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Stochastic net load optimization in distributed integrated energy systems - A forecast based scheduling approach

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ABSTRACT

The increasing integration of decentralized and volatile producers and consumers across sectors (electricity, heating and mobility) introduces significant operational challenges for distributed energy systems. This work presents a systematic stochastic optimization approach for generating day-ahead operation schedules in sector-integrated energy systems based on probabilistic net load forecasts, for local applications that require low data, low computing power and enable a high level of data security. The proposed method enables more robust decision-making under uncertainty, overcoming the limitations of deterministic point forecasts and optimizations or the requirements for large amounts of data.

The approach is demonstrated using the energy system of a logistics facility, focusing on the electrical preconditioning of refrigerated trailers under varying daily preconditioning frequencies. The study outlines how probabilistic net load forecasts can be transformed into representative scenarios and implemented as stochastic net load inputs within the energy system model.

A comparative analysis between the scenario-based stochastic optimization and three deterministic optimization variants highlights the advantages of the proposed approach. The stochastic method achieves up to 25 % lower total operating costs and reduces daily peak power exceedances by 30 to 66 % compared to deterministic scheduling. Furthermore, the analysis of regret costs indicates average daily reductions between 21 % and 69 %, depending on the number of reefers to be preconditioned, demonstrating enhanced robustness, cost efficiency, and operational reliability under forecast uncertainty.

1. Introduction

1.1. Motivation

The transformation of the energy system and in particular the expansion of renewable energies is growing rapidly. According to IEA forecasts, this growth will double (European Union or United States) or more than triple (China, India or Sub-Saharan Africa) in various regions of the world by 2030 [1]. This trend and its effects can already be observed today. The study of [2] highlights key challenges in achieving net-zero energy systems, including the integration of variable renewable energy, the need for efficient energy storage, limitations of current grid technologies, and inefficiencies in building energy management. Proposed solutions include advanced energy system modeling, technological innovation in storage and smart grids, and holistic approaches to optimize synergies across the energy system. The needed transformations of the energy sectors leads to great challenges especially in distributed energy systems. The electrification of more and more sectors towards an integrated sector coupled energy system and the synchronization with a growing share of renewable energy generation increases the need for predictive power and energy management solutions [3]. Small energy systems are particularly affected. The integration of, for example, a PV system, a heat pump and electromobility poses significant challenges for the balance of distributed energy systems and the connected public grid. But it provides also potentials of flexibilities and innovative cost efficient solutions [4,5]. An important parameter to show this synchronization or balance between load and renewable generation is the net load (NL). It indicates at which point in time more generation (negative NL), more consumption (positive NL) or it is exactly balanced (NL is zero). However, the sector coupling (sector integration) of the electricity, heating and mobility sectors also offers opportunities [6]. The article “Advancements in Smart Energy System Operation and Planning” emphasizes the importance of integrated, sector-coupled approaches that coordinate technologies, markets, and energy sectors to achieve effective decarbonization [7]. In addition

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Nomenclature

Abbreviations

ANN	Artificial Neural Network
CBC	Coin-or Branch and Cut solver
CDF	Cumulative Distribution Function
CVaR	Conditional Value at Risk
DES	Distributed Energy System
DR	Demand Response
EMS	Energy Management System
EV	Electric Vehicle
IEA	International Energy Agency
KPI	Key Performance Indicator
LP	Linear Programming
MILP	Mixed Integer Linear Programming
ML	Machine Learning
MTU	Market Time Unit
NL	Net Load
OEMOF	Open Energy Modeling Framework
PCHIP	Piecewise Cubic Hermite Interpolating Polynomial
PDF	Probability Density Function
PSLP	Personalized Standard Load Profile
PV	Photovoltaic
RLM	Registering Load Profile Measurement
SP	Stochastic Programming

Constants and Variables

$\Delta E_{\max}$	Excess energy due to $\Delta P_{\max}$ [kWh]
$\Delta P_{\max}$	Power exceedance above threshold [kW]
$\eta_i(t)$	Efficiency of input i at time t
$\eta_o(t)$	Efficiency of output o at time t
$C_{\text{energy,total}}$	Total energy cost (grid + PV) [ ]
$c_{\text{grid},t}$	Cost per unit of grid energy at time t [/kWh]
C_{grid}	Total grid consumption cost [ ]
$c_{\text{pv},t}$	Cost per unit of PV self-consumed energy at time t [/kWh]
C_{pv}	Total PV self-consumption cost [ ]
$C_{\text{service,total}}$	Additional service costs [ ]
c_{service}	Service cost rate for load threshold exceedances [/kWh]
$C_{\text{total,sum}}$	Total cost over observation period [ ]
$c_{i,t}$	Variable cost of unit i at time t [/kWh]
$E_{\text{total},t}$	Total energy at time t [kWh]
$g(x)$	Cost function value of a given optimization
$g(x^*)$	Cost function value of the perfect foresight benchmark
I	Set of all units, components, or processes in the energy system
$N_{\text{exceedances}}$	Number of time steps exceeding threshold
$P_i(t)$	Input power at time t for input i [kW]
$P_o(t)$	Output power at time t for output o [kW]
$P_{\text{net load},t}$	Measured real net load at time t [kW]
$P_{\text{peak,daily}}$	Daily peak power [kW]
$P_{\text{reefer},t}$	Reefer load at time t [kW]
$P_{\text{total,max}}$	Maximum peak load at grid connection [kW]
$P_{\text{total},t}$	Total load at time t [kW]
$Regret(x)$	Regret value of a solution compared to the perfect case
T	Set of all time steps (15-minute intervals)
$x_{i,t}$	Decision variable representing operation of unit i at time t

to decarbonization through the use of renewable energies, new business models can be developed through the optimized use of flexible consumers. Reliable operation schedules are needed for day-to-day business in all sectors. This requires forecasts for decentralized generation, methods for assessing uncertainty and operational optimization that takes this uncertainty into account [8]. But it is not only the uncertainty that needs to be measured. The article "Metrics to describe changes in the power system need for demand response resources" introduces seven metrics to assess how increased variable renewable energy generation and widespread deployment of energy efficiency measures affect the type, magnitude, and timing of demand response (DR) required to support the grid [9]. These metrics should help system operators identify complex interactions between demand-side and supply-side resources, ensuring that DR programs are designed to provide the most value to the evolving needs of the power system. In a dynamic integrated distributed energy systems (DES) with a high proportion of renewable generation from wind and solar power, solutions are needed that take this stochastic behavior into account in operation optimization. This paper shows an systematic approach how the local net load can be used for stochastic operational optimization in integrated DES.

1.2. Current state of research and related works

The use of forecasts of e.g. fluctuating wind and PV generation, but also the net load, to optimize energy systems has long been investigated in order to map the uncertainties as well as possible and thus minimize costs and maximize profits [10–12]. In particular, the net load forecast can be used as an indicator to predict the balance between load and generation within large and small scale energy systems [13,14]. These predictions are often based on the use of complex machine learning models that require a huge amount of data for training, as presented from [15,16] or [17]. Less frequently, in addition to the creation of prediction programs, compatibility with the application is also investigated or solutions are provided. Some of these studies deal with the use of deterministic forecasts in the energy management of decentralized energy systems, as described in [18–20]. However, one of the biggest challenges is to be able to assess and model the uncertainty in forecast based decision making, for which probabilistic methods are required [21]. To determine the net load probabilistically from generation and load forecasts requires the aggregation of probability densities and the modeling of independence of dependencies as [22,23] show in their work. Studies [17,24] introduce more complex machine learning approaches to predict the probabilistic net load and also discuss the use of non-parametric approaches. The study of [25] provides a comprehensive overview of net load forecasting methods, challenges, and applications, trends, highlighting that data-driven and hybrid machine learning approaches currently achieve the best performance, while a standardized and universally applicable forecasting framework is still lacking. However, net load is often viewed as a globally significant factor that indicates whether additional energy is required to cover consumption in addition to the generation of renewable energies. The authors consider it appropriate to use net load as a prediction and optimization variable in decentralized energy systems. It was first introduced as a prediction variable in [26] and, based on this, was used as an optimization variable in this study. Non-parametric approaches, as pursued in the previous work of this studies authors [26], are used less frequently. However, they are necessary in order to better model the variable behavior of generation and consumption in integrated DES. The approach of this study of using little data to make predictions of the net load in order to be able to make robust decisions under uncertainty while keeping sensitive data local and minimizing energy demand as well as data communication is pursued further in this study. The goal was to implement a stochastic scenario-based approach using the output of the "probabilistic net load forecasting framework" [26]. Stochastic programming or optimization has also been used for some time in the optimization of energy systems [27–30]. Stochastic programming aims to solve an optimization problem by considering multiple possible scenarios and determining the optimal decision that minimizes the expected objective function value [31]. The [29] study provides a comprehensive overview of stochastic optimization methods for renewable energy systems, analyzes their advantages and disadvantages and shows that these methods are superior to traditional deterministic approaches in social, technical and economic aspects to support an optimized integration of renewable energies into the grid. The study of [32] proposes an optimal scheduling strategy for mobile energy storage with variable-speed hydrogen-carrier vessels and solves it using a two-layer mixed-integer linear programming (MILP) optimization approach that first linearizes non-linear constraints and then coordinates power reserves and routing decisions for microgrid groups. The study of [33] develops a day-ahead scheduling optimization method for district integrated energy systems based on a "prediction-optimization" approach, which quantifies uncertainties in the energy forecast using a hybrid CEEMDAN-LSTM-GPQR (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise - Long Short Term Memory - Gaussian Process Quantile Regression) approach and enables more precise planning by means of stochastic optimization. Table 1 summarizes the contributions and limitations of literature, which relate most to the main contributions of our work.

In summary, it can be stated that there is a need for solutions for the optimized integration of renewable energy sources, that are not based on large amounts of data for and local applications with high data security requirements. Numerous scientific studies are already dealing with forecast-based operational optimization and approaches to decision-making under uncertainty. Many of these approaches are based on machine learning and require a lot of data to train the models. Also the use of stochastic optimization models has become increasingly important in energy system optimization in recent years. Stochastic operation optimizations in energy sector, were either based on very large energy systems or, when introduced for DES or microgrids, were based on large amounts of data input and ML (black box) approaches often with the goal of cloud applications. The authors see a need here to create a solution for integrated DES that is based purely on locally measured consumption and generation data and that runs reliably and robustly even in the face of uncertainty. The use of net load as a (stochastic) optimization variable has so far been considered for the market integration of renewables at the transmission grid level, but not for optimization in integrated distributed energy systems. Thus, the authors identify the local net load as the optimization variable, which, in contrast to the conventional net load, can take on positive and negative values and can indicate both the additional demand of a DES and surplus generation.

1.3. Contribution and distinction from previous work

In this paper, we present a scenario-based stochastic optimization approach for integrated distributed energy systems building on a probabilistic net load forecast and demonstrate the application of the integration of electrical preconditioning of refrigerated trailers (reefers) in a logistics property.

This work contributes to the optimized integration of renewable energies at the distribution grid level under uncertainty for applications with a high demand on data security. It is assumed that locally collected data can be used without dependence on third parties (e.g., a forecasting provider, cloud applications) and that reliable optimization is possible even without big data or complex and blackbox ML-models. Decentralized net load is an suitable optimization variable that can be used to optimally operate the increasing number of generation units, flexible consumers, and storage units in the integrated energy system. It is assumed that there is still a long way to go before smart meters are fully rolled out and data is completely available (especially in Germany). And even with a complete smart meter rollout and data availability, there will be various reasons why a company or even a private household would not want its consumption and generation data from its integrated DES to be handled by third parties. These could be security concerns, but also economic factors that do not allow for "expensive" forecast-based energy management. We see the need for local and robust solutions for forecast-based energy system optimization as the basis for exploiting the flexibility potential of decentralized generators, consumers, and storage units. This means operating an integrated DES in a way that benefits both the market and the grid. This is where we come in with the stochastic net load optimization approach and present a possible solution based on an applied example to demonstrate the functionality of the approach.

The contribution of this work essentially consists of the following parts:

- Presentation of an approach that systematically demonstrates how only locally collected data can be used to achieve robust stochastic day-ahead net-load optimization without relying on high computing power, cloud connectivity, big data or black-box ML models.
- Modeling of distributed net load for scenario-based stochastic optimization in the integrated energy systems. Reference model for stochastic optimization.
- Comparison and evaluation of the stochastic optimization approach with the results of deterministic optimizations. Using the example of scheduling optimization for electrically preconditioned reefers based on the net load of a logistics property.

In order to distinguish the contents of this work from previous works, reference should be made to the following works in which the authors or some of the authors are involved. In the work of [38], the modeling and operational optimization of reefers in an integrated DES is presented. In this work, the method for determining the electrical demand from reefer arrival and departure times and temperature setpoints is used, and a simplified form of reefer modeling is applied. From [26], we use the proposed method to create probabilistic net load forecasts as input data for this work. The resulting PDFs are the data input for our stochastic optimization approach. An initial idea of how uncertainty can be modeled in optimization with oemof.solph [37] was taken up and further developed by [36]. The combination of these approaches and new elements resulted in a proof-of-concept for a new stochastic net load optimization aimed at DES applications with high data security requirements and low computing power demand.

The non-objectives of this work are to develop a new scenario generation method nor to develop a stochastic optimization method or new mathematical formulations. In this work, a scenario-based approach is chosen to demonstrate the holistic approach from locally measured data, using a probabilistic net load forecast to optimize a DES under uncertainty, which performs more robustly compared to deterministic optimizations.

2. Methodology

2.1. Overview of the proposed approach

Fig. 1 shows an overview of the complete workflow of the study. The flowchart shows which input data (light yellow) and methods

Table 1
Comparison with most related work.

Source	Author/Year/Title	Main contribution	Limitations	Relation to this work
[10]	Zhang et al. (2023): *Net load forecasting and energy storage demand analysis for renewable energy integration*	Developed a combined forecasting and storage sizing model to balance renewable generation and demand.	Focuses on large-scale systems, not distributed ones.	Provides methodological background for integrating uncertainty in renewable systems.
[21]	Burghi et al. (2020): *Artificial Learning Dispatch Planning with Probabilistic Forecasts: Using Uncertainties as an Asset*	Proposed using probabilistic forecasts to enhance dispatch flexibility.	Focused on centralized grid operation.	Aligns conceptually with treating uncertainty as optimization input.
[22]	Binghui et al. (2021): *Copula-Enhanced Convolution for Uncertainty Aggregation*	Modeled correlations/dependencies between uncertain renewable and load forecasts using copulas.	Requires detailed dependency data.	Supports joint probabilistic modelling applied in this study.
[26]	Telle et al. (2023): *Probabilistic net load forecasting framework for application in distributed integrated renewable energy systems*	Proposed a convolution-based quantile regression framework for net load PDFs.	No optimization	Forms direct data basis (net load PDFs) for this study's scenario generation.
[25]	Tziolis et al. (2025): *Net Load Forecasting: A Comprehensive Literature Review*	Provided an extensive review of net load forecasting methodologies, including statistical, machine learning, and hybrid approaches, highlighting trends, challenges and applications.	Review-based; does not include an optimization or control framework.	Serves as a comprehensive foundation for probabilistic net load forecasting approaches and applications on different grid levels.
[28]	Alipour et al. (2018): *A multi-follower bilevel stochastic programming approach for energy management of combined heat and power micro-grids*	Formulated a bilevel stochastic model for CHP operation under uncertainty.	Complex model; tailored to CHP systems.	Demonstrates flexibility of stochastic models for multi-energy systems.
[34]	Tan et al. (2023): *A novel forecast scenario-based robust energy management method for integrated rural energy systems with greenhouses*	Proposed a robust scenario-based optimization for rural integrated energy systems with greenhouses.	Specific to agricultural contexts; high model complexity.	Reinforces the relevance of scenario-based stochastic control under uncertainty.
[32]	Sui et al. (2024): *Optimal Scheduling of Mobile Energy Storage Capable of Variable Speed Energy Transmission*	Formulated optimization for mobile storage with variable-speed energy transmission.	Focused on mobility constraints; large-scale scope.	Extends stochastic scheduling concepts toward dynamic energy transfer.
[35]	Yao et al. (2023): *Stochastic Economic Operation of Coupling Unit of Flexi-Renewable Virtual Power Plant and Electric Spring in the Smart Distribution Network*	Stochastic optimization framework for coordinated operation of VPPs and electric springs enabling joint energy and reactive power market participation under uncertainty.	Parametric uncertainty modelling approach requires assumptions about distributions.	Provides a methodological basis for uncertainty-aware distribution-level analysis
[36]	Schönfeldt et al. (2025): *Considering Uncertainty in Energy System Optimisation*	Discussed strategies for explicitly representing uncertainty in energy system models.	Conceptual	Supports this work on the use of oemof.solph [37] for the optimization of energy systems, taking uncertainty into account.

(light gray) are used for each step of the work and what results (light green) are produced. In addition, the main part, the stochastic net load optimization model, and the deterministic comparison model are shown in light blue. Accordingly to Fig. 1, the work can be structured into five parts.

1. The creation of day-ahead net load forecasts (PDFs) is based on the "probabilistic net load forecasting framework" which the authors have published in [26] and whose results will be further used in this work. In addition, deterministic forecasts are generated on the basis of a PSLP, which are used at a later date as a comparison scenario, and load profiles for the electrical preconditioning of reefers are generated (more details on this in Section 2.2).

2. In the second step of the paper, a method for generating scenarios from the probabilistic forecasts or probability density functions (PDF) is presented. To this end, a procedure was developed to generate the scenarios on the basis of convolved PDF of the net load and power differences between two time steps, with the option of restricting these through specific boundaries (described in Section 2.3).

However, other PDF's from different probabilistic net load forecasts or scenarios from different scenario generation methods and number of

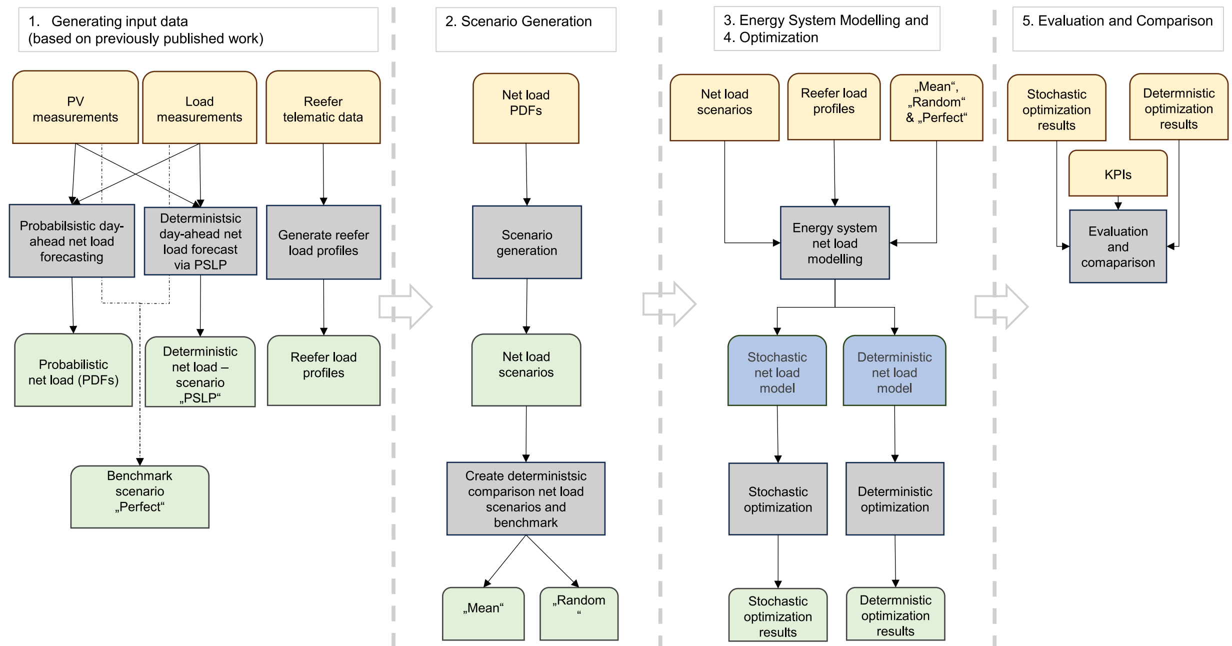

Fig. 1. Work Flow.

scenarios can also be used to generate input data and apply them for the stochastic optimization. Thus, the authors aim to present a systematic approach and to show the entire process, from data collection to optimization.

3. In the third step, the modeling of the energy system is presented, which is modeled and optimized using the open energy modeling framework (oemof) [37]. The main contribution is on implementing the net load in a decentralized and integrated energy system and introducing the possibility to process a large number of scenarios 2.5.

4. In step four, the applicability of stochastic operational optimization based on the net load 2.6 is demonstrated in a case study. The decentralized integrated energy system of a logistics property was selected for this purpose. The main objective is to precondition refrigerated trailers (reefers) at optimum cost within a specified time. To introduce variation into the optimization, different reefer cases are considered, which differ in the number of reefers to be preconditioned at the site 2.4.

5. In step five, the optimization results are evaluated and compared with those of a deterministic optimization and discussed. This work is a proof of concept for the methods presented. The aim is not to compare it to other methods that, for example, are based on a big data approach or involve complex multi-stage stochastic programs.

2.2. Data description

The following section describes and presents the data used in the work. A 15-minute resolution was chosen since the measured power data from [39] comes from an RLM-measurement (registered power measurement; german: "*registrierende Lastgangmessung*"), which typically provides a 15-minute resolution. Furthermore, this resolution is based on the 15-minute market time unit (MTU) of the intraday market and day-ahead market (since October 2025) of EPEX SPOT [40].

Table 2 shows the data used in the work and indicates their origin.

The local net load of the energy system under consideration P_{net} is calculated as the measured electrical demand P_{demand} minus the measured PV generation P_{PV}:

$$P_{\text{net}} = P_{\text{demand}} - P_{\text{PV}} \tag{1}$$

This can be transferred to determine the net load from the PSLP forecasts for electrical load and PV generation. To generate PSLP load and generation profiles are classified according to type of day (weekday, Saturday, Sunday/holiday) and seasonal characteristics (summer, winter, and transition periods) based on local measurement values from decentralized electrical consumers and generators and publically available weather reports. These profiles are then used to calculate personalized standard load profiles (PSLP) based on a defined number of profiles with the same characteristics from previous days and season, which can be also used as day-ahead forecasts (A more detailed description can be found in [26]). The probabilistic forecasts or rather the resulting PDFs used in this paper are based on the work of the authors and were published in [26]. Here, in a first step, In a second step, quantile regression is used to generate non-parametric probabilistic load and generation forecasts, quantile PSLP (QPSLP) from the PSLP. In a third step, the CDFs are determined and PDFs derived from the QPSLP using spline interpolation, separately for each point in the forecasted time series. Assuming that consumption and generation are mathematically independent of each other, the net load is determined by convolving the PDFs of generation and consumption. For this work, PDF files were created for the net load from electrical consumption and PV generation. The resulting CDFs were shown as heatmap in Fig. 2 for the entire observation period.

The work were performed on a standard commercial computer with a processor of the 11th Generation (i7-11850H, 2.50 GHz, 8 cores) and 16.0 GB of installed physical memory (RAM).

2.3. Scenario generation

CDFs and PDFs of the net load were generated and used as database for scenario generation in accordance with the procedure described in Section 2.2. The procedure for generating the scenarios can be divided into 4 main steps and is based on the probability distributions PDF of the net load PDF. In the following, the PDF is defined as a function of the power f(P) and the CDF as F(P).:

1. **Initialization and Selection of the Start Value**
   For the first timestep t_0, an initial power value P_0 is selected based on the probability distribution $f_{t_0}(P)$ of power values P:

$$P_0 \sim f_{t_0}(P) \tag{2}$$

Table 2
Overview of the data used in this study.

Data Type	Description	References
Electricity demand	P_{demand}; Measured power demand with 15-minute resolution.	[39]
PV generation	P_{PV}; simulated using `pv_lib` for a 200 kW_{peak} system, based on publicly available weather data. The PV system is east–west oriented with a 10° inclination angle and 15-minute resolution.	[41], [42]
Probabilistic da-ahead net load forecasts	Probability density functions (PDF) generated from the "net load forecasting framework" in a 15-minute resolution.	[26]
Deterministic net load forecast	Calculated from PSLP of load and PV generation in a 15-minute resolution	[26]
Synthetic reefer tours	Generated synthetic reefer tours (times of presence at the site) and temperature setpoints in a 15-minute resolution.	[43]
Reefer energy demand	Calculated energy demand for preconditioning (pre-cooling or heating) from synthetic reefer tours. Energy that had to be absorbed at the latest at the time of attendance.	[43]
Observation period	October 01, 2021 – July 14, 2022.	–

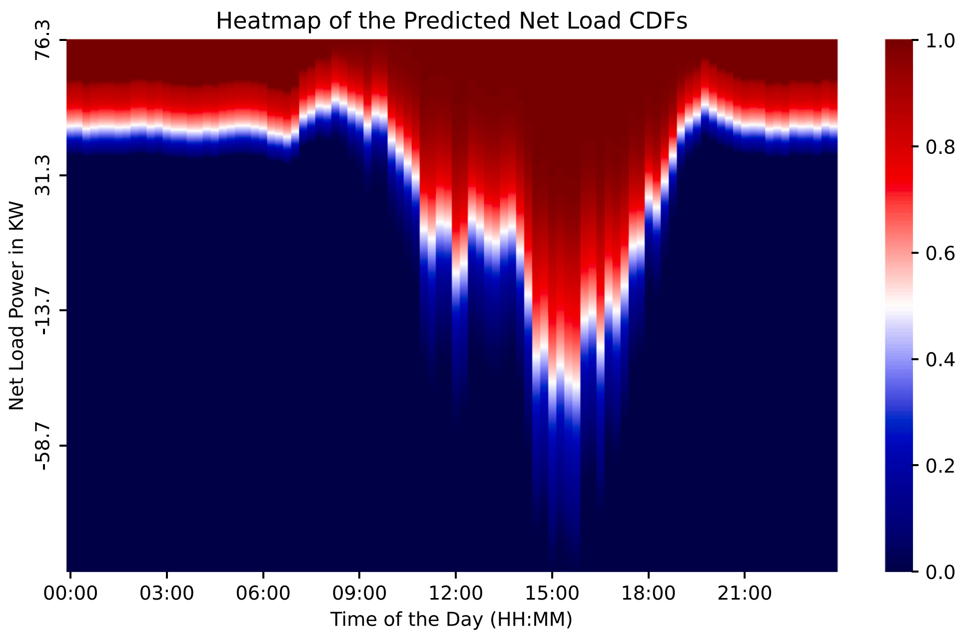

Fig. 2. Heatmap of the cumulative distribution functions (CDFs) of predicted net loads from [26] for every 15 min of an randomly chosen day, showing the 1st to 99th percentile range.

Here, P_0 is drawn as a random variable according to the normalized probability distribution at timestep t_0:

$$f_{t_0}^{\text{norm}}(P) = \frac{f_{t_0}(P)}{\sum f_{t_0}(P)} \tag{3}$$

2. **Limiting Power Changes via Quantiles**
For each subsequent timestep t_k, where $k = 1, 2, \ldots$, the cumulative distribution $F_{t_k}(P)$ of the normalized probability distribution is computed:

$$F_{t_k}(P) = \int_{-\infty}^{P} f_{t_k}^{\text{norm}}(P')\, dP' \tag{4}$$

To smooth the range of power values, upper and lower bounds can be determined (e.g., the 5th and 95th percentiles). To demonstrate the approach, this paper sets the lower limit at the 5th percentile and the upper limit at the 95th percentile, thus considering 90% of the probability mass in the scenario generation. This is a scientific guess for the data discussed here and will not be considered further in this paper. The selected boundaries can be freely chosen and can be determined, for example, depending on the distribution of the input data.

$$P_{\text{low},t_k} = F_{t_k}^{-1}(0.05), \quad P_{\text{up},t_k} = F_{t_k}^{-1}(0.95) \tag{5}$$

Only the power values P within this range are considered for drawing the next timestep's power value:

$$P_{t_k} \in \{P \in \mathbb{R} \mid P_{\text{low},t_k} \le P \le P_{\text{up},t_k}\} \tag{6}$$

3. **Drawing the Next Power Value**
The next power value P_{t_k} is randomly drawn from the restricted and renormalized distribution (PDF) $f_{t_k}^{*}(P)$:

$$P_{t_k} \sim f_{t_k}^{*}(P), \quad P_{\text{low},t_k} \le P \le P_{\text{up},t_k} \tag{7}$$

Here, $f_{t_k}^{*}(P)$ is normalized over the valid range:

$$f_{t_k}^{*}(P) = \begin{cases} \dfrac{f_{t_k}(P)}{\sum_{P \in [P_{\text{low},t_k}, P_{\text{up},t_k}]} f_{t_k}(P)} & \text{if } P_{\text{low},t_k} \le P \le P_{\text{up},t_k} \\ 0 & \text{else} \end{cases} \tag{8}$$

Table 3
Overview of the optimization variants.

Optimization variant	Description
stochastic	Stochastic optimization, using N generated scenarios based on probabilistic net load forecast [26].
mean	Deterministic optimization, calculating the arithmetic mean of each time point of N generated scenarios.
random	Deterministic optimization, a randomly selected scenario is drawn from the N generated scenarios.
pslp	Deterministic optimization based on the forecast from a Personalized Standard Load Profile (PSLP) [38,44,45].
perfect	Deterministic optimization, use of the theoretical optimum with perfect foresight. Serves as a benchmark for a priori evaluation.

Table 4
Overview of the reefer cases.

Reefer Case	Description
"Low"	Initial case with a maximum of 37 preconditionings per day.
"Medium"	Doubling of tours with a maximum of 74 preconditioning events per day
"High"	Tripling of tours with a maximum of 111 preconditioning events per day.

4. **Iteration Across all Scenarios and Timesteps**
   This process is repeated for N scenarios, where each scenario consists of a sequence of power values across all timesteps. Each scenario is generated independently, and the percentile-based limits are applied at each timestep to avoid abrupt power changes. In this work, $N = 100$ is specified. It should be noted that this number is a scientific guess and not a fixed parameter required to use this approach. This parameter is not fixed and may be subject to future optimizations.

2.4. Optimization variants

The optimization is carried out and evaluated using the example of the implemented energy system (see Section 2.5). We distinguish between four different optimization variants and one benchmark case in which, with perfect foresight, we optimize with the actual measured data in retrospect, as listed in Table 3.

The "Mean" and "Random" comparison scenarios are drawn directly from the 100 scenarios generated from the PDFs of the probabilistic net load forecast. The PSLP is generated separately from the measured data, as described in Section 2.2. This is to ensure that stochastic optimization does not perform better than deterministic optimization based on the forecast quality or distribution of the forecasted data. On the other hand, it also allows for the generation of a comparison scenario ("PSLP") that is independent of probabilistic prediction and scenario generation.

The different forecast-based optimizations are compared with each other using the "perfect" benchmark case. We also differentiate between three different reefer cases "Low", "Medium" and "High". These differ in the frequency of tours that are to be electrically preconditioned (precooled or preheated) at the logistics property, as shown in Table 4. To determine the electrical power consumption of the reefers at the site, real telematics data on arrival and departure times and target temperatures were analyzed. This data was then used to develop a method for generating randomized synthetic profiles or a specific number of reefer tours with arrival and departure times and a target temperature. This data and the losses relative to the ambient temperature can then be used to determine the energy required to reach the setpoint by the last point in time of attendance at the latest. This method was described in detail in [43]. For modeling and optimization, the varying number of reefers means that a varying number of infrastructure elements must be taken into account in the modeling and additional variables in the optimization. The number listed in Table 4 indicates the day on which most preconditioning must be carried out. However, the number varies from day to day over the observation period.

2.5. Energy system modeling

The energy system was modeled using the Python framework oemof.solph [46]. oemof provides a powerful tool for modeling and optimizing energy systems with its oemof.solph library. It enables the representation of complex energy systems through a modular and flexible framework. Users can model energy flows within a system using predefined components such as producers (*Source*), consumers (*Sink*), storages (*GenericStorage*) and transformation processes (*Converters*). the modeling is based on the mathematical formulation of the components, utilizing Linear Programming (LP) or MILP.

In this work, a decentralized energy system is created that can represent both a deterministic and a stochastic part. An example of the energy system is shown in Fig. 3. In the case of the deterministic optimization variants ("mean", "random" and "pslp"), the upper illustration in Fig. 3, A., is omitted and the system consists of a net load, the local grid and the reefers with its connections points. In the stochastic part, Fig. 3, B., the net load is generated as often as the number of generated scenarios (N scenarios).

Basically, the model is building upon the energy system model of the logistic property described in [43]. Unlike in [43], electrical demand and PV generation are modeled as net load. Here in both the deterministic and stochastic energy system. In addition to the net load, the energy system consists of the charging stations for the preconditioning (pre-heating or cooling) and the reefer trailers themselves, which are only present temporarily. The reefer presence time at the site and the temperature setpoint is assumed to be perfectly foreseeable due to a telematic system.

The net load is modeled as shown in Fig. 4, which is composed of various oemof.solph components. The net load consists of two central bus components: the "Net Load" and the "Scenario Bus". A "Grid In" source is implemented for the grid supply and a "Grid Out" sink for PV surplus. Since the property's grid connection is limited to a maximum value, there is an additional "penalty" source that makes it significantly more expensive (we have set 10 times) to draw power. In our case, these costs could be understood as the cost of expanding the grid connection or as the diesel costs for preconditioning the reefers when there is not enough electricity available at certain time. The penalty source is an important part of the modeling part. It indicates whether the system is under-dimensioned with its PV and the limited grid connection point. Typically, no energy should be obtained from this source, but it helps to avoid of creating infeasible problems and to quickly identify errors in the dimensioning. Depending on how many scenarios are considered in the optimization, the net load with all components is created as often as the number of scenarios. Stochastic

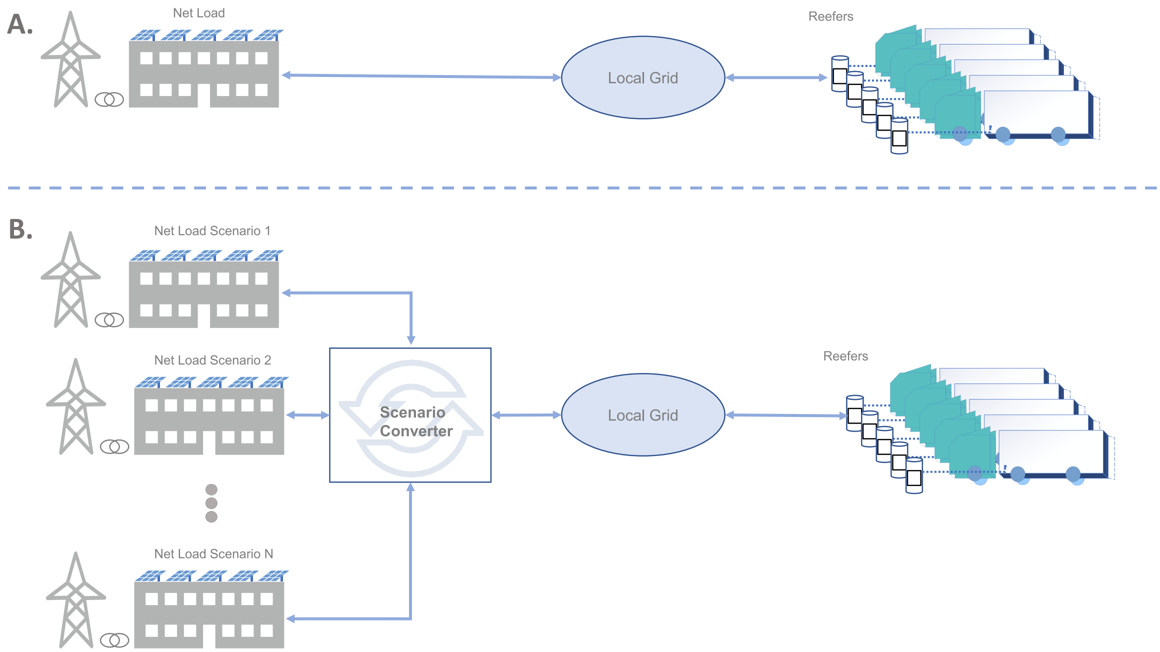

Fig. 3. Flow chart of the integrated stochastic net load model (left), the deterministic net load (top right) and the reefers to be planned (bottom right).

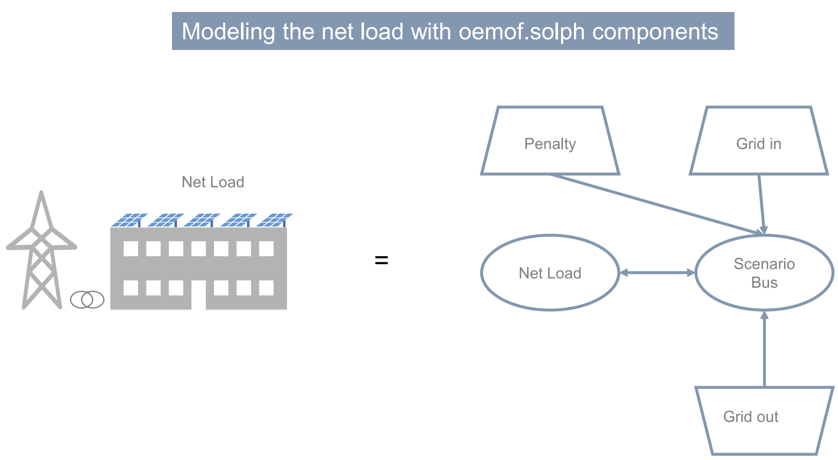

Fig. 4. Components of the modeled net load.

and deterministic systems are connected via a converter component called "Scenario Converter", building on the work of [36].

The linear relation of input an output of the "Scenario Converter" is given as:

$$P_i(t) \cdot \eta_o(t) = P_o(t) \cdot \eta_i(t) \quad \forall (i, o, t) \tag{9}$$

where:

- $P_i(t)$: Input power at time t for input i,
- $P_o(t)$: Output power at time t for output o,
- $\eta_i(t)$: Efficiency of input i at time t,
- $\eta_o(t)$: Efficiency of output o at time t.

This equation ensures the balance of power between inputs and outputs, adjusted by their respective efficiencies, at each time step t.

$$\sum_i P_i(t) \cdot \eta_o(t) = \sum_o P_o(t) \cdot \eta_i(t) \quad \forall t \tag{10}$$

If not otherwise defined with different weightings, this also applies to the sum of all inputs and outputs.

This equation ensures that the sum of all input powers, weighted by their efficiencies, equals the sum of all output powers, weighted by their efficiencies, for every time step t. The sum of the input and output weights is equal to 1 and ensures that we find an operating mode that works in all scenarios. These weightings can be adjusted if necessary to give extra weight to certain scenarios.

$$\sum_i \eta_i = 1 \quad \text{and} \quad \sum_o \eta_o = 1 \tag{11}$$

We take advantage of this. For a large number of scenarios, there is a correspondingly large number of net load groups of components, that are considered equally likely during the optimization.

2.6. The process of net load optimization

Stochastic programming is an optimization technique that is used to take into account uncertainties in decision-making processes. It is used when one or more parameters of an optimization problem are random and can be described by a probability distribution. The purpose of stochastic programming is to be able to make decisions that are robust in the face of uncertainty. In this work, the approach will be pursued of using the "scenario converter" (described in the previous Section 2.5) and probabilistic day-ahead net load forecasts to achieve robust operation optimizations in the described decentralized sector coupled energy system.

The linear optimization problem in oemof.solph can be expressed as minimization problem as follows:

$$\min \quad \sum_{t\in T}\sum_{i\in I} c_{i,t}\cdot x_{i,t} \tag{12}$$

- T: Set of all time steps (15-minutes) over which the model is optimized.
- I: Set of all units, components, or processes in the energy system (e.g., net-load, storage, reefers).
- $c_{i,t}$: Variable costs of unit i (kWh) at time t, such as costs for grid supply, operational costs, or CO_2 costs.
- $x_{i,t}$: Decision variable representing the operation of unit i at time t, such as energy flows or capacities.

To solve the linear program, we use a CBC solver. The CBC (Coin-or Branch and Cut) solver is an open-source mixed-integer programming (MIP) solver developed by the COIN-OR project [47]. It is designed to solve linear optimization problems, including linear programming (LP) and mixed-integer linear programming (MILP). CBC uses a branch-and-cut algorithm, which combines branch-and-bound techniques with cutting planes to efficiently handle integer constraints to find a global optimum [47].

2.7. Evaluation

2.7.1. Key performance indicators (KPI)

In order to evaluate which solution performs most cost-efficiently and runs most robustly benchmarked by the perfect solution, we first calculate the sum of the net load (perfect) and the respective prediction-based ("stochastic", "mean", "random" and "pslp") optimization and reefer scenarios ("Low", "Medium", "High"). This sum is defined as the "total load" depending on the different optimization and reefer scenarios. The total load $P_{\text{total},t}$ at a specific time t, calculated as the sum of the measured real load and the predicted reefer loads across all optimization variants j and reefer cases k. All calculations in the further course apply to all j and k and are not listed further.

$$P_{\text{total},t} = P_{\text{net load},t} + P_{\text{model},t} \tag{13}$$

- $P_{\text{total},t}$: The total load at time t.
- $P_{\text{net load},t}$: The measured real net load at time t.
- $P_{\text{reefer},t}$: The predicted reefer load at time t.

To measure and compare the performance of the optimizations, we define two target indicators: the maximum peak load $P_{\text{total, max}}$ at the grid connection point in kW and the total costs $C_{\text{total, sum}}$ over the observation period in €. These two target KPIs were selected because they allow technical and economic conclusions to be drawn about the DES under consideration. On the one hand, operating costs can be used to make a comparison with the status quo. On the other hand, they could also be used to evaluate investment decisions in, for example, renewable energy generation or a management system. The evaluation of peak loads has both a technical and an economic component. High peak loads may also mean high capacity charges (e.g. in Germany) and offer potential cost savings. From a technical point of view, peak loads are interesting for the house connection point or the distribution network, and it is possible to evaluate how network-friendly the DES operates, both in terms of feed-in and consumption behavior.

Total Costs:

The **total costs** $C_{\text{total, sum}}$ consist of two components: energy costs and additional service costs.

The energy costs $C_{\text{energy, total}}$ include:

- Costs for grid consumption C_{grid}: These costs occur when the total power P_{total} is higher than zero ($P_{\text{total}} > 0$).
- Electricity generation costs of PV (assuming that no taxes, levies or charges are incurred for self-consumption) C_{pv}: These costs are incurred in the range where the net load is less than zero and less than P_{total} ($P_{\text{net}} < 0 < P_{\text{total}}$).

The total energy costs can be expressed as:

$$C_{\text{energy, total}} = C_{\text{grid}} + C_{\text{pv}} \tag{14}$$

The grid consumption costs are defined as:

$$C_{\text{grid}} = \sum_{t\in\{t:P_{\text{total},t}>0\}} E_{\text{total},t}\cdot c_{\text{grid},t} \tag{15}$$

Where:

- $E_{\text{total},t}$: Total energy at time t in kWh.
- $c_{\text{grid},t}$: Cost per unit of grid energy at time t in €.
- t: Time points where $P_{\text{total},t} > 0$.

The PV self-consumption costs are defined as:

$$C_{\text{pv}} = \sum_{t\in\{t:P_{\text{net load},t}<0<P_{\text{total},t}\}} E_{\text{total},t}\cdot c_{\text{pv},t} \tag{16}$$

Where:

- $c_{\text{pv},t}$: Cost per unit of PV self-consumed energy at time t in €.
- t: Time points where $P_{\text{net},t} < 0 < P_{\text{total},t}$.

Additional Service Costs:

The **additional service costs** $C_{\text{service, total}}$ are incurred when the total power drawn from the grid exceeds the power limit of 120 kW ($P_{\text{total}} > 120\,\text{kW}$) during any time period. These service costs are calculated on the basis of the difference between the maximum power value P_{max} and the limit of 120 kW, the duration of the exceedance in h and a service cost rate of 3 €/kWh (set as 10 times the value of the fixed costs).

1. For each optimization scenario j and case k, the maximum power P_{max} is determined for each month:

$$P_{\text{max}} = \max_{t\in T} P_{\text{total},t} \tag{17}$$

2. The difference between P_{max} and the threshold value (120 kW) is calculated. Only values where $P_{\text{max}} > 120\,\text{kW}$ are considered:

$$\Delta P_{\text{max}} = \max\left(P_{\text{max}} - 120,\ 0\right) \tag{18}$$

3. The excess power ΔP_{max} is converted into energy (ΔE_{max}) by considering a 15-minute time resolution:

$$\Delta E_{\text{max}} = \frac{\Delta P_{\text{max}}}{4} \tag{19}$$

4. The additional service costs are then calculated by multiplying the excess energy ΔE_{max} with the service cost rate c_{service} (€/kWh):

$$C_{\text{service}} = \Delta E_{\text{max}}\cdot c_{\text{service}} \tag{20}$$

Where:

- c_{service}: The cost per unit of energy (€/kWh).
- ΔP_{max}: The power consumption in excess above 120 kW.
- ΔE_{max}: The excess energy consumption (kWh).
- C_{service}: The service cost

Finally, the total costs $C_{\text{total, sum}}$ are:

$$C_{\text{total, sum}} = C_{\text{energy, total}} + C_{\text{service}} \tag{21}$$

Load Peak Performance

The second key performance indicator is the peak load performance, which is statistically analyzed in two aspects:

1. Frequency of Exceedances: The number of times the power exceeds the threshold value of 120 kW ($P_{\text{total},t,j,k} > 120\,\text{kW}$).
2. Daily Peak Distribution: The distribution of daily power peaks ($P_{\text{peak, daily},j,k}$) over the evaluation period.

The frequency of exceedances is calculated as the count of time steps t where $P_{\text{total},t}$ exceeds the threshold of 120 kW. It is given by:

$$N_{\text{exceedances}} = \sum_{t\in T} \mathbf{1}(P_{\text{total},t} > 120) \tag{22}$$

Where:

- $N_{\text{exceedances}}$: The total number of exceedances.
- T: Sum of time steps in the evaluation period.
- $\mathbf{1}(P_{\text{total},t} > 120)$: An indicator function that equals 1 if $P_{\text{total},t,j,k} > 120\,\text{kW}$, and 0 otherwise.

The daily peak power values are determined as:

$$P_{\text{peak, daily}} = \max_{t\in T_{\text{day}}} P_{\text{total},t} \tag{23}$$

Where:

- $P_{\text{peak, daily}}$: The maximum power on a given day.
- T_{day}: Sum of time steps within a single day.

2.7.2. Regret analysis

The objective of regret analysis is to measure how much worse a given solution performs compared to the hindsight optimal ("perfect") solution. This quantifies the opportunity loss incurred due to incomplete or imperfect information. The regret for a solution x is defined as:

$$\text{Regret}(x) = g(x) - g(x^*), \tag{24}$$

where $g(x)$ is the cost function of the given solution, and $g(x^*)$ is the cost function of the hindsight perfect solution (Eq. (24)). In addition to the assessment of the costs, the peak loads that arise at the grid connection point are also assessed.

3. Results and discussion

Results were generated based on data from the observation period from October 1, 2021 to July 14, 2022. The optimization was carried out in a loop on a daily basis in order to simulate the schedule of the reefer preconditioning for the next day as a "day-ahead" schedule.

3.1. Generated scenarios

In the process, 100 scenarios ("stochastic") were generated per day as described in chapter Section 2.3. For each day, also a "mean", "random" and "pslp" scenario was generated.

Fig. 5 shows on three randomly chosen example days how the generated scenarios can look like. In the upper graph the 100 scenarios are shown (gray) versus the perfect foresight (measured data) "perfect" scenario (dotted-blue line). These three different example days also illustrate that the actual net load sometimes differs significantly from the predicted data or the resulting scenarios. The lower graph illustrates the deterministic comparison scenarios "Mean" (green dashed), "Random" (red dash-dotted line) and the "PSLP" (purple solid line). This visualization shows how accurately or inaccurately the scenarios reflect the measured values ("perfect"). While the base load in the morning and evening hours can always be well represented at all days, all scenarios underestimate the measured net load on the first and especially on the second example day, as shown in Fig. 5.

On the basis of the generated scenarios and the modeled energy system (Section 2.5), the stochastic and deterministic optimizations were run as day-ahead optimizations for a time period from October, 1st to July, 14th and all reefer variations. The example days clearly show how different the quality of the scenarios is and how the forecast errors from the net load forecast affect the generated scenarios.

3.2. Optimization results

The creation of the modeled energy system and the execution of a stochastic day-ahead net load optimization takes approximately 10 s for one day on the computer used. The optimizer requires 0.91 s for optimization of the energy system (reefer case "High"). In the first step, the optimization results are analyzed using the KPIs total costs and daily peak power. The KPIs are calculated as described in chapter Section 2.7.1 for the entire observation period.

Fig. 6 shows the energy costs for all optimization and reefer frequency. As expected, the costs are lowest under perfect foresight. In the forecast-based optimization case, the stochastic approach performs best. The improved cost performance in some cases is due to better utilization of the PV energy generated (self-consumption). Another cost driver is the cost of services in excess of 120 kW (see chapter Section 2.7.1).

To analyze this, we first look at maximum peak power and the total number of injuries of the 120 kW limitation at the grid connection point (see Table 5). With perfect foresight, there are no violations of the limit and the 120 kW limit is ideally utilized. In contrast, we achieve a maximum of up to 107 violations of the power limit and a maximum power of 213 kW (optimization: random; reefer frequency: High) in the forecast-based optimization cases.

Evaluating the load behavior, we generated the empirical CDF of the daily peak power in Fig. 7 and shown it for the optimization and reefer frequency.

In the "perfect" variant, with perfect foresight, the outputs go up to a maximum of 120 kW, while the other optimization variants violate these limit, due to imperfect informations. The more reefers have to be preconditioned (see Fig. 7: left graph, "Low"; middle graph, "Medium"; right graph, "High"), the greater the number of violations. What is already recognizable in absolute numbers in Table 5 becomes visible in Fig. 7 - the stochastic approach generates significantly lower load peaks than the deterministic pendents, mean, random and pslp. This effect becomes significant the more reefers are preconditioned daily (reefer scenarios "Low", "Medium" and"High"). In terms of the average number of violations across the three reefer cases, the stochastic scenario has 60% fewer injuries of the power limit than the mean scenario, 64% fewer than the random scenario, and about 54% fewer than the PSLP scenario.

Exceeding the maximum connection power is only a theoretical consideration. In reality the transformer and the fuses limit the power and the current respectively. The online energy management system would be tasked with preventing fuses to limit power as this has a huge cost in daily operations. That means, the reefer schedule would have to be shifted. For a larger energy system with more flexible participants, it could also mean that other flexible loads would have to be reduced and postponed at times, or that a storage unit could provide additional power. Fig. 8 shows an example of how this could look like for the deterministic case "mean" at "High" reefer frequency. As a comparison to the prediction-based optimization, the timetable under "perfect" foresight is shown in dashed blue. In red dashed, as a horizontal line, the power limit at 120 kW. In black the deterministically optimized schedule "Mean". Here you can see that this schedule exceeds the 120 kW limit several times. As a result, the shifted schedule is visualized in green so that no more violations occur.

We estimate the additional costs for this service at 10 times the grid procurement costs, at €3/kWh. This results in the following total costs, as shown in Fig. 9 above the bars. The share of additional service costs in the total costs is shown in the bar chart in Fig. 9 in shades of red. At the bottom, in shades of blue, are the energy costs for grid purchases and PV-self-consumption. Another possibility would be to assess how far the schedule of each individual reefer would have to be shifted, and to penalize this "waiting time". Both the total costs and the analysis of the daily peak power show that the stochastic optimization, compared to the deterministic optimizations, leads to more robust results due to

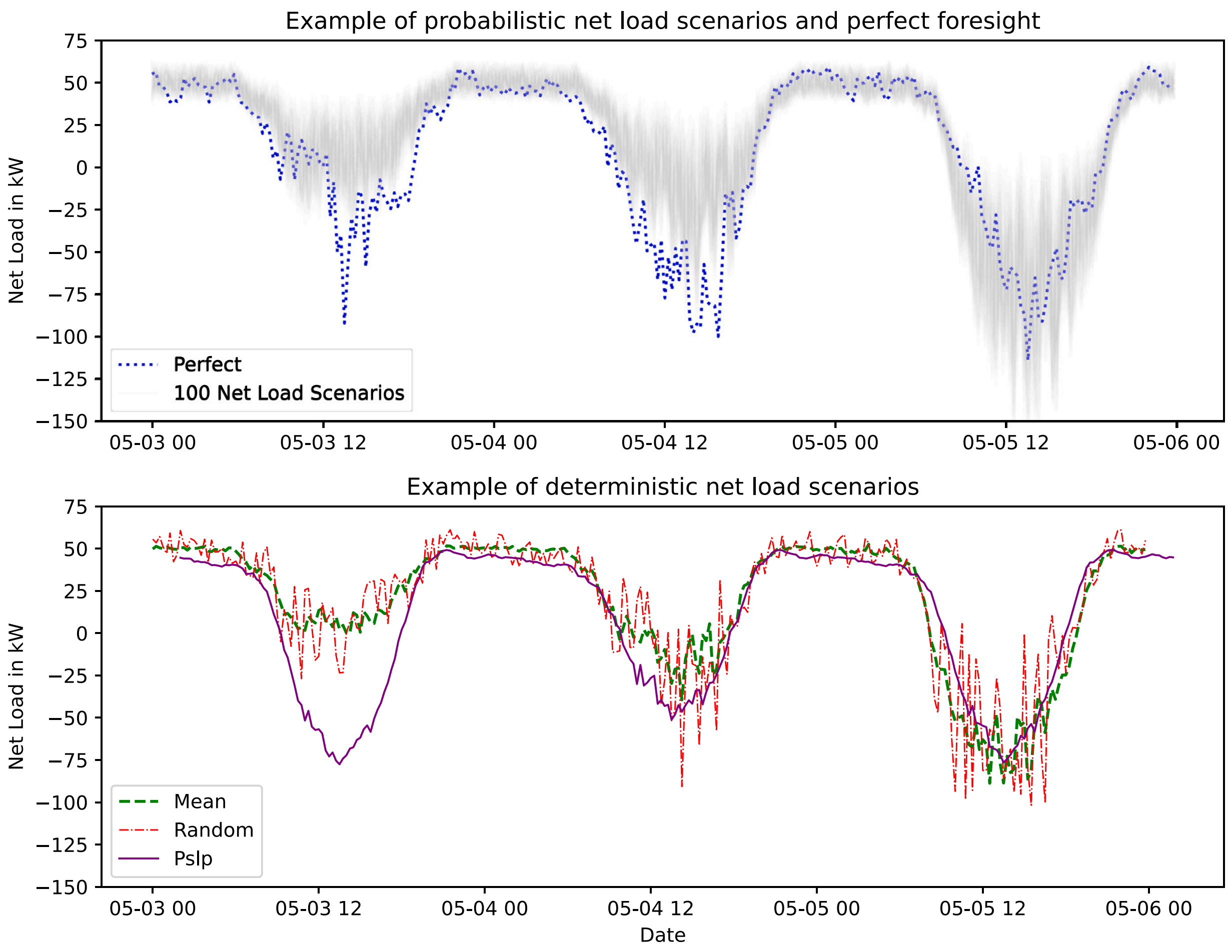

Fig. 5. Visualization of the generated scenarios ("Stochastic") and perfect foresight ("Perfect") in the upper graph and the deterministic comparison scenarios ("MEAN", "Random" and "PSLP") in the lower graph on three sample days.

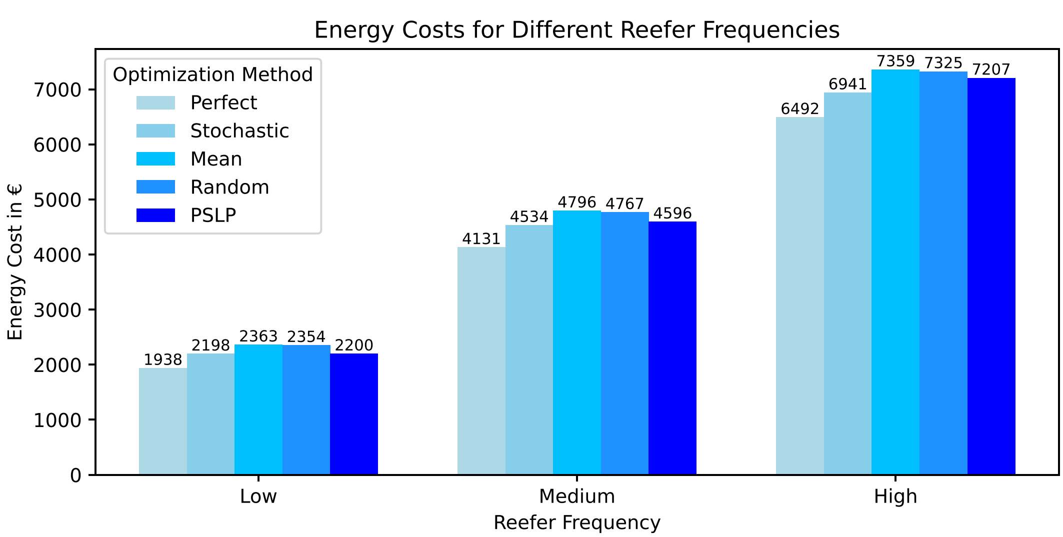

Fig. 6. Energy costs for each optimization variant grouped by reefer frequency.

a more defensive (less extreme) schedule and thus also minimizes the risk of overshoots and therefore high additional costs for extra services. Table 6 lists a summary of the mean, median and maximum values of the daily total costs over the entire observation period.

3.3. Regret analysis

To estimate the errors that are introduced into the optimization due to the misjudgment or rather the uncertainty occurs from forecast

Table 5
Injuries of the 120 kW limitation at the grid connection point (left side) and the maximum peak power for all optimization and reefer frequencies over the whole observation period.

Optimization/	Number of Injuries (kW > 120)			Maximum Power		
Reefer Frequency	Low	Medium	High	Low	Medium	High
Perfect	0	0	0	120 kW	120 kW	120 kW
Stochastic	9	24	36	156 kW	156 kW	173 kW
Mean	19	62	94	169 kW	194 kW	211 kW
Random	20	65	107	174 kW	184 kW	213 kW
PSLP	13	51	86	182 kW	182 kW	206 kW

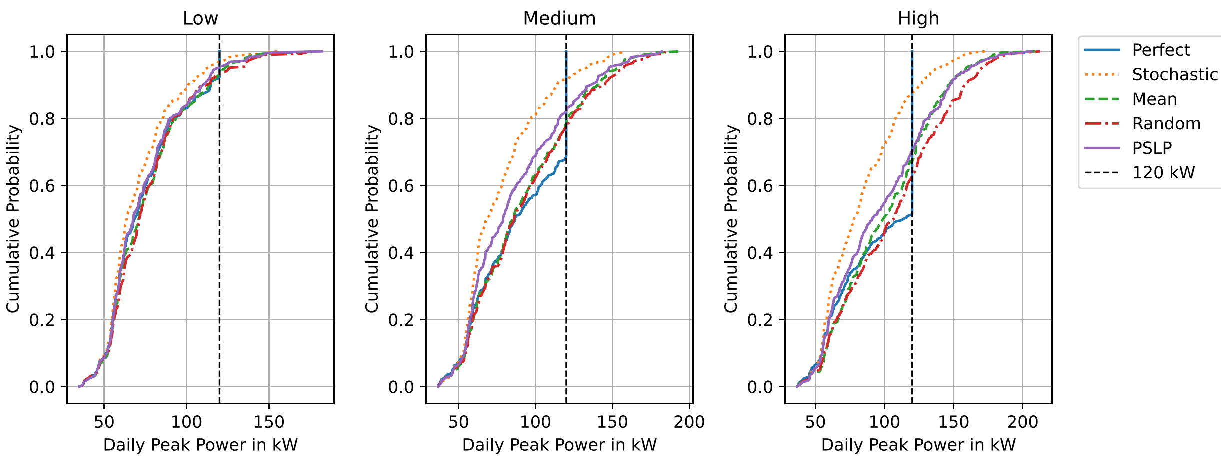

Fig. 7. Daily peak power of all optimization for reefer frequencies "Low" (left graph), "Medium" (middle graph) and "High" (right graph)

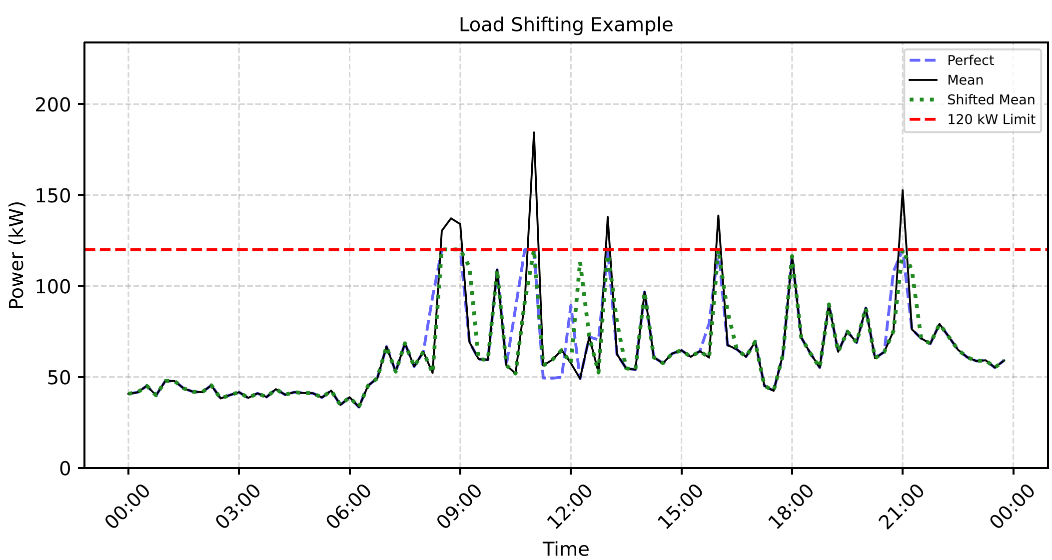

Fig. 8. Load shifting example for deterministic optimization "mean" and "High" reefer frequency.

Table 6
Summary statistics (mean, median, max) of the daily total costs in €.

	Low					Medium					High				
Metric	perf	stoch	mean	rand	pslp	perf	stoch	mean	rand	pslp	perf	stoch	mean	rand	pslp
Mean	6.7	8.0	8.9	9.3	8.3	14.3	17.2	20.9	21.7	19.6	22.5	27.1	34.0	37.3	33.5
Median	5.3	6.3	6.8	6.8	6.1	10.3	12.5	12.8	13.4	12.4	17.6	20.6	22.3	22.9	21.4
Max	35.4	54.1	68.8	83.9	73.7	71.1	112.2	131.4	146.8	125.3	105.8	166.5	202.6	224.4	219.8

errors and scenarios, we consider the regret analysis for the individual optimization and reefer frequencies. In Fig. 10, we have shown a comprehensive analysis of the regret functions for the daily regret costs, for the entire observation period. Fig. 10 shows in the upper graph the average regret costs for all optimization variants as bar groups divided by reefer frequencies. In order to better estimate the ratio of regret costs to total daily costs, the average daily total costs (see also Table 6) of the respective optimization variant and reefer case were displayed as "x" markers. The lower three graphs show the empirical CDFs of the regression factors over the entire observation period for the respective reefer

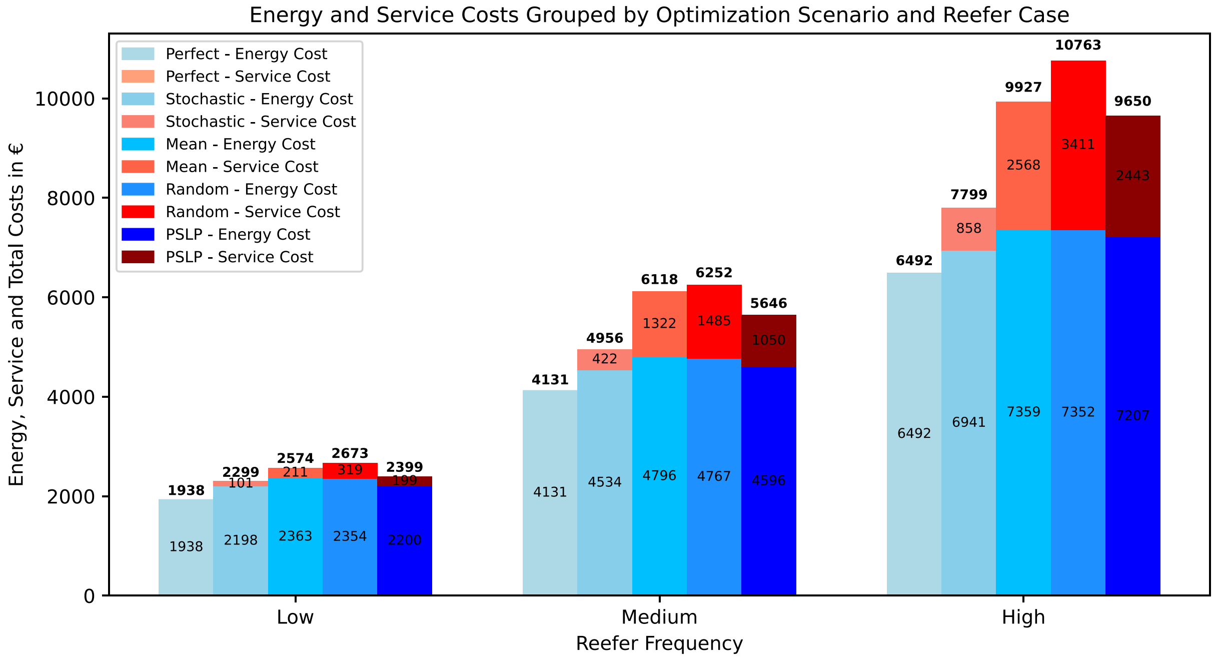

Fig. 9. total costs.

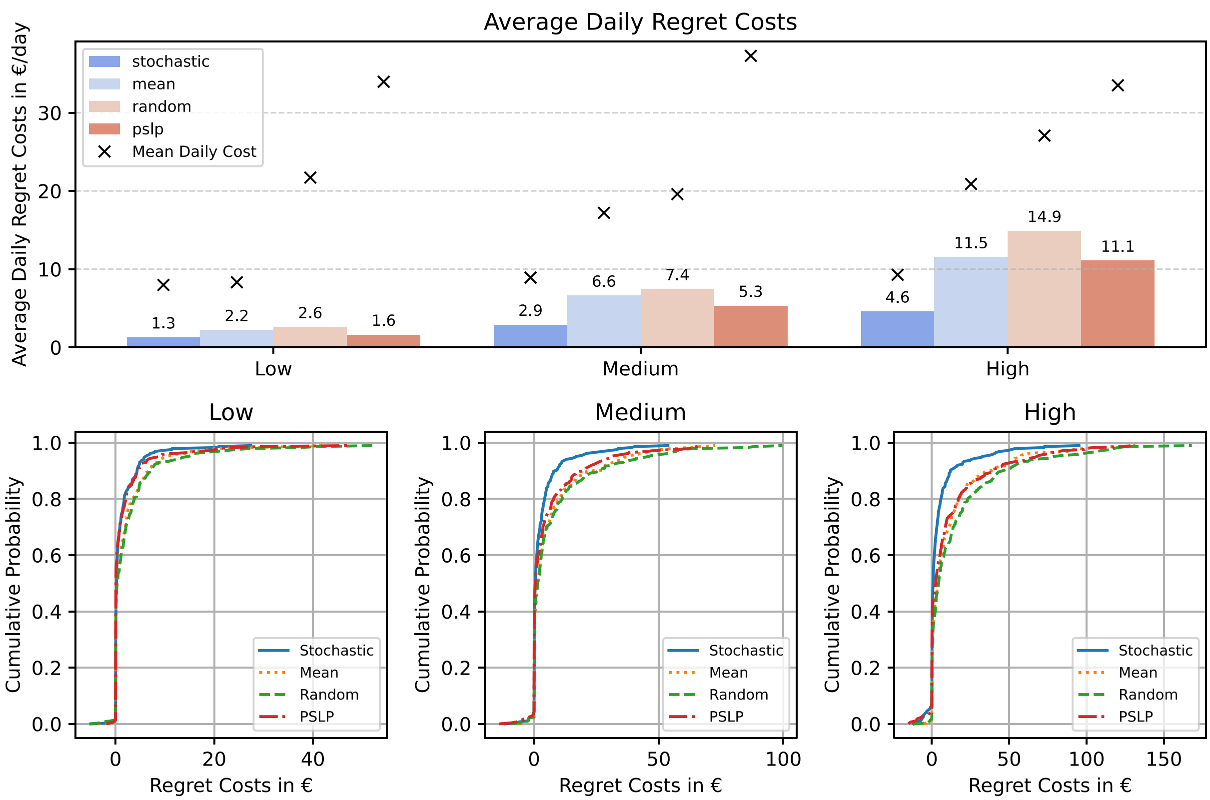

Fig. 10. Regret analysis. Average daily regret costs and daily mean total costs(upper graph) and empirical CDF (lower graphs) of the regret costs.

frequency. The mean regret costs (upper graph) shows that we have lower average regret costs with the stochastic optimization approach, compared to the other optimization variants. The more reefers have to be preconditioned (“Low” to “High”), the higher the regret costs. The three subplots below show the empirical CDFs of the regret costs for the respective reefer frequency (left - Low; middle - Medium; right - High), which can be used to analyze the distribution over the entire observation horizon. In the CDFs, the robustness of the stochastic approach compared to the deterministic optimization variants is clearly visible. This effect becomes more evident the higher the reefer frequency is and also the maximum regret costs are significantly lower in the case of stochastic optimization. While all optimizations rarely result in lower costs (negative regret costs) than the theoretical optimum under perfect foresight (“perfect”), stochastic optimization causes the lowest regret costs overall. Here we have average regret costs of €1.3, €2.9 and €4.6 per day (in comparison to that, average daily total costs of €8, €17.2,

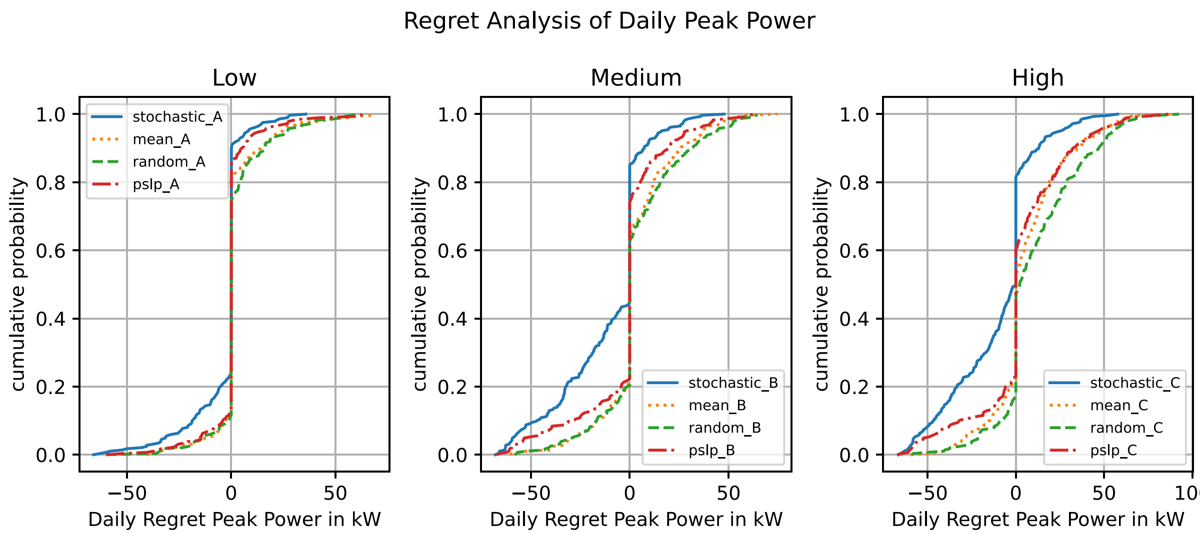

Fig. 11. Regret analysis. Average (upper left), maximum (upper right) and empirical CDF (lower graphs) of the regret load peak.

€27.1 per day) in the stochastic approach, while we have daily regret costs of €2.6, €7.4 and €14.9 per day in the "random" variant (average daily total costs of €9.3, €21.7, €37.3 per day). This can be explained by the missed benefits from PV self-consumption and the additional service costs for power supply above 120 kW, which play a key role the more reefers has to be pre-conditioned. Furthermore, the regret costs arise from the calculation compared to the theoretical optimum of perfect foresight. What serves as a good estimate and does not exist in the real world.

These characteristics can be shown even more clearly in Fig. 11 using the regret factor of the daily load peaks. For the stochastic optimization (blue solid line), it can be seen that lower daily peak powers are reached much more frequently and fewer extreme exceedances, which indicates for the robustness of the stochastic approach. The optimization variants "mean" (yellow dashed) and "random" ("green dotted") occur most frequently, with the highest maximum Regret daily peak power. The effects described also intensify in all scenarios the higher the reefer frequency is. The more defensive schedules of the stochastic optimization lead to less regret costs and lower daily power peaks at the grid connection point. In this case, a decision in favor of one of the deterministic optimization variants would lead to a higher risk of having higher costs without having the same chance of higher profits (negative regret costs). The more reefers have to be planned daily, the greater the advantage of stochastic optimization over deterministic optimization.

4. Conclusion and outlook

This work has presented a stochastic approach to perform operational optimizations under uncertainty based on day-ahead probabilistic net load forecasts. For this purpose, a method has been introduced (Section 2.3) that allows to generate scenarios from a predicted PDF of the net load of a distributed energy system. To demonstrate the application, a stochastic program was modeled using oemof.solph (Section 2.5), a new approach for modeling the net load and scenario-based implementation (Sections 2.5 and 2.6). The application was run as stochastic day-ahead schedule optimization for the preconditioning of reefers and evaluated in terms of total costs and daily peak power. The number of reefers to be preconditioned daily was divided into three different frequencies. The stochastic optimization was compared with three different deterministic optimizations and benchmarked by the optimization with perfect foresight. This proof of concept shows, that it is possible to make less risky and more robust decisions under uncertainty through scenario-based, stochastic optimization than based on a point prediction (deterministic), as shown in Section 3. We were able to show that stochastic schedule optimization leads to more robust and confident schedules, lower costs, significant fewer extremes in daily peak power and additional service costs, which helps to make better technical and economical decisions under uncertainty (Section 3.2). The maximum peak powers were evaluated first. This showed that the stochastic approach led to the fewest violations of the defined power limit, to more defensive schedules overall and thus to significantly more confident results. This was also reflected in the total costs, which were the lowest due to the stochastic optimization. This trend was particularly evident with many preconditioning processes to be integrated. It is to be expected that the assessment of CO_2 emissions will play an increasingly important role in the future and could be incorporated into future work on local net load as a further assessment or optimization parameter. A regret analysis showed how strong the positive or negative deviations from the benchmark case, perfect foresight, were. Again, it can be seen that stochastic schedule optimization leads to the lowest regret costs. The scope of this study is to a single DES and a limited time horizon. In summary, it can be said that the stochastic approach has clear advantages over the deterministic optimization variants and can lead to more trustworthy decisions under uncertainty. Summarized, the stochastic variant achieves up to 25% lower total operating costs and reduces daily peak power exceedances by 30 to 66% compared to deterministic scheduling. Furthermore, the analysis of regret costs indicates average daily reductions between 21% and 69%, depending on the number of reefers to be preconditioned, demonstrating enhanced robustness, cost efficiency, and operational reliability under forecast uncertainty.

The work shows a holistic process from local data collection to robust optimization under uncertainty. The goal was application-oriented and limited to the selection of specific methods and assumptions. This included the selection of the method for scenario generation. The functionality of the approach presented does not depend on the use of a fixed forecasting method, the exact type of scenario generation method, or the number of scenarios or a specific probability mass. Here, a simple, robust method was chosen to generate scenarios from the probability densities of probabilistic net load forecasts. To this end, a fixed number of 100 scenarios was used, as well as fixed limits for the probability mass (5th to 95th percentile). Both the method for scenario generation and the specified parameters are not fixed and can be part of optimizations in future work. Further research could focus on more complex scenario generation, scenario reduction methods and, for example, take into account the dependencies between two consecutive time steps, to avoid too large power changes within the scenarios and increase the robustness of the generated scenarios. A sensitivity analysis of the number of scenarios or the selected boundaries for the input data and the optimization results may be the subject of further work. Investigating the propagation of errors from the forecast to the scenarios in the optimization could also help to improve decision-making under uncertainty and to evaluate the techno-economic impact of prediction errors in stochastic optimization, as examined by [48,49]. The stochastic optimization applied should also be viewed as part of the process presented and is limited to the scenario-based approach presented. This work has adopted a scenario-based stochastic optimization approach to explicitly account for uncertainty in net load. Scenario-based stochastic optimization has been widely applied in energy system operation due to its flexibility and interpretability. This also applies to two- or multi-stage formulations, which provide a more realistic representation of sequential decision-making processes, but they come at the cost of a substantial increase in computational complexity. The number of decision variables and constraints grows rapidly with the number of stages and scenarios, often rendering large-scale or high-resolution problems computationally intractable. In contrast, single-stage scenario-based formulations, as adopted in this work, offer a computationally efficient approximation that captures uncertainty effects without explicitly modeling all recourse decisions, making them particularly suitable for distribution-level and operational studies. A multi-stage approach could be a useful way to further develop the work and, for example, consider the uncertainty of the logistics parameters at a different level, such as presented for energy systems applications from [20,23,34,35]. Future work could focus on linking the Python libraries mpi-sppy [50] and oemof.solph [37], both of which are based on pyomo [51]. In contrast to robust and distributionally robust optimization approaches, which focus on worst-case realizations and ambiguity sets, scenario-based stochastic optimization offers a less conservative and more interpretable representation of uncertainty based on realistic scenarios. Chance-constrained formulations provide explicit probabilistic guarantees but often rely on restrictive distributional assumptions and can become difficult to solve in time-coupled network problems. Risk-augmented formulations such as CVaR (Conditional Value at Risk) enhance tail-risk awareness but introduce additional modeling complexity and tuning parameters. Overall, scenario-based stochastic optimization represents a balanced compromise between model fidelity, robustness, and computational complexity. Future work could extend the proposed framework to multi-stage or risk-aware formulations in order to explicitly capture sequential decision processes and extreme events while ensuring computational manageability, or incorporate risk-aware formulations such as conditional value-at-risk (CVaR) to explicitly control tail risks, such as presented from [52–54].

Further work should extend the period under review and represent more complex energy systems with a higher number of variables. But also the consideration of further optimization variables (multi-objective optimization), such as the consideration of electricity price forecasts or further uncertainty events, such as spontaneously failing reefers, could be investigated in further work. Multi-stage stochastic methods with multiple random variables could be used here to map various uncertainty events. The net load is suitable as a stochastic variable that simultaneously reflects the volatile feed-in and load, in order to integrate flexible loads via it or to integrate optimized schedules for self-consumption, for example. In a sector-coupled energy system, this can also mean that the net load takes into account other electrical players, such as heat pumps. In addition, it could be investigated how the use of battery storage can be used to compensate for forecast errors that show up in the optimized schedules, or to integrate even more flexible temporally available consumers, as e.g. BEVs, into a decentralized system. Another interesting point that could be investigated on the basis of this work is what the interface between software implementation and hardware would look like. Questions such as how quickly inverters or the power electronics in charging stations can react could be investigated and is the time resolution of 15 min appropriate in order to be able to react sufficiently well to rapid changes.

Further uncertainty would arise from the fact that the presence of flexibly consumed energy that is temporarily present cannot be predicted exactly. For example, the telematics and distribution systems of vehicles such as refrigerators can only provide a good estimate of arrival and departure times, but cannot take traffic jams or accidents into account. For forecast-based schedule optimization, the presented approach provides a reference point for risk-based decisions under uncertainty and supports the integration of volatile renewable generators and flexible loads into decentralized sector-coupled energy systems. A regular intra-day update (several times a day) of the net load forecasts and other information, such as that of the telematics system, to update the operation schedules, can help to further reduce uncertainty in decision-making. Further work could investigate the influence of such regular intra-day stochastic net load optimizations.

CRediT authorship contribution statement

Jan-Simon Telle: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Patrik Schönfeldt:** Writing – review & editing, Validation, Supervision, Software, Conceptualization. **Sunke Schlüters:** Writing – review & editing, Validation, Software. **Benedikt Hanke:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Karsten von Maydell:** Supervision, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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