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A Systems Approach for Scheduling Aircraft Landings in JFK Airport

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***Abstract*— The aircraft landings scheduling problem at an airport has become very challenging due to the increase of air traffic. Traditionally, this problem has been widely studied by formulating it as an optimization model solved by various operation research approaches. However, these approaches are not able to capture the dynamic nature of the aircraft landing scheduling problem appropriately and handle uncertainty easily. A systems approach provides an alternative to solve such a problem from a systematic perspective. In this regard, the concept of general systems problem solving (GSPS) was first introduced in 1970s, and yet the power of the GSPS methodology is not fully discovered as it had only been applied to few domains. In this paper, a new general systems problem solving framework integrating computational intelligence techniques (GSPS-CI) is introduced. The two main functions of the framework are: (1) adaptive network based fuzzy inference system (ANFIS) to predict flight delays, and (2) fuzzy decision making procedure to schedule aircraft landings. The effectiveness of the GSPS-CI framework is tested on the JFK airport in USA, one of the most complex real-life systems.**

I. Introduction

AIR transport has become one of the fundamental modes of transportation for personal and business traveling, and commercial delivery [1], therefore, the demand of air transportation has been increased for multiple purposes. This increase of airtraffic has caused a drastic increase in number of aircraft takeoffs and landings within a given time period at a certain airport, that results in an overload issue in terms of airport capacity and a delay issue in terms of aircraft scheduling. Moreover, airline companies lose profits because customers are not satisfied with delayed traveling and delivery. In short, considering the increased air traffic the efficient management and scheduling of the aircraft takeoffs and landings (given limited resources such as time, budget, and etc.) has become more challenging and complex to the air traffic controllers.

The purpose of air traffic control (ATC) is to control the flow of traffic in order to prevent collisions and delays. The ATC is usually operated by humans and involve certain human errors [2]. Automated intelligent systems are being developed to control air traffic without human control [3]. Intelligent systems can also be used to optimize the airport capacity usage by assigning unused airspace and airport capacity to additional air traffic [4]. Additionally, the automated intelligent system can help airports save cost by less staff hiring, while helping airline companies to increase customer satisfactions by minimizing the delay time. To understand the importance of having such a system, it is worth pointing out that Federal Aviation Administration (FAA) has recently planned to stop funding 149 air traffic control towers in USA because of the budget cuts [5].

As mentioned previously, an important part of the ATC is aircraft landing scheduling, which is also the focus of this study. Aircraft landing scheduling can be defined as giving priority to different aircraft, which need to land at a certain time period in a specific runway. The problem becomes more significant for busy airports where lots of aircraft are intended to land at each time period and the resources (runways) are limited. Different objective functions based on different perspectives (i.e. airliners and airport managers perspective) can be defined for this problem. Considering the airport management perspective the main objective is to maximize the airport capacity usage (utilize runway usage), where as considering the airliners perspective the main objective is to minimize the deviation from targeted landing time. Ultimately, both objectives are related to cost and the final objective is to minimize direct and indirect costs associated with aircraft landing for both airliners and airport managers. The problem becomes more complex when considering the huge number of different parameters that are involved in this optimization process, such as flight delays, safety, customer satisfaction and etc. Further more, as aircraft landing scheduling contains so many uncertainties, the scheduling can constantly change based on the arrival of new information; this makes aircraft landing scheduling a highly dynamic problem.

The aircraft scheduling problem has been widely studied in operation research community, where it is formulated as an optimization problem such as minimizing the cost or delay time [2], [6]–[8]. However, most of these methods are not able to optimally solve the scheduling problem in real world settings, because of the increasing complexity and dynamic nature of this problem. As an alternative, adaptive intelligence systems are able to capture the dynamic nature of the aircraft (landing or takeoff) scheduling appropriately and handle uncertainty easily. In this paper, a new systems approach that integrates computational intelligence techniques is proposed to address the three main difficulties of aircraft landing scheduling problem including uncertainty, vast number of parameters, and conflicting objectives of airliners and airport managers. The main goal is to find an optimal landing sequence based on the expected delays, and the number of passengers that will utilize the airport

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capacity usage (runway usage) and customer satisfaction. As the proposed framework is based on systems concepts, additional parameters such as time and distance between two planes can be easily added to the model to extend its capabilities.

The organization of the paper is as follows. In Section 2, a background of aircraft landing scheduling problem is described and related work is briefly reviewed. In section 3, the proposed GSPS framework integrating computational intelligence techniques is illustrated. In Section 4, a real-life case of inbound flight scheduling at JFK airport is studied and solved by the proposed framework. In Section 5, the paper is concluded.

II. Background

In this section an overview of the common methods for aircraft landing scheduling is provided. Several models based on statistical and operations research concepts have been developed for different aspects of the flight scheduling problem.

Ernst and later Beasley [9], [10] have considered the problem from operations research perspective with the objective of minimizing cost (time), in a static case. Ernst uses a specialized simplex model inspired by machine job scheduling problem, and Beasle approaches this problem using mixed-integer zero-one formulation. Later, Beasley [11] have considered the same problem from decision making perspective and applied concepts of displacement problem for aircraft landing scheduling problem.

Abela and Sommer [12], [13] have considered the dynamics of the problem as well, which makes their approaches more applicable in real world situation. Abela considers the cost for the air traffic controller and proposes an approach based on genetic algorithm and mixed integer programming [13], whereas Sommer, considers the cost for the airliners and applies a heuristic local search method to this problem [12].

Considering the nature of air traffic management problem, using computational intelligence techniques can be helpful as these methods are very practical for non linear problems; additionally, because of the flexibility of computational intelligence models, they can be easily updated when the nature and condition of the problem changes [14]. This makes computational intelligence models suitable for dynamic problems. In this regards, Ciesielski and later Hansen have applied genetic algorithms to solve certain complexities associated with air traffic control and aircraft landing scheduling [7], [15].

III. Methodology

In this section the proposed GSPS-CI framework for scheduling the landing of aircraft is introduced. First, three fundamental components of this framework including GSPS, ANFIS and fuzzy decision making are briefly discussed, followed by working mechanisms of the overall framework.

A. General Systems Problem Solving (GSPS)

GSPS methodology, which was introduced by George Klir [16] is a general expert system framework for solving systems based problems in a way that is independent of the structure of the system [17]. The objective of this methodology is to build a problem solving technique that can be applied to different problems without considering the context of the problem. In other words, the objective is to study the relations instead of studying the objects themselves [16], [18]. In this regards, the GSPS approach models a real world system by identifying the support invariant relation among different variables of that system [19]. GSPS is based on mask analysis, which is a technique developed by George Klir using information theory concepts [20]. GSPS methodology is very practical for multidisciplinary problems where it is difficult to assign a problem to specific domain.

The GSPS framework consist of 5 different levels where each level corresponds to a new knowledge level that gives specific information about the object of investigation [19]; in other words, each level is an epistemological category of the system under investigation. These epistemological categories are partially ordered according to their information content [21]. This ordering indicates that each level contains all the information obtained from lower levels and adds some new information about the object of investigation. Each level of GSPS framework is briefly described as follows:

1) Level 0: Source System (sometimes referred as experimental frames): The source system is a descriptive list of components for the system under investigation. This means the investigator (system expert) needs to identify the basic and support variables for the system under investigation [21]. Basic variables are chosen based on the object of interest and nature of the problem, while the support variables (such as time and space) include parameters that represent change in the state of the basic variables. It can be concluded from the definition of the source system that two systems are comparable if they have the same source system [21]. Typically, before defining source system, premethodological consideration is performed, which is a cyclic approach to understand the objective of investigation (definition of problem).

2) Level 1 Data System: As the name implies, data system is about collecting the necessary data for each basic variable identified in the source system, by means of observation or measurement. The data should represent the state of the basic variables that correspond to the support state.

3) Level 2 Behavior System (sometimes called generative systems): Level two is based on the concept of mask sampling. Mask sampling can be considered as the process of moving a window among the basic variables of the system to identify the state of a basic variable and its neighbors at certain support state. In this regards, one of the important issues of behavior system is choosing the depth of the sampling mask which determines the amount of observable interactions in the behavior system; therefore, choosing the depth of sampling mask is a trade off between complexity and information availability. The larger sampling mask size results in a more computationally complex system, but the system analyst receives more information from it. In addition to choosing the sampling mask size, the investigator should be clear about whether relationship within observation or among observations is desired for the model. For the relationship within observation, a sampling mask of depth one (memory-less mask is suitable) [18]. After choosing the sampling mask, behavior of the system is analyzed by identifying the patterns in data system using mask sampling. Hence, in this level, the system scientist are looking for relation among the basic variables of the system in support invariant format [21]. Finally, after analyzing the behavior of the data system, mask analysis provide a solution set to determine the number of sampling variables to be used. This process is done by giving the best selection of sampling variables for different amount of complexities up to the full mask (which gives the maximum amount of information). The mask analysis gives the best solution set (best predictability) based on generative entropy, which is symbolized by $H(G|\overline{G})$. The formula for generative entropy is given by $H(G|\overline{G}) = H(C)H(\overline{G})$, where $H(C) = total$ amount of uncertainty in the entire system [18]. Based on the information retrieved from mask analysis, the field expert should choose the number of sampling variables considering the complexity-information trade off.

4) Level 3 Structure System: Structure system is the act of identifying subsystems that can generate the overall system behavior [22]. In other words, in this level, the investigator is trying to identify which subsystem can produce the required information with minimal cost. Therefore, the investigator analyzes all different structures of subsystems at different levels of sampling mask (reconstructability analysis) to see how much information will be lost by breaking the structure (simplifying). The two simplification methods that are used in reconstructability analysis are C-refinement and G-refinement [18]. After reconstructability analysis and finding the simplified subsystem structures with least amount of information loss, the next step is to use relational joint to combine these subsystems for building a hypothetical overall model. To test this hypothetical model, the information distance is used as a goodness of fit measurement. If the input and output variables of the system are not initially defined and they are unknown, the control uniqueness technique can be applied to determine the input and output variables of each subsystem [18].

5) Level 4 Meta System: Meta system introduces changes to the overall system. In other words, meta system is the evolution of the original system with the same core components, but with some new attributes and purposes.

B. Adaptive Network Based Fuzzy Inference System (ANFIS)

Modeling complex systems is one of the most useful and most challenging tasks in the field of systems analysis, especially, considering the fact that most systems include human expert knowledge that is difficult to integrate into the model. Fuzzy logic was introduced by Lotfi Zadeh [23] to address this issue. Fuzzy Inference System (FIS) is a fuzzy logic procedure which is designed to enable analysts extract the human expertise using linguistic variables and integrate them into their model [24]. Despite all the advantages of fuzzy inference system, one of the main challenges of FIS is to design an approach for defining fuzzy If-Then rules and the related membership functions based on input-output data [25]. Sugeno and Kang were among the first who tried to develop such a system [26], [27] and soon others followed their path. Adaptive Network based Fuzzy Inference System (ANFIS) developed by Jyh-Shing Roger Jang [28] is a method to facilitate the learning procedure of Sugeno model using neural network approaches. ANFIS model is based on two general concepts of gradient decent and least square error [28], and consists of five layers that are illustrated in Fig. 1. Each layer is briefly discussed here, the readers can

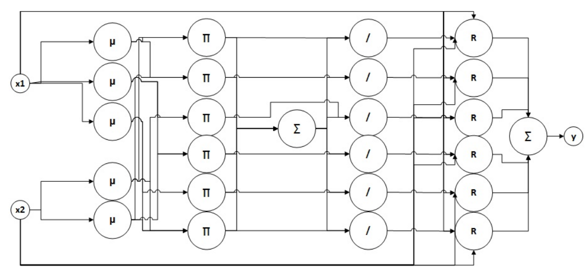


Fig. 1. ANFIS structure for two inputs

refer to Jang's original article about ANFIS model [28] for more details. Layer one generates membership grades for each of the linguistic variables in the system, which are adjusted using Gradient Descent (GD). Layer two uses a fuzzy conjunction operation to demonstrate the strength of each rule. Layer three is used to normalize the fuzzy rules, which represent the strength of each fuzzy rule relative to the total strength. At layer four, the contribution of each fuzzy rule towards the overall output is calculated. Finally, the sum of these contributions (the overall output of the system) is calculated at layer five [29].

C. Fuzzy Decision Making

One of the fundamental decision making methods is Multi Criteria Decision Making (MCDM) [30]. In this method, each criterion C_j has a weighting (importance) w_j, and each alternative A_i has a utility value a_{ij} relating to criterion C_j. A decision value dv_i is computed for alternative A_i as follows:

$$dv_i = \sum_{j=1}^{n} w_j \alpha_{ij} \tag{1}$$

Alternatives are prioritized based on their decision values. Table I represents a typical decision table. Using matrix multiplication $dv = AC^T$ the decision values of different alternatives are obtained. These values represent the priority $A_1 > A_3 > A_2$. In this table, the negative weight of criterion C_4 denotes that this criterion is inhibitive (For example cost).

TABLE I

WEIGHTS OF CRITERIA AND UTILITY VALUES OF A TYPICAL EXAMPLE

Criteria→	C1	C2	C3	C4
Weights→	.4	.3	.7	−.6
A_1	.8	.6	.3	.4
A_2	.3	.5	.7	.8
A_3	.7	.4	.5	.6

TABLE II

FUZZY DECISION MAKING DATA

Criteria→	C1	C2	C3	C4
Weights→	$[.3, .6, .2]$	$[.3, .8, .4]$	$[.7, .5, .3]$	$[.7, .6, .2]$
A_1	$[.7, .8, .5]$	$[.4, .6, .2]$	$[.1, .3, .7]$	$[.1, .4, .6]$
A_2	$[.1, .3, .5]$	$[.3, .5, .7]$	$[.4, .7, .3]$	$[.3, .8, .5]$
A_3	$[.4, .9, .8]$	$[.2, .9, .8]$	$[.1, .8, .4]$	$[.1, .6, .9]$

In fuzzy decision making the weights of criteria and utilities are fuzzy values [31]–[33]. The fuzzy values are calculated using bell shape membership function

$$\mu_A(x) = \begin{cases} \dfrac{1}{1+d(x-m)^2}, & (m-\frac{b}{2}) \leq x \leq (m+\frac{b}{2}); \\ 0, & Otherwise; \end{cases} \tag{2}$$

where x is an element of universe of discourse, d is the shape factor (controlling the width of bell shape), m is the median (the element of universe with maximum membership), and b is the base of bell shape. For example, for universe of discourse $u = \{0, 0.1, 0.2, \ldots, 0.9, 1.0\}, d = 20, b = 0.4$, and $m = 0.5$, the values for the medium verbal value are:

$$md = \{\frac{0}{0}, \frac{0}{.1}, \frac{0}{.2}, \frac{0}{.3}, \frac{.625}{.4}, \frac{1}{.5}, \frac{.625}{.6}, \frac{0}{.7}, \frac{0}{.8}, \frac{0}{.9}, \frac{0}{1}\}$$

To use a simple and fast logical method for fuzzy computations in decision making, each criterion is considered as an object. This way, the multi criteria decision making problem is analyzed from multi objective decision making perspective. Considering this perspective, for object C_j with weight w_j, the alternative A_j is chosen to achieve the object C_j with utility a_{ij}. In other words, the decision for choosing A_i is influenced by w_j. That is:

$$d_{ij} \equiv w_j \to \alpha_{ij} \; or \; d_{ij} \equiv \overline{w_j} \cup \alpha_{ij} = \max(1-w_j, \alpha_{ij}), \tag{3}$$

where d_{ij} is decision to choose alternative A_i for achieving object C_j with weight w_j [34]. To achieve all objects C_1, C_2, ... , C_n by choosing alternative A_i , the decision value dv_i is obtained as:

$$dv_i = d_{i1}, d_{i2}, \ldots, d_{in}$$

$$\Longrightarrow dv_i = \min_{j=1}^{n}(d_{ij}) \Longrightarrow dv_i = \min_{j=1}^{n}(\max(1-w_j), \alpha_{ij})) \tag{4}$$

This procedure for computing decision values of different alternatives is more suitable for problems with fuzzy values. Consider the simple illustrative example presented by Table II. The universe of discourse for all criteria and utilities is $u = \{1, 2, 3\}$. The fourth criterion is inhibitive, so the logical *not* of its original value ([.3,.4,.8]) is used. The fuzzy decision value for alternative A_1 is computed as $\mu_{DV_1}(x) = \min\{\max([.7, .4, .8], [.7, .8, .5]), \max([.7, .2, .6], [.4, .6, .2]), \max([.3, .5, .7], [.1, .3, .7]), \max([.3, .4, .8], [.1, .4, .6])\}$

$$\mu_{DV_1}(x) = \min\{[.7, .8, .8], [.7, .6, .6], [.3, .5, .7], [.3, .4, .8]\}$$

$$\mu_{DV_1}(x) = [0.3, 0.4, 0.6],$$

that is

$$DV_1(x) = \{\frac{0.3}{1.0}, \frac{0.4}{2.0}, \frac{0.6}{3.0}\},$$

and after defuzzifying by center of gravity method:

$$dv_1 = \frac{(0.3)\times 1 + (0.4)\times 2 + (0.6)\times 3}{0.3+0.4+0.6} = 2.2308$$

Using the same procedure, the fuzzy and crisp decision values of alternatives A_2 and A_3 is calculated as:

$$DV_2(x) = \{\frac{0.3}{1.0}, \frac{0.4}{2.0}, \frac{0.7}{3.0}\}, dv_2 = 2.2857$$

$$DV_3(x) = \{\frac{0.3}{1.0}, \frac{0.6}{2.0}, \frac{0.7}{3.0}\}, dv_3 = 2.2500$$

representing the priority $A_2 > A_3 > A_1$.

In traditional applications, the utilities are fixed and predefined (crisp or fuzzy) as shown in Tables I and II; but in real world applications there are cases where the utilities depend on independent variables such as time. For example, the utility (satisfaction of passengers) decreases when the variable (delay time of departure for a flight) increases. This phenomenon can be modeled by the response of a first order transfer function to a step input as shown in Fig. 2. [35]. In

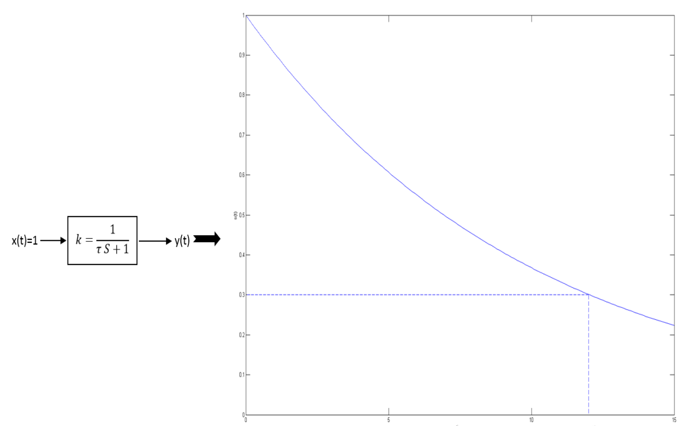


Fig. 2. First order transfer function model of dynamics of satisfaction level

this figure, k=1 is affecting factor, τ=10 is the time constant of the system, and $S(t) = 1-y(t)$ represents the satisfaction level. As an example, the level of satisfaction in this system will be 0.3 for a delay of $t = 12$ minutes. Conceptually, the unity step input to the system represents the unity impact on the satisfaction level of passengers caused by the delay time. In fuzzy decision making, this model can be used to find the medians of fuzzy utilities. An example of this procedure is provided using illustrative case study in the results section.

D. Computational Intelligence based GSPS framework (GSPS-CI)

Applying computational intelligence to GSPS model is not a new idea and it roots goes back as far as GSPS model itself. One of the most important examples is the Fuzzy Inductive Reasoning (FIR). Fuzzy inductive reasoning was introduced in 1979 [21] and is a tool for qualitative modeling. In this paper, a mixed quantitative and qualitative modeling technique based on GSPS methodology and computational intelligence (ANFIS and Fuzzy decision making) is developed to address the prediction and decision making problems in different systems. For the prediction problem, the support invariant relations of variables are studied using the GSPS model, and using these information the best input set for computational intelligence model (in this case ANFIS) is selected. Next, ANFIS model is used for support invariant prediction. For the the decision making problem a fuzzy decision making procedure is introduced as the meta system of GSPS framework. The overall framework is illustrated in Fig. 3. Here each of these steps are discussed.

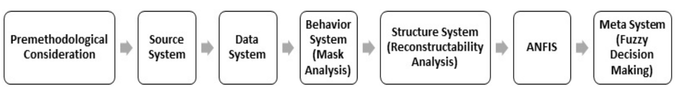


Fig. 3. GSPS-CI Framework

1) Step 1 Premethodological Consideration: At this step, the investigator should analyze the problem to understand what is the purpose and objective of investigation. As the proposed framework is intended for prediction and decision making problems, the objective of investigation should include at least one of these elements. Also, It should be noted that this step is a cyclic approach and it should be repeated until a satisfactory description of the problem is achieved.

2) Step 2 Source System: At this step, the basic and support variables (and their corresponding state sets) that are related to the prediction objective should be identified. It should be noted that the state sets of the variables should be discrete and it is recommended that no more than five state sets be chosen for any given basic variable. This is a key factor for reducing the computational time and complexity in next steps of the GSPS-CI model.

3) Step 3 Data System: Considering the identified basic and support variables in step two, the investigator should gather the data that represent the states of the basic variables corresponding to support set. As mentioned previously, for GSPS model the data set should be discrete, so if the original data set is in continues format a preprocessing step is required to discretize the data set. Additionally, a simplification process is recommended to reduce the number of discrete state sets to less than five for reducing the computational time. For example, if the basic variable is altitude, the values of this variable can be discretized and simplified to three states of high, medium, and low.

4) Step 4 Behavior System (Mask Analysis): Three main tasks for this step are deciding the sampling mask size, identifying patterns by applying mask sampling, and selecting the best generative subsystem. For deciding the sampling mask size, as the purpose of behavior system in this framework is feature selection for the prediction model, therefore, the memory less mask (mask of depth one) should be used. In order to consider a structure for the system, the identified patterns using mask sampling should be less than the total possible patterns. Finally, a solution set should be chosen for next steps of the framework based on the results of mask analysis. For data sets with small number of variables, a full mask (a sampling mask that includes all the variables) is recommended to get the maximum amount of information.

5) Step 5 Structure System (Reconstructability Analysis): This step is an iterative step of breaking down the system to different structures and comparing them based on the information loss parameter. In this step, the simplified subsystem structure with least amount of information loss is identified using C-refinement and G-refinement. Using relational joint and control uniqueness techniques of the GSPS model are unnecessary in this framework, because the input-output variables are predefined and overall system has been observed during the data collection.

6) Step 6 ANFIS: In this step, the ANFIS model is used for the prediction objective. Considering the previous step, the input variables of the ANFIS model are selected based on the identified subsystem structure with least amount of information loss. Identifying other parameters of the ANFIS model such as number of epoch are out of the scope of this paper. Readers can refer to Jang's original article about ANFIS model for more details [28].

7) Step 7 Meta System (Fuzzy Decision Making): The Meta system in the proposed framework is used for the decision making objective, therefore, all the additional variables that are relevant to decision making process should be added to the original data system. After developing the new data system based on the original data system, the introduced fuzzy decision making process is applied for prioritizing different alternatives.

IV. Results

In this section, the introduced GSPS-CI framework will be applied to a case study of inbound flight scheduling of JFK airport. The GSPS methodology was implemented using R GSPS package developed by Doug Elias [18], and the ANFIS model was implemented using MATLAB ANFIS toolbox.

A. Step 1 Premethodological Consideration

For the pre-methodological consideration, the overall purpose of investigation for this case study is to increase the efficiency of airport traffic management. One of the important elements of airport traffic management is scheduling the landing of aircraft and this task is defined as our system, so the object of investigation is to schedule the inbound flights in an efficient manner. This objective requires two main tasks of flight delay prediction (Steps 2-6 of the proposed framework) and decision making (step 7 of the proposed framework).

B. Step 2 Source System

The source system consists of five basic variables and two time-based support variables. Variables one to four are considered as input and variable five is considered as output of the overall system. Table III shows the basic variables of this system and the corresponding state sets. For support variables, two support bases include Day of Month and Scheduled Departure Time. The support state sets include $[1-31]$ for day of month and $[0-1439]$ for the scheduled departure time. The schedule departure time has been preprocessed to be used in the GSPS procedure by multiplying hours to 60 and adding up the minutes. For example for time 13:40 we have $(13 \times 60) + 40 = 820$. Additionally, the state set of basic variables in Table III are simplified in order to make them suitable for next steps of the GSPS-CI framework. State set of V1 is simplified into four different categories, and state sets of the rest of variables are simplified into three different categories.

TABLE III
BASIC VARIABLES FOR AIRCRAFT LANDING SCHEDULING CASE STUDY

Criteria→	Variable	Variable ID
$Origin\ of\ Departure$	V1	5 Digit Airport ID
$Departure\ Time$	V2	$[00:01-24:00]$
$Delay\ at\ Departure$	V3	$[00:01-24:00]$
$Scheduled\ Arrival\ Time$	V4	$[00:01-24:00]$
$Delay\ at\ Arrival$	V5	$[00:01-24:00]$

C. Step 3 Data System

For the data system, the inbound flight info of JFK airport in January 2012 and January 2013 were retrieved from The Bureau of Transportation Statistics (BTS) [36]. The data is preprocessed and organized to meet the requirements mentioned in step 2 of the proposed GSPS-CI framework. Considering the large data size, a sample of the data system is represented in Table IV.

TABLE IV
SAMPLE DATA SYSTEM FOR JFK CASE STUDY

$DAY\_OF\_MONTH \rightarrow$	1	1	1	1
$CRS\_DEP\_TIME \rightarrow$	420	440	520	525
$V1$	13303	10721	13204	14843
$V2$	831	747	1059	913
$V3$	91	27	139	28
$V4$	950	835	1105	1145
$V5$	71	17	129	21

D. Step 4 Behavior System (Mask Analysis)

As mentioned previously, considering the prediction objective, the memory less mask (mask of depth 1) is used. The behavior system indicates that a total of 210 patterns exist in our system. This is less than the total 324 possible patterns, which means a structure exist in this system. Furthermore, the probability distribution of these patterns is suitable for processing the next steps of GSPS-CI framework. A sample of the results of behavior system is presented here:

$$[1] : 21111@0.01273885$$

$$.........$$

$$[210] : 11322@0.0009099181,$$

which represent the identified patterns and their associated probability. After understanding the behavior of the system, mask analysis is used to determine the best generative system that can generate the identified patterns. The mask analysis for our system indicates that a full mask should be used to get the maximum amount of information. The solution set that is obtained from mask analysis is shown in Table V.

TABLE V
SOLUTION SET

Complexity	Generative Entropy	Mask
5	7.197283	$1, 2, 3, 4, 5$

E. Step 5 Structure System (Reconstructability Analysis)

The purpose of this step is to analyze the information loss of different subsystems. For this purpose, two methods of C-Refinement and G-Refinement are applied to the system of scheduling inbound flights. The results show that the least amount of information loss in the system occurs at 1 2 3 4/1 2 3 5/1 2 4 5/1 3 4 5/2 3 4 5 structure where only 0.2% of information will be lost. As the input and output variables of the system are already known, using control uniqueness method is unnecessary. Furthermore, as the overall system has been observed for data collection, using relational joint technique is unnecessary. The resulting system based on this information is shown in Fig. 4.

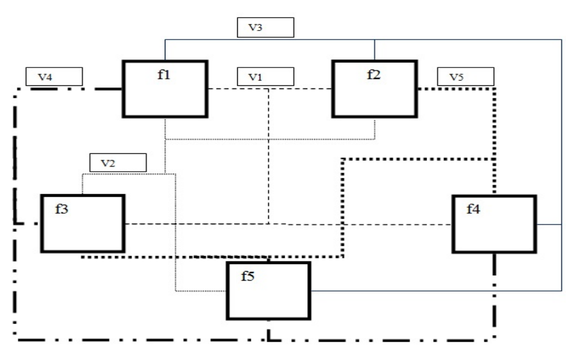


Fig. 4. Structure of subsystems with least amount of information loss

F. Step 6 ANFIS

Now that the structure of subsystems with least amount of information loss has been identified, an ANFIS model based on this structure and the overall system (including all input variables) will be developed to compare their accuracy. It should be noted that as the overall system's output is V5, only the subsystems that include this variable will be considered for ANFIS model. Before applying the ANFIS model, the data system should be further preprocessed to make it suitable for the ANFIS model. The data is preprocessed as follows:

V1 (ID code of origin airport) is converted to a number between 1 to 53 (number of available origin airports in the data set). V3 and V4 (delay times) are normalized to a value between 0 and 1.

The ANFIS model is trained based on the inbound flight data of JFK airport at January 2013 (using 3 triangular membership functions and 100 epochs). Next, the model is tested using inbound flight data of JFK airport at January 2012. The results of ANFIS model based on the overall system and identified subsystems are shown in Table VI. As it can be seen in this table, the ANFIS model based on all variables gives the minimum training error, however, the testing error is minimum for ANFIS model based on f4 subsystem. This indicates that the ANFIS model based on f4 subsystem can be more efficient in terms of generalization. Based on these results, it can be concluded that V2 (Departure Time) does not have a significant affect on the output variable.

TABLE VI

THE ERROR VALUE FOR DIFFERENT ANFIS MODELS

ANFIS Model Based on	Average Training Error	Average Test Error
All variables	0.012216	0.047236
f2	0.0126	0.044129
f3	0.047722	0.10722
f4	0.012592	0.039209
f5	0.012448	0.042394

Additionally, the results indicate that the testing accuracy of ANFIS model based on all subsystems (except f3) are better than the ANFIS model based on all input variables. Considering these results, an ANFIS model based on subsystem f4 results in higher accuracy and has less complexity when compared to ANFIS model based on all input variables.

G. Step 7 Meta System (Fuzzy Decision Making)

The objective of the meta system in this case study is to make decision about the landing privilege of inbound flights of JFK airport. For this objective, a new data system based on the original data system is introduced. In this new data system, flight number (V1) is the number given to all the incoming flights to the airport within 12 Hours. Time to arrival (V2) is defined as how much time is left for the aircraft to arrive at the airport (calculated based on the predicted delay at arrival time (V5) from previous step). Origin of departure (V3) is an ID assigned to each origin airport, and Number of passengers (V4) is a new hypothetical variable introduced for the decision making process.

As an illustrative example, the trained ANFIS model is used for predicting the flight delays of JFK airport at 18:30. Five flights with scheduled arrival times 18:15 to 18:45 are presented for landing scheduling. The estimated delay time for these flights are presented in Table VII, where time to arrival represents the difference between estimated arrival time and current time (18:30). Fig. 5 shows the dynamic system representation of fuzzy utility dynamics. The weights of criteria are considered to be predefined by following respective verbal values:

TABLE VII

INFORMATION FOR INCOMING FLIGHTS

Flight No.	Time to Arrival (min)	Origin Value	No. Passengers	Delay at Arrival (min)
1	14	0.82	92	72
2	20	0.59	106	44
3	5	0.78	110	41
4	18	0.82	260	56
5	8	0.55	160	28

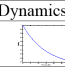
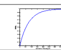
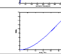
Tul.	Description	Transfer function	Dynamics of median of fuzzy value
m_{i1}	Time to arrival	$\frac{15S}{15S+1}$	
m_{i2}	Origin of departure	1	The output of this system is the origin value defined based on management policies
m_{i3}	Number of passengers	$\frac{1}{0.2S+1}$	
m_{i4}	Delay at Arrival	$\frac{1}{15S^2+S}$	

Fig. 5. Dynamic system representation of fuzzy utility dynamics

$$\{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8\} = \{sm, vb, md, bg, md, vs, bg, sm\}$$

The utility values of different flights are computed in two steps:

1) Feed the information of each flight to system dynamics of Table VII to compute the medians of fuzzy utilities. For number of passengers, normalize the data by dividing them to 400 (max. no. of passengers).
2) Find the memberships of utilities using Eq. 2.

For example, the utility of flight 1 for time to arrival criterion is computed as:

1) Using MATLAB commands:
   $\gg$response=step $(tf([15\ 0], [15\ 1]), 14)$;
   $\gg m_{11}$=response(length(response)); % Resulting $m_{11} = 0.3932$
2) Considering $u = [0, 0.1, 0.2, \ldots, 0.9, 1], d = 20, b = 0.4$ and $m = 0.3932$, we obtain the fuzzy utility from Eq.2.
   $$\alpha_{11} = \{\frac{0}{0}, \frac{0}{.1}, \frac{.0348}{.2}, \frac{.6684}{.3}, \frac{1}{.4}, \frac{.5833}{.5}, \frac{0}{.6}, \frac{0}{.7}, \frac{0}{.8}, \frac{0}{.9}, \frac{0}{1}\}$$

Other fuzzy utilities of decision table have been calculated in the same manner. Then, the fuzzy decision values for different flights have been obtained using the fuzzy decision making procedure. Fig. 6 shows the fuzzy values of weights of criteria, utilities, and decision values for data of Table VII. After defuzzifying the decision values by center of gravity method, the following crisp decision values will be obtained: $dv_1 = 0.6211$, $dv_2 = 0.2923$, $dv_3 = 0.4101$, $dv_4 = 0.4655$ and $dv_5 = 0.3016$; representing the landing privilege: $A_1 > A_4 > A_3 > A_5 > A_2$

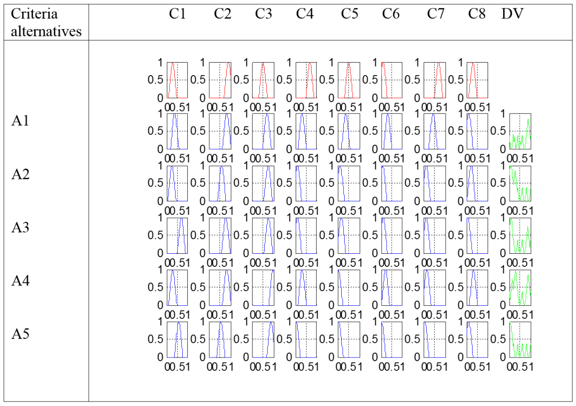


Fig. 6. Fuzzy values of weights of criteria, utilities, and decision values for data of Table VII

V. CONCLUSIONS

A systems approach of scheduling the landing of aircraft based on GSPS, ANFIS and fuzzy decision making procedures (GSPS-CI) was introduced. The proposed framework considers the dynamics of the inbound flight scheduling problem, and is able to handle the related uncertainty. As a case study, the framework was applied to schedule the inbound flights of JFK airport. Arrival flights of JFK airport during the time 18:30-18:45 were simulated using randomly defined weights of criteria, and then, fuzzy decision making procedure was applied to prioritize the arriving flights based on factors such as expected possible delay. The expected possible delay was predicted using ANFIS model, where input variables were identified by GSPS methodology. This paper presents how the GSPS methodology can be applied to complex dynamic problems to solve them using systems perspective.

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