Resources, Conservation & Recycling 236 (2027) 109065

Contents lists available at ScienceDirect

Resources, Conservation & Recycling

journal homepage: www.sciencedirect.com/journal/resources-conservation-and-recycling

Measuring success: A refined methodology for estimating long-term continuous improvement

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A R T I C L E I N F O

Keywords:
Efficiency
Energy intensity
Linear regression
Continuous improvement
Measurement and verification

A B S T R A C T

Successful resource management systems require current and detailed feedback on operational and corporate-level performance. As corporate accountability concerns intensify, the precision and reliability of these performance metrics have become crucial. Traditional savings estimation methods can be difficult to understand, particularly linear regression, and can provide varying results. This paper reviews common efficiency metrics and highlights underlying mathematical inconsistencies when estimating total and percent savings with current methods. A refined approach to calculating long-term utility savings is proposed that simplifies current methodologies utilizing ratios to define an adjusted baseline, allowing for consistent and fair aggregation of results across multiple scales from resources to corporate performance. A simplified example demonstrates how the proposed methodology improves upon existing methods, especially in intermediate years. This paper's major contributions are the simplified approach for converting modeled utility usage into estimated savings and the consistent roll-up methodology enabling more comparable, aggregable, and actionable results across scales.

Notation

Value	Name	Description
A	Actual Energy Consumption	The energy consumption of a facility measured by a meter or submeter.
M	Modeled Energy Consumption	The estimated energy consumption of a facility based on a model.
J	Adjusted Baseline Consumption	The modified energy consumption of a baseline facility accounting for changing conditions.
S	Energy Savings	The actual reduction in energy usage compared to a baseline.
%	Percent Improvement	The relative improvement in efficiency measured against a baseline.

Subscript	Name	Description
i	Analysis Period	A period the same length as the baseline used to determine performance improvement.
b	Baseline Period	The period used as the base of comparison for estimating efficiency improvement.
m	Model Period	The period used to determine a model of consumption based on relevant variables.

1. Introduction

Annual global energy consumption has risen almost every year over the last half century [Ritchie et al., 2020]. Energy demand from the emerging data center sector is projected to increase the growth rate of energy consumption over the next decade, particularly in the United States [U.S. Energy Information Agency (EIA), 2026]. Energy and resource efficiency is therefore at the forefront of corporate and policy frameworks to help alleviate demand growth issues [Ritchie et al., 2020; Ritchie and Roser, 2018] as efficiency is the most economic strategy for operational cost savings [American Council for an Energy Efficient Economy (ACEEE), 2016]. Efficiency can be pursued through many pathways including operational changes, retrofitting existing equipment, installation of more efficient technologies, or the adoption of smart manufacturing [Sundaramoorthy et al., 2023]. This can be seen in recent manufacturing energy efficiency assessments conducted by the U.S. Department of Energy's Better Plants Challenge program which found an average total energy savings of 19%, mostly from "low-hanging", quick-payback opportunities [Miera et al., 2024]. Adoption of best available technologies and development of more advanced efficiency solutions could save an additional 20–40% of total energy

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https://doi.org/10.1016/j.resconrec.2026.109065
Received 6 January 2026; Received in revised form 3 June 2026; Accepted 27 June 2026
Available online 20 August 2026

long-term in key industrial subsectors such as iron and steel, cement and lime, and glass [Worrell and Boyd, 2022]. A strategic energy management plan, such as the ISO 50001 standard [International Standards Organization (ISO), 2018], can help companies successfully and continuously improve their efficiency [McKane et al., 2017] by providing continuous feedback. Similar management standards are also available for organizations striving to achieve water (ISO 46001 [International Standards Organization (ISO), 2019]) and waste (ISO 14001 [International Standards Organization (ISO), 2026]) reductions. These standards generally outline key components of a successful management plan, but do not prescribe actual procedures for achieving or quantifying savings.

Resource efficiency goals come in many forms such as absolute or productivity-based intensity reductions. Energy goals are often intensity-based and can be calculated in terms of site energy to focus on usage within the corporate boundary or source energy to include generation and distribution losses. Energy procurement goals are commonly generation capacity goals or a specified percentage of total usage from a given source, either generated onsite or procured through contracting. Water reduction goals can also be absolute or intensity based, focusing on total water use, intake, discharge, or other metrics. Waste reductions goals are relatively new and have several options from waste diversion to absolute reductions [Chaudhari et al., 2024]. Other corporate goals focus on absolute reductions in common industrial byproducts (e.g., refrigerants, pollutants) [Ranganathan et al., 2015]. Internationally, individual countries and regions have their own goals and pathways towards efficiency, with countries such as China aiming to improve industrial intensity by 13.5% from 2020 levels [Huld, 2024] and the European Union implementing stronger efficiency policies including new minimum energy performance standards for non-residential buildings and a 16% improvement in energy performance of residential buildings by 2030, also against a 2020 baseline [The European Commission, 2024]. Consumer, employee, and shareholder expectations as well as the economic growth benefits of energy efficiency [Zakari et al., 2022; International Energy Agency (IEA), 2025] mean that energy and resource efficiency targets are receiving greater focus from scientific research and analysis [Kartal et al., 2024].

Measurement and Verification (M&V) is a crucial part of any successful organizational continuous improvement plan. M&V is “the process of planning, measuring, collecting, and analyzing data for the purposes of verifying and reporting [energy] savings” [Efficiency Evaluation Organization (EVO), 2012]. Without M&V, companies have limited feedback on their progress and whether their current course of action is effective and appropriate. Corporate reporting teams must be able to determine if energy savings are durable and the result of efficiency projects or if they are merely the result of lower production or milder weather. M&V methodologies vary in how they draw system boundaries and in the calculations used to estimate savings. For example, energy savings from a new piece of equipment can be estimated through equipment specifications or measured directly with submetering before and after installation. System-level factors such as run time or throughput can also be considered if using a regression-type approach to normalize savings between periods. These principles can also be scaled to the site level by establishing facility-wide baselines with utility bills and tracking usage before and after implemented changes with additional adjustments for external factors, such as weather conditions and production levels.

The influx of energy and resource efficiency goals has largely been a decentralized effort, with a variety of targets and scopes based on the organization or recognition program. For example, two notable U.S. energy efficiency programs are the Department of Energy’s Better Buildings, Better Plants program which aims for 25% energy intensity reduction over ten years and the Energy Star Challenge for Industry which targets a 10% reduction in five years. Both programs provide similar, but slightly different guidance on how to track and estimate energy savings [Price et al., 2020; U.S. Environmental Protection Agency (EPA), 2020]. There are numerous other state and utility-based programs, each with their own focus (e.g., the Tennessee Valley Authority’s EnergyRight® program, the Texas State Energy Conservation Office’s Texas Industrial Energy Efficiency Program). While the International Standards Organization (ISO) 50001 standard [International Standards Organization (ISO), 2018] outlines the components of successful energy management systems, it has limited implementation within the United States [International Standards Organization (ISO), 2024] and only recommends establishing energy-related key performance indicators without prescribing what those metrics might be.

The diversity in efficiency programs and lack of centralized guidance has led to uncertainties and conflict in how metrics for tracking improvements are calculated. Most guidance on energy tracking provides limited practical information on how to calculate adjustments for energy savings to account for real-world environments where weather, production, and other factors typically have a stronger impact on energy consumption than most efficiency projects. In these cases, rigorous and defensible adjustments are critical to distinguish energy savings from normal fluctuations in consumption. Current M&V protocols apply these adjustments by adding or subtracting from savings which leads to inconsistencies when also calculating percentage improvement, an inherently multiplicative metric. As discussed in Section 3, baseline adjustments, savings, and percent improvement are disconnected metrics leading to functional issues when combining or comparing results across energy streams or organizations. This paper explores these issues and traces them to additive adjustments used to normalize energy consumption to account for changes between periods. A new methodology for baseline adjustments is proposed to address this using ratios and proportions rather than addition/subtraction, creating a more streamlined, internally consistent methodology for estimating savings and combining results across multiple facilities that can easily be adopted into existing M&V protocols. This new methodology allows for easier and more widespread adoption of energy management programs and provides better and more trustworthy feedback on utility, facility, and corporate-level performance.

2. Current methods for tracking progress

The simplest way of estimating savings (S_i) over a specified period is to subtract analysis period energy consumption (A_i) from baseline period consumption (A_b), a process known as the absolute method discussed later in this section. For this paper, an ***analysis period*** is any segment of time that is equal in length to the baseline period against which performance is compared. The ***baseline period*** is the first analysis period and is commonly a single year. However, differences in external factors between periods can make it difficult to understand whether a facility is operating more efficiently. For example, a cold winter can lead to more natural gas usage regardless of newly installed building insulation. Many savings estimation approaches, therefore, adjust simple savings using a model to normalize between periods. M&V protocols such as [Efficiency Evaluation Organization (EVO), 2012], apply this normalization by adding or subtracting an adjustment to simple savings (Eq. (1)). This equation can also be used to define an “*Adjusted Baseline*” (J_i) for the current analysis period ‘i’ which represents the estimated consumption of the baseline facility given the conditions in the analysis period. With this definition, savings are simply the difference between this adjusted baseline and the actual analysis period usage.

$$S_i = A_b - A_i \pm Adjustment = (A_b \pm Adjustment) - A_i = J_i - A_i \tag{1}$$

Estimation of savings, therefore, begins by selecting a model that will project how a facility uses its resources. That model can be based on a set of independent variables such as production or weather to normalize between periods. There are three methods for calculating savings: absolute energy, energy intensity, and normalization [Therkelsen et al., 2016]. While there are many options for normalization, this paper focuses on linear regression as it is the primary method used in M&V protocols. The rest of this section reviews each of these methods, as well as a few other methods gaining prominence, and how they are used to estimate savings. Although this paper mostly centers on tracking energy performance, the methods discussed can also be used to evaluate other metrics such as water consumption or waste generation.

Absolute Energy Analysis is the simplest method for estimating savings and only requires tracking total energy consumption. Absolute analysis is suitable for organizations seeking reductions or elimination of a tracked metric or for those with diverse product mixes. The absolute method assumes a fixed model equal to the baseline period's actual consumption ($M_i = A_b$). Savings (S_i) are the difference between baseline period consumption (i.e., the model) and the analysis period consumption (Eq. (2)). The adjusted baseline for this method is, therefore, also equal to the baseline period actual energy consumption ($J_i = A_b$). Percent Savings ($\%_i$) are calculated by dividing analysis period savings by the baseline period energy consumption which is also the adjusted baseline (Eq. (3)).

$$S_i = M_i - A_i = A_b - A_i = J_i - A_i \tag{2}$$

$$\%_i = \frac{S_i}{A_b} \times 100 = \frac{S_i}{J_i} \times 100 \tag{3}$$

Savings with the absolute method are only realized when total utility consumption decreases. This can lead to distorted and volatile snapshots of overall performance as changes in energy consumption due to production levels, different weather conditions, and variations in other important factors between periods are not considered and may outweigh any efficiency improvements.

Classic Energy Intensity is another straightforward approach widely used to track energy efficiency improvements. This method requires tracking *both* total energy consumption and a productivity metric (P_i) such as widgets made, work hours, or sales. Intensity is a good option for organizations needing a single metric to track energy productivity across all of their operations or assess value added by production. Classic Energy Intensity is calculated by dividing total consumption by the productivity metric for a given period. The model for this method is the baseline period's energy intensity multiplied by the analysis period's productivity metric ($M_i = A_b/P_b \times P_i$). The model, therefore, estimates how much energy the baseline facility would have used given current production levels. Energy savings are again the difference between modeled consumption and actual consumption in the analysis period (Eq. (4)) which means that the adjusted baseline for this method is equal to the modeled energy consumption ($J_i = M_i$). Percent savings is calculated as the change in reporting and baseline period intensity which is equivalent to dividing savings by the adjusted baseline energy usage (Eq. (5)).

$$S_i = M_i - A_i = (A_b / P_b) \cdot P_i - A_i = J_i - A_i \tag{4}$$

$$\%_i = \left(1 - \frac{A_i/P_i}{A_b/P_b}\right) \times 100 = \frac{S_i}{J_i} \times 100 \tag{5}$$

Savings with the classic intensity method are realized when energy intensity decreases, even if absolute consumption increases. While a decrease in intensity can reflect a facility becoming more efficient, it may also be a result of changing product mix or simply greater production [Freeman et al., 1997]. While classic intensity does improve upon the absolute energy method by incorporating variations in productivity, one major issue is the inherent assumption of zero baseload energy consumption. This assumption is usually invalid as non-production loads like lighting, HVAC, and computers still draw power when a facility is not operating, which can lead to distortions in calculated savings if annual productivity varies significantly from baseline conditions [Wenning et al., 2017]. Intensity analysis also oversimplifies how facilities use energy, excluding the effects of other variables that can drive consumption such as temperature and humidity.

Linear Regression (LR) is the most rigorous of the three common methods for energy performance tracking and is good for organizations looking to capture a fuller picture of how they use energy. Normalization with the LR approach can help distinguish between improvements in energy performance due to efficiency projects or other external factors. However, LR does require more data collection and expertise than either absolute or intensity analysis. This statistical approach identifies linear relationships between energy consumption and multiple independent variables to find formulas like Eq. (6). In this equation, coefficients "$c_\square$" multiply combinations of predictor variables that often include production (P_i), average temperature (T_i), or humidity (H_i) to closely match a set of modeling data. Typically, a ***model period*** of at least 12 months of consumption and predictor data is used to find a model subject to statistical and data validity requirements [University of California, 2019]. The model period can be any series of consecutive data and does not need to be locked to a single calendar or fiscal year.

$$M_i = c_0 + c_1 \cdot P_i + c_2 \cdot T_i + c_3 \cdot H_i + \cdots \tag{6}$$

Calculating savings using the LR approach can be traditionally understood from Eq. (7) and Fig. 1 where model period selection will depend on the existence of valid models and on the "best fit" available across different model periods. When the model period and the baseline period coincide, the regression is known as "forecasting" and $A_b = M_b$. Forecast savings occur when future, modeled energy usage in the analysis period is greater than actual usage [University of California, 2019] (the shaded purple area in Fig. 1). This means that for forecast models, the adjusted baseline is the same as the modeled energy usage ($J_i = M_i$) and that both absolute and classic energy intensity analysis are simply subcases of the forecast methodology with specific models (i.e., a fixed constant and a single variable productivity model respectively). Percent savings for forecasting are calculated from the actual period energy consumption divided by the modeled energy consumption, which is equivalent to dividing savings by the adjusted baseline (Eq. (8a)).

$$S_i = \underset{(M_i - A_i)}{\text{Forecast}} + \underset{(A_b - M_b)}{\text{Backcast}} \tag{7}$$

$$\text{Forecast } \%_i = \left(1 - \frac{A_i}{M_i}\right) \times 100 = \frac{S_i}{J_i} \times 100 \tag{8a}$$

$$\text{Backcast } \%_i = \left(1 - \frac{M_b}{A_b}\right) \times 100 = \frac{S_i}{A_b} \times 100 \tag{8b}$$

$$\text{Chaining } \%_i = \left(1 - \frac{M_b}{A_b} \cdot \frac{A_i}{M_i}\right) \times 100 \neq \frac{S_i}{A_b M_i} \times 100 \tag{8c}$$

When the model period and the analysis period align, the regression is known as "backcasting" and $M_i = A_i$. Backcast savings are reversed: savings occur when past energy usage is greater than the modeled energy usage during the analysis period (the green shaded area in Fig. 1). Percent savings in the final year of a backcast are also reversed, calculated by dividing modeled baseline energy by actual baseline energy (Eq. (8b)). For model periods between the baseline and current analysis periods, the regression is called "chaining" and savings are the sum of both forecast and backcast savings (Eq. (7)) or the sum of the purple and green shaded areas in Fig. 1. With the current definition of savings in Eq. (7), there is no way to write percent savings for either a backcast or a chaining model in terms of the adjusted baseline. In fact, this issue is compounded with the chaining method as the denominator is a multiplication of A_b and M_i and the formula cannot be simplified to include savings in the numerator. Note that the formulas in Eqs. (8) only provide percent savings in the most *recent* analysis period. Appendix A from [U. S. Department of Energy, Advanced Manufacturing Office 2018] provides generalized formulas for percent savings between the baseline and current analysis periods.

Beyond the three common methods discussed, there are also many other methods that can be used to model utility usage for performance

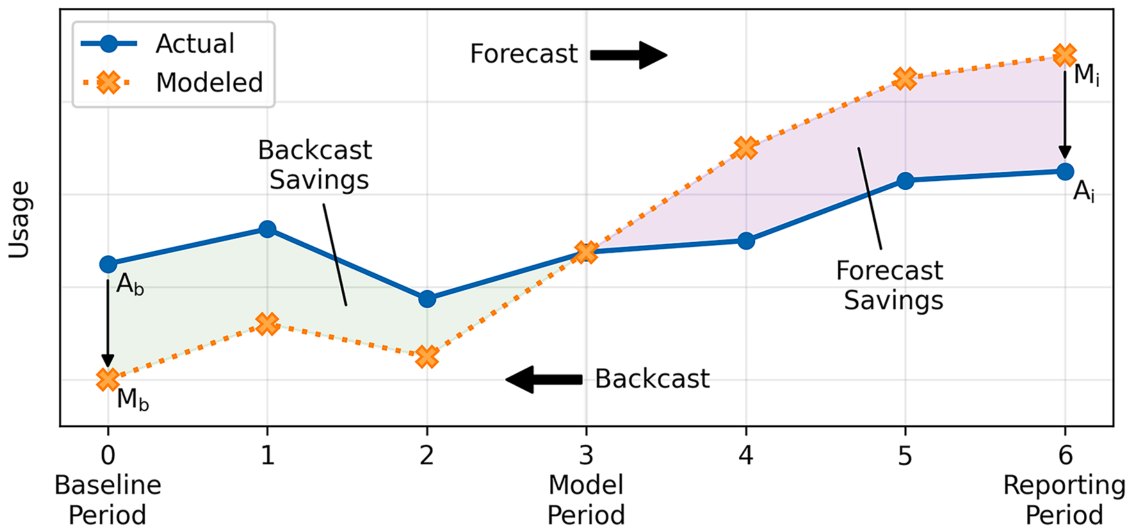

Fig. 1. Diagram of savings calculation for chaining regression using addition and subtraction approach.

tracking, usually with increased complexity. ***Modified Energy Intensity*** (MEI) was proposed by researchers in [Guo et al., 2019] to improve the accuracy of the classic energy intensity approach without requiring the large amount of data needed for LR analysis. Percent improvement for the MEI method is a weighted average of percent savings from absolute and classic energy intensity analysis based on an estimate of baseload energy. ***Variable-base Degree Day*** (VBDD) is a weather-only model that optimizes the selection of the degree day balance temperature by testing various options and selecting the best fit [Kissock et al., 2003]. ***Change-point Modeling*** is a linear piece-wise approach for non-linear usage profiles that can consist of multiple VBDD or multivariable regression models for different conditions. Other non-linear techniques including neural networks have been used to estimate industrial energy usage [Kialashaki and Reisel, 2014; Shiau et al., 2022; Helle et al., 2011].

Each of these modeling techniques must overcome the somewhat limited data available when modeling utility-level usage. Models are often developed from only twelve monthly data points and the data itself is usually low resolution, with usage from monthly utility bills and predictors from high level production aggregates or proxies. The end user must ensure that models make engineering sense and have statistical validity before deploying them to estimate savings. Ultimately, each of the methods discussed provide a model of utility usage and turning these models into estimated savings therefore proceeds in a similar manner to that used in LR. This paper discusses issues with current techniques for estimating savings after model selection has occurred and proposes a simplified method to achieve that task.

3. Challenges with current savings calculations

Companies often track the performance of different utilities or facilities using different methods. Properly weighting improvements from different sources when combining results into a company level, top-line savings number is important when evaluating the overall performance of an organizational energy management program. Despite this common practice, there is no current standard or consistent method for “rolling up” multiple performance metrics.

From the previous discussion, each method calculates its total savings and percent savings slightly differently. While forecast models (including the absolute and classic energy intensity methods) inherently measure progress against an adjusted baseline, backcast and chaining LR models do not. This points towards an inconsistency between approaches stemming from different points of comparison that makes combining results difficult. For example, the DOE’s Energy Performance Indicator (EnPI) tool combines percent improvement results using a weighted average, normalized by the modeled baseline period energy consumption (M_b) [U.S. Department of Energy, Advanced Manufacturing Office 2018]. However, none of the formulas in Eq. (8) have denominators equal to M_b, meaning that savings of individual utilities are not properly preserved with this roll-up methodology. Eq. (9) highlights this by calculating combined percent savings ($\overline{\%_i}$) for two facilities where Facility 1 used the absolute energy approach and Facility 2 used a forecast regression approach.

$$\overline{\%_i} = \frac{M_{b,1}\cdot\%_{i,1} + M_{b,2}\cdot\%_{i,2}}{M_{b,1} + M_{b,2}} = \frac{M_{b,1}\cdot\frac{S_{i,1}}{A_{b,1}} + M_{b,2}\cdot\frac{S_{i,2}}{M_{i,2}}}{M_{b,1} + M_{b,2}} \neq \frac{S_{i,1} + S_{i,2}}{A_{b,1} + M_{i,2}} \tag{9}$$

Finding a consistent divisor for each savings approach (absolute, classic energy intensity, regression, etc.) will allow for rolled-up savings results to maintain the understanding of calculated savings and fairly weight the contributions of each utility or facility toward the company-level performance metric. The next section presents a new, standardized way of rolling-up performance metrics by proposing a new definition for the adjusted baseline.

The effects of inconsistent divisors can be very subtle and are often overwhelmed by other factors like model selection or changes in production. In addition, true savings are unknown and unknowable, making it difficult to identify methodological inconsistencies. Challenges with the current additive approach for adjusting savings are, therefore, most easily illustrated through a simple example with known levels of improvement. Simplification allows the effects of noise in real-world data to be removed and inconsistencies in results to be more easily illuminated. Consider a facility whose consumption of *Utility A* over any given year ‘*i*’ can be exactly described by a simple linear equation with production in that year (P_i) as the only variable. If that facility has a known annual improvement of 2% against its baseline year (i.e., $i = 0$), Eq. (10) gives annual actual consumption. This equation can be used to create a “perfect” model of the utility energy consumption with an R-squared fit of 1.0 between production and usage by fixing the level of improvement to its value in a model year period ‘*m*’ (Eq. (11)). Fig. 2 shows actual and modeled usage generated from six years of example production data (see Appendix B for values used).

$$A_i = (100\cdot P_i + 1000)\cdot(1 - 0.02\times i) \tag{10}$$

$$M_i = (100\cdot P_i + 1000)\cdot(1 - 0.02\times m) \tag{11}$$

Applying the generalized formulas in Appendix A for the absolute and classic energy intensity methods as well as forecasting, backcasting,

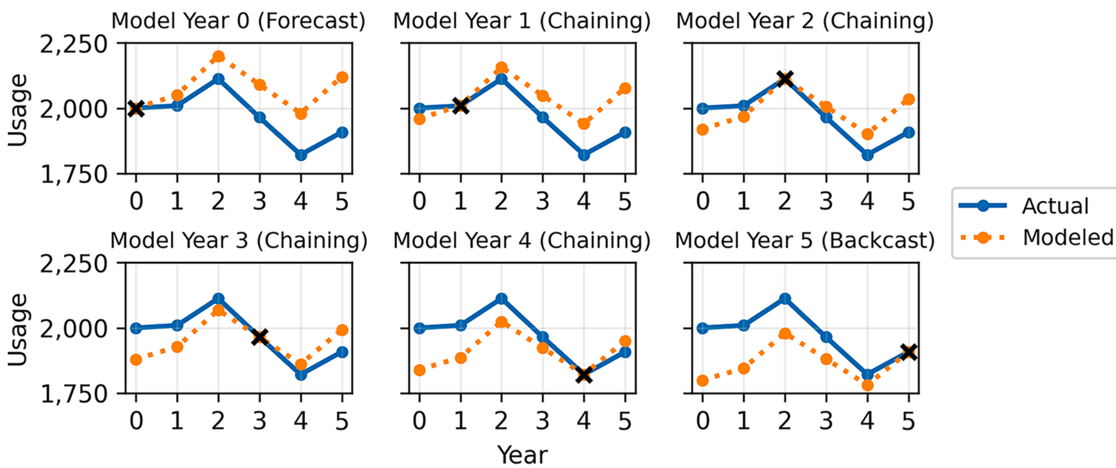

Fig. 2. Actual and modeled usage for a simplified case study.

and chaining regression models yields the results in Table 1. The results for absolute and intensity-based analysis show the inherent limitations of these methods to account for varying conditions. For the first two LR model years (Year 0 and Year 1), estimated percent savings ($\%_i$) match the designed results of 2% improvement each year. For model years after Year 2, estimated savings before the model year are close to the expected improvement but not exact (orange shading in Table 1). For all models, Eq. (1) is used to find a consistent adjusted baseline using the additive expression $J_i = S_i + A_i$, allowing for the alternate calculation of percent savings using the adjusted baseline (i.e., S_i divided by J_i). Calculating savings this way also does not match the designed 2% rate of improvement for any model year except a forecast. Further, and more concerningly, these values (yellow shading in Table 1) do not match the directly calculated savings ($\%_i$). If percent savings ($\%_i$) are not related to savings divided by the adjusted baseline (S_i / J_i), this raises the question: what is the divisor in percent savings ($\%_i$)? As discussed, attempting to resolve this question algebraically leads to inconsistent answers (i.e., modeled energy, actual energy) and meaningless quantities (i.e., energy squared).

The differences between calculated percent savings using Eq. (8) ($\%_i$), percent savings from S_i/J_i, and the designed 2% annual savings for this simple example show how the internal inconsistencies of these methods skew the estimated improvement. The key to understanding the differences is that while savings and adjusted baseline are defined using addition and subtraction (Eqs. (1) and (7)), percent savings is a ratio defined in terms of multiplication and division. For example, each ingredient in a recipe would be tripled when making a large batch of cookies instead of adding a cup to each measurement. This conflict in

Table 1
Example results using current additively based savings calculations.

Year	0	1	2	3	4	5
Production (P_i)	10.0	10.5	12.0	10.9	9.8	11.2
Actual Energy (A_i)	2000.0	2009.0	2112.0	1964.6	1821.6	1908.0
			$\%_i$			
Absolute	0.00%	-0.45%	-5.60%	1.77%	8.92%	4.60%
Classic Intensity	0.00%	4.33%	12.00%	9.88%	7.06%	14.82%
LR Model Year 0	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%
LR Model Year 1	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%
LR Model Year 2	0.00%	1.96%	4.00%	6.00%	8.00%	10.00%
LR Model Year 3	0.00%	1.92%	3.92%	6.00%	8.00%	10.00%
LR Model Year 4	0.00%	1.88%	3.83%	5.87%	8.00%	10.00%
LR Model Year 5	0.00%	1.84%	3.75%	5.74%	7.83%	10.00%
			S_i / J_i			
Absolute	0.00%	-0.45%	-5.60%	1.77%	8.92%	4.60%
Classic Intensity	0.00%	4.33%	12.00%	9.88%	7.06%	14.82%
LR Model Year 0	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%
LR Model Year 1	0.00%	1.95%	3.83%	5.92%	8.02%	9.90%
LR Model Year 2	0.00%	1.90%	3.65%	5.84%	8.04%	9.80%
LR Model Year 3	0.00%	1.86%	3.47%	5.76%	8.06%	9.69%
LR Model Year 4	0.00%	1.81%	3.30%	5.68%	8.07%	9.59%
LR Model Year 5	0.00%	1.76%	3.12%	5.59%	8.09%	9.49%

fundamental operations, additive vs. ratios, accounts for the differences between the $\%_i$ and S_i/J_i values in Table 1 as well as the deviations from the designed 2% annual improvement rate. These operational differences also make combining (rolling-up) results from multiple utilities and facilities difficult, because total savings and total percent savings will combine results from similarly mixed sets of fundamental operations.

In summary, the methodologies for calculating savings from a model are fundamentally different depending on the time interval used to create the model. This leads to differences in results not due to the models themselves, but from the calculation of savings from the models. Additionally, the actual absolute savings (S_i) are calculated with addition and subtraction entirely separately from percent savings ($\%_i$) calculated with division and multiplication, often making the results incompatible with each other. These effects are especially prominent when combining results for facility or corporate-level reporting.

4. Proposed method

As discussed, calculation of savings and percent savings using the current methodologies mixes fundamentally different mathematical operations and denominators. Estimating change in any parameter is usually done with geometric scaling or ratios rather than through addition/subtraction. For example, failure count estimation after a production increase would be calculated by *multiplying* the previous failure rate by the new production level and not by *adding* some adjustment to the previous number of failures. Applying this concept of ratios to the estimating of savings would yield an internally consistent and more intuitive set of calculations.

To address the identified issues, this paper proposes a new definition for an adjusted baseline and its consistent integration into a simplified workflow for the estimation of savings. As a starting point, Eq. (8c) was rewritten to have a similar form to a forecast model (Eq. (12)). This leads to a new definition of an adjusted baseline (Eq. (13)) where baseline consumption is multiplied by a new **Adjustment Ratio** (R_i) instead of being modified by addition. The adjustment ratio captures the model's prediction of how much consumption will change from the baseline to the analysis period based on changes in the model predictor variables (e.g., production, weather). Savings can now be calculated as the difference between the *adjusted baseline* and the actual *analysis period* energy usage (Eq. (14)) and percent savings are defined as savings divided by the *adjusted baseline* (Eq. (15)). The effect of the new definition is most clearly seen in Eq. (13) and Fig. 3 where A_b is *multiplied* by an adjustment instead of being added to an adjustment as in Eq. (1) and only one equation is needed regardless of the selected model year. Savings now occur only when current usage is lower than the adjusted baseline. For example, if the adjustment ratio predicts a 5% decrease in usage, then any additional decrease in analysis period actual usage is due to factors outside of the model's predictor variables and can generally be ascribed to the implementation of utility saving projects.

$$\%_i = \left(1 - \frac{M_b}{A_b}\frac{A_i}{M_i}\right) \times 100 = \left(\frac{A_b \cdot M_i/M_b - A_i}{A_b \cdot M_i/M_b}\right) \times 100 = \frac{J_i - A_i}{J_i} \times 100 = \frac{S_i}{J_i} \times 100 \tag{12}$$

$$J_i = A_b \cdot R_i = A_b \cdot \frac{M_i}{M_b} \tag{13}$$

$$S_i = J_i - A_i = A_b \cdot R_i - A_i \tag{14}$$

$$\%_i = \frac{S_i}{J_i} = 1 - \frac{A_i}{J_i} = 1 - \frac{A_i}{A_b} \cdot \frac{M_b}{M_i} \tag{15}$$

These definitions ensure that all results are calculated using a consistent reference (i.e., J_i). This is especially important when "rolling up" results for multiple utilities across a facility or multiple facilities across an entire company for organizational sustainability reports. Eq. (16) gives the formula for this roll-up where $\overline{\%}_i$, $\overline{S}_i$, and $\overline{J}_i$ are rolled-up values combining results for N utilities or facilities. The adjustment ratio, adjusted baseline, and savings should all be calculated at the same interval either directly at the annual level or from monthly data and then rolled up to various levels of analysis (see Appendix C for more information). For example, performance data from monthly utility bills could be calculated at the monthly level and then rolled up to the annual level using Eq. (16). Once an adjusted baseline is calculated, all further results should be found utilizing the roll-up formula in Eq. (16).

$$\overline{\%}_i = \frac{\overline{S}_i}{\overline{J}_i} = \frac{\Sigma_{n=1}^{N} S_{i,n}}{\Sigma_{n=1}^{N} J_{i,n}} = 1 - \frac{\Sigma_{n=1}^{N} A_{i,n}}{\Sigma_{n=1}^{N} J_{i,n}} \tag{16}$$

The proposed method eliminates the formulaic distinction between LR forecast, backcast, and chaining models and simplifies combining results from different methods. Further, Eqs. (13)–(15) apply not only to all three regression scenarios but also simplify to the special cases given in Eq. (8). This ensures that percent savings calculated in the most current analysis period will match results calculated using the conventional methodology and therefore only actual savings and the adjusted baselines will be different with this new method. The proposed methodology is also more easily explainable: the model applied to the

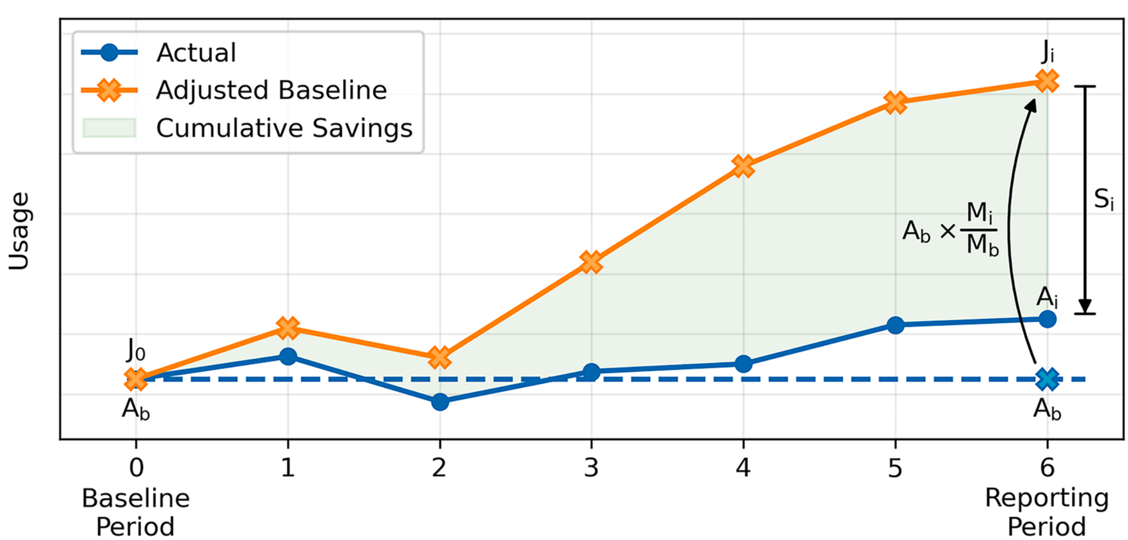

Fig. 3. Diagram of savings calculation using the proposed ratio approach.

baseline and analysis period conditions predicts a change in consumption and adjusts the baseline accordingly with savings occuring when consumption is below that adjusted baseline. Fig. 4 provides a visual flow diagram of how the method is applied after data collection and model selection and how it complements existing M&V protocols. Appendix E provides a detailed example of how the method can be applied to real facility energy data. As the method is applied after model selection, issues like model and regression quality as well as predictor uncertainty will still affect end results.

A minor issue with the new definitions of the adjusted baseline and percent savings is the introduction of division-by-zero edge cases. When the adjusted baseline is zero, percent savings is undefined and when the modeled baseline usage is zero, the adjusted baseline is undefined. This situation can occur for utilities like natural gas used for space heating at the monthly level when where there is essentially zero usage over the summer. Appendix D provides solutions for what to do when these situations arise. Future work with this method will also explore how to apply baseline adjustments to account for fundamental changes in utility usage not captured via modeling (e.g., adding large loads due to new environmental regulatory requirements) and how to capture previous savings when rebaselining.

The proposed methodology has no additional computational complexity when compared to current methods. All operations are common mathematical functions (e.g., addition, multiplication) and there are only a few edge cases that are discussed in Appendix D. All operations can be easily programmed in spreadsheet software or any programming language. In fact, the proposed methodology simplifies the process in a few important ways. Forecast, backcast, and chaining regression models no longer require separate equations, eliminating the need for conditional statements and logic to determine which modeling technique was used. Intermediate year savings are also easier to compute as they use the same equations regardless of if the model year is before or after the desired analysis year. Roll-up calculations are also simplified as all results are calculated relative to a common definition of the adjusted baseline. These simplifications make the method easier to explain and to implement and have allowed for integration of new complexities (e.g., non-routine adjustments) that will be explored in future work.

This section outlines how using scaling ratios is a more consistent and natural way to adjust baseline energy usage for various routine operational changes. The new proposed method simplified calculations by defining savings *and* percent savings in terms of a single adjusted baseline, making combining results easy while preserving the relative contributions of all utility and facility savings. Further, the proposed methodology eliminates internal inconsistencies in savings calculations observed in current M&V protocols.

5. Results from perfect model example

Revisiting the perfect model example shows how the new methodology offers improved analysis results. Results for absolute and energy intensity-based analysis remain unchanged. Applying the proposed Eqs. (13)-(15) across all LR model years, gives the results shown in Table 2. Annual savings now match the designed 2% annual improvement rate against the baseline for all analysis years, independent of the model year. Additionally, percent savings are now consistently calculated via savings and adjusted baseline, eliminating the discrepancy between $\%_i$ and S_i/J_i. This is a significant improvement compared to the results seen in Table 1 while also streamlining the overall calculations.

If this facility also consumed “Utility B”, these results could be easily “rolled up” using Eq. (16) to determine an overall facility-level performance level. Results could be further combined across multiple facilities to determine an overall company-level performance result. As all results use the adjusted baseline as a consistent denominator, the rolled-up results would preserve the relative contributions of each utility and facility towards the overall company-level metric.

While these improved results from the simple example may suggest that model year selection has no impact on calculated savings, in real world situations this is not the case. Variations in savings will be seen between forecast, backcast, and chaining models due to changes in baseline energy consumption, differences in processes and product mixes, and other effects. Statistical fits for regression models will also fluctuate and therefore the projections of usage will similarly vary. Model selection can therefore focus on attempting to find the most valid statistical models that make engineering sense, that may or may not yield the greatest possible savings. While the proposed method in this paper simply attempts to eliminate variations in savings estimation that are the result of methodology, the benefits of will still be realized even when dealing with data from real world conditions.

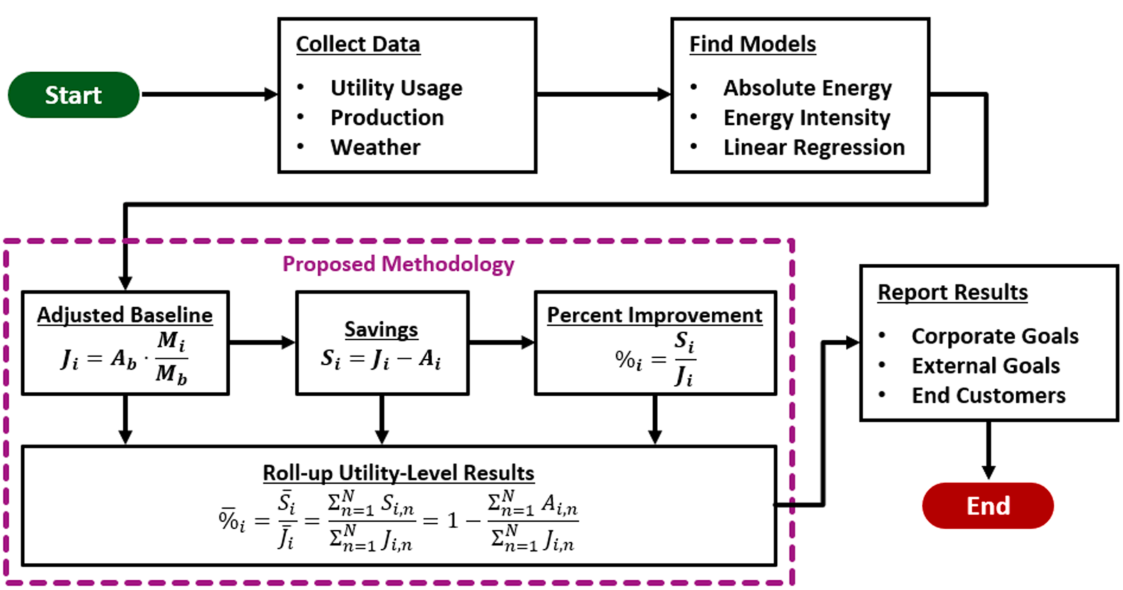

Fig. 4. Detailed view of the proposed methodology showing formulas for estimating facility-level energy savings within a standard M&V protocol, after model selection and before company-level roll-ups of results.

Table 2
Example results using proposed savings calculations methodology.

Year	0	1	2	3	4	5
Production (P_i)	10.0	10.5	12.0	10.9	9.8	11.2
Actual Energy (A_i)	2000.0	2009.0	2112.0	1964.6	1821.6	1908.0
				$\%_i = S_i \ / \ J_i$		
LR Model Year 0	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%
LR Model Year 1	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%
LR Model Year 2	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%
LR Model Year 3	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%
LR Model Year 4	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%
LR Model Year 5	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%

6. Conclusions

This paper proposed a new, internally consistent methodology for estimating savings and percent improvement for efficiency tracking. Baseline consumption is adjusted by a ratio of modeled usage in the reporting and baseline periods. Savings are then calculated by subtracting this adjusted baseline from actual current usage and percent savings are the quotient of these savings and the adjusted baseline. By incorporating the concept of adjusted baseline throughout the methodology, mixing of fundamental mathematical operations (i.e., addition and multiplication) is eliminated and therefore savings and improvements can be fairly, easily, and consistently rolled-up across utilities and facilities. A simple example demonstrated how the new methodology fixes differences in regression methodologies and how it correctly estimates known savings. Considerations and guidance on implementation issues are discussed in detail in several appendices.

The proposed methodology can be expanded in several ways to accommodate real issues encountered when trying to track efficiency performance across many years in changing facilities. Sometimes new equipment is installed (either because of expansions or because of regulatory requirements) or other causes beyond the control of energy management systems can affect a facility's efficiency. Baseline adjustments attempt to offset these kinds of changes to fairly compare current performance to the baseline period. These adjustments can be made directly to the current data or to the baseline itself. When these changes are large enough, rebaselining becomes necessary but past improvement should still be captured. Further incorporating these adjustments and considerations into the proposed methodology, especially for the near-zero considerations, are left to future development.

The new proposed methodology demonstrates how the application of an adjustment ratio can be used to more accurately calculate changes in energy efficiency and quantify energy savings. The method simplifies the calculations for savings, regardless of model type or year and provides a more consistent way of rolling up different utilities and facilities for more accurate reporting. This streamlined approach will allow for easier adoption, integration, and standardization of savings estimation in M&V protocols that support energy efficiency programs. Simplified calculations will aid industry as it continues to focus on quantifying these metrics to meet utility reduction and resource goals.

CRediT authorship contribution statement

Christopher Price: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kristina Armstrong:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Alexandra Botts:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation. **Mark Root:** Writing – review & editing, Visualization, Validation, Software, Methodology, Investigation, Data curation. **Paulomi Nandy:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation. **Thomas Wenning:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition.

Declaration of competing interest

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

Acknowledgements

Research supported by the Office of Critical Minerals and Energy Innovation, Industrial Technologies Office, and the U.S. Department of Energy under contract DE-AC05-00OR22725, Oak Ridge National Laboratory, managed and operated by UT-Battelle, LLC.

Appendix A. Intermediate period savings for current regression analysis

Forecast:	$\%_i = 1 - \frac{A_i}{M_i}$
Backcast:	$\%_i = \left(1 - \frac{M_b}{A_b}\right) - \left(1 - \frac{M_i}{A_i}\right) = \frac{A_bM_i - A_iM_b}{A_bA_i}$
Chaining ($i \leq m$):	$\%_i = \left(1 - \frac{M_b}{A_b}\right) - \left(1 - \frac{M_i}{A_i}\right) = \frac{A_bM_i - A_iM_b}{A_bA_i}$
Chaining ($i > m$):	$\%_i = 1 - \frac{A_iM_b}{A_bM_i} = \frac{A_bM_i - A_iM_b}{A_bM_i}$

Appendix B. Simple example data

Table 3
Actual and modeled energy for case study example using current methodology.

Year	0	1	2	3	4	5
Production (P_i)	10.0	10.5	12.0	10.9	9.8	11.2
Actual Energy (A_i)	2000.0	2009.0	2112.0	1964.6	1821.6	1908.0
M_i						
Model Year 0	2000.0	2050.0	2200.0	2090.0	1980.0	2120.0
Model Year 1	1960.0	2009.0	2156.0	2048.2	1940.4	2077.6
Model Year 2	1920.0	1968.0	2112.0	2006.4	1900.8	2035.2
Model Year 3	1880.0	1927.0	2068.0	1964.6	1861.2	1992.8
Model Year 4	1840.0	1886.0	2024.0	1922.8	1821.6	1950.4
Model Year 5	1800.0	1845.0	1980.0	1881.0	1782.0	1908.0
J_i						
Model Year 0	2000.0	2050.0	2200.0	2090.0	1980.0	2120.0
Model Year 1	2000.0	2049.0	2196.0	2088.2	1980.4	2117.6
Model Year 2	2000.0	2048.0	2192.0	2086.4	1980.8	2115.2
Model Year 3	2000.0	2047.0	2188.0	2084.6	1981.2	2112.8
Model Year 4	2000.0	2046.0	2184.0	2082.8	1981.6	2110.4
Model Year 5	2000.0	2045.0	2180.0	2081.0	1982.0	2108.0
S_i						
Model Year 0	0.0	41.0	88.0	125.4	158.4	212.0
Model Year 1	0.0	40.0	84.0	123.6	158.8	209.6
Model Year 2	0.0	39.0	80.0	121.8	159.2	207.2
Model Year 3	0.0	38.0	76.0	120.0	159.6	204.8
Model Year 4	0.0	37.0	72.0	118.2	160.0	202.4
Model Year 5	0.0	36.0	68.0	116.4	160.4	200.0

Appendix C. Sub-reporting Interval data

There are several operational factors to consider when estimating savings using the new method proposed in this paper. This appendix provides guidance on how to apply the method on data with time scales shorter than the reporting interval. While in most cases data will be from monthly utility bills and results calculated for annual improvement, the same principles apply to other data intervals as well (e.g., weekly, daily).

- *Model Period Selection:*

The most common source of energy data for energy efficiency tracking is monthly utility data. Model periods are therefore typically 12 data points of monthly usage starting in January. However, any 12 months of consecutive monthly data is allowable and, therefore, organizations that run on a fiscal year basis can select a model year that matches their fiscal year. Organizations that have more than twelve months of data available before the start of the goal period can create models from that data set. Using multiple years of data from within the goal period, while feasible, should be pursued with caution and will limit the total number of years over which savings can be accumulated. Models can also be developed from annual weekly or daily data if available.

- *Interval of Calculations:*

Calculations for this method can be done using two approaches. In the first approach, the formulas of Eqs. (13)-(15) are applied using annualized values for current actual, baseline actual, current modeled, and baseline modeled usage. This means results represent a rolling annual window that is compared to the baseline year. Sub-annual values for savings and adjusted baseline usage can be calculated by subtracting the previous N-1 values from the current rolling sum of N annual values. With monthly data, for example, this means subtracting the previous 11 months of calculated monthly savings from the calculated annual rolling savings. These calculated monthly values can be rolled up to the annual level or combined with results from other utilities as proposed.

The second approach applies Eqs. (13)-(15) directly to the sub-annual data. With monthly data, for example, this means that August in the analysis year is compared directly to August in the baseline year (see equation below). Annual results would be calculated by rolling up the monthly results. All calculations using this approach should be completed at the shortest time interval available and then rolled up to appropriate time spans. Once an adjusted baseline has been calculated, only roll up operations should be used to combine data. For example, a company with monthly utility data would estimate savings at the monthly level for each utility and then roll up results to the annual utility level, facility level, and company level. This provides granular results at the utility, facility, and corporate levels.

$$J_{Year\ 1,\ Aug} = A_{b,\ Aug} \cdot \frac{M_{Year\ 1,\ Aug}}{M_{b,\ Aug}}$$

- *Combining Results:*

Once an adjusted baseline is calculated, all combined results should be calculated from the roll up formula of Eq. (16). For example, results calculated at the monthly level should be rolled up to the annual level. If results are first calculated at a monthly level, annual results should ***not*** be calculated by summing monthly consumption and modeled usage before calculating an annual adjusted baseline. This order of operations is important in preserving the adjusted baseline and ensuring that results match across all intervals and utilities. This important consideration is summarized by the following equations:

$$J_1 = A_{b1} \cdot \frac{M_{i1}}{M_{b1}},\ J_1 = A_{b2} \cdot \frac{M_{i2}}{M_{b2}}$$

$$J_1 + J_2 \neq (A_{b1} + A_{b2}) \cdot \frac{M_{i1} + M_{i2}}{M_{b1} + M_{b2}}$$

Appendix D. Division by Zero Scenarios

Sometimes utility usage can be near zero for extended periods of time. This commonly occurs for utilities like natural gas that are used extensively for space heating during cold weather. During warm summer months, monthly usage is almost zero which can cause issues with the proposed methodology that now includes division in the definitions of adjusted baseline usage and percent savings. To account for these edge cases, the seven scenarios in Table 4 alter the calculations for adjusted baseline and savings. Savings are calculated using the additive approach of Eq. (7) and the adjusted baseline calculation is modified to account for the division by zero. Explanations of each scenario are also included. Model selection for these types of utilities is very important. Energy engineers should consider choosing a different model or adjusting model parameters if the model consistently predicts usage below zero.

Table 4
Scenarios for division by zero with new proposed methodology.

#	Case	$J_i =$	$S_i =$	$\%_i =$
1	$A_b = 0$	0	$(M_i - M_b) - A_i$	Undefined
2	$M_i = 0$	0	$(A_b - A_i) - M_b$	Undefined
3	$M_b = 0$	M_i	$(A_b - A_i) + M_i$	$1 - \frac{A_b - A_i}{M_i}$
4	$A_b = M_i = 0$	0	$-A_i - M_b$	Undefined
5	$A_b = M_b = 0$	M_i	$M_i - A_i$	$1 - \frac{A_i}{M_i}$
6	$M_i = M_b = 0$	A_b	$A_b - A_i$	$1 - \frac{A_i}{A_b}$
7	$A_b = M_i = M_b = 0$	0	$-A_i$	Undefined

Case 1: Actual usage increased from zero in the baseline period to $A_i \neq 0$ in the current period which is an undefined decrease in performance. Only accounting for the increase A_i excludes the prediction of the model. Therefore, savings should be estimated as the change in modeled energy consumption minus the actual usage in the current period. This savings value can be positive or negative depending on how much the modeled usage changes between the baseline and current periods.

Case 2: The model predicts zero energy usage in the current period and so any actual usage in the current period is an undefined decrease in improvement. Like Case 1, only accounting for the change in actual usage excludes how much the model estimates usage should change. Calculated savings can be positive or negative depending on how much the actual usage changes between the baseline and current periods compared to the baseline modeled usage.

Case 3: Baseline modeled usage is zero which means the adjustment ratio is undefined. The adjusted baseline in this case is redefined to be the current modeled energy, similar to the adjusted baseline when using a forecast model. Savings should be calculated as the change in actual usage plus the modeled energy consumption in the current period. Savings can be positive or negative depending on how much the actual usage changes between the baseline and current periods. Percent savings can be calculated as normal.

Case 4: Actual baseline and current modeled usage are both zero. This combines an undefined increase in actual usage with the model predicting zero usage in the current period. Both conditions mean there is an undefined decrease in percent performance. The negative savings are the sum of the baseline modeled and current actual usage.

Case 5: Actual and modeled baseline usage are both zero. This combines an undefined increase in actual usage with a similarly undefined increase in modeled usage. The adjusted baseline is redefined as the current modeled energy which is equivalent to defining $0/0 = 1$. Savings and percent savings can be calculated as normal.

Case 6: Current and baseline modeled usage are both zero. This combination essentially means the model predicts no change in usage. Redefining the adjusted baseline to be the actual baseline usage captures this effect which is equivalent to defining $0/0 = 1$. Savings and percent savings can be calculated as normal. The resulting formulas are the same as applying the proposed equations with an absolute savings model approach.

Case 7: Actual baseline usage as well as modeled current and baseline usage are all zero. Redefining the adjusted baseline to zero means savings and percent savings can be calculated as normal and is equivalent to defining $0/0 = 1$. Percent savings will be undefined due to the increase from zero actual usage in the baseline period to $A_i \neq 0$ in the current period. The resulting formulas are the same as applying the proposed equations with an absolute savings approach.

Appendix E. Application of new method on manufacturing facility data

This appendix provides a detailed example of how the proposed method can be applied to sample facility data to determine its energy performance. While data are inspired by actual manufacturing facilities, the data does not reflect a particular company or facility. Readers should note that the proposed method is only applied after data collection and modeling has been completed and is used only to estimate performance improvements.

Facility Information.

The example facility is located in Jefferson City, Missouri in the central United States with ZIP code 65109. The facility makes a single kind of product called "widgets" and consumes both electricity and natural gas. Electricity is used in the production process and also for some non-production end uses. Natural gas is primarily used for space heating during colder winter months but there is some baseload use of gas throughout the year.

Table 5 provides 3 years of manufacturing energy, production, and weather data for the example facility. Energy data was collected from monthly utility bills and has been calendarized to remove the effects of varying billing periods. Production data was collected from internal tracking systems. Cooling (CDD) and Heating (HDD) Degree Day data was calculated from hourly temperature data from the National Oceanic and Atmospheric Administration (NOAA) Local Climatological Data (LCD) tool using the Jefferson City Memorial Airport weather station and a balance temperature of 60°F.

Table 5
Example monthly facility data.

Month	Electricity (kWh)	Natural Gas (MMBtu)	Production (Widgets)	CDD (60°F)	HDD (60°F)
Jan-22	13,036	2323	101,245	0	914
Feb-22	11,953	2100	98,167	11	723
Mar-22	13,235	1925	100,967	52	428
Apr-22	12,937	1529	105,956	94	227
May-22	13,401	1339	104,371	321	41
Jun-22	12,722	1163	99,715	569	2
Jul-22	13,100	1174	99,288	680	0
Aug-22	13,339	1205	107,600	559	0
Sep-22	12,943	1254	101,246	334	36
Oct-22	13,350	1521	104,647	133	220
Nov-22	13,035	1823	108,222	62	473
Dec-22	13,241	2118	101,997	8	740
Jan-23	13,358	2125	108,156	6	647
Feb-23	12,360	1819	101,442	12	471
Mar-23	13,557	1804	107,315	29	453
Apr-23	12,982	1471	106,099	151	176
May-23	13,291	1291	104,347	336	39
Jun-23	12,911	1166	103,126	510	5
Jul-23	13,481	1192	108,681	629	0
Aug-23	13,346	1185	105,737	567	1
Sep-23	12,751	1205	102,353	369	13
Oct-23	13,017	1435	106,343	177	194
Nov-23	12,313	1630	99,238	42	413
Dec-23	12,443	1942	101,684	4	513
Jan-24	12,530	2142	99,990	0	947
Feb-24	11,900	1839	101,889	38	439
Mar-24	12,750	1586	99,167	80	313
Apr-24	12,648	1344	108,338	153	130
May-24	13,281	1238	106,233	316	8
Jun-24	12,827	1139	106,262	558	1
Jul-24	13,124	1161	106,337	561	0
Aug-24	12,981	1158	104,818	519	2
Sep-24	12,540	1168	104,877	344	19
Oct-24	12,776	1362	104,346	211	141
Nov-24	12,295	1556	102,052	39	337
Dec-24	12,665	1978	107,918	0	609

- *Modeling Process*

Linear regression modeling was applied to both the electricity and natural gas monthly usage data using combinations of the three relevant variables (production, HDD, and CDD). Combinations of each variable were tested on 12 data points corresponding to each of the calendar years of 2022, 2023, and 2024. For both utilities, 2023 was selected as the model year yielding the following monthly model equations:

$$Electricity\ (kWh) = 106.52 \times CDD + 36.973 \times Widgets - 85,090$$

$$Natural\ Gas\ (MMBtu) = 1.3764 \times HDD + 1,186.5$$

- *Applying the Proposed Method – Utility-level Results*

After the modeling step, the proposed method can be applied to estimate the savings for both electricity and natural gas. Tables 6 and 7 give the annual actual energy, modeled energy, adjusted baseline, savings, and percent improvement results from applying Eqs. (13-15) on annual data. A sample calculation for 2024 electricity savings is shown below:

$$J_{2024} = A_{2022} \times \frac{M_{2024}}{M_{2022}} = 45,804,659\ kWh \times \frac{45,577,355\ kWh}{44,882,417\ kWh} = 46,513,876\ kWh$$

$$S_{2024} = J_{2024} - A_{2024} = 46,513,876\ kWh - 44,639,701\ kWh = 1,874,175\ kWh$$

$$\%_{2024} = \frac{S_{2024}}{J_{2024}} \times 100 = \frac{1,874,175\ kWh}{46,513,876\ kWh} \times 100 = 4.03\%$$

Table 6
Annual electricity savings calculations using proposed method.

Year	Actual Electricity (kWh)	Modeled Electricity (kWh)	Adjusted Baseline (kWh)	Electricity Savings (kWh)	Percent Improvement (%)
2022	45,804,659	44,882,417	45,804,659	0	0.00%
2023	45,663,399	45,663,399	46,601,687	938,289	2.01%
2024	44,639,701	45,577,355	46,513,876	1,874,175	4.03%

Table 7
Annual natural gas savings calculations using proposed method.

Year	Actual Natural Gas (MMBtu)	Modeled Natural Gas (MMBtu)	Adjusted Baseline (MMBtu)	Electricity Savings (MMBtu)	Percent Improvement (%)
2022	20,063	19,474	20,063	0	0.00%
2023	18,264	18,264	18,817	552	2.94%
2024	17,670	18,291	18,844	1174	6.23%

- *Applying the Proposed Method – Roll-up to Facility Savings.*

After the utility-level results have been calculated, they can be combined (i.e., rolled-up) to find facility-level performance. Before the total adjusted baseline and total savings can be calculated, energy must be converted to a common unit. Table 8 converts all energy to MMBtu before calculating the rolled-up values for improvement.

$$\overline{J}_{2024} = J_{Elec,2024} + J_{Gas,2024} = 46,513,876\ kWh \times 0.003412142 \frac{MMBtu}{kWh} + 18,844\ MMBtu$$

$$\overline{J}_{2024} = 158,712\ MMBtu + 18,844\ MMBtu = 177,556\ MMBtu$$

$$\overline{S}_{2024} = S_{Elec,2024} + S_{Gas,2024} = 1,874,175\ kWh \times 0.003412142 \frac{MMBtu}{kWh} + 1,174\ MMBtu$$

$$\overline{J}_{2024} = 6,395\ MMBtu + 1,174\ MMBtu = 7,569\ MMBtu$$

$$\overline{\%}_{2024} = \frac{\overline{S}_{2024}}{\overline{J}_{2024}} \times 100 = \frac{7,569\ MMBtu}{177,556\ MMBtu} \times 100 = 4.26\%$$

Table 8
Annual facility-level roll-up performance using proposed method.

Year	Total Adjusted Baseline (MMBtu)	Total Savings (MMBtu)	Total Percent Improvement (%)
2022	176,355	0	0.00%
2023	177,828	3754	2.11%
2024	177,556	7569	4.26%

Data availability

Data will be made available on request.

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