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Government Consultation Response

Data for AI in the energy system I

Dr Ezhilarasi Periyathambi, Fariba Dehghan, Dr Jan Buermann, Professor Sebastian Stein, Professor Andrew Cruden

Written Response to the Department for Energy Security and Net Zero Call for Evidence: Data for AI in the energy system

Dr Ezhilarasi Periyathambi, Fariba Dehghan, Dr Jan Buermann, Professor Sebastian Stein, Professor Andrew Cruden

Faculty of Engineering and Physical Sciences, University of Southampton

About the Authors

Dr Ezhilarasi Periyathambi is a Research Fellow at the University of Southampton working across the FEVER and Citizen-Centric AI Systems (CCAIS) projects. Her expertise lies in applying AI to smart grid systems, with a focus on developing advanced smart charging algorithms for electric vehicles and building AI systems that prioritise fairness and public interest particularly in energy systems. **Fariba Dehghan** is a researcher at the University of Southampton working at the intersection of AI and sustainable energy. Her work focuses on smart electric vehicle charging station scheduling, including vehicle-to-grid technology. **Dr Jan Buermann** is an Enterprise Fellow at the University of Southampton, leading research impact and public engagement for the UKRI MINDS Centre for Doctoral Training. **Professor Sebastian Stein** is a Professor of AI at the University of Southampton and UKRI Turing AI Acceleration Fellow. His research focuses on incentive design in multi-agent systems and modelling user preferences in complex AI, applied to smart energy, on-demand mobility, and EV charging. **Professor Andrew Cruden** is Professor of Energy Technology at the University of Southampton and Principal Investigator of the FEVER programme grant. His expertise spans renewable energy, fuel cells, and wind turbine monitoring, with a growing focus on electric vehicles and energy storage.

Executive Summary

This evidence is submitted on behalf of a multi-disciplinary University of Southampton team from the EPSRC-funded Programme Grant on Future Electric Vehicle Energy networks supporting Renewables (FEVER, EP/W005883/1) project, which is developing grid-independent EV charging stations, and the Citizen-Centric AI Systems Turing AI Acceleration Fellowship, which investigates building artificial intelligence (AI) systems that can be trusted by all users. **The evidence highlights the lack of appliance level energy data as a key barrier to AI enabled applications across residential electricity networks and proposes a privacy preserving, standardised approach for sharing appliance or device level data via smart meters.**

Artificial Intelligence (AI) has significant potential to improve the efficiency, affordability, and resilience of the UK energy system. However, realising this potential, particularly in residential and low voltage electricity networks, is currently constrained by the lack of high quality, appliance level energy data. While smart meters provide half hourly aggregate household consumption, they do not offer visibility into the behaviour of individual high impact devices such as Electric Vehicle (EV) chargers, heat pumps, batteries, and electric heating systems.

In the absence of standardised appliance level data, stakeholders rely on either indirect inference, modelling, and estimation approaches - or - on fragmented, proprietary datasets controlled by individual device manufacturers [1]. These approaches introduce uncertainty and increase computational and integration costs, whilst limiting the scalability of AI applications. This, in turn, limits the effectiveness of demand side flexibility, local energy system optimisation and energy management, in addition to low voltage network management, whilst increasing reliance on centralised data collection that raises privacy and security concerns.

This submission proposes an **open, standardised protocol that allows smart devices to share appliance-level energy data directly with the smart meter**. The smart meter would act as a trusted local data hub - generating, storing, and processing data locally by default, with sharing only happening when the user consents. This approach offers several key benefits: it avoids vendor lock-in at both the data and platform level, improves data quality at source, and supports privacy-preserving AI by keeping data local and minimising unnecessary export. It also complements existing government initiatives to improve visibility of distributed energy assets [2].

Policy Recommendations

1. **Support the development of an open, standardised smart device to smart meter data protocol.** Government should support an open, vendor neutral protocol that allows appliance level energy data to be shared locally with smart meters, reducing data fragmentation and vendor lock-in while enabling AI enabled energy applications.
2. **Embed privacy by design and consent-based access principles in appliance level energy data governance.** Any approach to appliance level energy data should ensure local storage by default, clear limits on data retention, and explicit user consent for data sharing, maintaining trust and protecting consumer privacy while supporting innovation.

Detailed Response to Questions

Q1. What energy problem do you want to solve?

Residential electricity demand is becoming more complex due to the rapid uptake of:

- Electric vehicles and smart charging infrastructure
- Heat pumps and electric heating
- Domestic battery storage
- Rooftop solar PV and hybrid systems

Despite this, **smart meters currently provide only aggregate household electricity consumption**, typically at half hourly resolution. They do not provide direct visibility into the energy use or flexibility characteristics of individual appliances.

This lack of appliance level data creates several interrelated problems:

1. **Limited system level optimisation at low voltage networks:** Distribution Network Operators (DNOs) and local energy system operators lack reliable information about when and how flexible loads operate, making it harder to manage congestion, plan reinforcements, or safely connect new low carbon technologies.
2. **Constrained demand side flexibility:** Without device level insight, flexibility services rely on coarse proxies or static assumptions, reducing their effectiveness and increasing risk.
3. **Inefficient local energy system management:** Community energy schemes, peer-to-peer sharing, and neighbourhood level optimisation require granular demand information that is not currently available.
4. **Overreliance on indirect inference and estimation techniques:** In the absence of appliance level data, residential energy analytics and flexibility services rely on indirect inference, estimation, algorithmic modelling approaches to deduce device level behaviour from aggregate measurements. These approaches often require significant computational effort, become less accurate in modern homes with multiple high power and actively controlled devices, and are poorly suited to real-time control or actuation use cases where reliable, device specific responses are required.
5. **Centralised data risks:** Where appliance level data does exist, it is often held in proprietary manufacturer clouds, creating data silos, vendor lock-in, privacy concerns, and potential security vulnerabilities.

Q2. What kind of data is needed?

To enable effective use of AI in residential and local energy systems, the proposed dataset should consist of **time-stamped, appliance level electricity usage and flexibility data**. Rather than attempting to capture all household devices, the initial focus should be on **high-impact and high-power assets** that have the greatest influence on system demand and flexibility. These include electric vehicle (EV) chargers, heat pumps, electric heating systems, domestic battery storage, and other large or flexible electrical loads. These devices are increasingly prevalent in modern homes and play a central role in shaping peak demand, network congestion, and opportunities for demand-side flexibility.

For AI applications to be effective, the data must exhibit several key characteristics. First, it should be collected at **30-minute resolution**, allowing AI models to capture dynamic behaviour, rapid changes in demand, and short-term flexibility potential. Second, the data should be available in a **standardised format**, with consistent units, timestamps, and schemas, so that datasets from different devices, manufacturers, and households can be combined and analysed without extensive preprocessing. Third, the data should be **locally generated**, originating directly from devices within the household, rather than inferred through aggregate measurements. Finally, and critically from a privacy and security perspective, the data should be **stored locally by default**, retained within the smart meter or home environment rather than automatically transmitted to external platforms or central data centres.

In addition to raw energy usage data, a limited set of **non-personal metadata** is required to make the dataset meaningful and usable for AI analysis. This metadata should include information such as device type and category, rated capacity, and current operational mode, as well as basic flexibility characteristics, for example, whether a device is interruptible, deferrable, or time shiftable. Such metadata enables AI systems to distinguish between different classes of loads and to model their behaviour and flexibility accurately. Importantly, none of this metadata needs to include personal, behavioural, or lifestyle information about household occupants. By restricting metadata to technical and operational attributes, the dataset can support advanced AI applications while adhering to principles of data minimisation and protecting consumer privacy.

Q3. What work is needed to create or enable a useable dataset?

A key barrier to the creation of usable appliance level energy datasets is the **lack of a standard interface between smart devices and smart meters**. At present, smart devices such as EV chargers, heat pumps, and batteries communicate using a wide range of proprietary protocols and cloud-based Application Programming Interfaces (APIs). There is no open, standardised mechanism that allows these devices to share appliance level energy data directly with smart meters. This fragmentation results in datasets that are siloed across manufacturers, creates vendor lock-in, increases integration costs for AI developers due to bespoke integrations with multiple proprietary APIs and inconsistent data schemas, and leads to unnecessary duplication of hardware and software platforms for energy management.

To address this barrier, this submission proposes the development of an **open, interoperable smart device smart meter protocol** that enables smart devices to communicate appliance level energy data directly to the smart meter. The protocol would be vendor neutral and publicly documented, ensuring broad interoperability and long-term sustainability. Data exchange would be strictly read only, with no device control performed via the smart meter, preserving its neutral role within the energy system. Participation would be explicitly opt-in, requiring clear consumer consent, and data would remain local by default, with no automatic export to central systems or third party platforms.

Privacy and trust are central to the proposed approach. Appliance level data would be stored locally within the smart meter for a short, clearly defined retention period, for example one to two months, sufficient to support forecasting and flexibility analysis while minimising long term data accumulation. Where aggregation is required, this would occur locally wherever possible. Any external data sharing would require explicit, informed consent from the consumer, and there would be no default transmission of data to energy suppliers, device manufacturers, or central data centres. The proposed protocol would be designed to **integrate with existing and emerging energy system infrastructure**, rather than replacing it.

Q4. Who would the users of the dataset be?

The **primary users** of the proposed dataset would be **AI developers and researchers** working on demand response, forecasting, and optimisation of residential and local energy systems. Access to appliance level energy data would support research into new AI methods and approaches by enabling rigorous evaluation under realistic operating conditions. In particular, the availability of device level ground truth would strengthen the validation of models, assumptions, and analytical procedures used across energy system research, including those underpinning performance assessment and certification practices.

These datasets would also be of significant value to **Distribution Network Operators (DNOs) and local system operators** responsible for managing low voltage electricity networks, where improved visibility of flexible loads can support congestion management and network planning. In addition, **energy suppliers and aggregators** could use the data to design and operate more effective flexibility services, enabling better alignment between consumer demand and system needs.

Secondary users would include **consumers**, who would benefit indirectly through improved tariffs, increased automation, and enhanced reliability of energy services, rather than through direct interaction with the dataset. **Local energy communities and peer-to-peer energy schemes** could also use insights derived from the data to optimise local generation, storage, and sharing arrangements, supporting more resilient and community led energy systems.

Although appliance level data would be stored locally by default, access to the data would be governed through explicit, purpose limited, and consent based arrangements. Energy companies, aggregators, and DNOs would access data only with user authorisation and, where appropriate, in aggregated or time bounded form. Researchers would access data through opt-in participation by households, for example as part of consented pilot studies or time limited data sharing for specific research purposes. End-users (households) would retain control over their own data, including the ability to authorise when and how their data is shared, for example by allowing a time limited release to a trusted service or authorised party, under clear governance arrangements. In neighbourhood or local energy market settings, access would be managed through agreed governance structures, with role based permissions and aggregation used to safeguard individual privacy.

Q5. What scale does the dataset need to be?

The dataset does not need to be national from the outset. An effective approach would be to begin with pilot deployments involving a limited number of households, focusing on specific high impact device classes such as EV chargers and heat pumps, and working in collaboration with selected DNO regions. The scale of the dataset could then be expanded incrementally as evidence is generated, for example through demonstrated improvements reductions in congestion or curtailment costs, improvements in AI-enabled applications, and clearer benefits for consumers.

This phased approach would help balance cost, risk, and feasibility while building a robust evidence base to justify wider adoption.

Q6. What would enabling AI use of this dataset unlock?

Enabling AI access to appliance level energy data would deliver significant **technical and system level benefits**. Improved visibility of how high impact devices operate would support more accurate household and local demand forecasting, allowing networks and service providers to anticipate peaks and manage variability more effectively. AI systems could schedule flexible loads more precisely, improving coordination between devices such as EV chargers, heat pumps, and batteries [3].

The proposed approach would also generate substantial **economic and environmental benefits**. By optimising the use of existing network infrastructure and flexible demand, system costs could be reduced, limiting the need for costly network reinforcement and constraint payments. Smarter load management would enable greater utilisation of low carbon generation, helping to reduce emissions, while improved visibility and coordination would facilitate faster connections of renewable and low carbon technologies to the grid.

Finally, the availability of open, standardised appliance level data would deliver important **market and innovation benefits**. Reducing dependence on proprietary manufacturer datasets would mitigate vendor lock-in and lower barriers to entry for new AI developers and innovators. This, in turn, would encourage the development of more competitive, interoperable, and consumer focused energy services, supporting a more dynamic and resilient energy ecosystem.

Q7. What would be the arrangements for ongoing maintenance, governance and curation?

Ongoing maintenance, governance, and curation would be designed to preserve the smart meter's neutral role within the energy system. The smart meter would act as a **trusted local data holder**, rather than a central data exporter, controller, or optimiser. Governance arrangements could involve relevant standards bodies defining and maintaining the protocol, alongside oversight from Ofgem and DESNZ to ensure alignment with regulatory and policy objectives. Clear documentation, version control, and update processes would support long-term interoperability and reliability. Longer-term considerations would include **defined data retention limits** and **clear deprecation pathways for obsolete datasets or standards**, ensuring the approach remains secure, adaptable, and futureproof.

References

[1] Energy security and AI, POSTnote 735, December 2024, https://post.parliament.uk/research-briefings/post-pn-0735/

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