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Paper:

Hybrid Planning for an Air Gap Adjustment System Using Fuzzy Models

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Hybrid planning is an approach to couple continuous domains commonly found in mechatronic systems with discrete planning problems. An ongoing effort to bring self-optimization as a design means of improved overall system operation quality to mechatronic systems is the overall frame that this approach is embedded in.
An innovative rail-bound vehicle system propelled by a linear motor employs an Air Gap Adjustment System to control the air gap between the two motor parts and is presented as an application to the concept.

Keywords: hybrid planning, continuous effects consideration, mechatronic systems, self-optimization

Nomenclature

F_{Pro}	Propulsion Force of the linear drive
F_{Att}	Attraction Force between primary and secondary motor part
I_P, I_S	Power in the primary/secondary motor part
K_1, K_2	Engine parameter of primary/secondary motor part
δ_{ag}	Air Gap between primary and secondary motor part
δ_{ag}^{nom}	Nominal Air Gap of a system
δ_{ag}^{real}	Real Air Gap including tolerances
$\Delta\delta_{ag}$	Change / Tolerances of the Air Gap

1. Introduction

Self-optimization of mechatronic systems is the fundamental idea of the Collaborative Research Center 614 (CRC) "Self-Optimizing Concepts and Structures in Mechanical Engineering." The basic idea is a set of different and possibly conflicting objectives along with constraints that express the desired and required behavior of the mechatronic system. Both of these can change in a situation-dependent manner during runtime, for instance upon changes in the environmental conditions like weather. Other sources of changes are changing system properties or user requirements.

A system qualifies as self-optimizing if it is able to analyze its current situation, decide upon a set and weighting of objectives on the basis of this analysis along with the facilities to adapt the system behavior to follow these objectives. These three steps comprise the self-optimization process that is repeatedly run while the system is in operation. Examples for typical objectives are control quality, passenger comfort or energy consumption. Often there will be additional constraints like peak energy or a maximum average power consumption. One application of this approach to mechatronic system design is a novel transportation system that is developed in close collaboration with CRC 614.

Fig. 1. Autonomous shuttles traveling on the NBP test track at the University of Paderborn.

The research project "Neue Bahntechnik Paderborn" (NBP) aims to develop this novel and innovative transportation system which is competitive to common individual transport. The core of the system consists of rail-bound vehicles called RailCabs that enable groups of up to 12 passengers to travel directly without intermediate stops. The vehicles are driven by a linear motor. A test track in a scale of 1:2.5 and two RailCabs in the same scale have been built at the University of Paderborn. Ongoing work tries to increase the system efficiency by optimizing the linear motor's air gap using an Air Gap Adjustment System (AGAS).

The overall architecture for self-optimizing systems consists of a three-layer OCM (operator controller module) that divides a controller layer from a reflective layer and a cognitive layer. The latter does not carry realtime properties and is responsible for planning tasks including the hybrid planning detailed later. As part of this planning, parameters of the mechatronic system are evaluated and decided upon for each plan action. The air gap actuators are receivers of these parameters for trajectory generation and are the application example presented in this paper.

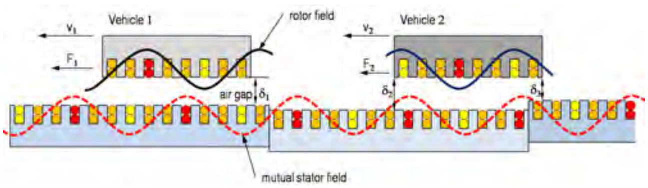

Fig. 2. Double-fed linear drive of the RailCabs.

2. Related Work

We have not found other ideas like this in the domain of rail-bound systems. Instead, we give an insight into the rationale behind the components used to ease the comparison with other ideas, and note where we see need for clarification.

The *Track Section Control* (TSC) is a development made within the CRC due to the necessity of decentral data processing. Besides the AGAS, other modules do also need a local data storage for their self-optimization process. These modules are the spring-tilt module, the energy management module, and the active tracking module [1].

Hybrid planning in the form as we introduce it in this work has not been found in prior work. However, the term itself has been used in different contexts that describe the combination of general purpose planning with domain specific reasoning [2], combining hierarchical domain properties with other planning concepts [3] or matching planning techniques to business processes [4]. Other than the authors of these works, we concentrate on the integration of discrete and continuous domains in planning. Nevertheless, techniques used in classical planning like hierarchical task networks and the refinement of plans are usable as part of a hybrid planning system too (see [5, 6]).

3. S.O. Air Gap Adjustment System

The research project NBP uses small autonomous vehicles (**Fig. 1**) for passenger and freight transport instead of conventional trains. These vehicles are propelled by a *double-fed linear drive*.

3.1. Propulsion System

This double-fed linear drive (**Fig. 2**) can be compared to an uncoiled three-phase winding motor [7]. Besides the advantages of the omission of conductor rails or overhead contact lines and the direct propulsion generation, the drive concept also features one disadvantage [8]. The minor efficiency compared to rotating drives of the same installed power is part of ongoing research in the CRC 614.

Figure 2 shows the principle concept of the double-fed linear drive. The *primary motor parts* (stators), which are mounted between the rails, are powered by distributed power supply stations. Five of these elements form a section, which can be powered separately in order to reduce the unavoidable copper losses. The *secondary motor part* of the linear drive, which is comparable to a conventional rotor, is fixed to the vehicles. Each vehicle features two secondary motor parts, one for each axis, powered by on board batteries. The double-fed linear drive allows the operation of two vehicles with different velocities on the same stator field. The *propulsion force* (F_{Pro}), which is generated in the air gap between the rotor and the stator, depends on the power of the rotor field (I_S) and the power of the stator field (I_P). Furthermore, it depends on the size of the air gap (δ_{ag}).

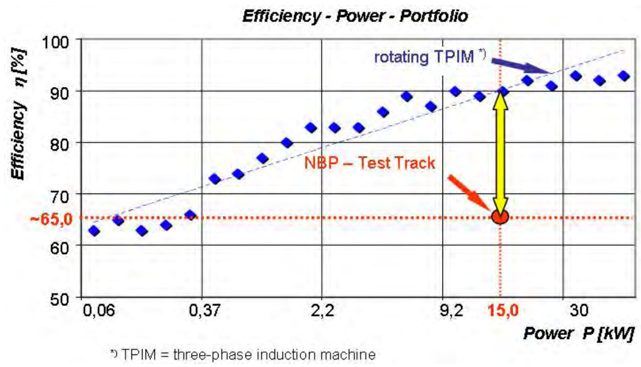

Fig. 3. Efficiency-Power-Portfolio.

$$F_{Pro} = \frac{1}{\delta_{ag}} \cdot K_1 \cdot I_P \cdot I_S$$

$$F_{Att} = \frac{1}{\delta_{ag}^2} \cdot K_2 \cdot I_P \cdot I_S$$

In contrast to conventional drives the *attraction force* (F_{Att}) is not subsumed to zero. In addition to that, the attraction force increases stronger than the propulsion force with an increasing power or decreasing air gap. The air gap is not a fixed factor. It varies along a track due to assembling tolerances of the stator fixation, influences of the shuttle (e.g. wear and tear of the wheels) and environmental influences (e.g. the setting of the shoulder or the wear and tear of the rails). Currently, the nominal air gap (δ_{ag}^{nom}) sizes 10 mm and the allowed assembling tolerance is set to $+/-$ 1 mm. This relatively wide air gap (δ_{ag}^{real}) is the main reason for the low efficiency compared to a three-phase induction machine with the same installed power (**Fig. 3**).

3.2. Air Gap Adjustment System (AGAS)

The solution for the optimization of the drive's efficiency, which has been developed within the CRC 614, is the self-optimizing *air gap adjustment system* (AGAS). From the CRC's point of view self-optimization is the key for the pareto problem of efficiency. The maximization of the drive's efficiency is not the only objective of a vehicle's drive system. Changing environmental influences and the needs of the users require the consideration of two more objectives. These objectives, which are weighted within an internal system of objectives, are *maximize efficiency*, *maximize propulsion force* and *maximize safety*. The AGAS picks up the drive's parameter air gap (δ_{ag}). By adding additional actuating elements the henceforth movable rotor can be adjusted vertically. This allows

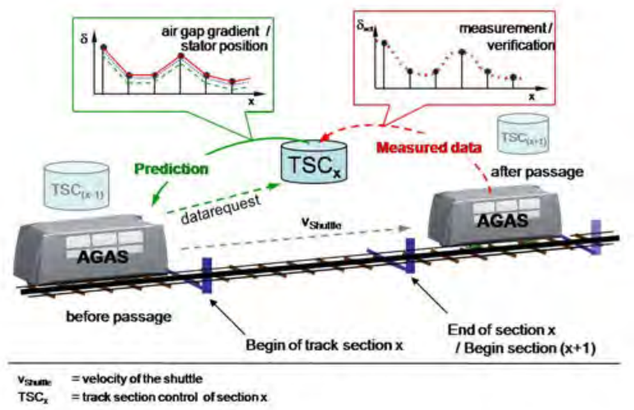

Fig. 4. Communication between the TSC and the onboard AGAS of a shuttle.

the adjustment of the air gap between rotor and stator according to the current situation and the followed objective. The supplementary actuators do not lift the rotor. The AGAS features mechanical spring elements, which force the actuators to push the rotor downwards against the springs in order to adjust a smaller air gap. This adjustment concept provides a fail safe system. The rotor is lifted upwards to a safe air gap in case of emergency (e.g. the breakdown of an actuator) instead of colliding with the stators between the rails.

The internal system of objectives determines the air gap for each track section by weighting the objectives. The on board actuators adjust the rotor depending on the track and situation in order to realize a maximum propulsion force, a maximum efficiency or a maximum safety. Up to now, the modification of the strategy is possible only at the borders of the statically fixed track sections. A change of strategy or a change of the planning horizon are not possible without the *hybrid planner*, which is described in section 5.

3.3. Track Section Control (TSC)

The AGAS consists not only of shuttle sided actuators including their information processing, but also of a so-called Track Section Control (TSC), which is placed along the track. A track is divided into sections and every section is equipped with a TSC similar to the distributed power supply units [9–11]. Their functions are the monitoring of the belonging track section and data storage. Passing RailCabs transmit the measured or calculated air gap gradient of a section to the TSC, which stores the data (**Fig. 4**). The stored data is used within the TSC for the model of the track and the prediction of a prospective air gap gradient. This allows arriving RailCabs to request the forecast of the air gap gradient in order to adjust an optimal air gap according to their internal system of objectives [12]. Therefore the hybrid planner, which is described in section 5, is embodied in the TSC.

Fig. 5. Test rig "AGAS" at the University of Paderborn.

3.4. Hardware-in-the-Loop (HIL) Test Rig "AGAS"

The Hardware-in-the-loop (HIL) test rig "AGAS" (**Fig. 5**) provides an experimental environment, simulating a test track consisting of 18 vertically adjustable stators. This allows tests of the self-optimizing concept under real-time conditions. The rig differs from the RailCabs in that the motor configuration if not double-fed but the primary motor parts are replaced by stators with permanent magnets. Therefore, the operating mode changes to a synchronous drive. A central load machine allows the simulation of different operation profile, such as driving on inclining or declining sections. The test rig features two powered rotors including an air gap adjustment system.

4. Modeling the Air Gap Gradient

To predict air gap sizes in simulation, a fuzzy model is used that emits a prediction of the expected air gap size given the system and environment state. Modeling nonlinear, multi-variable systems like the behavior of the air gap δ is extremely difficult. Although linear models for some parts like the thermal expansion of the air gap may be developed, they can hardly consider all parameters influencing its behavior nor the variety of operating conditions that may arise for instance due to uncertain weather conditions. In such cases a fuzzy identification based on expert knowledge or measurement data of the non-linear system provides a promising alternative to describe the system as a whole considering all relevant parameters and operating conditions. The principal adequacy of fuzzy rule systems for modeling dynamic systems was shown by Babuska [14]. Furthermore, Kosko proofed that they are able to approximate any input-output system with arbitrary precision [16]. A major advantage of fuzzy models is their support for an intuitive, linguistic interpretation of the model or results, which eases the step wise elaboration and adaptation of the approximated model during system operation.

In the following the fuzzy model for prediction of the course of the air gap's change ($\Delta\delta$) is described. According to the physical system structure two models were constructed: One for the track and the integrated stator elements and a second one for the shuttle including the rotor. Together these models comprise the environmental conditions influencing the air gap's change. This separation considerably decreased model complexity and eased their test and adaptation, since many influencing factors either belong to the shuttle model (e.g. wheel wear and tear or shuttle manufacturing tolerances) or to the track model (e.g. track laying tolerances or track wear and tear). Only a few like the shuttle weight had to be considered in both model parts.

The modeling process itself was also separated into two steps called *structure identification* and *parameter adaptation*. During *structure identification* the influencing factors for the shuttle and the track model were determined and structured in a so called influencing factor tree (IFT, see below). These input variables and the model outputs were fuzzified, and two fuzzy rule systems describing the input-output dependencies for the shuttle, respectively the track model, were constructed. The subsequent *parameter adaptation* step is responsible for adapting the parameters of the fuzzy membership functions of the system's input and output variables, for adapting the structure of the IFT and the set of rules and their weights according to new measurement data. Structure identification and parameter adaptation for the AGAS are described below in more detail.

4.1. Structure Identification

During structure identification at first the influencing factors for the two AGAS models shuttle and track were determined and classified. The classification structure for each model is represented as a so called *influencing factor tree (IFT)*. The root node of an IFT represents the model output, i.e. the change of the air gap resulting from the shuttle $\Delta\delta_{shuttle}$ or the track $\Delta\delta_{track}$ in our case. The total change of the air gap $\Delta\delta$ can then be calculated as: $\Delta\delta = \Delta\delta_{shuttle} + \Delta\delta_{track}$.

The leaf nodes of the IFT represent the influencing factors, i.e. the models' inputs, and the interior nodes of the tree mirror the classification hierarchy. **Fig. 6** shows part of the IFT for the shuttle model.

In the shuttle model the change of the air gap depends on three classes of influencing factors: *shuttle's wear and tear, thermal expansion of the wheels* and *manufacturing tolerances* (see **Fig. 6**). While *manufacturing tolerances* is a leaf node of the tree corresponding to an influencing factor, *shuttle's wear and tear* and *thermal expansion of the wheels* in turn depend on several classes of factors. The classification hierarchy for *shuttle's wear and tear* is omitted in the figure due to spatial reasons.

After their classification first the influencing factors (leaf nodes of the IFT) have to be fuzzified. As initial choice symmetrical triangular membership functions separating the influencing factors' domains in equal parts are reasonable. The domains and the number of membership functions (ranging between three and seven) were determined by domain experts. The *shuttle's weight*, for instance, may range from 6 tons to 32 tons. It is split into five parts by the membership functions *small, small-medium, medium, mediumlarge, large*. The *number of*

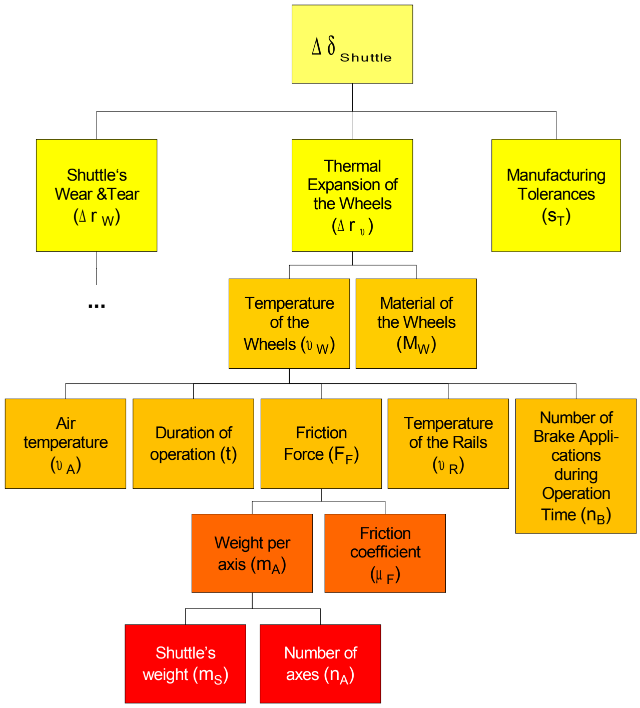

Fig. 6. Influencing factor tree of the shuttle model.

Table 1. Knowledge matrix related to the friction force.

$m_a \setminus \mu_f$	small	medium	large
small	small	small	small
medium	small	medium	medium
large	medium	large	large

axes for instance, lies between 2 and 8 and is represented by three membership functions *small, medium, large*.

Based on the fuzzification of all influencing factors and factor classes (internal IFT nodes) the fuzzy rule bases for the shuttle and track models were developed relying on the knowledge of domain experts. Each rule base is described by a so called knowledge matrix. For example, the rule base relating to the *friction force* contains 9 rules, because the influencing factors *weight per axis (m_a), friction coefficient (μ_f)* and the *friction force (F_f)* are represented by three membership functions each. The corresponding knowledge matrix is shown in **Table 1**. The upper row relates to μ_f, the leftmost column to m_a, and the body of the matrix specifies the resulting fuzzy value of F_f. The knowledge matrix of the *friction force* is completely occupied. But some knowledge matrices were only sparsely occupied. Hence, the initial rule base contained only a few significant rules. For example the rule base of the *temperature of the wheels* has only 17 rules (the complete rule base of the *temperature of the wheels* would contain 2205 rules).

Similar matrices were developed for all leaf and interior nodes of the shuttle and the track IFTs and combined to two knowledge matrices for the complete shuttle and track models afterwards. The complete rule bases hence reflected the IFT structure in their rule dependencies. The initial knowledge matrix of the shuttle model contained

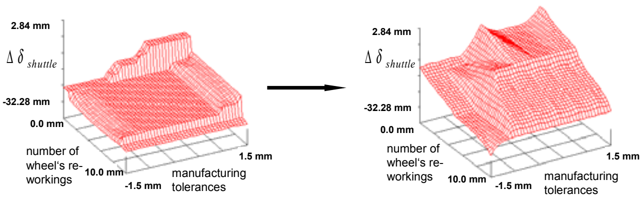

Fig. 7. Course of $\Delta\delta_{shuttle}$ before and after parameter adaptation.

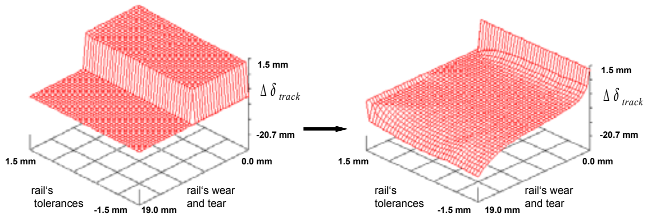

Fig. 8. Course of $\Delta\delta_{track}$ before and after parameter adaptation.

102 rows and the one for the track model contained 40 rows. These initial rule bases were tested and adapted during the parameter adaptation phase described below.

4.2. Parameter Adaptation

The correctness of the initial rule bases were checked by assigning values to the input parameters (influencing factors corresponding to IFT leaf nodes) for which the output (change of the air gap) was known. As expected, the outputs of the two rule bases deviated significantly from the expected ones, so each rule base was decomposed into sub rule systems corresponding to sub trees in the IFT, that span only two levels of hierarchy and had one root node.

Hence, for these sub rule bases the input parameters (corresponding to the leaf nodes of the sub tree) could be directly assigned and their influence on the output (corresponding to the sub tree's root) could be observed, facilitating an adaptation of rules and membership functions. In some cases also new nodes were inserted into the IFT hierarchy. For instance in the sub tree describing the *thermal expansion of the wheels* a new interior node *temperature* was inserted to combine the influencing factors *temperature of the rails* and *air temperature*. After decomposing the models and extending the IFT, the rule bases were extended. For the shuttle model 534 rules were created and the track model contained 81 rules. Although automatic adaptation of the the parameters is common and possible for such fuzzy models, in this case manual adaptation was done as the available data was not sufficient for automatic methods yet.

4.3. Implementation and Results

The fuzzy models for shuttle and track were realized using the freely available fuzzy development environment XFuzzy 3.0 [15]. During parameter adaptation the simulation facilities offered by XFuzzy were used to check the decomposed rule systems with manually generated and randomized input parameter values. In order to check the models of the air gap change the courses of $\Delta\delta_{shuttle}$ and $\Delta\delta_{track}$ subject to various input nodes and internal nodes were visualized before and after parameter adaptation.

Figure 7 shows the course of $\Delta\delta_{shuttle}$ in relation to the change of the influencing factors *manufacturing tolerances* and *number of wheel re-workings* with the initial shuttle model (left side) and after parameter adaptation (right side). The *number of wheel re-workings* is a leaf node in the IFT subtree of *shuttle's wear and tear* not depicted in **Fig. 6**. The value $\Delta\delta_{shuttle}$ is specified in millimeter. It can be seen that the influence of these influencing factors after parameter adaptation is much bigger than approximated by the initial model. This is based on additional information belonging to the tolerated *wheel's wear and tear* given by the *German Federal Railway Authority* (EBA) and the *German railway transport company* "Deutsche Bahn"(DB). Further adjustments have to be made using measured data.

Figure 8 shows the course of $\Delta\delta_{track}$ measured in millimeter in relation to the change of *rails' tolerances* and *rails' wear and tear* with the initial track model (left side) and after parameter adaptation (right side). Also in this model the parameter adaptation resulted in a considerable improvement of the model with regard to experts' expectations. In contrast to the initial model the current model shows a continuous effect to changing parameters without a stepped run of the trajectory as shown in the initial model. The improvement bases on additional and more finely granulated rules. Accordingly, one focus of future work will be on a further expansion of the rule base. The approximation results obtained by the fuzzy models have been approved by domain experts and they will be further checked and optimized by measurements in the near future.

The outcomes of both models have to be combined with the air gap's nominal value $\delta_{NV}(x)$. This value is set during the initial operation on a calibration track. $\Delta\delta_{track}$ and $\Delta\delta_{shuttle}$ change the nominal value for every stator of the track whereby the stator's position is described by two air gap values. Translating the models to the *NBP*'s track, which has a nominal air gap $\delta_{NV}(x)$ of 10 mm, the current air gap can be calculated as follows.

$$\delta_{current}(x) = \delta_{NV}(x) + \Delta\delta(x) \quad \ldots\ldots\ldots \quad (1)$$

$$\delta_{current}(x) = \delta_{NBP}(x) + \Delta\delta_{shuttle}(x) + \Delta\delta_{track}(x). \quad (2)$$

By comparing the current air gap $\delta_{current}(x)$ with the calculated value of the inverse model $\Delta\delta_{calculated}(x)$ a statement about the fuzzy model's accuracy will be enabled. Furthermore the difference between both values regarding the dependency on time or place enables statements about the alterations' reasons (i.e. wear and tear of rails or wheels, setting of the shoulder).

5. Hybrid Planner

Planning problems are an integral part of the design and operation of mechatronic systems when it comes to real world problems. Generating a plan that achieves a given objective under a number of constraints and following some global objectives (e.g. save energy, transport in minimal time) appears in most mechatronic systems. Operation needs to be planned along a timeline incorporating several dimensions of continuous physical effects. The intuitive example here is planning a path along a track network although other trajectories also need consideration. In the domain of the NBP, the air gap adjustment is an example of a subsystem that needs controlled trajectories over operation time. Under resource constraints like limited energy supply depending on environmental as well as plan details (e.g. air gap), consideration of more than the local control problem is needed. A planner needs to take into account these details to generate a plan that is actually executable. This is where hybrid planning is used. It does not only generate a plan that is feasible under discrete constraints like reaching the target position by traveling along a set of adjacent track sections but it also approximates the behavior of the system while the plan is being built.

Mechatronic systems naturally work in a continuous state and action space. Measurement data like positions, pressures and other physical dimensions can take an arbitrary value from an infinite number of states at any given time. Additionally, nearly all actuators are controlled using a continuous value. Mapping these values to a discrete planning problem, the problem of handling the discretization appears. The direct application of a reasonably discretized value space for actuator values to possible actions in each plan step leads to very large planning problems that are virtually impossible to find a plan in. Also the plan step granularity poses the same problem.

The term hybrid planning tackles an approach to integrate the continuous effects of physical system without giving up the possibility to build a plan. Discrete planners generally expect the outcome of an action to be deterministic. An action considered to be executed after another can expect a certain state. We extend this scheme by actively approximating the system state that the execution of an action will result in. It bases on discrete planning in that a discrete problem is expected as a basis. Along with the discrete problem, different discrete parameterizations of the planned system can be considered as alternative ways to execute an action.

The way to get the system state including the effects of an action is to run a simulation of the system or the relevant system part. **Fig. 9** shows the components used to implement such a system that is placed in the top layer of the OCM-architecture that has been developed for mechatronic systems within the CRC 614 [12]. The planner is equipped with overall external objectives and constraints that need to be fulfilled at any time. These can be system operation constraints like maximum peak energy use, constraints presented by other system components like desired acceleration levels or user mode selections like speed of movement versus comfort. While creating a plan, the planner initializes a *simulation* with the best known system and environment state for the considered action, parametrizes the simulation and runs it for the projected duration of the planned step. The result of

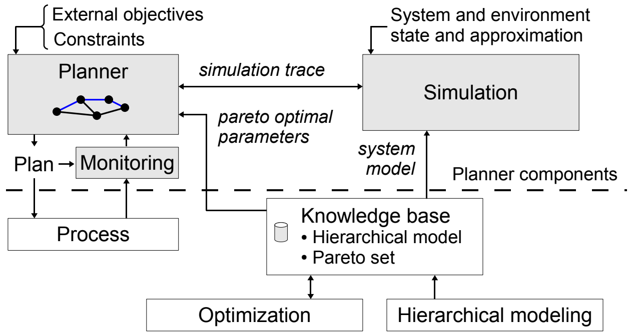

Fig. 9. Components of the hybrid planning architecture.

the simulation is a number of continuous value traces that are evaluated according to the constraints and objectives. The constraints are used to rule out an action, e.g. if the minimum energy reserve fell below the lower limit during the simulation. Likewise, the global objectives are used to evaluate the planned action and to decide upon possible alternatives.

When planning in a continuous domain like space over time for planning of a movement along a path, the set of actions the real system can take at every point in time is continuous. This means that there is an infinite amount of possible actions. Also as the time defines the action step width, there are no discrete steps but this domain is continuous too. The amount of plans that could be generated and would need to be evaluated in a discrete planner is therefore infinite. In a railroad-based movement the space domain in continuous planning can be reduced in complexity to those states that are actually desirable and reachable, e.g. staying on track. Further optimization can be made by clustering space states into distinct points on the rail. Track switches are natural points where it seems reasonable to allow a decision in the planning process. Considering the underlying system with other important state variables like energy consumption and remaining energy stored, additional points may be needed. The track sections introduced by the TSC (**Fig. 4**) are the basis for the decision points on the rail network.

The planning is not only done offline but the feasibility is also checked continuously during runtime. This helps ensure that the plan once created is still feasible under the actual system conditions. Imagine a battery failing or unexpectedly being in a worse condition than modeled. This could lead to energy reserve constraint violations and would trigger a replanning that would reconsider a possibly slower route with less energy use. The *environment approximation and state input* deliver the necessary information needed for simulating under the expected environmental conditions (e.g. wind, temperature, rainfall). In the presented simulation software this input is generated by a basic weather and climate simulation component that considers time of day, season and track parameters to generate an approximation of weather that is to be expected under comparable real situations. In a live system, these inputs would be fed by sensors on board a vehicle that measure temperature, wind speed, humidity and rain levels.

The *system approximation* component also uses expert knowledge and measured data and integrates historic data from the track section control (TSC) that manages data for a track section, e.g. known historic track quality data and current weather conditions. While unused in the simulation software, the battery condition on board the vehicle is a system component that is approximated as an exact model is not available yet.

The optimization and hierarchical modeling components are part of the works going on in CRC 614. The common interface is a *knowledge base* that holds information about the system in its current state. In this case it stores an abstracted model of the considered system and a set of pareto optimal parameter sets. These parameter sets are generated prior to runtime and stored for various system objective weightings. The objectives are conflicting so the pareto property ensures that an element of the set is optimal so no other point improves one objective without sacrificing another. Each element in the pareto set consists of a configuration for a part of or the whole considered system.

While the plan is executed, the *monitoring* component constantly compares the predicted and the actual system behavior. If the behavior does not match, the planner is advised to start replanning.

The different parameter sets are a discrete dimension of choice to the planner. While considering a step, it chooses from the parameters for the system to be configured accordingly. The quality of the choice is reflected in the results of the simulation.

In our presented example, the planner chooses a path along track sections. While considering an action, it considers parameters for the AGAS selecting a preference of safe, energy efficient or energy maximizing operation. Along with historic data of the TSC, the modeled air gap can be simulated for the track section and the actual modeled air gap can be evaluated against safety margins. Constraints are enforced by discarding parameter values that lead to violations along the simulated track section run. Other results include passenger comfort and consumed energy that can be weighted to come to a decision among parameter sets. The result of a complete planner run is a path along tracks with associated parameter sets for each section.

6. Evaluation

The evaluation is divided into three steps: *Model generation, Simulation* and *Plan updating*. The evaluation of the model generation is based on section 4. In this section the evaluation of both steps *model generation* and *simulation* are described in more detail. The last step *plan updating* is subject of ongoing work.

6.1. Model Generation

The developed fuzzy model (see section 4) is trained with data of the NBP's test track. For this purpose an

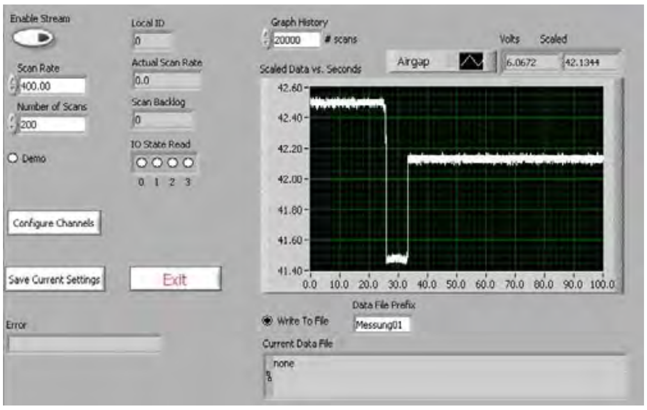

Fig. 10. LabView VI showing measured data of two primary motor parts including the gap between two PMPs' ends.

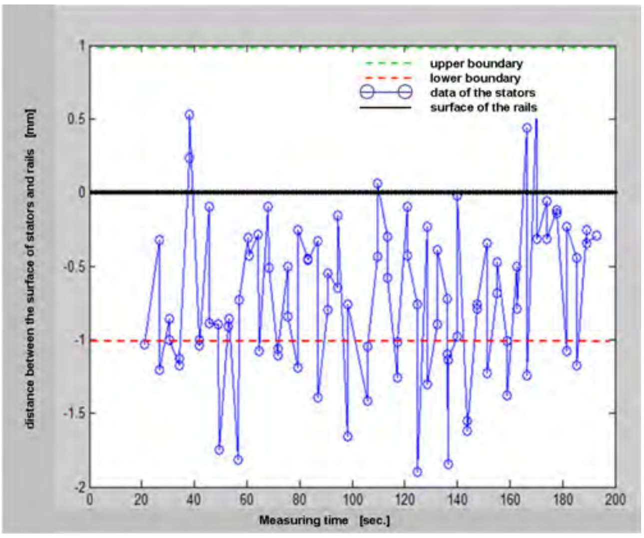

Fig. 11. Measured data over the course of the test track along with the nominal setup tolerances as dashed lines.

autonomous measuring vehicle (AMV), which features on board batteries and a servo drive in order to measure independently from the NBP's drive concept, has been developed.

The measured air gap is represented as the relative distance from the rails surface to the surface of the primary motor parts. Currently an on board dot-laser realizes this distance measurement. The next configuration level of the AMV will provide a line laser in order to measure the whole width of the primary motor parts. The measured values are acquired and stored for further editing by the measurement software *LabView*.

A high sampling rate (400 Hz) allows the operation of the vehicle without an additional position sensor. The gap between two primary motor parts, which averages 8 to 12 mm, can be sufficiently identified (see **Fig. 10**) for a vehicle's velocity of 0.3 m/sec. On the other hand the sampling rate induces a large amount of measurement data (e.g. 800,000 measuring points for the test track). This amount is reduced to two measuring points per PMP within an offline editing of the data (see **Fig. 11**) by noting the start and end values of a single PMP. The position of the PMPs is adequately described for lead off

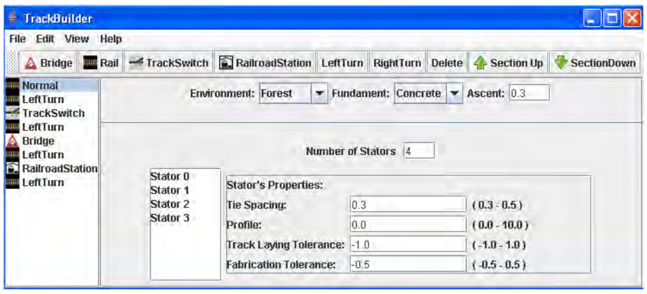

Fig. 12. TrackBuilder interface for building simulated track sections.

inquiries that way. Also note the nominal tolerances of ± 1 mm that the PMP setup in 2001 was validated against. Today, the lower tolerance boundary is violated. These tolerances cannot be held up although the track is rarely used. This gives a hint that a careful eye is needed as to how confident one can be that the vertical offset between track surface and PMP surface stay within tolerances. Possible form deviations (e.g. the convexity of the PMP's surface) are currently not considered. The wear and tear of the wheels is manually measured by measurements of the wheels' diameter. Likewise, the abrasion of the tracks will be measured at selected spots.

The fuzzy model is checked for its informational value within the second phase. The model data is verified with measured data. Emerging deviations will show if the model is well trained, or a further model optimization has to follow. The concluding third phase envisions the implementation of the hybrid planner into the Hardware-in-the-loop test rig "AGAS" (see **Fig. 5**). This test rig facilitates the analysis of two adjustment systems. The considered track section is reduced to 18 adjustable PMPs, which rotate underneath tne SMP. The synchronous PMPs, which are equipped with permanent magnets, can be replaced for a asynchronous operation mode with PMPs made of copper and steel.

6.2. Simulation

For executing of the simulation steps with various parameter values the Track Sectioning Control Simulation System (TSCSS) is realized. The TSCSS is used to test and analyze the air gap system using simulated tracks and simulated environment conditions. The system is split up into two components. The first one called *TrackBuilder* is used to construct a model of track sections (**Fig. 12**). A track is made up of different section elements like *track switch*, *station*, *bridge*, or *normal section*. Each of these sections has its own *TSC-unit*. The sections are surrounded by one specific environment like *forest*, *ocean*, *shadow*, *normal*, and *tunnel*. The substructure can be specified to be *gravel* or *concrete*. These parameters influence parts of the fuzzy approximation model for the air gap. A forest element has leaves on the rail in autumn and is generally cooler than in open terrain.

Additionally, each element is characterized by a slope value. A section consists of a number of primary motor parts that have a fixed length and are layed out with a regular spacing. Each primary motor part has *sleeper distance*, *profiling of the rails*, *assembling tolerance* and *manufacturing tolerance* as parameters. The parameters are used in the fuzzy approximation model of the air gap. The second component of the TSCSS is the simulation system (**Fig. 13**) with the track visualisation of a simulated track network (**Fig. 14**).

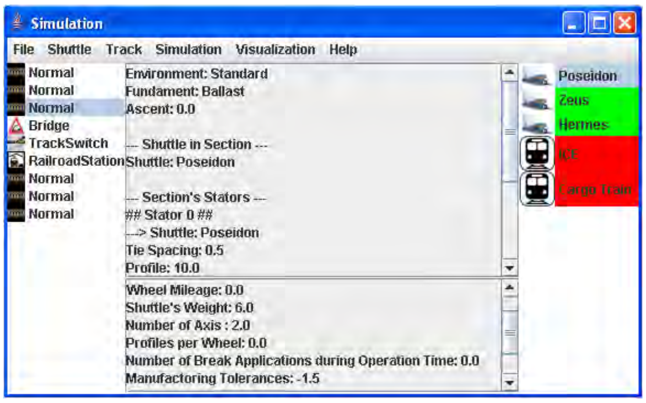

Fig. 13. Simulation user interface.

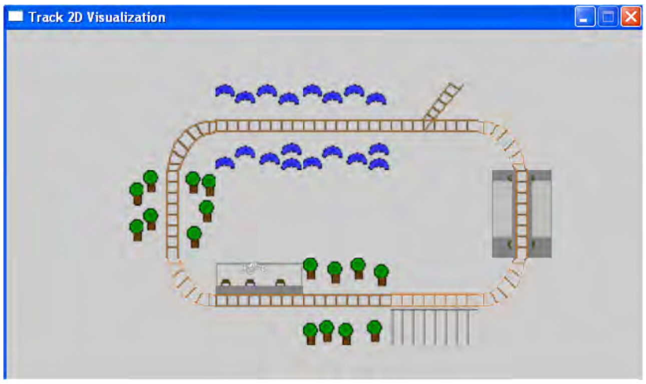

Fig. 14. Track visualization of a simulated track network.

RailCab-runs over a configured set of track sections can be simulated. The RailCab parameters can be configured as well: *average weight per wheel*, *total distance per wheel*, *total mass* and *number of brake activations*. These too are parameters to the fuzzy model. Apart from RailCabs, freight trains can be generated to test the load they place on a section and the influence this has on subsequent RailCab runs.

Global data in the simulation environment includes *weather*, *season*, *average global temperature* and *time of day*. These influences to the model can be held constant or be varied using a simple mechanism.

7. Conclusion

We have shown a system based on a hybrid planner generating feasible plans while considering continuous effects of planned action steps. The system under consideration is an air gap adjustment system (AGAS) that controls the air gap of a linear motor drive. A two-part fuzzy model of the air gap change was introduced to help predict the expected air gap under measured and predicted system and environment conditions. To evaluate the system, an autonomous measuring vehicle delivers the necessary data for the hybrid planner by measuring the displacement of the stators of the NBP's test track. Future work will include the integration of the air gap actuation system with the planning of the other system modules.

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