Putting a CO_2 Figure on a Piece of Computation

Conor Kelly
Dept. of Computer Science & Informatics
University College Dublin / Microsoft Ireland Research
Dublin, Ireland
conor.kelly3@ucd.ie

Eleni Mangina, Antonio Ruzelli
Dept. of Computer Science & Informatics
University College Dublin
Dublin, Ireland
{eleni.mangina, ruzzelli}@ucd.ie

***Abstract*—In recent years, energy efficiency has become a major focus of data centre designers and operators. This has predominantly been due to the rising cost of energy and the exponential increase in the absolute energy consumption of data centres. As carbon taxes, emissions trading and environmental imperatives become an increasing influence in the regions in which data centres are based, measuring and controlling the emissions resulting from the energy consumed in a data centre will become as important as controlling the energy consumption itself. In this paper, two bodies of research are investigated: granular energy monitoring in data centres and electricity generation emissions calculation. We propose a method to accurately calculate the emissions caused by a single piece of computation by correlating the two areas. It is shown that a saving of 45% of the resultant emissions of scheduling a piece of computation can be made by choosing one of two contrasting times with different marginal power plants on the Irish electricity grid. This saving increases to over 99% at times when wind generation is being curtailed.**

Keywords-component; datacentre energy, data centre emissions, emissions trading;

I. Introduction

THE amount of carbon emissions directly attributable to a piece of computation can be calculated by multiplying the amount of electricity the server consumed due to this computation by the emissions per kWh the generation of that electricity released. This requires two pieces of information:

1) How many kWh were consumed by the computation

2) How many grams of CO_2 were emitted per kWh generated on the grid

The emissions attributable to the electricity being consumed by the data centre is a function of all of the power generation sources feeding into the electricity grid from which the data centre is drawing power. Such a measure is called the carbon intensity of electricity and can be quantified in gCO_2 / kWh [1] [2]. The carbon intensity is an average figure for the entire grid however. To get the exact figure for the CO_2 that will be emitted due to the extra generation required for this piece of computation, should we choose to schedule it, we need to know what power plant will supply the extra demand. This can be established with some freely available information about the electricity market.

An extended figure of Emissions Intensity can also be calculated to include other polluting gases released such as carbon monoxide, methane and nitrogen oxides. However, carbon dioxide is the most common subject of emissions taxes and trading and so has the largest financial implications for energy generators and consumers. The *State and Trends of the Carbon Market 2010* report from the World Bank shows the global carbon market grew to $144 billion in 2009 [3]. Carbon dioxide is also by far the largest greenhouse gas (GHG) emitted by volume of the six GHGs covered by the Kyoto Protocol, representing about 80% of these gases associated with airborne pollution [4]. For these commercial and environmental reasons, carbon dioxide will be the primary focus of this paper.

The layout of this paper is as follows. Section II investigates related work in the area of energy monitoring and control in data centres. Section III proposes a method to measure the electricity consumption of a piece of computation. Section IV discusses electricity grid emissions and how these can be used to get an accurate measurement of the emissions attributable to a piece of computation, and Section V concludes the paper.

A. The Cost of Carbon - Why Large Electricity Consumers Should Worry About Emissions

On January 1st, 2005, a carbon dioxide Emissions Trading scheme was introduced in the EU. This covers a region of the world that accounts for about 20% of global GDP and 17% of the world's energy related CO_2 emissions [5]. It was the first such scheme to be attempted on such a scale. One main observation of Ellerman and Buchner [6] is that the biggest shortage of emissions allowances falls in the electricity utility sector. This will result in increased electricity costs from sources with high emissions. The success of this scheme makes the model a likely candidate for implementation by other regions around the world looking to limit emissions, particularly if a global agreement comes into force at some point in the future.

II. Related Work

A. Granular Energy Monitoring in Data Centres

It can be clearly shown that the electricity consumption of a server increases as it performs computation. In "The Case for Power Management in Web Servers" [7], Boher et al. measure the power consumption of a server's various hardware components while loading it with a real life server workload. In their measurements, visualised in figure 1, an unloaded CPU

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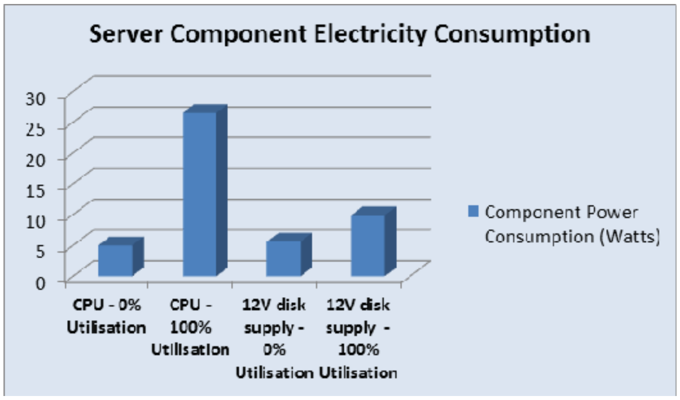

Figure 1. Showing the increase in energy consumption of a Server's CPU and hard disk between 0% and 100% utilisation as measured in [7].

consumed 5.0 Watts of power. At 100% utilisation, the consumption jumped to 26.5 Watts, an increase of 430%. The consumption of other components such as the disks and memory also increased under load, although less markedly.

B. *Measuring Energy Consumption of an Application - Current State of the Art*

A great amount of research has been dedicated to measuring, modeling and reducing the energy consumption of data centres. Most of this effort has been directed at the hardware components and power control of the servers – server virtualisation and consolidation etc.

Chen et al. [8] investigate server-power control methods to reduce energy costs for data centres when utilisation is low. They measure the effectiveness of automatically consolidating workloads and shutting down servers and/or modulating their operational speed to minimise electricity consumption while meeting the required SLA. They conclude their algorithm can save data centres $43 per server per year, or $219K per year for an enterprise-level data centre with 5000 servers. Voltage and frequency scaling is another popular method of reducing power consumption. Power savings of up to 30% are achievable with only a small drop in response times using a voltage scaling policy [7]. Talwar et al. [9] attempt to deal with power consumption in a data centre in all its forms – power delivery, electricity consumption, and heat management – together rather than separately. They cite an IDC report showing that worldwide spending on enterprise power and cooling to be more than $44 billion in 2010 and is likely even to surpass spending on new server hardware [10].

More recently, attempts have been made to develop algorithms to model, estimate or measure the energy consumed by individual applications running on servers. With the rise of cloud computing, the way in which servers in data centres are used has changed. The move towards machine consolidation onto virtual machines, several of which will run simultaneously on one server, means measuring electricity consumption at the server level is insufficient; measuring energy consumption at the thread or application-level gives data centre operators knowledge of not just where the energy was spent, but who was responsible for the energy consumption [11].

Mantis [12] is an algorithm for measuring the power consumption of each hardware component in a server. When an initial calibration of the model is complete, the algorithm can derive accurate predictions of overall and component-level power consumption. It uses a range of available performance monitoring information including OS event information such as perfctl and perfmon [13]. Resultant measurements are successfully validated using a data acquisition board which measures electricity consumption by the CPU, memory, hard drive, network devices and peripherals. The initial calibration phase is a cumbersome drawback to this method however.

The shortcomings of using older server-level power measurement methodologies for data centres employing virtual machine technology, and the challenges of creating an accurate virtual machine level power-measurement model, are outlined in *Virtual Machine Power Metering and Provisioning* [14]. *Joulemeter*, an application which uses existing instrumentation in server hardware and hypervisors to measure virtual machine (VM) level power to a higher degree of accuracy than existing methodologies, achieves errors within 0.4W – 2.4W. The model is essentially a summation of a VM's power footprint on each significant hardware resource. Joulemeter does not require pre-collected or calibrated information on hardware or operating systems and this is what sets it apart from other application-level power monitoring applications (*Mantis* for example). It uses the measured power to successfully implement VM power capping on server traces from several thousand real-world servers hosting Microsoft's cloud applications.

Embedded event counters alone (e.g. processor performance counters) can be used to investigate the energy usage patterns of individual threads [15]–[17]. Counters embedded in the target hardware are used to register events that imply the consumption of a certain amount of energy.

Because of a limitation in the number of available counters and in the difficulty and overhead of measuring them, approximations when using such counters are sometimes necessary. However, with the increasing interest in energy accounting systems, it is expected that future hardware generations will provide a rich set of event counters which will allow very accurate, low-overhead tracking of application-level power consumption [15]. For this reason, this paper believes that performance counters will prove to be the most cost-effective way of ascertaining application-level power consumption in the medium term.

Some ways have been proposed in which applications can become energy aware in order to dynamically react to their energy context. For instance, an application hosted in a data centre may decide to turn off certain low utility features if the energy budget is being exceeded, or an application on a mobile device may reduce its display quality when the battery is low [18]. *Fine-grained energy profiling for Power-Aware Application Design* [18] proposes a system, using Windows Performance Tools [13], which would allow developers to view and compare the energy implications of different calls while writing code. It does this by summating the energy consumed

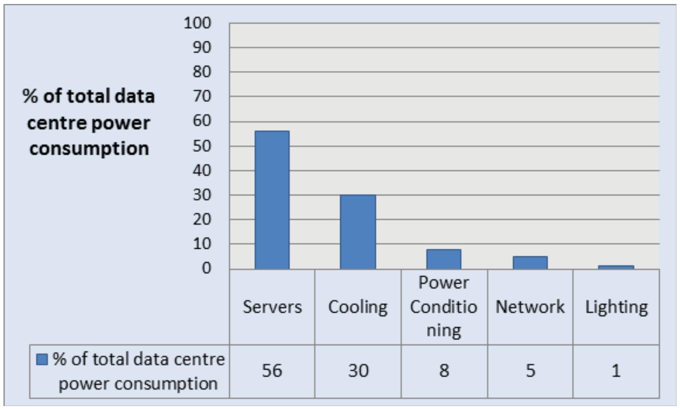

Figure 2. Showing the breakdown of the sources of data centre energy consumption [20]. The percentage of energy consumed by cooling in data centres utilising free air cooling will be considerably lower but this will be reflected in the PUE figure, which will still allow accurate computation of the non-server power consumption at the software application-level.

by the various subsystem components inside a machine in order to process the code. If nothing else, this highlights the opportunity seen in application-level energy savings. Energy Aware Applications are applications which dynamically modify their behavior to conserve energy. The main consideration is the trade-off between energy consumption (e.g. price) and user experience. When energy is plentiful, application behavior is biased toward a good user experience; when it is scarce, the behavior is biased toward energy conservation, achieving power savings of up to 50% [19]. This is a common decision facing web server operators when provisioning capacity. A balance must be struck between capacity cost and meeting users' requests in a reasonable time.

In summary, this body of existing research can be broken into three categories. The first and second categories deal with various methods of reducing energy consumption at the data centre level [7]–[9] and at the software level respectively [18], [19]. The third, which is of most interest to this paper, is that which measures energy consumption at the granularity of individual applications or virtual machines [11], [14]–[17]. This requirement has only recently emerged and papers use a variety of methods to calculate the energy footprint of applications. These initial efforts either lack the accuracy required to base commercial decisions upon, or impose too large a resource footprint on the server, and so are not yet practical. With commercial-level accuracy in mind and with the aim of minimising cost and server resource footprint, this paper believes that a model based on performance counters represents the best way to measure application-level energy. As energy consumption increasingly becomes a concern in future hardware design, richer sets of event counters will allow very accurate, low overhead tracking of application-level power consumption. For a more general approach that could be used on hardware without sufficient performance counters, approximation models like *Joulemeter* are an acceptable compromise.

III. CALCULATING THE ELECTRICITY CONSUMPTION OF A PIECE OF COMPUTATION

Increasing utilisation of computing resources also indirectly increases the energy consumption of a data centre. This can take the form of increased cooling requirements, energy lost in power supply units, energy consumed by networking devices and various other small losses. Figure 2 shows a breakdown of the major sources of power consumption inside a data centre and gives a good indication of where the indirect power consumption of a piece of computation will occur.

The sum of these loads is summarised in the form of a data centre's Power Usage Effectiveness or PUE. This figure is the ratio of power consumed by the entire data centre to the power consumed only by the servers, known as the critical power. A data centre with a PUE of 1.5 means that for every 1 watt of electricity consumed by the servers, 0.5 watts is consumed to provide cooling, power supply, networking and other functions. This summary figure removes the need to calculate each one of the sources of consumption separately.

$$\mathrm{E}comp = \mathrm{E}server \times PUE \tag{1}$$

Thus, to calculate the total energy consumption of a piece of computation, $\mathrm{E}comp$ (kWh), in a data centre after we have measured or calculated its direct electricity consumption on a server $\mathrm{E}server$ (kWh), we need only multiply it by the PUE for the data centre. For example, if the running of an application was calculated as having consumed 5kWh on a server in a data centre with a PUE of 1.5, then the total figure for the computation would be 7.5kWh.

IV. ELECTRICITY GENERATION EMISSIONS CALCULATION

A. *Equating the Energy Consumption Figure to a CO_2 Emissions Measure*

To measure the emissions per kWh consumed by a data centre, the carbon intensity of the electricity entering the data centre must be calculated. Bulk electrical power production comes from many sources, each with different characteristics including the fuel type and cost, and the efficiency of the power plant. The generation sources (i.e. Power Plants) on a grid can vary significantly and with it, the carbon intensity. Figure 3 shows the carbon intensity over a 24 hour period of Ireland's Electricity Grid. The rate of carbon emissions is calculated in real time using the generator's MW output, the individual heat rate curves for each power station and the calorific values for each type of fuel used. The heat rate curves are used to determine the efficiency at which a generator burns fuel at any given time. The fuel's calorific values are then used to calculate the rate of carbon emissions for the fuel being burned by the generator [1]. Taking the average CO_2 figure does not accurately represent the CO_2 emitted due to the piece of computation. To get this figure, we need to get the carbon intensity of the marginal unit of electrical power, i.e. the extra

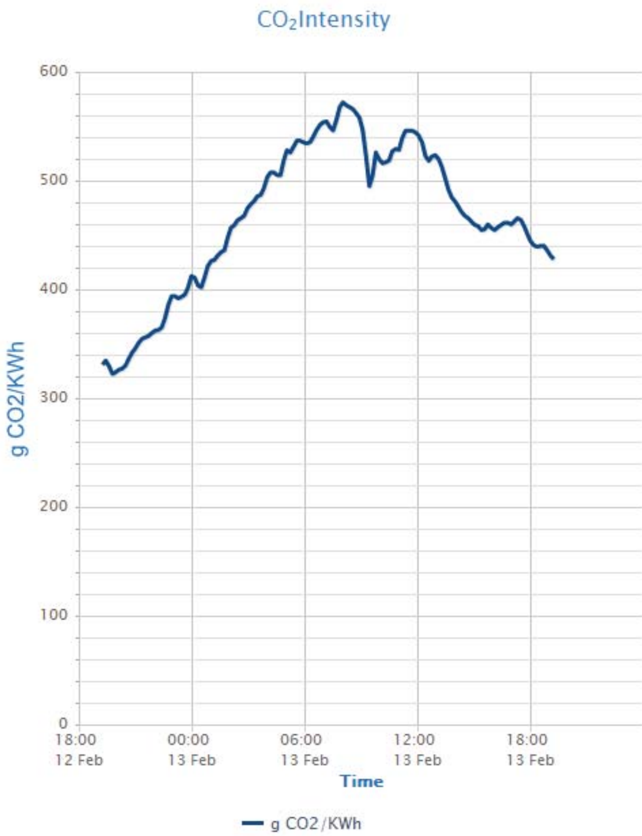

Figure 3. The CO_2 intensity of a 24 hour period on the Irish National Grid shows CO_2 intensity almost doubling during the course of one day. As demand increased and wind generation decreased, more fossil fuel power plants were brought online which increased the emissions per kWh generated.

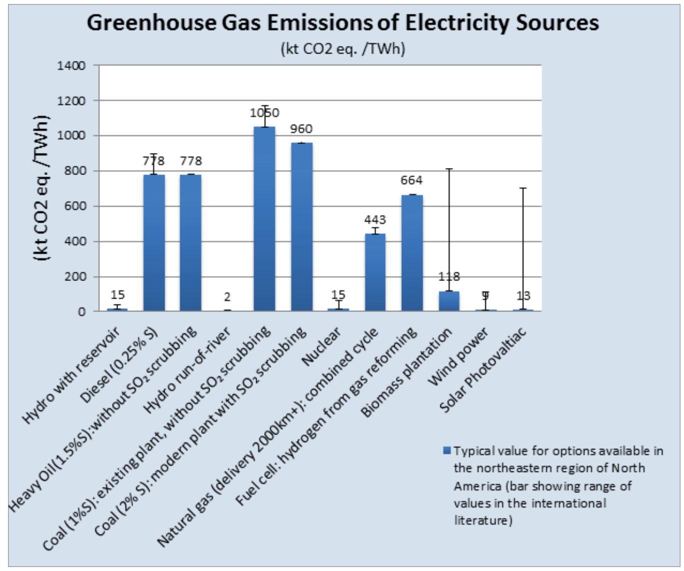

Figure 4. A comparison of carbon dioxide emissions of various electricity generation sources, collated from life-cycle assessments (LCAs) carried out around the world. A life-cycle assessment is an environmental assessment of all of the steps involved in creating a product including extraction, processing and transportation of fuels, building of power plants, production of electricity and waste disposal. [21].

carbon emitted if one more unit of electrical power was produced.

B. How Power Plants are Scheduled and How This Dictates the Price and Emissions of the Next Required kWh

Power plants are typically scheduled according to an augmented auction between power suppliers. Power plants first submit bids to reflect their costs of production. Capacity is then scheduled iteratively by the market operator from the next cheapest supplier until the total electrical demand is met at the least cost. The marginal price is the price of the most expensive generator currently supplying electricity to the grid, and this is the price paid to all suppliers for their electricity for that hour (or other time period). In this way, the market price will vary to reflect the level of demand.

Different generators will have different technical and economic characteristics. Conventional thermal plants can vary their output in response to demand, within certain limits. Wind plants can only produce up to the amount of wind production which is available at that instant, but a wind farm operator has only to consider its fixed costs (i.e. construction and maintenance), because its fuel is free.

Conventional generators are subject to a cost of starting, a no-load cost, i.e. the cost to overcome losses in the plant, and also a cost of production that is non-linear with respect to output, making it cheaper per kWh to produce 2 kWh than to produce 1kWh [22]. This means that their average cost is a complicated function of output.

Because wind and other, similar renewables have zero cost for their fuel, it is always in their interest to sell generation when it is available. To do this, they bid a price of zero on the electricity market. This means electricity generated from renewable power station will always be taken when it is available unless constraints on the power system limit its contribution. These constraints are to do with maintaining frequency and stability on the grid, the minimum operating levels of scheduled thermal units, and the ramp up ability of remaining power plants to meet a sudden drop in renewable generation [23] [24]. These periods have been experienced in areas with high wind penetration levels such as Ireland, and are a very interesting case. At times when wind contribution to the grid is being curtailed, it becomes the marginal generation on the grid. Extra demand will be supplied by the surplus wind energy available. Flexible electricity consumers can choose these times to increase demand if they wish to lower the effective emissions of the electricity they use.

We can use the market information discussed above, which is typically published by market operators, to work out the marginal power plant on the grid. That is, the last power plant to be added and the power plant that will generate the additional electricity required should our data centre schedule some computation. If exact emissions figures are not published by the market operators, two approximations can be used: an approximation based on average CO_2 emissions figures for the

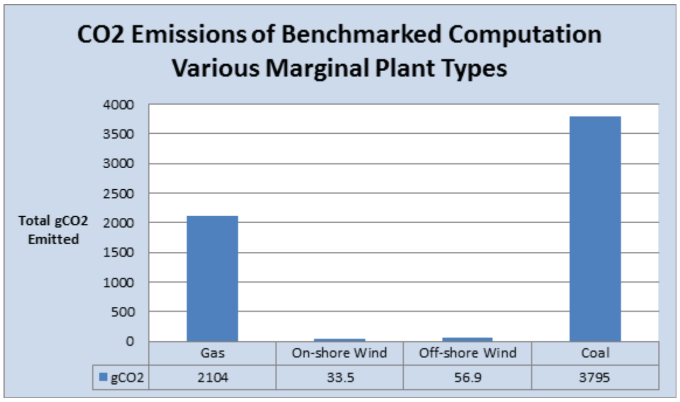

Figure 5. CO_2 Emissions of a Benchmarked Computation job for various Marginal Plant types on the Irish electricity grid. Power Plant emissions figures from [25] and [28].

TABLE I. THE EMISSIONS PRODUCED BY THE SAME COMPUTATION JOB WITH FOUR TYPES OF GENERATION SOURCES AS THE MARGINAL PLANT ON THE IRISH ELECTRICITY GRID

Marginal Power Plant Type	*Emissions for this plant type (gCO_2 / kWh)*	*Total Emissions for computation job (gCO_2 / kWh)*
Gas	610	2104
Coal	1100	3795
On-Shore Wind	9.7	33.5
Off-Shore Wind	16.5	56.9

given marginal plant type; or an approximation based on the average carbon intensity of the electricity produced on the grid.

If the power plant type of the marginal plant is known, approximate CO2 figures can be used for emissions from plants of that type. Figure 4 shows the Greenhouse Gas emissions of various electricity generation sources. There is a huge range for these figures in the literature [21], [25]-[28], which can be attributed to variations in plant and fuel efficiencies.

If no power plant specific information is available on an electricity grid, the second approximation that can be made is based on the average carbon intensity of the electricity being produced on the grid. An inefficient marginal plant will exert an upward pressure on the average carbon intensity, and so higher carbon intensity will usually indicate higher emissions from the marginal plant, and therefore higher emissions would result from scheduling energy consuming computation.

C. Calculating Emissions

Now that the total energy consumption of a piece of computation can be measured, and the emissions of the extra electricity required for this piece of computation can be calculated, we can make an accurate prediction of the emissions that a single piece of computation will create. This is given by

$$\Im Comp = \mathrm{E}Comp \times \Im MU \qquad (2)$$

$\Im Comp$ represents the emissions generated by the computation in gCO_2, which equals the energy consumed by the computation in the data centre, $\mathrm{E}Comp$ (kWh) multiplied by the emissions of the marginal power plant, $\Im MU$ (gCO_2 per kWh).

We can use this calculation to show the variability of emissions generated by the same piece of computation at different times on the Irish electricity grid, for which we have historic scheduling information.

Figure 5 uses the energy consumption of one particular application to display the emissions which would have been produced by a hypothetical computation job at various times on the Irish electricity grid. The emissions figures for four types of plants used on the grid are shown in table I.

These figures represent the full life-cycle greenhouse gas (GHG) emissions as surveyed by Schleisner [25] and Weisser [28]. The total energy consumption of the computation job is calculated at 3.45kWh. “The Benefits of Event–Driven Energy Accounting in Power-Sensitive Systems” [15] records a power consumption of 46 watts for a benchmarking workload running 800 million instructions per second. Scaling this up to 50 servers for one hour gives us a server energy consumption of 2.3kWh. Assuming a data centre PUE of 1.5 for the data centre in which we run the computation job, this results in a total energy consumption of 3.45kWh.

The results of this calculation show the very large variance of emissions produced by the same computation job scheduled at different states of an electricity grid. If the computation is scheduled when the coal plant is the marginal unit, meaning it will provide the electricity required for the computation, the total resultant emissions are 3.79 Kg CO_2. Scheduling the job at a time when the gas plant is the marginal unit results in 2.1 Kg CO_2, or 55% of the emissions of that produced by the coal plant. If we can schedule our computation at a time when on-shore wind generation is being curtailed, and is therefore the marginal unit, the emissions drop to 0.03 Kg CO_2 or less than 1% of the coal plant.

V. CONCLUSIONS

Several methods exist for the accurate modeling and measurement of the energy consumption of a single application running on a server. Combining this figure with the PUE of the data centre in which it is running allows the calculation of the total resultant electricity consumption of the scheduling of a piece of computational load (or the running of an application).

With some information on the electricity grid from which our data centre is drawing power, we can obtain a figure for the amount of emissions that will be emitted if we were to schedule a piece of computation now. The more accurate the information on the power plants contributing power to the grid, the more accurate our figure will be. Simply knowing the current average carbon intensity (gCO_2 / kWh) and comparing this to the monthly or yearly average will give us a general indication of whether drawing more power now will result in more or less emissions than usual. If we have further information on the marginal plant, or can acquire this knowledge from the market, we can calculate the exact figure for the emissions that would be released by the additional electrical load our computation will cause if we choose to schedule it.

An anecdotal calculation of the emissions produced by a piece of computation, run at times when two different power plant types are the marginal unit on the Irish electricity grid, shows that choosing one time over the other to schedule the computation could save 45% of the resultant CO_2 emissions. This saving increases to over 99% during times when wind generation is over the percentage of demand at which it is curtailed. This will become an increasingly common occurrence due to growing wind penetration, as countries strive to meet emissions-reduction targets.

With the introduction of carbon trading, carbon taxes, and increasingly tough regulations around the emission of greenhouse gases, measuring, controlling and considering such emissions in the technology sector will become increasingly important. As such, developing ways to measure emissions resulting from the functions of large energy consumers will be essential in order to mitigate against the increasing costs associated with energy consumption.

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