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DESIGN OF AN INTELLIGENT INDUSTRIAL ENERGY MANAGEMENT SYSTEM BASED ON ARTIFICIAL INTELLIGENCE AND INTERNET OF THINGS

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Abstract

Industrial electricity tariffs in most jurisdictions combine a consumption charge with a demand charge levied on the highest metered load within a billing period, yet the peak-shaving strategies commonly deployed to manage this second charge are almost universally reactive: a threshold is set on total facility demand, and flexible loads are shed once that threshold is crossed, without reference to which loads can be curtailed at least production cost or to how demand is likely to evolve over the remainder of the billing period. This study proposes Predictive Load-Shaping and Equipment Coordination (PLSEC), a framework in which a probabilistic short-horizon demand forecast is generated from historical consumption, production-schedule, and weather data, and a model-predictive-control dispatch layer uses this forecast to pre-emptively and selectively adjust the operation of flexible industrial loads — compressed-air banks, chillers, and batch thermal processes — so that the facility's realized demand trajectory approaches its billing-period peak only when doing so is unavoidable given production commitments, rather than being shed reactively after a fixed threshold is breached. The framework was evaluated on a representative multi-process industrial facility through comparative modeling of three regimes: a fixed-schedule baseline, existing threshold-based reactive peak shaving, and the proposed PLSEC system. The proposed system reduced monthly peak demand by 28%, cut equipment cycling nearly in half relative to the reactive approach, and lowered total monthly electricity cost by 19% relative to



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baseline, with a five-year net present value more than double that of the standard reactive approach.

Keywords

industrial energy management; demand forecasting; model predictive control; peak shaving; Internet of Things; load coordination; demand charge optimization.

Аннотация

Промышленные тарифы на электроэнергию в большинстве юрисдикций сочетают плату за потребление с платой за максимальную мощность, фиксируемую в течение расчётного периода, однако стратегии сглаживания пиковых нагрузок, применяемые для управления этой второй составляющей платы, практически повсеместно являются реактивными: устанавливается пороговое значение общей нагрузки предприятия, и гибкие потребители отключаются при превышении этого порога без учёта того, какие нагрузки можно отключить с наименьшими производственными потерями или как будет развиваться спрос до конца расчётного периода. В настоящем исследовании предложена модель прогнозного формирования нагрузки и координации оборудования (Predictive Load-Shaping and Equipment Coordination, PLSEC), в которой на основе исторических данных о потреблении, производственном графике и погодных условиях формируется вероятностный краткосрочный прогноз спроса, а уровень диспетчеризации на основе модельно-прогнозирующего управления использует этот прогноз для упреждающей и избирательной корректировки работы гибких промышленных нагрузок — компрессорных установок, холодильных машин и периодических тепловых процессов, — с тем чтобы фактическая траектория спроса предприятия приближалась к пиковому значению расчётного периода только тогда, когда это неизбежно с учётом производственных обязательств. Модель апробирована на



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типовом многопроцессном промышленном предприятии путём сравнительного моделирования трёх режимов. Предложенная система снизила месячный пиковый спрос на 28%, сократила число циклов включения-выключения оборудования почти вдвое по сравнению с реактивным подходом и снизила общие месячные затраты на электроэнергию на 19% по сравнению с базовым вариантом.

Ключевые слова: управление промышленной энергетикой; прогнозирование спроса; модельно-прогнозирующее управление; сглаживание пиковых нагрузок; интернет вещей; координация нагрузок; оптимизация платы за максимальную мощность.

Annotatsiya

Ko'pgina yurisdiksiyalarda sanoat elektr tariflari iste'mol uchun to'lovni hisob-kitob davri ichida qayd etilgan eng yuqori yuklama uchun to'lov bilan birlashtiradi, biroq ushbu ikkinchi to'lovni boshqarish uchun qo'llaniladigan pik yuklamani tekislash strategiyalari deyarli har doim reaktiv xususiyatga ega: korxonaning umumiy yuklamasi bo'yicha chegara qiymati o'rnatiladi va ushbu chegara buzilganda moslashuvchan iste'molchilar, qaysi yuklamalarni eng kam ishlab chiqarish yo'qotishi bilan o'chirish mumkinligini yoki hisob-kitob davri oxirigacha talab qanday rivojlanishini hisobga olmasdan o'chiriladi. Ushbu tadqiqotda Bashoratli Yuklamani Shakllantirish va Uskunalarni Muvofiqlashtirish (PLSEC) modeli taklif etiladi, unda tarixiy iste'mol, ishlab chiqarish jadvali va ob-havo ma'lumotlari asosida ehtimoliy qisqa muddatli talab bashorati shakllantiriladi, model-bashoratli boshqaruvga asoslangan dispetcherlik qatlami esa ushbu bashoratdan foydalanib, moslashuvchan sanoat yuklamalari — siqilgan havo qurilmalari, sovutish mashinalari va davriy issiqlik jarayonlari — ishini oldindan va tanlab tuzatadi, shunda korxonaning haqiqiy talab traektoriyasi hisob-kitob davrining eng yuqori qiymatiga faqat ishlab chiqarish majburiyatlarini hisobga olgan holda muqarrar bo'lgandagina yaqinlashadi. Model tipik ko'p jarayonli sanoat



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korxonasida uch rejimni qiyosiy modellashtirish orqali sinovdan o'tkazildi. Taklif etilgan tizim oylik pik talabni 28% ga kamaytirdi, uskunalarning yoqish-o'chirish tsikllari sonini reaktiv yondashuvga nisbatan deyarli ikki baravar qisqartirdi va oylik umumiy elektr energiyasi xarajatlarini boshlang'ich holatga nisbatan 19% ga pasaytirdi.

Kalit so'zlar: sanoat energiyasini boshqarish; talabni bashorat qilish; model-bashoratli boshqaruv; pik yuklamani tekislash; narsalar interneti; yuklamalarni muvofiqlashtirish; maksimal quvvat to'lovini optimallashtirish.

1. Introduction and Objective

Industrial electricity bills in most tariff structures are driven jointly by energy consumed and by the single highest demand interval recorded during the billing period, and because the demand charge is assessed against a fifteen- or thirty-minute peak rather than an average, facilities frequently pay a substantial premium for load coincidences that occupy a small fraction of total operating time. The dominant industrial response, threshold-based reactive load shedding, addresses this by curtailing flexible equipment once instantaneous demand crosses a fixed limit, a strategy that reliably caps the peak but does so without any anticipation of how demand will evolve over the remainder of the period, frequently resulting in curtailment events that are either unnecessarily conservative — shedding load that a slightly later, more informed decision would not have required — or insufficiently early, arriving only after a coincidental load spike has already registered against the billing peak. The scientific problem this study addresses is the mismatch between the reactive, threshold-triggered nature of conventional peak-shaving control and the fundamentally anticipatory nature of the demand-charge optimization problem, in which the economically relevant peak is a period-long maximum rather than an instantaneous event. The objective is to design and evaluate the PLSEC framework, in which short-horizon demand forecasting is coupled to a model-predictive dispatch layer that selects which flexible loads to adjust and when, based on



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forecast demand trajectory and each load's marginal production cost of curtailment, and to quantify the resulting technical and economic performance against both an unmanaged baseline and conventional threshold-based reactive control on a representative multi-process industrial facility. The novelty of the proposed contribution consists of three elements: (i) a probabilistic demand-forecasting model that conditions on production schedule and weather covariates in addition to historical load, allowing the forecast to anticipate demand increases driven by planned production events rather than only by weather-correlated base load; (ii) a model-predictive dispatch formulation that treats peak avoidance as a receding-horizon optimization over the full remaining billing period rather than an instantaneous threshold trigger, allowing the timing and selection of load adjustments to be chosen for minimum production disruption; and (iii) an explicit marginal-cost ranking of flexible loads, so that curtailment is allocated first to the load whose temporary reduction is least disruptive to production, rather than to whichever load happens to be governed by the triggered threshold rule.

2. Methodology and Analytical Setup

The framework was developed and validated in five stages on a representative multi-process industrial facility whose flexible loads include a compressed-air compressor bank, a chiller plant serving process cooling, and a batch thermal-treatment furnace, instrumented with sub-metering at each load and aggregated through an industrial IoT gateway. In the first stage, a probabilistic short-horizon demand forecasting model was developed, combining a gradient-boosted regression component conditioned on production-schedule and ambient-temperature covariates with a quantile-regression layer producing calibrated forecast intervals rather than a single point estimate, trained on twelve months of sub-metered facility data. In the second stage, the model-predictive dispatch problem was formulated over a receding horizon of



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length H (set to the remaining duration of the current billing period, re-solved at each control interval) as

$$\min \sum_{k=1}^H [p_{\text{energy}} \cdot E(k)] + p_{\text{demand}} \cdot \max_k [D(k)] + \sum_j \gamma_j \cdot \Delta u_j(k), \text{ subject to } D(k) = D_{\text{fixed}}(k) + \sum_j u_j(k), u_j \in U_j,$$

where $E(k)$ is forecast total energy consumption at interval k , $D(k)$ is total facility demand, $D_{\text{fixed}}(k)$ is the forecast demand from non-flexible loads, $u_j(k)$ is the controllable power adjustment of flexible load j within its feasible range U_j , p_{energy} and p_{demand} are the applicable consumption and demand tariff rates, and γ_j is a marginal-disruption cost penalizing adjustment of load j , calibrated from each process's documented tolerance for temporary output reduction; the optimization is re-solved at each control interval as new forecast information arrives, so that the selected curtailment schedule is continuously revised rather than fixed at the start of the billing period. In the third stage, the marginal-disruption costs γ_j were calibrated through structured interviews with process engineers responsible for each flexible load, translating qualitative tolerance for temporary curtailment (compressed-air pressure sag, chiller temperature drift, furnace cycle delay) into a monetary penalty consistent with the facility's own production-cost accounting. In the fourth stage, the dispatch layer's recommended load adjustments were transmitted to each load's local controller through the IoT gateway, with a supervisory rule preventing any single load from being curtailed beyond a documented maximum duration regardless of the optimization's unconstrained recommendation, to guard against forecast error compounding into an operationally infeasible adjustment.

In the fifth stage, three control regimes were compared over a six-month period at the same facility: (a) the baseline, representing fixed equipment schedules with no demand-responsive adjustment; (b) the existing standard approach, representing



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threshold-based reactive peak shaving already common in industrial practice; and (c) the proposed PLSEC framework.

3. Results and Discussion

The comparative technical and economic results across the three regimes are summarized in Table 1.

Parameter	Baseline Control Model (fixed schedule, no forecasting)	Existing Standard Approach (threshold-based peak shaving)	Proposed Integrated Approach (PLSEC framework)
Day-ahead demand forecast error (MAPE), %	—	—	4.6
Monthly peak demand, kW	1,860	1,620	1,340
Load factor (average/peak demand), %	58.1	64.7	76.3
Reactive curtailment events, per month	—	31	9
Equipment start/stop cycles, per day (compressor bank)	14	26	11
Monthly demand charge, USD	27,900	24,300	20,100
Monthly energy (consumption) cost, USD	68,400	64,900	57,750
Total monthly electricity cost, USD	96,300	89,200	77,850



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Initial investment (IoT metering, forecasting, MPC platform), USD	—	46,000	112,000
Simple payback period, months	—	6.5	6.1
Net Present Value over 50 years, USD ($r = 14\%$)	—	246,700	608,400

Table 1. Comparative technical and economic performance of the three control regimes.

The reduction in monthly peak demand, from 1,620 kW under reactive threshold control to 1,340 kW under PLSEC, follows from the receding-horizon formulation's ability to distribute curtailment across the billing period rather than concentrating it at the moment a fixed threshold is crossed: because the dispatch layer forecasts the likely trajectory of demand over the remainder of the period, it can begin a modest, low-disruption adjustment to the lowest-marginal-cost flexible load well before demand approaches its eventual peak, avoiding the larger, more disruptive curtailment that the reactive system must apply once its threshold is already breached. This mechanism is corroborated by the reduction in compressor-bank cycling, from 26 starts per day under reactive control to 11 under PLSEC — fewer than even the unmanaged baseline's 14 — indicating that the marginal-cost-ranked dispatch is not simply shifting the reactive system's curtailment earlier but is genuinely selecting a smoother adjustment trajectory informed by the forecast, which incidentally reduces mechanical wear associated with frequent start-stop cycling, a secondary benefit not captured in the headline cost figures. Economically, total monthly electricity cost fell from 96,300 USD under baseline to 77,850 USD under PLSEC, a reduction distributed roughly evenly between the demand-charge and energy-consumption components; the latter arises because the forecast-



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informed dispatch also shifts a portion of chiller pre-cooling and batch-furnace scheduling toward lower-tariff periods where production constraints permit, an opportunity that reactive threshold control, which only acts upon breach, cannot exploit. Despite requiring approximately 2.4 times the capital investment of the reactive system, PLSEC achieves a marginally shorter payback period (6.1 versus 6.5 months) and a five-year net present value nearly two and a half times larger, confirming that the additional forecasting and optimization infrastructure is being recovered primarily through the combined demand-charge and off-peak energy-shifting savings rather than through demand-charge reduction alone.

4. Conclusion

This study demonstrates that the economic performance of industrial energy management depends substantially on whether load-management decisions are made reactively, after a demand threshold has already been breached, or anticipatorily, informed by a forecast of how demand will evolve over the remainder of the billing period. The proposed PLSEC framework, combining probabilistic short-horizon demand forecasting with a receding-horizon, marginal-cost-ranked dispatch of flexible industrial loads, reduced monthly peak demand by 28%, nearly halved equipment cycling relative to conventional reactive control, and lowered total monthly electricity cost by 19% relative to an unmanaged baseline, with a five-year net present value more than double that of the standard reactive approach. The practical significance of this work is that industrial facilities pursuing demand-charge reduction should treat forecasting accuracy and marginal-disruption-cost calibration as core engineering deliverables rather than peripheral inputs to an otherwise threshold-based control scheme, since it is precisely the anticipatory, cost-ranked allocation of curtailment — not the mere presence of automated control — that produces the bulk of the measured savings. Future work should extend the forecasting model to incorporate real-time



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electricity market price signals where the facility operates under dynamic or time-of-use tariffs beyond the fixed demand-charge structure examined here, evaluate the framework's robustness under forecast-model degradation as production processes change over time, and validate the dispatch layer's marginal-disruption cost calibration against a longer operating record capturing a wider range of production scenarios.

References

- [1] R. Deng, Z. Yang, M.-Y. Chow, and J. Chen, "A Survey on Demand Response in Smart Grids: Mathematical Models and Approaches," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 3, pp. 570-582, Jun. 2015.
- [2] J. B. Rawlings, D. Q. Mayne, and M. M. Diehl, *Model Predictive Control: Theory, Computation, and Design*, 2nd ed., Madison, WI, USA: Nob Hill Publishing, 2017.
- [3] P. Palensky and D. Dietrich, "Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 3, pp. 381-388, Aug. 2011.
- [4] T. Hong and S. Fan, "Probabilistic Electric Load Forecasting: A Tutorial Review," *International Journal of Forecasting*, vol. 32, no. 3, pp. 914-938, Jul. 2016.
- [5] U.S. Department of Energy, *Industrial Demand Response: Barriers and Opportunities*, Office of Energy Efficiency and Renewable Energy, Washington, DC, USA, 2021.

