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Perspective

Achieving the UN's sustainable energy targets through dynamic operating limits

Wayes Tushar,[1,*] M. Imran Azim,[2] Mollah Rezaul Alam,[1] Chau Yuen,[3] Rahul Sharma,[1] Tapan Saha,[1] and H. Vincent Poor[4]

SUMMARY

Despite the world's relentless efforts to achieve the United Nations' sustainable energy target by 2030, the current pace of progress is insufficient to reach the objective. Continuous support and development across various domains of the energy sector are required to achieve sustainability targets. This article focuses on the potential of dynamic operating limits to drive the world's sustainability efforts, specifically in addressing critical challenges of distribution networks of the power system by progressively setting the nodal limits on the active and reactive power injection into the distribution network based on data-driven computer simulation. While the importance of dynamic operating limits has recently been recognized, its crucial role in the residential energy sustainability sector, which requires a significant push to provide universal energy access by 2030, has not been adequately investigated. This perspective explains the fundamental concepts and benefits of dynamic operating limits in encouraging the adoption of distributed renewable energy resources in the residential sector to support the United Nation's sustainable energy objective. Additionally, we discuss the limitations of computing this limit and applying it to the electricity network and some motivational models that can encourage electricity customers to come forward to address the challenges. Finally, we explore new research and implementation prospects for designing comprehensive, dependable, accountable, and complementary dynamic operating limit programs to accelerate the attainment of sustainable energy targets.

INTRODUCTION

The United Nations (UN) has set a goal for providing access to electricity to every individual worldwide by 2030.[1] To achieve this goal, adopting environmentally sustainable methods of building clean energy facilities, such as solar and wind farms, and grid-scale energy storage is crucial. However, recent studies have highlighted the negative impact of building large plants on environmental sustainability, including adverse effects on human health[2] and ecotoxicity.[3] To address these concerns, the concept of prosumers, i.e., consumers with generation capacity,[4] has gained significant importance. Incorporating prosumers at the edge of the grid to contribute to the national energy mix has become critical for achieving the UN's sustainable development goals. Given this context, the Australian Energy Market Operator's recent Integrated System Plan forecasts a 5-fold increase in prosumers with distributed energy resources (DERs) in Australia in the near future.[5]

There are two general categories of mechanisms through which prosumers can contribute to the 7th goal of the UN's sustainable development goals, which is to provide affordable and clean energy.[1] In the first category, prosumers act as passive elements of the network, without independent decision-making capability. They inject excess electricity from their DERs into the grid at a set price[6] or without payment,[7] and participate in demand response through a contract, allowing the grid to control their DER either directly or indirectly.[8] In the second type of mechanism, prosumers become active elements of the network. They have the autonomy to decide on the energy surplus they want to share with the grid or other stakeholders and can independently negotiate a fair price for their contribution.[9] Additionally, they can share their demand response capabilities, known as "negawatts"[8] by controlling their flexible devices and offering intended services for a suitable price. The second mechanism, also known as peer-to-peer (P2P) sharing,[9] is gaining

[1]The University of Queensland, St Lucia, QLD 4067, Australia

[2]Monash University, Clayton, VIC 3800, Australia

[3]Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798, Singapore

[4]Princeton University, Princeton, NJ 08544, USA

*Correspondence: w.tushar@uq.edu.au

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popularity among prosumers due to the flexibility it offers in negotiating the price and the amount of service they provide in exchange. This mechanism allows prosumers to actively contribute to achieving the UN's sustainable development goals.

In both the aforementioned mechanisms, the ability to engage a large number of customers to export electricity has been restricted by the grid operator's fixed export limit, which is imposed to ensure network security and reliability. This is because when multiple prosumers export electricity to the network beyond a certain threshold, it can increase the bus voltage and current well above the recommended limits for network integrity. As a result, a fixed export limit, also referred to as the operating limit, is placed at customers' connection points to regulate this excessive power flow. For instance, in Australia—the global leader in rooftop photovoltaics (PV) adoption[10]—the limit is fixed at 5 kW for residential customers.[11] However, this limit is calculated based on worst-case scenarios,[12] which can sometimes be overly conservative and inadequate for customers and can potentially motivate them to withdraw from trading energy. Examples of such customer withdrawals from participating in energy trading can be seen in the Yeloha energy-sharing marketplace,[13] which launched a solar energy trading market in 2012 but was discontinued due to a lack of consumer participation.[14]

Given this context, it is important to seek solutions that can keep prosumers with DER engaged in exporting renewable energy to the grid by ensuring better revenue from trading and avoiding adverse effects on the network. A promising solution to this issue is the dynamic operating limit (DOL) - also known as the dynamic operating envelope[15] - a novel concept that enables extensive market participation from the bottom-up system level. DOL considers the available network or power system capacity as a whole and provides a range of active and reactive power set points, also known as nodal limits, on real and reactive power injection. These nodal limits guarantee that the physical and operational boundaries of the network remain uncompromised.[16] Unlike fixed export limits at customers' connection points, DOL allows for optimal utilization of the existing electrical infrastructure while ensuring compliance with network statutory limits. As a result, maximum network capacity can be allocated to different prosumers in near real time.[12] Thus, DOL also allows prosumers with DERs to bid in energy and reserve markets while maintaining the network constraints.[17,18] At the same time, it enables distribution network operators to omit the voltage and thermal violations and ensure the integrity of medium and low-voltage networks.[19,20] In Antic et al.[21] and Lankeshwara et al.,[22] the authors show how DOL can also help to increase the hosting capacity of the network and integrate more distributed generation into the network. Further, Hashmi et al.[23] show that risk-averse and robust DOLs can be determined based on only nodal voltage measurement or forecast. A demonstration of DOL and how it is different from traditional fixed export/import limits is shown in Figure 1.

The investigation into the impact of DOL on the provision of flexibility and grid services is still in its early stages and has not received sufficient attention in the global discussions on sustainable development goals. Therefore, this perspective aims to answer the question: is there a significant opportunity to be seized here? We argue that there is, by providing unique insights into how DOL functions in the distribution network and its alignment with the UN sustainable development goals. These insights underscore the need for greater attention to the challenge of determining DOL in a distribution network and motivating prosumers to continually contribute to the DOL calculation for the benefit of energy and environmental sustainability. This perspective begins by discussing how DOL can be estimated in a distribution network and reviewing its benefits in achieving sustainable development goals. We then address the challenges involved in determining the DOL, including accessing prosumers' data, and highlight selected motivational models that can encourage prosumers to share their privacy-preserved data to fulfill their own benefits and the UN sustainable development goal.

DOL

The DOL is currently calculated by a computer using actual data of various power system parameters, including the net customer demand and voltage levels at different feeder points. Typically, three-phase power flow analysis is employed alongside context-aware heuristics to establish the maximum export/import limit for prosumers. The term "context-aware" refers to assumptions about the prosumers' objectives, such as maximizing exports or minimizing costs when supplying electricity to the grid. Depending on how network data are utilized to compute DOL for customers in an electricity network, the methods of DOL calculation can be broadly classified as either model-free or model-aware.

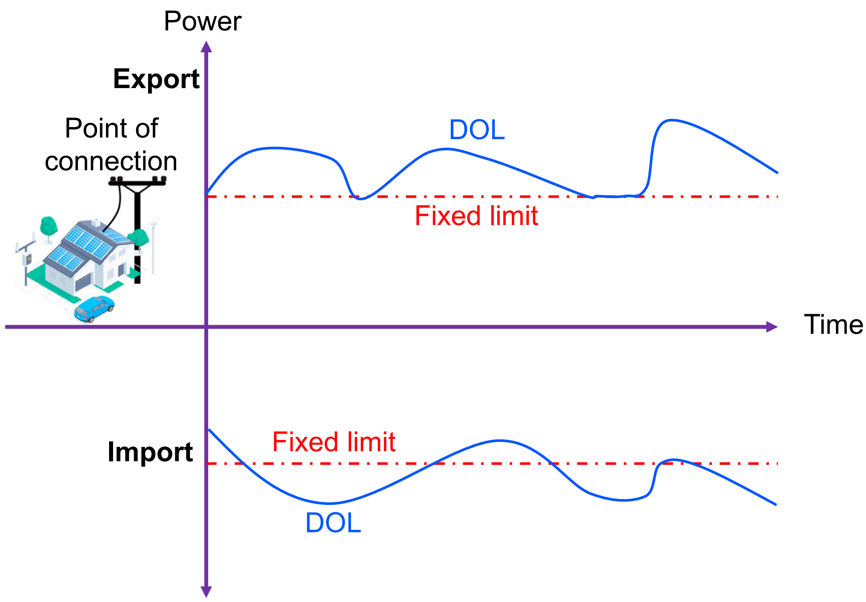

Figure 1. This figure shows how DOL sets different export and import limits for a prosumer compared to the currently established fixed export and import limits

Thus, DOL allows for optimal utilization of the existing electrical infrastructure while ensuring compliance with network statutory limits. The components used in the figure have been taken from a royalty-free source: pixabay.com.

Model-free method

In order to enable prosumers to export more electricity in a network where it is possible, DOL calculations require precise data regarding the electrical models of the low-voltage circuit, which include impedances, phase connectivity, and nodal placements.[24] However, this can be a challenging and time-consuming task. Consequently, some recent research has focused on developing algorithms and computation processes to estimate the maximum power export limit without relying on electrical models of low-voltage circuits. Because the model-free technique eliminates the need for conventional power flow analysis, it is faster than the model-aware DOL calculation method.

The model-free approach involves utilizing artificial intelligence techniques such as neural networks to understand the physics of a selected three-phase low-voltage circuit based on historical smart meter data. The neural network is trained using the energy demand and voltage magnitude data of individual customers from the past. After completion, the trained neural network can act as a substitute for conventional power flow analyses by capturing the physics of that specific network. The method for calculating operating envelopes to maintain safe voltage limits during export is developed independently. To verify if the export limits generated by a DOL algorithm fall within the statutory limits for a given network, the trained neural network is used to test the values. For a more detailed explanation of how smart meter data and neural network models can be used in a model-free approach to calculate safe operating voltages, please refer to Bassi et al.[25]

Model-aware method

Although the model-free approach offers faster calculations of operating envelopes with reasonable accuracy for low-voltage distribution networks, it requires smart meter data at each time interval for optimal power flow to determine DOL. A potential drawback is that the optimal power flow problem may involve numerous decision variables representing nodal voltages and power set points for end users, resulting in a computationally expensive process. Moreover, in many real-world low- and medium-voltage networks, only a limited number of meters are available, leading to partial or total unobservability due to meter failure or measurement deficiency at certain nodes. Consequently, there may not be enough measurement data to support the application of model-free estimation in distributed systems.[26] In such cases, model-aware methods are more suitable for DOL estimation as they are generally more robust and practical to implement. For instance, a model-aware model implemented in an Australian electricity network is described by Milford et al.[26]

The key stages in achieving DOL for a distribution network through a model-aware method, such as the one described by Milford et al.,[26] are distribution system state estimation and capacity-constrained state optimization. State estimation is a well-established analytical technique that can estimate node voltages and angles in power systems.[27,28] By minimizing errors through rigorous techniques, state estimation can provide accurate estimates of node voltages and angles in a power network. However, traditional distribution networks have limited visibility/observability due to minimum metering infrastructure. State estimation can identify unobservable locations and enable full observability by incorporating branch measurement devices in those locations. Thus, distribution system state estimation can effectively ensure accurate voltage and angle estimation, considering both theoretical and real-world aspects. For a more detailed explanation of how a model-aware approach calculates the DOL, please refer to Milford et al.[26] and Rigoni et al.[29]

BENEFIT OF DOL

Regardless of the method used to determine it, the primary advantage of DOL is its ability to maximize prosumers' exporting power limits to the electricity network while maintaining the network's physical security. Please note, in most time intervals, maximization yields increased export-power limits as compared to the fixed export limits which are in practice. The benefits of DOL are equally relevant to energy management schemes in which prosumers act as active (P2P trading) and passive (feed-in-tariff and net metering) components of the system. Nevertheless, since P2P sharing has been recognized as a more lucrative scheme than feed-in-tariff[6] and net metering[30] for actively involving prosumers in energy management, the ability of prosumers to actively negotiate prices and export energy quantities independently of the grid's set price has been improved; the remainder of this perspective will focus on how DOL can amplify the advantages of P2P and ensure the sustainable participation of prosumers in energy sharing. For this purpose, a simple dummy example and some case studies based on real data will be presented to illustrate the usefulness of DOL.

Suppose we have a hypothetical electricity network consisting of seven prosumers, each having a 10 kW rooftop solar system. Assume that at a given time, each prosumer has an 8 kW energy surplus, while the consumers' energy demand is greater than the available surplus. In this scenario, the P2P price is[31] AU$0.173 per kW. However, existing operating limits only allow each prosumer to export a maximum of 5 kW to the network, resulting in a total revenue of AU$0.865 and a maximum total benefit of AU$6.055 for a day.

With DOL, however, the maximum export limit for each prosumer can be set according to the network's physical and operational constraints, allowing them to contribute more renewable energy to the network without compromising its stability. Applying DOL to the previous example, if prosumers can safely inject their entire available surplus into the network, the total energy export and revenue would increase to 48 kWh and AU$8.304, respectively. By implementing DOL, each prosumer can inject an additional 3 kWh of clean energy into the network, resulting in an increase of AU$0.519 in revenue. This increase in renewable energy flow can translate into a reduction of 13,000 g of CO_2-eq, which would otherwise be produced by burning coal. This is based on the assumption that 1,000 g CO_2-eq per kWh is produced, in general, by burning coals.[32] These figures demonstrate the usefulness of DOL in maximizing the benefits of P2P trading and promoting sustainable energy management.

To evaluate the effectiveness of DOL-enabled P2P trading models in an actual electricity network setting, it is crucial to account for varying export limits that may be influenced by network conditions and prosumer behavior at different times of the day. To demonstrate this, we implemented a P2P energy trading algorithm for a 3-phase 0.415 kV Australian network, consisting of 102 single-phase houses. The distribution network was simulated using an OpenDSS-interfaced MATLAB platform, while the P2P algorithm was based on cooperative game theory as proposed by Azim et al.[33] DOL was calculated at different time intervals using the method described by Lankeshwara,[34] which involved solving the alternating current (AC) optimal power flow problem with the YALMIP toolbox (a MATLAB-based toolbox to model probably semidefinite prgramming). Network data were obtained from Lankeshwara,[34] while energy data for individual households were obtained from Cedi.[35] The study involved varying the magnitudes of power for houses with energy surplus (acting as sellers) between 0 kW and 10 kW, while power for houses with energy deficiency (acting as buyers) was varied between 0 kW and 5 kW.

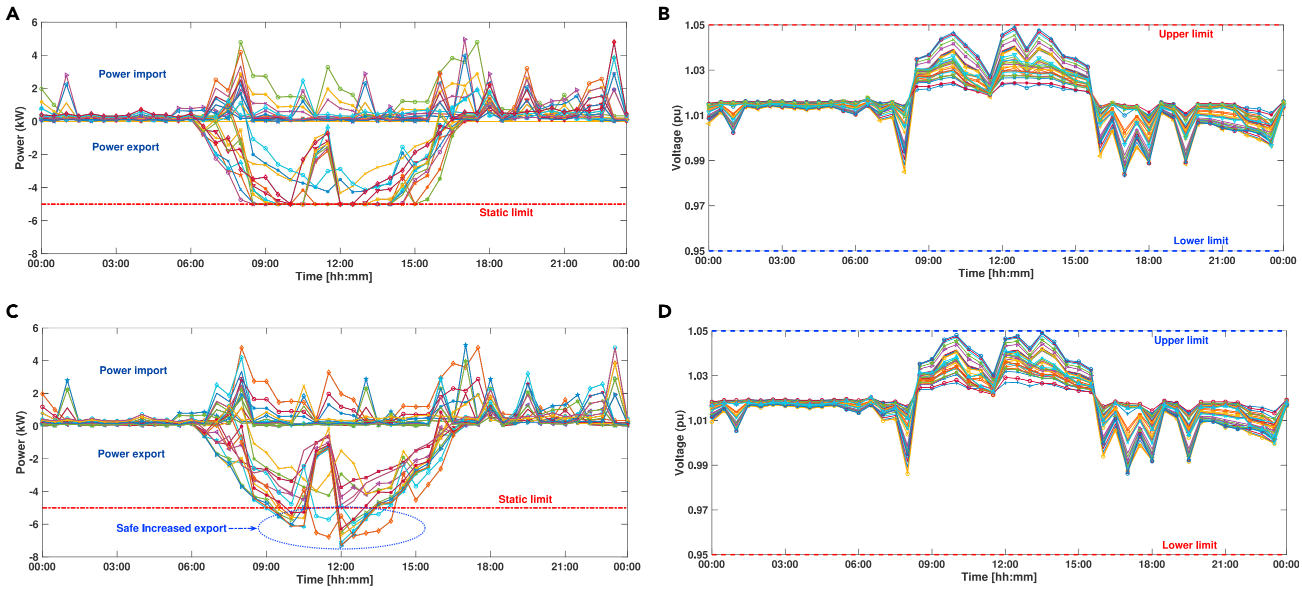

Figure 2. This figure shows how the dynamic operating limit enables residential households to export more of their surplus renewable energy to a network without compromising network security

The negative sign refers to the export amount of power while the positive sign indicates power import. The figure shows that the dynamic operating limit helps prosumers to achieve more economic stability and environmental sustainability with their existing renewable assets.

(A) In static operating conditions, if a household tries to export more than the threshold, the network operator overrides its inverter's export capacity and keeps the total export not more than the static operating limit.

(B) By forcefully keeping the export limit to a maximum of the fixed operating limit, it is ensured that the corresponding bus voltages do not violate the statutory limits.

(C) In a dynamic operating limit case, the limit on the maximum export changes over time depending on the network condition. Therefore, sometimes prosumers can export more than the existing fixed limit without compromising any power system constraints. As a result, more renewable energy flows within the network contributing to achieving environmental sustainability.

(D) This figure demonstrates that allowing prosumers more power to the network taking dynamic operating limits into account does not have a detrimental impact on the network condition. In other words, the voltages at the bus remain below the safe voltage limit for all participating prosumers allowing them to trade more with more economical and environmental benefits.

The surplus and deficiency of energy from prosumers and consumers, which are meant to be exported and imported to and from the electricity grid, are sent to an authorized distribution utility like a distribution system operator. The distribution system operator calculates the DOL using the intended energy data and the network data based on the physical locations of prosumers and consumers. This computation is done in two steps. In the first step, the distribution system operator conducts an AC power flow analysis to examine the network voltages and line loading. If there are no issues such as voltage rise, under-voltage problems, or line congestion, the intended surplus and deficiency amounts can be exported and imported to and from the electricity grid, respectively. This means that the permitted export and import amounts are equal to the intended surplus and deficiency amounts. However, if there are any network problems, the intended surplus and deficiency amounts are optimally adjusted in the next step.

In the second step, the distribution system operator performs an optimal power flow analysis to determine the maximum export and import amounts that prosumers and consumers can have while maintaining network integrity. The AC optimal power flow formulation considers the power limits of prosumers and consumers, system power balance, and power flow and operational constraints of the network. The goal is to assign DOLs as close as possible to the intended export and import amounts, minimizing the need for curtailment. As a result, the permitted export and import amounts are lower than the intended surplus and deficiency amounts. The computation of DOLs is carried out for all considered time periods by using time-series power flow analysis and, if necessary, optimal power flow analysis to always ensure network integrity.

Figure 2 illustrates how shifting from a traditional static threshold-based approach to a simulated operating condition-based approach for prosumer power export to the network can enhance the economic and environmental performance of the energy system and support the achievement of energy sustainability goals. The static threshold-based approach restricts prosumers with energy surplus from exporting more than a fixed threshold, which is 5 kW in the considered case, at any time of the day. If the export from any prosumer exceeds this limit, the network operator blocks their ability to export more to avoid exceeding the maximum allowed export, as shown in Figure 2A. This approach ensures that bus voltages remain within safe limits, as depicted in Figure 2B, and that the network condition is not compromised.

With DOL, the exchange of electricity in the same network and operating scenarios results in varying export levels for different prosumers. As demonstrated in Figure 2C, some prosumers export power beyond the traditional static operating limit of 5 kW at certain times of the day, such as between 10:00 and 14:30. However, unlike the static approach, these excess exports are not blocked by the network operator due to the implementation of either model-free or model-aware DOL techniques. These techniques calculate and set appropriate operating limits that enable prosumers to export power while maintaining network safety. For example, as shown in Figure 2D, exporting more than 5 kW does not breach any voltage limits at the network buses, demonstrating the efficacy of the simulated DOL in ensuring network integrity.

By incorporating additional energy from prosumers' DER into the energy mix, the DOL enables a higher influx of renewable energy into the network. For the case examined, the total power export increases by 43.94 kW (for single-phase connection) when the DOL is implemented. This increase, on the one hand, results in a reduction of total carbon emissions by 43,940 g, and on the other hand, prosumers can earn AU$7.60 more revenue compared to the traditional static operating condition scenario. It is important to note that these results are for a scenario with only 40 prosumers exporting their power to the network. With a larger number of prosumers, the benefits are expected to increase further on average.

DOL & HUMAN ENGAGEMENT

Realizing the economic and environmental benefits of implementing DOL is not a straightforward task. Transitioning from fixed limits to DOL poses various challenges, many of which are rooted in the difficulties surrounding customer data accessibility. For instance, a large volume of network information data is necessary to construct an appropriate network model for calculating the DOL at different times of the day. Unfortunately, such information is currently not readily accessible. However, with the rapid rollout of smart meters, it can be anticipated that these data will soon become available.

Consequently, the network operator will be able to access these data and develop algorithms for simulating and generating the DOL for customers.

In addition, it is crucial to take into account the ratio of demands from active and passive customers in the low-voltage feeder as it can impact the capacity of the feeder.[12] Thus, the accuracy of the DOL can be directly influenced by the precise prediction of these demands. Therefore, real-time insight into customer demand and generation data is necessary. However, concerns about data misuse and the potential for privacy and security breaches have made people hesitant to share their energy data. As a result, accessing these data in a legitimate manner and utilizing them to accurately estimate the DOL for the network have become a challenge.

Further, the head-of-feeder voltage serves as a reference point for the corresponding low-voltage feeder during the simulation to determine the DOL. Therefore, it is crucial to measure the head-to-feeder voltage accurately. This can be accomplished by installing monitoring devices in the distribution network and using the data from these devices to calculate the head-to-feeder voltage. However, this can also pose a challenge to customers connected to the specific low-voltage feeder as their power export and import behavior can affect the feeder voltage. Thus, continuous monitoring of this voltage may reveal customers' private information such as energy usage patterns, which raises privacy concerns.

Finally, to ensure the sustainable operation of energy management at the distribution level, it is crucial that network operators and customers collaborate effectively.[12] Therefore, a high level of commitment from prosumers, consumers, and the wider community is necessary. One way to achieve this is to create customized incentive schemes targeting specific participants. This is because different prosumers and consumers have unique circumstances and preferences when it comes to energy management. Consequently, a one-size-fits-all approach may not be effective in motivating all customers to participate in energy management. Hence, using customer data, such as energy generation, consumption, and their preferred price for energy sharing, incentives should be designed and tailored to each customer's individual needs to encourage their active participation.

Motivation for participation

After the preceding discussion, it has been established that customers' energy data are crucial in determining the DOL of a network and increasing renewable energy flow in the low-voltage network to achieve the UN's sustainable development goals. However, historically, customers have been hesitant to share their private data,[36] resulting in the termination of various energy projects in the past, such as the smart meter trial in Australia in 2014[37] and smart metering policy in the UK in 2020.[38] Therefore, finding a legitimate way to incentivize customers to share their data is critical for the successful implementation of DOL. While incentivizing customers with monetary payments has been the norm, recent studies, such as those by van der Werff et al.[39] and Tushar et al.,[40] have shown that factors such as environmental views, the impact of their choices on others, and repetitive positive impacts can also motivate customers. In short, if an activity or service can satisfy the attitude model, rational economic model, elaboration likelihood model, and positive reinforcement model, customers are more likely to engage in it. Hence, to determine whether customers will be motivated to share their private energy data for simulating DOL, it is necessary to evaluate how DOL aligns with the properties of the attitude model, rational economic model, elaboration likelihood model, and positive reinforcement model.

Let us provide a brief explanation of the key principles of the attitude model, rational economics, elaboration likelihood, and positive reinforcement models. The attitude model, as suggested by Shipwoth,[41] asserts that a person's willingness to undertake environmentally friendly actions is driven by their positive attitude toward the environment. This implies that individuals are more likely to act if they believe that their actions will have a beneficial impact on the environment. Therefore, if people can comprehend that sharing their energy data will facilitate network operators to generate simulated DOL for better environmental sustainability, they are more inclined to share their data. The rational economic model, on the other hand, focuses on how economic benefits can influence people's actions toward environmental sustainability.[41] For instance, the additional revenue that can be earned through the use of DOL during energy trading may encourage customers to make pro-environmental decisions continuously and enjoy long-term benefits. In contrast, the elaboration likelihood model[42] highlights the importance of clear communication when engaging people in environmental sustainability. The model acknowledges that people's eagerness to participate in environmentally friendly actions can be jeopardized if the communication process is not clear. Therefore, either the central path or peripheral path[43] must be used to communicate with energy users, informing them about the importance of sharing energy data and the benefits they will receive (monetary and environmental). Finally, the positive reinforcement model refers to the favorable stimuli that an energy user can receive when sharing their data for simulating DOL. As the user repeatedly shares their energy data with the network operator and sees that it has helped calculate DOL, they benefit both financially and environmentally, which encourages them to continue sharing their data.

In the example illustrated in Figure 2, the implementation of DOL leads to a promotion of environmental sustainability as prosumers connected to the three-phase network are able to export an additional 131.81 kW of renewable energy to the grid, reducing CO_2-eq emissions by 131.81 kg to meet customers' energy demands. This surplus renewable energy capacity also enables participating customers to earn additional revenue by selling power to other consumers or to reduce their electricity bills by purchasing more power from the prosumers. For instance, assuming a P2P energy price of AU$0.173 per kWh,[31] a feed-in-tariff price of AU$.06 per kWh,[44] and a grid energy price of AU$255 per kWh,[45] prosumers in a three-phase connection in a residential network can make an extra AU$22.803 by selling the surplus export power to the customers, while the consumers can save AU$25.703 by buying this power from the prosumers instead of purchasing it from the grid at a higher cost. The performance of DOL in enabling higher exports in the local energy market is always better or at least similar to that of the case without DOL, thus meeting the requirements of the attitude, rational economic, and positive reinforcement models.

Nevertheless, to persuade customers about the importance of DOL in promoting environmental sustainability and the benefits of prosumers sharing power with one another, it is crucial that customers are clearly informed about how DOL aligns with different motivational models. The central route is appropriate for

Table 1. This table summarizes different challenges of engaging prosumers in sharing their energy data and how the DOL satisfies different motivational models to address that

Challenges	Appropriate motivational model	Further reading
Enabling prosumers to take environmentally friendly action of sharing data for determining DOL.	The attitude model, according to which, individuals' inclination to engage in environmentally friendly actions is influenced by their positive attitude toward the environment. In other words, if people can understand that sharing their energy data enables network operators to create DOL for enhanced environmental sustainability, they are more likely to be willing to share their data.	Shipworth[21]
Influencing the participation of prosumers through economic incentives.	The rational economic model concentrates on the influence of economic benefits on individuals' behaviors regarding environmental sustainability. According to this model, the potential for additional revenue generated through the utilization of DOL during energy trading can serve as a continuous incentive for customers to consistently make pro-environmental choices and reap long-term advantages.	Shipworth[21]
Appropriately communicating with prosumers to motivate them to share their data.	The elaboration likelihood model emphasizes the significance of effective communication in engaging individuals in environmental sustainability efforts. The model recognizes that people's willingness to participate in environmentally friendly actions can be compromised if the communication process is unclear. It is essential to employ either the central path or peripheral path to communicate with energy users, informing them about the significance of sharing energy data and the monetary as well as environmental benefits they stand to gain.	Hockenbury,[42] Petty et al.[43]
Creating positive stimuli for prosumers to continuously share their energy data.	The positive reinforcement model pertains to the positive stimuli that an energy user can experience by sharing their data for simulating DOL. As the user consistently shares their energy data with the network operator and observes the tangible benefits it brings, both in terms of financial gains and environmental impact, it serves as a motivation for them to continue sharing their data.	Tushar et al.[40]

conveying the message when individuals are already concerned about an issue and have access to unambiguous information. This method is therefore suitable for cases where technologies have been available in the market for some time and the benefits of using them are well established. However, DOL is a recent phenomenon that has recently been adopted in countries like Australia,[16] Canada,[29] Croatia,[21] Belgium,[23] and a few other countries with significant behind-the-meter DER penetration. As such, encouraging customers to share their energy data to simulate DOL should be done using the peripheral route, by demonstrating published case studies on the benefits of DOL and explaining how customers can participate by sharing their data. A summary of how DOL can engage prosumers to share their energy data by satisfying different motivational models is shown in Table 1.

Several energy industries are currently working toward implementing DOL in their distribution networks. For instance, Energy Queensland, the primary distribution network service operator in the State of Queensland, Australia, is in the process of implementing DOL.[46] In Victoria, AusNet Services is collaborating with the University of Melbourne to introduce this technique in their distribution network.[47] Similar initiatives can also be observed in the Australian Capital Territory.[48] These examples clearly demonstrate that customers are aware of the influence of their data in calculating such models and are interested in assisting the distribution grid's

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adoption of renewable energy sources while maintaining grid security. Advancements in data privacy and security tools and techniques[49] have increased people's confidence in sharing their data, compared to the past. Further, there is an ongoing discussion in the government about defining policy and regulations for customers' energy data sharing and use.[50,51] Therefore, it is reasonable to expect that DOL will continue to be integrated into future distribution networks, contributing to the achievement of the UN's sustainable energy targets. Furthermore, DOL plays a crucial role in relaxing the strict constraints on existing energy export mechanisms, such as P2P sharing,[31] without introducing additional complexity to the platform or users' decision-making process. Hence, implementing DOL in the power system is a viable and practical application.

Future challenges

As more customers adopt DER, simulating the DOL based on their energy data requires a massive amount of data. Additionally, coordinating various flexible devices within homes and buildings adds to the complexity. Furthermore, the calculation of the optimal power flow, which is crucial in computing DOL,[52] becomes more difficult with the inclusion of discrete decision variables. This is due to the increased computational power required as the number of decision variables grows.[53] Consequently, meeting the substantial computational demands presents a challenge in computing DOL based on customers' energy data. In this context, quantum annealers have emerged as a relevant solution for addressing the computational overhead of power sector-related challenges. Specifically, they have the potential to tackle large-scale computational challenges related to operational flexibility,[53] thus, facilitating energy trading within the local electricity market.

Another challenge of implementing DOL for energy sharing in the local electricity market is determining which approach is best for calculating the DOL. The model-free approach relies heavily on customer smart meter data, which is dependent on customers' willingness to share their data with the network operator. Although DOL can motivate customers to share their data for improving energy trading, accessing such data may require multiple legislative approvals due to strict governmental regulations in some countries and can be time consuming. In such cases, model-aware DOL may be a more appropriate approach. However, accurate distributed system state estimation is critical for calculating the DOL since traditional distribution networks typically have minimum meters with limited observability. Therefore, both techniques have their advantages and disadvantages, and selecting the appropriate approach for calculating the DOL based on the operational context and the electricity network is essential to ensure a sustainable and reliable service.

It would be of considerable interest to explore how the integration of both model-free and model-aware approaches can enhance the performance of DOL. Currently, a model-free approach based on neural networks, as proposed in C4NET[24] and Bassi et al.,[54] can rapidly estimate accurate voltage and subsequently implement DOL utilizing smart meter data at a significantly higher computational speed—approximately 200 times faster than the model-aware approach. However, employing a model-free approach may lead to erroneous DOL estimates when information about topological changes in the network is lacking. In real-world scenarios, network topology changes can occur due to reconfiguration, reconductoring, or new customer connections.[54] On the other hand, a model-aware approach, leveraging precise network models and smart meter data, avoids such errors.[18] Nonetheless, the computational cost is relatively higher in this case.

By integrating model-free and model-aware techniques, it could be possible to achieve greater flexibility, reducing the computational burden and enabling the combined model to adapt to different networks with or without topological changes. For instance, by combining model-free and model-aware approaches, DOL at the customer's end can be estimated at short intervals of 1–5 min, leveraging the fast computational speed of the model-free approach. Meanwhile, topological changes can be identified on a less frequent basis, such as every hour, by comparing the estimated DOLs from the two approaches. Significant differences between the estimations can trigger updates to the model-free neural network approach. However, further advancements in current DOL technology are necessary to transform this into a practical reality.

CONCLUSION

This perspective highlights how DOLs can make a significant contribution to achieving the UN's sustainable energy target by 2030. We contend that homes equipped with DERs hold significant potential in meeting this objective, and a DOL derived from customers' energy data can serve as a critical tool in this effort. We acknowledge the challenges associated with calculating the DOL for a specific electricity network, given the sensitivity of customers' data. Nevertheless, we assert that the DOL can serve as a compelling incentive for individuals to willingly share their energy data. This motivation stems from the tangible advantages it offers to customers, aligning with various motivational models such as attitude, rational economics, elaboration likelihood, and positive reinforcement. Additionally, we highlight two significant challenges that must be overcome to facilitate the widespread implementation of DOLs in the electricity sector. These challenges encompass the increasing computational requirements and the identification of an appropriate DOL technique. Addressing these challenges will be crucial in enabling the United Nations to attain its sustainable energy objectives by 2030.

The idea of dynamically determining the lower and upper limits for power export can be extended to other fields such as wireless communications and transportation. In wireless communication, for instance, the water-filling method is employed to distribute power across communication channels and assigns different power levels to individual users based on channel capacities.[55] The water-filling method shares the same principle as DOL to determine the maximum power allocation per channel, enabling users to utilize them effectively.

Moreover, the DOL concept can be utilized to assess traffic conditions in congested areas, aiding drivers in selecting alternative routes through vehicle-to-vehicle communications. By leveraging real-time traffic information during peak hours and historical data, artificial intelligence can analyze traffic flow in different directions within heavily congested areas. This analysis can prioritize specific lanes for vehicles by appropriately using traffic lights, effectively mitigating delays. However, it is important to note that the application of DOL is still in its early stages. As the technology continues to mature, its fundamental insights will likely find further applications in various disciplines.

LIMITATIONS OF STUDY

This research examines the significance of DOL in attaining the UN's sustainability energy goals and explores the effectiveness of motivational models in obtaining customers' confidential energy information to calculate DOL with precision. Nevertheless, it does not give sufficient emphasis to potential remedies for situations where there is a large customer base, and some individuals may intentionally falsify their energy data to increase their earnings. It is crucial to establish explicit guidelines on how customers can share their data and develop methodologies to verify the authenticity of the data. However, this aspect is not addressed in this study. It presents an opportunity for future research to extend the scope of this investigation.

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AUTHOR CONTRIBUTIONS

Conceptualization: W. T.; Writing - Original Draft: W. T., M. I. A. and M. R. A.; Writing - Review & Editing: C. Y., T. S., R. S., and H. V. P.; Supervision: C. Y. and T. S.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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