], [7]. PSO and related algorithms have been applied to various complex air traffic problems: aircraft departure sequencing [8], conflict prevention and resolution [9], route optimization for Unmanned Air Systems (UAS) [10], optimization of arrival sequences [11], optimization of airway network design [12], and optimization of airline cargo operations [13]. In this paper we examine the SI characteristics that present greatest potential in traffic flow optimization problems, namely: autonomy, distributed functioning and self-organization. Sections 2 and 3 describe how the air traffic system works and show the limitations of the current approach to TFM. Sections 4 and 5 present an innovative solution to the air traffic optimization problem that relies on the SI traits of autonomy, adaptability, robustness and distributed functioning.

2. The air traffic flow management problem

The National Air Space System (NAS) is managed by four groups of actors: airlines, pilots, air traffic controllers and traffic flow managers. Air traffic controllers divide the airspace into smaller sectors to manage their work load; with the information provided by surveillance sensors and the flight plan filed by the operator, controllers provide instructions to pilots so as to keep all aircraft separated. Traffic flow managers on the other hand monitor the predicted demand for services and restrict flows when the estimated demand exceeds capacity. Capacity is dictated by controller's workload, number of runways and weather conditions.

TFM enforces flow constraints primarily by means of ground delays (the Ground Delay Program – GDP), weather reroutes, miles-in-trail (MIT) restrictions and arrival flow metering. When a weather event at an airport forces runway closures and/or the expected number of flights arriving during a planning time window exceeds the landing acceptance rate, TFM authorities delay the departure of future flights going to the affected airport. The miles-in-trail TFM initiative consists of aligning all flights going to a congested airport into a single linear flow with a prescribed built-in separation. The metering program works by looking at the estimated arrival flow to an airport and based on the arrival rate available at that airport at that time each flight is assigned an arrival time to a point in space (called the *meter fix*) where the flights are received for final approach and landing. Controllers guide the aircraft so that they meet the assigned time at the meter fix. Ideally traffic flow actions should prevent overloading while maximizing utilization of resources and minimizing airline delay costs. All of these TFM practices however are executed in a reactive fashion and based on heuristics that result in highly wasteful operations. Underestimating demand results in capacity underutilization and overestimating demand results in additional flight delays. The root of the problem is the centralized nature of control and the fact that TFM initiatives rely on predictions that are intrinsically uncertain. The problem is further compounded by the fact that Air Traffic Control (ATC) is not fully integrated with TFM, the control loops of air traffic operate on two different domains (see Fig. 1): ATC in the tactical domain (< 10 - 20 min) and TFM in the strategic domain (> 20 min). When tactical intervention is warranted to maintain aircraft separation, ATC actions supersede TFM planning and as a result flights are diverted and delayed beyond what TFM estimated.

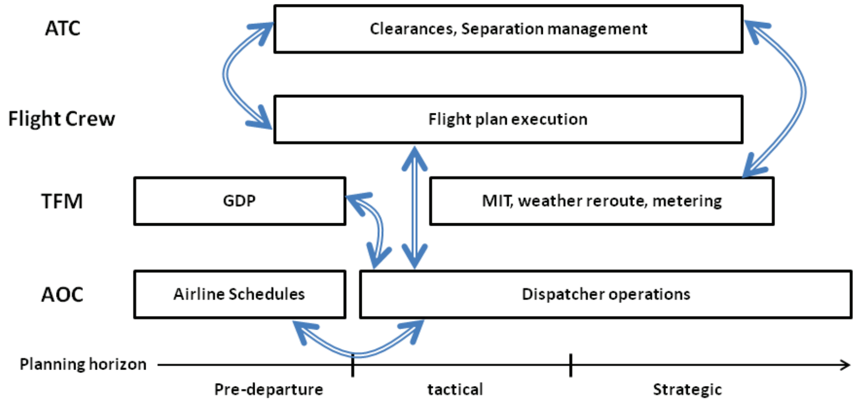

Fig. 1. Actors and control loops in the NAS (time line along planning horizon as the flight progresses)

Allocation of resources is performed based on predicted traffic load, which in turn relies on the four-dimensional (4D) trajectories generated for each flight. A trajectory is the predicted path in 3D that the aircraft will follow together with the expected arrival times at discrete points along the path. Trajectory prediction is subject to a large number of error sources that limit the achievable accuracy of the prediction. Sources of error in trajectory prediction span a wide range of factors going from wind turbulence to human behavior [14]: wind speed and heading, meteorological conditions, pilotage, route intent, aircraft guidance modes, aircraft performance models, earth models, kinetic models, takeoff time uncertainty, arrival times of connecting flights, crew scheduling, runway assignments, takeoff weight, etc. The performance of TFM initiatives depends on the predictability of the entire flow not just individual flights: each individual trajectory used for TFM planning increases the overall variance.

The performance of the current TFM approach is limited by trajectory prediction uncertainty. This fact is exposed by looking at the queue service model underlying TFM operations, metering in particular which is an everyday occurrence at major airports. Consider an inflow demand D (estimated arrivals per unit time), and airport capacity C (available number of landing slots per unit time). The average wait time in the service queue (a M/M/1 queue) T_q increases as the square of the coefficient of variance C_v:

$$T_q = (rC_v)^2/(2D(1-r)) \tag{1}$$

$$r = D/C; \quad C_v = sigma/mean$$

The formula above is valid for steady state conditions. The coefficient of variance measures the randomness of the queue: it is the variance of the time interval between consecutive arrivals in the sequence, normalized by the mean time gap. Note that all aircraft in the arrival queue contribute to the variance; hence even if some aircraft are equipped with technologies that allow meeting the meter time with high accuracy, the variance could be high due to the other aircraft with high prediction errors. If all flights arrive at the meter fix exactly at the assigned time (sigma = 0) there would be no delay, but in high demand situations (r → 1) the average queue wait time rapidly diverges even for moderate queue variance.

In real-world situations the scheduling of aircraft for hub operations tends to create demand peaks that temporarily make demand very close to or greater than capacity. In that case aircraft will get serviced, after a longer wait, during the demand lulls between bunches in the inflow. Meter time assignments are based on predictions when the flight is 100 nautical miles (nm) or further from the meter fix. With a wind speed uncertainty close to 15 knots [15], propagation of errors indicates that the uncertainty in the estimated arrival time to the meter fix is on the order of 30 sec, which could be a large fraction of the slot size. With D < C and quasi steady state conditions, for instance C = 60/hour, D = 54/hour, we obtain C_v = 0.63 and T_q = 1.8 min. An average wait time of 1.8 min multiplied by the number of arrivals, by the number of airports, by the number of days quickly adds up to millions of dollars in delay costs and tons of emissions. Fig. 2 shows the increase in average queue wait as the demand increases (for C = 60/min). Under ideal conditions in a carefully controlled and favorable environment it is possible to achieve trajectory prediction accuracies of 10-15 sec, but the benefit is severely limited if demand is near capacity because $T_q \rightarrow \infty$ as $r \rightarrow 1$. For instance, with a time prediction uncertainty of 15 sec and r = 0.98 (C = 60/min, D = 59/min) the average queue wait time is 3.6 min.

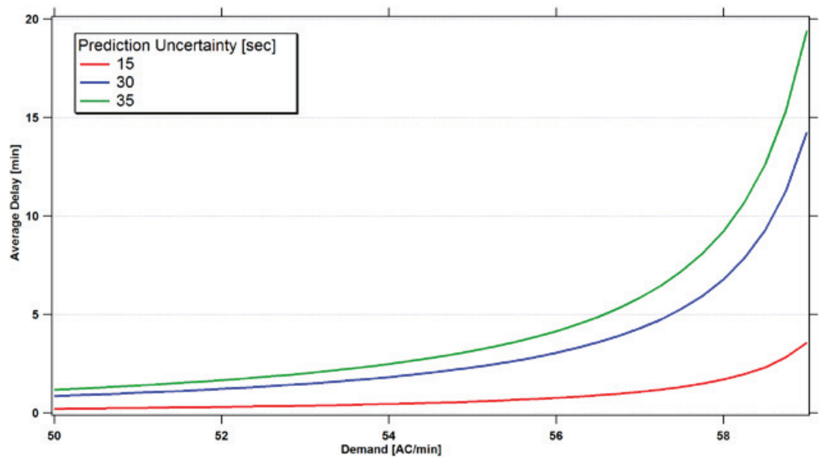

Fig. 2. Average delay time (steady state) as a function of demand and queue variance

It is envisioned that providing air traffic managers with the 4D trajectory of the flights should increase the predictability of the system as a whole and hence reduce costs. This concept, referred to as *trajectory based operations* (TBO), is the backbone of the FAA's Next Generation Air Transportation System (NextGen) and Europe's Single European Sky Air Traffic Management System Research (SESAR) systems. The tight dependency between service wait time and queue variance shows that the efficiency of the system as a whole is critically dependent on the accuracy of the trajectories, however one can see that the numerous sources of uncertainty and the stochastic nature of the processes involved in executing a flight plan severely limit the accuracy that can be realistically attained. Uncertainty in predicted 4D trajectories cannot be completely removed. No matter how much money and resources are spent in technological advances, there is a limit to the accuracy with which meteorological conditions can be predicted hours into the future. The queue model shows that due to the small margin between demand and capacity, even significant improvements in accuracy are not effective in reducing inefficiencies.

Time-based metering is a concept that aims at reducing queue variance by relying on the capability of modern Flight Management Systems (FMS) on board the aircraft to reach a given point at an assigned time. Using this function in conjunction with the assigned meter fix times to arrange the arrival flow into an airport should reduce meter fix arrival time uncertainty. Longitudinal uncertainty along the trajectory between the point where the meter fix time is assigned and the meter fix could result in potential conflicts and subsequent tactical interventions by the controllers that disrupt the planned inflow sequence.

3. The NAS optimization problem

A resource network model is commonly used to formulate the problem of optimizing allocation of resources to airspace users. In this model each flight is represented as an origin-destination (OD) pair, with O and D the end nodes and a number of links (resources) and nodes in between. The available resources depend on airspace capacity. Managing air traffic flow entails planning the distribution of the available resources within a planning time horizon. Finding a convex optimization formulation for the aggregate flow is the first challenge, furthermore the extremely large multidimensionality of the resource network makes the problem intractable. The associated multi-objective cost functions include airline operation parameters (which are proprietary), crew rotations, flight schedules, routing choices, wind data, meteorological forecasts, estimated fuel consumption, airport capacities, and many others. There are couplings between flights and OD pairs because of the hub structure of air traffic (a delayed arrival at a hub causes a delayed departure of the next flight using the same aircraft). A theoretical global optimizer would collect cost and flight planning information and consolidated constraint data for the entire NAS and would submit all this information to an optimization algorithm. With tens of thousands of flights within a planning horizon of a few hours and hundreds of operational parameters per flight, one can see that combinatorial optimization techniques are not an option. Distributed optimization has been discussed as an alternative [4], [16], [17] however with a centralized approach to traffic flow control the effectiveness of the solutions are still limited by inherent stochasticity. The unavailability of proprietary airline information (such as takeoff weight, cost index, etc.) also limits a global approach to optimization.

4. Self managed air traffic

It can be concluded from the previous two sections that the current approach to air traffic management (ATC and TFM) is vastly inefficient for the following reasons:

- TFM is centrally managed
- TFM relies on the predicted trajectory of the aircraft, which is limited in accuracy
- ATC is not fully integrated with TFM, tactical intervention may undo TFM planning
- ATC and TFM operate in different time horizons (strategic vs. tactical)
- ATC and TFM do not have a mechanism to systematically take into account user preferences in operational decisions
- The priorities of the system are –for good reason– placed first in safety and then in reduction of inefficiencies via TFM initiatives, but there is no explicit action to drive the system towards greater efficiency and capacity.

An SI approach to air traffic management is particularly suitable to solve these shortcomings. After all, air traffic *is* a multi-swarm system. The Self-Managed Air Traffic (Self-MAT) concept presented below removes the sources of inefficiency and provides mechanisms so that optimality results as an emergent behavior.

The Self-MAT solution consists of relinquishing centralized control all together and instead make the operator its own air traffic controller by providing sufficient situational awareness so that the operator is converted into a goal seeking agent that finds –applying its own business rules– the most efficient way to get to the final destination given the constraints. Once this operator's solution (the 4D trajectory) is generated, it is shared and incorporated as a new airspace constraint so that subsequent operators are aware of the airspace demand it created and can plan around it.

The concept relies on providing the operators with a complete view of airspace constraints including weather, capacity constraints, and safety constraints generated by the presence of other aircraft. With complete knowledge of constraints and taking into account processing limits of the FMS, operators can build the flight trajectory that will be used for guidance (by the FMS) so that *by design* it is conflict free and compliant with the meter fix schedule. Since the trajectory is used for guidance by the FMS the operator can commit to fly it within a known tolerance (referred to as the required navigational performance – RNP). In contrast with the current approach where a trajectory is a prediction subject to intrinsic uncertainty, in Self-MAT the trajectory is an expression of the planned 4D path that drives the closed-loop guidance of the aircraft, and since the containment envelope of that path is known, it can be used to reserve a tunnel in gridded 4D airspace. The reserved tunnel of airspace associated with this aircraft becomes a separation constraint for subsequent flight plans.

A four dimensional airspace grid (4D-grid) is an efficient mechanism to share constraints and provide situational awareness. The concept of a 4D-grid has been used in trajectory based methods to integrate gridded weather avoidance fields [18] and to develop efficient conflict detection algorithms (by storing a 4D trajectory on the grid, a doubly occupied cell indicates a conflict) [19]. In Self-MAT, airspace is parceled out in cells and time slices of size consistent with the navigational performance of the FMS systems forming a 4D-grid that serves as the common repository of consolidated constraints and airspace demand. The 4D-grid incorporates weather, the trajectories of all other aircraft that have already committed, meter fix allocations and other flow constraints. New aircraft that enter into the system integrate the shared 4D-grid in their FMS trajectory generation algorithm so that the FMS trajectory not only is generated based on user preferences but also is *conflict free* and *schedule compliant* by construction. If all aircraft are flying as committed there should be no need for the controller to react with tactical interventions to maintain separation and manage schedule. Note that self-managed air traffic does not mean that air traffic control is removed: in Self-MAT the traffic is strategically designed to be conflict free and conformant to capacity. The controller manages by exception; ATC and TFM are automatically integrated. The 4D-trajectory "reserve/commit" process is dynamic and iterative so that responses to changes are generated in the same user driven fashion. With the Self-MAT approach UAS operations are incorporated into the NAS in a natural manner: they are just another operator participating in the "reserve/commit/fly" loop. Fig. 3a shows a diagram of the concept.

Since in Self-MAT operators are agents that react independently, a situation could arise by which a change in the system could trigger unstable behavior. For instance, a region of cells already committed to cleared 4D trajectories changes due to weather and become unavailable, forcing the affected flights to change routing. In this case the reroute choice of one flight could affect the choice of another flight which in turn provokes another reroute of the former and so on, triggering instability in the system. This problem can be mitigated by introducing a cost to 4D clearance change requests. The cost of a change to the 4D trajectory increases in inverse proportion to the distance to the arrival fix and also increases with the number of changes already requested for the same flight. A cost system is also necessary to prevent gaming.

The Self-MAT concept represents a fundamental change in the way air traffic management is done. Its radical nature, however, does not mean that the concept is far from being an implementable solution. Self-MAT integrates technologies and concepts that are already developed or are in the NextGen roadmap: point-to-point navigation (area navigation RNAV) with required navigational performance RNP, vertical and lateral (VNAV/LNAV) autopilot functions, capability of FMS to meet a required time of arrival (RTA) to a fix, air traffic services provided based on avionics capabilities (performance based navigation, PBN), air-ground trajectory synchronization [20], and Data Communication standards to make the FMS 4D trajectory available to ground automation systems [21].

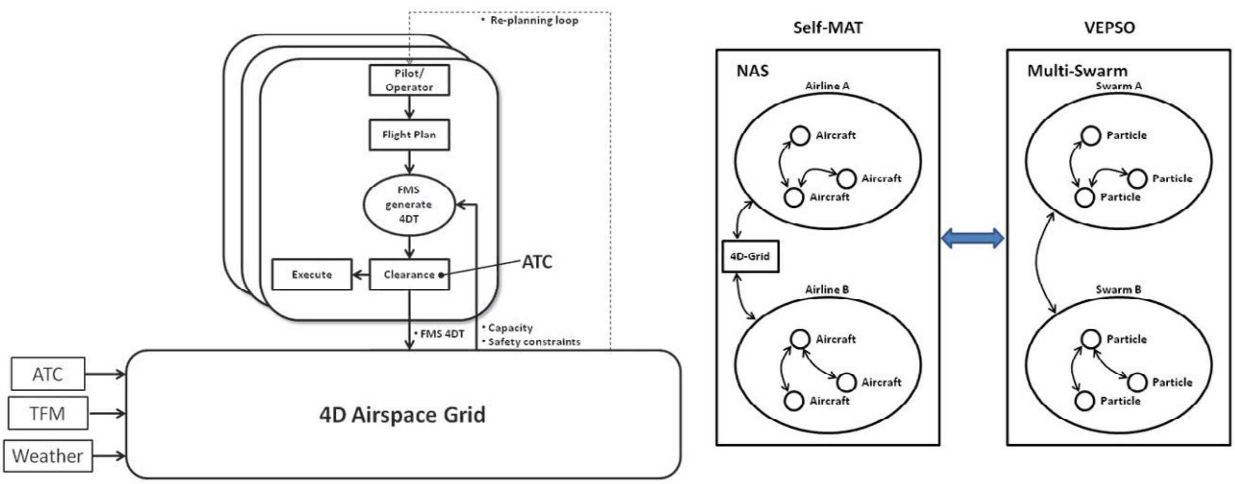

Fig. 3. (a) elements of the self managed air traffic (Self-MAT) concept; (b) mapping of Self-MAT to VEPSO framework

5. NAS optimization as an emergent behavior of self managed air traffic

Removing central control and providing complete situational awareness to operators endows the air traffic system with SI attributes that, driven by market forces, generate pressure on the system to adjust continuously towards an optimal use of resources. Airspace commoditization and opportunity costs (i.e. savings attained by being proactive and the high cost of not participating in Self-MAT) provide the market forces. Airspace as a commodity that can be purchased and traded (probably not with real money in the US but with a point system or stakeholder negotiation system not unlike that used in Collaborative Decision Making) would allow airlines access to the airspace and related services based on their business objectives. In Self-MAT each operator is searching for local minima of their objective function based on their business objectives. With these mechanisms in place the emergent behavior is the tendency to optimize the use of resources. The search for optimality is distributed to the operators. The first fundamental theorem of welfare economics indicates that such a system tends to a Pareto efficient allocation of resources.

A framework to show that Self-MAT has a natural tendency to optimality can be established by recognizing that there is a mapping (see Fig. 3b) between Self-MAT and multi-swarm optimization approaches, specifically the vector evaluated PSO (VEPSO) [22], [23] and the *tribes* algorithm [24]. An interesting twist in this argument is that whereas PSO algorithms were developed to emulate the efficiency of swarms to search for optimal solutions, here we are using the PSO formalism to bolster the optimality claims of Self-MAT. In other words Self-MAT recognizes that air traffic is a multi-swarm system and simply allows the system to behave as such. Operators on their own know how to and strive to optimize their operations.

The NAS optimization problem is characterized by multiple objective functions that need to be simultaneously minimized (airline, safety, and capacity management objectives). In the SI framework the architecture of the air traffic multi-swarm is best described by the VEPSO formalism where each airline is a swarm, each flight is a particle of the swarm and the NAS is a multi-swarm with particular social interactions: there is cooperation and free exchange of information between particles that are members of the same swarm (an airline can swap meter slots if it decreases the overall cost for the airline) but due to the competitive nature of the airline business the exchange of information between swarms is limited to the 4D trajectories that are committed to the 4D-Grid. To clarify the Self-MAT VEPSO mapping we'll examine the PSO mechanism of a single swarm (VEPSO works by allowing the exchange of information among multiple swarms).

Consider a bank of n aircraft (same airline) flying to airport D. In the PSO context each flight is a particle. The objective function (for that airline) is $f(x_1,\ldots,x_n)$, with x_i (in turn a multidimensional vector) representing the location in parameter space of the solution for the i-th flight. The search for the minimizers proceeds as follows:

$$x(k+1) = x(k) + v(k); \quad v(k+1) = w\, v(k) + c_s\Delta_s(k) + c_g\Delta_g(k)$$

where x(k) is a vector that captures the values of all operating parameters managed by the airline at a given iteration k, v is the displacement applied to x in order to evaluate the objective function at the next iteration, w is the inertia coefficient controlling the relative weight of local minima, Δ_s is the distance between x(k) and the x for the best solution thus far found for this flight (*personal best*), Δ_g is the distance between x(k) and the x for the best global solution (*global best*), c_s and c_g are two random coefficients that provide diversity in search space coverage. In a formal computer instantiation of the PSO problem all of the required information is presented to the algorithm to evaluate the objective function at each iteration. When the convergence criteria is met, the locations x of particles in the swarm provides the best solution. In Self-MAT the real world is the computer, each airline is searching local minima, market forces are at work providing optimization pressure, the 4D-grid acts as the collective consciousness of the multi-swarm. There is no explicit 'global best' shared among members of the swarms but the information contained in the 4D-grid does expose opportunities for further optimization, and hence plays a similar role. To find local minima each operator works with its own optimization algorithm, following its own business rules. The differences between algorithms are not important. An interpretation of the NFL theorem [25] (there is no such thing as a general-purpose universal optimization strategy) where each airline's algorithm is one of the set of all possible optimizers suggests that multi objective optimization of the NAS is a natural outcome.

6. Conclusions

Self managed air traffic (Self-MAT) is a paradigm shift in the way air traffic operations could take place in the future. Treating air traffic as a multi swarm system enables NAS wide optimization. Letting operators plan and execute their operations autonomously and based on their business rules is possible when they have access to a complete view of airspace constraints and can commit to fly the 4D business trajectory within known tolerances.

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