CIRP Annals - Manufacturing Technology 00 (2023) 1–4

Contents lists available at ScienceDirect

CIRP Annals - Manufacturing Technology

journal homepage: https://www.editorialmanager.com/CIRP/default.aspx

Machine learning based internal and external energy assessment of automotive factories

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ARTICLE INFO

Article history:
Available online xxx

Keywords:
Energy efficiency
Factory
Machine learning

ABSTRACT

In order to reduce industrial greenhouse gas emissions, systematic energy demand analysis and the derivation of improvement strategies are key. Against this background, a methodology for data driven energy demand prediction and performance benchmarking for factories is presented. The machine learning based approach enables to quantify performance influencing factors, identify "best in class" factories and fields of action for improvement. The results are validated within an automotive OEM internal and even external competitor assessment. The transferable approach based on well accessible public data also enables larger industry wide studies.

1. Introduction

As again pointed out by the IPCC report, human induced greenhouse gas emissions and related global warming are of critical concern nowadays [1]. The energy demand of the industrial sector is one of the largest contributors and therefore in special focus and of high importance to governments and regulatory bodies. Environmental and economic factors (e.g. rising costs) of energy demand also increase the relevance for individual manufacturing companies. From global industrial perspective the automotive industry certainly plays a key role with over 60 million cars produced each year [2]. Supplied car components come together in several hundred assembly plants worldwide operated by diverse automotive OEM (original equipment manufacturer) - just in Europe there are over 130 facilities in place [3]. This last phase of automotive manufacturing typically consists of three main steps – body shop, paint shop and final assembly. The life cycle assessment (LCA) of an automotive factory clearly indicates the use stage as most relevant for global warming potential (GWP) with a share of 77% over the total factory life cycle [4]. Within that, energy demand of both the production equipment and the necessary technical building services (TBS, e.g. heating, ventilation, air conditioning or lighting) are by far the most important factors. The most widely applied energy performance indicator (EnPI) for analysis and evaluation of automotive production plants is the specific energy consumption (SEC), expressed as energy required to produce one vehicle (kWh/veh) [5]. As shown in Fig. 1(a), based on sustainability reporting, the SEC of automotive OEMs significantly varies between 900 kWh/veh and 3500 kWh/veh. This variance could be driven by inhomogeneous scopes. But Fig. 1(b) narrows this down and shows the SEC of comparable assembly plants [6,7] with similar product

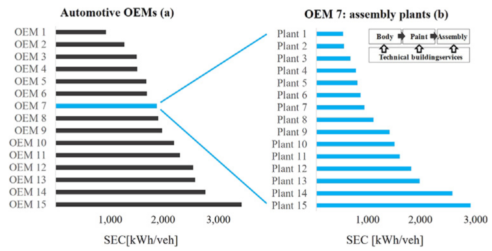

Fig. 1. SEC external benchmark (a) (based on sustainability reports from 11 automotive OEMs) and SEC internal benchmark (b) (own data).

types - but nevertheless the results range from 499 kWh/veh up to 2880 kWh/veh. Obviously, there are either further factors that need to be considered in terms of comparability and/or very high improvement potentials for the plants are given. But given the complexity of plants and confidentiality of involved data, proper assessments are hardly possible. Interesting approaches like in [8] with a deeper look into material input/output relations and their impact on factory energy demand are less applicable in this context.

Against this background, a machine learning based approach for factory energy assessment is suggested. It enables to identify critical influencing factors, to realistically benchmark plants among each other (to identify the best in class) and to eventually derive fields of actions for improvement. To overcome barriers for implementation and enable a broad transfer between plants operated by one OEM (internal assessment partially based on internal data) but even to external organizations (e.g. other OEMs for competitor benchmarking, researchers/politics/consultants or LCA based on public data) strong attention is paid to availability of data. The development and prototypical implementation of the approach are conducted in

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https://doi.org/10.1016/j.cirp.2023.04.038

context of automotive industry – however, in general the approach is transferable to other industries as well.

2. Background and research demand

For automotive industry, energy demand analysis of factories has been of interest in research and industry for some time. Given the holistic scope of the analysis on large scale and complex factories with all sub-systems (which practically impede the usage of bottom-up simulation approaches), data driven black-box approaches are typically used to analyze the performance, calculating baselines to represent an expected energy demand (e.g. result of regression analysis OLS; 9, 13, 14) or a stochastic single-factor input frontier line (SFA; 10, 11) to present the most efficient observation (Table 1). All mentioned methods have similar possibilities to identify the benchmark factories but have issues with quantifying the influencing factors and show higher standard errors on plant level. It also needs to be ensured that there is no multi-collinearity and auto correlations between the influencing factors (IF) and the confounding variables have an expected value of zero (all relevant IF are identified). The consideration of competitor data is only addressed by [9] and [10]. Whereas [9] considered publicly available energy data the limitation is clearly in the insufficient accuracy of the models due to inhomogeneous system boundary definitions. To overcome that, [10] aimed at strong individual company involvement, causing high effort and relies on voluntary participation. As summarized in Table 1, the review shows that there is still a major research demand to properly consider potentially more influencing factors but also their interdependencies, non-linearity and uncertainty. Even more, none of the existing benchmarking approaches is considering competitor EnPIs within homogenous system boundaries and is based on well accessible public data. Finally, existing approaches can support to derive best practice plants but - given their inherent logic - are less appropriate to identify causes for differences among plants (gap analysis) which are crucial to ensure a fair comparison and derivation of improvement actions.

Table 1
Benchmarking methods and influencing factors (IF) (*specific factors considered due to focus on automotive body shops).

	[9]	[10]	[11]	[12]	[13]	[14]	**here**
Method	OLS	SFA	SFA	OLS	C-OLS	PCA OLS	Statist. & ML
Comp. EnPIs	partly	partly	none	none	none	none	yes
Gap quantif.	no	no	no	no	partly	no	yes
Infl. Factors/IF	3	4	4	5	6	11	15
Volume	X						X
Heat-degree-days	X	X	X	X	X	X	X
Working-days				X		X	X
Building age	X				X	X	X
Wheelbase		X	X	X		X	X
Utilization		X	X		X	X	X
Cool-degree-days		X	X	X		X	X
Vehicle-weight				X	X		X
Floor area					X	X	X
Headcount					X	X	X
Weld-spots*						X*	
Robots*						X*	
Automation*						X*	
Line rate							X
Lead time							X
Direct run							X
OEE							X
Vehicle-size							X

3. Methodological framework

To address the research demand, this paper aims at developing a continuous performance management framework applying machine learning based methods to evaluate the energy performance and support the improvement of factories. Fig. 2 illustrates the methodological framework which consists of five different solution elements (SE) consisting of different data-driven functions (FU). SE1 focuses on system and data specification to ensure comparable scopes of data from different systems and to support to decide which data to collect. Influencing factors (IF) are identified and can be further broken down into disturbance factors (DF, non-controllable by system operator, e.g. outside temperature expressed in heating degree days/HDD) and performance factors (PF, potentially controllable, e.g. building floor area, overall equipment efficiency/OEE) [13]. Special attention is paid here on the differentiation between public available and internal factors which lead to different models for internal (different plants within one company) or external benchmarking (different plants over several companies). Based on that, a measurement plan is defined which typically consists of five main data groups for energy performance evaluation: weather, product, production, factory and energy data [13]. SE1 closes with a plausibility check and outlier detection, using a generalization of clustering and regression modeling, based on the RANSAC algorithm and numeric outlier evaluation [15].

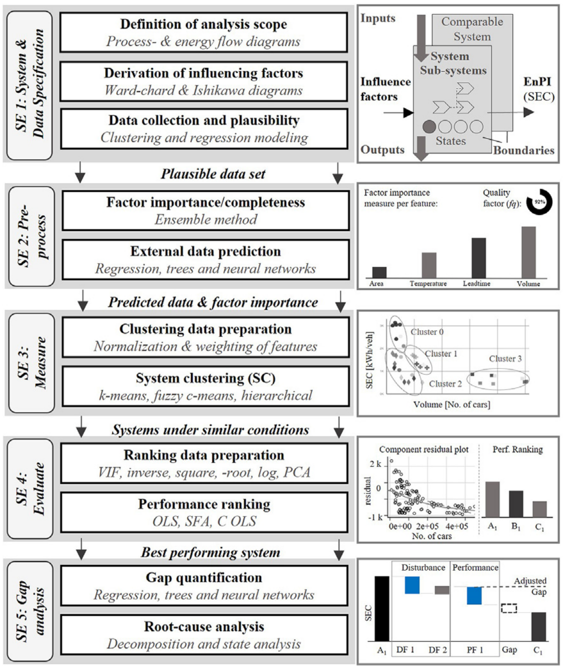

Fig. 2. Application cycle of the energy performance control-loop solution elements (SE) and related functions (FU).

Within SE2 (data preprocessing), the importance and completeness of the selected influencing factors are analyzed. It offers the option to generate weights of the IFs according to their importance and to assess factor completeness based on different prediction model quality results (*fq*). Several approaches are used here in combination as ensemble method, e.g. Lasso-, Ridge and Elastic net regression as well as different tree based methods (mean decrease impurity and -accuracy, extreme – and gradient boosting trees). Special attention is given to the overfitting problem with hyper-parameter tuning and cross-validation approaches. As ensemble result the normalized influencing factor importance value is calculated based on the weighted mean value of the *fq* of each model leading to the final factor importance measure (FIM). Furthermore, reduction approaches e.g. based on principle component analysis (PCA) and variance inflation factor (VIF) are applied. For the prediction function various models (linear- and poly regression, decision tree, random forest, gradient boosting tree and artificial neural network) are trained, validated and then selected based on a residual analysis. SE3 (performance measurement) clusters the data into comparable systems (SC), with similar disturbance factors and calculates the position of the application system (SA) towards the SC. Data is normalized and weighted according to the factor importance measures generated before. The elbow method based on the sum of squared distance error (SSE) is used for identification of the number of clusters, followed by the cluster algorithms (e.g. k-means). SE 4 delivers the performance ranking of the considered systems, referring to the reference indicator (EnPI). Output is the *fq* weighted performance ranking and the uncertainty factor of the resulting reference EnPI.

This is the basis for the quantification of the performance gap (SE5 – Gap analysis), which transforms the gathered data into knowledge by quantifying specific performance improvement measures. Rootcause analysis (RCA) and improvement measure development take place by combining the results of previous SEs, machine learning modeling with the operator's knowledge and automated quantification of what-if scenarios. The final output is a quantified energy performance gap walk, with a concrete calculation of the influence of different factors. The information is used to derive knowledge and an implementation plan for energy performance improvements.

4. Use cases and results

The approach presented before was applied in two different use cases. The internal analysis (IA) addresses benchmarking of different factories within one OEM, hereby also data from internal sources can be used to achieve best prediction results. The second use case takes a broader view and aims at externally assessing factories of different OEMs (EA). The general procedure is similar but given the competitive situation and related confidentiality issues just public data sources are used.

As described in SE1 comparability of scopes is crucial for the analyses. The focus for both use cases is on total site level of passenger vehicle assembly factories – this includes body-, paint-, general assembly shop and facility related consumption for all subsystems (through TBS). For the energy performance evaluation total energy demand [E_{total}] and SEC [kWh/veh] are used as EnPI. It is also assured that the major energy-consuming operations are similar among the plants [12]. IFs are derived by main subsystem analysis, literature studies [8–12] and through discussions with experts. The resulting fifteen IFs are visualized in Table 2, which shows their category, abbreviation, description, the type of influencing factor (disturbance or performance) and availability.

Table 2
EnPIs and influence factor selection on subsystem analysis.

Category	Abbr.	Description	IF	Available
Energy	SEC	SEC [kWh/veh]		Internal
	E_{total}	Energy consumption [kWh]		Internal
Weather	OT	Outdoor temperature [HDD]	DF	Public
	OT	Outdoor temperature [CDD]	DF	Public
Production	WD	Number of Working Days [No]	PF	Internal
	Vo	Volume/Number of vehicles build [No]	DF	Public
	LR	Line rate [No of units/hour]	PF	Public
	Util	Vo /LR x 16 hrs x 235 days [%]	PF	Public
	LT	Lead time [Work in process / LR]	PF	Internal
	DR	Direct run [1- (planed / produced)]	PF	Internal
	OEE	Overall equipment effectiveness [%]	PF	Internal
Product	wB	Average wheelbase [m]	DF	Public
	vS	Vehicle size [m^3]	DF	Public
	vW	Vehicle weight [kg]	DF	Public
Factory	BA	Building floor area [m^2]	PF	Public
	Bage	Building age [years]	DF	Public
	HC	Headcount	PF	Public

4.1. Internal analysis (intra company)

For the internal analysis 19 different plants from six years (2015–2020) are compared within the study (n = 114). Data sources are widely distributed leading to a variety of different formats, semantics and quality. Thus, plausibility checks and proper data treatment (e.g. RANSAC) were crucial before analysis of IF importance and completeness. Table 3 shows the results of the IF importance analysis (SE2), related to SEC for the internal analysis (IA). Based on the ensemble method, the top 5 IFs account for over 50% of the influence on SEC, with volume being the factor with highest importance. The DFs account for 34% while the PFs account for 41%. The resulting prediction quality factor of 92% is exceeding the defined threshold so no further data is needed.

Table 3
Internal (IA) and external (EA) analysis results for factor importance (%).

	Disturbance (FIM-%)				Performance (FIM-%)							fq
	Vo	OT	wB	vW	BA	Ut	LT	DR	OEE	LR	WD	%
IA	15	8	11	4	7		10	8	4	3	2	92
EA	10	6	4	4	32	3	–	–	–	8	–	87

Based on further steps as pointed out in Section 3 (SE3 and SE4) ranking of plants with respect to their SEC was derived. Fig. 3 shows the gap walk (SE5) for plant A1, ranked as most efficient, compared to the second most efficient plant B1. The first comparison would suggest that plant A1 has a 56% better energy performance than plant B1. However, the gap walk reveals the contribution of different DFs and PFs. Plant B1 produces bigger vehicles (product), which leads to extra 42 kWh/veh compared to plant A1. Due to different plant locations in Europe and less heating demand, plant B1 has a slight advantage of 59 kWh/veh. Plant B1 has also an advantage of 195 kWh/veh due to better utilization (volume and line rate). Concluding all that, the adjusted performance gap with 65% is even higher than initially suggested – plant A1 is clearly more energy efficient while taking into account all IFs and ensuring a fair comparison.

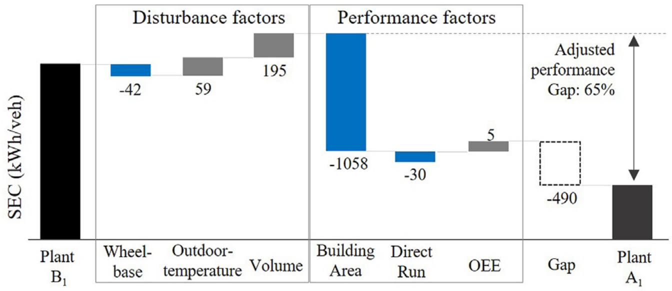

Fig. 3. Gap walk for two assembly plants based on internal assessment (IA).

The view on PFs reveals more controllable factors that are typically also the starting point for potential improvement measures. Building floor area has clearly the highest leverage (1058 kWh/veh) followed by some potential through improving the direct run ratio with 30 kWh/veh impact. For OEE, plant B1 actually performs better than plant A1. Finally, with an overall uncertainty of 7% there is a gap of 490 kWh/veh which cannot be broken down into specific factors yet but can be considered as further performance (and potential improvement) factors. Based on those insight specific improvement plans were derived. This includes the increasing of area utilization ratio by further consolidation activities, as well as increasing the direct run ratio with focus on paint rework strategies (to increase spot repair rate instead of respray). Additionally, more detailed technical analyses were initiated to get better insight into the performance gap.

4.2. External assessment (inter company)

This use case focuses on predicting energy related indicators of any automotive assembly factory in order to identify the best industry-wide plant as well as related improvement potentials. It offers the opportunity for OEMs to identify suitable external benchmark partners, as well as allowing third parties (NGOs, research institutes etc.) to predict energy demand, e.g. as part of LCA studies. As pointed out in Section 1 careful scoping of the analysis is important, focus here (like in use case 1) is clearly on passenger car assembly plants. As an important automotive industry report, the Harbour publication 2019 lists 145 global assembly plants as potential source for benchmarking studies [16]. Interesting variables are given there but comparable energy data is not a part of the metrics. Energy data is typically not publicly available with sufficient information about the underlying system scope. To calculate energy indicators, this external oriented use case is intentionally only based on the public data that has been collected via general web data [17,18], industry reports [16] and publications [13,19]. In line with the framework introduced above (SE2), Table 3 (EA) shows the considered IF and their calculated factor importance measure. Building area is clearly dominating here followed by volume/output of the plant, outside temperature influence and product (vehicle) characteristics. Detailed testing and validation through comparison with internal factor analysis and measured data could be done in one major automotive OEM (OEM1).

As expected, given the reduced number of considered factors compared to company internal analysis, results show that residuals slightly increase and, thus, general prediction quality *fq* slightly decreases (Table 3). However, with 87% it is still in a very feasible order of magnitude, especially given the strategic character of the analysis.

For OEM1 detailed information was available but for further testing of feasibility and validity more large automotive OEM with limited public data availability were considered. Based on expert talks and published data from [13] a satisfying accuracy could be confirmed for another large OEM (OEM2) with residuals of just 6%. Additionally, several automotive OEM have been analyzed concerning their potential SEC in order to identify the factory with the most promising energy performance prediction (OEM3). After initiating the exchange with experts from the related competitor plant, the predicted EnPI (SE2) could be confirmed with an accuracy of 4% (Fig. 4). In a next step, this factory from OEM3 (plant Ex) was compared with the plant A1 from OEM1 which turned out to be most efficient from internal analysis perspective, based on the clustering (SE3) and performance ranking results (SE4). As shown in Fig. 5 the initial performance gap based on SEC is 46%. Following the best prediction model (out of SE5) plant A1 has an advantage of 20 kWh/veh due to less heating demand given different plant locations in Europe. On the other hand plant Ex produces smaller vehicles (product), which leads to 31 kWh/veh advantage compared to plant A1. Finally, after consideration of the most important factor volume and line rate with −379 kWh/veh, plant A1 has an adjusted performance gap of 10% (or 101 kWh/veh). Even under consideration of the weighted total uncertainty (5%) it can be concluded that plant Ex has performance advantages, whose root-causes needs to be analyzed with the described functions and experts from both companies.

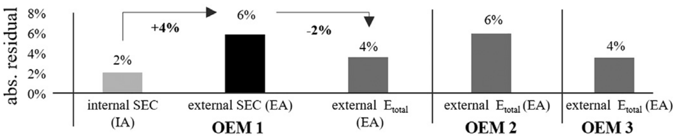

Fig. 4. Validation results for external analysis (EA) approach for three large OEM, for OEM1 also in comparison to the internal analysis (IA, see use case 1).

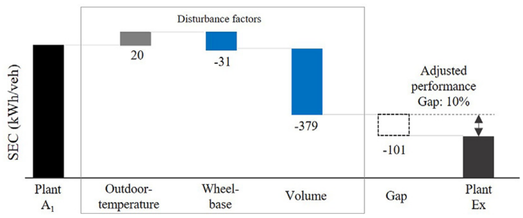

Fig. 5. Gap walk for two (competitor) assembly plants based on external assessment.

5. Summary, discussion and outlook

An approach for a data driven energy demand prediction and benchmarking for factories is presented. With this approach it is possible to quantify the impact of influencing factors on the energy performance, to identify "best in class" plants and to analyze the differences between compared factory systems. Given that, the results give detailed information about measures to reduce the determined performance gap. As an important point, the concept does not only offer a solution for company internal analyses, it is also possible to use the framework for factory energy demand prediction purely based on public available data. This enables interesting applications for inter company benchmarking but for e.g. larger industry wide studies or utilization for life cycle assessment (LCA). The methodological approach strongly originates from automotive background but is in general quite transferable to completely other sectors. The approach was applied and validated within an own conducted external benchmarking study, finally enabling the performance prediction for three different very large automotive OEM (representing nearly 40% of global market share), with residuals between 4% and 6%. The results underline that the energy demand of automotive production systems can be predicted very well based on public available data. However, there are of course also some challenges and further fields of action. Firstly, data-based models are typically black box approaches based on observed phenomena. This enables relatively easy application and is of specific value for highly complex processes (like automotive assembly plants). However, results need to be interpreted carefully because they might even lead to misleading actions without sufficient domain knowledge. Thus, the models should serve as starting point and complementary activity towards deeper, knowledge-based understanding. Secondly, the investigation purely focuses on energy demand and neglects impacts on other resources. For further applications, those aspects should be integrated to avoid problem shifting and point out potential conflicts.

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.

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Please cite this article as: D. Flick et al., Machine learning based internal and external energy assessment of automotive factories, CIRP Annals - Manufacturing Technology (2023), https://doi.org/10.1016/j.cirp.2023.04.038