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Multi-agent Collaboration for Conflict Management in Residential Demand Response

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ABSTRACT

Balancing electricity supply and consumption improves stability and performance of an electricity Grid. Demand-Response (DR) mechanisms are used to optimize energy consumption patterns by shifting non-critical electrical energy demand to times of low electricity demand (off-peak). Market penetration of electrical loads from Electrical Vehicles (EVs) has significantly increased residential demand, with a direct impact on the grid's performance and effectiveness. By using multi-agent planning and scheduling algorithms such as Parallel Monte-Carlo Tree Search (P-MCTS) in DR, EVs can coordinate their actions and reschedule their consumption pattern. P-MCTS has been used to decentralize consumption planning, scheduling the optimum consumption pattern for each EV. However, a lack of coordination and collaboration limits its reliability in emergent situations, since agents' sub-optimal solutions are not guaranteed to aggregate to an optimized overall grid solution.

This paper describes Collaborative P-MCTS (CP-MCTS), which enables EVs to actively affect the planning process and resolve their conflicts via negotiation and optimizes the final consumption pattern using collective knowledge obtained during the negotiation. The negotiation algorithm supports agents to actively participate in collaboration, arguing about their stance and making new proposals. The results obtained show a significant load-shifting in peak times, a smoother load curve, and improved charging fairness and flexibility.

1. Introduction

Demand Side Management (DSM) uses a set of techniques that optimize consumers' electricity consumption [1]. An important goal for DSM is to maximize utilization of the current energy capacity, avoiding renewable energy waste and unnecessary energy use at peak times and reducing the need to increase capacity, which can be expensive. A range of approaches to achieve these goals are at varying stages of maturity, including energy efficiency, fuel substitution, and Demand-Response (DR) [2–4]. DR can be defined as a process in which consumers change their consumption pattern based on changes in their incentives. It encompasses any intentional energy consumption pattern modification such as shifting the consumption to off-peak times, demand scheduling to minimize instantaneous demand, and changes in overall energy usage. Residential demand is not evenly distributed during the day. To illustrate this, Fig. 1, which depicts the real data acquired from a community of 90 houses in one day, shows increasing demand in the morning and evening peaks relative to varying daily activities of the inhabitants. Penetration of Electrical Vehicles (EVs) in residential areas doubles the household load [5]. Therefore, the demand would be higher than the standard available capacity of the grid, which leads to an increase in energy production costs and ultimately energy costs for the end-users. DR shifts the peak times non-critical demand to off-peak times, or intelligently distributes it over time, aiming to achieve a smoother load curve measured by Peak-to-Average Ratio (PAR).

Different approaches have been applied to address residential load management. They can be categorized into direct and indirect approaches. Direct approaches involve the supplier engaging, and are responsible for controlling households (e.g., [6–8]). Indirect approaches enable devices to use energy in a smarter and more efficient way, using artificial intelligence methods. The indirect category itself can be divided into centralized smart methods, and decentralized smart methods. Centralized approaches involve a controller (i.e., a coordinator which has access to each household's data and the current load) which generates a coordinated consumption schedule for households based on the current demand load, price and households priority status [9]. These approaches have reported effective results, but have been applied mostly for small scale scenarios [10]. Decentralized approaches, such as multi-agent systems, engage smart devices (e.g., smart meters) to

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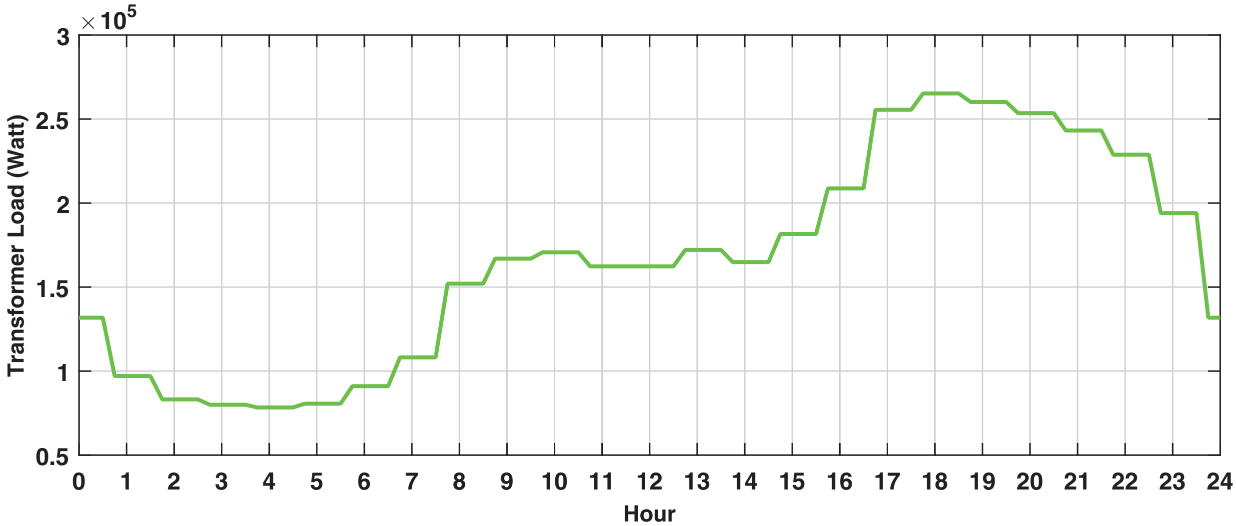

Fig. 1. Residential load of 90 houses in one day based on real data.

determine their consumption plan. In a smart decentralized method, agents can control electrical devices and learn from their previous actions and forecasted load for a better action selection in future [11]. For example, smart meter is used in each house to control consumption and defer the overload to off peaks. The smart meters decide and act as a house level controller [9,12,13]. Other approaches consider dynamic pricing, prediction and learning to control and shift the load [14]. To facilitate load balancing, prediction-based approaches determine if a preferable (i.e., cheaper energy, less load demand, etc.) time slot exists in the near future so the consumption can be delayed [15,16]. Although learning approaches are effective in this context, they require training time and they will not be able to handle emergent changes of the environment.

One of the promising approaches that has been recently used in DR and MAS is Monte Carlo Tree Search (MCTS). MCTS is a best first search method, which searches for the optimal decision by forming a search-tree with random sampling on the decision space. Recently, MCTS has been used with remarkable achievements in computer games and AI planning. It has also been used in optimization problems, planning and learning [13]. MCTS has been applied to DR, as a centralized electricity consumption planner. It has been run on various scenarios consisting of smart meters and electrical devices to find the best electricity consumption pattern considering electricity price and overall demand load [17,18]. The data gathered from these devices and smart meters is fed to the centralized algorithm by which the energy usage plan for each device is produced.

However, the MCTS approaches used in DR have certain drawbacks that limit the system's scalability, reliability and efficiency. Firstly, centralized coordinator-based MCTS is not scalable because there is a massive computational load carried by a single central coordinator. Secondly, the centralized coordinator is a potential single point of failure that risks the reliability of the system. Moreover, the agents in these approaches do not have any authority to make any changes over their own consumption plan, as it is dependent on others' plans. To overcome these drawbacks, a parallel variant of MCTS (P-MCTS) has been introduced [19]. P-MCTS allows players (analogous to agents) to have their own independent decision tree. However, this results in an optimal partial solution for each player that is not guaranteed to be an optimal overall solution. Moreover, the lack of coordination, cooperation or centralized control results in unreliable solutions in dynamic environments.

To address the disadvantages of P-MCTS, we previously introduced a collaborative approach called Collaborative Monte-Carlo Tree Search (CP-MCTS) [20]. CP-MCTS allows agents to run their independent MCTS threads considering their system's constraint. It also enables agents to avoid any constraint violation using collaborative decision-making process. This process allows agents to determine their priorities and negotiate to find an optimized plan.

This paper expands the collaboration process defined in CP-MCTS [20] by adding an argumentation-based negotiation approach. The negotiation process improves the decision-making process by enabling agents to resolve their conflicts while agreeing on a mutually accepted solution. Agents argue about the initial negotiation proposal (i.e. potential agreements) and justify their stance by proposing a new proposal. The extended CP-MCTS is applied in a DR scenario, including 90 houses with and 90 EVs, and addresses load balancing using a combination of artificial intelligent planning, multi-agent collaboration, negotiation, and collective decision-making.

The rest of this paper is organized as follows: Section 2 reviews the related background, Section 3 introduces the Negotiation-based Collaborative P-MCTS algorithm, Section 4 presents the experiment design, Section 5 describes empirical evaluation and the results. Finally, the conclusion and future work are discussed in Section 6.

2. Background

2.1. Monte Carlo Tree Search

MCTS is a search method that tries to find the optimal decision by forming a search tree based on the random samples of the decision space. MCTS has four main phases: Selection, Expansion, Simulation and Back-Propagation. In the Selection phase, the player starts traversing the tree from its root, until it reaches a leaf node. Then MCTS moves to its second phase, expanding the tree by adding a new leaf node. The Simulation starts from that new leaf node, and it ends when it reaches termination criteria. The last phase is Back-Propagation, which propagates the results of a simulated game backwards.

2.1.1. Upper Confidence Bound for Trees

MCTS behavior, and specifically its outcome, depends on the structure of the search tree, which is dependent on the node selection algorithm during the selection phase. Upper Confidence Bound