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Optimal industrial flexibility scheduling based on generic data format

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Abstract

The energy transition into a modern power system requires energy flexibility. Demand Response (DR) is one promising option for providing this flexibility. With the highest share of final energy consumption, the industry has the potential to offer DR and contribute to the energy transition by adjusting its energy demand. This paper proposes a mathematical optimization model that uses a generic data model for flexibility description. The optimization model supports industrial companies to select when (i.e., at which time), where (i.e., in which market), and how (i.e., the schedule) they should market their flexibility potential to optimize profit. We evaluate the optimization model under several synthetic use cases developed upon the learnings over several workshops and bilateral discussions with industrial partners from the paper and aluminum industry. The results of the optimization model evaluation suggest the model can fulfill its purpose under different use cases even with complex use cases such as various loads and storages. However, the optimization model computation time grows as the complexity of use cases grows.

Keywords: Industrial flexibility optimization, Mixed-integer linear programming, Generic flexibility description, Load dependency

Introduction

Traditional power systems are centralized since the electric flow is unidirectional, from bulk power plants to consumers. However, the transition into a modern power system enabled by Information and communication technology (ICT) and enacted policies to combat global warming increase Renewable Energy Sources (RES), distributed in many cases. These RES depend on weather conditions for their optimal operation and thus increase the challenge of sustaining power system stability. To meet this challenge, the energy system needs energy flexibility. Union of the Electricity Industry—EURELECTRIC aisbl (2014) defines the term flexibility as the “[...] *modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) to provide a service within the energy system*”. Energy

flexibility provision thus can have many different sources. Whereas options such as the enhancement of transmission lines or the building of new electrical storages or power plants are cost-intensive to implement (Palensky and Dietrich 2011; Heffron et al. 2020) (i.e., high investment costs), the adjustment of electricity demand has the advantage that the energy flexibility providing assets already exist (Heffron et al. 2020). The so-called DR, as one part of Demand Side Management (DSM), describes short-term changes at the electricity consumption side (Palensky and Dietrich 2011).

In Germany, the industrial sector has the highest share of final electricity consumption at 41% (Energiebilanzen 2021). Thus, it offers a high potential to impact a change of demand using DR. However, the identification and application of industrial energy flexibility are challenging tasks. Industrial companies have complex and a variety of industrial processes where industrial energy flexibility is not a core business for most of them. Hence, most industrial companies use tailored decision support systems to help them determine their optimal adjustment of electricity demand in terms of time and characteristics that require customized scheduling models. Thus, these tailored solutions pose a threefold challenge. First, they might require a relatively high investment, especially hurdling small and medium-sized companies (Bauernhansl et al. 2019). Second, they tend to lack interoperability features, notably in using a single, specific model to describe their energy flexibilities (Bauernhansl et al. 2019). This specific model instantly creates vendor lock-in problems (unable to switch between service providers easily) (Potenciano Menci et al. 2021; van Stiphoudt et al. 2021). Third, tailored models and existing literature tend to be use-case-specific, resulting in case-dependent models (Helin et al. 2017; Zhou et al. 2017; Xu et al. 2020) and the consideration of single processes (Howard et al. 2021). Therefore, industrial companies find several barriers to realizing their energy flexibility potential. To address these challenges, there is a need for a holistic, interoperable, and generic use-case-independent model, which industrial companies can use to support their decision of where (i.e., which market) and when (i.e., which times) they can market their industrial energy flexibility.

We propose an optimization model for calculating an optimal adjustment of electricity demand for industries that is generic, holistic, and interoperable for a given horizon. We achieve generality by building upon a generic data model that describes energy flexibility, introduced by Schott et al. (2019). This generic data model allows us to decouple model generation (flexibility description) and optimization, letting industrial companies specify their level of detail in their model's description. In addition, it enables us to consider in the optimization model the inclusion of connected systems, including a wide range of storage types (e.g., energy, heat, compressed air, electric) and dependencies between different processes and/or machines. We consider the model holistic because it allows industrial companies to run the optimization for various scenarios considering different optimization horizons, energy markets, or flexibility descriptions to compare potential benefits. Thus, it can assist industrial companies in selecting where and when to market their flexibility using the optimal schedule. By using defined and generic inputs and outputs to describe flexibilities, the model becomes interoperable: Companies that describe their energy flexibilities with the data model introduced in Schott et al. (2019) can apply this optimization model. Furthermore, industrial companies could

combine the optimization model we propose with other solutions which already use the same generic data model (Lindner et al. 2022; Bank 2021).

The paper is structured as follows. The “Related Work” section provides a brief overview of related work in energy flexibility optimization and scheduling. The “Model” section introduces the optimization and scheduling model formulation based on a mixed-integer linear programming approach. The “Use cases and results” section focuses on implementing the model under different use cases to evaluate its output. The “Discussion” section focuses on the discussion about the features of the proposed model based on the simulation results from the previous section. Finally, the “Conclusions” section summarizes the results but also acknowledges the limitations of the proposed model in addition to the research outlook.

Related work

Energy flexibility optimization focused on demand (household, industrial, etc.) or in combination with supply is a widely investigated topic within literature. In this context, DR applied to industrial energy flexibility refers to the deviation in the consumption patterns of an industrial consumer to take part in energy flexibility markets (any market trading power and capacity) (Fridgen et al. 2017; Commission et al. 2022; Shoreh et al. 2016). In this regard, a production plant can shift its production plan to make a monetary profit by taking part in current electricity markets (e.g., wholesale) and in new potential markets (e.g., local flexibility markets) with its energy flexibility (Bauernhansl et al. 2019).

Industrial companies mostly optimize their industrial processes focusing on efficiency regarding other production inputs than energy, which often prevents their industrial processes from being energy flexible. Additionally, industrial processes have different characteristics, limiting the availability of complete generic models (i.e., any model that can accept any process) (Schott et al. 2019).

One characteristic of industrial processes and their energy flexibility is the connection between industrial processes and/or machines (Shoreh et al. 2016). Each link creates a dependency. There is a need to consider these dependencies between processes and/or machines to create generic models for industrial energy flexibility. Nevertheless, for simplification purposes, many authors do not consider dependencies in their models and thus limit their models’ general application. For instance, in Angizeh et al. (2019), authors propose an energy flexibility scheduling method for industrial consumers considering on-site generation. However, they do not consider the dependency between loads. Likewise, the models proposed in Shrouf et al. (2014) and Varelmann et al. (2022) focus on optimizing the production scheduling and participating in different markets considering a single industrial machine, respectively. Therefore, they contribute to considering aspects such as different power states, load shifting, and participating in different markets but do not consider the dependencies within the industrial process.

Other authors employ material flow models to tackle such dependency problems in their optimization. Material flow models are one possible way to model dependencies. For example, using a material flow model, authors in Mitra et al. (2012) investigate an optimal production planning method for energy-intensive industrial plants (e.g., air separation plant and cement plant). Similarly, authors in Wanapinit et al. (2021)

present a modular energy flexibility model for industrial end-users using a material flow model. Their model covers energy flexibility features such as ramp rates and time limits for energy flexibility activation. Authors in Ashok and Banerjee (2001) proposed a method to minimize the electricity costs considering the process, storage, and manufacturing constraints. In Ruohonen et al. (2011), the authors present a model for cost-effective scheduling of paper pulp mill. The authors in Ramin et al. (2018) investigate the DSM of industrial processes considering production constraints. Authors in Khatri et al. (2021) propose a coupled generic modeling library and optimal control to react and control based on fixed or variable price signals. Their generic modeling library enables industrial companies to model down to individual machines and how to control them. Their optimization provides a schedule allowing the control model to act accordingly. Similarly, authors in Castro et al. (2009) proposed a resource-task-network approach to schedule continuous production plants based on electricity price. Nevertheless, their optimizations in many cases using material flow models could hurdle the generality of their model. This is because material flow modeling needs a detailed description of each industry. Thus, it might result in case-specific models.

Further improvement of generic industrial energy flexibility modeling has to do with the inherent features of the industrial energy flexibility such as ramping of the machines, energy storage modeling, and limited run-time of the machines, which the authors in Moon and Park (2014) and Barth et al. (2018) considered in their proposed model.

Moreover, there are contributions in the optimization domain that employ heuristic approaches (Gong et al. 2019). Heuristics' ability to calculate fast solutions has increased their application mostly in large-scale problems (Küster et al. 2021). Although heuristics might be a fast solution, they cannot guarantee the global (optimal) solution and might result in a locally optimal solution.

Nevertheless, demand modeling requires data transfer regardless of the feature selection and optimization model. To enable the data transfer between various sectors and provide standardization, having a data model is highly important but imposes a challenge. For instance, authors in Huber (2018) briefly explored the necessary parameters to describe a flexible data model for DSM. More extensively, authors in Schott et al. (2019) propose a generic data model which can describe various energy flexibility aspects, improve the information exchange, and enhance energy flexibility automation. This generic data model enables cross-sectoral usage (i.e., residential and industrial), facilitating targeted cross-sectoral optimizations. They challenged their proposed data model against the feature-checklist developed by Barth et al. (2018) and were able to include all features in the proposed data model. Authors in Lindner et al. (2022) for instance, leverage the potential of the generic data model to propose a possible merging service that could combine various descriptions into one. Authors in Bank (2021) propose a conceptual step step-wise approach to integrating the generic data model for production planning.

In summary, many authors solve their optimizations in a simplified yet efficient and fast manner, considering specific use cases. Within these specific use cases, many authors select a limited number of relevant features for their models to solve their optimization problems and thus, develop tailored solutions. These specific use cases face a threefold problem (Bauernhansl et al. 2019). First, they limit the holism of their model

due to their selection of relevant features for simplification and fast optimization solutions. Second, their models tend to lack interoperability across different demand types. Since their models usually only focus on one demand-type, it delimits the feature selection and optimization method. Third, they hurdle their model's replicability since it is a tailored solution across the same industry. This tailored model would require, in some cases, extensive modifications to adjust to other boundary conditions. Therefore, many demand models, even those focused on industrial demand flexibility, face holistic, interoperable, and replicable (transferable) limitations. According to Helin et al. (2017), such attributes are necessary for industrial flexibility modeling.

Model

The proposed optimization model (artifact) takes three different inputs and produces two different outputs, depicted in Fig. 1. The optimization uses a generic data model, the Energy Flexibility Data Model (EFDM) from van Stiphoudt et al. (2021); Schott et al. (2019). The EFDM is the core for describing (1) the flexibility potential and (2) the specific power profile the flexible loads have to follow, known as flexible load measure. Therefore, the EFDM offers companies an entire framework in JavaScript Object Notation (JSON) to work with flexibilities descriptions (Schott et al. 2019). We considered the guidelines proposed in Hevner et al. (2004) to design the optimization model. Moreover, we followed the iterative methodology for developing and evaluating the model proposed by Peffers et al. (2007). However, we only describe in this manuscript the final optimization model and not the multiple iterations needed for the model development. Hereafter, each subsection covers the inputs the optimization model uses, the mathematical description of the optimization model, and the optimization output. We coded the model in Python using the Gurobi solver (Gurobi Optimization 2022) and tested it on a computer with a Core i7 CPU @ 2.6 GHz processor and 32 GB RAM.

Inputs

Energy market prices

The first input to our optimization model is the energy market prices (i.e., electricity markets). Notably, the optimization can use the power exchange prices (i.e., European Power Exchange (EPEX)) from the spot market contained in the wholesale market as well as price forecasts expressed as time series. It supports data intake from the day-ahead and intraday (auction and continuous) since it allows for different time resolutions

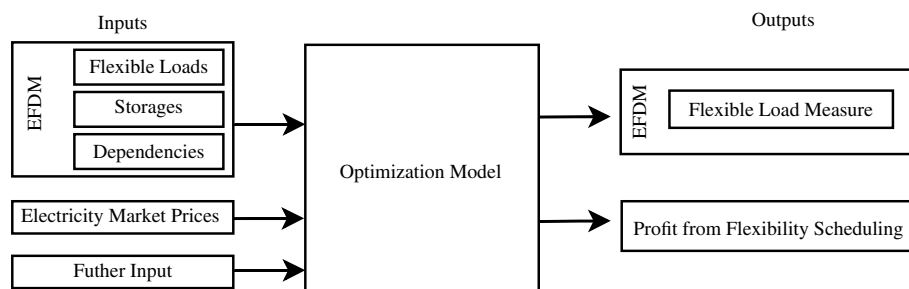


Fig. 1 Input and outputs of the optimization model

Table 1 Key figures of the EFDM as used by the optimization model

| Key | Value (type) | Description |
|-----------------------|---------------------|---|
| Validity | Integer ≥ 0 | The interval where using the flexible load is allowed for flexibility purposes |
| Power states | Continuous ≥ 0 | The deviation of flexible load from the normal operating point. The deviation is positive in the load increase type, and it is negative in the load decrease type |
| Holding duration | Integer ≥ 0 | The time length that flexible loads operate per usage |
| Usage numbers | Integer ≥ 0 | The allowed number of usages in the optimization period |
| Modulation number | Integer ≥ 0 | The number of permitted changes in the power state value per usage (without counting the power state change related to activation and deactivation) |
| Activation gradient | Continuous ≥ 0 | The power change rate during the activation |
| Deactivation gradient | Continuous ≥ 0 | The power change rate during the deactivation |
| Regeneration duration | Integer ≥ 0 | The time limitation to activate a load after deactivation |
| Costs | Continuous ≥ 0 | The cost of using flexible load, excluding the electric costs |

Table 2 Storage key figures of the EFDM as used by the optimization model

| Key | Value (type) | Description |
|---|---------------------|--|
| Maximum capacity | Continuous ≥ 0 | Maximum capacity of the storage |
| Initial energy content, including the timestamp | Continuous ≥ 0 | Value of energy content stored at specified timestamp |
| Target energy content, including the timestamp | Continuous ≥ 0 | Value of energy content that storage should reach at a specified timestamp |
| Energy loss | Continuous ≥ 0 | Lost energy from storage because of exchange with the environment |
| Suppliers | String | Flexible loads that are filling the storage. Suppliers and stored value in the storages are linked using conversion efficiency |
| Drain | String | Loads that storage must serve in the specified time interval |

(i.e., 15-min and 1-h values). The data input enables the analysis of price volatility in the electricity markets and the identification of the best possible marketing time, which may include times with negative prices.

EFDM: flexible loads, storages and dependencies

The second input of the optimization model is the flexibility description. Industrial companies can and are responsible to describe their flexibility using the EFDM developed in Schott et al. (2019) through its three main categories with any any level of detail they chose. These categories are the *flexible loads*, *storages*, and *dependencies*.

The *flexible load* category is the main flexibility description. It contains several key figures for the description, provided in Table 1.

Industrial companies might use a wide range of *storage* systems in their processes, such as heat, cold, compressed air, and electrical energy storage (EES). They can describe these *storages* using the *storage* category within the EFDM, utilizing several key figures, as described in Table 2.

Industrial companies can have complex processes. Their industrial processes involve machines that depend on one another. To capture industrial processes' complexity, industrial companies can describe these dependencies in the EFDM using the category

dependencies between flexible loads. However, using the EFDM as inputs to describe the flexibility restricts the use of a material flow for our model. The EFDM can cover a dependency between two flexible loads. Dependencies internally in the EFDM have different types. This constitutes the necessity of activation/deactivation of one flexible load before/after another. There can be a dependency between the activation/deactivation time of *Load1* and *Load2*, as we depict in Fig. 2 in two examples. On the left, *Load1* imposes the activation of *Load2* after activation of *Load1*. It additionally provides lower and upper dependency boundaries. Using lower and upper boundaries and not one specific time for the dependencies can extend the flexibility options and result in more chances to capture all possible flexibilities. On the right, the deactivation of *Load1* requires the activation of *Load2* after and within the allowed boundaries.

Further input

The third input to our optimization model includes additional information required for the optimization. The first additional input required is an optimization period. In addition to the validity time of the flexible loads passed with the EFDM, the optimization model requires an optimization period for which the optimization should perform the calculation. The second additional input is a selection of the electricity markets that the optimization model should consider. If no further input is selected, the optimization model considers all electricity markets for which electricity prices are available in the Electricity Market Prices input. The third additional input is the physical limitation of the grid connection point. The consideration restricts the power exchange to fulfill this grid constraint.

Mathematical model

Objective function

The core of the mathematical model is the objective function, which aims to maximize the profit by exploiting the market price differences and marketing industrial flexibility by either increasing or decreasing loads (i.e., modifying their power state). Equation (1) provides the objective function. L_{Neg} , L_{Pos} , L , and T are sets for load decrease flexibilities, load increase flexibilities, all the loads (union of L_{Neg} and L_{Pos}), and optimization horizon. The first term in the objective function (in the left) represents the profit obtained by decreasing the flexible loads. The second term (in the middle) represents the influence of increasing

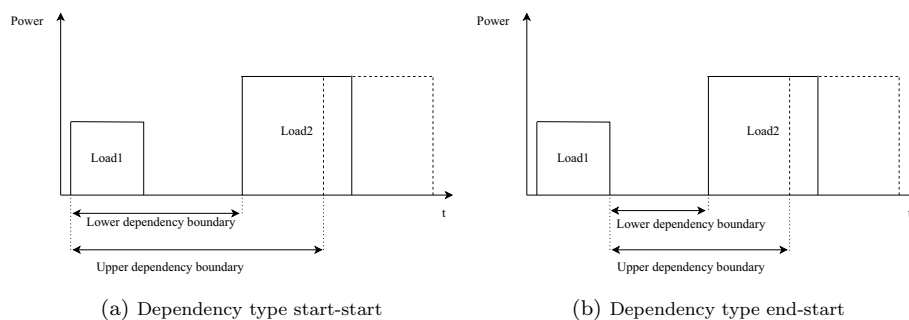


Fig. 2 Dependencies between different loads

the flexible loads. The third term (in the right) represents the costs associated with using the flexibilities (ac_l). In this objective function, $p_{l,t}$ is the variable expressing the magnitude of the power deviation, and $y_{l,t}$ is the binary variable which is equal to 1 in case flexible load l is activated at time t and is 0 otherwise. The parameters λ_t and ac_l express the electricity price at time t and the activation cost of flexible load l for flexibility purposes, respectively. Therefore, the objective function is as follows:

$$\max \left(\underbrace{\sum_{l \in L_{Neg}} \sum_{t \in T} p_{l,t} \lambda_t}_{\text{load decrease profit}} - \underbrace{\sum_{l \in L_{Pos}} \sum_{t \in T} p_{l,t} \lambda_t}_{\text{load increase profit}} - \underbrace{\sum_{l \in L} \sum_{t \in T} y_{l,t} ac_l}_{\text{load activation cost}} \right). \quad (1)$$

Power state constraints

The power state constraint forces the optimization to operate under a lower and an upper power deviation ($p_{l,t}$) is as follows:

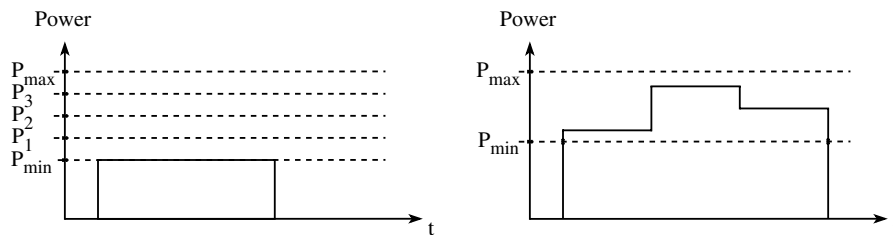
$$p_{l,min} I_{l,t} \leq p_{l,t} \leq p_{l,max} I_{l,t} \quad \forall l \in L, t \in T \quad (2)$$

where $I_{l,t}$ is the current status binary variable of the flexible load l . In case the flexible load l is active at time t , the binary variable $I_{l,t}$ is 1 and $I_{l,t}$ is 0 otherwise.

Nevertheless, some flexible loads might require to only operate at specific power states. In such an event requiring discrete power states, Eqs. (3) and (4) are necessary. The term $states_l$ equals the number of permissible power states of load l between $p_{l,min}$ and $p_{l,max}$. $Int_{l,t}$ is the integer variable controlling the power state value in case the power state is discrete, and $p_{l,min}$ and $p_{l,max}$ are minimum and maximum power deviation of flexible load l . Figure 3a provides an example of one flexible load l with 5 possible power states. Therefore, we have:

$$p_{l,t} = p_{l,min} I_{l,t} + \frac{p_{l,max} - p_{l,min}}{states_l + 1} Int_{l,t} \quad \forall l \in L, t \in T \quad (3)$$

$$0 \leq Int_{l,t} \leq (states_l + 1) I_{l,t} \quad \forall l \in L, t \in T. \quad (4)$$



(a) Representation of 5 discrete power states of a flexible load.

(b) Case without discrete power states and restriction on modulation number.

Fig. 3 Representation of power states

Some flexible loads might only be able to operate in one unique power state. For these type of flexible loads, we propose two equations as follows:

$$p_{l,t} - p_{l,t-1} \leq p_{l,max} y_{l,t} \quad \forall l \in L, t \in T \quad (5)$$

$$p_{l,t-1} - p_{l,t} \leq p_{l,max} s_{l,t} \quad \forall l \in L, t \in T. \quad (6)$$

They impose only one value for the power state during the activation period and model loads with 0 modulation numbers—the number of changes of the power state value during the holding duration. In this regard, only one increase and one decrease in the power are allowed in the flexibility's start-up and shut-down time, resulting in only one power state during the flexibility activation. The binary variable $s_{l,t}$ is equal to 1 if flexible load l shuts down at time t , and it will be 0 otherwise.

For those flexibility loads, which can freely operate under any power state, for example, as Fig. 3b depicts, only require the constraint given by Eq. (2).

Activation and deactivation constraints

Another set of constraints we subject the optimization function to are the activation and deactivation of the flexibilities which additionally cover other aspects. For instance, Eq. (7) provides the holding duration constraint for a given load l between the step limits $IT_{min,l}$ to $IT_{max,l}$ as follows:

$$y_{l,t} \leq \sum_{h=IT_{min,l}}^{IT_{max,l}} s_{l,t+h} \quad \forall l \in L, t \in T. \quad (7)$$

Moreover, each flexible load can have a regeneration time (DT_l) impeding the reactivation of the flexibility during that time, expressed as the following:

$$\sum_{h=t}^{t+DT_l-1} (1 - I_{l,h}) \geq DT_l s_{l,t} \quad \forall l \in L, t \in T. \quad (8)$$

Furthermore, flexibilities might be constrained to a specific time for their activation representing its validity for operation as follows:

$$I_{l,t} \leq \text{validity}_{l,t} \quad \forall l \in L, t \in T \quad (9)$$

where the $\text{validity}_{l,t}$ is a binary parameter equal to 1 if load l is allowed to be in active status and is 0 otherwise. We limit the number of usages a flexible load can have through Eq. (10). In it, $Usage_{l,min}$ and $Usage_{l,max}$ control the minimum and maximum number of times that flexible load l can be used during the optimization horizon respectively. Moreover, we impede the flexible load activation and deactivation at the same time using Eq. (11). Thus, these equations are:

$$Usage_{l,min} \leq \sum_{t \in T} y_{l,t} \leq Usage_{l,max} \quad \forall l \in L \quad (10)$$

$$y_{l,t} + s_{l,t} \leq 1 \quad \forall l \in L, t \in T. \quad (11)$$

The last constraint we consider for the activation and deactivation of flexible loads is to define the relationship between the binary variables and is as follows:

$$y_{l,t} - s_{l,t} = I_{l,t} - I_{l,t-1} \forall l \in L, t \in T \quad (12)$$

where $y_{l,t}$, $s_{l,t}$, and $I_{l,t}$ are binary variables used for starting time, ending time, and the status of the flexible load, respectively.

Storage model

We include storages into the optimization model using the following constraints. The first constraint is the energy storage balance given by Eq. (13). In this equation, ST is the set of the storages. It considers the stored energy in the storage at a given time t . Notably, $E_{e,t}$, $p_{e,t,ch}$, and $p_{e,t,dis}$ are variables for stored energy, charging rate, and discharging rate of the storage, respectively. $E_{e,loss}$ indicates the energy loss due to the energy exchange with the environment. Therefore, we have:

$$E_{e,t} = E_{e,t-1} + p_{e,t,ch} - p_{e,t,dis} - E_{e,loss} \quad \forall e \in ST, t \in T. \quad (13)$$

Equation (14) represents the storage charging balance. In this equation, $p_{e,t,ch}$ represents the storage charging using the flexible loads connected to storage e , demonstrated as $l \in \gamma_e$. The loads connected to each storage charge them considering the conversion efficiency eff_l . Therefore, we have:

$$p_{e,t,ch} = \sum_{l \in \gamma_e} eff_l p_{l,t} \forall e \in ST, t \in T. \quad (14)$$

The third storage related constraint defines the drain times given by Eq. (15). In order to model the “drain”, which is described in the EFDM, $p_{e,t,dis}$ should be equal to fixed parameter $p_{e,t,drain}$ at certain time slots. Moreover, the storage requires at certain times to charge up to the “target energy content” described in the EFDM. To do so, $E_{e,t}$ (energy content) should be equal to predefined values ($E_{e,t,target}$) at that certain time slots, as Eq. (16) collects. In Eqs. (15) and (16) the sets $T_{drain,e}$ and $T_{target,e}$ are the two constraints the optimization aims to satisfy. The former is the time to drain and the latter is the target energy content constraint. Therefore, these equations are:

$$p_{e,t,dis} = p_{e,t,drain} \forall e \in ST, t \in T_{drain,e} \quad (15)$$

$$E_{e,t} = E_{e,t,target} \forall e \in ST, t \in T_{target,e}. \quad (16)$$

Dependency

The inclusion of dependencies into the optimization model is not a trivial endeavour. Therefore we consider a set of five equations to introduce dependencies into the optimization model. These five equations (17), (18), (19), (20) (21) consider the effect of activating or deactivating one flexible load based on another flexible load creating based on the possible combinations of how they can interact. The following sets of load dependencies used in this model are:

- $D_{start-start-after}$: Activation of one load after activation of another.
- $D_{start-start-before}$: Activation of one load before activation of another.
- $D_{end-start-after}$: Activation of one load after deactivation of another.
- $D_{end-start-before}$: Activation of one load before deactivating another.
- $D_{exclusion}$: Restricts the activation of a load based on the activation of another load.

Pointedly, the first combination is as follows:

$$y_{l_i,t} \leq \sum_{h=a}^b y_{l_j,t+h} \quad \forall l_i \text{ and } l_j \in D_{start-start-after} \quad (i \neq j), t \in T \quad (17)$$

where it considers for the time steps from a to b that the optimization should activate the flexible load l_j after the activation of l_i . Differently, the second combination is Eq. (18). It is different from the previous equation as l_j must be now activated before the activation of the load l_i , formulated as follows:

$$y_{l_i,t} \leq \sum_{h=a}^b y_{l_j,t-h} \quad \forall l_i \text{ and } l_j \in D_{start-start-before} \quad (i \neq j), t \in T. \quad (18)$$

Another combination is to activate the load (l_j) after or before the deactivation of another load (l_i), represented as follows:

$$s_{l_i,t} \leq \sum_{h=a}^b y_{l_j,t+h} \quad \forall l_i \text{ and } l_j \in D_{end-start-after} \quad (i \neq j), t \in T \quad (19)$$

$$s_{l_i,t} \leq \sum_{h=a}^b y_{l_j,t-h} \quad \forall l_i \text{ and } l_j \in D_{end-start-before} \quad (i \neq j), t \in T. \quad (20)$$

The last combination for a dependency we consider is as follows:

$$\sum_{h=a}^b y_{l_j,t+h} \leq (1 - y_{l_i,t})(b - a + 1) \quad \forall l_i \text{ and } l_j \in D_{exclusion} \quad (i \neq j), t \in T \quad (21)$$

where a flexible load (l_i) prevents another flexible load's (l_j) activation. Thence, with these 5 equations creating a set of dependencies between two loads the model can consider interdependencies—two or more loads depend on each other and other loads—by creating a chain of loads which interdepend.

Grid constraint

The last constraint for our model can deal with the physical limitation of the grid connection point from industrial flexibilities. Therefore, we consider the physical grid constraint in the model through Eq. (22) to restrict the power exchange with the grid at the grid connection point. In the current version of the EFDM (Schott et al. 2019) the grid constraint is not included. Nevertheless, we consider this addition meaningful and propose to consider this adjustment in a future version of the EFDM. Thus, we have:

$$-P_{grid,t}^{max} \leq \sum_{l \in L_{Pos}} p_{l,t} - \sum_{l \in L_{Neg}} p_{l,t} \leq P_{grid,t}^{max} \quad \forall t \in T. \quad (22)$$

Outputs

The optimization model with its objective function (Eq. 1) and the subjected constraints (Eqs. 2–22) calculates the optimal solution and provides two main outputs.

EFDM: flexible load measure

One output of the optimization model is describing a specific flexibility measure. In other words, it provides the optimal schedule for an industrial flexibility. A flexibility measure describes therefore no longer a flexibility potential. A flexibility measure contains a fixed load deviation (fixed power state for the intervals) with fixed periods (holding duration, modulation duration, activation/deactivation duration). The EFDM (Schott et al. 2019) enables in a standard manner to describe the flexibility measure using the so-called “flexible load measure” category, with its defined JSON Schema (van Stiphoudt et al. 2021).

Calculated profit

The second output of the optimization model is the maximized profit that industries could potentially achieve by marketing their flexibility load measures. For the calculation, the optimization in Eq. (1) considers the electricity prices passed as time series from the wholesale spot market (Day-Ahead, Intraday) or forecasted values in a specified validity time, Eq. (9), as well as the activation costs (ac_l) of a flexibility load measure. The calculated profit is the potential total amount given in Euros achievable by executing the calculated flexibility schedule. The optimization model calculates the profit per flexibility schedule.

Use cases and results

To demonstrate the capabilities of the proposed model, we investigate and evaluate the model under three different use cases. In the first use case, we evaluate the model using four simple, flexible loads in a simple context (i.e., without dependencies and storages). In the second use case, we evaluate the model using four flexible loads within an interdependent context (i.e., with dependencies and without storages). In the last use case, the complexity rises, and we evaluate the model using eight flexible loads in an interdependent and connected context, including storages (i.e., with dependencies and storages) to assess the full potential of the proposed model. However, our primary inputs, the EFDM is not a digital twin of a specific process. Still, we built them upon the learnings from several workshops and bilateral discussions with industrial partners from the paper and aluminum industry. We discussed several industrial processes they currently have, their structural features, the technical parameters, and the values they might include when describing their flexibility using the EFDM. However, our model contains synthetic data generated when describing the flexible loads since our industrial partners were unwilling to reveal actual production data and specific processes for publication.

Use case I—simple flexible loads

This first use case explores the capabilities of the optimization model when dealing with simple, flexible loads. We consider in this use case four different loads with neither dependencies among them nor a connection to a storage system. Therefore, the optimization model implements:

- Optimization function: given by Eq. (1).
- Main constraints: subject to Eqs. (2)–(12).

We collect in Table 3 an overview of the four flexible loads and their characteristics included in their EFDM description. The electricity prices considered, input for the optimization (24 h horizon), corresponds to the EPEX Day-ahead auction DE-LU on the 08/08/2020 (Bundesnetzagentur 2022).

All considered flexible loads have the same type, 'decrease.' In other words, the flexibility they offer is to decrease their power consumption. For example, load *L1* can operate in between two power states (P_{max} and P_{min}). Three out of four loads do not face any restrictions concerning their validity (when the optimization cannot activate them). However, the optimization model can only activate load *L3* between 18:00 and 24:00. Similarly, almost all loads have no activation costs, except *L4*, which in this case it costs 130 € every time it gets activated. Each load has a different holding duration. For instance, load *L2* can remain activated for a minimum of 1 h and a maximum of 2 h. Only *L2* needs a period of 3h between activations regarding their regeneration time. Finally, the optimization can decide not to activate any of the loads. Contrary, if the optimization uses the loads, it is restricted by the usage number. For instance, the optimization can use *L1* up to three times or *L4* one time.

We collect the optimization results in Fig. 4. In it, the flexible load *L1* is a 'decrease' type; it should decrease its power consumption when the prices are high. Indeed, Fig. 4 corroborates this operation as *L1* decreases its power between 01:00–04:00, 17:00–20:00, and 21:00–24:00, also within the limits of the validity time and the usage number to achieve a higher profit (reduction of power when the electricity price is high).

Similarly, the optimization activates flexible load *L2* twice, in the beginning, between 01:00 and 03:00, and almost at the end, between 19:00 and 21:00. Although the activation between hours 18 and 24 could result in a higher profit (price is higher than hours 1–3), the 3-h regeneration time prevents it.

Table 3 Load's characteristics considered in use case I

| key figure | Units | L1 | L2 | L3 | L4 |
|----------------------|-------|----------|----------|----------|------------|
| Load deviation type | – | Decrease | Decrease | Decrease | Decrease |
| Power state | MW | [0, 1] | [2, 2] | [3, 4] | [0.5, 1.5] |
| Validity restriction | Time | None | None | 18–24 | None |
| Activation cost | € | 0 | 0 | 0 | 130 |
| Holding duration | h | [1, 3] | [1, 2] | [1, 1] | [2, 2] |
| Regeneration time | h | 0 | 3 | 0 | 0 |
| Usage Number | – | [0, 3] | [0, 2] | [0, 1] | [0, 1] |

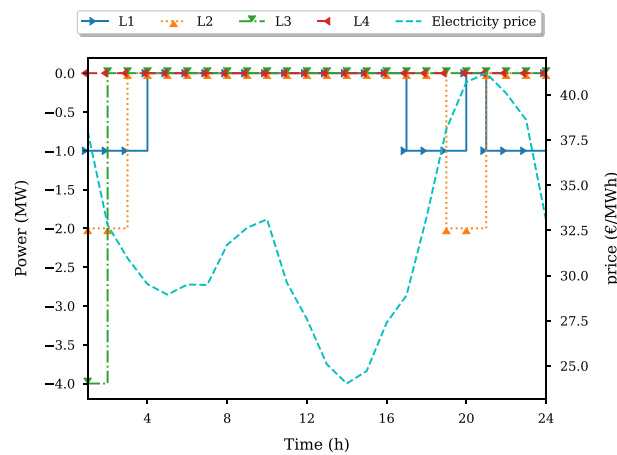


Fig. 4 Optimal scheduling for flexible loads in case I

The optimization reduces the power of flexible load *L3* by 4 MW only once during the entire optimization horizon. It makes the maximum profit based on the electricity market prices and the validity of this load, restricting its usage between 18:00 and 24:00. This restriction prevents the optimization from decreasing the power consumption when the electricity prices are the highest (19:00–23:00).

Concerning the last flexible load, the optimization does not activate (reduce the power of) *L4* since it has an activation cost, and it will decrease the total profit.

Finally, the model needed 0.180 s to converge in this use case to optimize these four flexible loads.

Use case II—flexible loads with dependencies

This second use case explores the capabilities of the optimization model when dealing more complex definition of flexible loads, as we consider dependencies between loads. In this use case, we consider a new four different loads without including a connection into a storage system. For this use case, the optimization model considers and implements the following:

- Optimization function: given by Eq. (1).
- Main constraints: subject to Eqs. (2)–(12).
- Dependencies constraints : subject to Eq. (17) for the $D_{start-start-after}$ dependency and Eq. (19) for the $D_{end-start-after}$ dependency.

Similar to the previous use case, we offer in Table 4 an overview of the four flexible loads and their characteristics included in their EFD description. Additionally, we describe the dependency between loads in Table 5. As in the previous use case, we consider the same date, simulation horizon (24 h), and source for the electricity prices, the EPEX Day-ahead auction in the area of DE-LU on the 08/08/2020 (Bundesnetzagentur 2022).

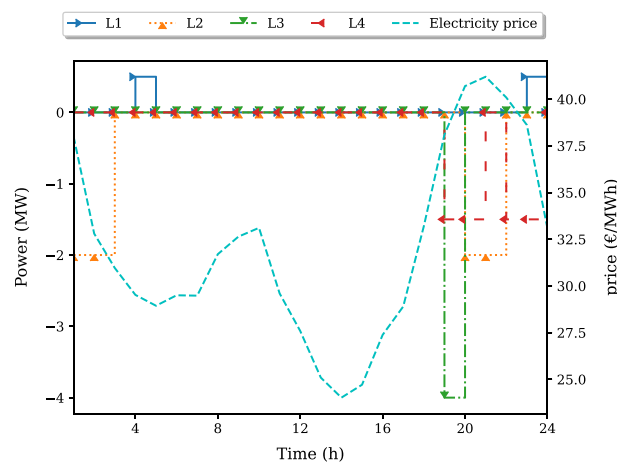
In this second use case, there is a mix of load types. Three loads (*L2*, *L3*, *L4*) are decrease type, while *L1* is increase type. In other words, the flexible load *L1* can increase

Table 4 Load's characteristics considered in use case II

| key figure | Units | L1 | L2 | L3 | L4 |
|-----------------------|-------|----------|----------|----------|------------|
| Load deviation type | – | Increase | Decrease | Decrease | Decrease |
| Power state | MW | [0.5, 1] | [2, 2] | [3, 4] | [0.5, 1.5] |
| Validity restrictions | Time | None | None | None | None |
| Activation costs | € | 0 | 0 | 0 | 0 |
| Holding duration | h | [1, 3] | [1, 2] | [1, 1] | [2, 2] |
| Regeneration time | h | 0 | 0 | 0 | 0 |
| Usage Number | – | [0, 3] | [0, 2] | [0, 1] | [0, 2] |

Table 5 Characteristics of dependencies in use case II

| Trigger load | Dependent load | Dependency type |
|--------------|----------------|--|
| L2 | L1 | L1 must start 1–3 h after the activation of L2 |
| L3 | L4 | L4 must start 2 h after deactivation of L3 |

**Fig. 5** Optimal scheduling for flexible loads in use case II

its power consumption contrary to the other loads. All loads in this use case have continuous power states, meaning they can only decrease or increase their power consumption by the values collected in Table 4. None of the loads have any activation costs or regeneration time. However, all loads face limitations imposed by the holding duration and the usage number. The former requires $L1$ to remain a minimum of one and a maximum of 3 h in each activation period. The latter limits the optimization to use a maximum of three times $L1$.

We collect the results of the optimization in Fig. 5.

The results provided by the optimization follow the imposed restrictions. On the one hand, the first dependency ($D_{start-start-after}$) in Table 5 forces $L1$ activation between 1 and 3 h after the activation of $L2$. In other case the optimization activates $L2$ between 01:00 and 03:00 while $L1$ between 05:00 and 06:00. However, the $L1$ and $L2$ dependency prevents $L1$ from increasing its power consumption during the lowest electricity price

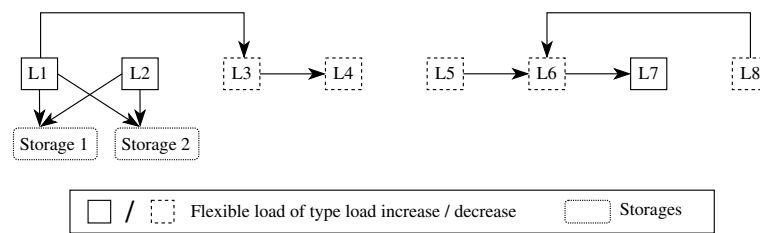


Fig. 6 Relationship between flexible loads and storages in use case III

Table 6 Characteristics of the loads' key figures of use case III based on the description of the EFDM

| key figure | Units | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 |
|-----------------------|-------|----------|----------|----------|-----------|-----------|-----------|-----------|-----------|
| Load deviation type | – | Increase | Increase | Decrease | Decrease | Decrease | Decrease | Increase | Decrease |
| Power state | MW | [1,2] | [2,2] | [1,2] | [0.5,1.5] | [2.2,2.7] | [1.8,3.2] | [1.2,2.2] | [1.3,1.7] |
| Validity restrictions | Time | None | None | None | None | None | None | None | None |
| Activation costs | € | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Holding duration | h | [1,3] | [1,2] | [1,3] | [2,3] | [1,2] | [1,1] | [1,1] | [1,2] |
| Regeneration time | h | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Usage Number | – | [0,5] | [0,4] | [0,2] | [0,3] | [0,1] | [0,2] | [0,2] | [0,3] |

period (13:00–15:00). The optimization considers the same logic for the second activation of $L2$ at 20:00 given the constraint of $L2$; the optimization can only activate it twice. On the other hand, the second dependency forces the optimization to use $L4$ after 2 h of deactivating $L3$. The optimization activates $L3$ by decreasing 4 MW the power and decreasing, 2 h later, by 1.5 MW the power consumption of $L3$. However, since $L4$ can have two activations, the optimization between 19:00 and 21:00 decreases by 1.5 MW the power of $L4$. For this use case, the optimization model needed 0.112 s.

Use case III—flexible loads with dependencies and storages

This last use case explores an even more complex case than the previous ones. In this use case, the optimization faces eight flexible loads with several dependencies. Additionally, this use case includes two storages systems. We depict this complex relationship in Fig. 6.

For this complex use case, the optimization implements:

- Optimization function: given by Eq. (1).
- Main constraints: subject to Eqs. (2)–(12).
- Dependencies constraints: subject to Eq. (17) for the $D_{start-start-after}$ dependency and Eq. (19) for the $D_{end-start-after}$ dependency.
- Storage constraints: subject to Eqs. (13)–(16).

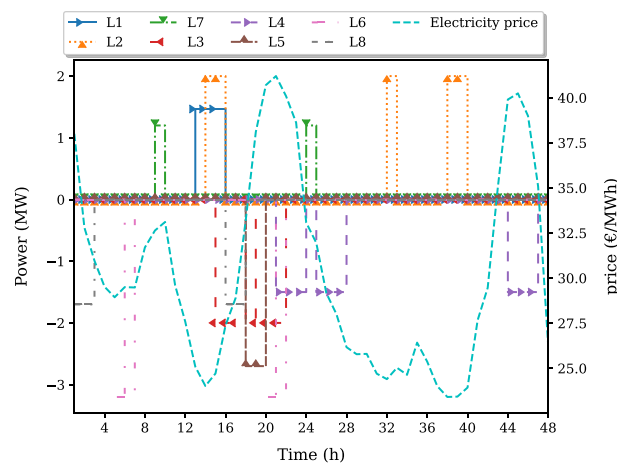
As previous use cases, we collect in Table 6 all flexible loads' characteristics contained in the EFDM description. Additionally, we collect in Table 7 the description of the dependencies constraints the loads have, whereas in Table 8 we collect the description of the two storages present in the use case. Both storages have 10 MWh capacity, modeled with 0 energy loss and specified drain time and quantity. Storage 1 should be drained between

Table 7 Characteristics of dependencies in use case III

| Trigger load | Dependent load | Dependency type |
|--------------|----------------|--|
| L1 | L3 | L3 must start 2 h after the activation of L1 |
| L3 | L4 | L4 must start 3 h after the deactivation of L3 |
| L5 | L6 | L6 must start 3 h after the activation of L5 |
| L6 | L7 | L7 must start 3 h after the activation of L6 |
| L8 | L6 | L6 must start 3 h after the deactivation of L8 |

Table 8 Characteristics of storages in use case III

| Storage | Max capacity [MWh] | Energy loss [MW/h] $E_{e,loss}$ | Drain time [hour] $T_{drain,e}$ | Drain quantity [MW] $\rho_{e,t,drain}$ | Connected to |
|-----------|--------------------|---------------------------------|---------------------------------|--|--------------|
| Storage 1 | 10 | 0 | [19,21] | 1 | L1, L2 |
| | | | [36,38] | 1.2 | |
| Storage 2 | 10 | 0 | [15,17] | 1.5 | L1, L2 |
| | | | [43,45] | 1.1 | |

**Fig. 7** Optimal scheduling for flexible loads in use case III

hours 19–21 and 36–38 with the power equal to 1 and 1.2 MW, respectively. Likewise, Storage 2 should be drained between hours 15 and 17 with 1.5 MW and during hours 43–45 with the amount of 1.1 MW. Both flexible loads, *L1* and *L2* connect to each storage system and have conversion efficiency (eff_i) equal to 1. Following the previous two use cases, the electricity prices input for the optimization considered corresponding to the EPEX Day-ahead auction DE-LU. In this case, the simulation horizon considers 48 h, therefore, the prices are for 08/08/2020, and 09/08/2020 (Bundesnetzagentur 2022).

We depict the optimization results in Figs. 7 and 8. The former presents the optimal load schedule for all loads. The latter presents the scheduling for the storage systems. The loads *L1* and *L2* must charge the storage systems to provide the energy demand required by the industrial process during the drain times. Therefore, it uses *L1* and *L2*

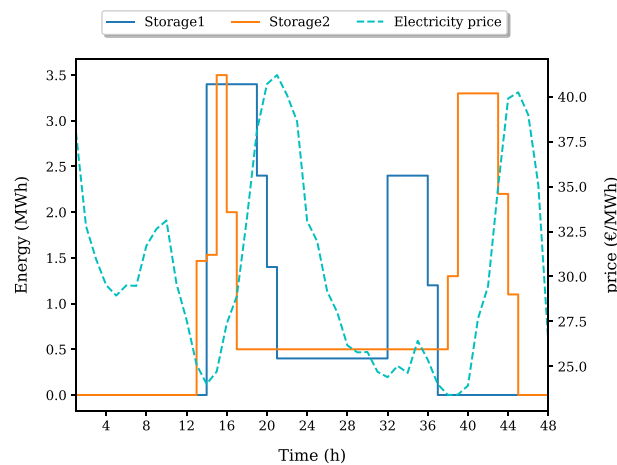


Fig. 8 Optimal scheduling for storages in use case III

several times during the optimization horizon (48 h) in the low-price hours accordingly between hours 12:00–26:00 and 32:00–40:00 (see Fig. 8). From our results (see Fig. 7), we can observe that optimization can deal with difficult constraints. For instance, $L1$, $L2$, and $L7$ increase their power consumption when prices are low without exciding the number of times the optimization can activate them. Nevertheless, these complex constraints provoke the activation of some flexible loads when the electricity price is not at its highest. For instance, the optimization activates $L6$ at hour 06:00, not the highest price hour, because it depends on $L8$.

Overall, all these complexities impact the optimization model, which requires a total of 3.3 s to converge.

Discussion

We tested the model in three synthetic use cases developed from discussions with aluminum and paper industries, where we exposed the optimization model against an increasing complexity in the industrial process description. We acknowledge the limitations of our evaluation, especially by not considering an existing industrial process due to the unavailability of data and not comparing our results to the benchmark of an exact process modeling.

Nevertheless, the model we propose performs as intended. We demonstrate the model's capability to offer a solution when facing complex EFDM descriptions. Examples of complex EFDM description are continuous power states, regeneration time, energy and material storage modeling, activation/deactivation ramping, different modulation numbers, holding durations, dependencies between flexible loads, and even connections to storage systems. The model's ability to handle EFDM descriptions has implications.

First, the optimization model does not require information on material flow nor information about the baseline power consumption of the industry, which industrial companies are not usually willing to share due to competitiveness. Thus, industrial companies can describe their processes without disclosing sensitive data and minimizing the necessary information. However, certain information still is required for the description using the EFDM, but not intrusive. On the one hand, the optimization using the EFDM might

yield a worse result than the exact modeling of a specific industrial process. However, it might depend on the level of detail expressed in the flexibility description using the EFDM. On the other hand, the model is generic and serves its purpose for any industrial process described using the EFDM. Consequently, the model is replicable. In other words, different companies can use the model for their industrial processes and would require only one model instead of many multiple specific models for each industrial process.

Second, the optimization model can handle different time steps (e.g., 1 h and 15 min) and horizons such as day-ahead and intraday markets, opening a potential marketing opportunity for industrial companies. However, the model might face constraints (i.e., computation time and resources needed) when calculating the optimal solution with many loads, dependencies, and storage systems.

Third, even though this paper concentrated on testing the model for industrial flexibility, the applications of the proposed optimization model can go beyond the industrial sector. For instance, if electric vehicles and residential buildings use the EFDM to describe their flexibility, they could use the model.

Conclusions

We presented an optimization model to generate an optimal load schedule based on electricity prices and a generic data model for flexibility description, the EFDM. The model provides the schedule also using the EFDM description, simplifying the communication, technical, and economic issues specific use-case-oriented optimization models face. We evaluated the model under several use cases to demonstrate its capabilities when facing simple or complex industrial flexibility descriptions considering electricity prices from a day-ahead market. The model handled all the complexities, although the computation time and complexity grow as the optimization needs to consider more flexible loads and dependencies between loads and storage systems. Therefore, the model might face some limitations against a significant number of variables or when misused (i.e., used for whole industrial process scheduling). Future research could tackle some inefficiencies (computation time) and other limitations we acknowledge (comparison of the results with an exact optimization model). Nevertheless, the proposed optimization model could help industries market their flexibility. The model could enable any demand-user, such as residential or electric vehicle charging management operators, to use the generic optimization model if they describe their flexibility using the EFDM.

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Author contributions

All authors contributed to the conception of the research. RB, MS and SPM contributed to the design of the work. RB, CvS and SPM drafted the first version of the paper. MS and GF supervised the research conception, provided feedback and participated in the paper revision. All authors read and approved the final manuscript.

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Declarations**Competing interests**

The authors declare that they have no competing interests.

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