





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Network-induced Unit Commitment – A model class for investment and production portfolio planning for multi-energy systems

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Abstract


In light of the energy transition production planning of future decarbonized energy systems lead to very large and complex optimization problems. A widely used modeling paradigm for modeling and solving such problems is mathematical programming. While there are various scientific energy system models and modeling tools, most of them do not provide the necessary level of detail or the modeling flexibility to be applicable for industrial usage. Industrial modeling tools, on the other hand, provide a high level of detail and modeling flexibility. However, those models often exhibit a size and complexity that restricts their scope to a time horizon of several months, severely complicating long-term planning. As a remedy, we propose a model class that is detailed enough for real-world usage but still compact enough for long-term planning. The model class is based on a generalized unit commitment problem on a network with investment decisions. The focus lies on the topological dependency of different energy production and transportation units.

Keywords: Multi-energy systems, unit commitment, investment planning

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1 Introduction

To achieve the goals of the Paris Agreement, the decarbonization of all energy sectors is necessary. This requires a shift from centralized technologies, which are based on fossil fuels, to the integration of renewable energy sources, decentralized technologies, and sector coupling. These aspects severely increase the complexity of energy systems. For the (investment and production) planning of energy systems, in particular, several decades have to be considered while simultaneously taking into account operational aspects such as short-term fluctuations [1].

To tackle such complex planning problems, the usage of mathematical models has become indispensable. Mixed-integer programming (MIP) in particular has become a widely used paradigm due to the ability to capture combinatorial structures which are exhibited by investment and operation decisions and the availability of effective algorithms and high-performance solvers.

For long-term energy production planning, it is an unsolved question how much detail is required in terms of the spatial and temporal resolution as well as the physical accuracy of the model. This also highly depends on the specific energy system and the research questions associated with the analysis of the model. It can be observed that there is a clear trade-off between the modeling efficiency, on one hand, and the modeling flexibility and meticulous representation of details, on the other. This particular difference divides the existing energy system modeling tools in the academic and industrial environments.

There is a variety of academic models and modeling tools (e.g. PyPSA [2], oemof [3], EnergyPlan [4] or AnyMOD [5]) for energy system analysis. Most of them are designed for analysis on a regional or continental scale. Therefore the level of detail is rather restricted. This makes it difficult to apply these tools to the industrial energy systems of individual energy providers. Apart from software frameworks, there are many articles e.g. [6, 7] that directly formulate a model for investment planning of multi-energy systems. However, these models are often designed for the analysis of the interplay of specific technologies, which makes it hard to apply them in a general setting. For instance, the authors of [8] argue that many models are specific to particular energy pathways and contain specific equations for each type of technology. This makes them difficult to be applied to a broader spectrum of problems. They propose an energy system model based on a value web and zones. This model class is suitable for a rough analysis of generation, conversion, storage, and transport technologies on an urban scale. However, depending on the scale of the energy system, it is necessary to model specific technologies in even more detail by introducing characteristic curves or polyhedral operation regions. Moreover, the topological dependency of different technological units (for instance in a steam-extraction-condensation cycle) must be considered. These aspects combined are not covered in academic modeling tools but can play a crucial role, especially for industrial energy portfolio optimization problems.

On the other hand, most industrial modeling tools (e.g. BoFiT by Volue¹, ResOpt by Kisters², Microgrid-Creator by Energenious³ or ENERGY OPTIMA 3 by Energy Opticon⁴) offer a much higher level of detail and modeling flexibility than academic tools. Industrial tools are designed to capture the technological components of the energy system individually as well as their topological dependency. This enables de-

¹<https://www.volue.com/product/bofit-optimization>

²<https://energie.kisters.de/loesungen-produkte/resopt-optimierung/>

³<https://energenious.eu/index.php/mgc/>

⁴<https://de.energyopticon.com/energy-optima-3/>

tailed production planning. However, as the users have high flexibility to make system constructions, the resulting models are highly unstructured and therefore rely on the usage of commercial solvers out-of-the-box, rapidly hitting a computational performance plateau. For large energy systems, the high level of detail of such models leads to a size and complexity that limits the considered time horizon to several months. In this way, investments cannot be formulated as decision variables but have to be manually simulated as individual scenarios. This makes holistic long-term investment planning practically impossible and hardly provides any insights about the obtained solution's quality.

In this article, we aim to bridge the gap between academic and industrial energy production planning models. We propose a novel model class that offers the level of detail and flexibility required for industrial usage while still being tractable for long-term planning.

The model class is based on a generalized form of a unit commitment (UC) model on a network with investment decisions. In its traditional form, the objective of the UC problem is to determine the on/off status and production level of all generating units to satisfy the energy demand at the minimum operating cost, taking into account the system-wide technical constraints [9]. While UC models have been introduced for power systems originally, they can be extended to multi-energy systems, where different energy resources such as heat, electricity and gas are considered simultaneously. Those models have mainly been used for short-term operational planning in the past, but as already pointed out, there is a necessity to include such short-term operational constraints in long-term planning models [10]. When spatial aspects are to be considered, generation and energy loads are distributed over a network. Nodes often represent zones or regions, where the demand and production of each energy resource are aggregated. While such a level of detail is sufficient for a regional or continental scale, it is not sufficient to model the energy production portfolio of a single energy provider. Here, different types of generators (e.g. CHP plants, gas turbines, steam generators, steam turbines, heating condensers, ...) and their topological dependencies have to be considered as well.

To the best of our knowledge, there does not exist any energy system modeling framework that combines all the aforementioned aspects. In contrast, our proposed model class captures the necessary level of detail for long-term energy production planning and offers modeling flexibility that makes it applicable to various energy systems in practice. The focus lies on the topological dependency of different energy production units. Further details, such as operational dependencies between technological units, are included and theoretically described from a network perspective. This analysis enables future avenues of research to thoroughly study the areas of combinatorial complexity in the models and utilize these insights for effective solution algorithms.

The size of the model heavily depends on the time granularity. For long-term planning models, it is a common practice to use representative time periods in order to keep the model size tractable [11]. The representative time periods reflect daily and seasonal patterns. Due to the integration of decentralized technologies and renewable energy sources, short-term operational aspects are gaining importance in long-term planning. For this reason, several authors (e.g. [12], [13], [14]) suggest to include operational constraints such as ramping or minimum up and down times in combination with representative time periods for long-term planning models. Our model class offers this option as well.

We introduce our model class in an abstract formulation. Nevertheless, it captures many aspects that can be found in industrial modeling tools for energy production

portfolio optimization. In this way, we ensure that our modeling approach can be used in practice.

2 Model

The model class is a generalized form of a UC model on a network. Each energy production or transportation unit is represented by a node and has its binary status variable that can be switched on and off. On each arc, there is a flow of a specific energy resource (e. g. fuel, steam, power, heat). Operational constraints on the flow variables are imposed by the nodes based on their binary status. A formalized version of the model is given below.

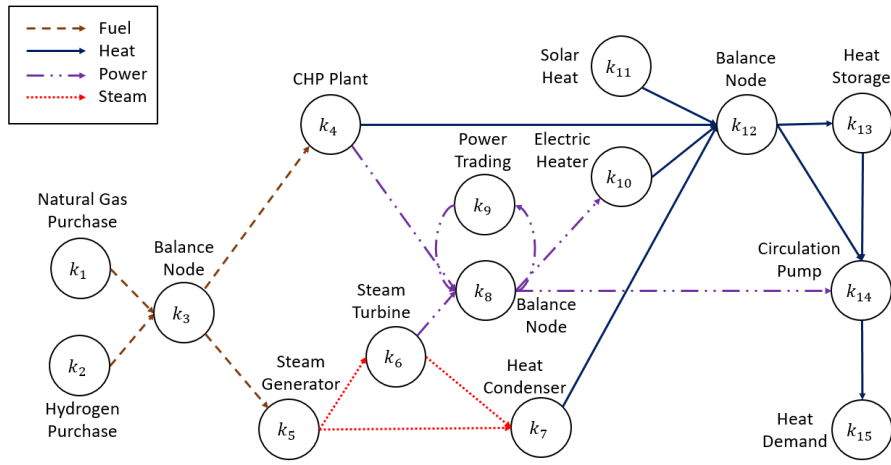


Figure 1: Sample energy system with 15 nodes.

The focus of this model class is energy production and the topological dependency of the production units. An example is given in figure 1. Here, an energy system for the production of heat and power is depicted. There are two fuel purchase contracts for natural gas and hydrogen, which are represented by the nodes k_1 and k_2 . Both fuels can be used for a combined heat and power (CHP) plant k_4 and a steam generator k_5 . The balance node k_3 models an equality between the total inflow and outflow of this node. Here, a prescribed input or output ratio of natural gas and hydrogen can also be modeled. The steam produced by the steam generator can be forwarded to a steam turbine k_6 producing power and a heat condenser producing k_7 producing heat. The total amount of power is summarized in balance node k_8 . Excess power can be sold to the power trading unit k_9 . Alternatively, additional power can be purchased. This power can be used for the electric heater k_{10} and the circulation pump k_{14} . There is an additional solar thermal unit k_{11} producing heat. The total amount of produced heat is accumulated in balance node k_{12} . Heat can be kept in a storage k_{13} or forwarded to the circulation pump k_{14} to cover the heat demand at node k_{15} . Cost is given by the operation of the nodes depending on the inflow and outflow, by start-ups of the nodes as well as by potential investment decisions to integrate further nodes into the network.

2.1 Network Aspects

In this and the subsequent sections, we give a formal definition of the model class. This part introduces the network aspects. Let $T = \{0, \dots, t_{\text{end}}\}$ denote the set of time points for the optimization problem. In a very fine resolution, these could be the beginning of each hour for every year of the planning horizon. For long-term planning models, this can also be time points of representative periods. We model the network as a directed graph $G = (K, L)$ with nodes $k \in K$ and arcs $l \in L$, which we refer to as (transport) lines. Nodes represent technological units, trading units or demands as in the example above. Lines represent an abstracted view of the transport options from one node to another. In the network, we have flows of different resources (e. g. fuel, steam, power, heat). There is one designated resource flow on every arc. This means, we can split the set of arcs disjointly by energy resource, i. e.

$$L = \bigcup_{r \in R} L^r, \quad (1)$$

where R denotes the set of resources. For every arc $l \in L$, we denote the flow during the time interval between time point t and time point $t + 1$ with a non-negative variable $x_{t,l}$. As every arc is associated with exactly one resource r , so is every flow variable. Therefore, we do not state r as an index. Every node in the network has an operational status which can be active or inactive. For this, we introduce a binary variable $z_{t,k}$ that describes the status of node k between the time points t and $t + 1$. The status variables of certain nodes are fixed, e.g. a demand node cannot be switched off. In practice, there is no binary variable for such nodes. Nevertheless, to keep the notation concise, we notate a binary variable for each node. Depending on this status, each node induces a feasible operation region for the flow variables of the incident arcs. To model this, we introduce for each node $k \in K$ at each time point $t \in T$ a set

$$\Lambda(k) = \{(i, k) \in L \mid i \in K\} \cup \{(k, j) \in L \mid j \in K\} \quad (2)$$

of incoming and outgoing arcs. Based on this set we define a vector of the respective flow variables

$$\mathbf{x}_{t,\Lambda(k)} = x_{t,l \in \Lambda(k)}. \quad (3)$$

We refer to the set that defines the feasible operation region on these variables based on the status variable of the node as $\mathcal{F}_{t,k}(z_{t,k})$. The constraints modeling this status dependency read

$$\mathbf{x}_{t,\Lambda(k)} \in \mathcal{F}_{t,k}(z_{t,k}) \quad \forall t \in T, \forall k \in K. \quad (4)$$

If the status of the node is inactive, then the inflow and outflow are equal to zero, i. e. $\mathcal{F}_{t,k}(0) = \{\mathbf{0}\}$. Note that the right hand side of this expression is a vector of zeros of the dimension of the number of incident arcs. If the node is active, the shape of the feasible operation region is specific for every node depending on what technological or economic unit it represents. The feasible operation region is time-dependent as it can be influenced by the outside temperature in the case of a technological unit or market data in the case of an economic unit. While this is a very general formulation, the feasible operation region of most units can be expressed in a compact way.

Figure 2 shows some examples of how feasible operation regions $\mathcal{F}_{t,k}(1)$ can look like. The left part shows a characteristic curve that describes the output of a heat

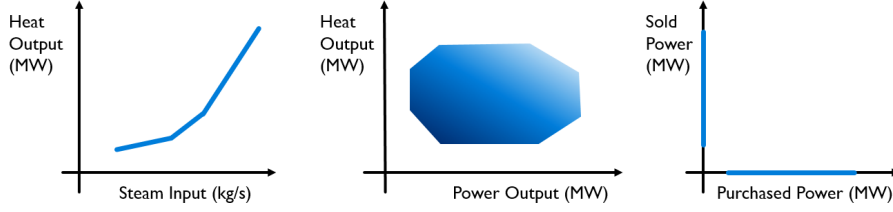


Figure 2: Examples of feasible operation regions

condenser (e.g. k_7 in figure 1 based on the incoming steam. Characteristic curves are often approximated using piecewise-linear functions, which allows a mixed-integer linear reformulation. For CHP plants as k_4 , depending on the specific technology, the ratio of produced heat and power can be fixed and or flexible. In the first case, the produced heat and power depend directly on the amount of fuel provided, which can again be described using two characteristic curves. In the second case, the range of heat and power output can be described as a PQ diagram that imposes a polyhedral operation set as depicted in the middle of figure 2. For each point within the PQ diagram, there is a different amount of fuel required. This is indicated by the color gradient. For transport technologies such as the circulation pump k_{14} , there is relation between the forwarded amount of heat and the required power. This can also be described using characteristic curves. Economic components such as the power trading unit k_9 impose minimum and maximum sales and purchase limits. Moreover, selling and purchasing power at the same time is not possible. The respective feasible operation region is shown on the right side of figure 2. Similar operation regions apply for storages, which are described in detail in section 2.1.

Costs are induced in a similar way as constraints. We denote the cost generated by node k with

$$\psi_{t,k}(\mathbf{x}_{t,\Lambda(k)}, z_{t,k}), \quad (5)$$

where $\psi_{t,k}$ is a cost function specific for node k at time t that depends on the incident flow variables and the status of the node. Costs can occur with the purchase of resources or reflect variable operation and maintenance cost associated with the operation of a power plant. In most cases, the cost is a linear or piecewise-linear function that depends on the inflow or the outflow of the respective node.

Further Model Aspects

While the model aspects that were introduced in the previous section address constraints that are independent for each node and each time step, the constraints described in this section link several nodes or time steps.

Storages

Energy resources such as heat and power can be conserved in storages. We denote the set of such nodes by $K^{\text{storage}} \subset K$. For each storage node $k \in K^{\text{storage}}$, we introduce a continuous variable $h_{t,k}$ modeling the storage level, which is bounded by a maximum storage level h_k^{max} . The constraints induced by a storage unit are

$$h_{t+1,k} = a_{t,k}^{\text{loss}} h_{t,k} + a_{t,k}^{\text{load}} x_{t,l^{\text{in}}(k)} - a_{t,k}^{\text{unload}} x_{t,l^{\text{out}}(k)} \quad \forall t \in T, \forall k \in K^{\text{storage}}, \quad (6)$$

where $a_{t,k}^{\text{loss}}$, $a_{t,k}^{\text{load}}$ and $a_{t,k}^{\text{unload}}$ denote efficiency parameters in terms of storing, loading and unloading of the storage. The variables $x_{t,\text{in}(k)}$ and $x_{t,\text{out}(k)}$ denote the total flow into and out of the storage. A simultaneous loading and unloading of the storage is not possible. This is included in the general constraint (4). Note that the loading, unloading and storage variables have different units. The loading and unloading variables $x_{t,\text{in}(k)}$ and $x_{t,\text{out}(k)}$ denote energy flows between the time point t and $t + 1$ and are given in MW. The variable $h_{t,k}$ denotes a storage level at time point t and is given in MWh. For this reason, the loading and unloading parameters are not only dependent of the outside temperature, they also depend on the size of the time interval $[t, t + 1]$. The same holds for the storage loss parameter $a_{t,k}^{\text{loss}}$.

Ramping

Certain power plants cannot change their energy output arbitrarily over time. Instead, there is a limit on how much the output is allowed to change from one time step to the next. We denote the set of nodes where such restrictions apply with K^{ramp} . A common way of setting upper and lower bounds on the variation of energy output from one time step to the next is by using ramping constraints

$$x_{t+1,\text{out}(k)} - x_{t,\text{out}(k)} \leq a_k^{\text{ramp-up}} \quad \forall t \in T, \forall k \in K^{\text{ramp}}, \quad (7a)$$

$$x_{t,\text{out}(k)} - x_{t+1,\text{out}(k)} \leq a_k^{\text{ramp-down}} \quad \forall t \in T, \forall k \in K^{\text{ramp}}. \quad (7b)$$

The total energy output of node k at time t is denoted by the variable $x_{t,\text{out}(k)}$. The constraint (7a) limits the change of energy output in the positive direction and the constraint (7b) limits the change of energy output in the negative direction. The magnitude of the limits on up-ramping and down-ramping $a_k^{\text{ramp-up}}$ and $a_k^{\text{ramp-down}}$ also depend on the step size between the time points t and $t + 1$. For a coarse time-resolution, these parameters can be so large that the ramping constraints become redundant.

Activation Constraints

We refer to the shift from an inactive to an active status of a power plant as an activation or start-up. In practice, this can lead to additional cost and fuel consumption. We denote the set of nodes with a start-up condition with $K^{\text{activation}}$. For these nodes, we introduce an additional binary variable $s_{t,k}$ stating whether the binary status variable $z_{t,k}$ changed from 0 in the last time step to 1 in the current time step, i. e.

$$s_{t,k} = 1 \iff z_{t-1,k} = 0 \wedge z_{t,k} = 1 \quad \forall t \in T, \forall k \in K^{\text{activation}}, \quad (8)$$

The logical constraint (8) can be reformulated using three inequalities

$$s_{t,k} \geq (1 - z_{t-1,k}) + z_{t,k} - 1 \quad \forall t \in T, \forall k \in K^{\text{activation}}, \quad (9a)$$

$$s_{t,k} \leq z_{t,k} \quad \forall t \in T, \forall k \in K^{\text{activation}}, \quad (9b)$$

$$s_{t,k} \leq 1 - z_{t-1,k} \quad \forall t \in T, \forall k \in K^{\text{activation}}. \quad (9c)$$

The activation of a node $k \in K^{\text{activation}}$ can be associated with a start-up cost, which we denote by $c_k^{\text{activation}}$. For each time step $t \in T$, we add the term $c_k^{\text{activation}} s_{t,k}$ to the target function. Beside cost, the start-up of a node can require additional fuel input. This means, the incoming flow of fuel has to be increased in the time step where the activation happens. We denote the set of nodes with a start-up fuel requirement as $K^{\text{activation.fuel}} \subset K^{\text{activation}}$ and introduce the constraint

$$x_{t,\text{fuel.in}(k)} = x_{t,k}^{\text{fuel.usable}} + a_{t,k}^{\text{fuel.requirement}} s_{t,k} \quad \forall t \in T, \forall k \in K^{\text{activation.fuel}}, \quad (10)$$

where $x_{t,l^{\text{fuel_in}}(k)}$ denotes the total incoming fuel, $a_{t,k}^{\text{fuel_requirement}}$ denotes the amount of fuel inflow necessary for the start-up and $x_{t,k}^{\text{fuel_usable}}$ denotes the remaining fuel that can be used to generate heat and power. The parameter $a_{t,k}^{\text{fuel_requirement}}$ is given in MW. It describes the necessary rate of fuel inflow between the time points t and $t + 1$. The parameter decreases with a growing time interval.

On top of the start-up aspects mentioned in this paragraph, it would be possible to differentiate between different types of starts. Based on the time a power plant has been inactive, it is possible to model hot, warm and cold starts all of which are associated with different costs and fuel requirements. This is however beyond the scope of this article.

Minimum up-time and down-time

When activated, certain nodes need to stay active for a minimum amount of time. When deactivated, certain nodes need to stay inactive for a minimum amount time. The latter can also be formulated as a minimum amount of time that a node needs to be inactive before a start-up can happen. To model such constraints, we use the activation variable $s_{t,k}$. For minimum up-time, we formulate the logical constraint

$$s_{t,k} = 1 \implies \bigwedge_{\tau \in T_{t,k}^{\text{up}}} (z_{\tau,k} = 1) \quad \forall t \in T, \forall k \in K^{\text{activation}}, \quad (11)$$

where $T_{t,k}^{\text{up}} \subseteq \{t + 1, \dots, t_{\text{end}}\}$ denotes set of time steps for which the node needs to be active after a start-up happened. This set depends on the minimum up-time of the node and the time step t . Depending on the length of the time intervals, it is possible that there are no minimum up-time constraints necessary. In this case set $T_{t,k}^{\text{up}}$ is empty, the right-hand side of constraint (11) is evaluated to true and the constraint becomes redundant. An arithmetic reformulation of (11) reads

$$\sum_{\tau \in T_{t,k}^{\text{up}}} (s_{t,k} - z_{\tau,k}) \leq 0 \quad \forall t \in T, \forall k \in K^{\text{up}}. \quad (12)$$

Minimum down-time can be modeled analogously. We use a constraint in which we state that a node needs to be inactive for a minimum amount of time before it can be activated, i. e.

$$s_{t,k} = 1 \implies \bigwedge_{\tau \in T_{t,k}^{\text{down}}} (z_{\tau,k} = 0) \quad \forall t \in T, \forall k \in K^{\text{activation}}, \quad (13)$$

Here, the set $T_{t,k}^{\text{down}} \subseteq \{0, \dots, t - 1\}$ contains the time steps for which the node needs to be inactive before a start-up can happen. The logical constraint (13) can be reformulated using the inequality

$$\sum_{\tau \in T_{t,k}^{\text{down}}} (s_{t,k} + z_{\tau,k} - 1) \leq 0 \quad \forall t \in T, \forall k \in K^{\text{activation}}. \quad (14)$$

Operational Status Dependencies

The operational status of technological units can depend on each other. For instance, an additional firing unit can only be operating when a preceding gas turbine is active as well. It can also be the case that two specific generators cannot operate at the same

time. Such operational dependencies can be modeled using the status variables $z_{t,k}$. For example, if node k_1 can only be active when k_2 is active, this can be modeled by the constraint $z_{t,k_1} \leq z_{t,k_2}$. If node k_1 and k_2 cannot be active at the same time, this would result in the constraint $z_{t,k_1} + z_{t,k_2} \leq 1$. To generalize this for our model, we define a set of hyper edges Ω representing the different sets of nodes for which a status dependency hold. For each hyper edge $\omega \in \Omega$, we define a set of feasible operation modes $\mathcal{M}_\omega \subseteq \{0, 1\}^\omega$ that defines the operational dependency of the respective nodes. This leads to the constraint

$$\mathbf{z}_{t,\omega} \in \mathcal{M}_\omega \quad \forall t \in T, \forall \omega \in \Omega^{\text{status}}, \quad (15)$$

where $\mathbf{z}_{t,\omega} = \{z_{t,k}\}_{k \in \omega}$ denotes the vector of all status variables of the nodes adjacent to the hyper edge $\omega \in \Omega$.

Investment Decisions

Investment decisions are a very important aspect in long-term energy production models. We consider investments with respect to technological units, which are represented by nodes in our model. For instance, an investment planning scenario for the energy system in figure 1 could be that the steam turbine k_6 and the heat storage k_{13} are not yet part of the network but can be integrated as investments.

To model investment decisions mathematically, we introduce a set $K^{\text{invest}} \subset K$ that contains all potential investment nodes. For each of these nodes, we introduce a binary variable \hat{z}_k . This variables serves as an upper bound on the status variable, i. e.

$$z_{t,k} \leq \hat{z}_k \quad \forall t \in T, \forall k \in K^{\text{invest}}. \quad (16)$$

From a topological point of view this means that the node is already part of the network. However, in order to use this node, the respective investment variable has to be set to one. This is associated with an investment cost c_k^{invest} . Single investment variables do not necessarily have to correspond to only one technological unit. For instances, consider the steam cycle of k_5 , k_6 , k_7 in figure 1. If this whole cycle is a single investment, the corresponding investment variable can be attached only to k_5 . In case the investment is not made, the steam generator k_5 is always inactive and so are the steam turbine k_6 and heat condenser k_7 as they get no steam input.

Note that all investment decisions are binary and can only be made with respect to nodes. The general idea of this model class is to differentiate between technological units and their technical characteristics individually. Therefore, each investment decision variable corresponds to one specific technological unit or combination of them. In practice, energy providers often have to chose between technologies of a fixed size and cannot chose a generation, transport or storage capacity arbitrarily. For this reason, we only model binary and no continuous investment decisions. While investment decisions are not defined with respect to arcs, it is nevertheless possible to model energy transport capacity extensions as nodes can also represent transport technologies such as the circulation pump k_{14} in figure 1.

For investment decisions, there can be additional restrictions. For instance, only one out of two specific investment candidates can be selected. Or there is the question of either constructing one large or three small generators. Such dependencies between investment candidates can modeled using the binary investment variables \hat{z}_k in a similar way as the operational status dependencies introduced in the previous paragraph.

On top of the aspects mentioned above, there is the option of making investment decisions time-dependent. This means, for each investment candidate $k \in K^{\text{invest}}$, there

is a set of investment times $T_k^{\text{invest}} \subset T$ to indicate when the investment can be made. For each investment time point $t \in T_k^{\text{invest}}$, we introduce a binary variable $\tilde{z}_{t,k}$. Each of these variables is associated with its own investment cost $c_{t,k}^{\text{invest}}$ at the respective time point. To indicate that the investment can only be made at one of these time steps, we use the constraint

$$\sum_{t \in T_k^{\text{invest}}} \tilde{z}_{t,k} = \hat{z}_k \quad \forall k \in K^{\text{invest}}. \quad (17)$$

The variable \hat{z}_k is still required for modeling restrictions with respect to other investment candidates as described above. When considering time-dependent investment decisions, the investment constraints (16) are replaced by the constraints

$$z_{t,k} \leq \sum_{\tau \in \tilde{T}_{t,k}} \tilde{z}_{\tau,k} \quad \forall t \in T, \forall k \in K^{\text{invest}} \quad (18)$$

where $\tilde{T}_{t,k} = \{\tau \in T_k^{\text{invest}} \mid \tau \leq t\}$ defines the set of investment time points that occur before time point t .

System-wide Constraints

There may be further restrictions that are related to the full energy system. For instance, there can be a maximum limit of CO₂ emissions for the full horizon. There can also be other environmental quotas, such as a minimum percentage of green heat, or technical quotas, such as a desired primary energy factor or a minimum percentage of power generated by CHP plants. In the following two paragraphs, we give two examples for such system-wide constraints.

CO₂ Limits

A crucial aspect for long-term energy planning models is CO₂ emissions. We denote the set of nodes associated to CO₂ emissions with $K^{\text{emission}} \subset K$. For each of those nodes, we introduce emission variables $e_{t,k}$. They are given as a function of the inflow and outflow variables of every node, i. e.

$$e_{t,k} = \zeta_{t,k}^{\text{emission}}(\mathbf{x}_{t,\Lambda(k)}) \quad \forall t \in T, \forall k \in K^{\text{emission}}, \quad (19)$$

where $\zeta_{t,k}^{\text{emission}}$ is a time-dependent function that is specific for every node. Emissions can be associated with the produced energy of a power plant. Alternatively, they can be connected to the output of each fuel purchase contract as certain heat power plants for instance can be run by different types of fuel all of which have a different level of CO₂ emissions. In most cases, the function $\zeta_{t,k}^{\text{emission}}$ is linear and given by a fuel specific parameter. To model a limit on the total amount of emitted CO₂ for the full time horizon $a^{\text{max.emission}}$, we use the constraint

$$\sum_{t \in T} \sum_{k \in K^{\text{emission}}} e_{t,k} \leq a^{\text{max.emission}}. \quad (20)$$

Such limits could also be defined with respect to each year.

Percentage of CHP power

There can also be goals to increase specific technical measures of the energy system such as the percentage of CHP power. To model aspects like this, we can again introduce sets of nodes that produce power K^{power} and nodes that produce heat and power K^{CHP} . For each of those nodes, we define functions $\zeta_{t,k}^{\text{power}}$ and $\zeta_{t,k}^{\text{CHP}}$ modeling the power generated in total and the amount of power generated by CHP units. Similarly to the emissions constraints above, we can use the constraint

$$\sum_{t \in T} \sum_{k \in K^{\text{CHP}}} \zeta_{t,k}^{\text{CHP}}(\mathbf{x}_{t,\Lambda(k)}) \geq a^{\text{CHP}} \sum_{t \in T} \sum_{k \in K^{\text{power}}} \zeta_{t,k}^{\text{power}}(\mathbf{x}_{t,\Lambda(k)}), \quad (21)$$

where a^{CHP} denotes the desired fraction of CHP power.

3 Conclusion

In this article, we introduce a new model class for investment and portfolio production planning for multi-energy systems. The model class is based on a generalized form of UC problem on a network with investment decisions. It is designed to capture all relevant aspects for industrial energy production portfolios such as the detailed and flexible modeling of generation units, their topological dependency as well as operational dependencies. Despite the high level of detail, the model remains tractable for long-term planning when using representative time periods and the abstract formulation on a network allows for the development of effective solution methods. Future work will cover a case study for a real, large-scale industrial investment and portfolio optimization problem .

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