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Time series aggregation for energy system design: review and extension of modelling seasonal storages

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Abstract

Using optimization to design a renewable energy system has become a computationally demanding task as the high temporal fluctuations of demand and supply arise within the considered time series. The aggregation of typical operation periods has become a popular method to reduce effort. These operation periods are modelled independently and cannot interact in most cases. Consequently, seasonal storage is not reproducible. This inability can lead to a significant error, especially for energy systems with a high share of fluctuating renewable energy. The previous paper, "Time series aggregation for energy system design: Modeling seasonal storage", has developed a seasonal storage model to address this issue. Simultaneously, the paper "Optimal design of multi-energy systems with seasonal storage" has developed a different approach. This paper aims to review these models and extend the first model. The extension is a mathematical reformulation to decrease the number of variables and constraints. Furthermore, it aims to reduce the calculation time while achieving the same results.

Keywords: Energy system, Renewable energy, Mixed integer linear programming (MILP), Typical periods, Time-series aggregation, Clustering seasonal storage

Introduction

Designing an energy system with the aim of a minimal ecological or economic impact is a very complex task. The increasing number of possibilities and complexity in energy form, time and space lead to an even more complex problem. These problems are challenging to solve analytically. Instead, mathematical programs can identify optimal solutions (Baños et al. 2011). These programs can use Mixed-Integer-Linear-Problem (MILP) solvers, which can determine the optimal solution concerning their assumptions and model accuracy.

The optimisation problems can be solved for the complete time series or typical periods representing the time series (Lythcke-Jørgensen et al. 2016). Typical periods are recurring time slots where characteristic charging and discharging patterns occur (Kotzur et al. 2018). Typical periods reduce the calculation time due to fewer variables and constraints to handle. One problem with these periods is the consideration of storage extending the period time. These storages are modelled with a linear behaviour. The classical cyclic modelling of storage with typical days would force the storage to have the same state at the period's start, and end (Renaldi and Friedrich 2017; Harb et al. 2015; Fazlollahi et al. 2014; Nahmmacher et al. 2016). This constraint leaves the typical days unlinked to each other. A transfer of storage content of one typical period to another is impossible.

Kotzur et al.'s model introduces two-time layers, one within the period and one for linking these periods (Kotzur et al. 2018). This model allows the solver to create a gradient within the typical periods since the typical period no longer ends with the same storage state as it began. The time frame outside the typical periods can use this gradient to determine the state of charge after several periods. Disregarding the state of charge within the period can lead to overcharging or undercharging the storage. On the other hand, cyclic storage formulation would keep the same stored energy at the period's start and end. In hydro power planning, multi-time horizon approaches have already been used but not modelled by MILP (Abgottspon and Andersson 2016; Beltrán et al. 2021; Flamm et al. 2018a; Bordin et al. 2021; Flamm et al. 2018b; Ming et al. 2021; Parvez et al. 2019).

Kotzur et al.'s two-time layers enable seasonal storage calculation while deploying typical days. In (Beck et al. 2022; Göke and Kendziorski 2022; Wirtz et al. 2021; Neumann et al. 2022; von Wald et al. 2022; Hoffmann et al. 2020) the storage formulation of Kotzur et al. was applied to calculate seasonal storages. Gabrielli et al. (2018) developed a different approach to calculate seasonal storage with fewer constraints but more variables. The approach creates a storage variable for the entire year with its yearly time step. Besides, it links the charging and discharging power of the period's time step to that yearly time step. This model is used, for example, in Borasio and Moret (2022), Fochesato et al. (2021), Petkov et al. (2021). Kotzur et al. (2021), Bistline et al. (2020) claim to review and validate these storage models.

Figure 1 explains the two-layer method. The day 0 until 100 and 200 until 280 are represented by period one. Period two represents the days 100 until 200 and 280 until the end.

Kotzur et al.'s seasonal model allows a positive gradient over period one and a negative gradient over period two. Consequently, the storage state of these days is increasing for days represented by period one and decreasing for days represented by period two. This state stays constant using the cyclic storage model since gradients are unconsidered.

The new idea presented in this paper is to combine storage states of periods represented by the same typical period and located after each other within the year. Figure 2 explains this approach. While the model of Kotzur et al. needs 20 variables and their connected constraints for 100 days, the new model has one. This reduction is possible since typical days occuring in a row are merged. This combination of storage states should lead to fewer variables, constraints and calculation time reduction.

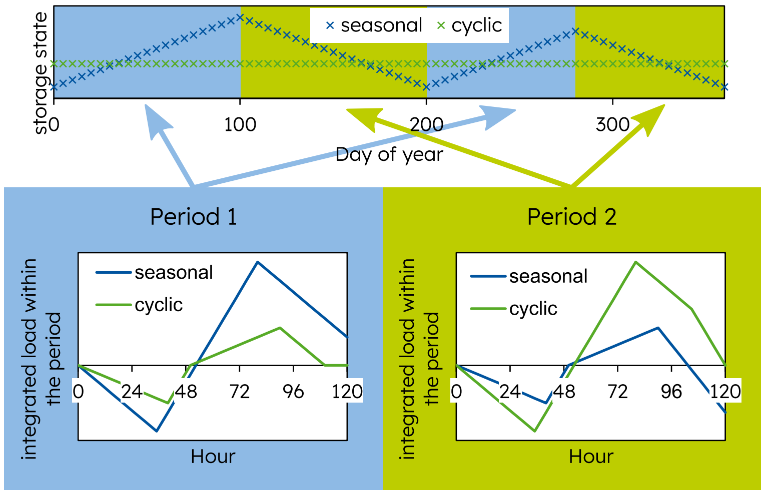

Fig. 1 Seasonal storage model of Kotzur et al. explanation

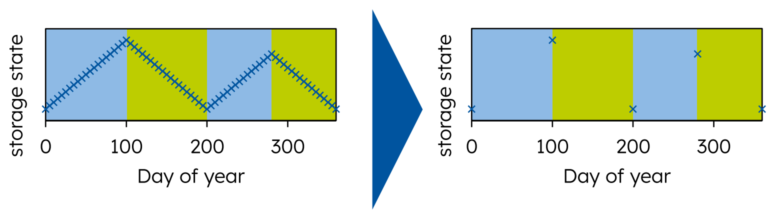

Fig. 2 Explanation of new seasonal storage model

This paper aims to review the model of Kotzur et al. with new load profiles and compare it to the model of Gabrielli et al. Furthermore, the new model is explained and compared to the current models. Therefore solving the problem with the new model should lead to the same results as the current model.

Storage models

The upcoming section explains the cyclic (called C) and three seasonal storage models (called S).

Cyclic storage model

The stored energy E_t is calculated from the charging P_t^c and discharging power P_t^d. Charging and discharging losses are considered by the corresponding efficiencies η_{charge} and $\eta_{discharge}$. Furthermore, a self-discharging rate η_{self} with the corresponding time step duration δt is considered.

$$E_t = E_{t-1} \cdot \left(1 - \eta_{self} \cdot \delta t\right) + \left(P_t^c \cdot \eta_{charge} - \frac{P_t^d}{\eta_{discharge}}\right) \cdot \delta t. \tag{1}$$

The stored energy (E_t) has to stay between zero and maximal capacity E_{max}.

$$0 \leq E_t \leq E_{max}. \tag{2}$$

The storage must have the same state of charge at the period's start and end ($E_{t=0} = E_{t=N}$). Additionally, this state of charge has to be the same for all periods.

Seasonal storage model of Gabrielli et al. (2018)

Seasonal storage model of Gabrielli et al. (2018) (called S-G) creates a storage variable for the entire year with its yearly time step (E_h). Besides, it links the charging $\left(P^c_{t=f(h)}\right)$ and discharging power $\left(P^d_{t=f(h)}\right)$ of the period's time step to that yearly time step. The function f gets the time step of the year h as an input and is returning the corresponding period with its period's time step.

$$E_h = E_{h-1} \cdot \left(1 - \eta_{self} \cdot \delta t\right) + \left(P^c_{t=f(h)} \cdot \eta_{charge} - \frac{P^d_{t=f(h)}}{\eta_{discharge}}\right) \cdot \delta t. \tag{3}$$

The cyclic boundary condition is used to connect the last and first storage variable of the total simulation interval ($E_{h=1} = E_{h=end+1}$).

Seasonal storage model of Kotzur et al. (2018)

The seasonal storage model of Kotzur et al. (2018) (called S-K) contains three types of constraints. The first constraint links the typical day's state of charge with the state of charge within these typical periods. The second constraint is limiting the state of charge within the typical days, which aims to avoid negative states of charge or overcharging. The last constraint considers the actual charging, discharging, and losses within the period. This equation applies to both models (S-K and the new one).

This charging and discharging constraint is formulated as follows:

$$\Delta E_t = \Delta E_{t-1} \cdot \left(1 - \eta_{self} \cdot \delta t\right) + \left(P^c_t \cdot \eta_{charge} - \frac{P^d_t}{\eta_{discharge}}\right) \cdot \delta t, \tag{4}$$

where ΔE_t is the stored or in case of negative values the extracted energy since the beginning of the period at the time step t. The charging P^c_t and discharging power P^d_t have a charging η_{charge} and discharging efficiency $\eta_{discharge}$.

The stored energy at the end of each period (E_p) is implemented as follows:

$$E_p = E_{p-1} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^N + \Delta E_{t=N}, \tag{5}$$

N is the number of time steps in the period. The cyclic boundary condition is used to connect the last and first amount of stored energy of the total simulation interval ($E_{p=1} = E_{p=end+1}$).

The boundaries during the period are implemented as follows:

$$0 \leq E_{p-1} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^N + \Delta E_t \leq E_{max}. \tag{6}$$

This equation should avoid overcharging. Due to the calculated self-discharging rate for the entire period (N) this is not ensured. This equation does not hold for filled storage at the period's beginning and a charging rate as high as the self-discharge loss of the period ($\Delta E_t = (1 - \left(1 - \eta_{self} \cdot \delta t\right)^N) \cdot E_{max}$). Equations (7) and (8) show this connection.

$$E_{max} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^N + \left(1 - \left(1 - \eta_{self} \cdot \delta t\right)^N\right) \cdot E_{max} = E_{max} \leq E_{max}. \tag{7}$$

$$\begin{aligned} & E_{max} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^1 + \left(1 - \left(1 - \eta_{self} \cdot \delta t\right)^N\right) \cdot E_{max} \\ & \quad = (1 + \left(1 - \eta_{self} \cdot \delta t\right)^1 - \left(1 - \eta_{self} \cdot \delta t\right)^N) \cdot E_{max} \not\leq E_{max} \\ & \qquad \forall \eta_{self} > 0 \text{ and } N > 1. \end{aligned} \tag{8}$$

Using the current time step within the period (t) instead of the total number of time steps within a period (N) as an exponent for the self-discharging rate avoids this over-charging. The resulting equation is:

$$0 \leq E_{p-1} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^t + \Delta E_t \leq E_{max}. \tag{9}$$

New seasonal storage model

The new model (called S-N) checks for periods of the same type during the year in a row ($M > 1$). If those periods occur, Eq. (5) which links the stored energy from the period to the inter period one, reformulates to:

$$E_p = E_{p-1} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^{N \cdot M} + \Delta E_{t=N} \cdot \sum_{i=0}^{M-1} \left(\left(1 - \eta_{self} \cdot \delta t\right)^N\right)^i. \tag{10}$$

The summation over the self discharging rate can be simplified to (F):

$$F = \sum_{i=0}^{M-1} \left(\left(1 - \eta_{self} \cdot \delta t\right)^N\right)^i = \frac{1 - \left(1 - \eta_{self} \cdot \delta t\right)^{N \cdot M}}{1 - \left(1 - \eta_{self} \cdot \delta t\right)^N}. \tag{11}$$

This simplification leads to:

$$E_p = E_{p-1} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^{N \cdot M} + \Delta E_{t=N} \cdot F. \tag{12}$$

.

The new model summarizes the periods of the same type within a row. Ensuring no overcharging or negative state of charges needs two new boundaries within the period. The first one ensures the current states for the first summarized period and the second one for the last. Equation (9) is accomplishing this for the first one. The second one needs the storage state at the beginning of the last summarized period. Equation (5) determines this state. The combination of this equation with Eq. (10) leads to the following equation:

$$\begin{aligned} 0 \leq\; & E_{p-1} \cdot \frac{\left(1 - \eta_{self} \cdot \delta t\right)^{N \cdot M}}{\left(1 - \eta_{self} \cdot \delta t\right)^N \cdot F} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^t \\ & + \frac{E_p \cdot \left(1 - \frac{1}{F}\right)}{\left(1 - \eta_{self} \cdot \delta t\right)^N} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^t + \Delta E_t \leq E_{max}. \end{aligned} \tag{13}$$

Methodology

This paper considers the C, S-G, S-K, and S-N model. It evaluates three system designs.

1 The first system considers a combined heat and power system with a boiler as backup. Furthermore, a hot tank stores the heat. An industrial hall building's electric and thermal demand has to be covered (Reger et al. 2020, 2019). The system has a connection to the power grid and gas grid.
2 The second system is a heat pump system. It consists of an air heat pump, an electric heater, and a hot tank as thermal storage. The power grid or a photovoltaic system covers the electric demand. An industrial hall building's electric and thermal demand has to be covered (Reger et al. 2020, 2019).
3 The third system is an island system. It contains a battery, photovoltaic, wind turbines, electrolyser, fuel cell, and hydrogen storage. The island system has a connection to the power grid. It can cover at maximum 10 % of the electric demand. This boundary forces the system to be grid independent. The electric demand of an example district has to be covered.

Blanke (2022) provides the used time series for the heating loads, electrical loads, the typical periods, and the python code. The TSAM aggregates typical periods with 24 h as time step (Hoffmann et al. 2021, 2022, Institute of Energy and Climate Research 2021). TSAM is a python package to aggregate typical periods from a time series. The clustering method is k-medoids. No extreme periods are integrated. The same number of typical days as in Kotzur et al. (2018) (3, 4, 5, 6, 7, 8, 9, 10, 12, 15, 21, 27, 36, 48, 60, 90, 120, 180, 365) are considered. Taking into account three typical days means each day of the year is assigned to one of these three typical days (Hoffmann et al. 2022). The optimization models, efficiencies and costs are taken from Kotzur et al. (2018). The only exception is the hydrogen system, where the investment costs are reduced by 10 %. Therefore a self-discharging rate of 1 % per day is considered. This modification enables the possibility to evaluate the seasonal storage models with a self-discharging rate. Considering the self-discharging rate should ensure the same results for S-models while using this rate.

The Gurobi solver 9.5.1 is chosen. Neither heuristic nor presolve algorithms are applied since the heuristics matches are random and the presolve is resulting in longer calculation times for a small number of typical days. The MIP-Gap is set to 1 %. Default values are applied to the rest of the solver settings. The hardware consists of two test machines containing 32 GB RAM with an AMD Ryzen 7 1700 Processor and 64 GB RAM with an Intel Xeon W-2155 Processor, respectively. Furthermore, the optimization uses 12 threads.

Equations (6) and (13) are simplified as explained in section Constraint reformulation.

Results and discussion

The results of the three systems are presented and discussed in the following section. All S-models lead within the numerical accuracy to the same results. Therefore the cost results are just shown for the one S-model (S). The time results are the mean of the two hardware configurations, whereby two runs on each configuration are performed. The reference model (ref.) optimizes the entire year with the original, hourly data without merging similar time series to typical days or typical periods. The modified model (mod.) optimizes the entire year with the hourly data aggregated by the typical days. This model allows the determination of the storage model usage error. The cost results are compared to both the reference and modified model. Costs are the combination of operating and component costs and the optimization objective. The relative error is calculated by the following equation:

$$C_{rel} = \left| 1 - \frac{C_{Operation_{\text{sce.}}} + C_{investment\,\text{sce.}}}{C_{Operation_{\text{ref./mod.}}} + C_{investment\,\text{ref./mod.}}} \right|. \tag{14}$$

A relative cost error of 2 % implies that the total cost difference between the reference (ref.) or modified (mod.) model to the considered storage scenario (sce.) (different model/ number of typical periods) is 2 %. This error will vary over the number of typical days since it compares the costs and not the energy system component sizes (like X kWh of battery). If the photovoltaic size is smaller than in the reference case, but the battery size is larger, this can lead to the same costs but with different component sizes.

For all cases, the ratio of the number of variables and constraints compared to the S-K-model is always lower than one. The ratio is less for the cyclic case since the storage is not linked. For the S-N-model, the ratio is logarithmically increasing over the number of typical days up to one since the number of the same typical periods in a row decreases with increasing typical days. For the S-G-model, it is slightly decreasing.

In General, the C-model is the fastest. The S-N-model is faster or nearly as fast as the S-K-model. Besides, the S-G-model is the slowest one.

CHP system

Figure 3 shows the calculation time for all storage models (a) and the total costs error (b). In most cases, the calculation time for a number of typical days below 27 is less than 35 % of the time of the complete year calculation. Especially the C-model stays below 5 % of the calculation time. This time reduction results from fewer variables and constraints used by the C-model. For the most number of typical days, the total cost error is less than 1 % compared to the reference model and less than 2.5 % compared to the modified model. The S and C-models lead to nearly the same error for a number of typical days less than 8. Afterwards, they differ. All S-models lead to an error of less than 0.2 %, which is slightly better than the C-model error of 0.6 %. This same error indicates that the primary storage usage is daily and not seasonal.

Figure 3c shows the number of variables (Var.) and constraints (Const.) as well as the calculation time relative to the S-K-model. In most cases, the S-N-model is more than 10 % faster and the C-model up to 80 %. The S-G-model is more than 40 % slower than the S-K-model in most cases.

Air heat pump system

Figure 4 shows the calculation time for all storage models (a) and the total costs error (b). For a number of typical days below 28, the calculation time amounts to less than 40 % of the time for the complete year calculation. Especially the C-model stays below 5

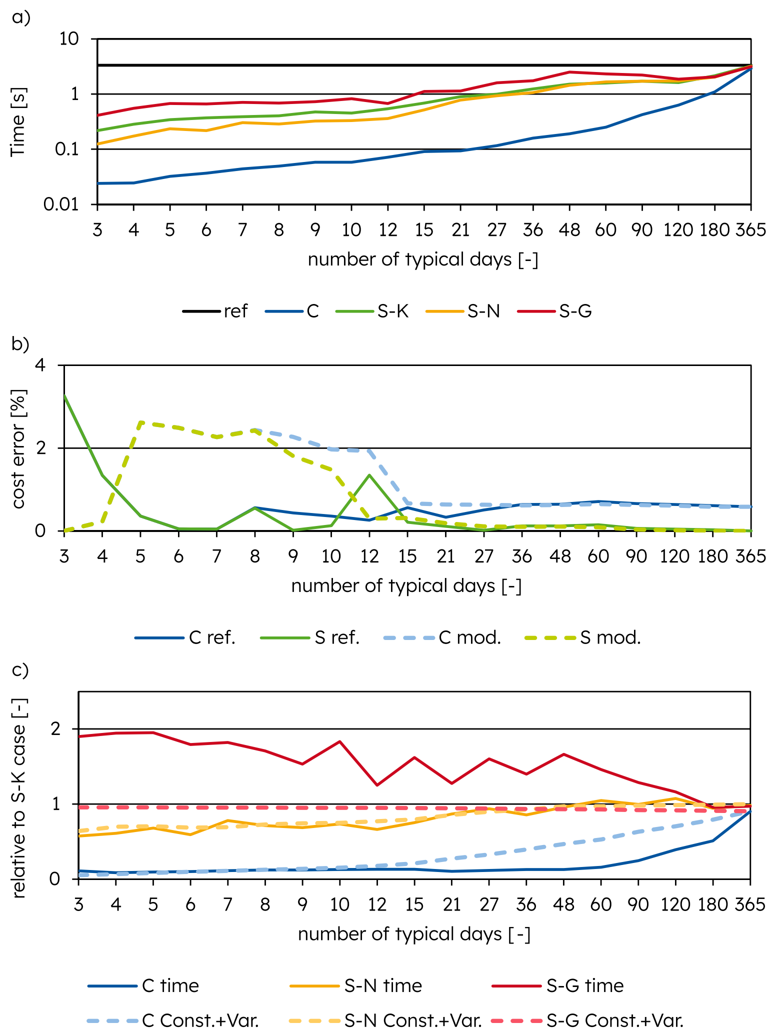

Fig. 3 Calculation time (**a**) and total costs error (**b**) for the different storage models and relative share of number of constraints and variables as well as time for C, S-G- and S-N- to S-K-model (**c**) for the CHP system

% of the calculation time. The total costs error stays below 2 % for the most number of typical days compared to both the reference and modified model. The S- and C-models reduce this error below 1 % for 27 or more typical days. Both models lead to almost the same error. The concordance between the errors indicates that the storage usage is daily instead of seasonal.

Figure 4c shows the number of variables (Var.) and constraints (Const.) as well as the calculation time relative to the S-K-model. In most cases, for less than 10 typical days, the S-N-model is about 20 % faster than the S-K-model. For more than 10 typical days, the S-N-model is as fast as the S-K-model. The C-model is up to 80 % faster in most cases. The S-G-model is about 100 % slower than the S-K-model in most cases.

Island system

Figure 5 shows the calculation time for all storage models (a) and the total cost error (b). The total cost error amounts to 45 % at its maximum. This error is significantly higher

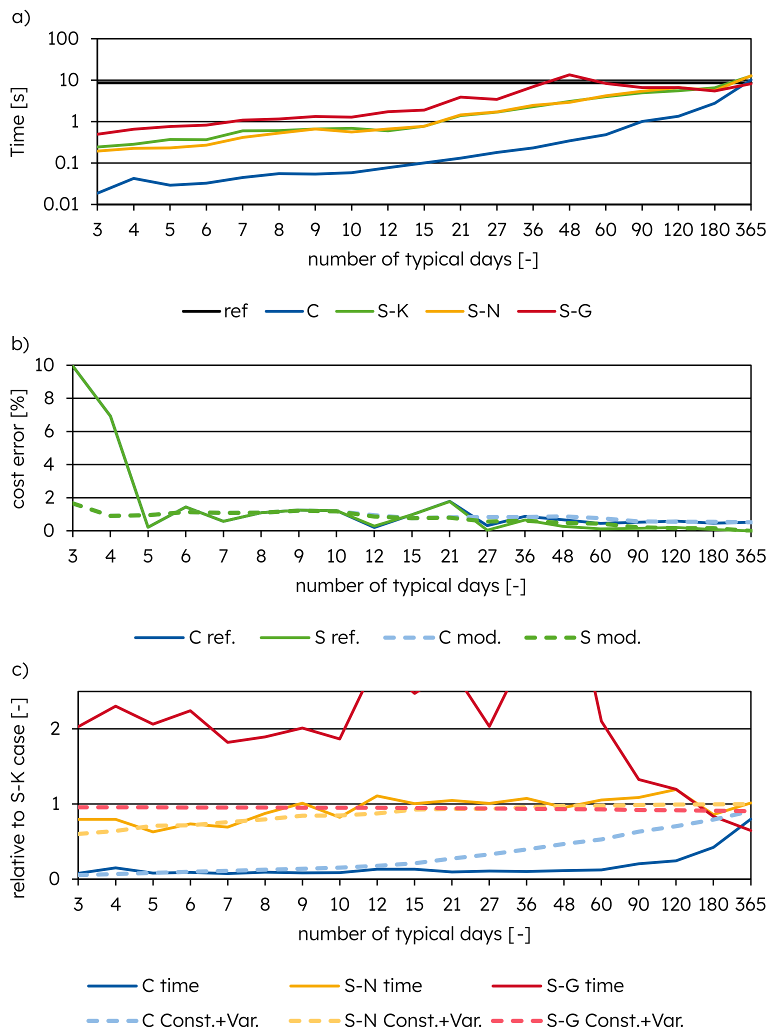

Fig. 4 Calculation time (**a**) and total costs error (**b**) for the different storage models and relative share of number of constraints and variables as well as time for C, S-G- and S-N- to S-K-model (**c**) for the air heat pump system

than the CHP and the Air heat pump system error. However, for the most numbers of typical days, the total cost error remains below 12 % compared to the reference model. Only in the case of more than 48 typical days does the cost error of the S-model differ from the C-model. The concordance between the errors in cases of up to 21 typical days indicates the storage usage as daily storage instead of seasonal storage. This statement is underlined by Fig. 6 since hydrogen storage is chosen for the number of typical days of 48 and more.

The cost error for a number of typical days less than 10 is below 2 % compared to the modified model. For a number of typical days of more than 48, the S and C-model errors differ. This trend indicates that the costs error for a number of typical days less than 10 is caused by the typical days and not by the storage models. For a number of typical days higher than 48, the error is caused by the storage model. So, the seasonal storage model has a lower error here.

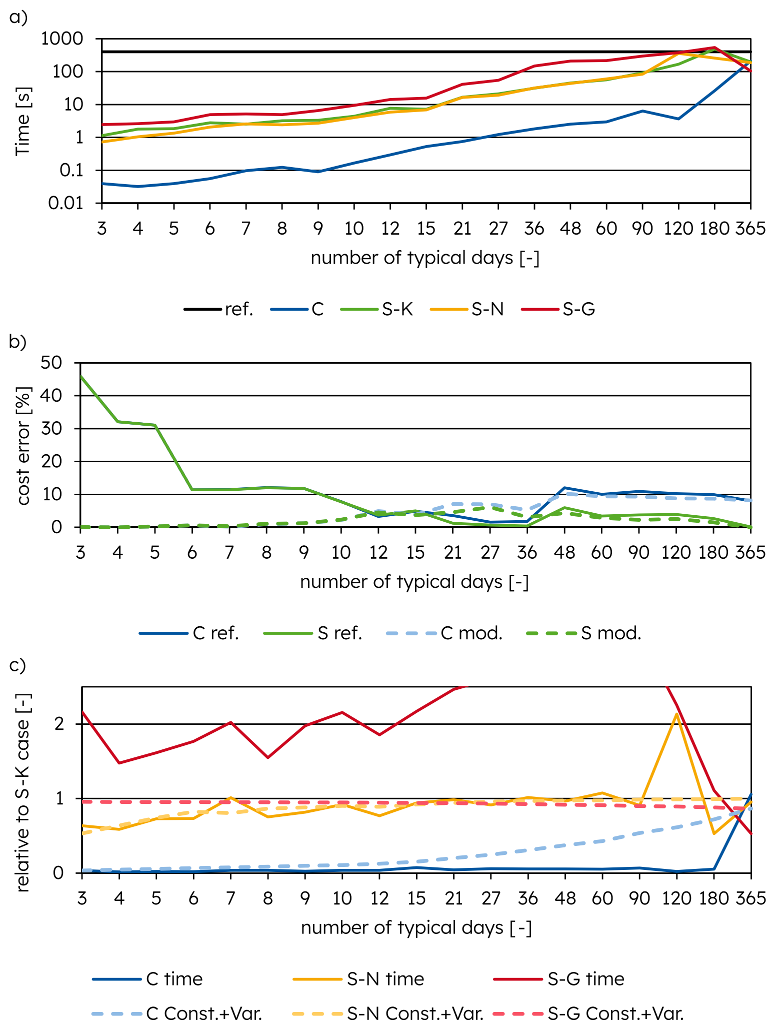

Fig. 5 Calculation time (**a**) and total costs error (**b**) for the different storage models and relative share of number of constraints and variables as well as time for C, S-G- and S-N- to S-K-model (**c**) for Island system

For a number of typical days below 36, generally, the calculation time is lower than 14 % of the full-year calculation time. Especially the C-model stays below 5 % of the calculation time.

Figure 5c shows the number of variables (Var.) and constraints (Const.) as well as the calculation time relative to the S-K-model. Up to 12 typical days, the S-N-model often calculates at least 10 % faster than the S-K-model. It is approximately as fast as the seasonal model for more typical days. The calculation time reduction decreases by an increasing number of typical days because of nearly the same number of variables and constraints for both models. The C-model is up to 90 % faster in most cases, and the S-G-model is, on average, 230 % slower than the S-K-model.

Figure 6 shows the total cost-share of the C-model, S-model, modified, and reference model. Until 21 typical days, the total costs increase for both storage models. Besides, the backup is used from a number of 6 typical days on. For less than 6 typical days, photovoltaic, wind turbine, and battery storage define the system. Hydrogen storage,

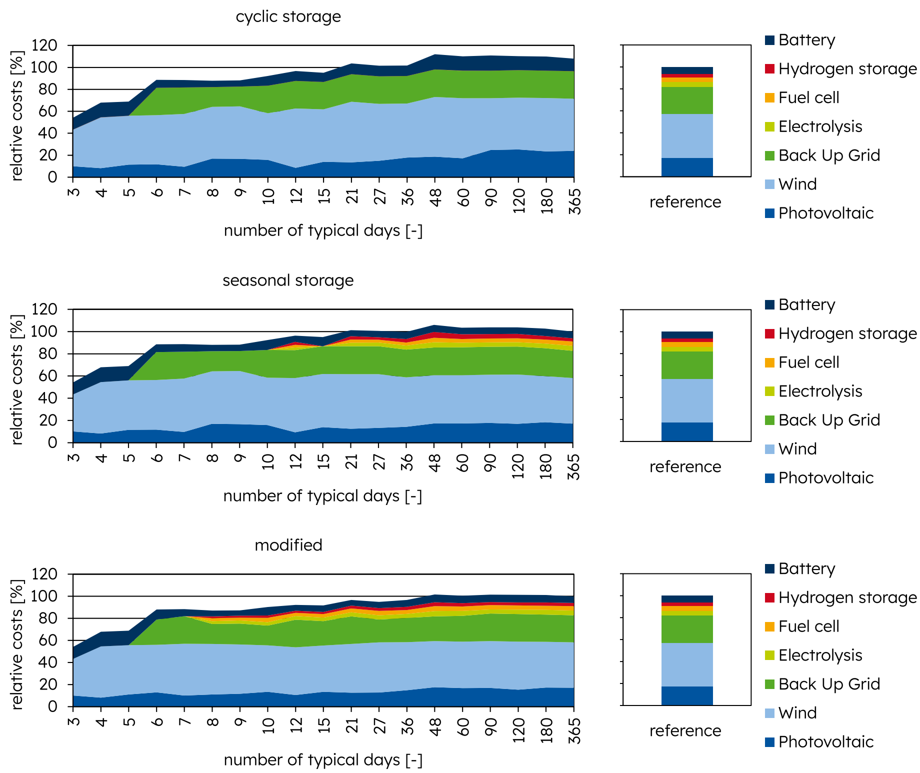

Fig. 6 Comparison of total costs share for cyclic and seasonal storage model for Island system

electrolyser and fuel cell are the components allowing seasonal storage. As of 21 typical days, the seasonal storage components are included in the system optimized using a seasonal storage model. The seasonal storage model leads to nearly the same results as the reference case for a number of typical days of 48 and more. The C-model cannot get the same result because it cannot consider hydrogen storage as seasonal storage.

Conclusions

The presented work reviewed the classical cyclic storage formulation using typical days, the seasonal storage model by Kotzur et al., and the seasonal storage model of Gabrielli et al. Furthermore, it presented and evaluated an extension of the seasonal storage model of Kotzur et al.

The review of the model of Kotzur et al. leads to the same results and conclusions:

- The seasonal storage model is not reasonable for system designs where seasonal storage is not an economical option. This model results in the same outcomes but with more calculation time than the not linked storage model.
- For a system that relies on seasonal storage, a seasonal storage model is a feasible option. It significantly reduces the computational time for a high number of typical days. Furthermore, it leads to nearly the same system design.

This conclusion also applies to Gabrielli et al.'s seasonal storage model. All seasonal storage models lead to the same results. Gabrielli et al.'s model reduces the number of variables and constraints by 5–10% compared to Kotzur et al.'s model. The calculation time of this model is significantly higher than for the model of Kotzur et. al. The new seasonal storage model summarises storage states of days in a row represented by the same typical period. It reduces the number of constraints and variables by more than 20 % for a small number of typical days. In this case, the calculation time is low for all models. So, this new algorithm is beneficial for an energy system with many seasonal storage components. So, it is valuable for extensive case studies. Also, the calculation time reduces by more than 10 % on the most numbers of typical days.

If seasonal storage should be considered, the seasonal storage model of Kotzur et al. should be used instead of the model of Gabrielli et al. The new model is a good choice, especially for a low number of typical periods or if many typical periods of the same type occur in a row.

Appendix

Constraint reformulation

This Eq. (6) can be reformulated using a support variable r to the following two equations:

$$r + E_{p-1} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^{N} + \Delta E_t = E_{max}. \tag{15}$$

$$r \leq E_{max}. \tag{16}$$

This Eq. (13) can be reformulated using a support variable r to Eqs. (16) and (17):

$$\begin{aligned} r + E_{p-1} \cdot \frac{\left(1 - \eta_{self} \cdot \delta t\right)^{N \cdot M}}{\left(1 - \eta_{self} \cdot \delta t\right)^{N} \cdot F} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^{t} \\ + \frac{E_p \cdot \left(1 - \frac{1}{F}\right)}{\left(1 - \eta_{self} \cdot \delta t\right)^{N}} \cdot \left(1 - \eta_{self} \cdot \delta t\right)^{t} + \Delta E_t = E_{max} \end{aligned} \tag{17}$$

Abbreviations

MILP	Mixed-integer-linear-problem
TSAM	Time series aggregation module
E_h	Stored energy at the time step h within the year [J]
E_p	Stored energy at the beginning of period p [J]
E_t	Stored energy at the time step t [J]
E_{max}	Maximal stored energy [J]
F	Self discharging factor for more then one period [–]
M	Number of same period i in a row [–]
N	Number of time steps in the period [–]
P_t^c	Charging power at time step t [W]
P_t^d	Discharging power at time step t [W]
ΔE_t	Stored or extracted energy from beginning of the period to time step tJ.
δt	Time step length [s]
η_{charge}	Charging efficiency [–]
$\eta_{discharge}$	Discharging efficiency [–]
η_{self}	Self discharging rate [1/s]
f	Function that returns the period time step for the input hour h [–]
h	Time step within the year [–]
r	Supporting variable to simplify constraints [J]
t	Time step within the one period [–]
C	Cyclic storage model

S	Seasonal storage model
S-G	Seasonal storage model of Gabrielli et al. (2018)
S-K	Seasonal storage model of Kotzur et al. (2018)
S-N	New seasonal storage model as and extension of Kotzur et al. model

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It will be filled out after the double-blind review.

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Availibility of data and materials
Blanke (2022) provides the used time series for the heating loads, electrical loads, the typical periods, and the code.

Declarations

Competing interests
The authors declare that they have no competing interests.

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