average slope of the road segments, or maximizing the number of energy subsystem infrastructure regions.

V. Conclusion

Increasingly high penetration of both electric vehicles (EV) and renewable energy sources (RES) will prove a tough challenge for future power and transportation systems. To enable integrated system design, we presented the TRANSP-0 design abstraction for rapidly formulating and evaluating integrated transportion and power system design options. In this paper, we described the individual components of the design abstraction in terms of static design parameters, dynamic aspects of system design and the requirements optimal control strategies for designs have to satisfy. Future work includes establishing large-scale integrated planning strategies and assessing their applicability for multi-modal passenger transportation and logistics problems.

- Multi - Modality
- Implementation + Evaluation

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- Find other constraints and objectives
- Improve the validity of the model (while keeping params low)

IV. Requirements on Transp-0 Dynamics

While the previous section outlined the state space of Transp-0 system designs, a concrete control strategy has not been proposed. In fact, we do not want to prescribe any specific control strategy. Rather, we want to highlight requirements that control strategies must satisfy in general. We assume that such requirements are expressed in terms of the constraints and objectives of the optimal control problem introduced in Section III. Subsequently, we first discuss the constraints in Section IV-A before elaborating on potential objectives in Section IV-B. Note that constraints and objectives could be defined over the static design space parameters (see Section II) as well. Examples include maximizing the average mechanical and electrical vehicle efficiency or constraining the number of road segments per area unit. However, we did not focus these "static" requirements in our work yet.

also example constraint !

A. Constraints

In principle, one can define arbitrary constraints over the dynamic (and static) system properties presented in the previous sections. In particular, we believe that such constraints might arise from design decisions made by transportation and energy system engineers. Hence, we do not want to prescribe the constraints. Rather, we provide two basic constraints which we believe to be part of any integrated system design. The first constraint makes sure that the road segment capacities RSC (i.e. the number of lanes) of the transportation subsystem infrastructure TSI are not exceeded (see Section IV-A1). The second constraint makes sure that the region capacities RC of the energy subsystem infrastructure ESI are not exceeded (see Section IV-A2).

vehicle state

1) Segment capacities: The road segment capacity constraint makes sure that no collisions occur in the states $S_t = (VS_t, ESS_t, CSS_t, RS_t)$ with $VS_t = (VP_t, VSOC_t)$ of the system dynamics. To derive the constraint, we first define the *overlapping vehicle pair* mapping $OVP_t : RSL \to VL \times VL$, which calculates for each road segment the pairs of overlapping vehicles such that $\forall rsl \in RSL$:

$$OVP_t(rsl) = \{(vl_1, vl_2) \in VL \times VL \mid \exists d_1, d_2 \in \mathbb{R}_0^+ :$$
$$VP_t(vl_1) = (rsl, d_1) \wedge VP_t(vl_2) = (rsl, d_2) \wedge$$
$$(|d_1 - d_2| < VS(vl_1)/2 \vee |d_1 - d_2| < VS(vl_2)/2)\}.$$

Note that the definitions says that vehicles must reside on the same road segment rsl and their half-sizes $VS(vl_{1/2})/2$ must be larger than their center distances $|d_1 - d_2|$. Then, from the overlapping vehicle pairs we can calcualte the *overlapping vehicle set* mapping $OVS_t : RSL \times VL \to \mathcal{P}(VL)$ with the power set operator $\mathcal{P}(\cdot)$, which calculates for each road segment and vehicle the overlapping pairs such that $\forall rsl \in RSL, vl \in VL$:

$$OVS_t(rsl, vl) = \{vl' \in VL \mid (vl, vl') \in OVP_t(rsl)\}$$

Note that the overlapping pairs are ordered such that duplicates are avoided by the previous definition. Finally, we can derive the *collision property* mapping $CP_t : RSL \to \mathbb{B}$ with the boolean set $\mathbb{B} = \{true, false\}$, which calculates for each road segment whether a collision occurred in state S_t or not such that $\forall rsl \in RSL$:

$$CP_t(rsl) \Leftrightarrow \exists vl \in VL : |OVS_t(rsl, vl)| > RSC(rsl).$$

Consequently, a state is collision-free if for all road segments the collision property is $false$. Note that our constraint definition operates on the state information only. However, collisions might occur in between two states, e.g. when one vehicle is overtaking another vehicle on a single-lane road segment within one time step. An advanced constraint definition is required to capture these cases also, but might be more difficult to compute. Alternatively, one might reduce the time resolution such that these cases do not occur.

2) Region capacities: In contrast, the region capacity constraint makes sure that the energy flow through each region does not exceed its capacity limit. To derive the constraint, we first define the *absolute energy flow* mapping $ASF_t : RL \to \mathbb{R}$ such that $\forall rl \in RL$:

$$ASF_t(rl) = (\sum_{sll \in SLL : SLR(sll) = rl} |SLP(sll)(t+1)| +$$
$$\sum_{esl \in ESL : ESR(esl) = rl} |ESB_{t+1}(esl)| +$$
$$\sum_{csl \in CSL : CSR(csl) = rl} |CSB_{t+1}(csl)| +$$
$$\sum_{rl' \in RL : RP(rl') = rl} |RB_{t+1}(rl')|) * RE(rl).$$

inflows

outflows

Note that in contrast to the region balance definition (see Section III-C4) the absolute energy flow uses the absolute balances of the subcomponents and subregions multiplied by the region efficiency. Consequently, the absolute energy flow is an indicator for the amount of energy that has to be transported through the region in each time step. Finally, we require the absolute energy flow for each region to be smaller or equal than the respective region capacity.

B. Objectives

In addition to constraints (see Section IV-A), our approach supports arbitrary objectives over the dynamic (and static) properties of the transportation subsystem (see Section II-A) and the energy subsystem (see Section II-B). In particular, we do not want to prescribe any particular objectives. Rather, we believe that it is the designers task to formulate different objectives and explore their effect on the system structure and dynamics. Among potential objectives of the system dynamics we consider minimizing traveling times, minimizing energy consumption during driving, and operating the individual energy subsystem infrastructure regions far from their capacity limits. Other objectives might include for example minimizing the free road segment space or minimizing energy storage usage. The "static" objectives might include - for example - minimizing the number of road segments, minimizing the

C. Transition function

Finally, the transition function T of the optimal control problem is modeled as a deterministic mapping $\mathbb{S} \times \mathbb{A} \rightarrow \mathbb{S}$ with ~~concrete~~ transitions $T(S_t, A_t) = S_{t+1}$ and time point $t \in \mathbb{N}$, where

- S_t represent the *state* of the system at time point t (i.e. the source state of the transition),
- A_t represents the *action* applied to the system at time point t, and
- S_{t+1} represents the *state* of the system at time point $t+1$ (i.e. the target state of the transition).

Note that we work with a deterministic transition function to reduce the complexity of the system dynamics. Consequently, one can solve the optimal control problem more easily in practice [20]. However, to obtain higher physical accuracy one might need to introduce a non-deterministic or even probabilistic transition function instead. This transition function could encode the uncertainty about the physical process involved, which occurs due to various simplifications made (see Sections II and III).

Having in mind that $S_t = (VS_t, ESS_t, CSS_t, RS_t)$ and $A_t = (VA_t, ESA_t)$ we decompose the transition function T into partial transition functions $VTF, ESTF, CSTF, RTF$, where

- $VS_{t+1} = VTF(VS_t, VA_t)$ represents the *vehicle transition function*,
- $ESS_{t+1} = ESTF(ESS_t, ESA_t)$ represents the *energy storage transition function*,
- $CSS_{t+1} = CSTF(VS_{t+1}, VA_t)$ represents the *charging station transition function*, and
- $RS_{t+1} = RTF(CSS_{t+1}, ESS_{t+1})$ represents the *region transition function*.

Subsequently, we describe the vehicle transition function in Section III-C1, the energy storage transition function in Section III-C2, the charging station transition function in Section III-C3, and the region transition function in Section III-C4.

Muss nicht so genau gezeigt werden

1) Vehicle transition function: We decompose the vehicle transition function VTF into two partial transition functions $VPTF, VSOCTF$, where

- $VP_{t+1} = VPTF(VP_t, VR_t, VS_t)$ represents the *vehicle position transition function* mapping the current position, route, and speed to the next position and
- $VSOC_{t+1} = VSOCTF(VSOC_t, VP_t, VR_t, VS_t, VB_t)$ represents the *vehicle state of charge transition function* mapping the current state of charge, position, route, speed, and balance to the future state of charge.

Note that the position transition function requires the road segment distances RSD (see Section II-A2a) to compute the follow-up vehicle positions on their routes. Furthermore, the vehicle state of charge transition function either requires the driving information (i.e. the position, route, and speed) or the balance information (i.e. the energy flow through the charging station) to compute the follow-up state of charge.

+ mechanical and electrical efficiency parameters, slope!

2) Energy storage transition function: In contrast, we decompose the energy storage transition function $ESTF$ into one partial transition function $ESSTF$, where

- $ESS_{t+1} = ESSTF(ESS_t, ESB_t)$ represents the *energy storage state of charge transition function* mapping the current state of charge and balance to the next state of charge such that $\forall esl \in ESL$ with $ESB_t(esl) < 0$: action

$$ESS_{t+1}(esl) = ESS_t(esl) - ESE(esl) * ESB_t(esl).$$

necessary ?

Note that we use the energy storage efficiency ESE (see Section II-B2b) to compute the state of charge during charging. Hereby, the efficiency factor models the energy loss during energy conversion (e.g. electric energy to potential energy or to chemical energy and vice versa). In particular, the efficiency factor models the combined loss in both directions. Therefore, during discharging the efficiency factor is not used.

3) Charging station transition function: Then, we decompose the charging station transition function $CSTF$ into one partial transition function $CSBTF$, where

- $CSB_{t+1} = CSBTF(VP_{t+1}, VB_t)$ represent the *charging station balance transition function* mapping the vehicle positions and balances to the charging station balances such that $\forall csl \in CSL$ with $\exists vl \in VL : VP_{t+1}(vl) = (csl, 0)$: actions

$$CSB_{t+1}(csl) = CSE(csl) * VB_{t\cancel{+1}}(vl).$$

Consequently, the charging station balance equals to the vehicle balance multiplied with the charging station efficiency factor. Note that the charging station efficiency factor must be greater than 1 to model energy loss.

4) Region transition function: Finally, we decompose the region transition function RTF into one partial transition function $RBTF$, where

- $RB_{t+1} = RBTF(ESB_{t+1}, CSB_{t+1})$ represent the *region balance transition function* mapping the static load profiles, energy storage balances, charging station balances, and subregion balances to region balances such that $\forall rl \in RL$:

$$RB_{t+1}(rl) = (\sum_{sll \in SLL : SLR(sll) = rl} SLP(sll)(t+1) + \sum_{esl \in ESL : ESR(esl) = rl} ESB_{t+1}(esl) + \sum_{csl \in CSL : CSR(csl) = rl} CSB_{t+1}(csl) + \sum_{rl' \in RL : RP(rl') = rl} RB_{t+1}(rl')) * RE(rl).$$

Note that the region balance transition function is defined recursively. Consequently, first the lowest-level region balances have to be computed (i.e. the regions without subregions). Then, the ~~following~~ levels can be computed successively. upper Furthermore, note that the sum of sub-balances is multiplied by the region efficiency RE to account for losses over the power lines.

+ neural networks (alternatively)

2) Energy storage states: The energy storage states ESS_t of the system state S_t are modeled as a one-tuple $(ESOC_t)$, where

- $ESOC_t : ESL \to \mathbb{R}_0^+$ represents a mapping from energy storage labels to their current *state of charge*.

Note that we omitted advanced effects such as wear of equipment, which can cause degrading storage efficiency [?]. Again, we believe that such effects can be neglected during early phase system-level design. Furthermore, depending on the time step resolution additional state parameters are required to model - for example - ramp-up times of pumped storage hydro power plants [21].

3) Charging station states: The charging stations states CSS_t of the system state S_t are modeled as a one-tuple (CSB_t), where

- $CSB_t : CSL \to \mathbb{R}$ represents a mapping from charging station labels to the current charging station *balance* (i.e. the amount of energy sent or received from a connected vehicle).

In an advanced version of the design abstraction one could also consider failure states or software control states of charging stations. For now we assume that all charging stations work properly. Furthermore, the control strategy is provided implicitly by the optimal control problem formulation.

4) Region states: The region states R_t of the system state S_t are modeled as a one-tuple (RB_t), where

- $RB_t : RL \to \mathbb{R}$ represents a mapping from region labels to the current region *balance* (i.e. the aggregated loads of connected energy subsystem regions and components).

Again, we neglect physical state parameters such as power line temperatures or failure modes (e.g. due to exceeded temperature limits or due to environmental influences). Consequently, we assume that the energy subsystem infrastructure is available during the entire system operation. In an advanced version of the design abstraction one might also consider failure modes and respective repair actions [?]. + other topological/physical characteristics

B. Actions

The actions $A_t \in \mathbb{A}$ with time point $t \in \mathbb{N}$ of the optimal control problem are modeled as a tuple (VA_t, ESA_t), where

- VA_t represents the actions of the *vehicles* ~~introduced in Section II-A2a~~ and
- ESA_t represents the actions of the *energy storages* ~~introduced in Section II-B2b~~.

Note that ~~the~~ vehicles and ~~the~~ energy storages are the only system components comprising actions. The states of the other components is influenced directly or indirectly by these actions. In the following, we describe the vehicle actions in Section III-B1 before explaining the energy storage actions in Section III-B2.

1) Vehicle actions: The vehicle actions VA_t of the system action A_t are modeled as a three-tuple (VR_t, VS_t, VB_t), where

- $VR_t : VL \to (\mathbb{N} \to RSL)$ represents a mapping from vehicle labels to their respective *route*, i.e. a sequence of connected road segments with $\forall vl \in VL, n \in \mathbb{N}$:

$$RST(VR_t(vl)(n)) = RSS(VR_t(vl)(n+1))$$

starting at the road segment position of the previous vehicle states with $\forall vl \in VL$ and $VP_{t-1}(vl) = (rsl, d)$:

$$VR_t(vl)(0) = rsl.$$

- $VS_t : VL \to \mathbb{R}_0^+$ represents a mapping from vehicle labels to the current vehicle *speed* ~~(i.e. the velocity of the vehicle along the road segments)~~, and
- $VB_t : VL \to \mathbb{R}$ represents a mapping from vehicle labels to vehicle *balances* (i.e. the amount of energy sent to or received from a charging station) such that

$$\forall vl \in VL : VB_t(vl) \neq 0 \text{ only if}$$

the current vehicle speed is zero ~~(i.e. the vehicle does not move)~~ or

$$VS_t(vl) = 0 \text{ and}$$

the vehicle is parked currently at a charging station ~~and connected to the energy subsystem~~, i.e.

$$\exists csl \in CSL : VP_t(vl) = (CSP(csl), 0).$$

Note that the routes VR_t have to cover the distances traveled by each vehicle with the respective vehicle speeds VS_t. Hereby, the vehicle speed also can be zero such that the route only contains the previous road segment. In particular, zero speed is required to park vehicles at charging stations for one time step. Consequently, the time step resolution also determines the time intervals for charging or discharging vehicle batteries. Furthermore, note that we neglect accelerations and decelerations in the model, which might have a considerable effect on energy consumption [?]. Instead, we assume ideal conditions, which we believe to be sufficient for early phase design. evaluation

2) Energy storage actions: The energy storage actions ESA_t of the system action A_t are modeled as a one-tuple (ESB_t), where

- $ESB_t : ESL \to \mathbb{R}$ represents a mapping from energy storage labels to energy storage *balances* (i.e. the amount of energy sent to or received from the parent region).

Note that physically one cannot control the (positive or negative) energy balance directly. Rather, for a pumped storage hydro power plant one might control a valve limiting the downhill water flow and an electric drive causing the uphill water flow [19]. In fact, the actual control parameters depend on the concrete storage type. We believe that considering the energy balance directly represents the smallest common denominator.

a) Static loads: The static loads SL of the energy subsystem components ESC are modeled as three-tuple (SLL, SLP, SLR), where

- SLL represents a finite set of static load *labels*,
- $SLP : SLL \to (\mathbb{N} \to \mathbb{R})$ represents a mapping from static load labels SLL to static load *profiles* (i.e. a predefined production and consumption curve), and

discrete time

- $SLR : SLL \to RL$ represents a mapping from static load labels to parent *region* labels (i.e. the region where the static load is attached).

Note that ~~a~~ static load profile associate~~s~~ a numeric load to each discrete time step. Hereby positive numbers represent energy production and negative loads represent energy consumption. Consequently, static loads can be used to model everything from home appliances to solar panels to conventional power generators. In particular, we assume such loads to be uncontrollable in our design abstraction. perspective of engineer

Berechnungsfunktion

b) Energy storages: Then, the energy storages ES of the energy subsystem components ESC are modeled as a five-tuple $(ESL, ESCA, ESE, ESS_0, ESR)$, where

- ESL represent a finite set of energy storage *labels*,
- $ESCA : ESL \to \mathbb{R}^+$ represents a mapping from energy storage labels to energy storage *capacities* (i.e. the maximum amount of energy that can be stored),
- $ESE : ESL \to \mathbb{R}^+$ represents a mapping from energy storage labels to energy storage *efficiencies* (i.e. a constant factor between inflow~~ing~~ energy and stored energy), and
- $ESS_0 : ESL \to \mathbb{R}_0^+$ represents a mapping from energy storage labels to initial *state of charges* (i.e. the amount of energy stored initially) such that

  $$\cancel{ESS_0 \text{ such }} \text{that } ESS_0(csl) \leq ESCA(csl), \text{ and}$$

- $ESR : ESL \to RL$ represents a mapping from energy storage labels to parent *region* labels (i.e. the region where the energy storage is attached).

Note that the energy storage model is analogous to the electric vehicle model present in Section II-A2a. However, electric vehicles additionaly define mechanical parameters, while energy storages are attached to regions statically. Furthermore, we currently target small batteries rather than large storage facilities. Larger facilities ~~might~~ require more parameters.

to be realistical

c) Charging stations: Finally, the charging stations CS of the energy subsystem components ESC are modeled as a four-tuple (CSL, CSP, CSE, CSR), where

- CSL represents a finite set of charging station *labels*,
- $CSE : CSL \to \mathbb{R}^+$ represents a mapping from charging station labels to charging station *efficiencies* (i.e. a loss factor for respective energy flows), and

BT?

- $CSP : CSL \to RSL$ represents a mapping from charging station labels to road segment labels with zero road segment distance, i.e. Note on that

  $$RSD(CSP(csl)) = 0, \text{ and}$$

- $CSR : CSL \to RL$ represents a mapping from charging station labels to parent *region* labels (i.e. the region where the charging station is attached).

Note that the charging station position mapping CSP and the charging station region mapping CSR define the static connections between the transportation subsystem and the energy subsystem. Consequently, vehicles (see Section II-A2a) are able to interact with arbitrary regions (see Section II-B1a) of the energy subsystem infrastructure at predefined road segments (see Section II-A1b). zero-length

III. Discrete-time TransP-0 Dynamics

While the previous section was concerned ~~only~~ with the static parameters of integrated transportation and energy system design, this section focuses on dynamic aspects instead. In effect, each system design defines an optimal control problem (or dynamic programming problem) [20] over the transportation and energy subsystem dynamics. We decided to use a discrete-time model of the system dynamics due to the high problem complexity involved in its control. In the following, we describe the respective state space in Section III-A, the action space in Section III-B, and the transition function in Section III-C. Note that the states, actions, and transitions do not have to be defined by the transportation and power system engineers. Rather, the definitions are the same for all system design expressed in the TransP-0 abstraction.

A. States

The overall system states $S_t \in \mathbb{S}$ with time point $t \in \mathbb{N}$ of the optimal control problem are modeled as a four-tuple $(VS_t, ESS_t, CSS_t, RS_t)$, where

- VS_t represents the states of the *vehicles* ~~introduced in Section II-A2a~~,
- ESS_t represents the states of the *energy storages* ~~introduced in Section II-B2b~~,
- CSS_t represents the states of the *charging stations* ~~introduced in Section II-B2c, and~~
- RS_t represents the states of the *regions* ~~introduced in Section II-B1a~~.

Note that we do not associate a state with the infrastructure of the transportation subsystem (i.e. we assume the infrastructure to be constant). In the following, we describe the vehicle states in Section III-A1, the energy storage states in Section III-A2, the charging station station states in Section III-A3, and the region states in Section III-A4. static loads

1) Vehicle states: The vehicle states VS_t of the system state S_t are modeled as a tuple $(VP_t, VSOC_t)$, where

- $VP_t : VL \to RSP$ represents a mapping from vehicle labels to road segment *positions* (see Section II-A1b) and
- $VSOC_t : VL \to \mathbb{R}_0^+$ represents a mapping from vehicle labels to their *state of charge* (i.e. the amount of currently stored energy).

Consequently, our design abstraction neglects effects such as changing vehicle weights [?] due to passenger load or changing friction coefficients due to wheel temperatures [?]. We omitted such effects to ease design formulation primarily and replaced them with mechanical efficiency coefficients VME (see Section II-A2a), which have to be selected carefully to achieve desired ~~statistical~~ effects. Why?

b) Demands: Finally, the demands D of the transportation subsystem participants TSP are modeled as four-tuple (DL, DV, DP, DT), where

- DL represents a finite set of demand *labels*,
- $DV : DL \to VL$ represents a mapping from demand labels to *vehicle* labels (i.e. the concerned vehicle),
- $DP : DL \to RSP$ represents a mapping from demand labels to road segment *positions* (i.e. where the concerned vehicle is expected to be), and
- $DT : DL \to \mathbb{N}^+$ represents a mapping from demand labels to *time* points (i.e. when the concerned vehicle is expected to be there).

Ref dynamics

Note that our abstraction is based on discrete time. However, we do not prescribe the time step resolution. For long travel distances and durations more coarse resolutions can be used, for shorted distances and durations more fine-grained resolutions are needed typically.

B. Power / energy subsystem

Similar to the transportation subsystem (see Section II-A), we decided to model the energy subsystem in a mesoscopic fashion [15]. Note that microscopic models represent the individual power lines and their physical characteristics [18], while macroscopic models aggregate the entire energy subsystem into a single market place without ~~critical~~ power line characteristics [19]. Our mesoscopic model takes an intermediate approach, where only selected characteristics of the energy subsystem topology are represented. In particular, we limit our representation to subnetworks of equal voltage level (i.e. the network regions) and their hierarchical connectivity. Consequently, balances can be computed also for single regions rather than the entire electricity market. Finally, the TRANSP-0 abstraction of the energy subsystem is illustrated in Figure 3.

Okay

power line

italic

transformers

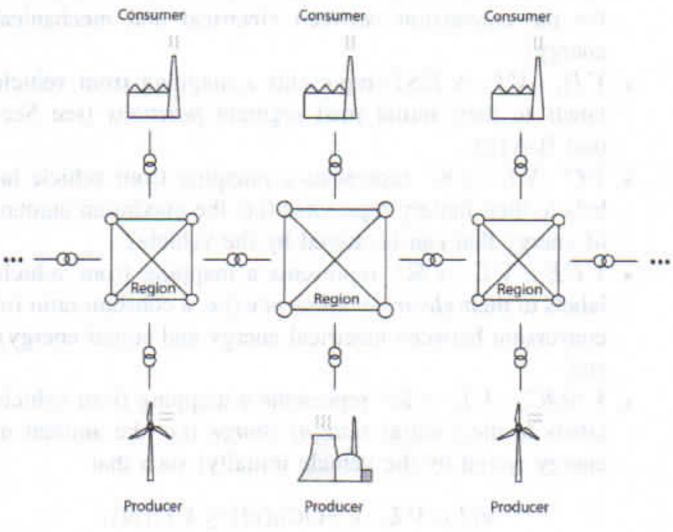

Fig. 3. Illustration of a energy subsystem design including an infrastructure (composed of regions) and components (i.e. producers and consumers).

Formally, the energy subsystem ES of the integrated design abstraction is modeled as a tuple (ESI, ESC), where

- ESI represents the energy subsystem infrastructure (i.e. the transmission and distribution network) and
- ESC represents energy subsystem components (i.e. the actual producers and consumers).

italic

Hence, we essentially separate the network characteristics and the network usage. In the following, we first explain the infrastructure in Section II-B1a before describing the components in Section II-B2.

1) Infrastructure: The energy subsystem infrastructure ESI of the energy subsystem ES is modeled as a one-tuple (R), where

- R represents the regions of the energy subsystem infrastructure, which are determined by the voltage levels and transformers of the network.

italic

Note that we selected a region model [15] over a power flow model [18] to reduce modeling effort and increase computational efficiency. In the following, we describe the regions in Section II-B1a. design formulation!

a) Regions: The network regions R of the energy subsystem infrastructure ESI are modeled as a four-tuple (RL, RC, RE, RP), where

- RL represents a finite set of region labels,
- $RC : RL \to \mathbb{R}^+$ represents a mapping from region labels to ~~region~~ *capacities* (i.e. the maximum amount of energy that can flow through ~~that~~ region in a predefined time interval), their each
- $RE : RL \to \mathbb{R}^+$ represents a mapping from region labels to ~~region~~ *efficiencies* (i.e. a constant factor determining the energy that is lost while flowing through that region), and their
- $RP : RL \to RP \cup \{\perp\}$ represents a mapping from region labels to their *parent* region label (i.e. the superordinate voltage level or the start symbol $\perp$). root

Note that regions must be assigned to at most one parent region. Consequently, our region model represents the energy system as a tree structure. The nodes of the tree represent *subnetworks* with distinct voltage levels. The edges of the tree represent *transformers* connecting the subnetworks instead. The region model can be derived ~~easily~~ from existing network topologies. easily

2) Components: The energy subsystem components ESC of the energy subsystem ES is modeled as a three-tuple (SL, ES, CS), where

- SL represents the *static loads* (i.e. loads assumed to be uncontrollable in our approach),
- ES represents the stationary *energy storages* (i.e. variable producers and consumers), and
- CS represents the *charging stations* for the electric vehicles (see Section II-A2a).

In the following, we first explain the static load design abstraction in Section II-B2a, before describing the energy storage design abstraction in Section II-B2b and presenting the charging station design abstraction in Section II-B2c.

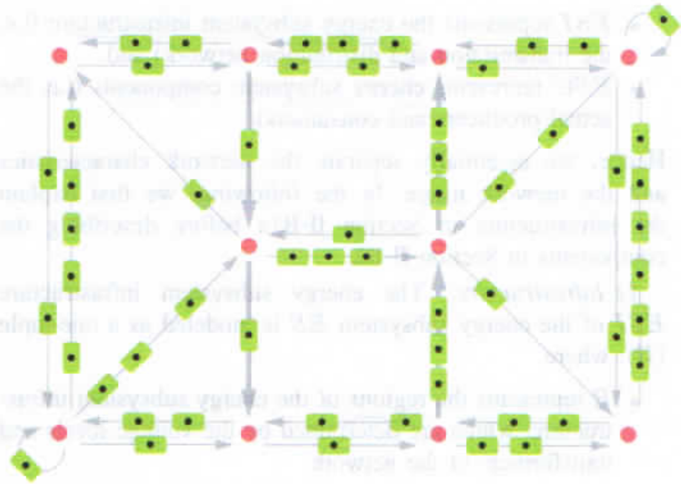

Fig. 2. Illustration of a transportation subsystem design including an infrastructure (composed of road intersections and segment) and participants.

Relate to colors

Hence, we use a directed graph to describe the transportation subsystem infrastructure. Subsequently, we first describe the road intersections in Section II-A1a before explaining the road segments in Section II-A1b. Why.

a) Intersections: The road intersections RI of the transportation subsystem infrastructure TSI are modeled - again - as a tuple (RIL, RIC), where

Capacity?

- RIL represents a finite set of road intersection *labels* and
- $RIC : RIL \rightarrow \mathbb{R}^3$ represents a mapping from road intersection labels to geometric coordinates.

Note that typically the coordinates are expressed in terms of latitude, longitude, and elevation. However, for simplicity in this work we use Cartesian coordinates instead. Consequently, distances can be computed more easily using the Euclidean metric. Moreover, transformations exist to switch between polar and Cartesian coordinates. [ref]

b) Segments: In contrast, the road segments RS of the transportation subsystem infrastructure TSI are modeled as a five-tuple $(RSL, RSS, RST, RSC, RSE)$, where

- RSL represents a finite set of road segment *labels*,
- $RSS/RST : RSL \rightarrow RIL$ represent mappings from road segment labels to their respective *source* and *target* road intersection labels,
- $RSC : RSL \rightarrow \mathbb{N}$ represents a mapping from road segment labels to their *capacities* (i.e. the number of lanes of the road segment), and
- $RSE : RSL \rightarrow \mathbb{R}^+$ represents a mapping from road segment labels to their *efficiency* (i.e. the surface material coefficient of the road segment).

Note that the previous parameters completely determine our road segment model. Consequently, we abstract from a variety of parameters typically considered such as the continuous elevation profile [?] or surface friction coefficients [?].

Furthermore, we derive the road segment distance $RSD : RSL \rightarrow \mathbb{R}_0^+$ as a mapping from road segment labels to distances and we use the Euclidean metric $E : \mathbb{R}^3 \times \mathbb{R}^3 \rightarrow \mathbb{R}_0^+$ to compute the road segment distance as

$$RSD(rsl) = E(RIC(RSS(rsl)), RIC(RST(rsl))).$$

Finally, we define road segment positions $RSP \subseteq RSL \times \mathbb{R}_0^+$ as tuples of road segment labels and traveled distances

$$RSP = \{(rsl, d) \in RSL \times \mathbb{R}_0^+ \mid d \leq RSD(rsl)\}.$$

We use the road segment positions RSP to locate traffic participants (i.e. vehicles) on the transportation subsystem infrastructure TSI as explained in Section II-A2. Note that the world coordinates can be obtained by a respective coordinate transformation. Segment Slope?

2) Participants: The transportation subsystem participants TSP of the transportation subsystem TS are modeled - again - as a tuple (V, D), where

- V represents the vehicles (i.e. the physical objects using the transportation subsystem infrastructure) and
- D represents the demands (i.e. the logical objects that cause the movement of the physical objects). italic

Consequently, we - again - distinguish between the static (i.e. the vehicles) and the dynamic (i.e. the demands) parts of the model. In the following, we first describe the vehicle design abstraction in Section II-A2a before explaining the demand design abstraction in Section II-A2b.

a) Vehicles: The vehicles V of the transportation subsystem participants TSP are modeled as seven-tuple $(VL, VS, VME, VP_0, VC, VEE, VSOC_0)$, where

Energiebereitung/funktion?

- VL represents a finite set of vehicle *labels*,
- $VS : VL \rightarrow \mathbb{R}^+$ represents a mapping from vehicle labels to their *size* (i.e. the length of the vehicle in road segment direction),
- $VME : VL \rightarrow \mathbb{R}^+$ represents a mapping from vehicle labels to their *mechanical efficiency* (i.e. a constant ratio for the conversion between electrical and mechanical energy),
- $VP_0 : VL \rightarrow RSP$ represents a mapping from vehicle labels to their initial road segment *positions* (see Section II-A1b),
- $VC : VL \rightarrow \mathbb{R}^+$ represents a mapping from vehicle labels to their battery *capacities* (i.e. the maximum amount of energy that can be stored by the vehicle),
- $VEE : VL \rightarrow \mathbb{R}^+$ represents a mapping from vehicle labels to their *electrical efficiency* (i.e. a constant ratio for conversion between electrical energy and stored energy), and
- $VSOC_0 : VL \rightarrow \mathbb{R}^+$ represents a mapping from vehicle labels to their initial *state of charge* (i.e. the amount of energy stored by the vehicle initially) such that

Berechnung/funktion?

$$\forall vl \in VL : VSOC_0(vl) \leq VC(vl).$$

Note that again we abstract from many parameters typically considered such as the vehicle weight [?] or the exact vehicle geometry [?]. In particular, we approximate mechanical and electrical efficiencies with constants only. Why? How valid is that?

Folgt das wirklich aus der vorigen Zusammenfassung?

fleets.

In summary, we found that current approaches do not sufficiently address the objectives and constraints of both transportation and power systems to holistically estimate the behavior within future power and transportation system scenarios. While approaches for scheduling EVs heavily address the effects of EVs within the power system, they neglect their effects on the transportation system. In contrast, routing approaches for EVs heavily address the effects of single or multiple EVs within the transportation system, in which routes are optimized, but neglect to address a detailed representation of the power system and it's underlying objectives.

könnte/sollte hier kommen

More importantly, addressing multiple objectives when considering interfacing transportation and power systems remains a central issue for stakeholders involved when planning those systems under high uncertainty. To enable rapid adjustment of control strategies has to be considered, when considering rapidly changing control parameters. ?

In [15] we presented a model of the electric power system suitable for large-scale computation, which divides the power system into regions and subregions. Then, in [16] we proposed a model which represents multi-objective traffic flows as an optimal control problem and microscopically captures the mobility demands of individual vehicles within transportation systems. Finally, in [17] we presented a systems modeling technique which allows one to microscopically model and express static and dynamic interaction between components of both power systems and transportation systems.

In this work, we describe an approach to system design for rapidly varying and evaluating parameters, objective and constraint configurations within integrated transportation and power system scenarios. For this, we formally describe our model for integrated transportation and power systems in terms of the microscopic behavior of individual components.

① Param Designs, ② Dynamics, ③ Requirements based on [15, 16, 17]

II. THE TRANSP-0 DESIGN ~~SPACE~~ framework

The TRANSP-0 design abstraction is intended to support both transportation and power system engineers during early project phases in formulating and evaluating different design options quickly. Therefore, transportation and energy system properties - both static and dynamic - have to be captured sufficiently precise. On the other hand, the design abstraction should omit unnecessary details to enable frequent design iterations. With these requirements in mind we have developed a candidate design abstraction, which is summarized in Figure 1. The abstraction comprises various transportation and energy subsystem parameters. Note that we have tried to reduce the number of parameters to a minimum. Hereby, we also accept potential losses in physical accuracy.

Reducing amount of early phases

In the following, we first describe the design space parameters for the transportation subsystem in Section II-A and the energy subsystem in Section II-B.

A.

A. Transportation subsystem

We decided to model the transportation subsystem in a mesoscopic fashion [?]. In particular, our model includes a

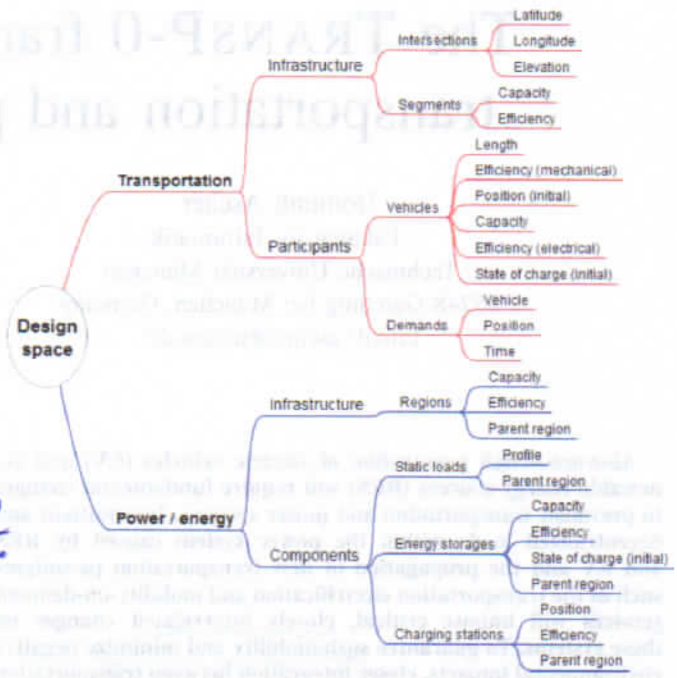

Fig. 1. Overview over the TRANSP-0 design space parameters comprising the transportation and the energy subsystem.

representation of the road network and each individual vehicle. The road network is modeled as a directed graph, where the nodes represent intersections and the edges represent the actual roads. Hereby, the edge weight defines the number of lanes and the edge direction indicates the prescribed driving direction. Consequently, two edges have to be used to describe bidirectional traffic flows. Then, the vehicles represent "particles" that are traveling along the road network. In particular, vehicles are assigned to points on the edges of the road network. Hence, vehicles are able to move along one edge and jump between edges at intersections. Finally, the TRANSP-0 abstraction of the transportation subsystem is illustrated in Figure 2. Segments

Formally, the transportation subsystem TS of the integrated design abstraction is modeled as a tuple (TSI, TSP), where

- TSI represents the transportation infrastructure (i.e. roads and their intersections) and italic
- TSP represents the individual traffic participants (i.e. passenger cars and goods vehicles).

Essentially, we distinguish between the static (i.e. the infrastructure) and the dynamic (i.e. the participants) parts of the transportation subsystem. In the following, we describe the the infrastructure design abstraction in Section II-A1 before explaining the participant design abstraction in Section II-A2.

1) Infrastructure: The transportation subsystem infrastructure TSI of the transportation subsystem TS is modeled as a tuple (RI, RS), where

- RI represents road intersections (i.e. the points in geometric space where roads intersect) and italic
- RS represent road segments (i.e. the actual roads leading from intersection to intersection).

The TRANSP-0 framework for integrated transportation and power system design

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***Abstract*—High penetration of electric vehicles (EV) and renewable energy sources (RES) will require fundamental changes to prevalent transportation and power systems. Intermittent and decentralized loads within the power system caused by RES and EV and the propagation of new transportation paradigms such as the transportation electrification and mobility-on-demand services will impose critical, closely interrelated changes on these systems. To guarantee sustainability and minimize negative environmental impacts, closer integration between transportation and power systems is necessary and integrated planing, operation and control strategies for these systems have to be established. In this paper, we present TRANSP-0, a system design abstraction for rapid and iterative formulation and evaluation of design options within integrated transportation and power systems. Firstly, we present the TRANSP-0 design space in terms of the static parameters for intelligent transportation and energy subsystem design. Secondly, we present the dynamic aspects of the subsystem design expressed by according optimal control problem formulation. Thirdly, we discuss the requirements to control strategies expressed by objectives and constraints of the underlying optimal control problems. Finally, we conclude with an outlook on the future scope of the proposed system design abstraction.**

I. INTRODUCTION AND MOTIVATION

High penetration of electric vehicles (EV) and renewable energy sources (RES) will require fundamental changes to prevalent transportation and power systems. Intermittent and decentralized loads within the power system and the propagation of new transportation paradigms such as the transportation electrification and mobility-on-demand services will impose critical, closely interrelated changes on these systems. To guarantee sustainability and minimize negative environmental impacts, closer integration between transportation and power systems is necessary. Allan et al. [1] assess a crucial challenge for successful EV adaption in terms of their integration with supporting infrastructure systems, i.e. the transportation system, the electric power grid and supporting information systems constituting the intelligent transportation system (ITS). More specifically, in terms of the power system, uncontrolled charging of a high number of EVs can impose increased peak loads within the distribution network [2], while increasing levels of fluctuating RES loads will impose challenges to power system operation [3]. Here, the ability of plug-in electric vehicles (PEVs) to contribute to balancing the fluctuation of intermittent RES has been shown in the past [4].

To comprehensively address the demands of integrated transportation and power systems, sustainable integrated planning, operation and control strategies have to be established for these systems. According strategies are frequently addressed within the concept of vehicle-to-grid (V2G), which describes a concept, where energy is released from EV batteries to the power system during times of increased power demand. By facilitating interaction between the power system and EVs, widespread V2G adaption possesses the potential to significantly reduce the amount of excess renewable energy produced within the power system and facilitates both environmental and economic benefits [5], [6], [7]. More specifically, key benefits of V2G include reduction of emissions, increased efficiency, as well as stability and reliability of the power system [8]. On the contrary, Mwasilu et al. [7] argue that for V2G adoption central technological issues have to be addressed first, which include rapid battery degradation of EV batteries and currently low penetration of EVs with V2G functionality.

Intelligent scheduling methods are widely discussed as key approaches to integrate electric vehicles into the power grid by minimizing single or multiple objectives within given power systems [9]. To sufficiently address technical and economic objectives for PEVs, Andreotti et al. [10] argue higher suitability of multi-objective optimization methods over single-objective optimization methods to evaluate model effectiveness in terms of operational limits and used objective functions. Zakariazadeh et al. [11] propose a multi-objective scheduling method for electric vehicles within a smart distribution network addressing economic and environmental objectives as well as technical constraints which manages to reduce operational costs and emissions and achieve Pareto-optimal solutions. To achieve optimal charging decisions for EVs, Ota et al. [12] propose a decentralized V2G control scheme to address the intermittency of RES energy production using electric vehicles.

Felipe et al. [13] propose multiple heuristics for routing electric vehicles which consider different partial recharge strategies and recharge technologies while traveling along routes. Integrating both scheduling and routing approaches for EV, Barco et al. [14] present an approach for minimizing operation cost for battery electric vehicle (BEV) fleets, which achieves optimal routing and scheduling of charge for EV