Integration of Prediction Uncertainty into a Human Operator Planning Model Realized with Coloured Petri Nets

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Abstract This contribution integrates uncertainty in human performance models based on Coloured Petri Nets to predict human performance more realistically. As decisions often have to be made under uncertainty and existing models of human cognitive performance use if-then rules, the arising questions are about the combination of uncertainty with these rules. Uncertainty is present, if the environment is not exactly known or cannot be predicted precisely. As discrete uncertainty can be well integrated into Petri Nets, but continuous uncertainty is at least of equal importance, this contribution extends Coloured Petri Nets to represent continuous uncertainty as well which was not realized before. First, a probability distribution is selected and subsequently implemented in Coloured Petri Nets. Finally, the integration into an application example is shown. An experiment demonstrated that a planning model including prediction uncertainty is able to describe the performance of human operators during interaction scenarios more realistically.

Keywords: Human factors, human error, state-space, petri-net, search methods

1. INTRODUCTION

Recently, a lot of effort was made for the development of models to describe human cognitive performance. Besides the reproduction of human behavior within Human-Machine System (HMS) using simulations leading to the enhancement of human cognition, these models are also applied for the evaluation of human performance. In these cases, human operators' decisions are compared to those resulting from model-based predictions to detect errors of human operator and problems with specific tasks (e.g. Oberheid et al. [2011], Hasselberg and Söffker [2013b]).

As humans often do not apply formal optimization methods (Gigerenzer and Todd [2001], Klein [2001]), their behavior can in general not be predicted with a model making always optimal decisions. Instead of optimization methods, human often use less extensive strategies. Following these strategies, humans are able to reach similar or even better results as if they would try to use optimization methods. The success of optimization methods can not be guaranteed due to limitations. It should be stated that optimal models should not be used during training or as basis for technical assistance. Human operators would be compared to a formal standard they cannot hold (Klein [2001]). If they want to conform to the model, they have to adapt their working methods which can result into performance decreases due to insufficient time or cognitive resources. Models of human performance should therefore provide realistic solutions instead of optimal solutions taking into account human cognitive limitations. As decisions often have to be made under uncertainty (e.g. uncertain information or uncertain predictions) and uncertainty strongly affects decisions, it should be integrated into models of human performance.

Recently, some approaches of human performance modeling have been proposed modeling the controlled machine or environment as Coloured Petri Net (CPN) implemented with CPN Tools (see Hasselberg and Söffker [2013a,b], Oberheid et al. [2011], Hasselberg et al. [2009]). These approaches allow finding possible options to complete a task by analyzing the discrete state space of the CPN model. Discrete state spaces can be described mathematically by graphs (e.g. Kraiss [1985]). Each state is represented by a node of the state space.

All possible changes of states are represented as directed arcs in the graph. According to the existing approaches, continuous variables changing with time are discretized and each time step is treated as an event. Thus, the dynamics is modeled by automatic state transitions. On the other hand, actions of human operator are modeled by state transition activated externally. Consequently, each node has at least one successor node in a dynamic systems. For each possible action of human operators in a state, this state has an additional successor node.

In Hasselberg et al. [2009], the time remaining until a critical situation occurs is calculated by analyzing the discrete state space of a CPN. The remaining time is calculated assuming both that no counteractions are executed and that a predefined action sequence is executed. In Oberheid et al.

[2011] the feasibility of different actions to avoid critical situations is analyzed. Both approaches have in common that they use the search functions integrated in CPN Tools. Further, they both first define the action sequence and then determine its consequences during the state space analysis, consider only a fixed sequence and only the immediate execution of this sequence. Both approaches concentrate only on one type of critical situations. The ignore other important though not critical aspects.

In Hasselberg and Söffker [2013a,b] an improved approach was presented. It also analyzes the state space of a Colored Petri Net model. However, it applies Access/CPN (see Westergaard and Kristensen [2009]) to read and modify the state of the net. This is a requirement to allow developing specific search functions independent from the functions integrated in CPN Tools. The approach presented in Hasselberg and Söffker [2013a,b] differs from the previous approaches as it does not require action sequences to be predefined but generates them during the search. Therefore a human cognitive planning model was developed.

This models aims to mimic the human behavior and not to find optimal solutions. The model follows the macro-cognitive modeling approach defined by Cacciabue and Hollnagel [1995]. It does not claim to model the cognitive function and processes of human operators in detail but to predict the overall performance of the modeled function and processes. As estimating the consequences of options is difficult even if all required information is available (see Oberheid et al. [2011]), this contribution aims to integrate the effect of imprecise predictions into the human cognitive planning model based on CPNs to predict human performance more realistically. As the model stores procedural knowledge using if-then rules, the arising questions are about the combination of uncertainty with these rules. This contribution extends CPNs to represent continuous uncertainty which was not realized before. This continuous uncertainty is applied to model prediction uncertainty. Discrete uncertainty can be well integrated into CPN approaches. Consequently this contribution enables the modeling of both kinds of uncertainty with CPNs.

In the following, the application example is introduced first (see section 2). Consequently, the human operator cognitive planning model developed previously is presented in section 3. Then the extension of this model by the integration of uncertainty is explained in section 4. Finally, some results are presented to illustrate the difference between the precise and imprecise predictions generated with that model (see section 5).

2. APPLICATION EXAMPLE MICROWORLD MAGIE

The human cognitive planning model extended by uncertainty in this contribution was developed for the application example Micro Air Ground Integration Environment (MAGIE). The simulation environment MAGIE was built as a mid-fidelity simulator to evaluate prototypes of new procedures and assistance systems for air traffic control in an approach sector within a simplified and highly controlled setting (for details see former studies using this simulation environment e.g. Oberheid et al. [2009, 2010]). The simulation environment MAGIE consists of a CPN to simulate the aircraft's physical behavior and a Graphical User Interface (GUI) which is shown in Fig. 1. Implementing the simulation of MAGIE as a CPN enables analyzing human behavior by contrasting the CPN's state space to queried operators' perception and to measured consequences of decisions.

In the arrival concept implemented in MAGIE, aircraft are divided into two groups depending on the capability of their Flight-Management-System (FMS). Aircraft equipped with a 4D-FMS are able to fly specified trajectories with a high time/location-precision and follow a direct approach. They negotiate a fixed time with an implemented Arrival Manager (AMAN) and are allowed flying their preferred profile as long as they can meet the time restrictions at the Late-Merging-Point (LMP) (Oberheid et al. [2008]).

Aircraft, which are not equipped with a 4D-FMS, have to be guided in the conventional way manually from Standard Terminal Arrival Routes (STARs) over the path-stretching area consisting of downwind leg, base leg, and extended centerline. They start turning from the downwind leg towards the extended centerline after being instructed. Unequipped aircraft are merged into the stream of equipped aircraft at the LMP (Oberheid et al. [2008]). Both groups of aircraft fly along the final to the runway. To ensure a safe separation between the aircraft, it is crucial to stretch the flight path of the unequipped aircraft in the right amount.

Assistance in shape of ghosting was developed to support the operator in this task (Oberheid et al. [2010]). If ghosting is activated, a copy (ghost) of each equipped aircraft is projected onto the runway centerline extension to indicate positions later occupied by equipped aircraft. Ghosting reduces the length of predictions human operators have to make. Without assistance, the positions of equipped and unequipped aircraft have to be predicted up to the late merging point. If ghosting is active to indicate positions for equipped aircraft, the positions of unequipped aircraft can be predicted relative to the ghosts.

As MAGIE was developed to analyze the benefits of that new concept of arrival management and visual assistance, the task of the human operator is derived from that concept. Consequently, the operator has to control the unequipped aircraft by issuing clearances. Unequipped aircraft fly along their STAR into the path-stretching area if not instructed otherwise. In contrast, equipped aircraft and aircraft outside the control zone, which ranges from short before the downwind leg to short after the LMP (gray zone in Fig. 1), cannot be influenced.

The route structure and the actual position of the aircraft together with their current and cleared speed and altitude are also indicated in the GUI (see Fig. 1). The aircraft equipped with a 4D-FMS are shown in red (light gray in the figure), whereas the unequipped aircraft are shown in yellow (dark gray in the figure). Clearances are given by clicking on an aircraft label, choosing a clearance from the selection window, and confirming it by another click. In this manner, the operator can change the speed and altitude of the aircraft. The possible altitude ranges from 3000 ft to 8000 ft. The available speed ranges from 160 kn to 250 kn. The operator must further instruct aircraft to

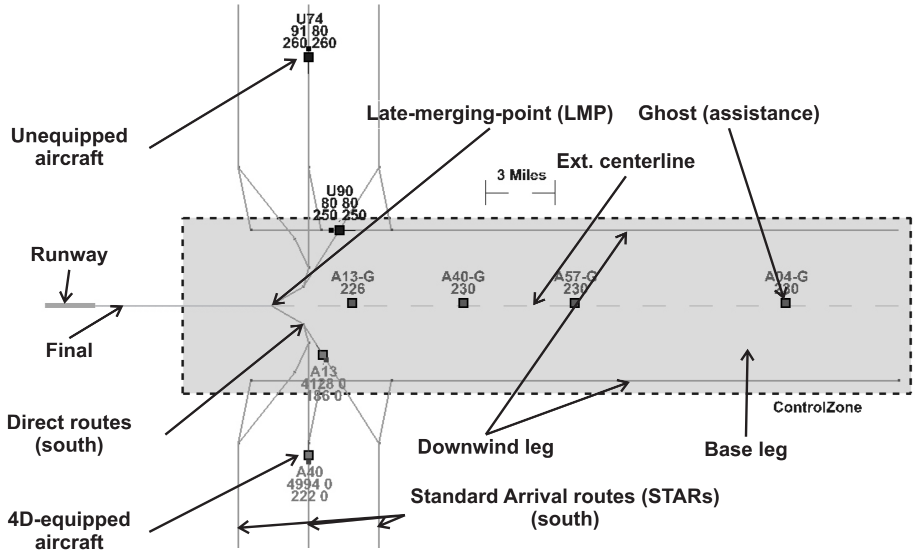

Figure 1. The GUI of the simulation environment MAGIE displays the route structure consisting of arrival routes, downwind leg, base leg, extended centerline, LMP, final, and direct routes, which connect the STARs directly with the LMP. The call signs of aircraft equipped with a 4D-FMS start with “A” and are shown in red, the call sign of aircraft without a 4D-FMS start with “U” and are shown in yellow. The call sings ending with “G” indicate ghosts, which are projections of the 4D-FMS equipped aircraft onto the extended centerline.

start the turn maneuver from the downwind leg to the extended centerline.

The main objective of the human operator is to ensure a safe separation between all aircraft. This is defined in MAGIE as 3 nm for each pair of aircraft. The separation is of utmost importance. The operator further has to ensure an efficient trajectory. This is implemented as constraints for different sections of the aircraft’s route (as shown in Table 1) and by the objective to guide the aircraft quickly to the airport (of minor importance compared to the other objective). In summary the operator has the three objectives (in order of decreasing priority): *separation*, *constraints*, and *throughput*.

Table 1. Constraints on route sections requiring reductions of speed and altitude

Section	Speed		Altitude	
	Min	Max	Min	Max
Downwind leg	180 kn	250 kn	5000 ft	8000 ft
Base leg	180 kn	250 kn	3000 ft	8000 ft
Ext. centerline	160 kn	230 kn	3000 ft	6000 ft
LMP	160 kn	180 kn	3000 ft	3000 ft
Final[a]	160 kn	180 kn	0 ft	3000 ft
Runway[a]	160 kn	160 kn	0 ft	0 ft

[a] Not to be controlled by the human operator as outside controlled sector

3. COLOURED PETRI NET BASED PLANNING MODEL

The human cognitive planning model developed in Hasselberg and Söffker [2013a] (see also Hasselberg and Söffker [2013b]) and extended by imprecise prediction in this contribution is based on a CPN model of the controlled technical system and a task specific set of rules to model the goal-directed normative behavior of human operators. These two models are part of the planning process which generates one goal directed interaction sequence in each run. This planning process is in turn a part of the planning model which applies the planning process to generate plans for each state during a simulation (s. Fig 2).

3.1 Models of Task Environment and Operator Behavior

In the planning model, the CPN model to simulate the aircraft as part of MAGIE is applied as model of the task environment. Therefore only slight modifications are necessary. For example, the functions to connect with the GUI are removed.

Each rule in the model of human operator behavior consist of a problem definition, which indicates the necessity to modify the planned interaction sequence, and a modification which is applied to the already generated part of the interaction sequence. The problem definitions are deducted from the objectives whereas the modifications to counter the problems or derived from the set of available actions.

This has been done for the example application MAGIE (see Hasselberg and Söffker [2013a]). The problems were derived from the objectives *separation*, *constraints*, and *throughput*. The modifications were deducted from the available actions (change altitude or speed or initialize the turn maneuver). Due to the simplifications in the example application, each problem can be solved by only one specific action. The set of rules deducted for MAGIE is given in Table 2.

3.2 The Cognitive Planning Model

The cognitive planning model is illustrated in Fig. 2. At first, the simulation protocol is loaded which describes

Table 2. Set of rules to model human operators behavior in MAGIE

Objective	Problem	Problem definition			Modification		
		Route	Other AC	Additional condition	Modificator	Action	Time
Separation	P_{S1}	Fixed	Behind	P_{S2} occurred & Spd = spd_{old}	Move	Spd spd_{old}	Later
	P_{S2}	Fixed	Behind		Add	Spd max + Spd spd_{old}	Earliest
	P_{S3}	Fixed	Ahead	P_{S4} occurred & Cl. spd = spd_{other}	Move	Spd spd_{other}	Later
	P_{S4}	Fixed	Ahead	Ongoing conflict	Add	Spd 160 kn + Spd spd_{other}	Earliest
	P_{S5}	—	Ahead	On final	Add or move	Spd spd_{other}	Now/earlier
	P_{S6}	Fixed	Ahead	—	Add or move	Spd spd_{other}	Now/earlier
	P_{S7}	Variable	—	—	Move	Turn	Later
	P_{S8}	Downwind	—	P_{S9} occurred & Cl. spd = 250 kn	Move	Spd 250 kn	Later
	P_{S9}	Downwind	—	Spd < 250 kn	Add	Spd 180 kn + Spd 250 kn	Earliest
		Position		Additional condition			
Constraints	$P_{downwind}$	On downwind		Turn not in sequence	Add	Turn	Now
	$P_{toSlowBD}$	On base or downwind		Cl. spd < 250 kn	Add	Spd 250 kn	Now
	$P_{toSlowc}$	On centerline		Cl. spd < 230 kn	Add	Spd 230 kn	Now
	$P_{missLMP}$	North or south of LMP		Variable route	Move	Turn	Later
	$P_{toHighD}$	On downwind		Cl. alt > 5000 ft	Add	Alt 5000 ft	Now
	$P_{toHighBC}$	On base or centerline		Cl. alt > 3000 ft	Add	Alt 3000 ft	Now
	$P_{toHighLMP}$	At LMP		Alt > 3000 ft & variable route	Move	Turn	Later
Restrictions	P_{speedC}	On centerline		Spd > 230 kn	Add or move	Spd 230 kn	Now/earlier
	P_{speedF}	On final		Spd > 180 kn	Add or move	Spd 180 kn	Now/earlier
	P_{alt}	On trombone		Cl. alt < 5000 ft	Add	Alt 5000 ft	Now/earlier

spd = speed, alt = altitude, cl. = cleared

the recoded/measured interaction of a human operator as a sequence of states. This is used as input to the model. The model selects the first state and focus on specific variables, called focused state. Focusing on specific variables allows generating plans for the different parts of the overall system individually and reducing the required effort significantly. In the planning process an interaction sequence is generated to transfer that focuses state into a goal state.

The plans for separate parts of the system are integrated step by step into the overall plan by extending the focus to an additional part of the system. The sequences generated for former focused states are considered during the simulation in further repetitions, to allow the detection of problems which affect the complete state. However, the previously generated sequences cannot be modified neither are they considered for the application of rules. Finally. an interaction sequence results which can transform the original state into a goal state. This procedure is repeated for the remaining states in the simulation protocol.

The planning model utilizes the direct access to the CPN provided by the Access/CPN. This allows an arbitrary marking to be defined and a focused state to be loaded and simulated.

3.3 The Planning Process

The planning process generates a goal directed interaction sequence by adding one action after the other. This process consists of three steps and uses the CPN of the technical system to predict future states and problems of the systems as well as the set of rules.

The planning process starts with one state loaded into the CPN. This is the foucesed state in the first cycle. Then the internal dynamics of the system are simulated. If an action sequence is already generated, the actions in that sequence are executed during the simulation. All states reached during the simulation are checked for problems defined in the set of rules. If one of these state meets the problem condition of one rule, this rule will be activated.

The activation of a rule causes the action sequence to be modified. This is the third step of the planning process. The modification either adds a further action or changes the execution time of an existing action. If an action is modified, the following actions in the sequence are deleted because the modified action may change the systems states and the potential problems after its execution.

After the modification, the simulation is reset to the latest state which is not effected by the modification. These three steps are repeated until an action sequence is found which is suited to transform the initially loaded state into a goal state.

The modifications of actions are applied step by step until either the problem is solved or the action will be applied as early as possible. In the latter case, the problems requiring a further modification of this action are ignored during the further procedure as they cannot be solved and are unavoidable.

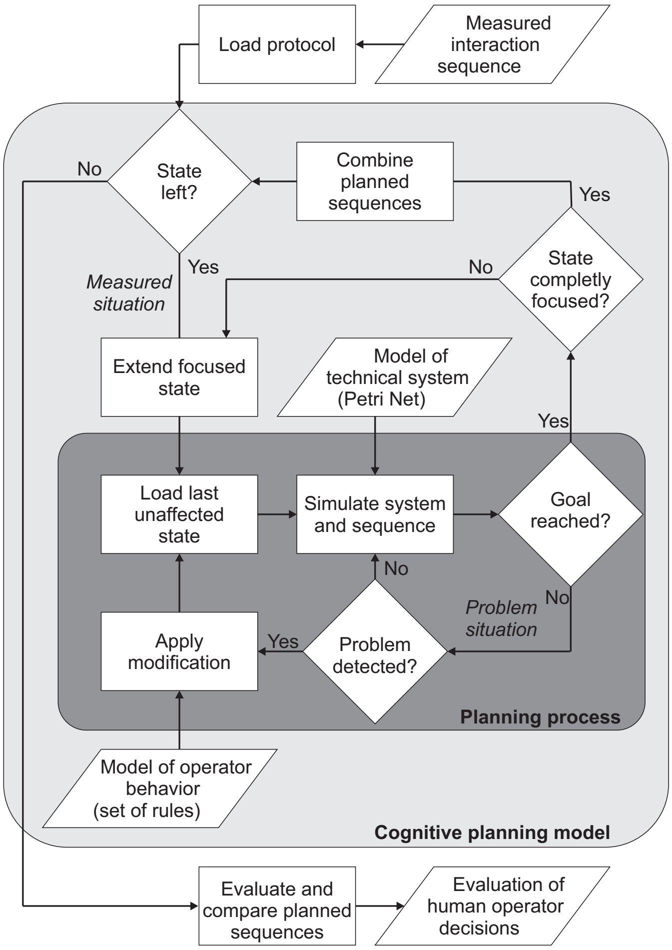

Figure 2. Processes in the cognitive planning model.

An exemplary planning process to generate a goal directed action sequence is illustrated in Fig. 3. In this example, the planning process has four iteration cycles. It starts with the first prediction from state 0 at time $t = 0$ and simulates the system until a problem is detected in state 4 ($t = 4$). The transitions from 0 to 4 are only caused by internal dynamics. As a problem defined in the set of rules is detected in state 4, the action sequence is modified. In this example, the action A_1 is added at time $t = 2$. Consequently, state 2, which is just before the execution of action A_1, is loaded into the CPN. During the next run, the simulation starts at state 2 and applies the action in the calculated interaction sequences at first and then simulates the internal dynamics. The states $5 - 9$ result. To solve the next detected problem, a second action is added to the sequence (A_2) at $t = 4$. During the third run of the simulation (from $t = 4$ to $t = 7$, resulting in the states $10 - 13$), the second action A_2 is simulated and a third problem is detected in state 13. This is solved by a modification of the second action. The time of its execution is decreased by one second from $t = 4$ to $t = 3$. Consequently, the fourth run will start at $t = 3$ from state 6. This simulation run leads to state 18, which is a goal state. Thus the resulting action sequence $[A_{1(t=2)}, A_{2(t=5)}]$ transforms the initial state into a goal state.

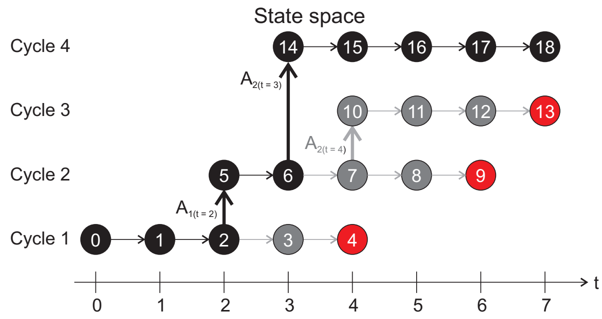

Figure 3. Exemplary simulation of a planning process. An interaction sequence is calculated by analyzing the state space. States and situation included in the final sequence are labeled in black. States and situations withdrawn during the calculation are labeled in gray. Red states indicate the presence of a problem (Hasselberg and Söffker [2013a]).

3.4 Application of the Planning Model to MAGIE

In the application example MAGIE, a situation contains all aircraft currently in or near the controlled sector. As there is no interdependency between the individual aircraft, it is possible to focus on only some of the available aircraft and to generate plans for each aircraft individually. In the first cycle of the planning process, only one aircraft is focused. The focus is extended in each repetition and one additional aircraft is considered until all aircraft are in focus. If one of the problems defined in the set of rules is detected during simulation, the corresponding modification is activated. The simulation stops if a goal is reached and all aircraft have arrived at the runway.

4. INTEGRATION OF UNCERTAINTY

In the following, a concept is proposed to integrate imprecise predictions into existing models of human behavior based on a set of rules and implemented as CPN. This concept is demonstrated and integrated into an human operator planning model for an air traffic simulation as an example.

The concept integrated into the model should fulfill the following requirements to be transferable to other applications. First, CPNs are able to model discrete uncertainty but cannot represent continuous uncertainty. Therefore, this approach should extend the capability of CPNs to represent continuous uncertainty as well. Furthermore, a variable my not be exactly known but an upper or lower boundary is given. Therefore, it should be possible to restrict the probability distribution to these boundaries. Additionally, changing the probability distribution should be possible without much effort to facilitate the transfer to other applications. For example, it should be possible to assign lower probabilities to larger prediction errors and higher probabilities to smaller prediction error.

To integrate imprecise prediction into the planning model, an appropriate modeling approach and a probability distribution are selected first. Next, the approach is implementation with CPNs. Then, this implementation is integrated into the human operator planning model for the air traffic control task. Moreover, some modifications in the planning

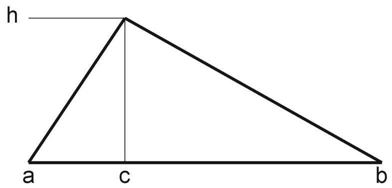

Figure 4. Triangular distribution, defined by the minimum value a, the maximum value b and the value with the highest probability c.

process are necessary. These four steps are explained in the following.

4.1 Modeling of Probability Distributions

Uncertainty can be formalized by different methods, with probability the most common used formalism (Henrion [1999]). Probabilities are described by values between 0 (is not true/will not happen) and 1 (is true/will happen). Thereby the sum of the probability of all possible values/consequences has to be 1. The probability of continuous characteristics can be described by probability distribution functions. Such a function assigns a probability to each element within an interval. The functions can be distinguished depending on the size of the interval which can be infinite ($[-\infty, +\infty]$), bounded ([a,b]) or one-sided infinite ($[0, \infty]$).

As it should be possible to restrict uncertainty to a limited interval with high probabilities in the intervals center and lower probabilities at the interval borders, the triangular distribution is selected. This distribution is a simple distribution fulfilling these requirements. A triangular distribution is defined by the lower limit a, the upper limit b, and the mode c with $a < b$ and $a \leq c \leq b$. An example is shown in Fig. 4. As the area of the triangle is $A = 1$, the height (and the probability of mode c) is $h = \frac{2}{b-a}$.

The probability density function of a triangular distribution is given by

$$f(x) = \begin{cases} 0 & \text{for } x < a \\ \frac{2(x-a)}{(b-a)(c-a)} & \text{for } a \leq x \leq c \\ \frac{2(b-x)}{(b-a)(b-c)} & \text{for } c < x \leq b \\ 0 & \text{for } b < x \end{cases} \tag{1}$$

and the cumulative density function is given by

$$F(x) = \begin{cases} 0 & \text{for } x < a \\ \frac{(x-a)^2}{(b-a)(c-a)} & \text{for } a \leq x \leq c \\ 1 - \frac{(b-x)^2}{(b-a)(b-c)} & \text{for } c < x \leq b \\ 1 & \text{for } b < x \end{cases}. \tag{2}$$

It is assumed that the characteristic is known exactly at the beginning of the prediction at t_0, thus $a(t_0) = b(t_0) = c(t_0)$. To assign a higher probability to smaller prediction errors and a lower probability to larger prediction errors, the mode $c(t)$ is calculated without prediction error and the limits of the distribution $a(t)$ and $b(t)$ are calculated with the maximal possible prediction error e. Consequently, assuming a constant change rate $r > 0$, the triangular distribution after prediction time t can be described by

$$c(t) = c(t_0) + r \cdot t, \tag{3}$$
$$b(t) = c(t_0) + r \cdot t \cdot (1 + e), \text{ and} \tag{4}$$
$$a(t) = c(t_0) + r \cdot t \cdot (1 - e). \tag{5}$$

Additionally, an upper boundary d_{max} and a lower boundary d_{min} of the variable can be given. If this is the case, the distribution has to be restricted to values within these boundaries. However, the probability of these boundaries itself can be larger than 0. For example, a constant change rate inevitably causes the limits of the distribution to reach the boundary. From then on, the probability of the boundary is increasing. Consequently, just defining d_{max} or d_{min} as a and b of a triangular distribution is not sufficient.

To simplify the representation of the probability distribution with boundaries, a bundle of rays is used. The outer rays represent the limits a and b while the middle ray represents the mode c. Each ray r_n with $n = 1 \ldots N$ rays is calculated by

$$ray_n(t) = c_0 + r \cdot t \cdot (1 + E(n)). \tag{6}$$

with the ray specific relative prediction error

$$E(n) = e \cdot \frac{2n - N - 1}{N - 1}. \tag{7}$$

Using this formula, the differences between the individual errors magnitudes are equal, while the differences between the cumulative probabilities are not. The cumulative probability for each ray n can be calculated using the triangular distribution with $a = 0$, $c = \frac{N}{2}$, and $b = N - 1$ by

$$F(ray_n) = \begin{cases} 0 & \text{for } n < 0 \\ 2\frac{n^2}{(N-1)^2} & \text{for } 0 \leq n \leq \frac{N-1}{2} \\ 1 - 2\frac{(N-n-1)^2}{(N-1)^2} & \text{for } \frac{N-1}{2} < n \leq N - 1 \\ 1 & \text{for } N - 1 < n \end{cases}. \tag{8}$$

If three rays are used, no difference to a triangular distribution appears. However, increasing the amount of rays makes possible to describe boundaries. Instead of setting only the outer ray (or a limit a or b of the triangular distribution) to the value of a boundary, several rays can be set to the value of the boundary. This makes it possible to model a probability for the boundary. Furthermore, exchanging the probability distribution is possible without much effort. Just another cumulative probability distribution function F has to be implemented.

As the bundle should be integrated into the discrete CPN model, its calculation is discretized. This allows to handle boundaries changing with time in an easy manner. Furthermore, the calculation of rays is modified so that prediction errors can not only be relative to the exact change Δ but to an arbitrary value R. Consequently, a ray is calculated by

$$ray_n(t) = ray_n(t-1) + \Delta + R \cdot E(n). \tag{9}$$

4.2 Implementation of Continuous Uncertainty in Coloured Petri Nets

To integrate the above described approach to represent uncertainty by a bundle of rays into CPNs, a new colorset is defined first. This realizes a bundle of rays as a list of integers to describe the uncertainty distribution. Each of the list's elements represents one ray. To allow a variable to be represented with uncertainty when needed but to be able to represent it precisely, a colorset for a hybrid variable is defined which can either include a precise variable or a bundle of rays. Furthermore, to transform a variable without uncertainty into a variable with uncertainty and the other way around, two functions are defined.

If the variable with uncertainty changes, every ray has to be updated. This is realized by six functions. These functions have in common that they expect the last value of the variable, the exact change Δ, which specifies how much the mode c changes, and the maximal prediction error e as input. The first function implements equation 9 with $R = \Delta$. The second function can be used if the uncertainty distribution has boundaries. It additionally expects a boundary as input and verifies that no ray exceeds the given boundary. Finally, the third function can be used, if the uncertainty added to each ray should not be relative to the exact change Δ. This function expects additionally R as input. These three functions are implemented twice, once expecting an uncertain variable and once expecting a hybrid variable. If the hybrid variable contains an precise variable, just the specified Δ is added by each function.

Furthermore, some functions were implemented to access the probability distribution modeled by the rays. This requires first a function to calculate the cumulative probability for every ray n out of N rays by implementing equation 8. A further function is defined to calculate the cumulative probability for any given value by calculating the cumulative probability for both nearest rays and returning the interpolation. Finally, a function is defined for the opposite query, expecting a bundle and a cumulative probability and returning the corresponding value. This function first searches for those both rays, which cumulative probabilities surround the given probability, and returns the interpolation between those rays.

4.3 Integration into the Planning Model

The implemented data types and functions are integrated into the air traffic control simulation as part of the human operator planning model described in the section 3.

A representation of an aircraft in the CPN contains variables to describe the current position (in X- and Y-coordinates), its altitude, its speed, and its current position on route (given as distance to the last waypoint). As these variables changes with time, they have to be predicted by the cognitive planning model. Therefore, the type of these variables is changed to the new hybrid type.

To be able to transform aircraft data stored in the precise data type without uncertainty into the newly defined hybrid data type and vice versa, two functions are defined, which integrate both functions to transform hybrid variables. Because access to aircraft characteristics is encapsulated in get- and set-functions, only these functions have to be adapted to the new hybrid data type. In order to reduce further changes, the get- and set-functions return the exact value by default. If uncertainty has to be handled explicitly, the uncertain characteristics of aircraft are accessed directly.

Table 3. Variables represented with uncertainty depending on the aircraft's equipage and the activated assistance

	Ghosting activated	
Variable	Equipped	Unequipped
X	Exact	Uncertain^B
Y	Exact	Exact
Altitude	Exact	Uncertain^A
Speed	Exact	Uncertain^A

^{A} Proportional to change of parameter
^{B} Proportional to change relative to ghost

When the ghosting assistance is activated, human operators predict if the unequipped aircraft fit between the ghosts on the centerline and the change of the distance between ghost and equipped aircraft up to the LMP. As ghost and unequipped aircraft fly in the same direction with a similar speed on the centerline, it is assumed that the position of the unequipped aircraft is predicted according to the position of the ghost. Consequently, not the change of absolute position of the aircraft generates uncertainty, but the change of its distance to the ghosts. Therefore, the uncertainty of the X-Position of the unequipped aircraft is implemented relative to the difference between its speed and the the ghost's speed. For example, when the unequipped aircraft is on the centerline and flies with the same speed as the ghosts, the uncertainty does not change. However, if an aircraft just started a turn and is flying in the opposite direction compared to the ghosts, the uncertainty increases proportional to the sum of both speeds in X-direction.

As the distance to the ghosts is used as indicator for conflicts if the ghosting functions is active, the position of the equipped aircraft is not of interested and consequently not predicted. The variables predicted with uncertainty, if ghosting assistance is activated, are summerized in Table 3.

4.4 Adaption of the Planning Model

The cognitive model of human operators planning must be modified slightly to generate plans under uncertainty. First, the CPN model has to be extended to model also uncertainty. Further some definitions used by the rules have to be modified to scope with imprecise predictions. If continuous values, which are associated with uncertainty in the model, have to be kept between certain limits, neither the maximal nor the minimal prediction error should exceed the limit. Thus, the minimal predicted values has to be compared to lower limits and the maximal predicted values has to be compared to upper limits. If this is strongly obeyed, the limits will never be violated.

Additionally, the rules regarding *separation* are changed in the following way. If the minimum of all calculated distances is below the minimum separation distance, a conflict is detected and the corresponding rule is activated. Furthermore, the rules defined to comply with the constrictions are modified to check both the minimal and maximal predicted value. After these changes are made, the planning model can generate human-operator-like plans including prediction uncertainty.

If the model generates a plan without uncertainty, the execution of a planned interaction sequences can be simulated exactly as planned. However, if uncertainty is included, a difference between the plan and the later execution will result. When generating a plan, the decisions about actions and their timing are based on predictions which have the time of the plan's generation as reference point. While the plan is executed it can be adapted continuously. Consequently, decisions can be based on predictions that have the time of the execution of an action as reference point. Thus the prediction horizon is shorter, the prediction is more precise and the actions fit more to the real conditions.

If now uncertainty is considered by the model of human operator's planning, the generated sequences are planned interaction sequences but not predictions of human behavior. To generate interaction sequences as predictions for actual behavior, it is important to allow updating a plan when better (more exact) prognoses are possible.

When a plan generated under uncertainty is executed, the accuracy of predictions is steadily increasing allowing updates of the plan. However, often replanning is elaborately and only slow increases of accuracy are expected. One possibility is to generate a more precise plan only right before an action is executed to check if this action is still necessary or if it should be delayed or canceled. The action is executed only if it is confirmed by the updated plan. Independent from the execution of this action, the plan is updated again right before the next action is planned to be executed (according to the updated plan). This action has to be confirmed or refused by a further update of the plan.

The cognitive planning model is modified in three ways to implement that concept to get predictions of behavior. These modifications are a further rule, a variable indicating the execution horizon t_e of an interaction sequence and a function to reset uncertainty. The additional rule specifies that when an interaction sequences reaches a goal but contains an action behind the execution horizon (problem $\mathrm{P_{PLAN}}$), the algorithm jumps back to the execution of the first planned action (first action after t_e). If the action is planned directly at t_e, the action is necessary according to the best available prediction as its time of execution. Therefore, its execution is simulated by jumping to the state after its execution and setting t_e correspondingly to the time of this successor state. Otherwise, the algorithm jumps to the state before the action is executed. A further planning cycle is necessary to confirm the planned action. In both cases, the uncertainty of the state t_e is removed. In other words, the uncertainty range for each variable is set to zero. By activating this rule, the execution of a part of the plan is simulated. As the jump back to an action removes all later actions from the iteration sequences, a new plan has to be generated next. This plan uses predictions with the execution horizon t_e as reference point. The resulting interaction sequence thus contains an expected behavior (before t_e) and a plan (after t_e). This procedure is repeated until an interaction sequence is generated which contains no action after the execution horizon and hence contains not a plan but an expected behavior.

5. RESULTS OF INTEGRATING PREDICTION UNCERTAINTY INTO THE PLANNING MODEL

The extended model is used to generate interaction sequences with imprecise predictions to describe the behavior of human operators more realistically. The reported results concentrate on the differences between an exact and an uncertain prediction. The considered situation and the predicted consequences are shown in Fig. 5. The black lines in this figure indicate the route structure. The LMP is located at $X = 100000, Y = 100000$. In the example situation at $t = 70$ the unequipped aircraft U92 is located at X = 113399, Y = 94221 and was just instructed to start the turn maneuver. It has a speed of 230 kn. U92 should arrive behind the equipped aircraft A62 at the LMP and keep a minimum separation distance of 3 nm (= 5558 m). The uncertain prediction is calculated with the maximal prediction error set to $e = 18\%$ and the amount of rays set to $N = 5$ rays.

In the example scenario in which the depicted situation occurred, an *throughput* performance of 0.9816 was reached by the operator. As the planning model with prediction uncertainty should be able to explain the difference between the maximal and the reached performance, the maximal prediction error has to be selected so that the interaction sequence generated for the initial state of an interaction reaches a similar *throughput*. If exact predictions are made, an optimal *throughput* of 1 is reached. The higher the maximal prediction error e is defined, the lower the reached *throughput*. The maximal prediction error is iteratively increased by 0.02 until an interaction sequence with a *throughput* similar to that reached by the human operator is found. As an interaction sequence generated with $e = 18\%$ reaches a *throughput* of 0.9880 and an interaction sequence generated with $e = 20\%$ reaches a *throughput* of 0.9648, the maximal prediction error is set to $e = 18\%$.

In the shown example situation, an exact prediction is generated first. As U92 can increase its speed, the problem $\mathrm{P_{toSlowBD}}$ is detected and a speed increase to 250 kn is added as first element to the interaction sequence. After the immediate execution of this action and an acceleration to 250 kn a conflict is predicted (and would occur) at $t = 166\,\mathrm{s}$. This is detected as the problem $\mathrm{P_{S6}}$. As a consequence, a speed reduction to the speed of A62 (180 kn) is added to the sequence. When this action is executed at $t = 113\,\mathrm{s}$, a conflict is still predicted but A62 has reduced its speed in the meantime. Thus, another speed reduction is added. For the same reason, a third speed reduction is added later. The list of generated clearances is given in Table 4.

For the same situation, a prediction with uncertainty is generated. Here, also a speed increase to 250 kn is added immediately. According to that prediction a conflict is predicted at $t = 153\,\mathrm{s}$ (s. Fig 5). Similarly to the exact prediction, a speed reduction to 180 kn is added. However, even if this speed reduction is executed as early as possible and also overwrites the immediate acceleration, the conflict is still predicted at $t = 181\,\mathrm{s}$. This is a result of the imprecise prediction. As the conflict cannot be solved (according to the prediction) it is defined as unavoidable and no longer detected as problem during the simulation. As no other problems occurs, the already generated interaction sequence is suitable. However, the planned action is just behind the current execution horizon t_e. Therefore, the rule $\mathrm{P}_{\mathrm{PLAN}}$ is detected and the action is simulated. After the execution, the uncertainty is reset. Then another planning process starts which considers prediction uncertainty. However, as the the reference point changed only slightly, the result is the same: The conflict cannot be avoided according to the uncertain prediction. As the sequence guides the aircraft to the runway, no other problem is detected, and no action is executed after t_e, this sequence is the output of the planning process. It reflects the decrease of throughput caused be prediction uncertainty.

Table 4. Expected speed clearances with precise and imprecise predictions.

Precise		Imprecise	
t	Speed	t	Speed
70	250 kn	70	180 kn
113	180 kn		
207	170 kn		
263	160 kn		

6. CONCLUSION

The aim of this contribution is to extend human operator planning models based on CPNs to allow more realistic predictions of human behaviors. It is assumed, that this can be achieved by integrating imprecise predictions into the model, as the perceived prediction uncertainty has a dominant impact on human operator's decision making Oberheid et al. [2011]. Beyond that, the developed implementation of uncertainty should be applicable to other models. Therefore, a concept for the representation of prediction uncertainty was developed, modeled, realized in CPN Tools, and applied to an example application.

The integration of prediction uncertainty allows models of human behavior based on CPNs to make more realistic predictions. As the realized data types allow both, exact and uncertain representations, and are accessed by encapsulated functions, integration into the existing planning processes is possible without much additional effort. The selected approach of modeling uncertainty as a bundle of rays has the advantage that switching to other interval distributions is possible and requires implementing only the corresponding cumulative probability distribution.

The implementation of uncertainty in the example application indeed resulted into predictions which can predict the performance more realistically. However, the results have to be analyzed in future work. The main question will be the analysis how exact the interaction sequences based on uncertain predictions can predict the human behavior. Therefore, the parameters, in particular the maximum prediction error, have to be defined. Consequently, it is necessary to compare the generated interaction sequences to the measured behavior of human operators.

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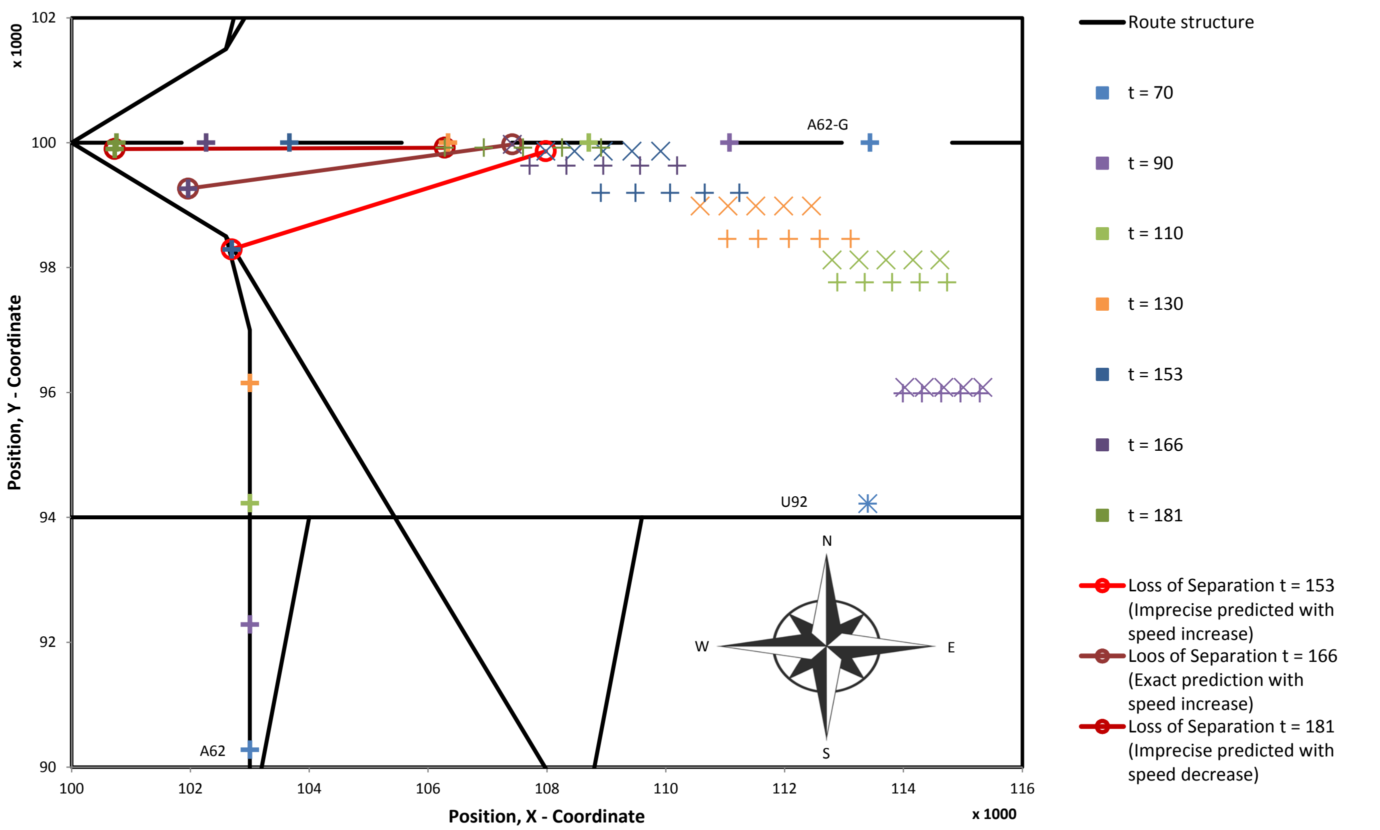

Figure 5. Uncertain predictions of the position of U92 and A62 with ghosting assistance and $t = 70\,\mathrm{s}$ as reference. The prediction of U92 calculated with an immediate speed increase to 250 kn is indicated with "'x"'. The prediction calculated with an immediate speed decrease to 180 kn is indicated with "'+"'. According to the imprecise prediction with an immediate acceleration, the separation between U92 and A62 is first violated at $t = 153\,\mathrm{s}$. If the prediction is exact, the separation would be violated at $t = 166\,\mathrm{s}$. According to the imprecise prediction with an immediate declaration, the separation is first violated at $t = 181\,\mathrm{s}$.