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RESEARCH PAPER

Industrial Demand Response Scheduling under Time-of-Use Pricing: A Possibilistic Programming Approach

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Abstract

Persistent imbalances between electricity supply and demand remain a significant challenge in many developing economies, where energy-intensive industries exert considerable pressure on power systems. Demand response (DR) programs, particularly Time-of-Use (TOU) pricing, are widely implemented to encourage load shifting and mitigate peak demand. However, in heavy industries such as steelmaking, the effectiveness of TOU tariffs is strongly influenced by operational feasibility, production continuity requirements, and the imprecision of production-driven energy needs. This study develops an optimization-based framework for industrial demand response scheduling using operational and tariff data from the Iranian Alloy Steel Company. The deterministic formulation is first developed as a baseline model to minimize electricity costs while satisfying operational and production constraints. The proposed approach then extends this formulation within a credibility-based possibilistic programming framework, where production-driven uncertainty in daily energy requirements is represented using triangular fuzzy numbers. The results indicate that implementing the possibilistic formulation improves operational reliability by increasing the off-peak load share from 35% to 42% under uncertain production conditions, incurring only a marginal cost increase of 4.85% compared to the baseline deterministic model. Furthermore, the credibility-based schedule reduces the peak load exposure by 5.7% (from 140 MWh to 132 MWh), avoiding excessive peak-hour concentration. Overall, the findings quantify a clear trade-off, revealing that a 4.85% investment in an operational safety margin yields a more balanced and secure schedule, significantly reducing the risk of severe cost escalations in steelmaking demand response.

Keywords:
Demand Response; Time-of-Use Pricing; Industrial Load Scheduling; Possibilistic Programming; Steel Industry.

1. Introduction

The increasing imbalance between electricity supply and demand has become a critical challenge in many countries, particularly in developing economies such as Iran, where recent assessments report a substantial supply deficit. Heavy industries, especially the steel sector, account for a significant share of national electricity consumption and are therefore primary

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candidates for demand-side management (DSM) strategies. The steel industry is among the most energy-intensive sectors worldwide, responsible for a considerable portion of industrial energy use, with substantial potential for efficiency improvements through advanced technologies and optimized energy management (He & Wang, 2017; He, Wang, & Li, 2020).

Demand response (DR) programs have been widely adopted to mitigate peak demand and enhance the reliability of power systems. Among price-based DR mechanisms, Time-of-Use (TOU) pricing is considered one of the most cost-effective instruments for influencing consumption behavior by incentivizing load shifting from peak to off-peak hours (Celebi & Fuller, 2012; Wang & Li, 2015). In the context of industrial consumers, the effectiveness of TOU pricing depends on the ability of firms to adjust operational schedules without compromising production targets. Previous studies have demonstrated the potential of TOU tariffs to reduce operational costs in both residential and industrial settings (Datchanamoorthy et al., 2011; Yang, Tang, & Nehorai, 2013; Vuelvas, Ruiz, & Gruosso, 2021).

Despite the growing literature on industrial DR and TOU pricing, many existing optimization models rely on deterministic assumptions. In practice, industrial operations are subject to uncertainty arising from production variability, efficiency fluctuations, and external market conditions (Gajdzik, Wolniak, & Grebski, 2022). Ignoring such imprecision may lead to schedules that are cost-efficient under nominal conditions but difficult to implement in real industrial environments. To better reflect operational realities, uncertainty-aware approaches such as possibilistic programming have been adopted in various industrial decision problems where reliable probabilistic information is unavailable (Ferreira, Barroso, & Carvalho, 2012a; Ding, Xu, Hao, & Xia, 2023).

Recent research in energy systems has highlighted the importance of incorporating uncertainty into optimization-based planning models (Liu, Hu, Duan, & Pathak, 2021; Parvar & Nazaripouya, 2022; Papageorgiou, 2023; Wang et al., 2024; Zhao & You, 2021). However, most of these studies focus on system-level applications such as dispatch, storage operation, or market design. Comparatively fewer works develop plant-level industrial scheduling models that explicitly integrate production-driven energy requirements with uncertainty-aware modeling, particularly in energy-intensive sectors such as steelmaking.

To address this critical gap, the present study proposes a comprehensive optimization framework for industrial demand response (DR) scheduling under TOU tariffs, specifically tailored to the steel manufacturing sector. The research initially formulates a deterministic baseline model designed to minimize total electricity expenditure while rigorously enforcing technical operating limits and production-driven utility. Recognizing the inherent uncertainties of real-world industrial environments, this baseline is subsequently advanced through a possibilistic programming approach. This extension effectively captures imprecise, production-related parameters utilizing fuzzy information and credibility-based constraints. By systematically comparing the deterministic and possibilistic schedules, this study illuminates the fundamental trade-offs between nominal cost efficiency and operational reliability. To establish a clear trajectory for this investigation, the specific research questions and the primary contributions, which further clarify the positioning and contribution of this work within the existing literature, are formally articulated at the end of Section 2.

The remainder of this paper is structured as follows. Section 2 provides a critical review of the relevant literature concerning industrial DR, TOU pricing, and uncertainty-aware optimization, culminating in the explicit identification of the core research questions and contributions (Section 2.6). Section 3 outlines the problem setting and system architecture. Section 4 details the mathematical formulations of both models. Section 5 presents the numerical results and comparative analyses. Section 6 elaborates on the derived managerial insights. Finally, Section 7 concludes the study and proposes promising avenues for future research.

2. Literature Review

Energy consumption management has become a central concern for governments and industrial organizations, as excessive electricity use increases operational costs while intensifying sustainability and reliability challenges. Consequently, a substantial body of research has focused on optimization-based energy management across various application domains. For example, Haddadi (2016) proposed a goal programming model to manage electricity consumption in hospitals by balancing multiple operational requirements with energy reduction objectives. Such studies illustrate the relevance of structured optimization approaches for improving electricity management performance.

2.1 .Energy Management in Steel and Energy-Intensive Industries

The steel industry is widely recognized as one of the most energy-intensive industrial sectors, accounting for a considerable share of global final industrial energy consumption (He & Wang, 2017). Beyond reviewing energy-efficient technologies, He et al. (2020) emphasized that adopting best available technologies and restructuring production processes can significantly reduce energy consumption in steelmaking.

In addition to technological advancements, macro-level analyses have highlighted the sensitivity of steel production to electricity price fluctuations. Gajdzik et al. (2022), for instance, examined the Polish steel sector under the combined effects of the COVID-19 pandemic and geopolitical disruptions, showing that rising electricity prices can directly constrain production and alter energy intensity patterns. Luo et al. (2026) proposed an economy-carbon co-optimization framework for industrial multi-energy systems considering process coupling and flexible by-product gas utilization, highlighting the growing importance of integrated operational energy management in industrial environments.

Furthermore, integrated sustainability-oriented modeling approaches have been developed in other energy-intensive supply chain contexts to jointly improve economic and environmental performance (Rasekh et al., 2023; Sahebi et al., 2024). Despite these contributions, most existing works focus on technological improvements or macro-level analyses rather than plant-level operational scheduling under dynamic pricing schemes.

2.2 .Demand Response and TOU Pricing Mechanisms

Demand response (DR) has been extensively studied as a mechanism for modifying electricity consumption in response to price signals and system conditions. Among price-based DR mechanisms, Time-of-Use (TOU) pricing aims to reduce peak demand by encouraging load shifting toward low-price hours. More recently, Hall and Posner (2026) investigated optimal energy scheduling under TOU tariffs from a scheduling-theoretic perspective, further emphasizing the importance of temporal electricity pricing in operational decision-making. Singh et al. (2025) further demonstrated that integrating price-elastic demand response within microgrid optimization frameworks can simultaneously improve both economic and environmental performance.

Wang and Li (2015), through a survey and scenario analysis of U.S. utilities, reported that TOU tariffs can be particularly effective for industrial consumers when operational flexibility exists. From a modeling perspective, Datchanamoorthy et al. (2011) proposed an iterative linear programming framework for TOU optimization in residential settings, while Celebi and Fuller (2012) quantified welfare gains under TOU compared with uniform pricing. Yang et al. (2013) developed a game-theoretic formulation for optimal TOU pricing decisions, and Vuelvas et al. (2021) employed a Stackelberg framework for coordinating EV charging without relying on explicit price elasticity estimation.

More recent research has emphasized the importance of incorporating risk and coordination

considerations in local energy systems, including microgrids and peer-to-peer energy trading environments (Sahebi et al., 2023; Mohseni & Pishvaee, 2023). Nevertheless, many existing TOU studies rely on stylized settings or residential applications, while plant-level industrial scheduling models incorporating production-driven constraints remain comparatively limited.

2.3 .Uncertainty-Aware Optimization in Energy Systems

Uncertainty plays a critical role in modern electricity systems due to price volatility, demand fluctuations, and operational variability. As a result, optimization approaches have increasingly incorporated uncertainty considerations.

Ferreira et al. (2012a) introduced robust optimization formulations capturing correlations in electricity price uncertainty for demand response planning. Zhao and You (2021) developed a multistage robust framework for renewable transition planning, demonstrating that deterministic solutions may underestimate costs under uncertain conditions. Ding et al. (2023) integrated robust optimization into a Stackelberg game model for energy storage and pricing decisions. Additionally, distributionally robust optimization (DRO) models have been applied to dispatch and electricity market problems to improve reliability (Liu et al., 2021; Parvar & Nazaripouya, 2022; Papageorgiou, 2023; Gu et al., 2023; Wang et al., 2024).

Beyond robust and stochastic approaches, possibilistic programming has been proposed as a suitable alternative when uncertainty is characterized by imprecision rather than well-defined probability distributions. In sustainable supply chain contexts, hybrid robust–possibilistic models have demonstrated the value of incorporating fuzzy information into decision-making (Pishvaee et al., 2012; Mohseni et al., 2016). From a broader sustainability perspective, Nielsen et al. (2026) proposed a conceptual framework for sustainable energy management modeling in circular industrial hubs, emphasizing the importance of coordinated and uncertainty-aware decision support tools in future industrial energy systems.

Despite these methodological advances, most uncertainty-aware optimization studies are concentrated at system or market levels. In particular, modeling imprecision in production-related parameters at the plant level remains relatively underexplored, particularly in steelmaking environments characterized by strict production continuity requirements.

2.4 .Summary and Motivation

Overall, the literature can be categorized into four interrelated strands:
(i) energy management and efficiency improvement in steel and energy-intensive industries,
(ii) demand response and TOU pricing mechanisms,
(iv) uncertainty-aware optimization approaches in energy systems.

Table 1 summarizes representative studies according to application context, methodology, and treatment of uncertainty. The table highlights the diversity of methodological approaches and shows that most uncertainty-aware studies are concentrated at system or market levels rather than plant-level industrial scheduling. While robust and distributionally robust approaches are well developed at system levels, fuzzy and possibilistic modeling remain relatively limited in plant-level industrial DR applications. This gap motivates the development of a scheduling model that explicitly incorporates production continuity requirements and fuzzy representations of daily energy needs.

Despite the growing body of recent research on uncertainty-aware energy optimization, most studies focus on system-level dispatch, microgrids, or integrated multi-energy coordination. Comparatively limited attention has been devoted to plant-level industrial DR scheduling under production-driven epistemic uncertainty and strict operational continuity requirements.

Table 1. Comparative summary of representative studies on industrial demand response, TOU pricing, and uncertainty-aware energy optimization

Study	DR / Pricing Context	Uncertainty Type	Objective	Key Decision Variables	Key Constraints	Solution Method	Case Study
Datchanamoorthy et al. (2011)	TOU scheduling	Deterministic	Electricity cost minimization	Appliance scheduling	Household operational limits	Iterative linear programming	Residential electricity
Celebi & Fuller (2012)	TOU pricing	Deterministic	Welfare maximization	Pricing decisions	Market equilibrium conditions	Welfare analysis	Power systems
Pishvaee et al. (2012)	Supply chain planning	Possibilistic + robust	Sustainable supply chain optimization	Supply chain design decisions	Fuzzy and robust uncertainty	Hybrid robust–possibilistic programming	Sustainable supply chains
Ferreira et al. (2012)	Demand response scheduling	Robust (correlated prices)	Cost minimization under uncertainty	Electricity scheduling decisions	Price uncertainty constraints	Robust optimization	Power systems / DR
Yang et al. (2013)	TOU pricing strategy	Deterministic	Optimal pricing design	TOU tariff levels	User response behavior	Game-theoretic optimization	Power systems
Wang & Li (2015)	TOU tariffs	Deterministic	Evaluation of TOU effectiveness	Load shifting behavior	Consumer flexibility	Survey and scenario analysis	Industrial consumers (US)
Haddadi (2016)	Electricity consumption management	Not explicitly modeled	Multi-objective energy management	Electricity allocation levels	Operational requirements	Goal programming	Hospitals (Iran)
Mohseni et al. (2016)	Sustainable operations planning	Possibilistic + robust	Sustainable operational planning	Operational planning decisions	Fuzzy uncertainty	Hybrid robust–possibilistic programming	Sustainable supply chains
He & Wang (2017)	Energy efficiency analysis	N/A	Review of energy-saving opportunities	N/A	N/A	Literature review	Steel industry (global)
He et al. (2020)	Industrial energy efficiency	N/A	Reduction of industrial energy use	Technology adoption decisions	Process restructuring requirements	Technology and process review	Steel industry (China)
Vuelvas et al. (2021)	Demand response coordination	Deterministic	Coordinated EV charging	Charging schedules	Charging demand satisfaction	Stackelberg game	EV charging clusters
Zhao & You (2021)	Renewable energy planning	DRO / multistage robust	Cost minimization under uncertaint	Capacity expansion decisions	Renewable uncertainty	Data-driven multistage robust	Renewable transition (US)

Study	DR / Pricing Context	Uncertainty Type	Objective	Key Decision Variables	Key Constraints	Solution Method	Case Study
			y			optimization	
Liu et al. (2021)	Dispatch optimization	DRO	Reliable dispatch improvement	Dispatch decisions	Regulation uncertainty	Data-driven DRO	Power systems (real-time)
Gajdzik et al. (2022)	Electricity price impacts	External market disruptions	Analysis of energy intensity behavior	Production and energy indicators	Economic and geopolitical conditions	Econometric modeling	Steel industry (Poland)
Parvar & Nazaripouya (2022)	Energy storage operation	DRO	Storage operation optimization	Charging/discharging schedules	Ambiguity-set uncertainty	Data-driven DRO	Battery storage systems
Rasekh et al. (2023)	Sustainable energy management	Scenario-based uncertainty	Economic and environmental improvement	Operational and sustainability decisions	Sustainability requirements	Integrated sustainability modeling	Energy-intensive supply chains
Sahebi et al. (2023)	Local energy coordination	Risk-aware uncertainty	Risk-aware energy management	Energy trading decisions	Reliability constraints	Risk-aware optimization	Microgrids / P2P energy
Mohseni & Pishvaee (2023)	Energy management planning	Robust	Robust operational planning	Planning decisions	Uncertainty robustness	Robust optimization	Energy systems
Ding et al. (2023)	Pricing and storage coordination	Robust	Joint pricing and storage optimization	Storage dispatch and pricing	Demand uncertainty	Robust Stackelberg game	Energy storage systems
Papageorgiou (2023)	Market coordination	DRO	Contracting and spot allocation optimization	Market allocation decisions	Market uncertainty	Data-driven DRO	Electricity markets
Gu et al. (2023)	Dynamic dispatch	Robust / multistage	Dynamic power flow optimization	Multi-stage dispatch decisions	Operational uncertainty	Multi-stage robust optimization	Power flow optimization
Sahebi et al. (2024)	Energy-aware supply chain coordination	Uncertain operational conditions	Integrated sustainability optimization	Supply chain operational decisions	Sustainability and operational constraints	Integrated optimization framework	Energy-intensive supply chains
Wang et al. (2024)	Renewable-integrated dispatch	DRO	Coordinated dispatch optimization	Dispatch scheduling	Wind uncertainty correlations	Data-driven DRO	Power system dispatch

Study	DR / Pricing Context	Uncertainty Type	Objective	Key Decision Variables	Key Constraints	Solution Method	Case Study
Singh et al. (2025)	Price-elastic demand response	Deterministic	Economic and environmental optimization	DR participation and energy dispatch	Microgrid operational constraints	Metaheuristic optimization	Microgrids
Hall & Posner (2026)	TOU-based scheduling	Deterministic	Optimal energy scheduling	Time-dependent scheduling decisions	Temporal operational constraints	Scheduling optimization	Energy scheduling systems
Luo et al. (2026)	Industrial energy coordination	Operational uncertainty	Economy-carbon co-optimization	Multi-energy dispatch decisions	Process coupling constraints	Multi-objective optimization	Industrial multi-energy systems
Nielsen et al. (2026)	Sustainable energy management	Conceptual uncertainty considerations	Sustainable industrial energy coordination	Energy management interactions	Circularity and coordination requirements	Conceptual framework	Circular industrial hubs
The present study	Industrial TOU-based demand response scheduling	Fuzzy epistemic uncertainty in production-related energy requirements	Electricity cost minimization while preserving production continuity	Hourly electricity consumption scheduling	Minimum production utility, saturation effects, daily energy requirements, operational continuity	Deterministic LP + credibility-based possibilistic programming	Steel plant (Iran)

2.5. Research Gap and Contributions of the Present Study

Although prior studies have examined energy efficiency in steel production (He & Wang, 2017; He et al., 2020) and the effects of electricity prices on industrial output (Gajdzik et al., 2022), relatively few works formulate plant-level optimization models that explicitly schedule electricity consumption while preserving production continuity.

Moreover, many TOU-based DR models (Celebi & Fuller, 2012; Wang & Li, 2015; Datchanamoorthy et al., 2011; Yang et al., 2013; Vuelvas et al., 2021) rely on deterministic assumptions, limiting their applicability in industrial environments characterized by operational imprecision.

Although robust, stochastic, and DRO approaches (Ferreira et al., 2012a; Zhao & You, 2021; Ding et al., 2023; Liu et al., 2021; Parvar & Nazaripouya, 2022; Papageorgiou, 2023; Gu et al., 2023; Wang et al., 2024) have enhanced uncertainty modeling in energy systems, their application to plant-level industrial DR scheduling remains limited. Furthermore, possibilistic programming approaches (Pishvaee et al., 2012; Mohseni et al., 2016) suggest that fuzzy representations are particularly appropriate when decision-makers rely on expert knowledge rather than large probabilistic datasets.

Driven by these gaps, this study seeks to answer the following core research questions: (i) How can industrial electricity consumption be optimally scheduled under TOU tariffs while preserving production continuity? (ii) How can possibilistic programming effectively mitigate the operational imprecision inherent in manufacturing parameters? and (iii) How does the inclusion of such uncertainty affect load shifting decisions and operational feasibility?

Addressing these questions, the present study makes three main contributions:

1. **Integrated DR Optimization Framework:** It develops a plant-level optimization framework for industrial demand response scheduling under TOU pricing, effectively balancing electricity cost minimization with production continuity requirements.
2. **Operationally-Grounded Utility Modeling:** It introduces a an operationally grounded piecewise-linear utility formulation that captures real-world manufacturing constraints, including minimum operating thresholds, production saturation effects, and day-night productivity asymmetry, which are often ignored in standard DR models.
3. **Credibility-Based Possibilistic Scheduling:** It proposes a credibility-based possibilistic programming approach to handle the inherent imprecision in daily production-driven energy requirements. By transforming fuzzy constraints into tractable deterministic equivalents at high confidence levels, the model ensures operational feasibility without requiring large probabilistic datasets.

3. Problem Definition

The problem addressed in this study is the optimal daily scheduling of electricity consumption for the melting section of a steelmaking plant operating under a Time-of-Use (TOU) tariff. The planning horizon is a single day discretized into hourly intervals ($h \in \{1, \dots, 24\}$). Let the decision variable $e_h$represent the electricity consumption (in MWh) during time interval h.

The core technical challenge is to determine the optimal consumption profile $e_h$that minimizes the net daily operational cost, defined as the total electricity expenditure minus the monetized utility derived from production, while satisfying technical operating limits and a daily energy requirement.

To accurately reflect the operational realities of the steelmaking process, the utility of energy consumption is not modeled as a simple linear function. Instead, it is formulated using a piecewise-linear structure comprising distinct operational **segments**:

- **Minimum Operating Threshold:** Below a specific energy consumption level, the process cannot yield a stable or usable output, resulting in zero utility.
- **Active Production Segment:** Between the minimum threshold and a nominal capacity limit, the production utility increases linearly with electricity consumption.
- **Saturation Segment:** Beyond the nominal capacity, additional energy consumption yields no further increase in production utility due to physical equipment limits.

Additionally, the technical definition of the problem incorporates day/night shift asymmetry, adjusting the utility parameters to reflect different productivity levels across shifts. Since industrial operations are exposed to process variability (e.g., fluctuating daily energy requirements), this uncertainty is incorporated using a credibility-based possibilistic programming approach to ensure robust and feasible scheduling.

It should be noted that while physical steelmaking processes (such as Electric Arc Furnaces) operate in discrete batches driven by the on/off states of machinery, this study adopts a macro-level aggregate approach at an hourly resolution. To avoid the high computational complexity of Mixed-Integer Linear Programming (MILP), which becomes computationally prohibitive when integrated with the proposed possibilistic uncertainty framework, energy consumption (e_h) is modeled as a continuous aggregate variable. The discrete, "batch-like" nature of the real system is practically approximated through the minimum threshold of the piecewise-linear utility function. If the allocated energy falls below the operational threshold required to complete a stable batch, the model yields zero utility, effectively penalizing unrealistic partial operations.

3.1. Problem Assumptions and Scope

To simplify the complexity of the decision problem and ensure consistency with industrial

practice, the following assumptions are adopted:

1. Utility-based consumption definition: Consumer utility is defined solely based on electricity consumption, without explicitly modeling network-imposed restrictions or rationing policies during peak months.
2. Embedded production constraints: Other production constraints (e.g., raw material availability, labor constraints, and process limitations) are implicitly embedded within the utility function and feasible consumption bounds rather than modeled separately.
3. Scope of industrial operation: The studied production system is restricted to the melting section of a steel plant, including three electric arc furnaces (EAFs) and three ladle furnaces (LFs). Other sections such as rolling and heat treatment are excluded for tractability.

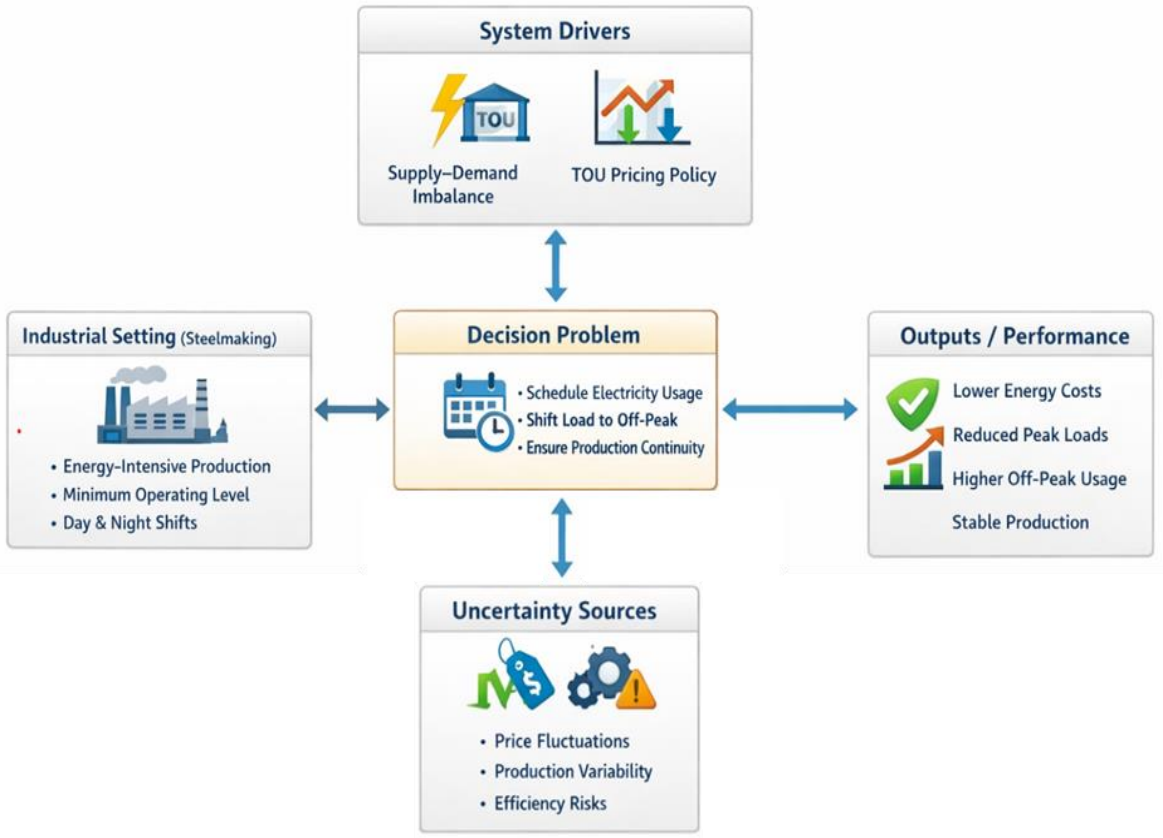


Fig.1. Conceptual structure of the industrial demand response scheduling problem under TOU tariffs, including system inputs, operational constraints, uncertainty representation, and optimization outputs.

As shown in Figure 1, the addressed problem concerns scheduling industrial electricity consumption under TOU tariffs while maintaining production continuity under technical operating limits. The decision-making context is further influenced by imprecision in production-related parameters such as daily energy requirements and process efficiency.

4. Methodology

This study develops an optimization framework for industrial demand response (DR) scheduling under Time-of-Use (TOU) pricing, with application to an energy-intensive steelmaking setting. As illustrated in Figure 2, the methodological procedure is organized into three phases. First, the problem is conceptualized through a structured literature review and the formulation of research questions. Second, a deterministic scheduling model is developed as a benchmark to represent cost–utility trade-offs in daily electricity consumption planning. Third, the baseline model is extended using possibilistic programming to represent imprecise production-driven energy requirements through fuzzy information.

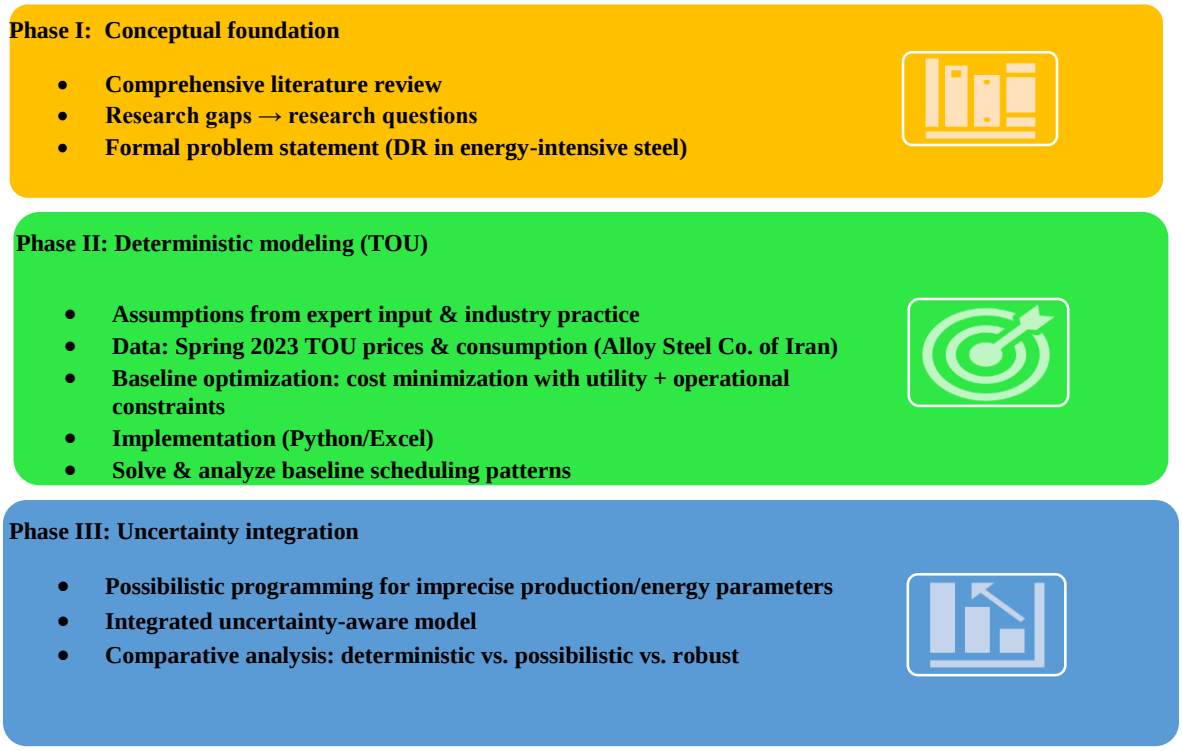


Fig.2. Methodological framework

After establishing the conceptual basis of the study, Phase I frames the research problem through a structured review of industrial demand response and uncertainty-aware optimization, leading to the formulation of the analytical scope. Phase II develops a deterministic scheduling model under TOU pricing to generate a baseline benchmark for industrial electricity consumption planning, capturing the trade-off between electricity expenditure and production-driven utility subject to operational feasibility limits. Phase III introduces a possibilistic extension in which the daily energy requirement is represented by a triangular fuzzy number and enforced through credibility-based constraints (Pishvaee et al., 2012). Finally, the obtained schedules are evaluated using scenario-based sensitivity analysis as an ex-post validation tool to assess how schedules respond to plausible operational variations.

The mathematical notation is summarized in Table 2.

Table 2. Nomenclature

Group	Symbol	Description	Unit
Sets and indices	H	Set of time periods (hours), H={1,...,H}	–
	h	Index of time period (hour), h ∈ H	–
	M	Set of segments in the piecewise-linear utility function	–
	m	Index of utility-function segment, m ∈ M	–
Decision variables	e_h	Electricity consumption scheduled in time period h	MWh
	$u_h = \alpha_h^m . e_h + \beta_h^m$	Utility associated with consumption in time period h	$
Deterministic parameters	e_T	Total daily energy requirement over the horizon	MWh
	λ_h	Electricity price in time period h	$/MWh
	$e_{h,min}$	Minimum feasible electricity consumption in period h	MWh
	$e_{h,max}$	Maximum feasible electricity consumption in period h	MWh
	α_h^m	Slope of segment m of the utility function in period h	$/MWh
	β_h^m	Intercept of segment m of the utility function in period h	$
Uncertainty-related parameters	$\tilde{e}_T = (e_T^L, e_T^M, e_T^U)$	Fuzzy daily energy requirement (triangular fuzzy number)	MWh

4.1. Deterministic Mathematical Model

The first stage of the framework formulates a deterministic optimization model for hourly electricity consumption scheduling under TOU tariffs. The model seeks to minimize total electricity cost while accounting for the operational value (utility) associated with sustaining steel production. The deterministic scheduling model minimizes the net operating objective defined as electricity expenditure minus the production-driven utility:

$$\min Z = \sum_{h=1}^{H} (\lambda_h e_h - u_h) \quad (1)$$

It should be noted that minimizing the net difference between electricity cost and monetized production utility (Equation 1) is mathematically equivalent to maximizing net operational profit. This cost-minimization framing is adopted to reflect the primary perspective of the industrial energy manager, consistent with established industrial Demand Response frameworks (Ferreira .et al, 2012; Wang and Li ,2015)

The objective function is formulated entirely in monetary terms to ensure dimensional consistency. The electricity cost component directly represents the financial expenditure associated with hourly electricity consumption under TOU pricing. The utility component represents the estimated economic benefit derived from productive electricity usage and is calibrated using industrial economic parameters, including steel selling price, production profit margin, and energy-to-production conversion factors. Consequently, both components are expressed in consistent monetary units (USD), allowing their direct integration within the optimization objective.

The model is subject to the following constraints. Constraint (2) ensures that total planned consumption satisfies the required daily energy level e_T. Constraint (3) enforces hourly technical operating limits. Constraint (4) defines the piecewise-linear utility representation by restricting the utility variable to lie below all linear segments. Finally, Constraint (5) ensures non-negativity of decision variables.

$$\sum_{h=1}^{H} e_h = e_T \quad (2)$$

$$e_{h,\min} \le e_h \le e_{h,max} \quad , \quad \forall h \in H \quad (3)$$

$$u_h \le \alpha_h^m e_h + \beta_h^m \forall h \quad , \quad \forall m \in M \quad (4)$$

$$e_h \ge 0, u_h \ge 0 \quad , \quad \forall h \in H \quad (5)$$

Constraint (4) represents the concave piecewise-linear utility function through an upper-envelope linearization. More specifically, the utility value in each period is constrained to remain below all affine segments, such that the optimal solution implicitly selects the minimum active segment. Since the objective function minimizes electricity cost minus utility, the model equivalently maximizes utility, forcing the utility variable to attain the highest feasible value under these inequalities. Consequently, the resulting formulation accurately reproduces the intended concave piecewise-linear utility structure while preserving linearity and computational tractability.

The utility Function in the proposed model represents the production value derived from electricity consumption across different time periods. Based on expert interviews with managers and operators in the steel industry, it was confirmed that the marginal utility of energy consumption is higher during daytime hours compared to nighttime. The main reasons include greater workforce efficiency during day shifts, as well as the availability of specialized maintenance teams to address unplanned disruptions. From an economic perspective, the profit

margin of steelmaking is approximately 70,000 IRR (≈0.12 $) per kilogram of steel, which corresponds to about 120 $ per ton. Considering the production technology of the case company, one megawatt-hour of electricity yields approximately 1.2 tons of molten steel. Accordingly, the utility function is modeled as a concave piecewise-linear function of electricity consumption, with different segment coefficients for daytime (06:00–24:00) and nighttime (00:00–06:00) operations. In the baseline calibration, the night-shift utility is scaled by a factor of 0.9 to reflect lower operational efficiency during nighttime production.

The parameters $\alpha_h^m \; and \; \beta_h^m$ denote the slope and intercept of utility segment (m) in period (h), respectively, and are calibrated using production data, operational characteristics, and estimated steelmaking profit margins. Based on expert consultation and operational observations, the utility function is specified using a concave piecewise-linear structure to better represent the production behavior of continuous steelmaking processes. In the adopted formulation, utility remains zero for energy consumption below a threshold of 50 MWh (insufficient to sustain continuous steelmaking), increases linearly between 50 MWh and 75 MWh, and remains constant beyond 75 MWh. Although the utility function exhibits saturation beyond nominal production levels, the upper consumption bounds in Constraint (3) remain necessary to enforce technical and operational feasibility limits (figure 3).

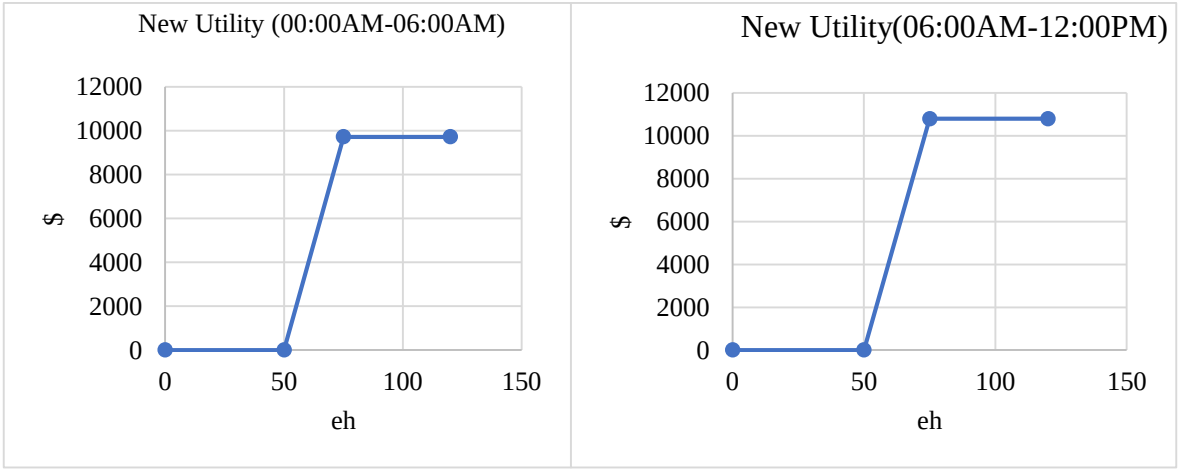


Fig. 3. Concave piecewise-linear utility functions for daytime (06:00–24:00) and nighttime (00:00–06:00) steel production operations

The adopted utility representation captures three important operational characteristics of steel production systems: (i) minimum operating thresholds below which production continuity cannot be sustained, (ii) approximately linear growth of production value within feasible operating ranges, and (iii) saturation effects beyond nominal production capacity.

The piecewise-linear utility formulation is implemented through segment-wise upper-bound constraints to preserve continuity across operational regions while maintaining linear model structure. In this representation, the utility associated with each consumption level is determined by the active feasible operational segment. Therefore, the formulation does not imply economic minimization of utility; rather, the objective function maximizes the achievable production-related utility subject to the operational structure of the piecewise representation.

4.2. Possibilistic Programming Formulation

In practice, the daily production-driven energy requirement is subject to imprecision due to variability in furnace conditions, scrap quality, downtime, and operational disruptions. When probabilistic distributions are not reliable or sufficient historical data are unavailable, possibilistic programming provides a suitable framework to model epistemic uncertainty using fuzzy numbers (Pishvaee et al., 2012). Accordingly, the daily energy requirement is represented

by a triangular fuzzy number:

$$\tilde{e}_T = (e_T^L, e_T^M, e_T^U) \quad (6)$$

where e_T^L, e_T^M, and e_T^Udenote the pessimistic, most likely, and optimistic estimates of daily energy requirement, respectively.

Following a credibility-based possibilistic approach, the fuzzy equality constraint of meeting the daily energy requirement is converted into a crisp constraint at a confidence (credibility) level $\alpha \in [0,1]$:

$$Cr(\sum_{h=1}^{H} e_h \geq \tilde{e}_T) \geq \alpha \quad (7)$$

It should be noted that, for triangular fuzzy numbers, the deterministic equivalent of a credibility chance constraint is generally piecewise with respect to the confidence level a. Since industrial demand response scheduling requires high-confidence operational feasibility to preserve production continuity and avoid energy shortages, the present study focuses on the practically relevant case of α≥0.5. this assumption, the credibility chance constraint reduces to the following deterministic linear inequality:

$$\sum_{h=1}^{H} e_h \geq e_T^M + (1-\alpha)(e_T^U - e_T^M) \quad (8)$$

Therefore, the possibilistic scheduling model is formulated as:

$$\min Z = \sum_{h=1}^{H} (\lambda_h e_h - u_h) \quad (9)$$

subject to:

$$\sum_{h=1}^{H} e_h \geq e_T^M + (1-\alpha)(e_T^U - e_T^M) \quad (10)$$

$$e_h^{\min} \leq e_h \leq e_h^{\max} \forall h \quad (11)$$

$$u_h \leq \alpha_{h,m} e_h + \beta_{h,m} \forall h, \forall m \quad (12)$$

$$e_h \geq 0,\ u_h \geq 0 \forall h \quad (13)$$

The parameter αreflects the decision-maker's confidence level: higher αleads to more conservative energy planning, ensuring that production targets are met even under unfavorable realizations of the imprecise requirement.

4.3. Uncertainty Characterization

Industrial demand response in energy-intensive industries is exposed to operational variability that may reduce the feasibility and economic performance of deterministic schedules. In the studied steelmaking process, uncertainty primarily arises from imprecision in the daily production-driven energy requirement. Such imprecision is caused by furnace conditions, scrap quality fluctuations, unplanned downtime, workforce variability, and maintenance interruptions.

Given the limited availability of reliable probabilistic distributions for these disruptions, uncertainty is modeled using a possibilistic framework. Specifically, the daily energy requirement is represented as a triangular fuzzy number and incorporated into the optimization

model through credibility-based constraints.

Triangular fuzzy numbers were adopted to represent uncertain daily energy requirements due to their simplicity, interpretability, and suitability under limited historical data availability. The triangular representation enables uncertain parameters to be characterized using only three practically meaningful values: minimum, most likely, and maximum estimates derived from operational expertise. More complex fuzzy structures such as trapezoidal fuzzy numbers were not considered necessary because sufficiently detailed information regarding plateau-like membership regions was unavailable. Similarly, probabilistic distributions such as Gaussian models were not adopted due to the lack of statistically reliable historical observations required for distribution fitting and validation.

4.3.1. Uncertain Parameters

To maintain tractability while capturing the most influential source of variability, uncertainty is represented through a single key parameter:

- **Daily energy requirement e_T:** the total electricity required to meet the daily production target. Due to operational disruptions and production variability, the required energy level may deviate from its nominal estimate and is therefore modeled as a triangular fuzzy number $\tilde{e}_T = (e_T^L, e_T^M, e_T^U)$.

4.3.2. Uncertainty Representation in the Proposed Optimization Models

The above uncertainty characterization is incorporated into the optimization framework through possibilistic programming. The fuzzy daily energy requirement is transformed into an equivalent deterministic constraint using a credibility level parameter $\alpha \in [0,1]$. Higher values of $\boldsymbol{\alpha}$correspond to more conservative scheduling decisions, ensuring that production targets are satisfied even under unfavorable realizations of the imprecise energy requirement.

No interval-based or worst-case uncertainty sets are considered in the present study, as the focus is on modeling epistemic imprecision rather than bounded adversarial deviations.

4.3.3. Justification of the Adopted Uncertainty Modeling Approach

Selecting an appropriate uncertainty modeling framework is a critical methodological decision in industrial energy optimization problems. In the present study, the uncertainty associated with the daily production-driven energy requirement is primarily epistemic in nature, arising from operational imprecision rather than statistically observable stochastic variability. Specifically, fluctuations in furnace operating conditions, scrap quality, maintenance interruptions, workforce efficiency, and production-related expert estimations introduce ambiguity into the required daily electricity demand of the steelmaking process.

In practical industrial environments, sufficiently large and reliable historical datasets are often unavailable for accurately estimating probability distributions of such operational disturbances. Furthermore, the uncertainty considered in this study does not represent adversarial worst-case deviations, but rather managerial and operational imprecision characterized by incomplete knowledge and expert-based estimation. Under these conditions, possibilistic programming provides a more appropriate representation framework than purely probabilistic or worst-case robust approaches.

The adopted credibility-based possibilistic framework offers several advantages for industrial demand response scheduling. First, it allows uncertain operational requirements to be represented through triangular fuzzy numbers constructed from expert knowledge and operational observations. Second, the credibility level parameter enables decision-makers to explicitly control the trade-off between operational reliability and economic efficiency. Third, the resulting deterministic equivalent remains computationally tractable and preserves the linear structure of the optimization model.

To further clarify the rationale behind the adopted methodology, Table 3 compares the main characteristics of deterministic, robust, and possibilistic uncertainty modeling approaches in the context of industrial demand response scheduling.

Table 3. Conceptual comparison of uncertainty modeling approaches for industrial demand response scheduling

Aspect	Deterministic Optimization	Robust Optimization	Possibilistic Programming (This Study)
Uncertainty treatment	Ignores uncertainty	Worst-case bounded uncertainty	Epistemic imprecision using fuzzy estimates
Data requirement	Precise parameter values	Uncertainty bounds	Expert-based fuzzy estimates
Conservatism level	Low	High	Moderate and controllable
Operational flexibility	High	Limited due to worst-case protection	Preserved through credibility levels
Computational complexity	Low	Moderate to high	Low (linear equivalent)
Suitability for limited historical data	Weak	Moderate	Strong
Risk of excessive conservatism	None	High	Moderate
Applicability to industrial expert knowledge	Limited	Limited	Strong

As shown in Table 3, robust optimization frameworks are highly effective for protecting against worst-case uncertainty realizations, but they may produce overly conservative schedules with unnecessary electricity expenditures in industrial demand response applications. In contrast, the possibilistic approach adopted in this study provides a balanced compromise between operational feasibility and economic efficiency by explicitly incorporating expert-driven uncertainty representations while avoiding excessive conservatism.

Accordingly, the proposed credibility-based possibilistic formulation is considered particularly suitable for the studied steelmaking environment, where operational uncertainty is characterized more by imprecision and incomplete information than by statistically observable random behavior.

4.4. Scenario-Based Stress Testing (Post-Optimization Validation)

To complement the optimization models and provide an interpretable assessment of schedule stability, a scenario-based sensitivity analysis is conducted as a post-optimization validation step. This analysis is not used to generate optimal schedules and therefore does not replace the optimization formulations. Instead, it serves as an ex-post evaluation tool to examine how the obtained schedules (deterministic and possibilistic) perform under plausible operational variations.

Specifically, a finite set of representative scenarios is constructed by varying the daily production-driven energy requirement within a reasonable range consistent with the fuzzy estimates (e_T^L, e_T^M, e_T^U). For each scenario, the deterministic and possibilistic schedules are re-evaluated to quantify their sensitivity in terms of electricity cost, peak-hour exposure, and feasibility indicators. This validation provides a transparent comparison of the baseline and possibilistic schedules and helps interpret the practical value of incorporating imprecision in production-related requirements under TOU pricing.

4.5. Evaluation Indicators

To quantitatively compare deterministic and possibilistic scheduling performance, the following evaluation metrics are adopted:

Percentage cost variation relative to the deterministic baseline:

$$\Delta\text{Cost}(\%) = \frac{Z_P - Z_D}{Z_D} \times 100 \tag{15}$$

where $Z_D$and $Z_P$denote the objective function values of the deterministic and possibilistic models, respectively.

Peak-load reduction percentage:

$$\text{Peak Reduction}(\%) = \frac{E_D^{\text{peak}} - E_P^{\text{peak}}}{E_D^{\text{peak}}} \times 100 \quad (16)$$

where $E_D^{\text{peak}}$and E_P^{peak}represent the total peak-period electricity consumption under deterministic and possibilistic scheduling, respectively.

Off-peak load shifting percentage:

$$\text{Off-Peak Shift}(\%) = \frac{E_P^{\text{off}} - E_D^{\text{off}}}{E_D^{\text{off}}} \times 100 \quad (17)$$

where $E_D^{\text{off}}$and E_P^{off}denote the total off-peak electricity allocation under the deterministic and possibilistic scheduling approaches, respectively.

5. Numerical Results

This section presents the numerical results of the proposed industrial demand response (DR) scheduling framework under Time-of-Use (TOU) pricing. The performance of two modeling approaches is compared: (i) a deterministic optimization model serving as a baseline benchmark, and (ii) a possibilistic programming model that captures imprecision in production-driven energy requirements using fuzzy information. The analysis is conducted for a real industrial case study in the Iranian steel sector using operational and tariff data from Spring 2023.

5.1. Case Study Description and Input Settings

The numerical experiments are based on operational data from the Iranian Alloy Steel Company, a major producer of special alloy steels located in Yazd Province, Iran. As an electricity-intensive industrial consumer, the company provides an appropriate context for evaluating industrial DR strategies under TOU pricing.

The analysis focuses on the melting and refining section of the plant, which includes three electric arc furnaces (EAFs) and three ladle furnaces (LFs). Other production units (e.g., rolling and heat treatment) are excluded to maintain modeling tractability and to preserve a direct relationship between electricity scheduling decisions and molten steel production.

The planning horizon consists of one operational day discretized into 24 hourly periods. The average daily production target is 2,000 tons of molten steel. Based on expert interviews and operational records, the electricity intensity is estimated at 0.8 MWh per ton of molten steel, resulting in an average daily electricity requirement of approximately 1,600 MWh. To account for operational uncertainty in the possibilistic model, the total production energy target $\tilde{e}^T$is modeled as a triangular fuzzy number. Considering a 10%deviation around the nominal deterministic value of 1,600MWh, the fuzzy parameters $(e_T^L, e_T^M, e_T^U)$are set to $(1440, 1600, 1760)$MWh, respectively. Hourly electricity consumption is constrained within technical lower and upper operating bounds to ensure feasible furnace operation.

Electricity prices follow the TOU tariff scheme regulated by Iran's Ministry of Energy, consisting of three pricing windows: off-peak, intermediate, and peak periods. The tariff structure and the corresponding operating limits used in the numerical experiments are

summarized in Table 4.

Table .4. Time-of-Use tariff structure and technical operating bounds used in the numerical experiments (Spring 2023)

Type of tariff	Hours	$e_{h,min}$ (MWh)	$e_{h,max}$ (MWh)	price ($/MWh)
Off-peak	00:00-08:00	50	120	100
Intermediate	08:00-14:00 and 17:00-24:00	50	120	200
Peak	14:00-17:00	50	120	400

All models are solved under identical deterministic input settings to ensure a fair comparison between the deterministic and possibilistic approaches. The reported performance indicators include total electricity cost, peak-period exposure, and the share of electricity allocated to off-peak hours.

5.2. Deterministic Results

The deterministic model generates the baseline daily electricity schedule by minimizing total electricity expenditure net of production-driven utility under the nominal TOU tariff structure. The resulting schedule satisfies the required daily energy demand of approximately 1,600 MWh while respecting hourly technical operating bounds.

As expected, the optimization allocates a considerable share of electricity consumption to off-peak periods in order to exploit lower tariff levels. At the same time, the model maintains adequate consumption during daytime hours, where the marginal production utility is higher, thereby preserving production continuity and operational efficiency.

Under nominal parameter values, the deterministic solution achieves the lowest electricity cost among the evaluated approaches. However, because all parameters are treated as fixed and precise, the resulting schedule does not explicitly incorporate margins against imprecision in the daily energy requirement. Consequently, its performance may deteriorate if the actual production-driven energy needs deviates from its nominal estimate. This limitation motivates the development of a possibilistic extension to enhance schedule stability under imprecise production conditions.

5.3. Possibilistic Programming Results

To account for imprecision in the daily production-driven energy requirement, the deterministic model is extended using possibilistic programming. In this formulation, the nominal daily energy requirement $e_T$is replaced by a triangular fuzzy number $\tilde{e}_T = (e_T^L, e_T^M, e_T^U)$, representing pessimistic, most likely, and optimistic estimates of the required energy level.

The fuzzy constraint is transformed into an equivalent deterministic form using a credibility-based approach at a selected confidence level $\alpha \in [0,1]$. In the numerical experiments, the model is solved for a representative value (e.g.,$\alpha = 0.8$), reflecting a relatively conservative planning attitude.

Compared to the deterministic benchmark, the possibilistic schedule incorporates an implicit safety margin to ensure that production requirements are satisfied even when the actual daily energy need deviates from its nominal estimate. As a result, the load profile becomes more balanced and less concentrated in peak-price periods. The model tends to increase allocation toward off-peak and intermediate hours while maintaining feasibility under imprecise production conditions.

This enhanced protection against uncertainty leads to a moderate increase in nominal electricity cost relative to the deterministic solution. However, this cost increment can be interpreted as a stability premium that reduces the risk of under-supplying the required production energy. Overall, the results indicate that possibilistic programming provides a structured and practically interpretable trade-off between cost efficiency and operational

reliability when uncertainty is characterized by imprecise or incomplete information rather than well-defined probability distributions.

5.4. Sensitivity Analysis on Credibility Level

In order to investigate the impact of the possibility theory parameters on the system's performance, a sensitivity analysis was conducted on the credibility level (α). As presented in Table 5, the total operational cost is highly sensitive to the chosen value of α. The deterministic model yields the lowest cost (275) since it does not account for uncertainty. However, in the possibilistic model, as αincreases from 0.60to 0.95, the total cost increases from 290to 415. This upward trend represents a clear trade-off between economy and reliability: higher values of αensure a higher margin of safety against uncertainties (more reliable operation) but force the system to adopt more conservative and costly energy scheduling strategies.

Table 5. Sensitivity analysis of the total operational cost with respect to different credibility levels (α).

Model Type	Credibility Level (α)	Objective Function Value
Deterministic	-	-275
Possibilistic	0.6	-290
	0.7	-315
	0.8	-345
	0.9	-385
	0.95	-415

5.5. Comparative Discussion

Table 5 compares the overall performance of the deterministic and possibilistic scheduling approaches under the TOU pricing scheme.

The deterministic model achieves the lowest nominal electricity cost under fixed parameter assumptions. However, because it treats the daily energy requirement as a precise value, it does not explicitly incorporate a safety margin against imprecision in production conditions.

In contrast, the possibilistic model improves schedule stability by incorporating a credibility-based margin on the daily energy requirement. As reflected in the load profile (Figure 4), the possibilistic schedule redistributes part of the demand toward off-peak and intermediate periods and avoids excessive peak-hour concentration. This results in a more balanced and operationally secure schedule, albeit at a modest increase in nominal electricity cost.

It is worth noting that in a cost-minimization framework, the solver naturally binds exactly to the lower bound of the total energy constraint to avoid unnecessary expenditures. Therefore, the possibilistic safety margin is not achieved by spontaneous overconsumption, but rather dictated by the crisp equivalent boundary, which mathematically shifts according to the selected confidence level (e.g., $\alpha = 0.8$).

Overall, the comparison highlights a clear trade-off: the deterministic approach prioritizes nominal cost efficiency, while the possibilistic formulation enhances reliability under imprecise production requirements.

Table .6. Comparative performance of deterministic and possibilistic scheduling approaches under TOU pricing

Model	Total energy (MWh/day)	Nominal cost (thousand $/day)	Peak load (MWh)	Off-peak share%
Deterministic	1600	51.6	140	35
Possibilistic ($\alpha = 0.8$)	1600	54.1	132	42

It should be emphasized that the proposed scheduling framework does not imply a complete transfer of steelmaking operations toward nighttime periods. Due to operational continuity requirements and higher daytime productivity conditions, a substantial portion of electricity consumption remains allocated to daytime operating hours. The possibilistic formulation

primarily affects the flexible portion of the industrial load by moderately redistributing consumption away from expensive peak periods toward intermediate and off-peak intervals. Therefore, the resulting schedules remain consistent with practical production-leveling considerations while improving operational reliability under uncertainty.

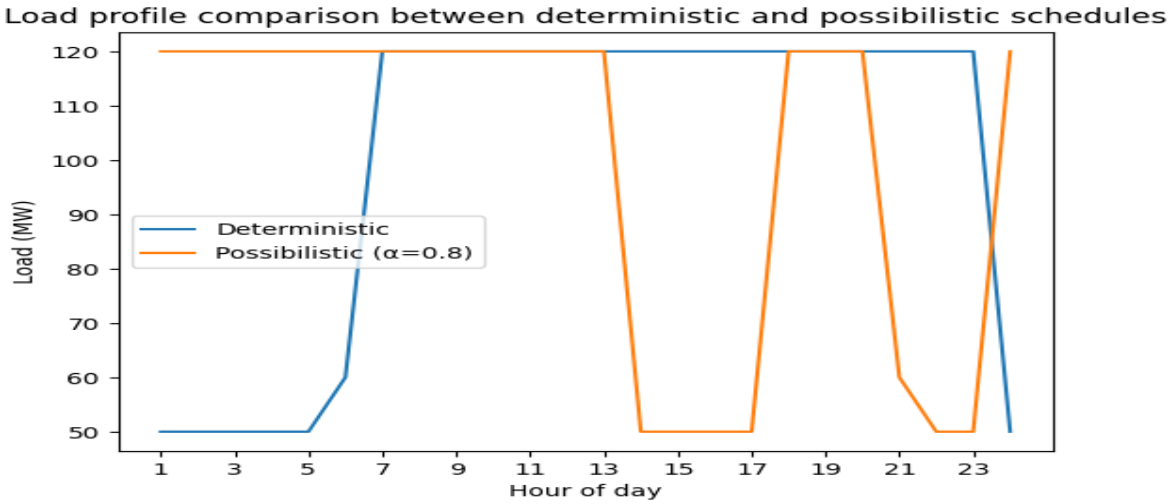


Fig.4. Load profile comparison between deterministic and possibilistic schedules under TOU pricing

5.6. Model Comparison in Terms of Objective Value

To provide a detailed view of the operational strategy and to address the reviewer's comments, Figure 5 illustrates the optimal 24-hour energy consumption profiles for both the deterministic and possibilistic models. The figure 5 visually confirms that the optimization framework successfully shifts a significant portion of the energy load away from the high-cost on-peak hours (14:00–17:00) and toward the cheaper off-peak tariff window (00:00–08:00).

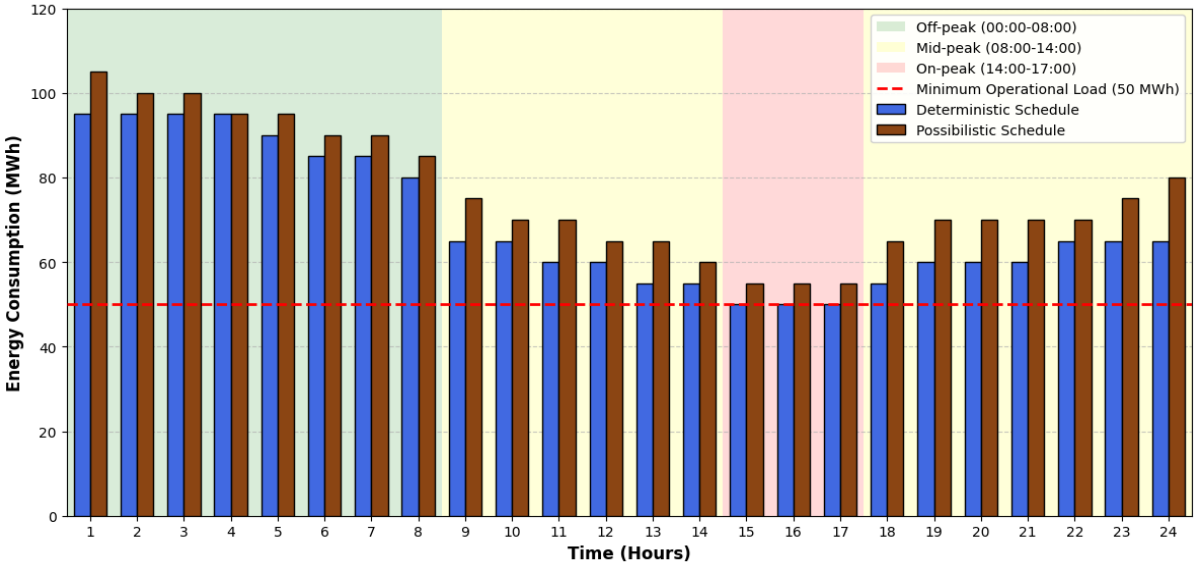


Fig. 5. Comparison of the 24-hour optimal energy scheduling profiles for the deterministic (blue) and possibilistic (brown) models. The background colors indicate the off-peak (green), mid-peak (yellow), and on-peak (red) tariff periods. The dashed red line represents the minimum operational load constraint of 50 MWh.

A critical aspect demonstrated in Figure 5 is the strict adherence to operational constraints. Both scheduling strategies ensure that the energy consumption in every hour remains at or above the 50 MWh minimum operational bound, which is essential for maintaining furnace feasibility (as clearly seen during the on-peak hours where consumption hits this exact lower

bound to minimize costs). Furthermore, the figure highlights the fundamental difference between the two approaches: while the deterministic schedule (blue bars) aggressively minimizes costs by operating closer to the limits, the possibilistic schedule (**brown bars**) generally maintains a higher consumption level. This additional energy acts as a "robustness buffer," hedging against the uncertainty and imprecision of the total daily energy requirement.

This strategic difference in hourly scheduling directly translates to the final objective value, as presented in Figure 6. The figure compares the net operating cost per day for both models. As expected, the deterministic model achieves a lower nominal cost, as it is optimized for a single, fixed scenario without accounting for uncertainty. The possibilistic model yields a slightly higher objective value, which represents the cost of ensuring operational reliability. This quantifiable difference can be interpreted as the "price of robustness"—a premium paid to create a schedule that is more resilient to real-world fluctuations in production demands.

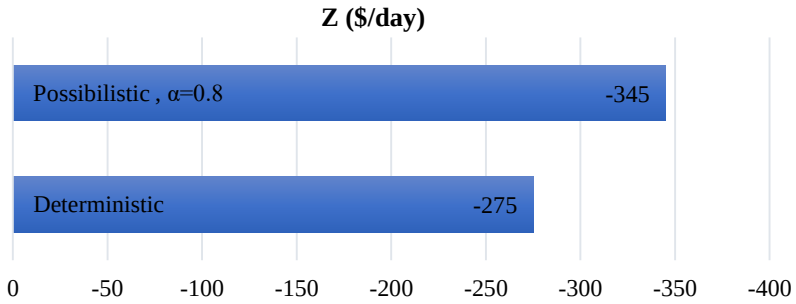


Fig.6. Comparison of deterministic and possibilistic objective values under TOU pricing

The figure 6 compares the net operating cost per day for both models. As expected, the deterministic model achieves a lower nominal cost, as it is optimized for a single, fixed scenario without accounting for uncertainty. The possibilistic model yields a slightly higher objective value, which represents the cost of ensuring operational reliability. This quantifiable difference can be interpreted as the "price of robustness" a premium paid to create a schedule that is more resilient to real-world fluctuations in production demands.

In summary, the combined analysis of Figure 5 and Figure 6 reveals a clear trade-off: the deterministic solution offers maximum cost efficiency under ideal conditions, whereas the possibilistic solution enhances operational resilience at a quantifiable, moderate cost increase. This demonstrates the practical value of the proposed possibilistic framework for robust industrial demand response scheduling.

5.6. Scenario-Based Uncertainty Assessment (Post-Optimization Stress Testing)

To provide an interpretable assessment of schedule stability, a scenario-based sensitivity analysis is conducted as a post-optimization evaluation step. Importantly, these scenarios are not used to construct the optimization models; instead, they serve as an ex-post validation tool to examine how the obtained schedules respond to plausible deviations in production-related requirements.

Three representative scenarios are defined: favorable, nominal, and adverse. The favorable scenario reflects a lower-than-expected daily energy requirement, while the adverse scenario represents a higher effective production-driven energy need due to operational disruptions. The nominal scenario corresponds to the baseline Spring 2023 conditions. The scenario settings are summarized in Table 7.

Table .7. Definition of stress-testing scenarios for daily energy requirement deviations

Scenario	Electricity price deviation	Daily energy requirement deviation	Interpretation
S1 (Favorable)	−5%	−10%	high efficiency, low effective demand
S2 (Nominal)	0%	0%	baseline Spring 2023 conditions
S3 (Adverse)	10%	10%	price spike + higher effective demand

The deterministic schedule is re-evaluated under each scenario to assess its sensitivity to deviations in the required daily energy level. Table 7 reports the resulting cost and operational indicators. The results indicate that even moderate increases in the effective daily energy requirement can significantly raise total operating cost and increase peak-period exposure when uncertainty is not explicitly considered. In contrast, lower-than-expected energy requirements reduce total cost and improve off-peak allocation.

Table .8. Comparative cost and operational indicators under stress-testing scenarios (Deterministic vs. Possibilistic schedule at $\alpha = 0.8$)

Scenario	Model	Total cost ($ thousand/day)	Peak-period consumption share (%)	Off-peak consumption share (%)	Feasibility risk
S1 (Favorable)	Deterministic	46.5	18	47	Low
	Possibilistic	47.2	17	49	None
S2 (Nominal)	Deterministic	51.6	22	35	Medium
	Possibilistic	52.3	20	38	Low
S3 (Adverse)	Deterministic	60.9	28	30	High
	Possibilistic	54.8	22	34	Low

To validate the robustness of the proposed framework, Table 8 compares the stress-test performance of both the deterministic and the possibilistic schedules (at $\alpha = 0.8$). As observed, the deterministic schedule is highly sensitive to adverse conditions (S3), resulting in a sharp cost increase (to 60.9 thousand/day) and a high feasibility risk due to unpreparedness for higher-than-expected energy requirements. In contrast, the possibilistic schedule exhibits strong resilience. While it incurs a marginal 'cost of robustness' in favorable and nominal scenarios due to conservative pre-allocation of loads, it significantly outperforms the deterministic model in the adverse scenario (S3). Under S3, the possibilistic schedule maintains a low feasibility risk and avoids severe cost spikes by having proactively secured off-peak consumption capacity. This comparative analysis explicitly substantiates the capability of the possibilistic approach to immunize industrial operations against deep uncertainties.

Overall, the stress test confirms that deterministic schedules can be sensitive to deviations in production-driven energy requirements. These findings support the use of possibilistic programming as a structured approach to incorporate imprecision into industrial DR scheduling and enhance operational reliability under TOU pricing.

From a practical implementation perspective, the proposed scheduling framework can operate as a supervisory decision-support layer integrated with existing industrial Energy Management Systems (EMS) or SCADA infrastructures. The optimized hourly electricity allocation profiles generated by the model may be periodically updated using operational measurements and communicated to lower-level process controllers responsible for coordinating furnace loading and production scheduling. In this manner, the possibilistic scheduling framework can support economically efficient and operationally reliable demand response implementation without requiring major modifications to existing industrial automation systems.

6. Managerial Results

The findings of this study provide actionable insights for industrial managers and policymakers seeking to implement demand response (DR) strategies in energy-intensive sectors such as steelmaking.

(i) The importance of plant-level scheduling under TOU pricing

The results confirm that Time-of-Use tariffs can generate tangible electricity cost savings when supported by structured optimization-based scheduling. However, effective participation

in DR programs requires explicit consideration of technical operating limits and production continuity constraints. Industrial firms should therefore adopt plant-level scheduling tools rather than relying on simplified assumptions about price responsiveness.

(ii) Managing production imprecision through possibilistic planning

Industrial production environments are often characterized by imprecise information regarding daily energy needs due to scrap variability, furnace conditions, and operational disruptions. The possibilistic framework demonstrates that incorporating fuzzy production-driven requirements enables managers to introduce precautionary margins without requiring full probabilistic forecasts.

From a tactical planning perspective, possibilistic scheduling offers a structured method to balance cost efficiency and feasibility under incomplete or vague information. This makes it particularly suitable for industries where expert knowledge plays a significant role in operational planning.

(iii) Cost–reliability trade-off in industrial DR participation

The comparative results highlight a fundamental managerial trade-off: deterministic scheduling minimizes nominal cost under stable conditions, while possibilistic scheduling enhances operational reliability under imprecise production requirements at a moderate cost increase.

Managers should therefore calibrate their planning approach according to the level of informational uncertainty they face. When production targets are stable and predictable, deterministic optimization may suffice. When daily energy requirements are uncertain or difficult to estimate precisely, possibilistic programming provides a more resilient alternative.

7. Conclusions

This study developed an optimization-based framework for industrial demand response (DR) scheduling under Time-of-Use (TOU) pricing in an energy-intensive steelmaking environment. The proposed approach combines a deterministic benchmark model with a possibilistic extension to address imprecision in production-driven energy requirements. The framework enables daily electricity scheduling while balancing electricity expenditure, production-related utility, and technical feasibility constraints.

The numerical results demonstrate that the deterministic model achieves the lowest nominal cost under fixed parameter assumptions. However, its performance is sensitive to deviations in the required daily energy level. In contrast, the possibilistic formulation enhances schedule stability by incorporating a credibility-based margin on the fuzzy daily energy requirement. Although this approach leads to a moderate increase in nominal electricity cost, it improves operational reliability when production inputs are imprecise and decisions rely on expert judgment rather than complete probabilistic information.

The scenario-based sensitivity analysis further confirms that deterministic schedules may experience substantial cost escalation and increased peak-period exposure when actual production requirements deviate from their nominal values. These findings justify the incorporation of imprecision-aware scheduling mechanisms in industrial DR planning under TOU pricing schemes.

From a managerial perspective, the results highlight a clear cost–reliability trade-off. Deterministic optimization is suitable for short-term scheduling under stable and predictable conditions, whereas possibilistic programming provides a structured and tractable approach for planning under vague or incomplete production information.

Although the adopted credibility-based possibilistic framework provides a computationally tractable representation of epistemic uncertainty, more advanced uncertainty modeling approaches such as fuzzy robust possibilistic or distributionally robust optimization may

provide stronger protection against uncertainty realizations. Extending the proposed framework toward hybrid robust–possibilistic scheduling formulations represents an important direction for future research. The proposed framework is intended to support moderate and operationally feasible load flexibility rather than complete production migration toward off-peak periods, thereby maintaining consistency with practical production-leveling requirements in steelmaking operations.

While the current study focuses on a single plant section over a daily scheduling horizon, the proposed possibilistic framework can be extended in several directions. First, to enhance operational realism, future research could extend the current continuous approximation into a Mixed-Integer Linear Programming (MILP) model to explicitly capture exact batch-level scheduling and machine on/off sequencing. Second, researchers may explore multi-day or multi-stage scheduling formulations, as well as the integration of additional flexibility assets such as energy storage systems and on-site generation. Finally, expanding this foundational individual-facility model into a multi-firm framework represents a highly promising avenue. Specifically, the model can be scaled to explore Industrial Symbiosis (IS) networks, where multiple adjacent facilities within industrial clusters coordinate their production schedules, share backup utilities, and exchange by-products to achieve collective resilience and maximize cost reductions.

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