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DEPARTMENT OF THE BUILT ENVIRONMENT
AALBORG UNIVERSITY

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# 1. Introduction

The correct evaluation of the performance of models used in the field of energy, building and indoor environment modelling is crucial to correctly assess the reliability of the results and the suitability of the model for the purpose.

This technical report is supplementary material to the work of Johra et al., 2023 [1], who conducted an extensive literature review of 259 papers to provide an overview of the evaluation metrics used by the energy, building and indoor environment research community.

The information gathered from the 259 reviewed papers is compiled in the spreadsheet attached to that technical report.

This technical report provides an overview of all the time series comparison metrics found for building energy and indoor environment modelling validation, using a consistent notation and naming convention and any alternative names for the respective metric (Table 1).

Such an overview should provide valuable guidance to both practitioners and researchers within the energy, buildings and indoor environment community.

Furthermore, the use of a consistent naming and equation notation should reduce the possibility of misunderstanding, which has been highlighted in Johra et al., 2023 [1].

In addition to this overview, Section 3 discusses possible limitations and pitfalls when evaluating models within the field of energy, building and indoor environment modelling, which provide additional support.

# 2 Metrics overview

**Table 1 Overview of all metrics found, based on the work of Johra et al., 2023** [1]**; the reference column lists all reviewed works that use the respective metric. It should be noted that the notation has been standardised and possibly simplified for the sake of simplicity and clarity and may therefore differ slightly from that given in the references.** $x$ = true/reference value; $y$ = predicted/simulated value; $n$ = number of data points; $\bar{x}, \bar{y}$ = mean values; $\sigma_x, \sigma_y$ = standard deviations

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Graphical | Qualitative graphical assessment | - | Qualitative graphical assessment | | | | | [2–219] |
| Absolute error based | MaxAE | - | Maximum Absolute Error | $MaxAE = max\{\lvert y_i - x_i \rvert\}$ | X | [0,+∞] | 0 | [36,72,111,121,176,220,221] |
| | 0.5°C Percentage Error | - | 0.5°C Percentage Error (or 1°C depending on the threshold) | $0.5°C\ Percentage\ Error = \frac{\sum_{i=1}^{n} \lvert y_i - x_i \rvert > 0.5°C}{n}$ | | [0,1] | 0 | [176] |
| | MAE | - | Mean Absolute Error | $MAE = \frac{\sum_{i=1}^{n} \lvert y_i - x_i \rvert}{n}$ | X | [0,+∞] | 0 | [47,70,72,76,87,92,110,112,125,146,148,159,177,182,186,187,192,198,199,202,205,211,216,217,220–230] |
| | NMAE | MAE% | Normalised Mean Absolute Error | $\mathrm{NMAE} = \frac{\sum_{i=1}^{n} \lvert y_i - x_i \rvert}{\sum_{i=1}^{n} x_i} \times 100(\%) = \frac{MAE}{\frac{1}{n}\sum_{i=1}^{n} x_i} \times 100(\%)$ | % | [0,+∞] | 0 | [99,102,148,192] |

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Absolute error based | MANMAE | - | Mean Absolute Normalized MAE | $\mathrm{MANMAE} = \frac{\sum_{i=1}^{n}\lvert y_i - x_i\rvert}{\sum_{i=1}^{n}\lvert x_i\rvert} \times 100(\%) = \frac{MAE}{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i\rvert} \times 100(\%)$ | % | [0,+∞] | 0 | [148] |
| | RNMAE | NMAE | Range Normalized Mean Absolute Error | $\mathrm{RNMAE} = \frac{1}{max\{x\} - min\{x\}} \cdot \frac{\sum_{i=1}^{n}\lvert y_i - x_i\rvert}{n} \times 100(\%) = \frac{1}{max\{x\} - min\{x\}} \cdot MAE \times 100(\%)$ | % | [0,+∞] | 0 | [87] |
| | ZMAE | - | ZMAE | $ZMAE = \frac{1}{\sigma_x} \cdot \frac{\sum_{i=1}^{n}\lvert y_i - x_i\rvert}{n} \times 100(\%) = \frac{1}{\sigma_x} \cdot MAE \times 100(\%)$ | % | [0,+∞] | 0 | [162] |
| | rMAE | relative MAE | Relative mean absolute error | rMAE = MAE(forecast) / MAE(baseline) | - | [0,+∞] | 0 | [228,230] |
| Bias based | MBE | - | Mean Bias Error | $MBE = \frac{\sum_{i=1}^{n}(y_i - x_i)}{n}$ | X | [-∞,+∞] | 0 | [12,17,33,63,73,74,77,79,87,105,109,116,117,122,132,136,160,170,174,190,192,218,226,230–237] |

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Bias based | NMBE | RPE, RAE | Normalised Mean Bias Error | $NMBE = \frac{1}{\bar{x}} \cdot \frac{\sum_{i=1}^{n}(y_i - x_i)}{n} \times 100(\%) = \frac{1}{\bar{x}} \cdot MBE \times 100(\%)$ | % | [-∞,+∞] | 0 | [78,83,88,89, 95,97,98,103,108,114,119,122,143,145,147–149,162,167,176,181,188–190,192–195,197,212,213,233,238–246] |
| | RNMBE | - | Range Normalized Mean Bias Error | $RNMBE = \frac{1}{max\{x\} - min\{x\}} \cdot \frac{\sum_{i=1}^{n}(y_i - x_i)}{n} \times 100(\%) = \frac{1}{max\{x\} - min\{x\}} \cdot MBE \times 100(\%)$ | % | [-∞,+∞] | 0 | [142] |
| Absolute Percentage Error | MaxAPE | MaxAPE | Maximum Absolute Percentage Error | $MaxAPE = max\left\{\left\lvert\frac{y_i - x_i}{x_i}\right\rvert\right\}$ | X | [0,+∞] | 0 | [23,36,72,111,220] |
| | MedianAPE | med(absRTE), MdAPE | Median of the absolute relative total error | $\mathrm{MedianAPE} = median\left\{\frac{\lvert y_i - x_i\rvert}{x_i}\right\}$ | X | [-∞,+∞] | 0 | [154,238] |
| | MAPE | MAPD | Mean Absolute Percentage Error | $MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - x_i}{x_i}\right\rvert \times 100(\%)$ | % | [0,+∞] | 0 | [36,51,59,70, 72,92,97,98, 101,106,107, 113,118,122, 125,129,143, 154,159,164, 166,179,183, 186,198,202, 205,208,210, 211,216,220, 222,223,230, 233,237,247] |

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Square error based | MSE | - | Mean Square Error | $MSE = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}$ | X² | [0,+∞] | 0 | [70,125,132, 166,184,186] |
| | NMSE | - | Normalised Mean Square Error | $\text{NMSE} = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \times 100(\%) = \frac{n}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \cdot \text{MSE} \times 100(\%)$ | % | [0,+∞] | 0 | [160] |
| | IA | - | Index of Agreement | $IA = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(\lvert y_i - \bar{x}\rvert + \lvert x_i - \bar{x}\rvert)^2} \times 100(\%) = \frac{n}{\sum_{i=1}^{n}(\lvert y_i - \bar{x}\rvert + \lvert x_i - \bar{x}\rvert)^2} \cdot \text{MSE} \times 100(\%)$ | % | [0,+∞] | 0 | [70,221] |
| | EF | - | Modelling efficiency | $EF = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2 - \sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \times 100(\%) = \frac{n}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \cdot \left(\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n} - \text{MSE}\right) \times 100(\%)$ | % | [-∞,+∞] | 100% (1) | [221] |
| | Theil's U | - | Theil's coefficients of inequality | $U_m = \frac{(\bar{y} - \bar{x})^2}{MSE};\ U_v = \frac{(\sigma_y - \sigma_x)^2}{MSE}$ <br> $U_c = \frac{2(1 - \text{r}_{\text{xy}}) \cdot \sigma_y \sigma_x}{MSE};\ U_m + U_v + U_c = 1$ | - | $U_m = [0,1]$ <br> $U_v = [0,1]$ <br> $U_c = [0,1]$ | $U_m = 0$ <br> $U_m = 0$ <br> $U_c = 0$ <br> A perfect match leads to non-definition | [85] |

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Square error based | RMSE | RMSD, DRMS | Root Mean Square Error | $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} = \sqrt{MSE}$ | X | [0,+∞] | 0 | [9,24,28,33,40,42,68,70,75,78,80–82,92,94,100,109,117,119,122,125,127,128,132,138,140,141,145,151,152,156–159,161,164,169,173,176,177,180,183,186,187,189,190,192,196–198,200,203,207,208,210,211,216–218,221,223,228,231–233,235,241,246,248–253] |
| | RMSEP | - | Root Mean Square Error Percentage | $RMSEP = \sqrt{\frac{\sum_{i=1}^{n}\left(\frac{y_i - x_i}{x_i}\right)^2}{n}} \times 100(\%)$ | % | [0,+∞] | 0 | [51,91,94,110,200] |
| | RNRMSE | - | Range Normalized Root Mean Square Error | $RMSEP = \frac{1}{max\{x\}-min\{x\}} \cdot \sqrt{\frac{\sum_{i=1}^{n}(y_i-x_i)^2}{n}} \times 100(\%) = \frac{1}{max\{x\}-min\{x\}} \cdot RMSE \times 100(\%)$ | % | [0,+∞] | 0 | [78,87,109,116,132,142,186] |

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Square error based | CVRMSE | (CV)RMSE, NRMSE, RMSE%, RRMSE | Coefficient of Variation of Root Mean Square Error | $CVRMSE = \frac{1}{\bar{x}} \cdot \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \times 100(\%) = \frac{1}{\bar{x}} \cdot RMSE \times 100(\%)$ | % | [0,+∞] | 0 | [12,17,28,33,42,48,60,63,73–75,78,79,83,85,88–90,95,97–99,102,103,105,108–110,114,116,132,143,145,147–149,160,162,167,170,171,174,175,181,186–190,192–196,203,212,213,232–234,236–238,240,242–245,254–256] |
| | RMSEIQR | - | Root Mean Square Error normalised by the interquartile range (IQR) | $RMSEIQR = \frac{1}{IQR\{x\}} \cdot \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \times 100(\%) = \frac{1}{IQR\{x\}} \cdot RMSE \times 100(\%)$ | % | [0,+∞] | 0 | [186] |
| | RMSLE | - | Root Mean Square Logarithmic Error | $RMSLE = \sqrt{\frac{\sum_{i=1}^{n}(\log(y_i + 1) - \log(x_i + 1))^2}{n}}$ | X | [0,+∞] | 0 | [186,257,258] |

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Square error based | ZRMSE | - | ZRMSE | $ZRMSE = \frac{1}{\sigma_x} \cdot \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \times 100(\%) =$ $\frac{1}{\sigma_x} \cdot RMSE \times 100(\%)$ | % | [0,+∞] | 0 | [162] |
| | NRMSE | | Normalized root mean squared error | $NRMSE = \frac{\sqrt{\sum_{i=1}^{n}(y_i - x_i)^2}}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}} \times 100(\%) =$ $\frac{n}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}} \cdot RMSE \times 100(\%)$ | % | [0,+∞] | 0 | [259] |
| Based on statistical dispersion | Var | - | variance | $Var(x) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}$ $Var(y) = \frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n-1}$ | X² | [0,+∞] | - | [85] |
| | sd_ratio | - | standard deviation ratio | $sd_{ratio} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(y - \bar{y})^2}{n-1}}}{\sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}} = \frac{\sigma_y}{\sigma_x}$ | X | ]0,+∞] | 1 | [85] |
| | sd_error | - | standard deviation of any error metric | $sd_{error} = \mathrm{sd}(\text{any error metric})$ | X | [0, +∞] | 0<br>A perfect match leads to non-definition | [47,48] |
| | Cov | - | covariance | $cov(\mathrm{x}, \mathrm{y}) = \left(\frac{\sum(\mathrm{x_i} - \bar{\mathrm{x}})(\mathrm{y_i} - \bar{\mathrm{y}})}{n-1}\right)$ | X² | [-∞,+∞] | 1 | [85] |

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Correlation based | r | - | Pearson correlation coefficient | $\mathrm{r_{xy}} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$ | - | [-1,+1] | 1 | [48,85,125,203,208,236] |
| | $r_s$ | ρ | Spearman's rank correlation coefficient (Pearson correlation on ranks of x and y) | $r_s = \mathrm{r_{R(x)R(y)}}$ | - | [-1,+1] | 1 | [76,167,208] |
| | T | τ | Kendall rank correlation coefficient | $\tau = 1 - \frac{2(\text{number of disconcordant pairs})}{\left(\frac{n(n-1)}{2}\right)}$ | - | [-1,+1] | 1 | [208] |
| Relative difference based | Calibration signature | - | Calibration signature | $Calibration\ signature_i = \frac{-(y_i - x_i)}{max\{y\}} \times 100(\%)$ | X | [-∞,+∞] | 0 | [178] |
| | CRM | - | Coefficient of residual mass | $CRM = \frac{\sum_{i=1}^{n} y_i - \sum_{i=1}^{n} x_i}{\sum_{i=1}^{n} x_i}$ | X | [-∞,+∞] | 0 | [221] |
| Miscellaneous | SSE | SSR | Sum of Squared Errors | $RSS = \sum_{i=1}^{n}(y_i - x_i)^2$ | $X^2$ | [0,+∞] | 0 | [25,28,82,211] |

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Miscellaneous | $R^2$ | - | Coefficient of determination (R squared) | $R^2 = \frac{ESS}{TSS} = \frac{\sum_{i=1}^{n}(y_i - \bar{x})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} = 1 - \frac{RSS}{TSS} = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$ | - | [0,1] | 1 | [22,23,28,34,60,69–71,74,78,85,88,97–99,103,108,109,116,123,125,127,130,133,136,141,145,146,149,151,154,157,159,162,167,169,171,175,186,189,192,194,196,198,207,208,210–212,216,217,219,222,230,236,237,241,243,244,252,254,255] |
| | GOF | - | Goodness of Fit | $GOF = \sqrt{\frac{\omega_{CVRMSE}^2 \cdot \mathrm{CVRMSE}^2 + \omega_{NMBE}^2 \cdot NMBE^2}{\omega_{CVRMSE}^2 + \omega_{NMBE}^2}} \times 100(\%)\ OR\ \sqrt{\frac{\omega_{CVRMSE}^2 \cdot \mathrm{CVRMSE}^2 + \omega_{MBE}^2 \cdot MBE^2}{\omega_{CVRMSE}^2 + \omega_{MBE}^2}} \times 100(\%)$ | % | [0,+∞] | 0 | [88,103,160,178] |
| | nCPBES | - | normalised Cumulated Periodogram Boundary Excess Sum | | | | | [260] |
| | DTW | - | Dynamic Time Warping | | | | | [132,186] |

| | Main acronym | Alternative acronyms | Full name | Equation | Unit | Range | Optimum value (perfect model fit) | Reference |
|---|---|---|---|---|---|---|---|---|
| Miscellaneous | COR | - | Dissimilarities based on Pearson's correlation | | | | | [186] |
| | CORT | - | Dissimilarities based on temporal correlation and raw value behaviours | | | | | [186] |
| | Frechet distance | - | Frechet distance | | | | | [186] |
| | Auto-correlation | - | Auto-correlation | | - | [0,1] | ACF at non-zero lags should be (close to) 0 | [94] |

# 3 Preliminary discussion on metrics limitations and pitfalls

Common issues that may arise when evaluating a model in the energy, buildings and indoor environment sectors are outlined below.

The first issue discussed arises when true values are close to or equal to zero. Such situations arise, for example, when dealing with energy used for heating in temperate climates, where heating may not be used during (some periods of) summer. Another possibility is large amplitude changes over the evaluated time series, requiring units that result in values close to zero for part of the data. In such a case, a "value by value" normalisation, such as is done for MAPE, can lead to instability or undefined values. One way to avoid such problems is to normalise the results on a higher temporal granularity, for example, daily.

Such normalisation is commonly done using the mean of the reference data over the whole time series, for example, for CVRMSE or NMBE. However, while such an approach avoids the above problem and can therefore handle data with values close to or equal to zero, a problem arises for data with varying magnitude. Such (seasonally) varying magnitude is common when evaluating energy use data and can lead to biased results, as periods with high magnitude are likely to have a higher weight. For instance, when evaluating the accuracy of a building space heating demand model with CVRMSE, the results will vary greatly (it can be several orders of magnitude) if computing the metric on a monthly basis (normalization by the monthly average), a yearly basis (normalization by the yearly average), or computing the CVRMSE for each month with normalization by the yearly average. For a constant model bias, the CVRMSE is much higher in the periods when the average is low (i.e., during the summer periods for the considered example case) and much lower in the periods when the average is high (i.e., during the winter periods). Similarly, shifting the average over the entire analysis period will significantly change the CVRMSE results. For example, for the same model, increasing the overall/average heating demand (introducing a constant bias for both the reference and the tested model) will improve (decrease) the CVRMSE while the Coefficient of Determination ($R^2$) will not change. This issue was also discussed in Johra et al., 2021 [186] and can be mitigated if data are normalised on an appropriate temporal granularity, for example, daily, before aggregation. This issue also highlights the potential disadvantage of using metrics such as RMSE that are based on a certain distance (in the unit of the data or some modified unit of data) without considering the possible varying size of the data.

A similar issue arises when evaluating the performance of a model over different time series, for example, different buildings or different types of quantity (energy or temperature). In such a case, metrics in the unit of the quantity (or squared unit, etc.) are not appropriate, as possible differences in magnitude would distort any aggregation or make manual comparison difficult. Unitless and normalised metrics are more appropriate in such cases, as they allow aggregated results across different time series and quantities. However, the abovementioned problems can arise from normalisation and must be considered.

The next issue can arise when the reference data has outliers or possibly erroneous values. In such cases, metrics based on the squared error (such as MSE or RMSE), which penalise larger deviations more severely, can lead to biased results as a few data points can determine the metric result. Such a problem can be avoided by using metrics based on a distance other than the squared error and/or by normalising the results at some appropriate temporal level before aggregation, thus reducing the effect of a few extreme values.

From these few highlighted situations, which are not exhaustive, it can already be seen that care must be taken when selecting a metric for evaluation in order to avoid biased results. The main issue seems to be the problem of appropriate normalisation of metric results to take into account a possible variation in the magnitude of the quantity across the data and to be able to deal with (near) zero values.

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