Improving Thermal Management of Electric Vehicles by Prediction of Thermal Disturbance Variables

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***Abstract*— In addition to the powertrain, heating and air-conditioning represents the second-largest energy consumer in electric vehicles. Optimization in this area can therefore contribute significantly to enhance the range of these vehicles. A new approach exploiting this optimization potential is the use of a model predictive controls. These controllers are based on a mathematical process model, which predicts the trajectories of the output variables. The predicted output variable trajectories are then evaluated by a non-linear cost function in order to find the corresponding optimal manipulated variable trajectory. Since external disturbances also affect the system in addition to manipulated variable, it is also necessary to predict these disturbances with sufficient precision. This is the core problem of this control approach and is not adequately addressed in previous approaches. For vehicle cabin heating and air-conditioning, the disturbances correspond to the thermal loads. These loads are mainly caused by the energy input of solar radiation, outside temperature, wind speed and humidity. In the following work, we will show how the coupling of methods of machine learning with Car2X technologies can lead to a high-precision prediction of thermal disturbances for an electric vehicle.**

Keywords- Model Predictive Control; BEV; Applied Machine Learning; HVAC; Mobile Data Mining

I. INTRODUCTION

The limited range of Battery Electric Vehicles (BEV) continues to be a major cause of the low market penetration of this technology. In addition to the drive train, the energy requirement for climate control is a key factor here. The energy requirement for heating, ventilation, and air-conditioning and (HVAC) can reduce the range by up to 50% [1] [2]. A recent promising approach reducing this additional energy demand is the replacement of conventional controls by Model-Predictive Controls (MPC). MPC are based on a linear or nonlinear model (NMPC) of the system to be controlled, which predicts future states for given input variables. The resultant states over a prediction horizon are then evaluated with a cost function. By means of an optimization method, the manipulated variables are then adjusted until an overall optimal state of the system is achieved. In various previous investigations [3] - [5], the potential of this method in the field of the vehicle thermal management was demonstrated. For example, an NMPC was used in [6] to simultaneously control the battery temperature and the vehicle cabin temperature. Compared to a conventional PI controller, it was shown that the set-point values were achieved considerably faster, nearly without overshoot while maintaining a high degree of overall energy efficiency. However, all these investigations showed a weak spot. The future disturbance variables were either assumed to be known in advance, were not taken into account or predicted by a very weak estimate. The disturbance variable over the current prediction range is most frequently estimated by the last measured value. This is unrealistic, since in the real world, however, the outside temperature, but also the solar radiation, fluctuate very dynamically over the course of the journey.

In this paper, we will first discuss the state of the art, discuss the impact of the prediction accuracy in Section III and then introduce our approach to a structure of the disturbance variable prognosis system in Section IV. Our approach is to train machine learning algorithms with data from weather forecasts for an upcoming vehicle ride and obtained vehicle sensor data of a subsequent measurement ride. The trained functions are then used to generate a forecast for the thermal disturbances of an upcoming trip using the current weather forecast. We will show in Section V how the data collection and processing is carried out with the help of an electric vehicle and the corresponding server structure. Finally, we will explain the applied machine learning techniques in Section VI and discuss the results of the test runs in Section VII.

II. STATE OF THE ART

As already mentioned, no precise prediction of the disturbance variables was used in any known work in the field of vehicle HVAC. In [6] and [7] the ambient temperature is kept constant over the prediction horizon, [8] analyzed HVAC power consumption for different given ambient temperatures, [9] estimates disturbance variables from measurement data, [4] and [10] use no ahead prediction at all. For vehicle cabin heating and air-conditioning, the disturbances correspond to the thermal loads. These loads are mainly caused by the energy input of solar radiation, outside temperature, wind speed and humidity. The prediction of these magnitudes is, however, a sub-area of the scientific discipline of atmospheric science and, in particular, of meteorology, which has a major focus on weather forecasting. The findings from this research are applied in various neighboring sciences such as agricultural meteorology, aviation meteorology, maritime and technical meteorology. The meteorological weather forecast is based on Synoptic Meteorology. Here, a network of ground-based atmospheric observing stations is used to perform measurements under a standardized procedure. These observations take place uniformly throughout the world at fixed time intervals. The information obtained is then supplemented by radiosonde ascents, satellite observations and aircraft measurements. The collected data is then mapped in weather maps and is used, on the one hand, for the shortest-term forecast (0-2h forecast), the so-called nowcasting and further as input for Numerical Weather Models (NWM). One of the most widespread NWM is the global GFS model (Global Forecast System) of the US National Oceanic and Atmospheric Administration (NOAA). Using the NWM, very short-term forecasts (2-12h), short-term forecasts (12-72h) and medium-term forecasts (3-10d) are then prepared by state and private weather services [11].

In recent years, dramatic progress has been made in the field of weather forecasting. The quality of the weather forecast fluctuates during the year. Thus, in the summer, more reliable forecasts can be drawn up in more stable weather conditions than in winter. For example, the average forecast error of the daily high temperature for a one to two-days forecast of the German weather service fell from 2.5 K in the year 1984 to 1.6 K in the year 2008 [12].

The use of weather forecasts for control engineering applications in combination with model predictive controllers has already been investigated in several scientific papers [13]-[19]. The main application area was the climate control of buildings. In [17], the impact of forecasting accuracy of different prediction models on the quality of a model-predictive control for climate control of buildings was investigated. Different methods based on historical data (TMY2 predictor, same-as-yesterday predictor, bin predictor) were compared with methods based on unbiased random walk and on seasonal autoregressive and moving average prediction model (SARIMA). It was observed that the bin predictor models, in particular the 30-days and 60-days bin models provide the best performance. Furthermore, it was found that in comparison to the model predictive control with perfect prediction, the quality of the methods with bin predictor were only slightly behind. In [18], an improved disturbance prediction method as well as an extended MPC method, the stochastic MPCs (SMPC), have been used. Stochastic MPCs take into account the uncertainties of the measuring system, the overall system and the state estimator. An overview of SMPC can be found in [19]. For the prediction of the weather, results of the numerical weather prediction model COSMO-7, locally measured weather by the SWISS Meteological Network and building measurements were used. Furthermore, a linear error model was generated, which then provided the forecast in combination with the weather data via a Kalman filter. The use of online weather predictions is discussed in [20] and [21]. In order to forecast the future temperature value, the predicted temperatures of various online accessible weather services were combined in [21] to an improved prediction. Furthermore, the prediction of the solar radiation, which is not part of the weather forecast, is discussed. In this case, a method is proposed, which calculates the theoretical global radiation as a function of location and time for a clear sky as well as a method for calculation reduction in the irradiation through the predicted cloudiness. By means of a linear regression model, these forecast data are then linked with actual measured data.

In summary, it can be said that the results obtained are a great advance for application to the regulation of building climate control, but can be transferred only partly to the area of electric vehicles HVAC. There are several reasons for that. Due to the size, design, the storage capacity and thermal insulation, the entire system responds much slowly to external disturbances. As a result, short-term fluctuations do not have a very strong effect on the overall system. Furthermore, the system is generally operated continuously and not as in the case of the vehicle from only a few minutes to a few hours. This requires for building climate control a rather long-term forecast, which tolerates a wider standard deviation in the sense of the distribution of the forecast error. Secondly, buildings do not rotate and do not change their positions either. As a result, the associated weather observation stations and also the distance to this stations do not change, which can lead to a different prediction quality. The relative position to the sun in the case of buildings depends only on astronomical laws. This, on the other hand, affects the maximum possible global solar radiation as well as the side of the system facing the sun. Similarly, the relative position to shadow-causing obstructions like neighboring buildings, plants and trees does not change. In addition, a moving object is obviously exposed to bigger weather fluctuations, since the weather can differ from place to place. In [22], a high resolution system for routes, which monitors not weather data but road infrastructure based on acquired vehicle sensor data and machine learning was introduced. In [20], a range prediction system was introduced, which considers continually updated and locally resolved GFS weather data. The finest resolution of this system is 1 km. This resolution is too low for our application since, e.g., shadow-causing obstructions are not taken into account. All this require a more elaborate prognosis technique than in the upper case, which will be presented in this study.

III. IMPACT AND EVALUATION OF THE PREDICTION ACCURACY

The quality of control of a model predictive control essentially depends on the accuracy of the predicted manipulated variables, the accuracy of the predicted variables of the constraints and the range of the prediction horizon. Since the control optimizes only within the range of the prediction horizon, the optimum found is locally limited to this horizon. If a manipulated variable is predicted incorrectly in this horizon, the control deviation is also predicted incorrectly, which is why the control cannot find the true optimum for the given boundary conditions. The prediction value of the future behavior of the manipulated variables is subject to two uncertainties. On the one hand, it is subject to the accuracy of the process model, which is not part of this work, and, on the other hand the consideration of the disturbance variables of the control. If a disturbance variable changes only slowly in relation to the range of the prediction horizon, then the prediction accuracy can be improved by integrating the current values of the measurable quantities into the control. Additionally, immeasurable state and disturbance variables can be estimated by using observers or Kalman filters [20]. Since in the case of vehicle air conditioning, the disturbance variables, such as temperature and solar radiation, are subject to strong fluctuations with respect to the forecast horizon, these measures are only limited sufficient.

The exact quantification of the impact of a tangible prediction error, e.g., in terms of energy saving is difficult, as this effect depends on the particular MPC model and the state of all system parameters and variables. The quality of the forecasting method is therefore evaluated below in relation to the quality of the existing methods and the measurement inaccuracy of the respective sensor. In the case of the outside temperature prediction, the temperature sensor has a resolution of 0.5 K. This equates to an RMSE of 0.5, which is used as reference value. Since in this study the forecast horizon is assumed to be the duration of a journey up to one hour, the best state of the art reference estimate of the temperature is used on the basis of historical data and a naive prognosis. The estimated value of the naive prognosis corresponds to the first measured value of the temperature. The historical data estimate is usually in 1 hour increments. So, here it is assumed that this can be represented by the mean value of the vehicle measurement. The evaluation of the radiation prognosis is carried out analogously, whereby in this case the measurement inaccuracy is in each case 10% of the measured value.

IV. STRUCTURE OF THE DISTURBANCE VARIABLE PROGNOSIS SYSTEM

The task of the disturbance variable prognosis system is to predict the thermal disturbances acting on the system precisely in terms of extent and, if applicable, effective direction for the period of an impending journey with an electric vehicle. The accuracy must be described with a rating system. Each predicted single value for a variable corresponds to the realization of an event. Since this realization of an event is subject to a certain probability, a good prediction method must also predict a whole probability distribution for each individual event to be predicted [24].

The reference system is thus the continuous time of travel in the vehicle. Since the disturbances are caused externally and locally, the reference system must be related to the local state. This is done by two successive predictions. First of all, the location, time and orientation of the vehicle are predicted for the course of the journey. For this purpose, the route is discretized in road sections. Secondly, a prediction of the local disturbances is made for each discretized road section at the predicted time, taking into account the direction of travel. The forecasting procedure is described below. In this case, it is assumed that the destination of the trip is known to the system in advance.

A. *Location – Time Prediction*

As already mentioned, the prediction for the upcoming journey takes place in the form of a series of predictions for the separate road sections of the route ahead. Every road section is referred to as a segment in the following. A segment always consists of 2 nodes. The nodes used here originate from the OpenStreetMap data model (OSM). A node consists of a single point in space defined by its latitude, longitude, altitude and node ID. Currently, as of June 2017, 3,900,000,000 points are defined in the OSM data model.

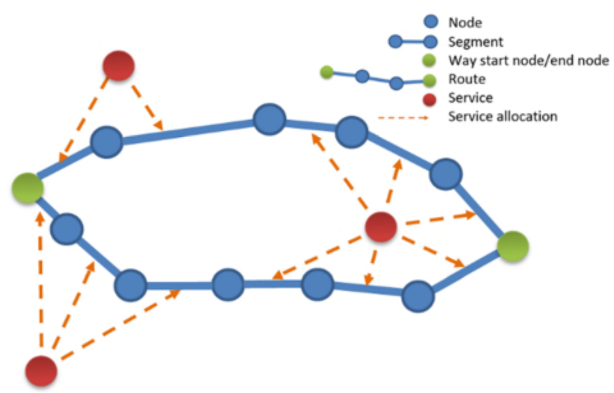

Figure 1. Definition of map elements

A journey is made on a defined way. The way is defined by its start and end nodes. Several routes are possible for each way. The allocation of ways and routes is done in a separate table of the database of the system. Each route is defined by a fixed sequence of segments. The definitions used here are shown graphically in Figure 1. For the first prediction, it is now necessary to predict the segment entry time and the dwell time of the vehicle in this segment. This must be done successively for all segments to be traversed on the entire route. For this purpose, it is necessary in a first step to find an optimal path between the start and the destination. This can be accomplished with the aid of a suitable route planning algorithm, e.g., the Dijkstra's algorithm. Since the finding of the optimal route is not subject of this investigation, the routing API of the open source routing library GraphHopper was used for this purpose. The GraphHopper API provides the optimal route for a given way in the form of individual waypoints of OSM-nodes and associated time points. From this, a predicted dwell time can be derived for each segment, and additionally, since the length of the segment can be calculated, a predicted velocity in the segment can also be derived. In the context of vehicle measurements, however, it was found that these prognosticated times are not suitable as a basis for the following predictions of the disturbance variables. Although on average the arrival time is predicted relatively well, there are strong deviations in the individual segments. This is based on the fact that depending on the type of road, a certain average speed is assumed and individual conditions such as the occurrence of traffic lights are not taken into account individually.

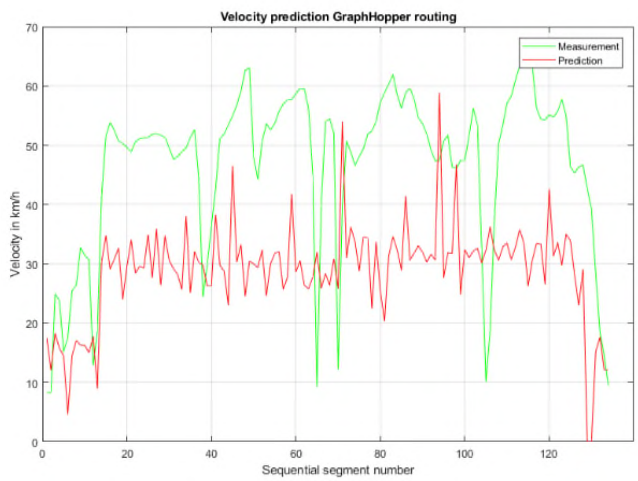

Figure 2. Predicted velocity by GraphHopper routing

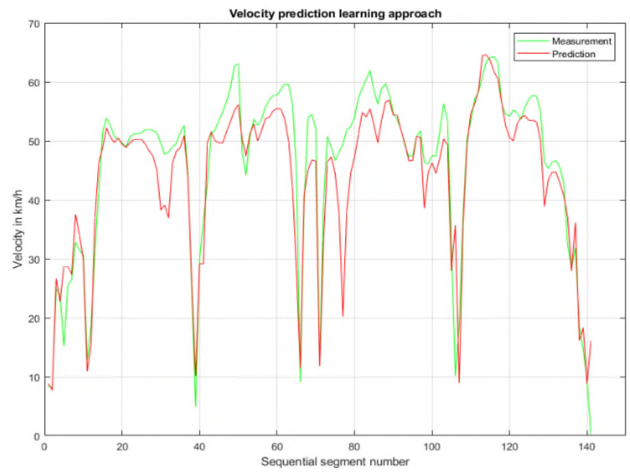

Figure 3. Predicted velocity by wknn-approach

Figure 2 shows the comparison of a velocity prediction made with the GraphHopper routing and a corresponding vehicle measurement. However, a more precise prognosis of the dwell time in the segment is necessary, since it is necessary to determine how long the vehicle will be subjected to the respective disturbance variable, e.g., of the solar radiation, in the individual segment. For this purpose, a forecast function based on machine learning was developed, which more accurately predicts both the time of arrival and segment dwell time. Figure 3 shows the comparison of the predicted velocity and the actual measured velocity. The prediction function is described in more detail in Section VI.A.

B. Prediction of Disturbances Variables

In the subsequent second prediction, the prediction of the disturbance variables must now be performed for each segment at the predicted arrival time. The measured values of local weather stations, local weather forecasts and the last known measured value of the vehicle are used as input for the prediction function. Various online weather services are available for querying weather data. These include, for example, YR (Norwegian Weather Service), DWD (German Weather Service), OpenWeatherMap (Extreme Electronics LTD), Weather Underground (IBM) and Here (Intel, Audi, BMW, Mercedes, etc.). These services provide current and historical weather data as well as weather forecasts to developers of web services and mobile applications. In this study, primarily OpenWeatherMap is used. However, further services will be integrated into the system in perspective. OpenWeatherMap uses, among other tools, the already mentioned GFS model of the NOAA as a NWM. An API can be used to access data on cloudiness, air temperature, air pressure, wind speed, wind direction, precipitation and humidity. These data also include the coordinates of the assigned weather station, the time of the last measurement as well as the projected time period for the

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forecast of the predicted weather events. The data of the weather services are referred to below as services. A number of specific services are assigned to each individual segment. The assignment of services to segments is determined by a request to the respective weather services and then registered in a separate table of the database. This is done once when creating a new route. The entities are in a many-to-many relationship. This means that each segment can be assigned to several services and each service can be valid for several segments. Since the segment sequence is fixed for each route based on the primary prediction, all associated services can now be determined for an upcoming journey. In advance to the disturbance variable prediction, the weather data for all services for all affected segments are queried and stored in the database. The weather data are supplemented by additional data to interpret their informative value. For example, the relative position of the affected weather station to the affected segment, as well as the time difference between the segment entrance time and the weather forecast time are stored. To predict the disturbance variables, all these data are entered into a mathematical algorithm, which outputs the desired variables. This algorithm is based on machine learning. Each segment is initially considered independent of other segments. The approach for the learning is so-called supervised learning. The algorithm learns a function from given pairs of inputs and outputs for each segment. The correct result of the function is available during the learning process as training data. The goal of supervised learning is to train the system until it can establish the correct associations.

In addition to the input data, the output data are also required for the learning process. In this case, this corresponds to the measured disturbance variables. The measurement and preparation of this data are subject of the next chapter.

V. DATA COLLECTION AND PROCESSING

For this investigation, an electric vehicle of the VW e-Golf type was used. This vehicle is equipped, as standard, with various sensors for recording vehicle and climate data. These are, for example, the ambient air temperature sensor, the fresh air intake duct temperature sensor, the humidity sensor, the sunlight penetration photo sensor, the brightness and rain sensor of the windscreen wiper. In addition, the current position can be determined via GPS and, of course, the speed can also be measured. The signals from the sensors can be tapped via the various CAN busses as well as via the onboard diagnostic interface (OBD). Since, in the case of the Can bus, the data can be recorded in finer time frames with cycle times of 20 ms to 200 ms, access was made to these data. For the vehicle measurement, the powertrain-CAN, infotainment-CAN and comfort-CAN were cut free and connected to a data logger. The data logger, on the other hand, can transfer the recorded data wirelessly to the central server via WiFi or 3G. These measurement data are organized in a first processing step in such a way that a vector of time stamp, geographical length, geographical latitude, outside temperature of the air, precipitation quantity, solar radiation, air humidity and vehicle speed are assigned to each measured time point in the 200 ms time grid. In a further processing step, each of these vectors is assigned to a known segment of the database. For this purpose, it has always been ensured that the segments have already been registered in the database as part of the prediction. Depending on the vehicle speed and time grid, the number of measuring points per segment varies in each case. Figure 4 shows the location of the measurement points (red dot) and the predicted segments (colored line with segment number) for a part of a trip.

The mapping of the vectors to the segments is carried out by means of a mapmatching algorithm, taking into account the distance from the measured point to the center of the segment as well as the segment length. In order to improve the route planning, the determined segments are compared with the predicted segments and, when appropriate, a new path is registered in the database. If no measured value is measured for a prognosticated segment, this segment is not subsequently learned.

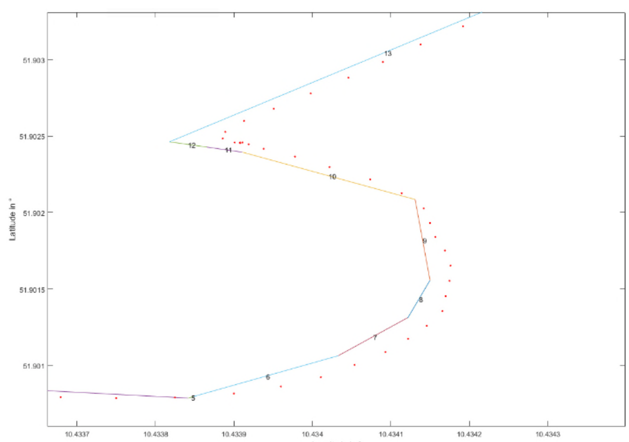

Figure 4. Predicted segments and measurement points

In the next processing step, all the values of assigned measuring points of a segment are aggregated to a single value x_s for each variable

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$$x_S = \frac{\sum_{i=1}^{n} t_i * x_i}{\sum_{i}^{n} t_i} \quad (1)$$

After this step, the target data for the learning functions are ready for use.

VI. APPLIED MACHINE LEARNING TECHNIQUES

There is a wide range of different methods of machine learning for different tasks like classification, regression or clustering. For our underlying problem of regression, there are a number of methods that differ by calculation effort, ability to generalize, fast convergence or overfitting. Since we have a huge number of road segments, which we have to train separately, we choose the procedures with the least computational effort. These methods are based on k-nearest neighbor and linear regression algorithms.

A. *Vehicle Speed and Segment Dwell Time*

The vehicle speed in a segment is related to vehicle type, driving style, traffic situation, road type, road geometry, and possible obstacles, e.g., traffic lights or construction sites. In the first approach, it is assumed that these influencing variables are essentially related to the time of the trip and are subject to similar patterns. While the road type and road geometry hardly change, the other factors tend to vary more. Our approach is based on the assumption that, e.g., the overall situation on a Monday morning always behaves similarly and again different than on Saturday night. Therefore, a dwell time in the segment is to be predicted depending on the time and the day of the week.

$$
\begin{array}{ll}
V: S \times T \times D \to R & \\
S \subseteq \mathbb{Z} & segment\ ID \\
T = \{0 \ldots 86400\} & \\
T \subseteq \mathbb{Z} & continuous\ second\ of\ the\ day \\
D = \{1 \ldots 7\}\ D \subseteq \mathbb{Z} & day \\
R \subseteq \mathbb{R} & dwell\ time
\end{array}
\qquad (2)
$$

The non-parametric distance-weighted k-nearest-neighbor method, which has already been published in [25], was used for this purpose. The wkNN algorithm is one of the simplest machine learning algorithms and due to the multitude of segments to be learned well suited. The feature space (labeled examples) consists of all the aggregated measured data of the segment. The output consists of the property values of the k closest training examples in the feature space. The Euclidean distance is used as a distance metric. Since the feature space is circular in both dimension, e.g., the Monday (numerically represented as 1) beside the Sunday (numerically represented as 7), the feature space at the edges was expanded by copies of the opposite edge. For the k-property values, a weight w is calculated according to their distance.

$$w_n = \frac{\frac{1}{d_n}}{\sum_{i=1}^{k} \frac{1}{d_i}} \qquad (3)$$

With these weights of the individual neighbors, the resulting total value for the prediction r_{pred} is then calculated.

$$r_{pred} = \sum_{i=1}^{k} w_i * r_i \qquad (4)$$

As Figure 4 shows, the quality of the results is already significantly higher than that of the route planning. Figure 5 shows the distribution of the error for this measurement run.

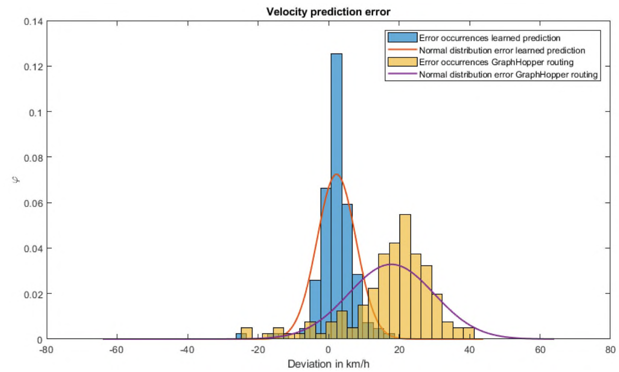

Figure 5. Velocity prediction error

As can be seen from this, it can be approximated with standard normal distribution. The dwell time for each segment can now also be determined from the vehicle speed. The prediction is performed sequentially one step ahead for all segments of an upcoming trip. To calculate the segment entry time of the following segment t_{k+1}, the predicted dwell time r_{pred} of the last segment is added to the segment entry time of the last segment.

$$t_{k+1} = t_k + r_{pred_k} \qquad (5)$$

B. *Temperature Prediction*

The prediction of the ambient temperature is based on the work described in Section II. and extended to routes. On the basis of data from online weather services the local temperature in a specific segment is to be predicted. As already mentioned, in the first instance only the OpenWeatherMap service was used for this purpose. Our following machine learning approach is based on the assumption that the temperature of two different places at the same time within a close area has a fixed offset. The second assumption is that the temperature changes by a constant slope over a limited period of time. This slope is assumed to be constant in a limited area for limited time span. The slope is calculated from the weather forecast for the next 3 hours. The input to the learning process is the last measured value and the predicted time slope of the 2 closest weather stations for every segment.

For temperature prediction, a learning method with a weighted multivariate regression is used. The weights w are used to represent the temporal change of the temperature of a segment and correspond to the time elapsed since the query of the respective weather date. Using the weights a multiple linear regression analysis using least squares algorithm is performed for the following equation:

$$y = b_0 + \sum_{i=1}^{2} b_i * T_i \ + \sum_{i=2}^{4} b_i * w_i * \Delta T \qquad (6)$$

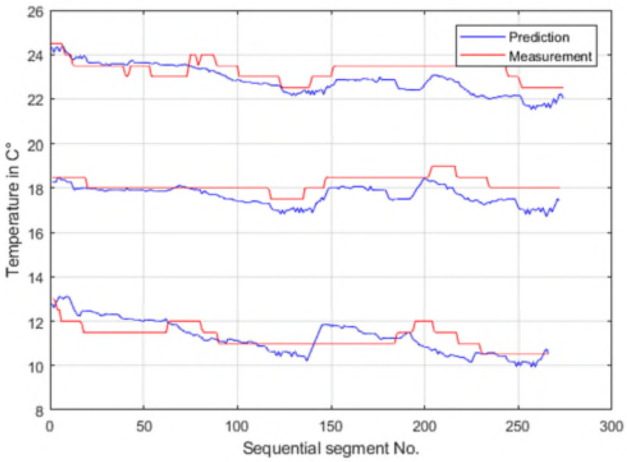

Figure 6. Temperature forecast and measurement

The system was trained by 30 test runs and tested in 3 further vehicle measurements to validate the learned function. The 3 test runs averaged a RMSE of 0.626. As can be seen in Figure 6 the predicted results were not very accurate. The reason for this was the strong deviation of the forecasted openweathermap weather data from the actual temperature value. Therefore, the openweathermap weather data for Clausthal was substituted by weather data retrieved from the control engineering institut weather station in Clausthal and applied in another test series. The system was subsequently trained and tested again.

Figure 7 shows the results of the prediction and measurement for a test run from Goslar to Clausthal and back. Both places have a height difference of 300 meters, which explains the strong temperature change. Two additional test runs were performed, which gave similar results. The quality of the prediction can be evaluated by calculating the root mean square error (RMSE).

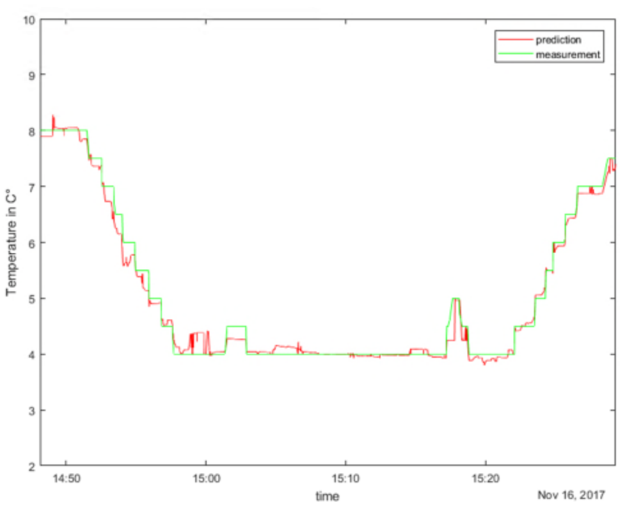

Figure 7. Temperature forecast and measurement

The test runs averaged a RMSE of 0.151, which is significantly lower than the naïve prognosis (RMSE 3.325), the historical data estimation (RMSE 1.3459) and resolution (RMSE 0.5K). The error probability can approximately be described with a standard normal distribution. The prognosis procedures for humidity and air pressure are carried out analogously to the temperature prognosis method. Therefore, a further explanation thereof will be omitted.

C. Prediction of Solar Radiation

The energy input to a vehicle by solar radiation is essentially dependent on the relatively constant radiation power of the sun, the angle of solar irradiation, the degree of atmospheric reflection and absorption, the cloudiness and the position of shadow-causing objects. The solar radiation consists of direct and indirect radiation. The prediction of solar radiation is more difficult, since weather services do not provide a direct forecast for radiation. The weather services provide only a description and prediction of the cloudiness in the form of a scalar valuation from 0 to 100. However, studies in the fields of agricultural meteorology [26] and regenerative energy systems [27] show that the proportion of direct radiation can be calculated very well when the position of the sun relative to the own location is known. However, if diffuse solar radiation occurs due to dispersion of the light through obstacles, fog or clouds, the irradiance can hardly be calculated. In our approach, it is assumed that if there is no cloud or mist, the energy input by solar radiation can be learned. The reason for this is that the reduction in the radiation caused by shadow causing obstacles (buildings, plants and trees) again depends only on the angle of the sun radiation. The shadow as a function of the sun position is thus learnable. The position of the sun can be described by the azimuth and the solar altitude. Azimuth and solar altitude can be calculated with the values predicted in Section IV.A. by using the astronomical formula referred to in [27]. If now additionally information about the weather, as the extent of the cloudiness, is added, this effect is also be learnable. The input variables for the prediction algorithm are therefore the position of the sun, described by azimuth and sunshine, as well as the predicted degree of cloudiness by the weather service. In analogy to the calculation of the temperature, normalized weights are calculated for the cloud values from the weather data in order to compensate the temporal offset between predicted segment entry time and measurement time. This initially predicts the degree of cloudiness. In the first approach, the recorded and aggregated signals of the brightness sensor of the windshield wiper control were used as training data. The distance-weighted k-nearest-neighbor approach from Section VI.A is again used as a learning method. The system was again trained by 30 vehicle measurements, then tested in 4 measurements in August and November.

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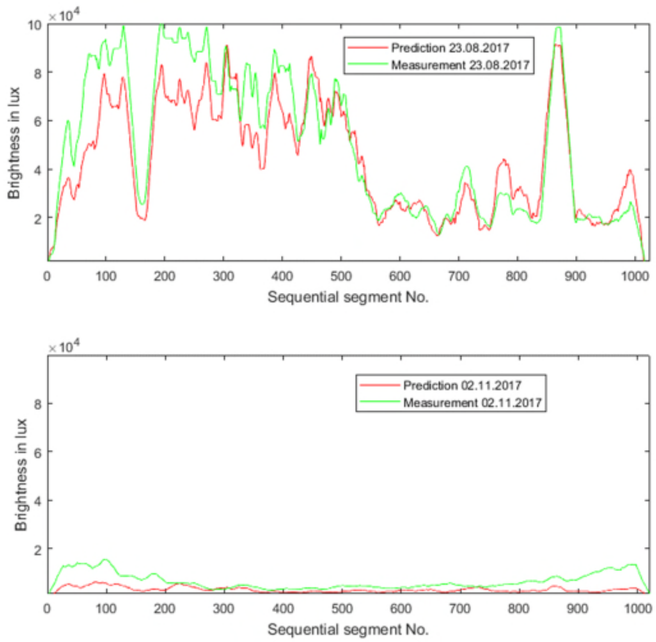

Figure 8. Results of the solar radiation prediction

Figure 8 shows the results of the experiment. In this case, it can be seen that the course of the radiation acting on the vehicle is relatively well predicted, but in absolute terms there are sometimes high deviations. This can be explained by the small number of measuring journeys, which did not adequately reflect the possible constellations of cloudiness in the training data. The prediction for the test runs averaged an RMSE of 1131.2, which is significantly lower than average RMSE for the naïve prognosis (RMSE 5499.4) and the historical data estimation (RMSE 3097.4). As can be seen in Figure 8, the predicted brightness is partly significantly lower than the later measured brightness. The reason for this is that the samples gained in the training had a lower degree of cloudiness compared to the test run. This error can be predicted by evaluating the aggregated mean distance from formula (3). The difference of the cloudiness of the k-similar samples to the expected cloudiness is represented by the distance weight w_n. To tackle this problem, the quality measure J of the prediction is determined in advance.

$$J = \frac{\frac{1}{k}\sum_{n=1}^{k} w_n}{\sqrt{3}} \qquad (7)$$

If the prediction is insufficient, due to insufficient learning data, an error handling routine must be integrated in the MPC algorithm. This could be realized, for example, by the temporary use of a conventional controller.

VII. CONCLUSION

The limited range of BEV is still a big challenge. To tackle this, we have shown an approach to improve the promising MPC-control strategy. We have trained machine learning algorithms with data from weather forecasts and vehicle sensor data to generate various prediction functions for the individual thermal disturbance variables. The quality of the thermal disturbance variable prediction strongly depends on the weather forecast quality and on the quality and quantity of the training data. Increasing this quality will be the subject of the upcoming work steps. In order to increase the quality of the input forecasts for the individual segments, further weather services are to be integrated into the system on one hand. On the other hand, the use of several vehicles in the course of a fleet test should result in a larger training data volume.

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