A Multi-Agent Planning Problem for the Coordination of Functions Modules

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Summary

This paper addresses the problem of coordinating several function modules within mechatronic systems. The coordination intends to improve the overall behaviour of the mechatronic system according to a flexible system of objectives. The contribution introduces a model that enables the application of multi-agent-technologies in order to provide decentralised, fast and adaptive coordination of the activities within a mechatronic system. The introduced model is suitable to be partially created by machine learning techniques.

Keywords

Interacting Functions Modules, Coordination, Multi-agent Planning, Cooperation, Self-Optimization

1 Introduction

A self-optimizing system determines its currently active objectives on the basis of the encountered influences. For example, while a rail system is in normal operation mode the objectives include a high level of comfort and minimal power consumption.

Self-optimizing systems are able to adapt their objectives autonomously. This includes modifying the relative weighting of the objectives, adding new or discarding existing ones. Adapting the objectives must result in an adaptation of the system behavior. To determine the suitable adaption of the system behavior, the objectives are used to formulate corresponding optimization problems. The solutions of the optimization problems indicate the suitable behavior adaptation. This is realized by adapting parameters (e.g. changing a control parameter) or the structure of the system (e.g. replacing the current controller).

We express self-optimization as a sequence of three actions that are generally carried out repeatedly:

1) Analyzing the current situation: Here the current situation includes the state of the system itself and all the observations that have been made about its environment. Such observations may also be made indirectly by communicating with other systems.

2) Determining the system of objectives.

3) Adapting the system behavior according to the new objectives.

This sequence of actions is called a self-optimization process. From a given initial state, the self-optimization process passes, on the basis of specific influences, into a new state, i.e. the system undergoes a state transition.

1.1 Planning for Mechatronic Systems

We call planning the task of determining a sequence of operations which is able to fulfill a job assigned to a mechatronic system. A job has to be understood as an instance of the overall function of the system, e.g. for a vehicle to transport a good from place A to place B or for a machining center to machine a given material in a specified manner.

Self-optimization enables mechatronic systems to implement different sequences of operations to fulfill a job. The system has to choose the sequence depending on the current system of objectives. Since planning determines the sequence in advance, this technique is especially interesting for all applications where the application of certain operations may block the later application of other operations due to its influence on the environment and system state. This is always the case when we introduce limited resources like battery power.

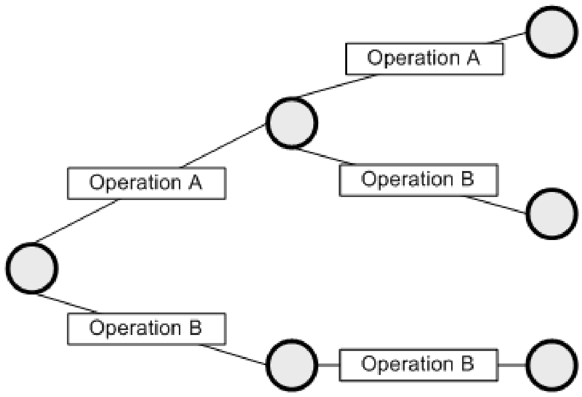


Figure 1: State Space of a Planning Problem

The most intuitive interpretation of the general planning problem is given by a state-space diagram. A state space diagram visualizes possible sequences of activities – in case of mechatronic systems called operations – and states in form of a tree. A quality function depending on states and operations is used to evaluate the plan. A simple example of a quality function is the energy consumption of the operations, which depends on the intermediate state in which an operations is performed. The planning procedure tries to find the sequence of operations that fulfills a job with minimal energy consumption.

To create a plan an appropriate modeling of the activities and possible states of relevant parts of the system and the environment is required. If such a model is available common planning procedures like state-space search or plan-space search can be applied to generate a feasible plan.

1.2 Problem Statement

In order to implement self-optimization mechatronic function modules (MFM) may implement several modes of operations. These modes offer different qualities according to a system of objectives, depending on environmental influences. The achievable quality depends not only on the environmental influences but also on the activities of other MFM. Thus two tasks can be identified: to select the best mode of operation according to environmental influences and the coordination of the activities of MFMs. We consider self-optimizing systems, thus the coordination approach must be able to consider a flexible and changing system of objectives.

The planning and coordination problem addressed in this paper encompasses the following elements:

- M, a set of MFM

- O_m , a set of possible operations per MFM m
- OM_{O}, a set of possible modes of operation per operation
- Ω, set of objectives
- $weight: \Omega \to [0,1]$, with $\sum_{\omega \in \Omega} weight(\omega) = 1$, a function denoting the importance of the objectives
- $T \subseteq \mathbb{N}$, a discrete set of time periods
- S, a set of states, variables describing the environment's and the system's state

The task of planning and coordination is to define which operations are carried out in which mode of operation for each MFM in such a way that the behavior of the overall system is optimized regarding the currently pursued system of objectives. For the sake of compactness we will call the performance of an operation in a certain mode an activity.

2 State of the Art

Multi-agent systems (MAS) or agent based systems are recognized as a new approach to the coordination of different subsystems within a mechatronic product. MAS are concerned with the coordination of the behavior of several autonomous, partially intelligent systems, called agents [BG88]. Goehner et. al. give an overview about agent technologies in engineering applications with several application examples [WUG03]. Another example is an agent based energy management for cars which is entirely based a reactive behavior [HWH04]. Pavlícek et. al introduce a MAS for diagnostics in automotive electronic systems, where agents assigned to several ECU (electronic control units) perform behavior prediction in order to detect possible critical states [PPMF07].

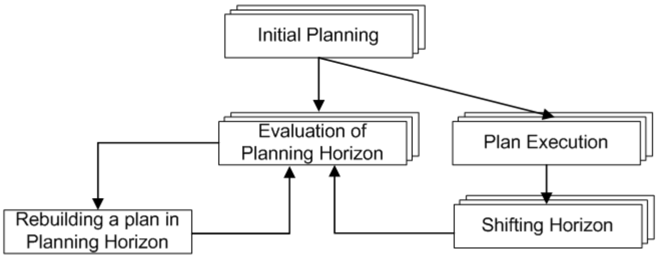
Multi-agent planning is rarely used in mechatronic products today, although it is applied to many real world applications. Multi-agent planning is commonly defined as the combination of planning and coordination [WMW05].

There are several approaches to create plans for the multi-agent planning problem. Boutilier and Brafman introduce an extension of partial global planning, which is able to consider concurrent, interacting activities [BB01]. Their approach is based on the planning formalism STRIPS [FN71] which is very limited in its expressiveness. Furthermore the approach of Boutilier and Brafman is centralized and requires a central model of the planning problem, which is not suitable for mechatronic system with buy parts. A more suitable approach is Generalized Partial Global Planning (GPGP) [DL00]. GPGP is a generalization of coordination mechanism for vehicle monitoring [DL87]. In GPGP each agent constructs an individual plan in order to achieve its goals. In order to improve the coordination agents can exchange their individual plans. An agent that has knowledge of more than one individual plan generates a so called partial global plan and can use this information to coordinate the individual plans by altering them. The alteration of plan is driven by relations between the planned activities of the agents. An example of such a relation is *facilitate* where the execution of an activity A facilitates the result of an activity B. The coordination tries to maximize positive relationships and minimize negative relationships between the local plans. An extension of GPGP is presented in [CB03]: Shared Activity Coordination (SHAC). SHAC interleaves the plan coordination and plan execution. Therefore it introduces a so called commit window for every activity. All coordination regarding an activity has to take place before the commit window is expired. In order to maintain the commit windows, SHAC implements different coordination mechanism from complex negotiation protocols to simple master-slave relations. SHAC chooses more simple coordination mechanisms the closer the end of the commit window is. The coordination encompasses very rigid mechanisms like master-slave interactions.

Both GPGP and SHAC operate on single activities. This approach implies that the activities are rather independent and the alteration of an activity cannot interfere with the execution of other activities. This assumption cannot hold true for the coordination and planning in function modules.

3 A Multi-Agent Approach to the Coordination of MFM

The multi-agent paradigm enables an intuitive modeling of the planning problem concerning several MFM and helps to divide the planning task into subtask. In our approach, every MFM is represented by an agent and is responsible for planning its local activities. The intention of the formal model introduced in this paper is to enable the agents to consider the impact of their activities towards the other systems in order to achieve a good overall behavior of the mechatronic systems. Figure 2 illustrates the overall concept of our multi-agent planning approach. It is split up into two separate phases. The first phase is the initial local planning in which each MFM constructs a local plan. The second phase encompasses two interacting processes. The first process improves the coordination between MFM. In a first step, each MFM evaluates the quality of its local plan regarding the plans of the residual systems and estimates the coordination potential. Based on the coordination potential a single MFM is selected to rebuild its local plan in such a way, that the coordination is improved. Afterwards the evaluation has to be updated and the next MFM is selected for rebuilding the plan. In order to limit the computational effort and to be able to interleave the coordination with plan execution, both evaluation and plan rebuilding operate on a limited planning horizon which has to be selected depending on the nature of the interaction between the activities of the MFM.



Figuree 2: Sketch of the MAS Planning Approach

The second process in the second phase is the plan execution. It starts operations in each time period according to the current plans. To uncouple the plan execution and the plan coordination a so called frozen zone is introduced, in which the coordination is not allowed to make any changes. Thus coordination is limited to the activities in between the frozen zone and the planning horizon. In order to implement a planning approach as sketched, it is necessary to provide the MFM with information about the interaction of activities. In order to model the planning for each MFM independently this information is provided in a black box manner – each MFM only requires knowledge about which MFM can perform which operations in which mode and how the activities interact according to the possible system objectives. The black box modeling helps to divide the modeling into independent sub process and increases the flexibility of the overall system.

A cooperative behavior shall be achieved by integrating the knowledge about the interactions in the quality function of the planning procedure. Thus the quality function encompasses two different aspects: the local goal achievement and a social component. In the next chapter we will provide a model for the interactions and derive two possible objective functions, one for each initial planning and coordination.

3.1 Coordination before planning

In this section we address the problem of modeling the interactions between the operations of different MFM and how to use this information in the local selection of operations and their mode.

The first information required for coordination in the initial local planning is how often the MFM execute certain operations under given conditions. The relative frequency depends on two different kinds of influences: the current system of objectives and the assumed environmental influences. It is denoted by the term: $\mathrm{freq}(o|\Omega^*, S)$, where $o \in OM$ and Ω^* denotes current system of objectives and S the assumed environmental influences. The relative frequency of the selected mode is the second variable: $\mathrm{freq}(om, |\Omega^*, S)$. Beside the quantity of the application of certain operations and modes the quality resulting from the application is required for coordination as well. Therefore we use an evaluation function which evaluates the result of operations according to an objective $\omega \in \Omega$:

- $eval: T \times \Omega \times O_m \times S \rightarrow [0,1]$

The evaluation function assigns a value between zero and one to each application of an operation in a given mode of operation. From this evaluation the average performance $eval_{avg}^{\omega}(om|e)$ of an operation in given operation mode can be calculated. This value is used to determine the interaction between two operations, while $eval_{avg}^{\omega}(om|om^{+}, e)$ denotes the average performance of operation om when operation mode om^{+} was performed at the same time, $eval_{avg}^{\omega}(om|\neg om^{+}, e)$ denotes average performance when om^{+}om was not performed at the same time. $eval_{\Delta}^{\omega}(om|om^{+}, e)$ is the difference between the two values. A positive difference indicates a positive relationship, a negative difference a negative relationship. Due to the domain of the evaluation function the domain of $eval_{\Delta}^{\omega}(om|om^{+}, e)$ is normalized to [-1,1]. These values are used to determine a social quality function for each mode of operation:

$$\mathrm{qual}^{\omega}(o_m^{+}) = \sum_{m \in M} \sum_{om \in OM_m} freq(om) \cdot eval_{\Delta}^{\omega}(om|om^{+})$$

The social quality function regarding the system of objectives can be calculated by:

$$qual(om^{+}) = \sum_{\omega \in \Omega} w(\omega) \cdot \mathrm{qual}^{\omega}(om^{+})$$

($w(\omega)$ denotes the relative weighting of objective ω). To include the information provided by the social quality function in local decision making, a MFM must be aware of its own and the other systems relevance regarding certain objectives. This relevance of MFM regarding a objective is expressed in a rank function $\mathrm{P}: M \times O \rightarrow [0,1]$. The summation of the rank function over all MFM for a given objective must be equal to one. The information about the relevance of MFM can be used to establish an objective function which consists in two parts, a local and a social part:

$$\sum_{t \in T} \sum_{om \in OM} \sum_{\omega \in \Omega} d \cdot (\, w(\omega) \cdot \mathrm{eval}(\omega, t, om, e)) + (1 - \mathrm{qual(om)});$$

where d is a binary decision variable which is 1, if the corresponding activity is carried out in time period t and $N(om)$ denotes the interactions with activities of other MFM considering their relevance towards the objectives:

$$qual(om) = \sum_{\omega \in \Omega} \sum_{m \in M} \sum_{om \in OM_m} i \cdot eval_{\Delta}^{\omega}(om|om^{+}, e))$$

Where $i = w(\omega) \cdot \mathrm{freq(om)} \cdot \mathrm{rank}^{\omega}(\mathrm{m})$ determines the importance of the dependency between the modes of operations.

In this way the social quality function considers all relevant information of the planning problem: the current system of objectives, the frequency of activities, the relevance of the several MFM and finally the interaction with activities of other MFM. The introduced quality function is used to evaluate different possible schedules of operations which lead to the desired overall function. By applying this objective function MFM behave egoistic if they have high relevance for the currently followed objectives and behave altruistic if they are no significant direct influence to current followed objectives.

3.2 Coordination after Planning

The initial local planning is supported only by a forecast of the application of activities. After the initial local planning not only the exact frequency of activities is known but also exact timing of activities. This information can be used to define time dependent utility functions for each activity:

$$eval_{\Delta,t}^{\omega}(om|om^{+})$$

This information enables the calculation of a more precise utility function for the performance of a given activity in a given period of time depending of the local plan of the other MFM:

$$\mathrm{qual}(om_t) = \sum_{m+\in M} \sum_{om\in OM_{m+}} weigh(\omega) \cdot \mathrm{rank}^{\omega}(\mathrm{m+})\mathrm{d} \cdot \mathrm{eval}_{\Delta}^{\omega}(\mathrm{om}|\mathrm{om_t})$$

The formula calculates the social cost of the application of om_t of an MFM m depending on the activities carried out by other MFM at the same time. The variable d is again a binary decision variable denoting if the activity om is applied in time period t. The time dependent social utility function can be again integrated in the evaluation function for local plans. Furthermore it can be used to estimate the coordination potential of each local plan created during the initial planning. We distinguish two of coordination actions:

- Replacing an activity in mode om with an operation mode om+, estimated by: $\mathrm{qual}(om_t) - \mathrm{qual}(om +_t)$
- Shifting the starting time of an activity om_t from time period t to t+, estimated by: $\mathrm{qual}(om_t) - \mathrm{qual}(om_{t+})$

The coordination actions are not actually used to coordinate the local plan of MFM but to estimate the coordination potential of the local plan of each MFM m:

$$\sum_{t*\in T, t*\geq t} \sum_{m*\in M/m} \sum_{om_{t*}} \sum_{\omega\in\Omega} w(\omega) \cdot eval_{max}(om_{t*}|om_t) - eval_{curr}(om_{t+}|om_t)$$

Where $eval_{curr}(om_{t+}|om_t)$ denotes the current utility of the interactions between om_{t+} and om_t and $eval_{max}(om_{t+}|om_t)$ the best possible configuration of the om_{t*} and om_t which can be achieved by shifting om_t in time or replacing it with a different mode of operation. $eval_{max}(om_{t+}|om_t)$ is a static value and must only be calculated once. The estimation of the coordination potential is used to rank the MFM and the coordination is organized in subsequent rounds. MFM h_1 with the highest estimated coordination potential starts to rebuild its plan according to new and accurate utility function. In rebuilding the plan with the new utility function the plan is implicitly coordinated with the other local plans.

All parameters besides the ranking of the MFM can be derived from historical data. Furthermore it is possible to model each of the parameters as a Bayesian Network [Charn91]. Literature offers various efficient methods for learning the probability distribution $P(X_i|Parents(X_i))$ if the structure of the network and thus the parents of X_i are known. Examples of such algorithms are Maximum Likelihood Estimation, which can be used if no expert knowledge about the relative frequency is available [Mitc97, S. 157) or learning of parameters with Dirichlet Distributions [Nea04] if hypothesizes about the relative frequency are available. For both algorithms standard implementation are available, e.g. for MATLAB [Murp01].

The sketched coordination process cannot guarantee any optimality. With round wise selection of MFM for the replanning it behaves like a classical greedy approach. On the other hand side the approach is able to realize a gain in coordination in shortest time, which is an important property if the coordination is interleaved with plan execution.

4 Application Example

An important application example for the work in the Collaborative Research Centre 614: "Self-optimizing concepts in mechanical engineering" is the railcab system that is developed within the project "Neue Bahntechnik Paderborn" (NBP) [LEHS02]. The railcab system consists of small autonomously driven rail-bound vehicles that are propelled by a doubly fed linear motor. The vehicles consist of several innovative subsystems (MFMs) that are designed to perform specific tasks. Each subsystem has its own information processing to enable special self-optimization techniques. However, their tasks and behavior are not independent from each other. To coordinate the MFMs, the approach presented here can be used. We focus on the coordination of three subsystems: the driving module including the adjustment system that controls the air gap between the stator at the track and the secondary motor part in the vehicle, the active suspension module and the energy storage system. The data processing and communication hardware that is necessary for the control of the railcab system and the vehicles can additionally be used to store information about the properties of the track sections that a vehicle is going to travel on.

4.1 Modes of Operation of the Function Modules

To make use of the approach presented here the behavior of the function modules has to be divided into specific *modes of operation* which are explained for each module in the next paragraphs.

Energy Storage

Besides the propulsion of the vehicle, the doubly fed linear motor of the railcab system offers a power transfer from the primary to the secondary motor part and thus from the track to the onboard supply system of the vehicle. This power transfer depends on the operating point of the linear motor, the maximum power transfer being approximately proportional to the driving force and reciprocally quadratically proportional to the air gap of the motor.

As the linear motor cannot transfer sufficient energy to supply the MFMs in every operating condition, an electrical energy storage has to be installed on the vehicle. It has to compensate for the difference between the transferred power of the motor and the demanded power of the modules. A power management strategy is necessary to control the power flow of the energy storage and thus to assign power to the modules.

The power management strategy hast o choose from three modes of operation $OM_{es} = \{charge, discharge, inactive\}$:

- *charge* – the energy storage is charged,
- *discharge* – the energy storage is discharged,
- *inactive* – the energy storage does not contribute to the power flow in the system.

In mode c*harge*, a percentage of the transferred power is stored in the energy storage, thus not being available for the power demand of the modules. In mode *discharge*, a percentage of the power demand of the MFMs can be taken from the storage, while in mode *inactive* the power demand has to be satisfied solely by the transferred power of the motor.

The power management strategy follows two objectives Ω_{es}. Firstly, the energy storage has to *supply* the *MFMs* with the demanded power. Secondly, the *state of charge (SOC)* of the energy storage has to be *maintained* at a high level (while preventing overcharge) to have the capability to sustain further power demands of the modules. So the objectives can be described as $\Omega_{es} = \{supply, charge\}$ $\Omega = \{\text{supply,charge}\}$.

It is not possible to achieve both objectives at the same time according all cirumstances. If for example the transferred power of the motor is sufficient, all modules can be supplied optimally while at the same time the energy storage can be charged. But if the transferred power is to low and charging has to be maintained, the power of the other MFMs has to be restrained. Thus, a reduction in functionality results. The decision which mode of operation has to be selected is dependent on the environmental variables *power difference* between demanded and transferred power and *SOC* of the energy storage: $S_{es} = \{power\ difference, SOC\}$.

For example, the value of the evaluation function for the objective *supply MFMs* is high if the modules can be supplied with the demanded power, but gets lower the less power is supplied. The value of the evaluation function for the objective *maintain SOC* is high if the mode of operation leads to a high SOC (i.e. charging), but gets lower if a mode results in a low SOC. Discharging as the SOC is low is penalized stronger than as it is high or medium.,

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Active Suspension Module

The main task of the active suspension module (AS) is to maximize the comfort for the passengers. To avoid the propagation of track excitations to the coach body of the vehicles the body is mounted via springs to the carriage without any passive dampers. The necessary damping forces are induced by displacing the spring bases actively depending on the relative movement between the body and the carriage. In this way it is possible to adjust the characteristics of a virtual spring-damper system as needed. On very rough track sections with large excitations a feed forward compensation of disturbances can be used additionally, if information about the track is available in advance [TMV06].

The second objective of the active suspension module is the minimization of the energy consumption and the reduction of the maximum hydraulic power respectively that is needed for its operation. Hence the active suspension system has two objectives: $\Omega_{as} = \{maximize\ comfort, minimize\ energy\ consumption\}$

- *Maximize comfort* – The movement of the coach body in vertical and lateral directions is minimized.
- *Minimize energy consumption* – The hydraulic energy needed for the suspension system is minimized.

These objectives are pursued with three *modes of operation*: $OM_{as} = \{inactive, active, active\ with\ compensation\}$, where:

- *Inactive:* Only the passive springs are in use.
- *Active:* Forces are induced by displacing the spring bases to damp the body.
- *Active with compensation:* Track information is used to compensate the excitations additionally.

Depending on the characteristics of different track sections, the two objectives are achieved with different degrees of performance in each of these modes. So which of these modes is selected depends on the one hand on the characteristics of the track section and on the other hand on the available energy on this section:

$$S_{AS} = \{track\ characteristics, available\ energy\}$$

If the track is totally smooth, e.g., no active suspension is necessary for optimal comfort and therefore no hydraulic energy is consumed. In this example both objectives can be fulfilled completely for the operation mode “inactive suspension”. If the track is rough, maximum riding comfort can be achieved with the operation mode “active suspension with disturbance compensation”. However in this operation mode the maximum power is needed. So it would only be selected if there is enough energy available for this track section.

Propulsion Module (PM) and Air Gap Adjustment System (AGAS)

The air gap δ between the secondary motor part, which is fixed to the shuttle, and the stators, which are placed between the tracks, is a non-constant parameter considering an arbitrary railway track. Depending on place and time, the air gap is changing as a result of any displacements of the track, e.g. erosion of the shoulder, temperature effects and the wear and tear of tracks and wheels. Therefore, the propulsion module (PM) is extended by a module for the adjustment of the air gap, abbreviated AGAS – Air Gap Adjustment System. Both modules are strongly linked. In further considerations, they are realized as only one module working out the following combined tasks:

- to set propulsion / brake force (PM)
- to transmit energy into the shuttle (PM)
- to adjust air gap depending on situation (AGAS)

The AGAS with its function ”adjust air gap“ will be examined in the following details. There are three different operational modes available for that module:

OM_{agas} = {adjust once per section, moderate adjustment, continuous adjustment}

- Adjust once per section: The AGAS adjusts the air gap only once per track section.
- Moderate adjustment: The adjustment of the air gap occurs several times per section but not continuously.
- Continuous adjustment: The AGAS adjusts the air gap continuously.

The AGAS pursues three different objectives. Depending on the driving situation, external influences and the knowledge of the track, the weights of the objectives ”maximize propulsion“, ”maximize efficiency“ and “maximize energy transmission“ are adjusted. In general, the AGAS tries to maximize the propulsion module's efficiency in consideration of its own energy needed for the air gap's adjustment. The module's objectives can be annotated as:

$$\Omega_{agas} = \{max\ propulsion\ brake\ force,\\ efficiency, max\ energy\ transmission\}$$

The selection of the objectives for the local planning depends on the track characteristics, shuttle user's specifications (regarding travelling time and costs) and the estimated energy consumption. The given track characteristics strongly influence the suitability of the operation modes:

$$S_{\ agas} = \{track\ characteristics, specifications\ energy\ consumption\}$$

If the AGAS does not receive any information about the air gap's gradient of a track or the available data is out of date, then the AGAS will choose a forth objective – to adjust a safe air gap. Summing up, the air gap is set in a secure distance in order to avoid any collision of rotor and stators.

4.2 Interactions between the Modules

Energy Storage – Air Gap Adaptation System

The transferable power of the linear motor depends on the width of the air gap. The smaller the width, the more power can be transferred. Thus, a higher activity when adjusting the air gap leads to a smaller air gap and thus may lead to a higher power transfer, although the adjustment consumes more power itself. That way, the objectives of the energy storage can be achieved in a better way. E.g. if the difference of the transferred power changes from negative to positive by adjusting a smaller air gap, both objectives *charge energy storage* and *provide power* can be achieved.

Energy Storage – Active Suspension Module

The sufficient supply of energy is a basic condition for the operation of the active suspension module of a vehicle. If there is not enough energy available, the objective maximize comfort cannot be achieved entirely on a rough track section. So the amount of energy that is provided by the energy storage affects directly the degree of performance of the active suspension.

4.3 Social Decision Making

Planning a tour of a RailCab vehicle is divided into several phases. First the propulsion module plans a velocity schedule along the route based on the characteristics of the specified track sections. This schedule depends on the user's requests and includes the desired time of arrival and a possible payment and other objectives like the desired comfort. The air gap adjustment system specifies a mode of operation for each track section. Which of the modes is selected depends on the characteristics of the track section in view and on the objectives pursued locally by the module.

Simultaneously the active suspension module plans its modes of operation along the route with respect to the track characteristics. Here also the local objectives of the active suspension are focused at first.

During the following phase both the propulsion module including the air gap adjustment system and the active suspension module estimate their provided and desired power respectively. These estimations are transferred to the energy storage. Thus the energy storage is able to predict the occurrence of critical states of charge during the tour. If so, the plan built during the first phase has to be changed. Therefore the data about the differences of performance of operation modes E_{Δ} is used. In the case presented here there are two opportunities to avoid the critical state of charge of the energy storage, e.g.: On the one hand the active suspension module could change to a less comfortable but more energy saving mode of operation. On the other hand the air gap adjustment system could switch to the continuous mode to transfer more power to the energy storage, however taking a loss of efficiency. The operation mode to choose is the one that fulfills the requests of the user in a better way.

By means of the approach presented here in this way a plan for the entire route can be generated that achieves the global objectives as well as possible, even if some local objectives have to be neglected temporarily.

5 Conclusion & Further Work

This contribution presented a modeling approach for multi-agent planning problem for interaction function modules. The application of multi-agent technology will help to divide the complex planning task into sub problems. Thus the planning problem of involved MFM can be modeled separately by the corresponding domain expert and can make extensive use of problem specific properties of the local planning task in order to achieve effective planning procedure. With the division of the planning task and the distributed solving of sub problems the new problem of coordination arises, because the sum of local optima equals not necessarily a global optimum. The introduced modeling of activities and interactions between activities enables the agents to reason about local and social utility.

An application example from the demonstrator of CRC 614 was introduced to illustrate the need for such planning approach and the possible application of the modeling approach.

The concept of multi-agent planning for MFM has to be exemplified on the application example. As a first step a more detailed modeling is required, e.g. a finer graduation of modes of operations is required to achieve a more accurate representation of the possible behavior of the modules. The most complex task is the development and implementation of problem specific local planning procedures. Local planning procedure may make use of smart search heuristics in order to create a good or optimal local planning result in shortest time.

For the implementation as a distributed multi-agent system requires a proper definition of the communication and interactions between the agents, respectively MFM. Different design options regarding the structure of the MAS have to be evaluated. Examples of such structures include blackboard and peer-to-peer architectures. In blackboard architectures a central entity would be used for the exchange of information. The blackboard could be used as instance for learning the planning parameter and for the analyses of the individual plans. These alternatives have to be evaluated on the background of the application example.

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