DAILY DECISION MODEL FOR INDUSTRIAL ENERGY FLEXIBILITY CONSIDERING ECONOMIC RISK THROUGH CONDITIONAL VALUE-AT-RISK

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Abstract: Energy flexibility in industrial systems helps maintain system stability and reduces production costs at the same time. Industrial consumers must schedule their energy flexibility in advance for maximum cost reduction. It is crucial to understand the economic risks associated with scheduling energy flexibility. The paper proposes a daily decision model for industrial energy flexibility, incorporating the Conditional Value-at-Risk to address economic risks. The results demonstrate that the daily decision model supports industrial companies in scheduling energy flexibility based on their risk appetite for the following day. It provides a compromise between risk-taking behaviour, offering high cost reduction but high risk, and risk-averse behaviour, providing low risk but limited cost reduction. Additionally, the study shows that normal, t-location-scale, and lognormal distribution functions for energy prices modelling generate minor differences in the decision model's results.

Keywords: Industrial energy flexibility, day-ahead scheduling, stochastic optimization, conditional value-at-risk (CVaR)

1 Introduction

Integrating renewable energy generation poses challenges to electricity system management [1]. Additional flexibility on the demand side is required to guarantee the balance between generation and demand [2]. In addition, the increased and more volatile electricity prices experienced in Europe since 2022 are causing higher energy costs for industrial companies that have to decide on their production and investment plans facing unpredictable production costs development [3]. Industrial energy flexibility (EF) can help the energy system to maintain

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stability [4]. Moreover, it contributes to reducing production costs and to the industrial sector's competitiveness [2]. The energy flexibility measures (EFMs) are scheduled one day in advance to exploit the potential for energy cost reduction and combine it with production planning [5, 6]. EFMs model industrial EF through standard parameters, such as maximum power, activation time, and specific costs [5, 6]. Scheduling in advance brings uncertainties for decision-making and, thus, corresponding economic risks [7]. Understanding risks is crucial for industrial companies as they must be aware of potential losses when taking decisions [7]. The Conditional value-at-risk (CVaR) is a risk measure representing the average losses after a defined confidence level and can be included in linear programming for optimal decision-making [8]. The CVaR needs probabilistic forecasts of uncertain variables as input and is sensitive to scenarios modelling coming from distribution functions [9]. Another risk measure is the Value-at-risk (VaR), which represents the losses at a confidence level and corresponds to the lower bound of the CVaR at the same confidence level [9]. However, the CVaR is superior to the VaR, which stems from factors such as the possibility of integrating it into optimization functions and its ability to consider scenarios beyond the confidence level [8]. Previous work showed the potential of the CVaR combined with the scheduling of energy flexibility [7]. However, the optimization was not carried out for the entire day and a local minimum was being targeted.

This paper proposes a decision model for energy flexibility scheduling considering potential economic losses. The optimization considers the one day and includes two parts. The first part of the optimization function considers the cost variation, while the second part corresponds to the CVaR. A similar integration of the CVaR in decision-making approaches for energy scheduling and managing economic risk at the same time has been proposed in literature [10-13]. However, EF modelling by means of EFM, as in [5], was not considered in previous works, thus lacking a general description for managing and using industrial energy flexibility. In addition, this paper assesses the impact of different distribution functions for electricity prices on the proposed daily decision model. The goal is to investigate how large the difference caused by different price distribution functions is. The characteristic parameters of the chosen distribution functions were defined based on historical data. This paper is organised as follows. In Section 1, the context and previous works are introduced. Section 2 describes the decision model, and the results over one day are shown. In Section 3, the effect of price distribution functions on the decision model´s results is evaluated and discussed. Section 4 presents the conclusions and an outlook for future research.

2 Energy Flexibility Decision Model

In this section, the energy flexibility decision model is introduced. It is based on the one proposed in [7] and uses mixed-integer linear programming (MILP) stochastic optimization to minimize the industrial company's daily electricity costs. The risk is considered in the optimization through the risk measure CVaR. Prices are included as probabilistic scenarios extrapolated from cumulative distribution functions based on historical data. The main novelty of this decision model is the optimization over one day and not for each time step separately, aiming at the minimum global daily costs. Moreover, only the energy cost reduction is aimed, not the trading on different markets [7]. The decision model is described in the first part of this section. The second part presents and discusses the results.

2.1 Method Description

The optimization goal aims at minimizing the total cost variation resulting from the minimization function in eq. 1. This optimization is carried out considering the time steps *t,* which belongs to the evaluated entire day d: $t = 1 \dots T,\ t \in d$.

$$\min[\omega E\big(CV_d(EFM)\big) + (1-\omega)CVaR_{\alpha,d}(EFM)] \quad (1)$$

The first term in eq. 1 is the expected cost variation over one day ($CV_d(EFM)$), achievable through the EFM scheduling (eq. 2):

$$E\big(CV_d(EFM)\big) = \sum_\xi \rho_\xi \left[\sum_i \sum_t E_{EFMi}^t \,(C_{DAM,\xi}^t + C_{GC_{Energy}} + C_{EFMi}^t)\right] \quad (2)$$

The cost variation includes hourly prices $C_{DAM,\xi}^t$, the energy cost component of the grid charges $C_{GC_{Energy}}$, and EFM-specific activation costs C_{EFMi}^t [6]. Hourly prices for the following day are defined through scenarios with the respective probability $\rho_\xi, \forall\xi = 1 \dots \Xi$. The cost variation considers energy $E_{EFMi}^t, \forall i = 1 \dots n$ of the $i-th$ EFM at each time step t of the considered day. The use of the EF is profitable if, e.g., the EFM activation costs for reducing the load during price peaks are less than the corresponding achieved cost.

Optimization variables are subject to system boundary constraints (eq. 3), i.e., constraints related to the maximum energy peak over 15 minutes at a grid connection point E_{max}, and EFM power limit constraints, i.e., the limit on the EFM maximum and minimum power for each time step *t* (eq. 4). Both constraints are inequality constraints expressed as energy constraints considering the average power over 15 minutes, $E_{15\text{min}} = \overline{P_{15\text{min}}}/4$.

$$\sum_{i=1}^{n} E_{EFMi}^t + E_{load}^t \leq E_{max} \quad (3)$$

$$E_{EFMi,min}^t \leq E_{EFMi}^t \leq E_{EFMi,max}^t \quad (4)$$

For EFMs with storage behaviour, additional constraint on the State of Charge (SoC) limit (eq. 5) and end value constraint (eq. 6) are defined, the last being an equality constraint. Each SoC_j^t is computed using the energy of the EFMs that model the load increase and load decrease of a storage system, $\forall\, j = 1 \dots n_{ESS}$.

$$SoC_{j,min}^t \leq SoC_j^t \leq SoC_{j,max}^t \quad (5)$$

$$SoC_j^T = SoC_j^{end} \quad (6)$$

The second term in eq.1 is the risk measure CVaR in the linearized form as in [7, 11] (eq. 7), which is subject to additional constraints on additional variables τ_d and $\kappa_{\xi,d}$ (eq. 8).

$$CVaR_{\alpha,d}(EFM) = \tau_d + \frac{1}{1-\alpha}\sum_\xi \rho_\xi\, \kappa_{\xi,d} \quad (7)$$

$$\kappa_{\xi,d} \geq 0\ ;\ \kappa_{\xi,d} \geq CV_{\xi,d}(EFM) - \tau_d \quad (8)$$

The confidence level α is used to define which results are considered for the evaluation of risk, i.e., the cost variation with a probability of occurrence higher than $(1-\alpha)\%$ [14]. The company´s risk appetite, i.e., willingness to risk for achieving high cost reduction, is modelled through $\omega \in [0,1]$. Choosing a high value of ω prioritizes cost variation, thus for a risk-taking approach, while a ω close to zero focuses on reducing risk for a risk-averse approach [7].

Table 1: Description and parameters of the use case´s energy flexibility measures (EFM) [5-6, 15].

EFM number	**Flex. unit**	**Direction**	**Flex. power [kW]**	**Duration time [h]**	**Specific activation costs [ct€/kWh]**	**Validity**
EFM1 (charge) EFM2 (discharge)	ESS	load shift (↕)	0 - 160	SoC dependent	0.33	always
EFM3 (charge) EFM4 (discharge)	EV	load shift (↕)	0 - 45	SoC dependent	0.17	weekdays 7 a.m.-5 p.m.
EFM5 (charge) EFM6 (discharge)	CA	load shift (↕)	0 - 30	SoC dependent	0.44	always

2.2 Use Case and Results

The industrial facility of the use case includes EFMs of an energy storage system (ESS), charging stations for electric vehicles of employees (EV), and a compressed air storage system (CA) (Table 1). ESS, EV, and CA can cause a temporary load reduction or load increase at the grid connection point. A load reduction measure corresponds to discharging the storage system, thus decreasing the corresponding SoC (EFM1, EFM3, and EFM5). A load increase measure corresponds to the charging phase, which increases the corresponding SoC (EFM2, EFM4, and EFM6). Specific activation costs are input for the decision model and are defined from the method proposed by Tristan et al. [15], excluding investment costs. ESS and CA can be planned at any time, while EV has limited validity. It is assumed that a company´s employees use charging stations to charge their EV from 30% to 90% SoC at the end of the working day. For ESS and CA, the SoC end of the day equals the SoC at the beginning.

Price scenarios are calculated for typical seasonal weekdays and weekend-days [11, 16] using hourly day-ahead market prices [17]. Prices are assumed seasonal and normally distributed [18]. The decision model uses seven price scenarios extrapolated from the defined normal distribution functions ($\Xi = 7$), as in Figure 1.b. Figure 1.a shows an extract of the results of one autumn weekday for a risk-averse ($\omega = 0.2$) and a risk-taking approach ($\omega = 0.9$) and confidence level α of 0.9.

The risk-taking approach prioritizes the results of the stochastic optimization, choosing to schedule an ESS load increase at 4 a.m. (39.6 €/MWh). This does not correspond to the minimum average forecasted price (in Figure 1: sc. 4) of the first part of the day, which happens at 3 a.m., however, it corresponds to a lower price variance than at 3 a.m.. The risk-averse approach takes more into account the economic risk associated with the scenarios with high prices (In Figure 1: sc. 6 and 7) and thus schedules the same ESS load increase at 5 a.m., when not only the average forecasted price is low (40.0 €/MWh) but also the high price scenarios (up to 55.5 €/MWh). The risk-taking approach schedules ESS, CA, and EV load decreases at 9 a.m., corresponding to the maximum average forecasted price of the day (48.6 €/MWh). In addition, it schedules an EV load increase at 7 a.m. to enable a higher load

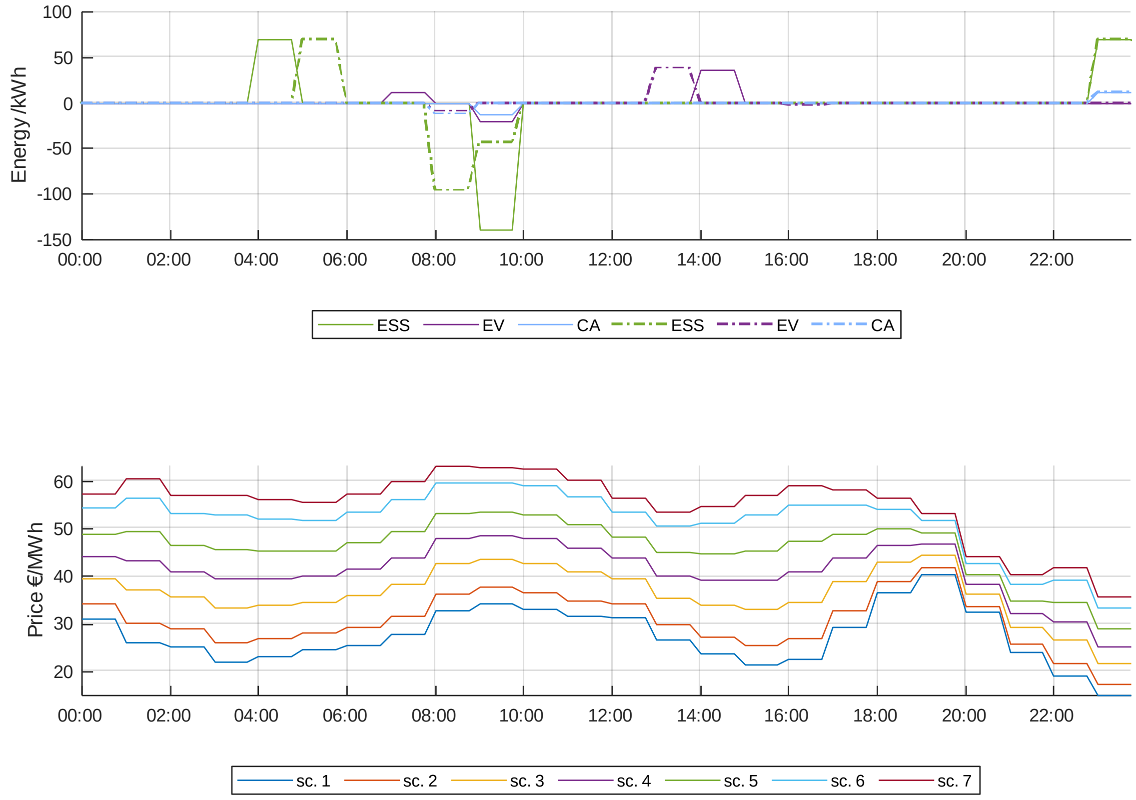

Figure 1: Results of the decision model for energy flexibility on a typical autumn day for risk-averse ($\omega = 0.2$) and risk-taking ($\omega = 0.9$) approach at confidence level $\alpha = 0.9$: hourly EFM scheduling (top, a, line: risk-taking; dashed line: risk-averse) and corresponding price scenarios (bottom, b).

reduction at 9 a.m.. The risk-averse approach compromises between the peak of the average forecasted price and the high price scenarios (63.1 €/MWh at 8 a.m. and 62.9 €/MWh at 9 a.m.). Therefore, it splits ESS load decrease between 8 and 9 a.m. and shifts to 8 a.m. the ones of EV and CA. Moreover, the EV load increase at 7 a.m. is not scheduled. This divergent behaviour is due to the different price gap between the time of the load decrease and the price at 7 a.m. considered by the approaches: the risk-taking sees a difference of up to 5 €/MWh between the peak price at 9 a.m. and the price at 7 a.m., while the risk-averse approach sees a difference of 3.2 €/MWh in the high prices scenario. This makes the additional activation at 7 a.m. not convenient for the risk-averse approach. The risk-taking approach plans EV charging at 2 p.m.. As before, this hour does not correspond to the lowest price between 7 a.m. and 5 p.m., which happens at 3 p.m.. However, the variance is lower then at 3 p.m. and the high price scenarios present lower prices. The risk-averse approach schedules of the EV load increase at 1 p.m.. This is due to the price minimum for high price scenarios at 1 p.m. compared to prices at 2 p.m.. However, the scheduled energy is higher than the one scheduled by the risk-taking approach, enabling an EV load decrease at 4 p.m.. At this hour, the high price scenarios show a peak, which could cause high prices for the industrial company, and thus, the risk-averse approach prefers to schedule a load decrease at this time. Finally, a load increase for ESS and CA are scheduled by both approaches at 11 p.m., when the average price scenario and the high price scenarios reach the daily minimum. The EV is not available anymore and thus is not scheduled.

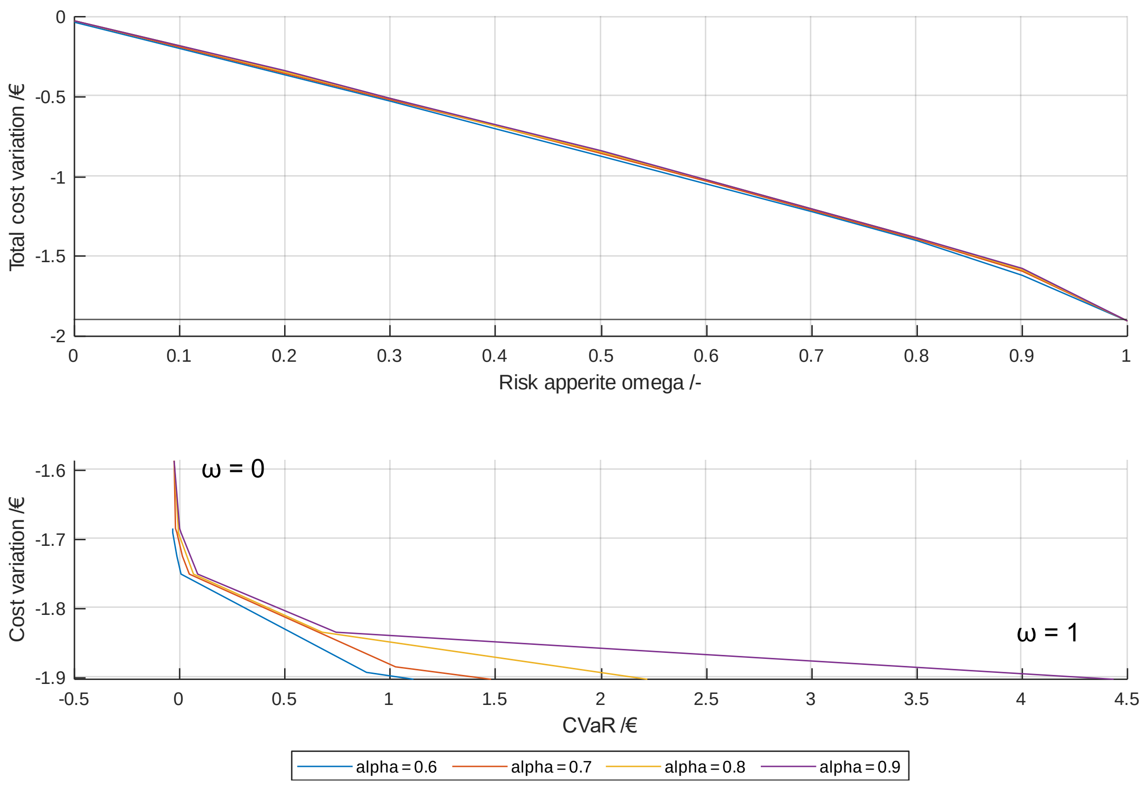

Figure 2: Results of the total cost variation as in eq.1 (top, a), cost variation and CVaR as in eq. 2 and eq.7 respectively (bottom, b) for different values of confidence level α.

Results in Figure 1 shows that a risk-taking approach considers all the scenarios and takes scheduling decisions according to the expected cost variation based on stochastic optimization. A risk-averse approach prioritizes the risk component and takes the EFM scheduling decision also considering the scenarios with high prices.

Figure 2.a shows the results of the total cost variation (eq.1) for different values of risk appetite ω. The case of $\omega = 1$ corresponds to an optimum of the expected cost variation without considering risk. It is the maximum cost variation (most negative value), which can be reached with the forecasted prices and equals the results obtained by the deterministic equivalent of the optimization, represented by the horizontal line in Figure 2.a. For ω values close to one, the total cost variation remains in absolute value high, but less than the optimum at $\omega = 1$ due to the fact that the model considers the economic risk, and progressively reduces for lower values of omega towards a risk-averse approach. The minimum total cost variation in absolute value is reached for $\omega = 0$, which represents only the risk measure CVaR. Figure 2.b shows the cost variation and CVaR values for the same day. The cost variation is equivalent to the electricity cost reduction, which is computed considering the electricity costs and the energy cost of the grid charges, including the EFM activation costs (eq. 2). The CVaR corresponds to the results of eq. 7. Figure 2.b shows that the economic risk (CVaR) increases if the cost reduction is higher in absolute value. This happens for ω values closer to one. The CVaR range is larger than the one for the cost variation, being 4.5 € and 0.3 €, respectively, showing that the risk increases faster than the possible cost reduction. In Figure 2.b,the role of confidence level α is also visible. A low value of α means that the optimization problem considers more price scenarios for calculating CVaR. Since the CVaR is the average of economic risk at a confidence level, the CVaR for a low confidence level is also lower. However, it does not represent a lower economic risk. An interesting result can be deduced from Figure 2. For low

ω values, the CVaR assumes negative values. This means that the EFM scheduling of a risk-averse approach could bring a negative cost variation. This is possible due to the highest price scenarios, which show that a significant difference between hours of the day and the EFM scheduling of the risk-averse approach can support reducing costs as well.

3 Price Distribution Function Evaluation

In this section, the results of different price distribution functions are compared. The goal is to evaluate how modelling the forecasted electricity prices with different distribution functions affects the results of the energy flexibility decision model described in Section 3. The first part contains the evaluation approach's description, and the second part discusses the results.

3.1 Evaluation Approach

The approach proposed r to evaluate the decision model´s results considering different price distribution functions is here briefly described. First, historical data are used to define the distribution function parameters, or forecast characteristics, for each distribution function type considered in this paper (Table 2). Distribution function types are normal distribution, t-location-scale (t-scale) distribution, lognormal distribution, and gamma distribution [19]. For example, Figure 3 shows the named distribution functions as probability density functions fitted for the prices between 8-9 a.m. of a workday. Afterwards, price scenarios are extrapolated and used as input for the decision model using multiple α and ω ($\alpha \epsilon [0{,}6; 0{,}7; 0{,}8; 0{,}9; 0{,}99], \omega \epsilon [0; 0{,}1; 0{,}2; 0{,}3; 0{,}4; 0{,}5; 0{,}6; 0{,}7; 0{,}8; 0{,}9; 1]$), and results are stored. In the last step, results obtained with normal distribution are compared to the ones obtained with the other distributions ζ. The comparison is based on the daily cost variation difference between one distribution ζ and the normal distribution and the hourly EFM energy difference scheduled by the optimization (eq. 11-12). The values are expressed respectively as percentage of the average daily energy costs, including grid charges, and the maximum EFM energy that can be scheduled during one hour.

Table 2: Distribution function types used for modelling price probabilistic forecasts and their descriptive parameters [19].

Parameter for each time step t	Normal distribution	T-location-scale distribution	Lognormal distribution	Gamma distribution
Form	Symmetric	Symmetric	Left-skewed	Right or left-skewed
Probability density function (PDF)	$\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-y)^2}{2\sigma^2}}$	$\frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sigma\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)}\left[\frac{\nu+\left(\frac{x-\mu}{\sigma}\right)^2}{\nu}\right]^{-\left(\frac{\nu+1}{2}\right)}$	$\frac{1}{2\pi\sigma x} e^{(-\frac{(\ln(x)-\mu)^2}{2\sigma^2}}$	$\frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$
Parameter	Location parameter μ Scale parameter σ	Location parameter μ Scale parameter σ Shape parameter ν Gamma function Γ	Scale parameter μ Shape parameter σ	Location/shape parameter α Scale parameter β

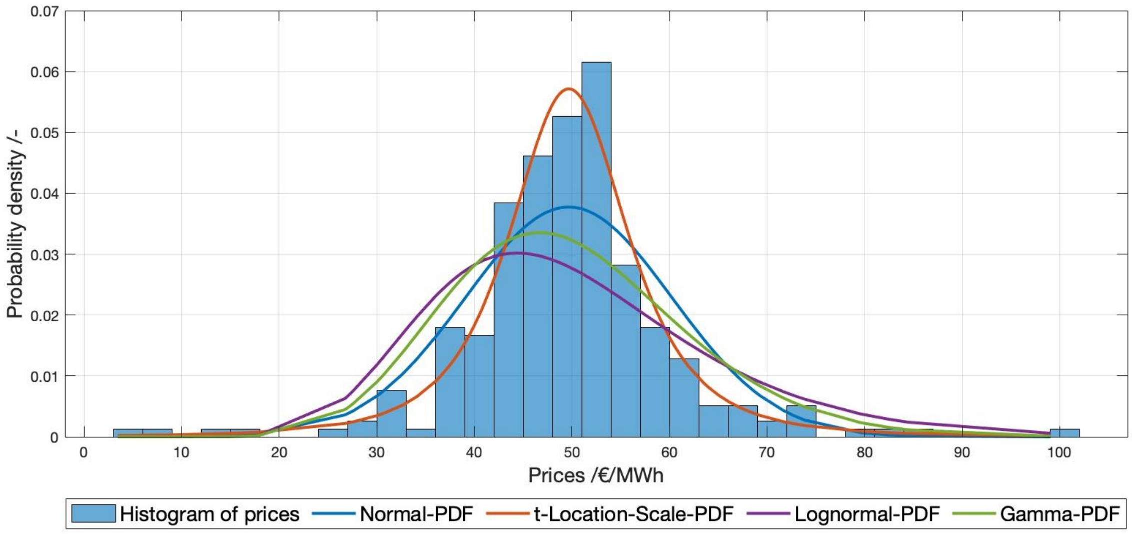

Figure 3: Histogram of electricity prices for the time slice from 08:00-09:00 of a weekday including the corresponding probability density functions (PDFs) using the distributions evaluated in this paper [17,19].

$$\Delta CV^d{}_{\zeta\%} = \frac{CV^d{}_{\zeta} - CV^d{}_{Normal}}{min(CV^d{}_{Normal})} * 100 \quad (11)$$

$$\Delta EFM^h{}_{energy,\zeta\%} = \frac{EFM^h{}_{energy,\zeta} - EFM^h{}_{energy,Normal}}{\max(\sum_i E^h_{EFMi})} * 100 \quad (12)$$

3.2 Results Discussion

Tables 3 and 4 summarize the comparison results considering the risk-taking approach of Section 2. Table 3 shows the maximum, mean absolute error (MAE), minimum, and standard deviation of cost variation difference $\Delta CV^d{}_{\zeta\%}$ between each distribution function ζ and the normal distribution, while Table 4 presents results related to hourly EFM energy difference $\Delta EFM^h{}_{energy,\zeta\%}$. Table 3 shows that modelling prices with t-scale distribution gives comparable results to the modelling with normal distribution. Values of maximum, MAE, and standard deviation of $\Delta CV^d{}_{\zeta\%}$ are less than 1% of the highest cost variation in absolute value reached with normal distribution, and only minimum value is over -3,5%. The lognormal distribution also gives comparable results, even if the minimum value is lower than -6.3% and the MAE is higher. However, the maximum value and maximum standard deviation decrease compared to the normal distribution. Gamma distribution shows comparable results to the normal distribution, as for the other two distributions. This means that the cost variation forecasted with the three distributions does not largely vary from normal distribution results. Considering the scheduled EFM energy, the difference is higher for all distributions (Table 4). Minimum and maximum values reach up to 79% of total schedulable EFM energy, for t-scale distribution and 89% for lognormal distribution. These values correspond, e.g., to ESS and CA scheduled at different hours or to EFM energy scheduled at the same hour in opposite directions (increase and decrease). Standard deviation varies up to 8,9% and 11,1% for t-scale and lognormal distribution, respectively. For the gamma distribution, the results are comparable to the other two distributions. In conclusion, even if it is more reliable to use a price distribution that suits the historical data, the normal distribution could be used alternatively to t-scale, lognormal, or gamma distributions for modelling prices in the daily scheduling proposed in this paper. The distributions provide cost variation results comparable to normal

Table 3: Percentage daily cost variation difference between distribution ζ and the normal distribution. Results are shown for one case (α=0.9, ω=0.8). Maximum standard deviation is refers to all the cases (eq.10).

Distribution function ζ	**$\Delta CV^d{}_{\zeta\%}$ for α=0.9 and ω=0.8 [%]**				**$\Delta CV^d{}_{\zeta\%}$ for all values of α and ω [%]**
	Maximum	**MAE**	**Minimum**	**Standard deviation**	**Maximum standard deviation**
t-scale	0,82	0,23	-3,54	0,49	2,09
Lognormal	0,42	0,66	-6,37	1,32	1,49
Gamma	0,42	0,30	-4,31	0,71	1,90

Table 4: Hourly scheduled EFM energy difference between distribution ζ and normal distribution. Results are shown for one case (α=0.9, ω=0.8). Maximum standard deviation is refers to all the cases (eq.10).

Distribution function ζ	**$\Delta EFM^h{}_{energy,\zeta\%}$ for α=0.9 and ω=0.8 [%]**				**$\Delta EFM^h{}_{energy,\zeta\%}$ for all values of α and ω [%]**
	Maximum	**MAE**	**Minimum**	**Standard deviation**	**Maximum standard deviation**
t-scale	79,4	1,9	-79,4	8,9	11,4
Lognormal	79,4	2,6	-88,9	11,1	11,3
Gamma	79,4	1,4	-79,4	8,1	9,0

distribution. As regards the scheduled EFM energy, higher difference has to be taken into account. But also in this case, standard deviation and MAE values are acceptable.

4 Conclusion

This paper proposes a decision model for energy flexibility that minimizes energy costs and incorporates the risk measure CVaR. The optimization problem formulation over one day helps finding the daily optimum, and the risk appetite parameter ω defines the balance between energy cost reduction and economic risk. Furthermore, the evaluation approach for comparing results from different price distribution functions shows that the proposed decision model allows the use of normal, t-location scale, lognormal, and gamma distributions. Alternatively, it allows for modelling prices. The EFM schedule suggested by the decision model and its risk-managing approach are also reliable in the case of different price modelling. Further improvements include integrating additional scenarios for the prices and forecast scenarios for load and renewable generation. The decision model could also integrate heat and cooling needs to use the relative flexibilities and optimize multiple sectors at the same time (sector coupling). The impact of different distribution functions on modelling price forecasts can be expanded by incorporating more scenarios and additional historical data.

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