Transactive control of a residential community with solar photovoltaic and battery storage systems

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Abstract. Transactive energy is a two-way exchange of energy between the electric power grid and a community’s distributed energy resources, offering opportunities for efficiency improvements through market-based economic and control techniques. A community’s distributed energy resources include electricity-producing resources and controllable loads. Increased usage of unsynchronized generation of non-dispatchable solar photovoltaic energy and household demand at the community level can adversely affect the power quality, reliability and network balancing of the electricity grid. A solution was developed in this paper in the form of energy storage and demand side management on a solar residential community. An agent-based transactive energy management system was developed and simulated using multiple prosumer houses with roof-top PV systems and local energy storage. Experimental work conducted on an archetype house, near Toronto, Ontario, Canada, was used to model an all-electric residential house and clusters were created with varying orientations and building properties to mimic different efficiency levels of the houses within the virtual community. A machine learning algorithm using historical data and weather forecasts from Natural Resources Canada (NRCan) was used to forecast the community’s energy generation as well as building’s thermal loads. In this community, consumers can curtail their loads based on price signals sent to smart devices in homes. Open-loop mixed integer linear programming technique (MILP) and model predicted control (MPC) were compared and evaluated. The simulation shows promising results with a 9% energy savings during the summer solstice day and 5% during the winter solstice day when compared to the normal operation of houses’ mechanical equipment.

1. Introduction
Between 1990 and 2016, the world has doubled its electricity demand and is expected to continue growing in the next 25 years [1]. Of particular interest is the building sectors’ role in energy consumption. In 2012, residential buildings accounted for 17% and 22% of Canada’s and the United States’ energy consumption, respectively [2]. At the same time, the global power supply is shifting away from the traditional dispatchable fossil fuels to clean distributed renewable energy resources [1]. Advancements in digital technologies have changed the dynamics of generation and consumption, allowing consumers
to become producers (prosumers) and creating new business models like the transactive energy model. This work proposes a model that integrates a residential community’s electricity demands, battery storage and renewable energy resources with real-time and forecasted weather and electricity market price to control the operation of the community’s microgrid system. An agent-based transactive energy and model predictive control (MPC) were simulated as the control strategy. An optimized energy management system where residential prosumers in a community microgrid are incentivized to save energy by participating in the energy market is one of the keys to the successful operation of the microgrid. Existing energy management systems will face difficulties adapting to the increasing penetration of non-dispatchable renewable resources or energy storage devices. Currently, there is no standard for the design of an energy management system and is therefore an area of great interest for the development of the smart grid.

2. Microgrid control
The control scheme presented in this work is a decentralized agent-based hierarchical control scheme using a centralized controller and distributed agents. The central controller handles the aggregated community generations and demands. The distributed agents in this work were made up of controllable and non-controllable loads, solar PV systems and battery banks. These agents are responsible for monitoring, predicting the consumption or generation of their respective devices and communicating with the central controller. In this paper, the open-loop mixed integer linear programming (MILP) was compared to the closed-loop MPC strategy for the optimal operation of the central controller. Other types of control can be found in [3,4].

3. Transactive energy control
The transactive energy framework allows energy producers and consumers to interact and actively participate in the marketplace [5]. The participants in a transactive energy network can include smart flexible loads via adaptive thermostats, distributed generators, entire buildings or the grid itself. There is not a single rigid model in which a transactive energy model must operate, but many guidelines for their design have been proposed. A transactive control mechanism to manage distributed generation and peak demand with 60,000 end users was demonstrated in [6]. A capacity management market using transactive controllers was simulated in [7]. The transactive energy control used in this work utilized distributed agents to simulate smart interactive controllers to forecast demand, formulate bids and receive resource allocations from the central controller. The resource allocations are in the form of power level curtailment, on-off command, and battery usage.

4. Methodology
A concept community of 144 residential houses (Figure 1) was simulated based on the parameters of the Archetype Sustainable House (ASH) (Figure 2) located in Kortright Centre, Vaughn, Ontario. The concept community boundary was limited to the residential units only. The Kortright ASH was used as the basis for the model of the houses due to the availability of high-resolution equipment operating data, real-time weather data and actual house specifications [8]. Each of the house’s electricity consumption was simulated on a per minute resolution.

Figure 1. Concept community.
The YALMIP [9] toolbox of MATLAB was used to model the controller to solve the open-loop and MPC MILP optimization problems. YALMIP is a high-level modelling language and supports different optimization algorithms. It interfaces with multiple freeware and commercial solvers. In this work, Gurobi [10] was used as the optimization solver with a temporal resolution of one hour. The simulation focused on two days only, winter solstice and summer solstice.

5. Market Policy
The objective of the virtual microgrid was to serve the total demand of the community through the maximal utilization of local energy resources before exporting excess renewable energy to the distribution grid. Demand-side bids were evaluated every hour. Two types of controllable loads were simulated: heating, ventilation and air conditioning (HVAC), and DHW production. A local controller/agent controlled the residential thermostat and DHW appliance by submitting separate bids and can receive signals to stop the heating or cooling operation or adjust the water heater outlet temperature. The bid dollar amounts were based on the Hourly Ontario Energy Price (HOEP), indoor temperature deviation, and hot water demand. HOEP can be downloaded from [11]. Figure 3 illustrates the 2017 electricity prices during the summer and winter solstices. These prices do not include riders, distribution charges, global adjustment price and other surcharges. HOEP of $0 and below indicate low demand and excess generation. During these hours, the utility company will pay consumers to use the excess energy. In 2017, there were 2688 hours when the grid price was $0 and below. Excess PV generation exported, being non-dispatchable, were always paid according to the HOEP at that hour. Figure 4 shows the HVAC bidding curve formulated in this work. This work is a different strategy from [4] where the bid price was based on Time-Of-Use pricing. The simulations performed here were not meant to demonstrate the optimal method of formulating bids but to investigate the complexities of modelling the electricity demands of a community of residential buildings, transactive energy control, model predictive control and multi-agent framework.

6. Model Summary
All houses in the virtual community were assumed to have the same structural features as the ASH as described in [12]. House model parameters were varied randomly within the acceptable realistic ranges as described in [4,13].
6.1. Controllable loads

The air-source heat pump (ASHP) performance parameters used in the simulations were taken from the experimental work conducted at the ASH in [14,15]. The ASHP model was broken down into heating and cooling modes and has a rated capacity of 11.06 kW and 9.82 kW, respectively. During normal operation, the thermostat temperature setpoints were set to 24 °C in summer and 22 °C in winter. An artificial neural network (ANN) model was used to predict the operation of the heat recovery ventilation (HRV) using the outdoor ambient temperature and the indoor temperature. Space conditioning is distributed throughout the house via a single-zone air handling unit (AHU) drawing a constant 226 W when not in operation and 336 W when heating or cooling is requested, based on 2016 recorded data.

The simulated DHW system was based on work conducted at the ASH in [16]. For the simulations in this work, the water heater was operated in electric mode only with a subsequent power consumption of 1.5 kW per house for a total of 216 kW for the whole virtual community.

6.2. Non-controllable loads

Hourly appliance usage characteristics from the US Department of Energy [17] were used to simulate non-controllable load demands. Appliances simulated were refrigerator, freezer, dishwasher, clothes washer and dryer, cooking range and lighting. Simulations were run to reflect 17 low (13.2 kWh/day/household), 72 medium (22.3 kWh/day/household) and 55 high (35.6 kWh/day/household) consumption Canadian homes.

6.3. Electrical Systems

Each house was assumed to fit twelve PV panels with a rated peak power (Wp) of 340 W for a community total of 587.5 kWp. The slopes of the PV panels were randomly varied from 30° to 43.84° (the latitude of the site). Two different PV orientations were simulated and compared: all PV panels facing south for maximum annual throughput and PV panels facing different orientations (27 houses facing east, 38 facing west and 79 houses facing south). In this work, a commonly used white box model described in [18] was employed to forecast PV generation of houses with different roof orientations. Although a GIS model to predict the solar radiation received by the buildings in the same site as this study was created in [19], the real-time weather and solar data collected by the ASH’s data acquisition system made it a preferable source to predict PV generation. Figure 5 is a plot of PV power profile during the summer solstice (June 21) when PVs installed facing east generate power earlier in the day while those facing west generate power later in the afternoon than those facing south.

A battery model was implemented with a turnaround charging and discharging efficiency of 90% and ignoring certain operating parameters such as battery temperature. Each house was given a 12-kWh battery bank for a total community energy storage capacity of 1,728 kWh. Each battery bank cannot be discharged lower than 20% of its capacity and a maximum charging and discharging rate of 1 kW per hour was imposed for each house.

6.4. Microgrid model predictive control

In an MPC strategy, the optimal control problem is solved over a pre-defined horizon but only the control action of the first sample is implemented. The horizon is then shifted to the next sampling time and the optimization problem is solved again using the new control setpoints, input signals and forecasts. In this work, the optimization objective was to minimize the operating cost of the community microgrid at each point in time based on 24-hour forecasts of controllable loads, PV generation and energy prices. The optimal control signals at the current point in time are passed on to the distributed controllers/agents.
The thermal demand and power requirements of each house are then recalculated based on the control signals received and the optimization problem is solved again. The MPC policy to minimize the cost of operating the microgrid (grid import, battery charging and curtailment cost) to meet the predicted load demand was formulated as described in [20].

\[
J(k) = \min \sum_{j=0}^{T-1} \left[ C^b(k+j) P^b(k+j) \delta^b(k+j) + \gamma(k+j) C^b(k+j) P^b(k+j) \delta^b(k+j) + \sum_i B_i^c (D_i^{c1,x} - D_i^{c1}) \beta_i + \sum_n B_n^c D_n^c \alpha_n \right]
\]

(1)

In compact form this can be expressed as:

\[
J(k) = \min \sum_{j=0}^{T-1} \left[ c(k+j) u(k+j) + \rho^b(k+j) C^b(k+j) P^b(k+j) \delta^b(k+j) - C^b(k+j) (F(k+j) u(k+j) + f w(k+j)) \right]
\]

(2)

where:

\[
c = [C^g ... B_i^{c1}(D_i^{c1,x} - D_i^{c1}) ... ... B_n^{c2}(D_n^{c2} ... ...)]
\]

(3)

\[
F = [1 ... (D_i^{c1,x} - D_i^{c1}) ... ... D_n^{c2} ... ...]
\]

(4)

\[
u = [P^g ... \beta_i ... ... \alpha_n]'
\]

(5)

\[
f = [1 ... 1 ... 1 ...]
\]

(6)

\[
w = [P^{res} ... D_i^{c1} ... ... D_n^{c2} ... ... D]'
\]

(7)

A term was added to the objective function to penalize fluctuations in grid usage:

\[
J(k) = J(k) + \rho^g HOEP(k) \sqrt{[P^g(k) - P^g(k-1)]^2}
\]

(8)

The following constraints were introduced:

i. storage model:

\[
x^b(k+1) = \left( \eta^{b,c} - 1/\eta^{b,d} \right) \delta^b(k) P^b(k) + 1/\eta^{b,d} P^b(k) - x^{sb}
\]

(9)

ii. battery allowable depth of discharge and maximum capacity

iii. battery rate of charge and discharge

iv. minimum and maximum allowable curtailment for the DHW

v. grid power flow limit

vi. demand and generation balance:

\[
P^{res} + P^g = P^b + D + \beta_i D_i^{c1} + (1 - \beta_i D_i^{c1,x}) + (1 - \alpha_n D_n^{c2})
\]

(10)

The decision variables are: power imported from (+P^g) or exported (-P^g) to the grid, on-off command (\beta_i) to the controllable loads, curtailment percentage command (\alpha_n) to the variable loads, the energy exchanged with the storage unit P^b, and the storage energy level x^b, P^{res}, D^{c1}, D_i^{c1,x}, D_n^{c2}, D, B_i^{c1}, B_n^{c2}, C^b and C^g are the 24-hour forecasts for PV generation, curtailed on-off loads, uncurtailed operation of the on-off loads, uncurtailed operation of the variable loads, non-controllable loads, interactive controller bids, power level bids, battery cost and market clearing price, respectively. The battery cost C^b includes the operating and maintenance cost [21] and the cost of purchasing power from the grid. Parameters used were: the penalty to limit grid fluctuations \rho^g; the penalty applied to control the frequency of battery use \rho^b; storage self-discharge \eta^{b,d}; energy storage charging \eta^{b,c} and discharging \eta^{b,d} efficiencies; battery rate of charge \epsilon^{b,c} and discharge \epsilon^{b,d}; and grid power flow limit T^g. The following logical variables were used to ensure that there is only one direction of power flow at any time instant: \delta^b is binary state of the power exchange between the grid and the microgrid (1=import, 0=export) and \delta^b is binary state of the battery (1=charging or idle, 0=discharging).
7. Preliminary results and discussions
Table 1 shows the forecasted load demands and PV generation of the 144 houses using actual 2017 weather data collected at the ASH site. It should be noted that even though the simulation produced a lower DHW demand during the winter solstice day, the overall DHW demand in winter is higher compared to summer. Batteries were charged at 10 am in summer (Figure 6 and Figure 7) using excess solar PV energy instead of selling the power to the grid. As can be seen in Figure 6, the battery banks were charged at its maximum charging rate from 11 pm to 6 am in summer and at 2 am to 5 am in winter. Charging of the batteries at its maximum charging rate was deferred to avail of the free energy or to get paid for using the excess grid capacity. The penalty factor $\rho_b$ can be used to adjust the charging and discharging frequency of the batteries. Figure 7 shows the demand and supply curves produced by the MPC controller with different PV orientations. The MPC strategy managed to shift the HVAC and DHW demand outside of the high-demand hours (reflected by high energy prices). Table 2 is a comparison of the solutions obtained between open loop MILP and MPC strategies when compared to operating the microgrid with no controls. In both strategies, solar PVs that were oriented east, west and south-facing directions resulted in better performance than all south-facing PVs. In terms of financial savings, south-facing PVs resulted in more savings due to the timing of PV generation and high energy price. Less savings was observed during the heating season, with negligible savings under the open-loop MILP. MILP imported energy from the grid in winter in the mixed-orientation scenario. Between the two optimization strategies, MPC produced the most energy savings in community consumption and grid imports. These results are preliminary and future work is underway to include other renewable resources, demand from electric vehicles and GHG emissions.

Table 1. Simulated community consumption and generation under normal operation

|                      | Annual [MWh/yr] | Summer solstice [MWh/day] | Winter solstice [MWh/day] |
|----------------------|-----------------|---------------------------|---------------------------|
| HVAC load            | 1,097           | 2.132                     | 4.267                     |
| DHW load             | 588             | 1.256                     | 1.062                     |
| Non-controllable load| 1,383           | 3.839                     | 3.682                     |
| PV Generation (mixed orientation) | 503             | 2.188                     | 0.183                     |
| PV Generation (facing south) | 551             | 2.151                     | 0.194                     |

Table 2. Community savings under different control strategies & PV orientations

| Control Strategy | PV Orientation | Summer Solstice | Winter Solstice |
|------------------|----------------|-----------------|-----------------|
|                  | Demand kWh savings | Grid Import kWh savings $ savings | Demand kWh savings | Grid Import kWh savings $ savings |
| MILP South-facing | 3.37% 6.28% 26.2% | 0.02% 0.02% 0% | 3.47% 6.81% 20.6% | 0.02% -0.10% -0.10% |
| Mixed            | 5.79% 8.71% 35.0% | 4.57% 4.67% 8.2% | 5.88% 9.33% 31.0% | 5.05% 5.04% 8.2% |
| MPC South-facing | 5.79% 8.71% 35.0% | 4.57% 4.67% 8.2% | 5.88% 9.33% 31.0% | 5.05% 5.04% 8.2% |
| Mixed            | 5.79% 8.71% 35.0% | 4.57% 4.67% 8.2% | 5.88% 9.33% 31.0% | 5.05% 5.04% 8.2% |
Figure 6. Battery usage in the (a) summer solstice and (b) the winter solstice using MPC.

Figure 7. Comparison of generation and demand in the summer solstice between different PV orientations using MPC Sections, subsections and subsubsections.

8. Conclusion and future work
In this paper, a mixed integer linear programming-based model predictive control approach to the modelling and optimization of a solar community was introduced. The performance of MPC and open-loop MILP with different PV setups were compared using the normal operation of the mechanical equipment as the benchmark. Open-loop MILP does not capture the thermal dynamics of each house at each time step since there is no feedback loop. Using MPC, the local agents recalculated the thermal demand of each house at each sampling time. The transactive energy framework was applied to the optimization problem allowing each consumer to participate in demand-side bidding. Savings were observed in both MILP and MPC approaches with mixed-oriented PVs under the MPC scheme producing more savings. For future work, reduction of GHG emissions as part of the community’s objective will be investigated, a sensitivity analysis on the effect of various bidding prices will be performed and other renewable resources and demand from electric vehicles will be added to the community’s supply and demand profiles.

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