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Abstract

The electrical load of steel processing plants is set by induction motors, drives and transformers whose behaviour changes with operating regime. We analysed 35,040 fifteen-minute meter records (2018) from a Korean steel plant. A path model with day-block bootstrapping related tariff-period regime to reactive energy, power factor and active energy. Multilayer perceptrons (MLP) and random forests were tested as non-linear benchmarks against linear regression and a seasonal-naive forecast. Simulations evaluated power-factor correction, idle-load reduction, load shifting and grid decarbonisation under Scope 2 accounting. Maximum-load periods drew 8.1 times the energy of light-load periods. Power factor fell from about 91% at high load to 54% at idle; one-third of the energy differential co-varied with reactive energy. A schedule-only MLP reached a test R^2 of 0.72 (naive forecast: 0.32). In-plant measures abated 1.7% of 440 tCO₂/yr. Shifting peak energy to night raised emissions whenever night-time marginal emissions exceeded daytime ones. Moving evening load into midday solar hours instead cut emissions by 8–25 tCO₂/yr under the solar-rich grid profile.

Keywords: Multilayer perceptron; Power factor; Reactive power; Scope 2 emissions; Steel manufacturing; Structural equation modeling

Nomenclature

Symbol	Description	Unit
E	Active energy per 15-min interval	kWh
P	Active power (demand)	kW
Q	Lagging reactive energy per interval	kVarh
S	Apparent energy, $\sqrt{(E^2 + Q^2)}$	kVAh
PF	Lagging power factor, E/S	%
EF	Grid emission factor	tCO ₂ /MWh
MEF	Marginal emission factor	tCO ₂ /MWh
L	In-plant distribution loss share	—
s	Share of peak-period energy shifted	—
β	Standardised path coefficient	—
R^2	Coefficient of determination	—

1. Introduction

Iron and steel production causes about 7% of global energy-related CO₂ emissions, and no other industry uses more energy (IEA 2020). Much of the downstream work in steel plants, such as rolling, coiling, cutting and finishing coils and plates, runs almost entirely on electricity. For these plants, most of the carbon footprint is Scope 2: the indirect emissions from bought electricity, found

by multiplying metered energy by a grid emission factor (WRI and WBCSD 2015). At national level, electricity use and CO₂ emissions rise together (Keshavarzian and Tabatabaieinasab 2022).

Walk through a coil-processing shop and the sources of this load are easy to list: induction motors on the mill stands and coilers, hydraulic power packs, overhead cranes, fans, compressors, and the transformers that feed them. Much of what these machines draw has little to do with output.

Machine-tool and process studies have shown this many times over (Gutowski et al. 2006, 2009; Kara and Li 2011; Zhou et al. 2016), and the specific energy consumption (SEC) model, $SEC = C_0 + C_1/MRR$, writes it down directly. When a machine is lightly used, the constant C_0 takes over (Duflou et al. 2012; Kara and Li 2011).

A similar story holds for power factor (PF). An idling motor still needs its magnetising current, and so does a transformer on light load; the reactive part of the current barely falls while the useful part does, and PF sinks (IEEE 2010; Saidur 2010). Reactive current heats cables and transformer windings too (Jyothi et al. 2017), and in Korea a low PF also shows up on the electricity bill as a surcharge. So how hard the plant is working, how clean its power is and how much energy it uses are physically tied together. We wanted to know how tight that tie is in an actual plant, and whether it matters for CO₂.

The clock is the other half of the picture. Korean industrial users buy electricity on a time-of-use (TOU) tariff with light, medium and maximum load periods. Such tariffs, together with demand charges, are the usual levers for steering factory demand (Albadi and El-Saadany 2008; Azimi and Hooshmand 2023; Currie 2020; Zhang and Grossmann 2016). They were designed around system peaks and money, though, and carbon was never part of the design. If a plant pushes work from the afternoon into the night, its CO₂ changes by whatever the marginal power station emits at each of those hours. The single annual factor in a corporate carbon report cannot show that (Callaway et al. 2018; Hawkes 2010; Hemmati et al. 2026; Siler-Evans et al. 2012).

We work with the open DAEWOO Steel dataset. Earlier papers on it were mostly forecasting contests between algorithms (Sathishkumar et al. 2021a, b), as is much of the wider load-forecasting literature (Sharma et al. 2023; Vasenin et al. 2025). They did not measure how operating regime, reactive power, PF and energy are related, did not compare their models with simple baselines, as standardised forecasting benchmarks recommend (Aurus and Guerard 2025), and did not turn the results into decisions about the shop floor or Scope 2 emissions.

This study fills these gaps in four ways. First, we fit a path model, a structural equation model with observed variables, that links the tariff-period operating regime to reactive energy, PF and active energy. We resample whole days to handle the correlation between neighbouring readings and test

the model on each half of the year. Second, we use multilayer perceptrons (MLP) and random forests to check whether non-linear effects of the operating schedule improve energy prediction compared with multiple linear regression and a seasonal-naïve forecast. Third, we simulate PF correction, idle-load reduction and load shifting from basic electrical relations and compare them with grid decarbonisation and renewable power purchase. We also derive the condition under which load shifting raises emissions. Fourth, we report three features of the dataset that anyone modelling it should know about.

Fig. 1 shows the framework. We test six hypotheses (Table 1).

Table 1 Research hypotheses

	Hypothesis
H1	Energy use is higher in medium and maximum tariff periods than in light periods, and lower at weekends.
H2a	PF is higher in medium and maximum periods, that is, PF drops at part load.
H2b	Part of the extra energy used in busier tariff periods moves together with reactive energy.
H3a	Moving maximum-period energy to the night lowers peak demand and energy cost without changing total energy use.
H3b	This shift increases CO ₂ when coal supplies the extra power at night, and reduces it on a grid with much solar power.
H4	A cleaner grid cuts more Scope 2 CO ₂ than all in-plant measures together.

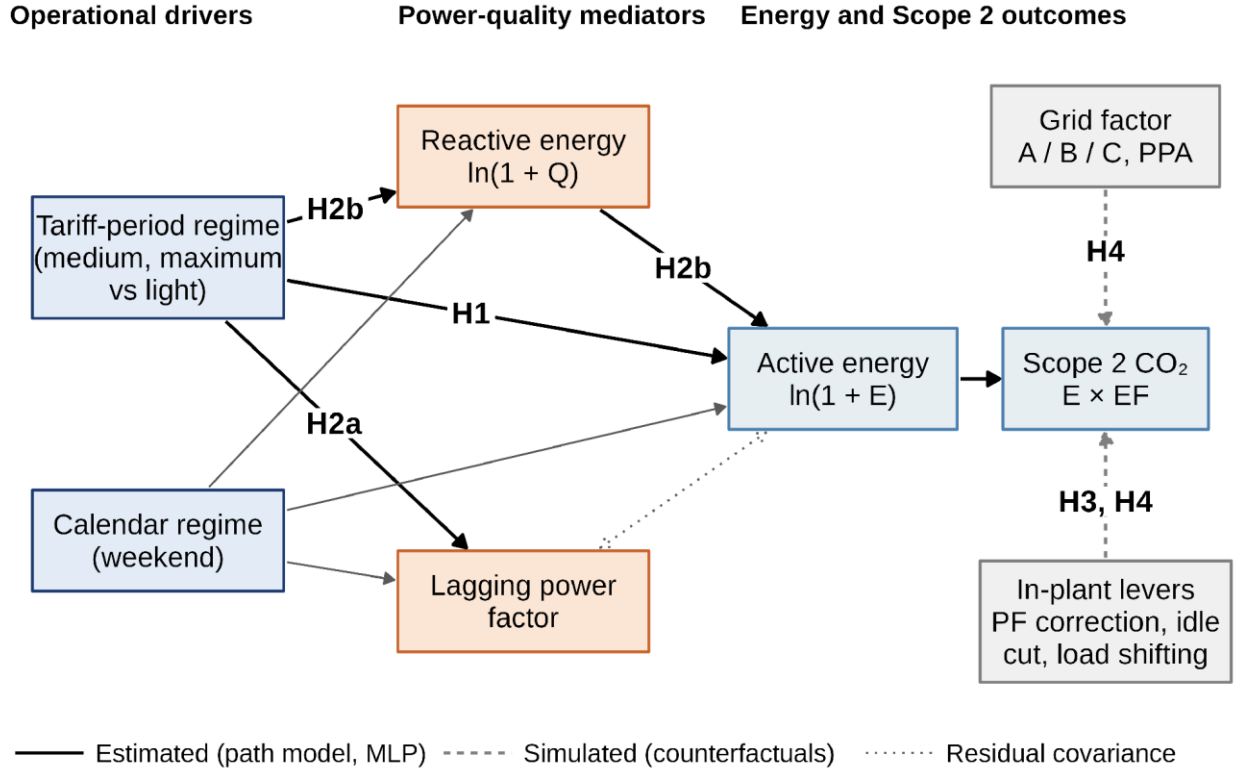


Fig. 1 Conceptual framework: operational drivers, power-quality mediators and energy and Scope 2 outcomes. Solid arrows are estimated (path model, MLP), dashed arrows are simulated, and the dotted line is a residual covariance; H1–H4 mark the hypotheses

2. Plant Description and Data Collection

2.1 Plant and metering

DAEWOO Steel Co. Ltd. in Gwangyang, Republic of Korea, is a small steel processing plant that makes coils, steel plates and iron plates (Sathishkumar et al. 2021a). It is not an integrated steel mill. Its mean demand is 109.5 kW, its highest 15-min demand is 628.7 kW, and it used 959.6 MWh in 2018. Many electrified metal-processing plants of this size exist, and almost all of their emissions are Scope 2.

The meter recorded energy every 15 minutes from 1 January 2018 00:15 to 1 January 2019 00:00, giving 35,040 records. The data are published in the UCI Machine Learning Repository (dataset 851) under a CC BY 4.0 licence (Sathishkumar et al. 2021b). Each record holds active energy (kWh), lagging and leading reactive energy (kVarh), lagging and leading PF (%), CO₂ (tCO₂), seconds from midnight, weekday or weekend, day of the week, and a load-type label (Light, Medium or Maximum).

2.2 Data retrieval and checks

We downloaded the data with an R script. The UCI site could not be reached from our analysis computer, so the script used a fixed copy of the original file and stored its MD5 checksum so that it can be compared with the UCI file.

All fifteen data checks passed. There are 35,040 records with no missing values or repeated timestamps, every step is exactly 15 minutes, and the calendar fields agree with the timestamps. Both power factors can be recalculated from the energy values, $PF = E/\sqrt{E^2 + Q^2}$, in 100% of records.

Three features of the data needed attention. First, each day's 24:00 reading is labelled "00:00" under the same date, so we moved these 365 records to the next day. Second, the load-type label is not a measured machine state but the TOU price period (Fig. 2). It follows a fixed clock: 23:00–09:00 is always "Light", Sundays and holidays (about 62 days) are "Light" all day, and daytime hours are split into "Medium" and "Maximum" according to the season. Third, the CO₂ column turned out not to be a measurement at all. Dividing it by energy gives the same number again and again, and $\text{round}(E \times 0.4585/1000, 2)$ reproduces it in 99.87% of rows. In other words, the plant used a constant factor of $EF = 0.4585 \text{ tCO}_2/\text{MWh}$, which is close to the national electricity factors published by the Greenhouse Gas Inventory and Research Center of Korea (GIR) for emissions-trading reports (about 0.45–0.48 tCO₂eq/MWh in recent years; GIR n.d.). The rounding sets 60% of records to zero and lowers the yearly total from 440.0 t to 403.8 t. We therefore calculate all CO₂ values without rounding, as $\text{CO}_2 = E \times EF / 1000$.

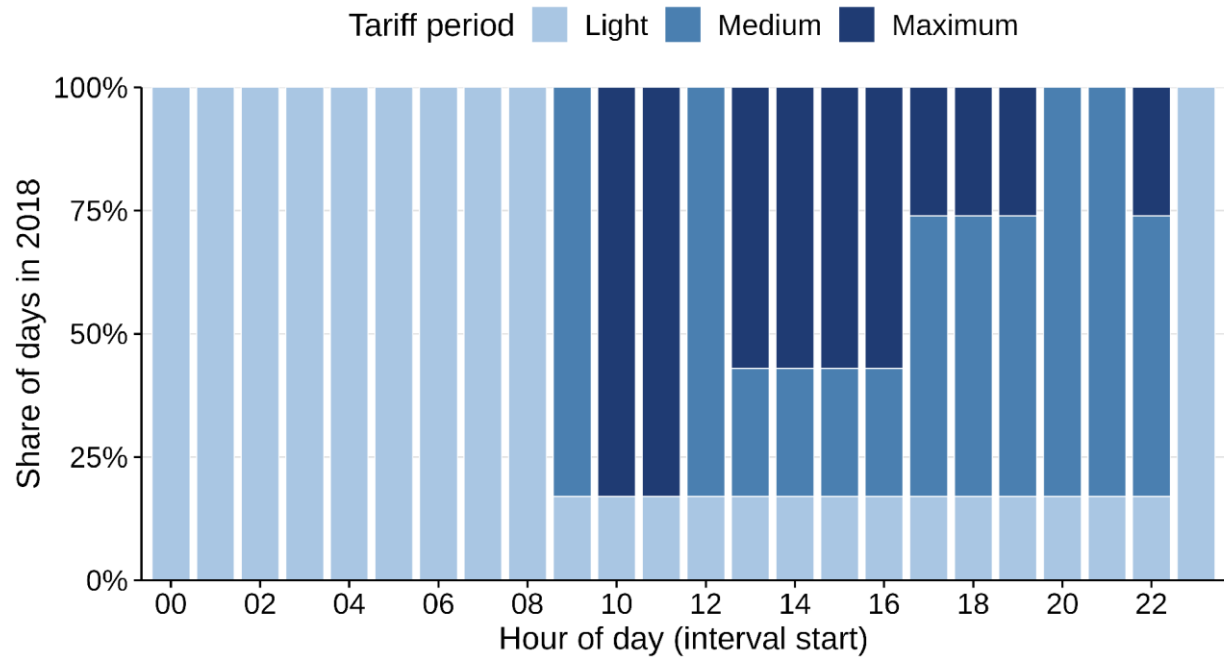


Fig. 2 The load-type label follows a fixed time-of-use schedule: share of days on which each hour is classed as light, medium or maximum load

2.3 Descriptive statistics

Table 2 summarises the main variables and Table 3 splits energy and PF by tariff period.

Table 2 Descriptive statistics (n = 35,040)

Variable	Mean	SD	Media n	Max	Skewnes s	Share of zeros
Active energy E (kWh/15 min)	27.39	33.44	4.57	157.18	1.20	0.0%
Lagging reactive energy Q (kVarh)	13.04	16.31	5.00	96.91	1.44	20.5%
Leading reactive energy (kVarh)	3.87	7.42	0.00	27.76	1.73	67.4%
Lagging PF (%)	80.58	18.92	87.96	100.00	-0.61	0.0%
Leading PF (%)	84.37	30.46	100.00	100.00	-1.51	0.0%

Table 3 Energy and power quality by tariff period

Tariff period	Hours/yr	Energy (MWh)	Share of energy	Mean demand (kW)	Energy-weighted lagging PF	CO ₂ (t)
Light	4,518	155.9	16.2%	34.5	74.9%	71.5
Medium	2,424	372.8	38.8%	153.8	92.3%	170.9
Maximum	1,818	431.0	44.9%	237.1	90.6%	197.6
Total	8,760	959.6	100%	109.5	88.2%	440.0

On weekdays, demand stays at 250–280 kW from 08:00 to 17:00, falls sharply at the 12:00 lunch break, and stays near 200 kW in the evening until 21:00 (Fig. 3). Weekends use about one-third of the energy of a weekday (1,126 vs 3,228 kWh/day). At night, equipment left switched on draws a base load of 12.7 kW, which adds up to about 11.6% of the year's energy. The load factor (mean divided by peak) is only 0.174.

PF depends strongly on how heavily the plant is loaded (Fig. 4). The energy-weighted PF is 89–92% in the four highest demand deciles but only 54.5% in the lowest. Light periods use 16% of the energy but account for 45% of the reactive energy above what a PF of 0.95 would need (79.5 of 177.1 MVarh/yr).

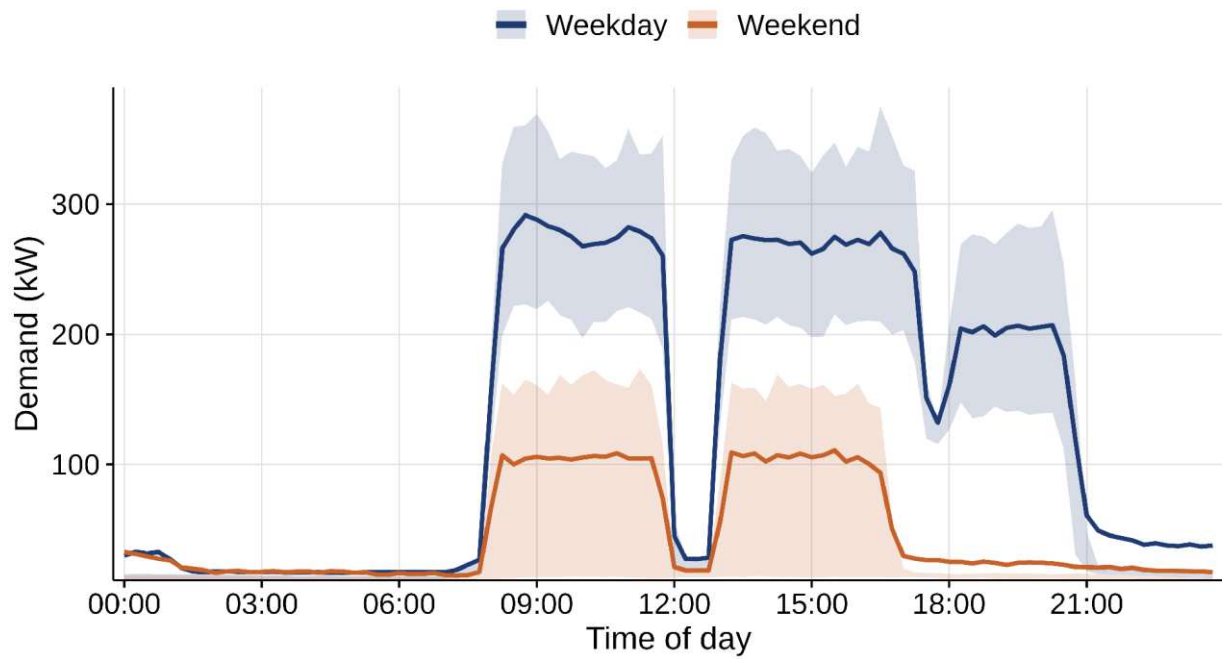


Fig. 3 Diurnal demand profile, weekday vs weekend, at 15-min resolution: mean demand (lines) and interquartile range (bands)

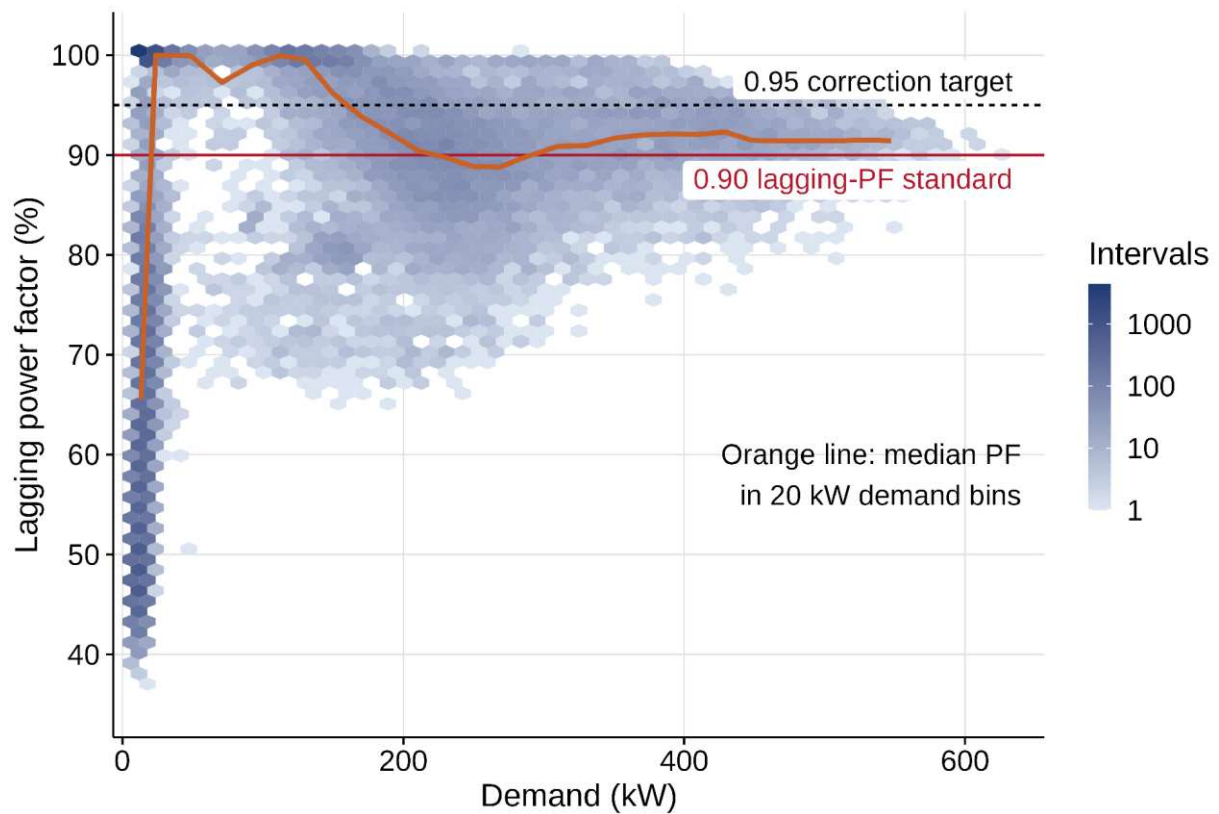


Fig. 4 Lagging power factor versus demand for all 15-min intervals (hexagonal bins, log-scaled counts), with the median power factor in 20 kW demand bins, the 0.90 lagging-PF standard and the 0.95 correction target

3. Methodology

3.1 Variables

Table 4 defines the variables of the path model.

Table 4 Variables of the path model

Variable	Role	Definition
Tariff-period operating regime	Exogenous	Two dummies, MED and MAX (Light = reference)
Calendar regime	Exogenous	WKND = 1 at weekends
Reactive energy demand	Mediator	$\ln(1 + Q)$
Power quality	Mediator	Lagging PF/10
Active energy demand	Outcome	$\ln(1 + E)$
Season	Control	sin and cos of month

We used logarithms for E and Q because both are strongly right-skewed.

3.2 Path model

We estimated the path model (R1) in lavaan (Rosseel 2012) with robust maximum likelihood (MLR):

$$\ln(1 + Q) = a_{1m}MED + a_{1x}MAX + e_1WKND + \varepsilon_1 \quad (1)$$

$$PF = a_{3m}MED + a_{3x}MAX + e_3WKND + \gamma_3 \cdot Season + \varepsilon_2 \quad (2)$$

$$\ln(1 + E) = b_1\ln(1 + Q) + c_mMED + c_xMAX + c_2WKND + \gamma_4 \cdot Season + \varepsilon_3 \quad (3)$$

with residual covariances $\psi(\varepsilon_1, \varepsilon_2)$ and $\psi(\varepsilon_2, \varepsilon_3)$.

E , Q and PF are tied together by an identity. A direct path from PF to E , given Q , would therefore measure that identity rather than how the equipment behaves, so we let PF and energy share a residual covariance instead. A sensitivity model with the $PF \rightarrow E$ path included gives the same total effect. From the model we report the indirect effect $a_{1x}b_1$, the total effect $c_x + a_{1x}b_1$, and the share of the total effect that passes through reactive energy.

To make the fit indices meaningful, we did not let the season terms act directly on reactive energy ($df = 2$), and we judged fit with CFI, TLI, RMSEA and SRMR (Hu and Bentler 1999; Satorra and Bentler 2001). Our first model, R0, also assumed that weekends affect reactive energy and PF only through the tariff period. R0 did not fit (Section 4.1), so we freed the weekend paths and used R1. We report this change openly. As further checks, we refitted the model with a single ordinal tariff score (1–3) and with PF as a second mediator.

Readings within the same day are correlated, so ordinary standard errors would be too small. We therefore took confidence intervals and p-values from a day-block bootstrap (Künsch 1989; Preacher and Hayes 2008): we resampled whole days 1,000 times, refitted the model each time, and used percentile intervals. To check stability, we also fitted R1 separately to January–June and July–December, and used a two-group model to test whether the paths were the same in both halves.

3.3 Multilayer perceptron and benchmark models

The prediction task was to estimate the energy in each 15-min interval (and from it, CO_2) from two sets of inputs. The first set, OPS, contains only schedule information that a production planner knows in advance: tariff-period dummies, weekend, Sunday, three pairs of time-of-day terms (sine and cosine), and day-of-week and month terms. The second set, OPS+R, adds the measured lagging and leading kVarh, so it estimates energy from live electrical readings. We left PF out of both sets because PF and kVarh together fix E exactly.

We randomly assigned whole weeks to training (70%; 24,288 records), validation (15%; 5,376) and test (15%; 5,376) sets, so that neighbouring readings never fell into different sets. Inputs were scaled to the range of the training data.

We fitted three types of model:

1. A feedforward MLP with one hidden layer (logistic hidden units, linear output; nnet; Venables and Ripley 2002). We chose the number of hidden units (6, 12 or 18) and the weight decay (0.001 or 0.01) by 3-fold cross-validation on whole weeks in caret (Kuhn 2008), and recorded training and validation loss every 10 iterations, keeping the best checkpoint.
2. An MLP with two hidden layers of 10 and 5 units, trained by resilient back-propagation in neuralnet (Günther and Fritsch 2010).
3. Three benchmarks: multiple linear regression (MLR), a random forest with 300 trees (Breiman 2001; Liaw and Wiener 2002), and a seasonal-naïve forecast that uses the reading from the same quarter-hour one week earlier.

To check that the results did not depend on one particular split, we repeated the week-based split 10 times and report the mean $\pm$ SD of the test scores. We measured the importance of each group of inputs by permuting it 10 times and recording the rise in test error (Fisher et al. 2019).

3.4 Simulations

Table 5 lists the simulated measures, the models behind them and their assumptions.

Table 5 Simulated measures, models and assumptions

Measure	Model	Assumptions
PF correction to 0.95	Losses $\propto S^2 = E^2/\text{PF}^2$, so $\Delta E = \sum L \cdot E_t \cdot [1 - (\text{PF}_t/0.95)^2]$ for $\text{PF}_t < 0.95$	$L = 2, 4, 6\%$
Idle-load reduction	$\Delta E = r \cdot 12.7 \text{ kW} \cdot 4,518$ light-period hours	$r = 10, 20, 30\%$
Load shift S1	Share s of each day's maximum-period energy moved evenly into 00:00–08:00; $\Delta E = 0$	$s = 10, 20, 30\%$
Load shift S2 (exploratory)	Share s of 17:00–23:00 medium/maximum energy moved into 10:00–16:00	$s = 10, 20, 30\%$
Grid (location-based)	$\text{CO}_2 = E \cdot \text{EF}$	A 0.4585 (plant); B 0.236 (40% renewables); C 0.10 (deep-decarbonised grid)

Measure	Model	Assumptions
Renewable PPA (market-based)	EF = 0 for covered energy	50% and 100% coverage

We based the scenario B factor on Korea's 2018 electricity mix (72.8% fossil, 4.7% renewable; Ritchie et al. 2023) and assumed that new renewable power replaces fossil power in proportion:

$$EF_B = 0.4585 \times \frac{72.8-35.3}{72.8} = 0.236 \text{ tCO}_2/\text{MWh} \quad (4)$$

For load shifting, we looked at daily, monthly and yearly peak demand, and at energy cost as an index for light:medium:maximum price ratios of 1:1.5:2 and 1:2:3. The change in CO₂ is $\Delta\text{CO}_2 = \sum \Delta E_t \cdot \text{MEF}_t$, which we worked out for two simple profiles of marginal emission factors. In profile P1, coal supplies extra power at night (23:00–09:00; 0.80–0.95 tCO₂/MWh) and gas by day (0.36–0.50 tCO₂/MWh). In profile P2, the grid has much solar power, so the factor is 0.00–0.20 tCO₂/MWh between 10:00 and 16:00 and 0.40–0.50 tCO₂/MWh at other times.

In strategy S1 all the moved energy leaves daytime hours and arrives in night hours, so the break-even condition is simple:

$$\Delta\text{CO}_2 = E_{\text{moved}} \cdot \text{MEF}_{\text{day}} \cdot (R - 1), \quad R = \text{MEF}_{\text{night}}/\text{MEF}_{\text{day}} \quad (5)$$

The simulations apply fixed rules to the measured data, so their results carry no sampling error. We therefore describe them by their spread across days instead of testing them for significance.

All processing used R 4.3.3 with tidyverse, lavaan 0.6-17, semPlot 1.1.6 (Epskamp 2015), caret 6.0-94, nnet 7.3-19, neuralnet 1.44.2 and randomForest 4.7-1.1. The analysis runs as a set of scripts with fixed random seeds, and running them again gives the same results.

4. Results and Discussion

4.1 Operating regime, power quality and energy

Table 6 Path-model fit (MLR)

Model	n	χ^2 (scaled)	df	CFI	TLI	RMSEA [90% CI]	SRM R
R0 pre-specified	35,040	5,227.1	4	0.960	0.818	0.197 [0.193, 0.202]	0.069
R1 final	35,040	78.2	2	0.999	0.995	0.033 [0.027, 0.040]	0.008
R1, January– June	17,376	236.1	2	0.996	0.966	0.085 [0.076, 0.094]	0.017
R1, July– December	17,664	286.2	2	0.996	0.965	0.091 [0.082, 0.100]	0.023

R0 did not fit (Table 6; TLI 0.818, RMSEA 0.197) because weekends lower reactive energy and raise PF directly, not only through the tariff period. R1 meets the usual cut-offs on all four indices (Hu and Bentler 1999). With 35,040 records, its χ^2 is still significant, as expected. When fitted to each half-year separately, R1 keeps good CFI and SRMR values, but RMSEA rises to 0.085–0.091. Forcing all paths to be equal in both halves lowers CFI by 0.019, so how the effect is split between paths changes somewhat with the season.

Table 7 Path estimates, model R1 (day-block bootstrap, 1,000 resamples; raw coefficients with 95% CI; β = std.all)

Path	Estimate	β	95% CI	p
MAX $\rightarrow \ln(1+Q)$ (a_{1x})	1.139	0.35	[1.020, 1.249]	< .001
MED $\rightarrow \ln(1+Q)$ (a_{1m})	0.036	0.01	[−0.056, 0.125]	.484
WKND $\rightarrow \ln(1+Q)$	−0.983	−0.34	[−1.081, −0.891]	< .001

Path	Estimate	β	95% CI	p
MAX $\rightarrow$ PF (a_{3x})	2.307	0.49	[2.199, 2.431]	< .001
MED $\rightarrow$ PF (a_{3m})	2.512	0.59	[2.409, 2.630]	< .001
WKND $\rightarrow$ PF	0.824	0.20	[0.661, 0.999]	< .001
$\ln(1+Q) \rightarrow \ln(1+E)$ (b_1)	0.619	0.63	[0.593, 0.645]	< .001
MAX $\rightarrow \ln(1+E)$, direct (c_x)	1.381	0.44	[1.341, 1.426]	< .001
MED $\rightarrow \ln(1+E)$, direct (c_m)	1.243	0.43	[1.210, 1.279]	< .001
WKND $\rightarrow \ln(1+E)$, direct	0.128	0.05	[0.079, 0.184]	< .001
Indirect MAX $\rightarrow Q \rightarrow E$	0.705	0.22	[0.633, 0.770]	< .001
Total MAX $\rightarrow E$	2.086	0.66	[2.012, 2.157]	< .001
Total MED $\rightarrow E$	1.265	0.44	[1.195, 1.330]	< .001
Share of MAX effect via Q	33.8%	–	[31.3%, 35.9%]	–
Total WKND $\rightarrow E$	–0.480	–0.17	[–0.551, –0.406]	< .001

The model explains 82% of the variance in $\ln(1+E)$ ($R^2 = 0.82$), 44% in PF and 27% in $\ln(1+Q)$.

H1 is supported (Table 7). Compared with light periods, the total effect of the maximum period on $\ln(1+E)$ is 2.086, which means about 8.1 times as much energy ($e^{2.086}$). The medium period effect is 1.265, or about 3.5 times. Weekends use less

energy (total effect -0.48). The maximum-period effect is almost the same in both halves of the year: 2.07 in January–June and 2.10 in July–December.

H2a is also supported (Fig. 5). PF is 23–25 percentage points higher in medium and maximum periods than in light periods. This is what the fixed term C_0 of the SEC model looks like electrically (Duflou et al. 2012; Kara and Li 2011). In light periods, transformers and motors stay switched on at low load and draw magnetising current while delivering little useful power.

H2b is supported as well. About one-third (33.8%) of the extra energy used in maximum periods moves together with reactive energy; the share is 29.7% in January–June and 37.8% in July–December. The medium period shows no such link ($a_{1m} \approx 0$), so the extra reactive load appears only at full operation. Our reading is that more motor-driven machines, the mill stands and coilers in particular, are on line in peak periods. We should be careful here. The path is a statistical one; kVarh and kWh climb together because the same motors draw both, and a capacitor bank would not take away the rolling work that the motors are doing.

Neither sensitivity model changed this. Scoring the tariff period as 1–3 gave a total standardised effect of 0.66, 27% of it through reactive energy, and adding PF as a second mediator left the total maximum-period effect at 2.086.

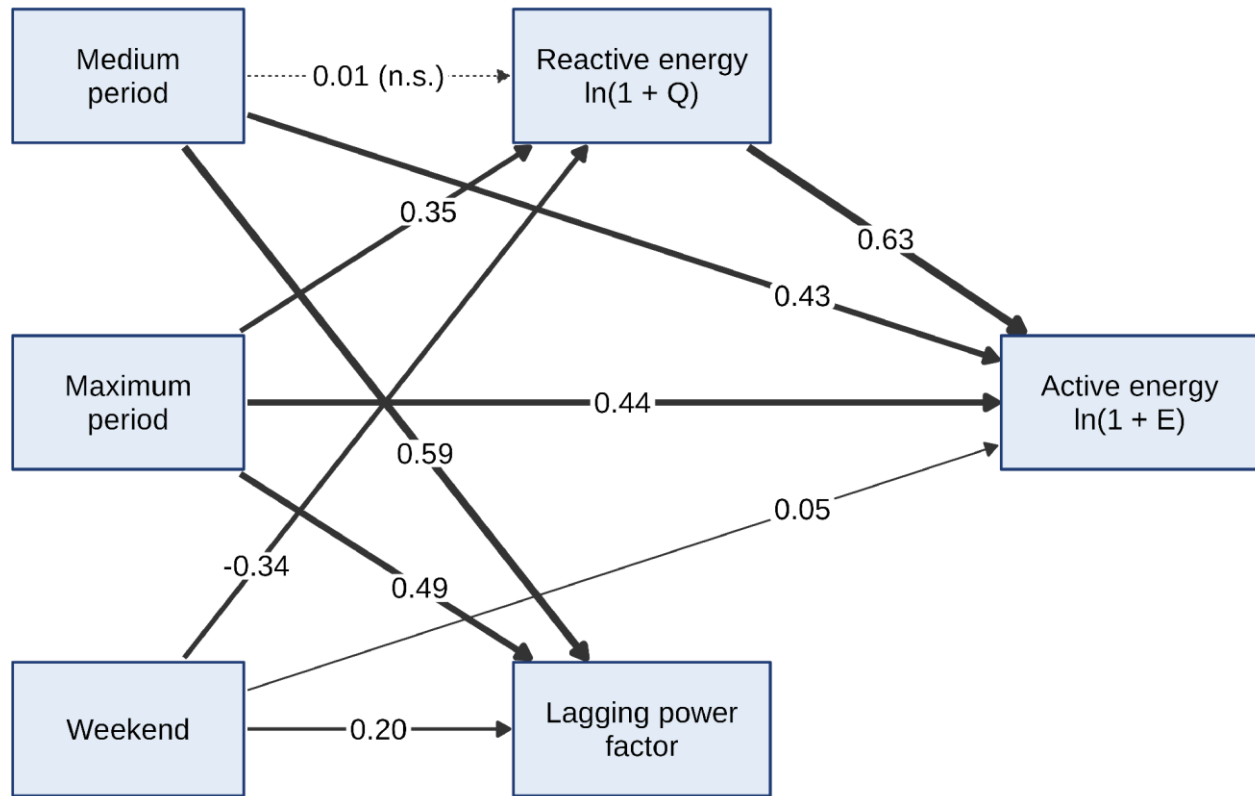


Fig. 5 Path model R1 with standardised coefficients (β , std.all). Light period is the reference; the month terms were estimated but are left off the drawing. Thicker lines mean larger $|\beta|$. Only the dashed MED $\rightarrow$ reactive-energy path is non-significant ($p = .48$); the rest have $p < .001$ by day-block bootstrap. Residual covariances: $\ln(1+Q) \sim PF = -0.37$; $PF \sim \ln(1+E) = 0.75$

4.2 Predicting interval energy

Table 8 Accuracy on the held-out test weeks for one random split (kWh per 15 min; mean test-week load about 27.4 kWh). Results for 10 splits follow below

Inputs	Model	RMSE	MAE	R ²	Test-period total error
—	Seasonal naive (previous week)	27.47	14.91	0.318	—
OPS	MLR	22.49	15.74	0.543	+2.6%
OPS	Random forest	19.46	10.79	0.658	+2.5%
OPS	MLP, 1 hidden layer (6 units, decay 0.01)	18.55	11.59	0.689	+0.4%

Inputs	Model	RMSE	MAE	R ²	Test-period total error
OPS	MLP, 2 hidden layers (10–5)	17.72	10.68	0.716	+2.5%
OPS+R	MLR	10.70	7.19	0.897	+3.0%
OPS+R	Random forest	8.39	4.20	0.936	–1.5%
OPS+R	MLP, 1 hidden layer (12 units, decay 0.01)	8.98	5.38	0.927	–2.2%
OPS+R	MLP, 2 hidden layers (10–5)	8.65	4.85	0.932	–2.1%

With nothing but the schedule as input, the two MLPs reached R² of 0.69 and 0.72 on the test weeks (Table 8). Linear regression managed 0.54 and the seasonal-naïve forecast 0.32. That gap tells us the clock, the tariff period and the calendar combine non-linearly, and that last week is a poor guide to this week in a plant that runs in batches. Summed over the test weeks, the one-hidden-layer MLP was off by only 0.4% in energy. Per interval the error is larger; at the plant’s factor it comes to roughly 8 kg CO₂ (8.1–8.5 kg).

Once live kVarh readings are added (OPS+R), R² climbs to 0.93–0.94. That is handy for real-time control, but it is not a forecast, because kVarh is measured at the same time as the energy it helps to estimate.

The results hold across different splits. Over 10 repeated week-based splits, the schedule-only MLP reached a mean test R² of 0.681 ± 0.036 , compared with 0.518 ± 0.032 for MLR, 0.664 ± 0.050 for the random forest and 0.282 ± 0.130 for the seasonal-naïve forecast (Online Resource 1, Table S6d). With live kVarh, the random forest and the MLP reached 0.939 ± 0.007 and 0.936 ± 0.007 .

Training and validation loss level off after 400–500 iterations (Fig. 6), and the two-hidden-layer MLPs converged after 12,603 (OPS) and 2,482 (OPS+R) training steps. The MLP is least accurate in maximum periods (OPS+R test R² 0.77, compared with 0.94 in light and 0.91 in medium periods; Fig. 7). Among the scheduled inputs, time of day and tariff period matter most: permuting them raises the test RMSE by 16.4 and 12.8 kWh (Fig. 8). In the OPS+R model, lagging kVarh matters most (+23.4 kWh), which agrees with the reactive-energy path in the path model.

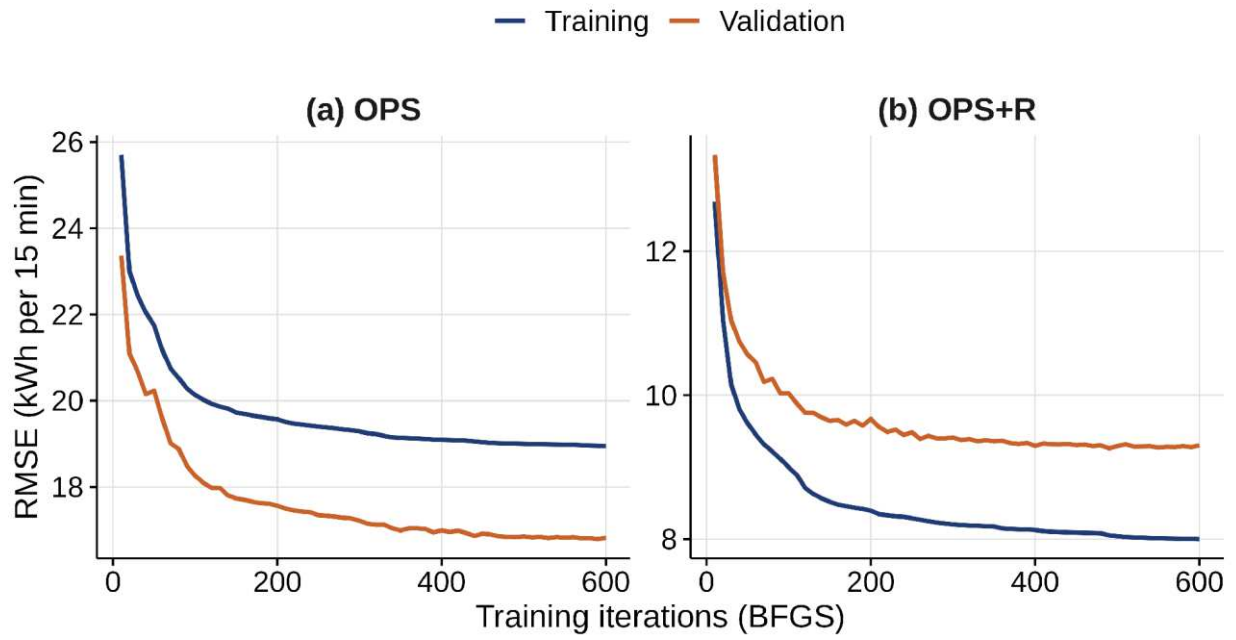


Fig. 6 Training and validation loss (RMSE, kWh per 15 min) of the selected single-hidden-layer MLPs: (a) schedule inputs only (OPS); (b) schedule inputs plus measured reactive energy (OPS+R)

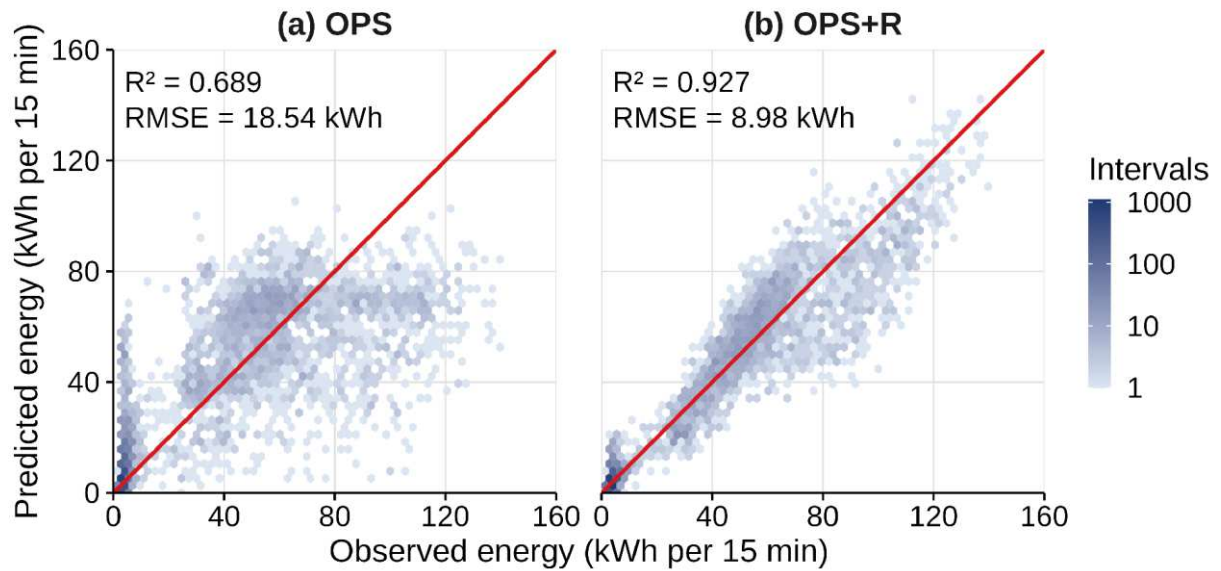


Fig. 7 Parity plot of predicted versus observed interval energy on held-out test weeks (single-hidden-layer MLP; hexagonal bins, log-scaled counts; diagonal line = 1:1): (a) OPS; (b) OPS+R

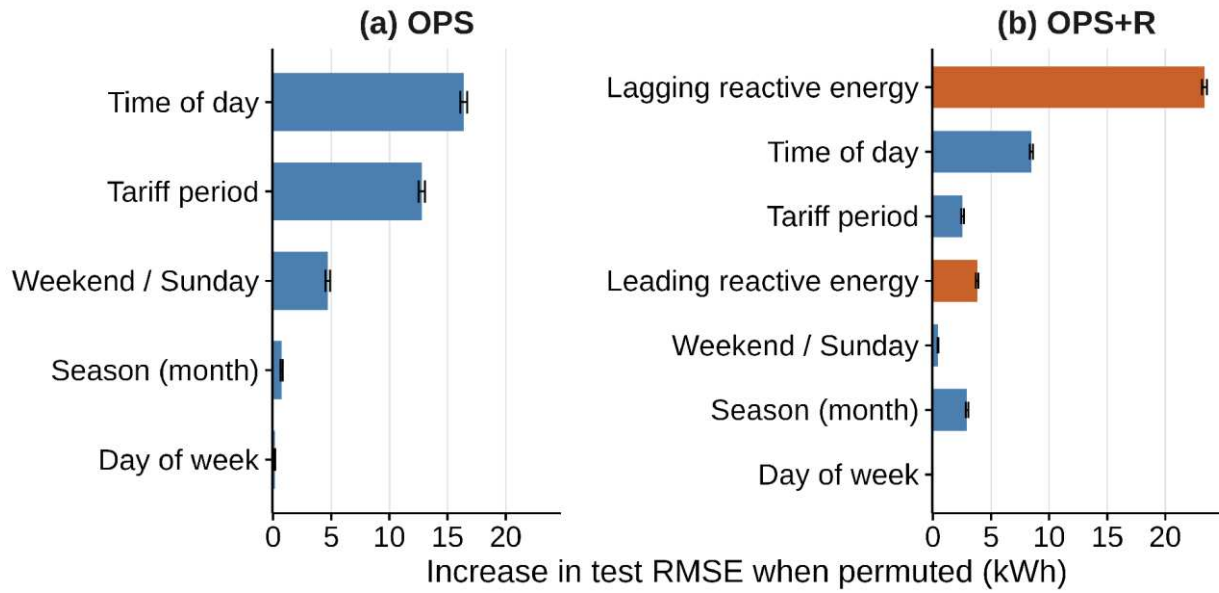


Fig. 8 Grouped permutation importance of the tuned MLP on the test set (mean increase in RMSE over 10 permutations $\pm$ SD): (a) OPS; (b) OPS+R. Reactive-energy inputs are shown in orange

4.3 Energy and emission scenarios

Correcting PF to 0.95 saves 2.3–6.8 MWh/yr (0.24–0.71% of energy, or 1.0–3.1 tCO₂ in scenario A) for in-plant loss shares of 2–6%. Its main benefits are elsewhere: apparent energy falls by 7.8% (from 1,087.8 to 1,003.1 MVAh), transformer capacity is freed and PF surcharges are avoided. An automatically switched capacitor bank of about 81 kvar, sized at the 95th percentile of excess reactive demand, would achieve this. Cutting the idle load by 10–30% saves 5.7–17.2 MWh/yr (0.6–1.8%, or 2.6–7.9 tCO₂).

Table 9 Load shift S1 (maximum period $\rightarrow$ 00:00–08:00)

s	Mean daily peak	Days with lower peak	Energy-cost index (1:1.5:2 / 1:2:3)	Δ CO ₂ , P1 [range]	Δ CO ₂ , P2 [range]
10%	–3.0%	39.7%	–2.7% / –3.9%	+19.8 [+12.9, +25.4] t	+11.0 [+6.3, +15.7] t
20%	–4.2%	39.7%	–5.5% / –7.9%	+39.6 [+25.9, +50.9] t	+22.0 [+12.5, +31.4] t

s	Mean daily peak	Days with lower peak	Energy-cost index (1:1.5:2 / 1:2:3)	ΔCO_2 , P1 [range]	ΔCO_2 , P2 [range]
30%	-4.8%	39.7%	-8.2% / -11.8%	+59.5 [+38.8, +76.3] t	+32.9 [+18.8, +47.1] t

H3a is supported. Shift S1 lowers the mean daily peak by 3.0–4.8%, lowers the mean monthly peak from 564 to 557 kW, and cuts energy cost by 2.7–11.8% while total energy stays the same (Table 9). Peaks fall on 39.7% of days, mostly working weekdays, and rise on about 1% of days. The yearly maximum of 628.7 kW does not change, because it happened during a morning ramp-up in a medium period (22 November, 09:30–09:45) that S1 does not touch.

H3b is only partly supported (Figs. 9 and 10). A 20% shift moves 86.2 MWh/yr. Under profile P1 it adds 25.9–50.9 tCO₂/yr, as expected. Under profile P2 it also adds emissions (+12.5 to +31.4 t), because the plant's maximum period overlaps the 10:00–16:00 solar hours, so the expected reduction does not appear. Equation (5) explains why: the shift raises emissions whenever the night-time marginal factor is higher than the daytime one ($R > 1$). With the central P1 values ($R \approx 2.1$) **it adds about 40 t/yr, while at $R = 0.8$ it would save about 7 t/yr.** Moving evening load into midday hours instead (S2) cuts emissions under P2 by 8.2–24.6 t/yr, but under today's tariff it raises the mean daily peak by 0.8–5.0% and the cost index by 0.3–1.1%.

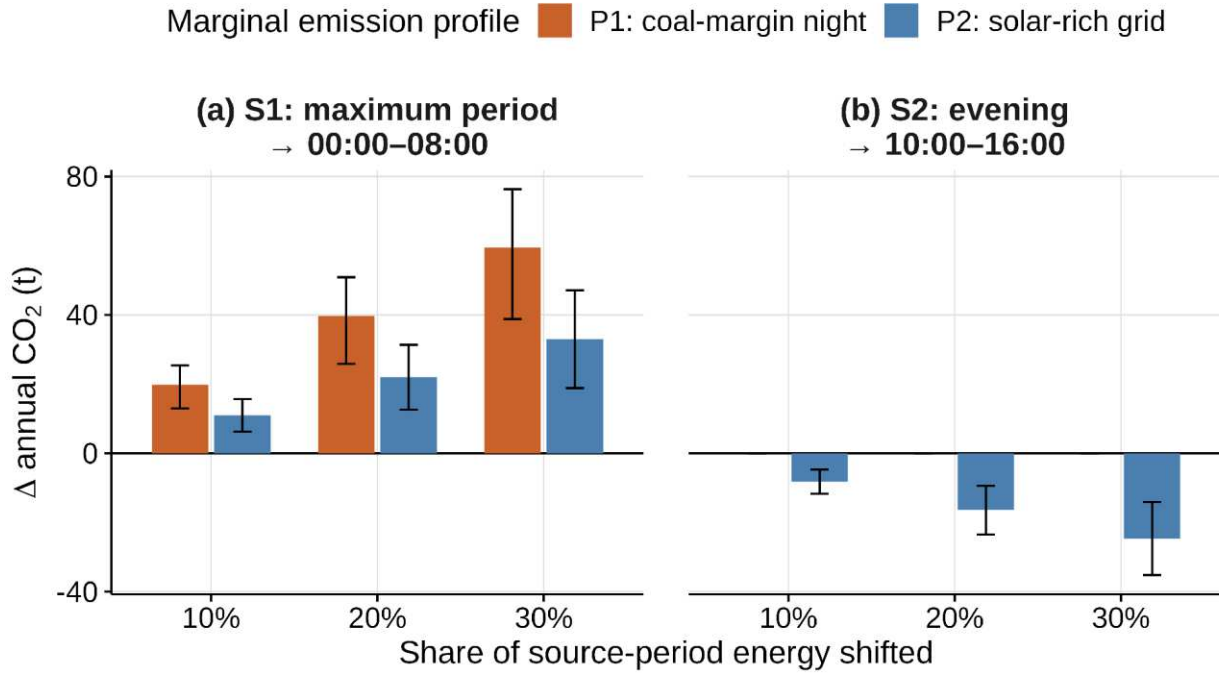


Fig. 9 Change in annual CO_2 from load shifting under two hourly marginal emission profiles (bars: central values; error bars: minimum–maximum over the sensitivity grid): (a) S1, maximum-period energy moved to 00:00–08:00; (b) S2, evening energy moved to 10:00–16:00

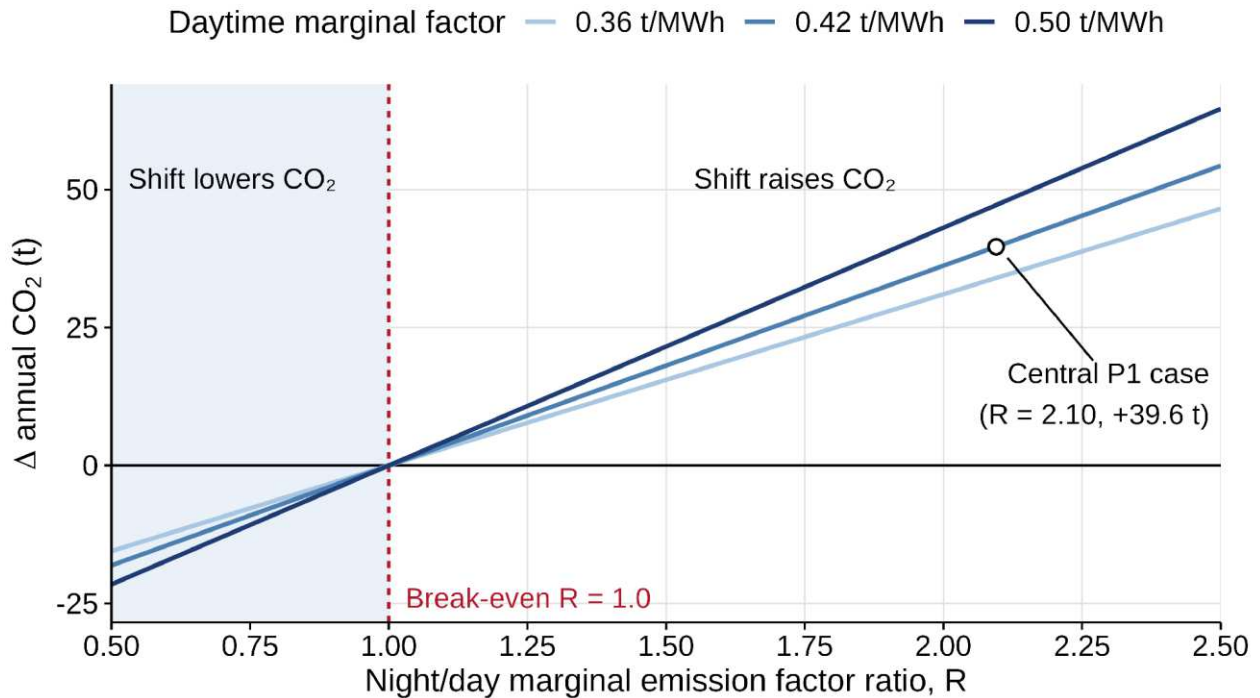


Fig. 10 Break-even of a 20% peak-to-night shift: change in annual CO_2 against the night/day marginal emission factor ratio R for three daytime marginal factors. The shift lowers CO_2 only for $R < 1$ (shaded); the open circle marks the central P1 case

Table 10 Abatement relative to scenario A (440.0 tCO₂/yr; central assumptions $L = 4\%$, idle cut 20%, $s = 20\%$)

Measure	Accounting	Emissions (t/yr)	Abatement (t)	Abatement (%)
PF correction to 0.95	Location	437.9	2.1	0.5
Load shift 20% (annual-average EF)	Location	440.0	0.0	0.0
Idle-load cut 20%	Location	434.7	5.3	1.2
In-plant portfolio	Location	432.7	7.3	1.7
Grid A → B (40% renewables)	Location	226.6	213.4	48.5
Grid A → C (deep- decarbonised)	Location	96.0	344.0	78.2
Renewable PPA, 50% of energy	Market	220.0	220.0	50.0
Renewable PPA, 100% of energy	Market	0.0	440.0	100.0

H4 is supported (Table 10 and Fig. 11). In all nine combinations of loss share and idle-load cut, moving from grid A to grid B cuts 19–58 times more CO₂ than all in-plant measures together. And because $\text{CO}_2 = E \times \text{EF}$, each kWh saved is worth less CO₂ as the grid gets cleaner: the in-plant measures save 7.3 t under grid A, 3.8 t under grid B and 1.6 t under grid C. Equipment efficiency should therefore be justified mainly by lower energy cost, freed capacity and better power quality, rather than by CO₂ savings alone. Table 11 summarises the tests of all six hypotheses.

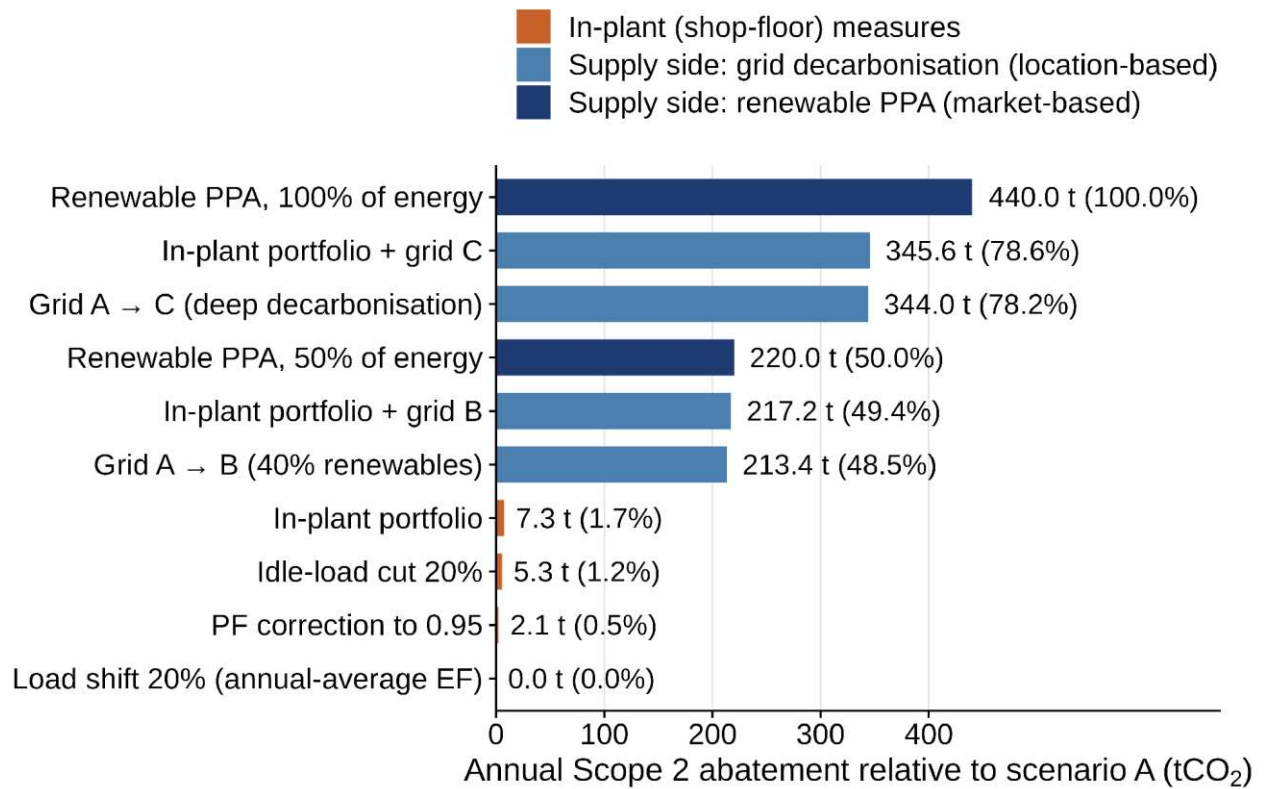


Fig. 11 Annual Scope 2 abatement relative to scenario A (440.0 tCO₂/yr) for in-plant (shop-floor) measures, location-based grid decarbonisation and market-based renewable PPAs (central assumptions)

Table 11 Summary of hypothesis tests

Hypothesis	Key evidence	Result
H1	Maximum/light energy ratio 8.1 (total 2.086, CI [2.012, 2.157]); same in both halves	Supported
H2a	PF +23 to +25 points in medium/maximum periods	Supported
H2b	33.8% of the maximum-period effect via reactive energy (CI 31.3–35.9%)	Supported (statistical link)

Hypothesis	Key evidence	Result
H3a	Daily peak -3.0% to -4.8% ; cost -2.7% to -11.8%	Supported (not the yearly maximum)
H3b	ΔCO_2 positive under both P1 and P2; break-even at $R = 1$	Partly supported
H4	19–58 times larger in 9 of 9 cases	Supported

5. Industrial Implications

Start with the idle load. At night the plant never drops below about 12.7 kW, and it sits there for 4,518 light-period hours a year at a PF of only 55–75%. Nothing else in the data is as easy a target. Simple interlocks that switch off or idle the hydraulic packs, compressors, fans, cooling pumps and lightly loaded transformers in light periods would save 0.6–1.8% of the energy for very little money. They would also take away most of the hours in which PF is at its worst.

Fit PF correction, but in stages. Roughly 81 kvar of load-switched capacitors would cover most of the 177 MVarh/yr of excess lagging reactive energy and end the surcharge risk. A fixed bank would be a mistake. The meter already logs 135.6 MVarh/yr of leading reactive energy, and fixed capacitors left on at light load would push the plant further into overcompensation. Someone should also measure harmonics and voltage before the bank is sized.

Forecast from the production calendar. For day-ahead energy budgets, contract-demand settings and carbon reporting, the schedule-only MLP is good enough as it stands (R^2 about 0.72, test-period energy within 0.4–2.5%). If the plant wants real-time load control, it needs live kVarh metering, which lifts R^2 to about 0.93.

Look at start-up, not just the tariff. The year's highest 15-min demand did not come from a maximum period at all. It came from a morning ramp-up in a medium period. Starting the big motors one after another at shift change, rather than all at once, would probably cut the demand charge by more than any shifting of energy between tariff periods.

Do the carbon arithmetic before shifting load. Night-time work is cheaper here, but whenever the night-time marginal plant is dirtier than the daytime one, Scope 2 emissions go up. With coal at the margin overnight, every 20% of peak energy moved costs about 40 tCO₂ a year. A plant with a

Scope 2 target needs hourly emission factors for this decision. As Korean solar capacity grows, the better move may well be the opposite one, from the evening into midday.

For big reductions, change the supply. Covering 50–100% of the energy with a renewable power purchase agreement (PPA) removes 50–100% of Scope 2 emissions. All the in-plant measures together remove under 2%. That does not make them pointless; they still cut cost, improve power quality and shrink the amount of renewable power the plant would have to contract.

6. Conclusion

We took one year of 15-min metering from a Korean steel processing plant and studied it three ways: with a path model, with MLP and benchmark forecasting models, and with simulations built on basic electrical relations.

Four results stand out. The tariff period, which in practice tracks how hard the plant is running, sets energy use; maximum-period intervals use 8.1 times the energy of light ones, in both halves of the year. PF collapses to around 55% when equipment idles and is 23–25 points higher once the plant is loaded, and about a third of the extra peak-period energy moves in step with reactive energy. The production schedule on its own is a decent predictor of energy (R^2 about 0.72 on unseen weeks against 0.54 for linear regression and 0.32 for a seasonal-naïve forecast). Most importantly for carbon, PF correction and idle-load cuts remove less than 2% of Scope 2 emissions, while a cleaner grid or a renewable contract removes 48–100%. Shifting peak load into the night saved money in every case we ran, yet it raised emissions whenever night-time marginal emissions were higher, and it did so even in our solar-rich grid profile.

There are clear limits to what one dataset can show. We had a single plant and a single year (2018), and no production tonnage, so energy per tonne was out of reach. Our first path model did not fit and had to be revised, and the split of effects between paths shifts with the season. The reactive-energy link is an association, and we do not claim it is causal. Finally, the marginal emission profiles and tariff ratios are assumptions that we varied over ranges; they are not measured Korean values or published tariff rates.

The obvious next step is data from several plants with production output and sub-metering of the main motors and drives. Measured hourly marginal emission factors for the Korean grid would make the load-shifting analysis much sharper, and with them, production could be scheduled for cost and carbon together inside the process limits.

Statements and Declarations

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

Ethics approval and consent: Not applicable. The study analysed publicly available plant meter data and involved no human participants or animals.

Data availability: The plant data are openly available from the UCI Machine Learning Repository (dataset 851; <https://doi.org/10.24432/C52G8C>). The electricity-mix data are available from Our World in Data (<https://github.com/owid/energy-data>).

Code availability: All R scripts and intermediate results are available from the corresponding author on request.

Author contributions: Amit Vishwakarma: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review and editing. Rajender Kumar Guneja: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review and editing. Both authors read and approved the final manuscript.

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