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Delivering the Smart Grid: Challenges for Autonomous Agents and Multi-Agent Systems Research

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Abstract

Restructuring electricity grids to meet the increased demand caused by the electrification of transport and heating, while making greater use of intermittent renewable energy sources, represents one of the greatest engineering challenges of our day. This modern electricity grid, in which both electricity and information flow in two directions between large numbers of widely distributed suppliers and generators — commonly termed the 'smart grid' — represents a radical reengineering of infrastructure which has changed little over the last hundred years. However, the autonomous behaviour expected of the smart grid, its distributed nature, and the existence of multiple stakeholders each with their own incentives and interests, challenges existing engineering approaches. In this challenge paper, we describe why we believe that artificial intelligence, and particularly, the fields of autonomous agents and multi-agent systems are essential for delivering the smart grid as it is envisioned. We present some recent work in this area and describe many of the challenges that still remain.

Introduction

To meet the challenge of reducing greenhouse gas (GHG) emissions and ensuring energy security in the face of dwindling oil and gas reserves, governments around the world are increasingly setting ambitious targets to transition to a low carbon economy. For example, the Kyoto Protocol was ratified by 191 countries, committing them to ensure that average GHG between 2008-2012 were 5.2% lower than 1990 baseline levels. Going further, the UK has legislated to reduce emissions by 80% by 2050 (again compared to 1990 levels). Achieving this aim requires that the direct use of fossil fuels that we are familiar with today is almost entirely eliminated. Thus, the use of electric vehicles (EVs) and high-speed electric trains will have to become widespread in order to reduce our reliance on oil for transportation. Likewise, our homes and offices will have to be heated by efficient ground and air source heat pumps powered by electricity rather than existing natural gas and oil fired boilers (UK Department of Energy and Climate Change 2009).

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To avoid further fossil fuel consumption and GHG emissions, this increased demand for electricity will have to be largely met by renewable sources, such as wind and solar, rather than the coal and natural gas power plants that we use today. It is this increased demand for electricity, and the requirements for its generation, that present perhaps the greatest challenge. In most countries, the electricity grid has changed very little since it was first installed, and all existing grids are predicated on the central idea that electricity is produced by a relatively small number of large fossil fuel burning power stations and is delivered to a much larger number of customers, often some distance from these generators, with the constant requirement that supply should always match demand. The grid itself relies on ageing infrastructure (40 year old transmission lines and transformers, and 20 year old power stations), is plagued by poor information flow (most domestic electricity meters are read at intervals of several months), and has significant inefficiencies arising from losses within the transmission and distribution networks (close to 10% in the UK).

However, an electricity grid that makes extensive use of renewable generation presents significant challenges. Renewable generation is both intermittent and distributed, with the output of such generators being determined by local environmental conditions that can vary significantly over minutes and hours. Thus, it will no longer be possible for supply to continuously follow the vagaries of consumer demand, but rather, the demand-side will have to be managed to ensure that demand for electricity is matched against the available supply. Against this background, there is a growing consensus that existing grids cannot simply be extended to address these challenges, but rather, a fundamental reengineering of the grid is required; one that envisages the creation of a smart grid, described by the US Department of Energy (2003) as:

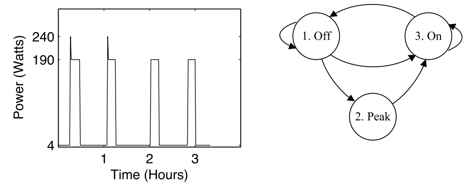
> A fully automated power delivery network that monitors and controls every customer and node, ensuring a two-way flow of electricity and information between the power plant and the appliance, and all points in between. Its distributed intelligence, coupled with broadband communications and automated control systems, enables real-time market transactions and seamless interfaces among people, buildings, industrial plants, generation facilities, and the electric network.

Transitioning from our current electricity grid to the smart grid represents an unprecedented challenge that may take 20-40 years and presents a number of key challenges along the way. In most countries, the starting point for the deployment of the smart grid is the installation of smart meters within domestic and commercial buildings. These meters measure electricity consumption over short periods of time (typically 15 to 30 minutes) and facilitate time-of-use electricity tariffs that better reflect the true cost of the electricity being supplied; the first step in delivering a grid where demand will follow supply. In the long-term, the smart grid envisions smart appliances automatically responding to these price signals. However, the transition period is likely to see consumers being faced with more complex electricity pricing to which they will have to respond appropriately.

Likewise, the increased demand for electricity is likely to create additional strains on the existing distribution infrastructure. This is likely to be particularly acute if there is rapid growth in electric vehicles use (Clement-Nyns, Haesen, and Driesen 2010). The batteries of these vehicles exhibit charging rates that are up to three times the typical maximum demand of a home, and today's distribution networks were planned around future additional domestic demand growth and house building, and not the much faster rate of electric vehicle take-up. Thus the capacity of the distribution network, power not energy, is likely to become a scarce resource which must be appropriately allocated across the various competing demands and users; all of whom are likely to have different incentives and interests.

Finally, the widespread deployment of renewable generation within the distribution network (often encouraged by attractive feed-in tariffs) represents a radical departure in the way in which electricity flows within such networks. Rather than flowing one way to domestic and commercial buildings which are simple consumers, electricity will flow in both directions between buildings which are both generators and consumers depending on the time of day, and on activity within them. Coordinating and controlling such systems to avoid overloading networks that are already highly capacity constrained represents a novel challenge which has previously not needed to be addressed.

When taken together, the central role that consumers play in shaping demand, the increasing need to efficiently allocate resources across competing demands and users in a constrained network, and the highly distributed nature of an electricity network composed of millions of generators and consumers, presents a challenge for existing power system engineering approaches. However, providing autonomous assistance to users in complex decision making tasks, allocating resources efficiently under competing demands and coordinating decentralised systems have long been the focus of the artificial intelligence researchers; in particular those working in the fields of autonomous agents and multi-agent systems. Hence, in this challenge paper we will describe why we believe that techniques developed within these fields can help in delivering the smart grid as it is envisioned. In particular, we present three illustrative examples[1], and we show (i) how autonomous agents that can learn and model home energy use to assist consumers in the transition to time-of-use electricity tariffs, (ii) how scarce resources can be efficiently allocated by carefully designing novel allocation mechanism that account for the different incentives of the participants, and (iii) how the problem of coordinating generators within a distribution network can be mapped onto an existing formalism and solved through efficient message passing algorithms. While this work represents a valuable first step, many challenges remain, and we highlight these here in order to suggest an agenda for autonomous agents and multi-agent systems research within the smart grid.



(a) (b)

Figure 1: Generic refrigerator model showing (a) the appliance power and (b) state transition model.

Supporting Consumers in the Transition to a Smart Grid

As discussed above, the first step in the transition to a fully smart grid is the installation of smart meters and the introduction of time-of-use tariffs to encourage energy consumption patterns that better match available supply. To this end, much work has attempted to address the challenge of automatically coordinating energy use within the home, and as such, assumes the existence of networked appliances whose use can be deferred automatically to periods when energy is less costly. Such ideas were first introduced by Schweppe, Daryanian, and Tabors (1989), and more recent work has described fully automated systems to optimise both appliance use and heating loads given a fixed energy budget (Yu et al. 2012). In our own previous work, we have considered the coordination of home energy storage devices and deferrable loads (Vytelingum et al. 2011; Ramchurn et al. 2011a).

While this is undoubtedly the end state for such as system, getting there presents a number of challenges. In particular, the roll-out of smart meters will facilitate more complex pricing tariffs, and yet, householders already struggle to understand and control their energy use. Thus, in this section, we present work that uses autonomous agents to automatically model and predict energy use within the home, in order to provide feedback and advice to the householders to help them better manage their energy consumption. This represents a critical step on the road to a fully autonomous smart home, but is a necessary one, if the latter is ever to materialise. Our first example considers the automatic analysis of electricity consumption from a single aggregate measure-

[1] We would refer the reader to the original papers, and also to Ramchurn et al. (2011b), for more details and examples.

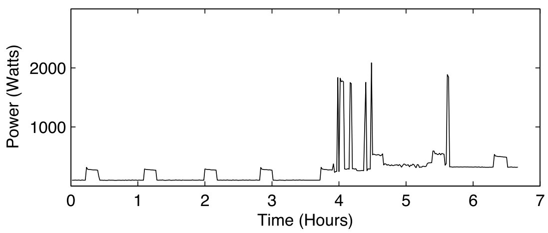


Figure 2: Example of aggregate power demand

ment to advise householders on appliance use, while the second, considers home heating optimisation.

Energy disaggregation, or non-intrusive appliance load monitoring (NIALM) as it is often termed, aims to break down a household's aggregate electricity consumption into individual appliances (Hart 1992), such that householders are empowered to take steps towards reducing their energy consumption (Darby 2006). Recent contributions in this field have applied principled machine learning techniques; using both supervised methods, which assume that sub-metered (ground truth) data is available for training (Kolter and Johnson 2011), and also, unsupervised methods (Kim et al. 2011; Kolter and Jaakkola 2012) in which no prior knowledge of the appliances is assumed, but which often requires appliances to be manually labelled after disaggregation, or assumes knowledge of the set of appliances in the home.

While this work grounds NIALM in a principled probabilistic framework, the assumptions made do not address the most likely real world settings; where sub-metered data and complete knowledge of the appliance set is not available, but some prior information about typical appliance performance might be known. Thus, in our work, we have addressed the problem using an approach that uses generic appliance models, that are then trained to the specific appliances within the home, using only the aggregate electricity measurements available at the smart meter (Parson et al. 2012).

More formally, the problem we face is that given a discrete sequence of observed aggregate power readings $\mathbf{x} = x_1, \ldots, x_T$, we must determine the sequence of appliance states $\mathbf{z}^{(n)} = z_1^{(n)}, \ldots, z_T^{(n)}$, where n is one of N appliances. Each appliance state corresponds to an operation of approximately constant power draw (e.g. 'on', 'off' or 'standby') and t represents one of T discrete time steps. Each appliance has K possible states, and the transition probabilities from state i at $t-1$ to state j at t are represented by the matrix $\mathbf{A}$ such that:

$$p(z_t = j | z_{t-1} = i) = A_{i,j} \tag{1}$$

Our approach models each appliance as a variant of the difference hidden Markov model (HMM), where step changes in the aggregate power are modelled explicitly as an observation sequence such that the emission probabilities for $\mathbf{x}$ are described by Gaussian distributions with means and variances that depend on the particular appliance state transition.

Our training approach takes this generic model of an appliance type (e.g. a typical refrigerator as shown in Figure 1), and trains it to a specific appliance instances (e.g. a particu-

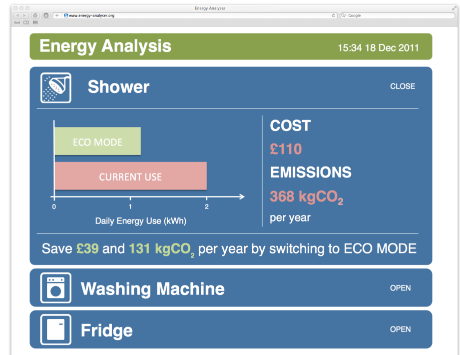


Figure 3: Prototype interface of live deployment

lar refrigerator installed in a particular home) using only the household's aggregate power demand. It does so by identifying and exploiting periods during which only a single appliance changes state. For example, Figure 2 shows an example of the aggregate power demand taken from a trial home in the UK. From hours 1 to 3 it is clear that only the refrigerator is cycling on and off. Transitions observed within this period provide a good match with the generic model, and the precise parameters of the model can be learnt through maximum likelihood optimisation. This specific refrigerator appliance model can then be used to disaggregate the refrigerator's load for the whole duration. Subtracting the refrigerator's load will consequently clean the aggregate load allowing further appliances to be sequentially disaggregated. To actually perform the disaggregation we use a modified Viterbi algorithm to infer the most likely appliance state at each time step, while filtering observations deemed more likely to have resulted from other appliances.

An evaluation using the Reference Energy Disaggregation Dataset (REDD) (redd.csail.mit.edu/) shows that our approach displays performance comparable to that of state of the art approaches that used sub-metered training data. In addition, we have applied it to live data collected from six UK households. Figure 3 shows a prototype of the user interface to the system. Using the disaggregation algorithm described above, the system is able to provide the householders with personalised energy saving suggestions. The figure shows a comparison of the energy consumption of the shower in a particular home. To calculate these figures, a prior model is first estimated from the shower's operation manual. This prior model is then trained using the approach presented here and used to disaggregate its energy consumption. Since the shower was used entirely on the 'high' setting, the system could use the prior model to estimate the corresponding energy consumption had the 'eco' setting been used. The potential savings are presented in terms of both cost and carbon.

Now, while appliance use is a significant source of energy consumption within the home, energy is also used in space and water heating. Indeed, in the UK this accounts for over 60% of domestic energy consumption. The shift to electrified heating and the introduction of variable time-of-use tariffs creates additional challenges here, since the links be-

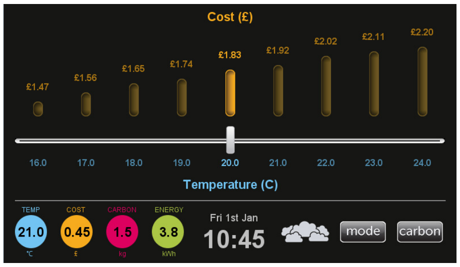


Figure 4: Home heating agent graphical user interface.

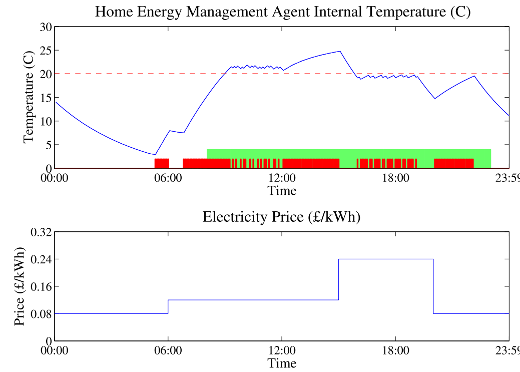


Figure 5: Example showing the optimised heating use to maintain comfort whilst minimising cost in a setting with a high price period between 15:00 and 20:00.

tween heating control settings and energy consumption are already poorly understood by consumers (Kempton 1986). Thus, it is essential that future home heating systems can assist users in making appropriate energy use decisions.

In recent work, we have described a home heating management agent that learns the thermal characteristics of the home in which it is installed, and the environment in which it operates, and uses the resulting model to provide feedback to the householder at the thermostat (Rogers et al. 2011). Using internal and external temperature sensors, and by monitoring the activity of the home's heating system, the agent is able to learn the thermal characteristics of the home. It does so by representing the temperature changes within the home through a set of parameterised stochastic differential equations in terms of the internal temperature, T_{in}, the flow of heat from the homes heating system, $\mathcal{R}$, and the leakage, Φ, to the external environment, T_{ext}. The simplest such model is given by:

$$T_{in}^{t+1} = T_{in}^{t} + \mathcal{R}\eta_{on}^{t} - \Phi\left(T_{in}^{t} - T_{ext}^{t}\right) + \epsilon_t \qquad (2)$$

where η_{on}^{t} is an indicator variable stating whether the heater is on or off in time period t, and ϵ_t is Gaussian noise. A regression process then fits the parameters of this model to the observed temperature history.

The agent then predicts the local external temperature over the next 24 hours by combining local measurements from the external sensor with predictions from an online weather forecast. It does so using a multi-output Gaussian process, to create a *site-specific* forecast for the next 24 hours; explicitly considering both the periodic nature of its own sensor data, and the likely correlation with the online forecast data. Using this prediction, and the thermal model learned above, the agent can predict the consequences of any thermostat setting and provide this information to the householder at the thermostat; informing them of the predicted daily cost and carbon consequences of their intended future actions (see Figure 4 and the video at www.ideasproject.info/research.php).

Going further, the agent is then able to fully optimise the use of heating (using either an optimal CPLEX implementation or a computationally efficient greedy heuristic). In doing so, it provides the same level of comfort as a standard thermostat operating at the same set-point temperature (evaluated using a comfort model based on the ASHRAE thermal comfort standard — ANSI/ASHRAE Standard 55-2010) whilst also minimising either cost or carbon. For example, Figure 5 shows simulation results for an example setting where the home heating management agent optimises heating to avoid a critical pricing period (i.e. the time period 15:00 to 20:00 where the price of electricity is £0.24 per kWh) by increasing the temperature of the home before the period (exaggerated for clarity in the plot) to minimise the heating required within it.

Challenges

While these examples represents an important first step, in that they both take raw data and use machine learning techniques to extract meaningful information, there is much more to do in order to deliver agents that really assist householders; especially if the aim is to elicit behaviour change. Not only must the machine learning approaches be extended and made robust to real world deployment, but a principled approach must be developed such that the agents can explicitly model the householders that they interact with, and apply behavioural change theories and persuasive technologies to appropriately tailor the feedback that they provide (Fogg 2003). Going further, once capable of autonomous control, they should incorporate ideas of flexible autonomy such that they can vary the degree of human intervention required within their decision making; knowing when they should act autonomously, and when they should seek approval for their decisions (noting that the latter also requires the ability to explain those decisions to the householder).

Allocating Scarce Resources Within A Constrained Distribution Network

As discussed earlier, promoting the use of electric vehicles (EVs) is a key element in many countries' initiatives to transition to a low carbon economy. However, there are significant concerns within the electricity distribution industries regarding the possibility that the widespread use of such vehicles could overload local electricity distribution networks at peak times. Indeed, in the UK, the Royal Academy of Engineering (2010), noted that street-level transformers servicing between 10-200 homes may become significant bottlenecks in the widespread adoption of EV. Thus, the challenge of accommodating the demands from electric vehicle charging serves as an example of how increasing scarce resources may be allocated within the smart grid. For example, enewable generation embedded within the distribution network may come up against the same local constraints.

To address these concerns, electricity distribution companies that are already seeing significant EV use have introduced time-of-use pricing plans for electric vehicle charging that attempt to dissuade owners from charging their vehicles at peak times, when the local electricity distribution network is already close to capacity (see for example www.pge.com/about/environment/pge/electricvehicles/fuelrates/). While such approaches are easily understood by customers, they fail to fully account for the constraints on the local distribution networks, and they are necessarily static since they require that vehicle owners individually respond to this price signal and adapt their behaviour (i.e., manually changing the time at which they charge their vehicle). Looking further ahead, researchers have also begun to investigate the automatic scheduling of EV charging. Typically, this work allows individual vehicle owners to indicate the times at which the car will be available for charging, allowing automatic scheduling while satisfying the constraints of the distribution network (Vandael et al. 2010; Clement-Nyns, Haesen, and Driesen 2010). However, since these approaches separate the scheduling from the price paid for the electricity (typically assuming a fixed per unit price plan), they are unable to preclude the incentive to misreport (e.g., an owner may indicate an earlier departure time or a greater journey length in order to receive preferential charging).

However, the allocation of scarce resources (in this case the capacity of the local transformer which limits the number of electric vehicles that can charge simultaneously) that are subject to the conflicting demands of multiple users has long been an area of research within the multi-agent systems community. Specifically, the field of computational mechanism design provides a mathematical framework for designing effective allocation mechanisms. It departs from standard game theory in that it also considers the computational and algorithmic resources imposed by the mechanism since the participants are assumed to be computational entities rather than unbounded rational agents (Dash, Parkes, and Jennings 2003). A key aim within this area is the design of *incentive compatible* allocation mechanisms (often based upon canonical the Vickrey-Clarke-Groves (VCG) mechanism) in which it is in the best interest of each participant to truthfully declare their requirements (their *type*) to the allocation mechanism. This removes the need for each participant to strategise over their actions (in our setting, this might correspond to a vehicle owner misreporting when they will need their car, or delaying plugging in their vehicle on arriving home, depending on the actions of their neighbours). It ensures that the resources are allocated to those who value them most, and that each participants pays an appropriate price for the resource that they receive.

The setting described here is a special case of online mechanism design, since allocation decisions must be made sequentially as participants arrive and depart over time (Parkes 2007). However, the setting also poses new challenges for mechanism design researchers. Unlike more traditional settings where a single item is being allocated and each participant has a single parameter describing the value that they attribute to it (so-called *single-valued* domains), our participants require multiple units of electricity. Furthermore, they have reducing marginal utility for each kilowatt hour (kWh) of electricity that they receive, since journey length is uncertain, and any shortfall in battery charge will have to be made up by using the vehicle's more costly internal combustion engine (in the case of plug-in hybrid or range-extended electric vehicles).

In recent work, we have shown that it is possible to derive an incentive compatible mechanism in this setting. In an evaluation using data from a real EV trial in the UK, the mechanism was shown to increase the efficiency with which charging capacity was allocated; allowing up to 40% more electric vehicles to share the same constrained local network (Gerding et al. 2011). Furthermore, it has proved possible to consider a number of more complex settings in which vehicles charge at different rates, and the increased share of the capacity, that the high speed chargers use, is appropriately reflected in the price that they pay (Robu et al. 2011).

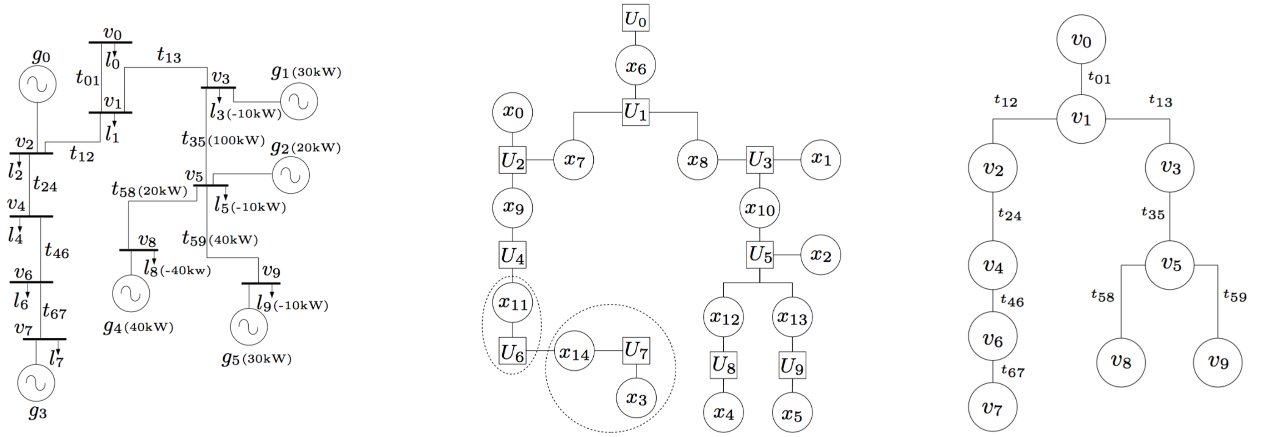
Challenges

These results indicate the mechanism design is a powerful tool for designing novel allocation mechanisms and payment schemes. Rather than designing allocation rules and testing their properties empirically, mechanism design provides a framework to formally describe the desired properties of the allocation mechanism and to evaluate candidate solutions against these criteria. However, many of the core assumptions of mechanism design need to be carefully considered in these settings. People often behave in irrational ways (Kahneman 2011), and have difficulty assessing multiple competing alternatives in a consistent manner (Ariely 2008). Thus, eliciting the preferences of the users, such that they can be effectively represented within the mechanism, is a challenging task in all but the simplest of settings.

Likewise, while we have only discussed electric vehicle charging here, the same approaches find application is other diverse areas such as distributing payments within collectives of renewable power plants (so called *virtual power plants*), scheduling access to local generation within a micro-grid, or facilitating novel collaborative energy purchasing mechanisms. The last example is particularly challenging, as it opens up the possibility of extremely large numbers of participants, thus requiring allocation mechanisms that not only have attractive economic properties, but are also computationally tractable at scale.

Coordinating a Decentralised Smart Grid

Finally, we consider the challenges posed by embedding renewable generation within the distribution network. Such networks were originally designed to distribute electricity in a single direction from the national transmission network to individual domestic and commercial buildings. However, the widespread deployment of renewable generation, and the



(a) (b) (c)

Figure 6: A typical electricity distribution network with (a) embedded generators, loads and capacity constrained distribution cables, (b) a factor graph representation with exemplar groupings of graph elements, and (c) the equivalent agent tree.

constrained capacity of the existing infrastructure, suggest that flows within the distribution networks will have to be actively managed to make optimal use of renewable generation without overloading the network. While this form of optimal dispatch is common in the transmission network (Davidson et al. 2009), the far greater scale of the distribution network (with millions of loads and generators), suggests that existing centralised approaches are inappropriate, and thus, a more efficient decentralised solution is required.

Now, decentralised algorithms that allow collective coordinated decisions to be reached through local computation and communication have long been the focus of research within the multi-agent systems community. Many such algorithms address the formalism of the distributed constraint optimisation problem (DCOP), and our own recent work has addressed the challenge of casting the optimal dispatch problem into a DCOP (Miller, Ramchurn, and Rogers 2012).

In more detail, we have considered a typical distribution network consisting of a set of k nodes $\{v_1, ..., v_k\}$. Distributed across these nodes are n generators $\{g_1, ..., g_n\}$, each of which has a certain discrete power output variable $\alpha_i \in S_i$ (kW), where $S_i = \{s^i_1, ..., s^i_{q_i}\}$ and q_i is the number of power output values for generator g_i, and a set of m loads $\{l_1, ..., l_m\}$. Finally, a set of s distribution cables connect the nodes within the network, and each has an associated thermal capacity, t_{ij} (kW), which is the maximum power that it can safely carry. See an example network in Figure 6a.

We show that given a particular criteria, such as minimising the carbon emissions of the generators within the network, we can construct a constrained optimisation problem that will optimise this criteria whilst also ensuring that overall demand and supply are in balance, and that the thermal capacity constraints of the cables are satisfied. To do so, we construct a factor graph representation of the problem, where function nodes, $\mathbf{U}$, represent the objective function and constraints, and decision variables, $\mathbf{x}$, represent the generator outputs and cable flows on which they depend (see Figure 6b). The resulting factor graph can then be optimally solved by allocating elements of the factor graph to computational agents located at the nodes of the original electricity network (see Figure 6c), and using an appropriate message passing algorithm, such as those based on the generalised distributive law (Aji and McEliece 2000). Since, the tree-like structure of distribution network is explicitly represented within the optimisation algorithm, a computationally efficient algorithm results.

Challenges

While we have made progress in solving such problems, many challenges remain. Distribution networks are not always structured as trees. Indeed, cyclic networks would be more robust to component failures; reducing the chances of a blackout occurring due to a single component or cable failure. However, the power flows within such networks are much more complex, and thus, with current manual approaches to configuring and managing the distribution network, they are rarely used. Thus computationally efficient decentralised algorithms that could autonomously manage complex network topologies would have great value.

However, this is not straightforward since the power flow equations that describe how the electricity flows within these networks cannot easily be represented and computed locally. The tree structured network that we have considered is a special case where doing so is more straightforward. While iterative algorithms for solving the power flow equations do exist within the power system engineering literature, decentralised versions which address the scale required for the smart grid have yet to be demonstrated. Thus, hybrid approaches that combine the formalism of the decentralised constraint optimisation problem, and existing iterative approaches, may be the way forward. Furthermore, it may be necessary to sacrifice overall efficiency while still ensuring that the capacity constraints of the network are not exceeded; calculating bounded, rather than optimal, solutions.

Conclusions

In this challenge paper we have argued that many of the problems posed by the transition to a smart grid have long been the focus of research within the field of autonomous agents and multi-agent systems research. Thus, we contend that these tools will be essential for delivering the smart grid as it is envisioned. While work that has been done in this area to date represents a valuable first step, the smart grid domain represents many new challenges. Not least, as in the examples discussed here, the need for autonomous agents that can apply persuasive technologies and flexible autonomy in order to encourage behaviour change and coordinate energy use within the home, novel computational mechanism design approaches that effectively elicit the preferences of the user and scale to potentially millions of participants, and efficient decentralised coordination approaches that can address the full complexity of settings where non-local constraints exist. For these reasons, we believe that addressing the challenge of delivering the smart grid represents a compelling research agenda for the field of autonomous agents and multi-agent systems research.

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