

Capturing the Energy Efficiency Opportunity

Colm Gallagher, Dominic O’Sullivan

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Results

- Machine learning reduces the uncertainty in energy savings
- A broader scope of analysis using larger data sets increases accuracy
- Prescriptive modelling methodology developed
- Advanced practices can be adopted without increasing the costs & labour requirements
- *IntelliMaV* application developed

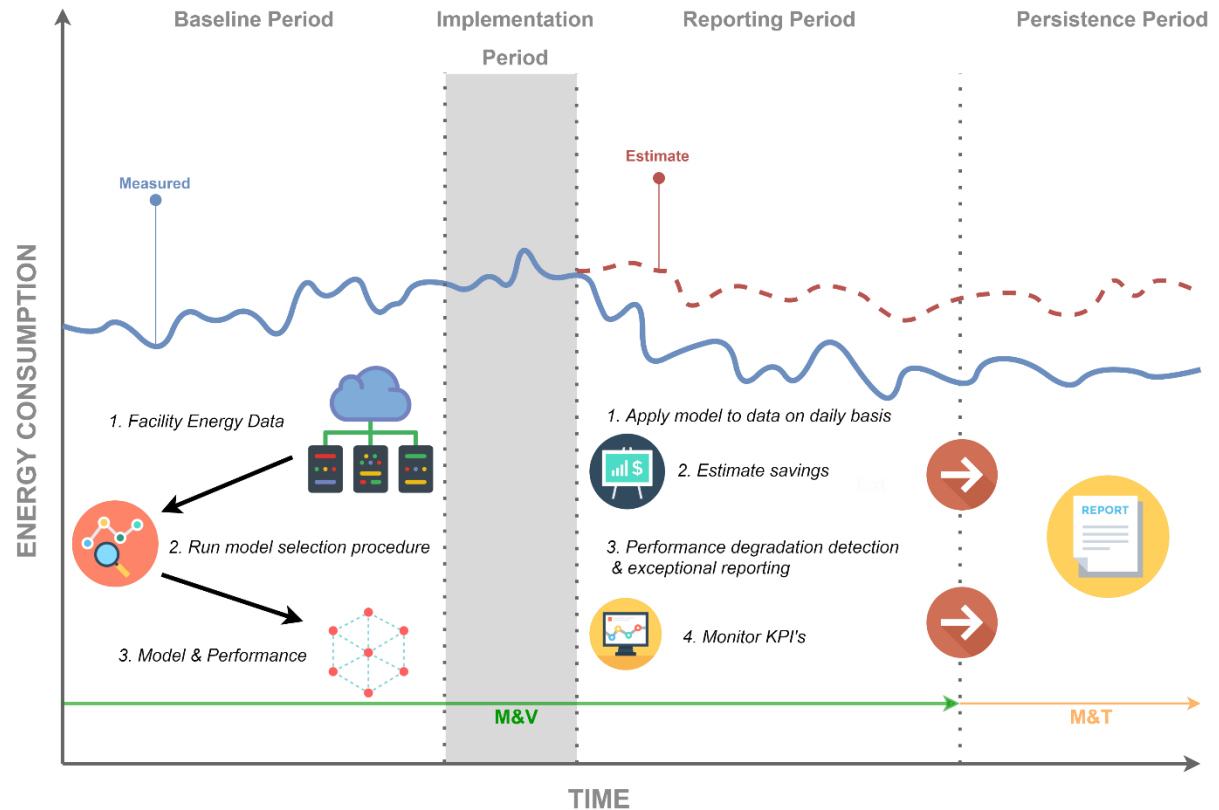


Fig. 1: Overview of M&V process & representation of methods developed

Impacts

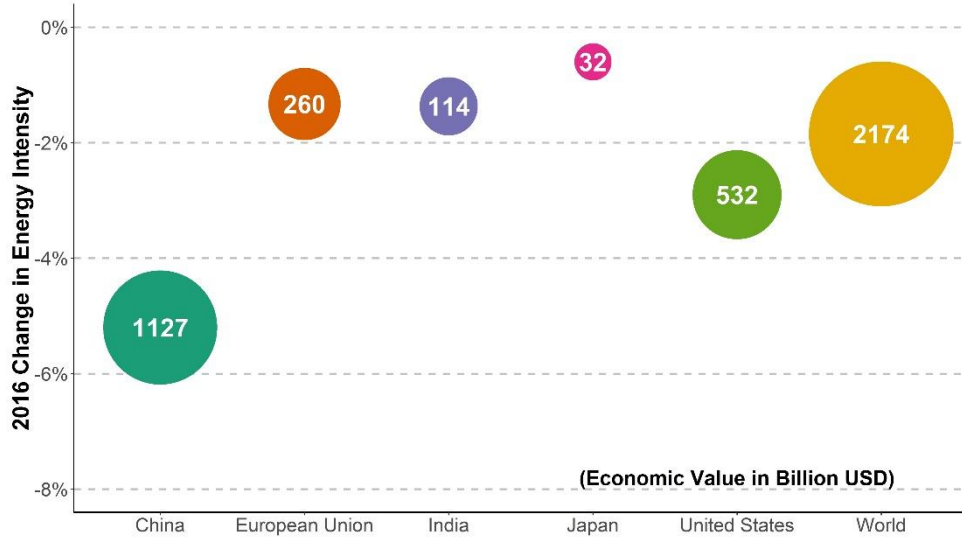


Fig. 2: Economic value of changes in energy intensity

- Aid the removal of barriers that prevent investment in cost-effective energy efficiency (EE)
 - Risk
 - Cost
 - Uncertainty in energy savings
 - Skills gap in workforce

- Populate the knowledge gap
- Minimise the costs of completing M&V
- Accurate performance verification enables the development of targeted EE policy

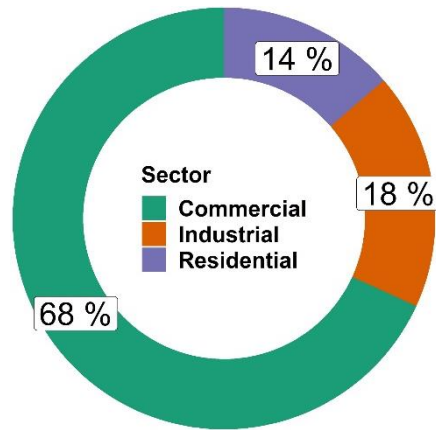


Fig. 3: Sectoral breakdown of M&V 2.0 tools on the market

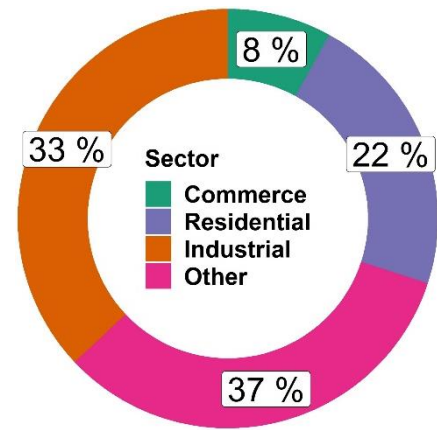


Fig. 4: Sectoral breakdown of global TFE

Policy Insights

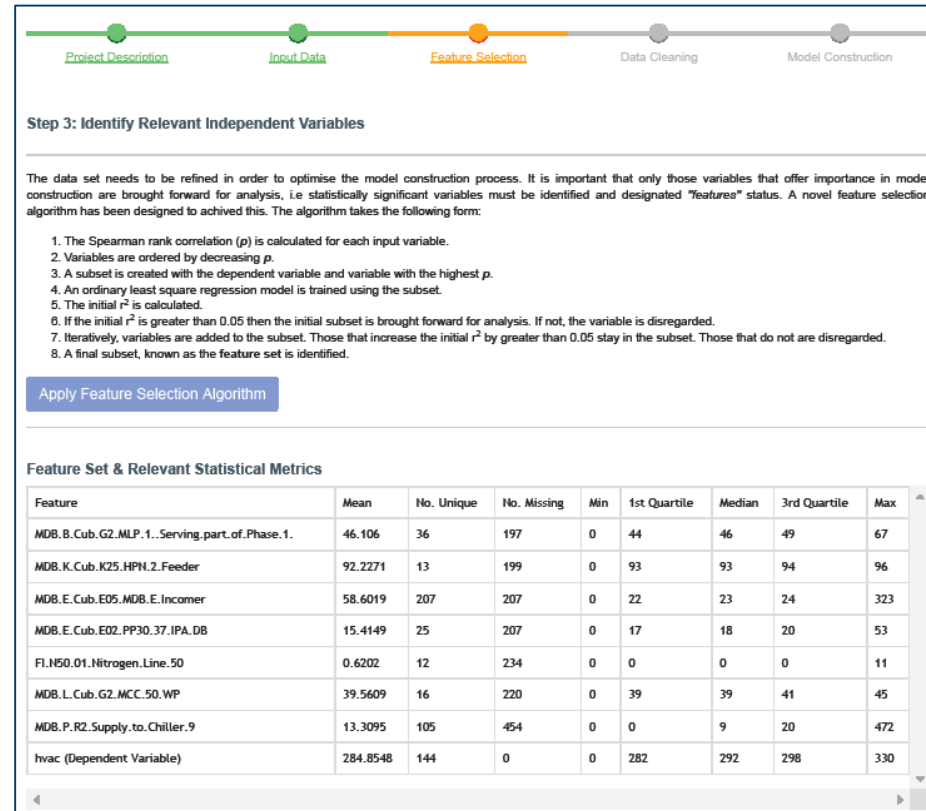
- Issues with current policy:
 - Standards need to be raised
 - Lack of focus placed on persistence of savings
 - Challenges faced on individual project level

Year	New Energy Savings	Cumulative Energy Savings
1	1.5%	1.5%
2	1.5%	3%
3	1.5%	4.5%
4	1.5%	6%
5	1.5%	7.5%
6	1.5%	9%
7	1.5%	10.5 %

- Energy Efficiency Directive must embrace M&V 2.0 practices
- Successful EE obligation scheme
- How **confident** can we be in savings reported in 2020?
- What will **change** as we progress towards 2030?

Opportunities

- Data-driven energy modelling using machine learning techniques
- Automated performance verification
- Real-time M&V to maximise the opportunity
- Prescriptive guidance for practitioners to implement
- IntelliMaV: a data science-based cloud computing application for M&V 2.0



Step 3: Identify Relevant Independent Variables

The data set needs to be refined in order to optimise the model construction process. It is important that only those variables that offer importance in model construction are brought forward for analysis, i.e. statistically significant variables must be identified and designated "features" status. A novel feature selection algorithm has been designed to achieve this. The algorithm takes the following form:

1. The Spearman rank correlation (p) is calculated for each input variable.
2. Variables are ordered by decreasing p .
3. A subset is created with the dependent variable and variable with the highest p .
4. An ordinary least square regression model is trained using the subset.
5. The initial r^2 is calculated.
6. If the initial r^2 is greater than 0.05 then the initial subset is brought forward for analysis. If not, the variable is disregarded.
7. Iteratively, variables are added to the subset. Those that increase the initial r^2 by greater than 0.05 stay in the subset. Those that do not are disregarded.
8. A final subset, known as the feature set is identified.

Apply Feature Selection Algorithm

Feature Set & Relevant Statistical Metrics

Feature	Mean	No. Unique	No. Missing	Min	1st Quartile	Median	3rd Quartile	Max
MDB.B.Cub.G2.MLP.1..Serving.part.of.Phase.1.	46.106	36	197	0	44	46	49	67
MDB.K.Cub.K25.HPN.2.Feeder	92.2271	13	199	0	93	93	94	96
MDB.E.Cub.E05.MDB.E.Incomer	58.6019	207	207	0	22	23	24	323
MDB.E.Cub.E02.PP30.37.IPA.DB	15.4149	25	207	0	17	18	20	53
Fl.N50.01.Nitrogen.Line.50	0.6202	12	234	0	0	0	0	11
MDB.L.Cub.G2.MCC.50.WP	39.5609	16	220	0	39	39	41	45
MDB.P.R2.Supply.to.Chiller.9	13.3095	105	454	0	0	9	20	472
Hvac (Dependent Variable)	284.8548	144	0	0	282	292	298	330

Fig. Example of *IntelliMaV* web-based user interface