From M&V to M&T: An artificial intelligence-based framework for real-time performance verification of demand-side energy savings

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***Abstract*—The European Union's Energy Efficiency Directive is placing an increased focus on the measurement and verification (M&V) of demand side energy savings. The objective of M&V is to quantify energy savings with minimum uncertainty. M&V is currently undergoing a transition to practices, known as M&V 2.0, that employ automated advanced analytics to verify performance. This offers the opportunity to effectively manage the transition from short-term M&V to long-term monitoring and targeting (M&T) in industrial facilities.**

The original contribution of this paper consists of a novel, robust and technology agnostic framework that not only satisfies the requirements of M&V 2.0, but also bridges the gap between M&V and M&T by ensuring persistence of savings. The approach features a unique machine learning-based energy modelling methodology, model deployment and an exception reporting system that ensures early identification of performance degradation. A case study demonstrates the effectiveness of the approach. Savings from a real-world project are found to be 177,962 +/- 12,334 kWh with a 90% confidence interval. The uncertainty associated with the savings is 8.6% of the allowable uncertainty, thus highlighting the viability of the framework as a reliable and effective tool.

***Index Terms*—performance verification, machine learning, energy efficiency, M&V 2.0, energy modelling**

I. Introduction

In 2015, industry accounted for 25.3% of total final consumption in the European Union (EU) [1] and 20.9% in Ireland in 2016 [2]. The European Parliament have issued the Energy Efficiency Directive in an attempt to maximise the efficiency with which energy is consumed in industry [3]. Under the terms of the Directive, member states are obligated to achieve 20% energy efficiency savings by 2020. The success of energy conservation measures (ECMs) implemented to achieve this target can only be measured using measurement and verification (M&V). Thus, accurate M&V is a necessity for ECMs to be confidently relied upon when assessing the effectiveness of EU policy.

Commonly used protocols for evaluating the success of any ECM include the Efficiency Valuation Organization's (EVO) international performance measurement and verification protocol (IPMVP), the American Society of Heating, Cooling, Refrigerating and Air-Conditioning Engineers' (ASHRAE) Guideline 14 and ISO 50015 [4]–[6]. Robustness and applicability across a wide-range of projects make these protocol appealing to M&V practitioners. Although, a lack of prescriptive guidance on the regression modelling task within M&V is seen as a significant deficiency in these approaches [7].

There are three periods of interest in M&V: the baseline (pre-ECM), implementation and reporting (post-ECM) periods. The duration of all three periods varies depending on individual project parameters. A commonality amongst all projects is the retrospective nature of the analysis. Energy savings realised are typically quantified at the end of the reporting period. As a result, any degradation in performance over the reporting period is not identified until the period concludes. This highlights one such challenge that is facing M&V; the need for a more dynamic process that ensures savings are maximised over a project lifetime.

A crucial step in M&V is the estimation of the adjusted baseline in the reporting period. This is found by normalising the post-ECM energy consumption to pre-ECM conditions.

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Typically, engineering or statistical methods are applied to construct a baseline model capable of performing this normalisation. Consequently, M&V is not an exact science and maintaining accuracy throughout the process is critical to its success.

In contrast to the mature residential and commercial sectors, the industrial sector poses many barriers for accurate M&V. The complex energy systems in industrial facilities can make M&V resource intensive, as many variables impact on consumption. Effective and efficient data processing methods are required to prevent M&V from becoming a resource intensive task. In addition, the task of ensuring savings persist beyond the reporting period presents a significant challenge for the continued effectiveness of M&V. Monitoring and targeting (M&T) is an energy management technique used to gain an insight into systems by relating energy consumption to site-specific variables. It is a continuous task that is essential for the successful delivery of an energy management system.

Performance verification in energy systems is evolving with automated, advanced analytics becoming increasingly common. The term M&V 2.0 is used to identify approaches to M&V that employ these more powerful and less resource intensive techniques. This represents a shift from the traditional retrospective and static approaches to modern, real-time and dynamic processes. Franconi et al. identified the use of granular data coupled with automated processing as the most opportune manner with which to progress M&V [8]. The use of real-time advanced analytics enables more frequent savings quantification. This offers the opportunity to improve the practices with which persistence of savings is ensured beyond just the reporting period. This paper presents a novel, robust and open-source framework that not only seeks to satisfy M&V 2.0 needs, but also bridge the gap between M&V and M&T to ensure long-term persistence of savings.

II. Research questions

The following research questions are addressed in the analysis detailed Sections IV and V:

1) Can advanced analytics and granular energy data be utilised in an efficient and effective manner for M&V in industrial facilities?
2) Is it possible to formalise a technology agnostic framework for performing real-time M&V in an automated manner? Can a performance deviation detection system be incorporated in such a framework for exception reporting?
3) How can M&V be smoothly transitioned to M&T to ensure energy savings persist over a projects lifetime?

III. Related work

The widely used generalised M&V methodologies, such as the IPMVP, have the distinct benefit of being robust and applicable under a wide variety of project requirements. Despite this, the lack of prescriptive guidance on the calculation process in the baseline period is a significant constraint to their effective implementation. In addition, the retrospective nature of the analysis has the potential to be a hindrance as M&V 2.0 practices become more common.

Alternative methodologies have been developed to offer M&V practitioners alternative solutions. Kelly Kissock and Eger proposed a whole-facility approach that can utilise sub-meter or billing data to quantify savings in industrial facilities. This is achieved by accounting for weather and production [9]. Rossi and Velázquez developed an industrial applications specific methodology for energy savings verification with a case study on a combined heat and power plant [10]. Diaz et al. developed a model that combines an internal temperature model and an energy consumption model based on transfer functions. A key advantage of this approach is the shorter baseline periods required relative to traditional approaches [11]. Reducing the length of training periods is advantageous in minimising the resources required to perform, however, it has the significant drawback of requiring significant metering infrastructure. Gallagher et al. identified machine learning techniques as a means of maximising the usefulness of available granular energy data [12].

To address these constraints, M&V 2.0 solutions have been presented and evaluated in published literature. In the commercial buildings sector, Granderson et al. assessed the accuracy of 10 different solutions. This approach was found to be useful in evaluating 'black-box' models containing proprietary information [13]. Kupser et al. presented a review of a range of M&V 2.0 offerings with a focus on residential and commercial buildings [14]. Granderson et al. assessed the state of technologies available [15]. Gallagher et al. developed a formal, prescriptive methodology for applying machine learning techniques to construct baseline energy models in M&V [16]. Finally, Ke et al. have developed a cloud-based M&V 2.0 solution [17].

A significant quantity of research has been undertaken in energy modelling outside of the scope of M&V and it is prudent to consider these findings when attempting to evolve the energy modelling component of the process. Zhao and Magoulés conducted a comprehensive review of simplified engineering, statistical and AI methods for the modelling and prediction of energy consumption in buildings [18]. Yildiz et al. conducted a review of simple regression and machine learning models for electricity load forecasting in commercial buildings [19]. Fan et al. utilised both supervised and unsupervised deep learning to model and predict in the short-term the cooling load of a building [20]. Foucquier et al. reviewed machine learning, thermal and hybrid approaches used to model energy consumption, heating/cooling demand and indoor temperature in buildings [21].

IV. Methodology

The proposed framework is sub-divided based on four periods of analysis that occur sequentially over a projects lifetime. These are the baseline, implementation, reporting and persistence periods. The baseline period is the first stage in the process. It is used to develop a model of the energy systems consumption prior to any works taking place. All ECMs are installed and commissioned during the implementation period. The reporting period is used to quantify the savings realised in the energy system following the completion of all implementation works. The persistence period is a novel addition to the M&V process which occurs following the completion of traditional M&V and has been developed to be integrated with M&T. This enables a transition from M&V to M&T, thus ensuring savings are maximised over an ECMs lifetime, in contrast to the reporting period in isolation. Figure 1 provides a graphical illustration of the framework.

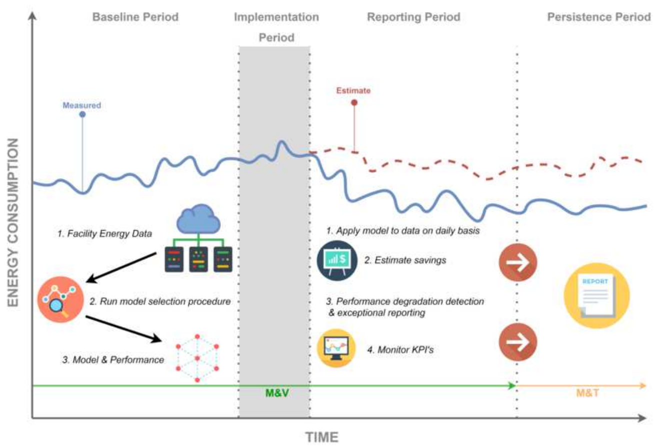

Fig. 1. Illustration of the proposed real-time M&V 2.0 framework.

The framework takes advantage of the data recorded by advanced metering infrastructure (AMI). AMI is now common place in most facilities operating an ISO 50001 certified energy management system. However, it is critical that the resources required to carry out M&V are not increased when employing these large quantities of data. Innovative feature selection and powerful modelling techniques are incorporated to discover knowledge from existing data in an efficient manner to overcome this challenge. This is also advantageous in negating the requirement to install additional metering for the sole purpose of performance evaluation.

A. Baseline period

1) Data gathering: The two primary resources required for accurate M&V are skilled practitioners and metering infrastructure. An approach that can utilise available data and automatically compute savings in complex environments is essential to minimising the overall costs of completing M&V. An evaluation of the available data must be completed to assess the ability of this data to be used for reliable performance verification. If the data available is insufficient, additional metering infrastructure must be installed, thus increasing project costs. This can also delay ECM implementation as baseline period data must often be gathered with the new metering equipment. Data gathering consists of identifying suitable data sources and recording the characteristics of each relevant data source. This should include the type of data, measurement frequency, storage methods and access protocol. The objective is to outline a means of accessing data from each distributed data source to enable data extraction.

2) Baseline energy model development: The construction of an accurate model of the energy systems performance in the baseline period is a critical step in M&V. An accurate baseline energy model can then be applied post-ECM to normalise consumption to pre-ECM conditions; a requirement for computation of final savings. Modelling error is a prominent source of uncertainty in M&V and thus, it must be kept to a minimum to ensure the uncertainty associated with the final savings is within acceptable limits.

It has been discussed in Section I that a lack of prescriptive guidance on the construction of a baseline energy model in the most commonly used protocol is a hindrance to their effective implementation. Gallagher et al. developed a methodology that employs machine learning techniques to populate this knowledge gap in the field. The methodology provides detailed guidance on the application of advanced regression algorithms to construct the optimal baseline energy model for any given project [16]. This methodology has been incorporated into the proposed framework as it is technology agnostic. A full description of the modelling process is available in the associated publication. It is at the discretion of each M&V practitioner as to which modelling approach to employ.

A key feature of the modelling methodology is a computationally efficient wrapper-based feature selection algorithm that can be employed to automatically identify relevant independent variables. This is significant in reducing the need for subject-matter knowledge on each individual ECM. The algorithm relies on the adjusted coefficient of determination (R^2_{adj}), p-value and t-statistic to determine significance.

The advanced regression techniques applied by the model are multiple ordinary least squares (OLS) regression, k-nearest neighbours (k-NN), multi-later perceptron feed-forward artificial neural networks (ANN) and support vector machines (SVM). An exhaustive approach to modelling is employed with each algorithm and a range of measurement frequencies bring utilised to produce an array of baseline models.

3) Identification of optimal model: The exhaustive approach to energy modelling requires the optimal model to be identified. The performance of each model is evaluated on a previously unseen data set. This is achieved by partitioning the data available in the baseline period into two data sets. An 80:20 random split ratio is used to generate training and testing datasets. This is in contrast to the approaches presented in the IPMVP and Guideline 14 in which 100% of the baseline period data is used to construct the baseline energy mode. This approach is prone to over-fitting the model and hence, decreases its usefulness outside of the baseline period.

The optimal model is chosen to minimise the uncertainty introduced by the baseline energy model. This uncertainty is calculated using the process outlined by the IPMVP [22]. Equation 1 outlines how the range of savings is calculated using the critical value of the two-tailed t-statistic (t) and the standard error (SE) of the baseline energy model. Therefore, the optimal model for any given project is that with the smallest value of standard error computed on the testing data set. The standard error is calculate using Equation 2, where y_i is the actual value, $\hat{y}_i$ is the predicted value, p is the number of independent variables in the baseline regression model, and n is the total number of predictions in the period of analysis.

$$\text{Range of possible savings} = \text{Savings} \pm (t * SE) \quad (1)$$

$$SE = \sqrt{\frac{\Sigma_{i=1}^{n}(\hat{Y}_i - Y_i)^2}{n-p-1}} \quad (2)$$

B. Implementation period

It is important to clearly define the implementation period in any M&V project. This period is used to fully implement and commission all ECMs. A poorly defined implementation period could result in irrelevant data being used for model construction and/or deployment. No analysis is carried out during this period as the energy system is in transition.

C. Reporting period

1) Model application: The baseline energy model constructed is applied at regular intervals in the reporting period. Specific to each individual project, the model is to be applied with the same frequency as that of the data used to train it. The measurement frequency of the training data is critical to enabling real-time performance evaluation.

2) Real-time savings quantification: The energy savings are calculated using the IPMVP approach defined in Equation 3. This is a measure of the success of the ECMs implementation and the continued operation of the system. Non-routine adjustments are project specific measures taken to adjust the reporting period conditions. They are necessary when static factors change over the project lifetime. For example, changes in the size of a facility or manufacturing process schedules would require a non-routine adjustment as the baseline energy model was constructed under different operating conditions.

$$\begin{aligned} \text{Savings} = {} & \text{Adjusted Baseline Predicted Consumption} \\ & -\text{Reporting Period Measured Consumption} \\ & \pm\text{Non-Routine Adjustments} \end{aligned} \quad (3)$$

3) Exceptional reporting of performance deviation: Prior to the implementation of an ECM, a feasibility study will generally be carried out to assess the potential savings and associated costs. This will result in an estimation of performance. If this has not taken place, an engineering first-principles approach should be used to estimate the savings that will be achieved. This estimation of savings can be compared with the actual system performance to set upper and lower control limits to identify performance deviations.

Energy performance contracts (EPCs) offer a more rigid savings estimations that can be employed. An EPC is a finance mechanism used in the energy services industry in which customers 'pay for performance'. In cases where EPCs are in place, then this figure should be used as the primary estimation of savings.

The actual performance found using the baseline energy model is compared with the expected performance to establish if the savings are on track. Any deviations from expected performance triggers an exception report to the engineering team. As a rule of thumb, a 20% deviation is defined as a deviation from expected performance. This threshold was arrived at after considering the potential error in the preliminary estimation of savings used to compute it. Practitioners may chose to employ a lower threshold for stricter control. This automated system provides an insight into system performance, enabling corrective action to be taken to maximise the savings realised.

4) Monitor KPIs: As suggested by ASHRAE in Guideline 14, the model can only be applied for periods where independent variables are no more than 110% of the maximum and no less than 90% of the minimum values of the same variables used for constructing the baseline energy model. This is a straightforward step that can easily be automated. If independent variables stray outside of these bounds, then the error metrics associated with them are no longer valid. The model must be retrained with more suitable variables in these circumstances.

D. Persistence period

The persistence period occurs outside the scope of traditional M&V. This is the point at which M&T takes over the evaluation of system performance. This new period of analysis enables performance evaluation to be an ongoing task.

1) Persistence plan: A plan is required to ensure persistence of savings over the lifetime of an ECM. This includes the continuous operation of the automated system for performance tracking. The persistence plan should also detail responsible individuals in cases where the performance tracking system must be revisited, such as independent variables no longer being within bounds. Integrating these key elements of M&V into the M&T process allows for longer term savings tracking.

2) Adjustments: Adjustments are required on a project-by-project basis. This includes reconstruction of a baseline model in cases where independent variables are no longer relevant and applying scaling factors when significant changes occur to the facilities' operating conditions.

V. Case study: Results and discussion

The proposed framework was applied to quantify the savings resulting from an ECM carried out on a set of air handling units (AHUs) in a large biomedical manufacturing facility in Limerick, Ireland. The facility operates a continuous production process on a 24/7 basis. The ECM consisted of optimising the control logic for each individual AHU. The new control logic is more intelligent than the previous one, with an ability to respond to the space heating and cooling requirements of the areas served. This is in contrast to the static system in place pre-ECM, which supplied a fixed volume of air to each area. The logic utilised variable speed drives (VSDs) already in place to vary the volume of air supplied

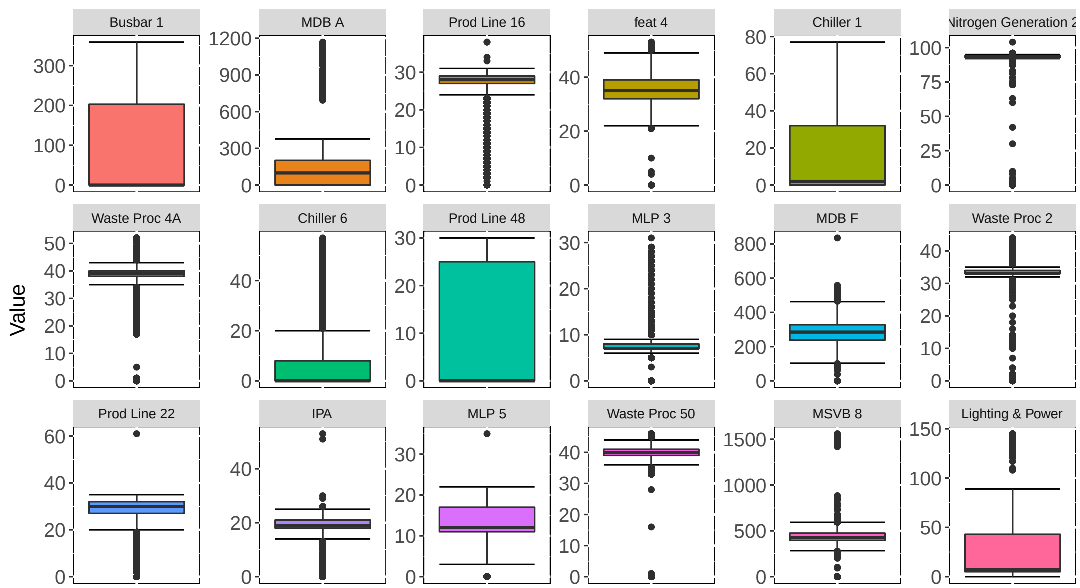

Fig. 2. Box and whisker plots of each independent variables used to construct baseline energy model.

depending on the requirements of the environment being treated. In existence pre-ECM, was electricity consumption meters on each AHU. Therefore, the decision was made to assess the savings in the total electricity consumptions of all AHUs, i.e. the cumulative consumption of all individual units.

A. Baseline period

The modelling methodology discussed in Section IV-A2 was applied to identify the independent variables relevant to the total AHU electricity consumption and subsequently, model the performance of the system in the baseline period. The baseline period was selected to begin on January 1st, 2016 and it concluded on October 4th, 2017. This period encompassed more than one full 12-month cycle of analysis of the system, hence covering a wide spectrum of operating conditions. This is important to ensuring the model's validity is maintained in the long-term.

The optimal approach that minimised model uncertainty was a k-NN model trained with data having an hourly measurement frequency. 18 independent variables from across the site were used to construct this model. Figure 2 contains box and whiskers plots of each feature to summarise the spread of values. These were selected based on statistical significance to the dependent variable. All data was gathered using existing metering infrastructure.

The performance of this optimal model was quantified as having a standard error of 15.99 kW when evaluated on the unseen testing data set. Figure 3 illustrates the fit of the model on a sample of data in the baseline period.

B. Implementation period

The implementation period began on October 5th, 2017 and concluded on November 11th, 2017. No installation or commissioning works were carried out outside of this period.

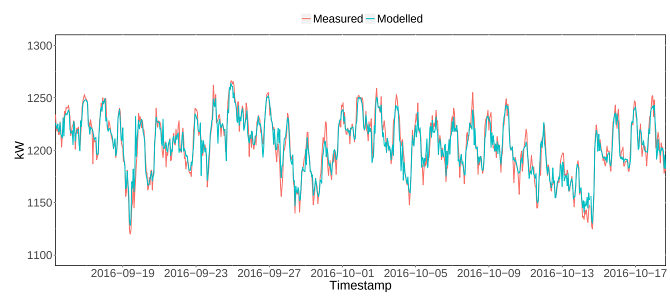

Fig. 3. Sample of model fit in baseline period.

C. Reporting period

The reporting period began on November 12th, 2017 and concluded on December 1st, 2017. This is a relatively short period of analysis that was limited by research project parameters. Despite this, the lack of seasonality in the electricity consumption of the AHUs and the wide array of conditions in the baseline period ensure the findings are reliable.

The optimal model was trained using hourly data, hence this is the minimum frequency with which it could be deployed. The application of the optimal model over the 19.5 days reporting period resulted in energy savings being quantified to be 177,962 +/- 12,334 kWh with a 90% confidence interval. This is equivalent to a 380.1 kW reduction in electrical load on the system. The uncertainty associated with the savings are 8.6% of the allowable uncertainty as defined by the IPMVP.

A feasibility study carried out prior to any implementation works being carried out estimated a reduction in the electrical load of the AHUs of 385 kW. This estimation was based on assumed VSD motor efficiencies and run-hours and perfect implementation for the duration of the reporting period. This figure was used to develop a rule that could be employed to identify periods of performance degradation. If the actual savings found using Equation 3 were less than 80% of the expected savings (i.e. 385 kW) for 4 consecutive hours or more, then an exception report is generated. This alerts the on-site facilities team to investigate and take the necessary corrective action. A graphical representation of two periods of performance degradation identified is included in Figure 4. Corrective action was taken to ensure performance returns to expected levels. Thus, the savings realised can be maximised. This would not be possible using a traditional M&V approach as the savings are not quantified until the reporting period is concluded and as one of the degradation events occurred within 3 days of implementation, it is unlikely that corrective action would be taken in sufficient time.

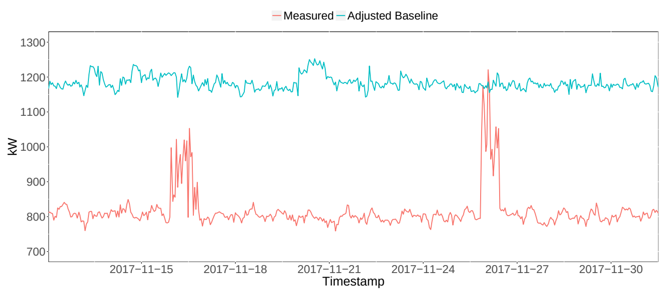

Fig. 4. Illustration of performance deviations, associated alerts and corrective actions.

D. Persistence period

A persistence plan was developed to ensure the maximum possible savings are realised over the lifetime of ECM and that the ongoing monitoring of savings is integrated into regular M&T activities. This plan was agreed with the on-site facilities team to ensure responsible parties are identified for possible future works. Additionally, the action to be taken should the operating conditions of the site significantly change is outlined in the persistence plan.

VI. Conclusions

Accurate, reliable and efficient M&V of energy savings is a necessary tool in tracking the performance of energy projects. To continue to play an effective role in future energy systems, M&V 2.0 must become common place across residential, commercial and industrial applications. A technology agnostic framework for automated, real-time M&V was developed to offer a solution to this challenge. This is a useful tool that can be employed to ensure M&V evolves to a more mature state of operation. The benefits of the proposed framework were demonstrated using a case study. Two instances of performance degradation were automatically identified, allowing corrective action be taken.

The proposed approach represents an evolution from static retrospective M&V to more powerful, efficient and dynamic M&V solutions. This simple means of performance degradation identification is incorporated to enable a smooth transition from short-term M&V to long-term M&T, thus ensuring savings persist over a projects lifetime. The proposed approach will have an increased applicability in energy management as ISO 50001:2019 will place a renewed emphasis on demonstrating clear energy performance improvements.

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