Economic dispatch for microgrids with constrained external power exchange

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Abstract: This paper examines microgrid unit dispatch, with hourly bounds on energy exchange with the macrogrid and minimum storage level constraints. These goals can be used to meet market constraints and to ensure there is sufficient energy reserved for future periods, respectively. In particular, economic model predictive control is used to minimize cost while ensuring these scheduling goals and other operational constraints are satisfied. Simulation of a dynamic microgrid system over a 24-hour period shows that the proposed dispatch strategy is able to effectively reject forecasting errors and meet the established energy exchange and storage level goals.

Keywords: Model based control, Stochastic control, Electric power systems, Renewable energy systems, Computer-aided control system design

1. INTRODUCTION

A microgrid is a local power distribution system which operates autonomously and may be connected to the external macrogrid (Lasseter et al. (2002)). Microgrids include distributed generation and storage units as well as local energy demands. Operating these distributed units close to the ultimate demand reduces transmission losses and congestion on the macrogrid (Lasseter et al. (2002)). Moreover, waste heat from fuel-fired units can be recovered to serve low grade thermal loads like space heating, space cooling, and hot water supply (Lasseter et al. (2002); Pepermans et al. (2005)). These systems are of particular interest in the context of renewable power because dispatchable units (e.g. batteries or microturbines) can be used to complement the renewables when there are mismatches between demand and renewables availability. Other potential microgrid benefits, such as improved power quality, resilient power supply, peak shaving, and decreased emissions are also well documented in the literature (Lasseter et al. (2002); Pepermans et al. (2005)).

During real-time operation, a microgrid must be controlled to minimize operational cost, satisfy demands, and comply with any exogenous regulations (e.g. interconnection standards or emission constraints). Operational decisions are traditionally decomposed into two subproblems: the scheduling of which units to operate (unit commitment) and the dispatch of setpoint signals to each unit (unit dispatch). These two problems may be solved simultaneously or sequentially. The focus of this work will be on unit dispatch.

The microgrid control problem is complicated by the stochasticity of weather and demand, the lack of electrical inertia for typical distributed units, and inherent nonlinearities in distributed units. Optimization-based control methods have been used to cope with these challenges in stand-alone microgrid systems (e.g. Trifkovic et al. (2014a,b); Barklund et al. (2008); Pourmousavi et al. (2010)). These methods allow the microgrid operator to incorporate a variety of objectives into the control problem, such as minimizing fuel usage, meeting energy demands, and regulating local voltage and frequency. For grid-connected systems, the macrogrid may provide electrical stability by acting as a buffer for any imbalance in local active and reactive power supply. Since the macrogrid acts as a slack bus to regulate voltage and frequency, purely economic or environmental objectives are typically pursued (e.g. Zhang et al. (2013); Mazidi et al. (2014); Silvente et al. (2015)). Due to the stochasticity of the renewables, the residual load (or net load) that the macrogrid serves is more variable and uncertain than the normal load. In grid-connected control problems, this stochasticity is typically only considered in order to minimize the expected cost over multiple scenarios as in Mazidi et al. (2014), or to minimize the worst-case cost as in Zhang et al. (2013). At low penetrations of distributed generation, the inherent inertia of the macrogrid is able to absorb the added stochasticity, but operation of distributed generation in this manner at deeper penetrations has the potential to impact both the power quality and cost to other customers (Eid et al. (2014); Brouwer et al. (2015)).

To address these issues, a novel market structure is considered in this paper where microgrid operators must schedule their net energy exchange with the macrogrid over each hour. Microgrid operators are charged/remunerated for the realized net energy exchange each hour at some pre-established rate. However, they are heavily penalized for large deviations from the scheduled energy exchange. Such a market structure preserves the transparency and simplicity of current tariff structures while relieving distribution system operators of much of the uncertainty added.
by distributed renewables. In addition, energy exchange commitments may be regulated to smooth the residual load and reduce the ramp rates required of macrogrid power plants. This work examines the challenge of microgrid unit dispatch under such a market structure where commitments for net energy exchange in each hour have been established a priori at a scheduling stage. In general, energy exchange targets and discrete unit states would be determined using mathematical optimization or a heuristic approach, but these values are treated as exogenous inputs in this study as the focus is on the dispatch problem. An economic model predictive control (E-MPC) approach is proposed for this dispatch problem and shown to be effective at satisfying both process constraints and market constraints.

2. PROBLEM FORMULATION

A generic microgrid is considered consisting of rooftop photovoltaic (PV), gas-fired microturbines, a battery bank, and a bi-directional connection to the macrogrid. The energy flow diagram is shown in Fig. 1. A central controller is used to dispatch setpoint signals to the individual units and the macrogrid acts as a slack bus to correct any power imbalance. The unit dispatch problem is subject to a number of constraints based on decisions made during scheduling. The scheduling variables (e.g. the number of microturbines committed) are treated as exogenous inputs to the dispatch problem. The term “scheduling hour” will be used to denote an hour over which scheduling decisions are constant (e.g. the period from 8 AM to 9 AM). In particular, the following scheduling inputs are used:

- Number of microturbines turned on
- Charge/discharge state of the battery
- Maximum and minimum energy exchange with the macrogrid over each scheduling hour
- Minimum battery state of charge (SOC) at the end of each scheduling hour

The central controller determines unit setpoints over a 60-min receding horizon using a linear E-MPC formulation to minimize the cost subject to the operational and scheduling constraints. Since the optimization horizon of the E-MPC will typically end in the middle of a scheduling hour, terminal constraints and costs are added to the problem formulation to ensure that the scheduling constraints can still be satisfied. Hourly scheduling decisions are assumed to be optimized over a longer horizon (e.g. 24-48 hours), so these inputs to the dispatch problem are available over the entire E-MPC horizon. In the following sections, the dynamic models used for each local unit are described and then the E-MPC problem formulation is presented. Finally, results from the implementation of the dispatch strategy over a 24-hour period are presented.

2.1 Macrogrid Connection

The microgrid is connected to the external macrogrid via a single, bi-directional point of common coupling. This connection acts as a slack bus to instantaneously correct any power imbalance in the system, and thus is not directly controllable. The cost/revenue of the energy exchanged with the grid is calculated based on the net exchange over each scheduling hour. No explicit limits are placed on the amount of power that can be exchanged with the macrogrid, but economic penalties are incurred for exceeding the scheduled energy exchange bounds.

2.2 PV Array Model

A dynamic integrated electrical and thermal model of a photovoltaic cell is used based on Liu and Dougal (2002). The electrical model is based on the single diode $R_{p}$-model equivalent circuit. The electrical properties of the equivalent circuit are taken to be temperature-dependent with parameter values representative of a typical silicon solar cell (Liu and Dougal (2002); Santbergen and van Zolingen (2008)). A modified perturb-and-observe algorithm is used to track the power request from the central E-MPC controller by varying the reference voltage of the PV array. Maximum power point tracking (MPPT) is not used since it may be desirable to curtail PV power to avoid exporting excessive power to the macrogrid. If curtailment is not needed, the power setpoint can be set to some arbitrary high value which will result in de facto maximum power point tracking. The total area of the PV array is taken to be 1800 m$^2$ (corresponding to a peak power of $\sim$ 185 kW). All cells in the array are assumed to operate at identical conditions, so a static gain is used to obtain the power output of the entire PV array. The DC-to-AC inverter is modeled as a static 95% efficiency gain.

2.3 Battery Bank Model

A dynamic electrical and thermal model is used for the battery bank based on the flooded lead-acid model presented in Ceraolo (2000). The electrical model consists of an equivalent circuit, and the thermal model represents the dependence of the battery temperature on ohmic heating and external heat transfer. The parameter values are scaled to correspond to a 600 kWh battery bank (Ceraolo (2000)). A local PI controller is used to track power setpoints from the central controller, and the inverter is modeled as a static 95% efficiency gain.

The terminal voltage, current out, power out ($V_b$, $I_b$, and $P_b$, respectively) are considered to be the only directly measurable battery states. Since the battery SOC and temperature need to be controlled, an approximate model is used for on-line prediction of the battery states which are not measurable using the following assumptions:

- Current in the parasitic branch is negligible
- All internal losses are due to ohmic heating
- Battery capacity is a linear function of temperature
- Efficiency is a linear function of SOC and current
As a note, though the estimated states may drift from the true states due to the accumulation of errors over time, other methods for off-line battery state estimation (such as electrolyte density measurements) may be used to periodically correct the estimates.

2.4 Microturbine Model

The microturbine dynamic model is made up of a mechanical system which generates torque via combustion of natural gas, a permanent magnet synchronous generator (PMSG) which converts torque into high frequency AC power, and a power electronics system which converts this power to grid frequency. The modeled microturbines have a rated power of 30 kW. The mechanical system (compressor, combustion chamber, and turbine) is modeled based on Kish and Lehn (2011). The time delays in the model are replaced by first order lags to improve computational speed of the microgrid model, but this does not significantly impact the results since these delays are ∼1 ms. The compressor outlet temperature, combustion chamber outlet temperature, air to fuel ratio, and exhaust gas heat capacity are assumed to vary linearly with the per-unit power based on the data in Kish and Lehn (2011). The microturbine PMSG is modeled following Mohamed (2008). A viscous loss term is added to the rotor speed differential equation with a damping coefficient of 1.125·10^-4 kg·m^2/s. The AC-DC-AC converter (which transforms the high frequency AC power out of the PMSG to grid frequency power) is modeled as a static 95% efficiency gain. The mechanical system which generates torque via combustion of natural gas is modeled following Mohamed (2008). The microturbine PMSG is modeled following Mohamed (2008).

2.5 Central Controller

The central controller uses E-MPC to decide power setpoints for the battery bank, PV array, and microturbines over a 60 minute receding horizon. The constraints on energy exchange with the macrogrid and battery SOC are assumed to operate at the same time as decided during scheduling. In addition to the bounds on macrogrid energy exchange and battery SOC, the following process constraints are considered in the E-MPC formulation:

- Microturbines must be dispatched between 10% and 100% of their rated power when on to maintain stable operation.
- The battery may only be charging or discharging each hour as decided during scheduling.
- The battery temperature must be kept below 35°C.

The problem is formulated as a discrete-time optimization with the 60 minute prediction horizon divided into 30 second time periods. The E-MPC formulation does not attempt to reproduce the full dynamics of each unit since they typically respond to setpoint signals within ∼10 ms to ∼10 seconds. Slow time scale dynamic properties, in particular the battery temperature and SOC, are included in the E-MPC problem.

The E-MPC is formulated as a linear program to ensure computational tractability. To linearize the problem, battery capacity, terminal voltage, and efficiency are considered to be constant over the prediction horizon. In addition, all power lost in the battery is assumed to contribute to ohmic heating. The optimization problem is then formulated as:

\[
\text{minimize} \quad \text{OpCost} + \text{TerminalCost} + \text{PenaltyCost} \quad (1)
\]

subject to:

Operational cost constraints

\[
\text{OpCost} \geq \zeta_m \sum_{t} P_m(t) \leq \zeta_b \left( E^0_g + \sum_{t \in t_1} P_g(t) \right) \quad (2)
\]

\[
\text{OpCost} \geq \zeta_m \sum_{t} P_m(t) \leq \zeta_s \left( E^0_g + \sum_{t \in t_1} P_g(t) \right) \quad (3)
\]

\[
\text{TerminalCost} \geq \zeta_m E_m + \zeta_b \left( E_b + \sum_{t \in t_2} P_g(t) \right) \quad (4)
\]

\[
\text{TerminalCost} \geq \zeta_m E_m + \zeta_s \left( E_b + \sum_{t \in t_2} P_g(t) \right) \quad (5)
\]

Penalties on grid exchange, battery SOC

\[
\text{PenaltyCost} = \zeta_g (\epsilon_1 + \epsilon_2) + \zeta_c (\epsilon_3 + \epsilon_4) \quad (6)
\]

\[
E^\text{min}_{g,1} - \epsilon_1 \leq E^0_g + \sum_{t \in t_1} P_g(t) \leq E^\text{max}_{g,1} + \epsilon_1 \quad (7)
\]

\[
E^\text{min}_{g,2} - \epsilon_2 \leq E_g + \sum_{t \in t_2} P_g(t) \leq E^\text{max}_{g,2} + \epsilon_2 \quad (8)
\]

\[
\text{SOC}(t_f) \geq \text{SOC}^{\text{min}}_t - \epsilon_3 \quad (9)
\]

\[
\text{SOC}(t_f) - \frac{1000 E_b}{C_b V_b} \geq \text{SOC}^{\text{min}}_t - \epsilon_4 \quad (10)
\]

Power and energy balances

\[
P_g(t) + P_m(t) + P_b(t) + P_b(t) = P_t(t) \quad (11)
\]

\[
E_g + E_m + E_a + E_b = E_t \quad (12)
\]

Feasible operational range

\[
0 \leq P_t(t) \leq P_{\text{forecast}}(t) \quad (13)
\]

\[
0 \leq E_s \leq E_{\text{forecast}} \quad (14)
\]

\[
0.1 x_m(t) P_m^{\text{rated}} \leq P_m(t) \leq x_m P_m^{\text{rated}} \quad (15)
\]

\[
0.1 x_m P_m^{\text{rated}} f \leq E_m \leq x_m P_m^{\text{rated}} f \quad (16)
\]

\[
M (\chi_b(t) - 1) \leq P_b(t) \leq M \chi_b(t) \quad (17)
\]

\[
M (\chi_b(t) - 1) \leq E_b \leq M \chi_b(t) \quad (18)
\]

Battery dynamics

\[
T_b(t) \leq T_b^{\text{max}} \quad (19)
\]

\[
\text{SOC}(t) = 1 - Q_e(t)/C_b \quad (20)
\]

\[
P_b(t) = \frac{I_b(t) V_b}{1000} \quad (21)
\]

\[
Q_e(t) = Q_e(t - 1) + I_b(t) / 120 \quad (22)
\]

\[
T_b(t) = T_b(t - 1) + \frac{\gamma_b(t) P_b(t)}{120 C_b} + \frac{T_{\text{amb}}(t) - T_b(t)}{120 C_b R_b} \quad (23)
\]

\[
\gamma_b(t) = (2 \chi_b(t) - 1) \frac{\eta_b}{1 - \eta_b} \quad (24)
\]
where the decision variables are the power setpoints (in kW) over the E-MPC horizon (i.e. $P_m$, $P_g$, $P_s$, and $P_b$), the energy contributions (in kWh) of each unit over the remaining time in the second scheduling hour (i.e. $E_m$, $E_g$, $E_s$, and $E_b$), the battery state variables (i.e. $T_b$, $SOC$, $I_b$, and $Q_e$), the deviation from scheduled energy exchanges (i.e. $\epsilon_1$, $\epsilon_2$, $\epsilon_3$, and $\epsilon_4$), and the cost variables (i.e. $OpCost$, $TerminalCost$, and $PenaltyCost$).

Equations (15)-(18) enforce scheduling decisions about the discrete operational states of the battery and microturbine (i.e. charging/discharging and on/off, respectively). This ensures that units do not rapidly cycle between these states due to high frequency disturbances in load and weather since that could reduce unit lifespan.

The prediction horizon will typically contain some time periods in the current scheduling hour and some in the subsequent scheduling hour. The time periods $t_1$ belong to the first scheduling hour which ends at $t_{1f}$, and the time periods $t_2$ belong to the second scheduling hour. The final final time period in the optimization horizon is $t_f$. The value $E_g^0$ refers to the net amount of energy exchanged with the microgrid so far in the current scheduling hour. The constants $C_b$, $V_b$, and $\eta_p$ are set equal to their current estimates when the optimization is called, and the values for $x_m$, $\chi_b$, $E_{g,1}^\min$, $E_{g,1}^\max$, $E_{g,2}^\min$, $E_{g,2}^\max$, $SOC_{1}^{\min}$, $SOC_{1}^{\max}$ are determined by the scheduling inputs. The parameter $f$ refers to the fraction of the second scheduling hour which lies outside of the prediction horizon. All other parameter values are shown in Table 1.

The prediction error and update the predictions for load and renewable availability in the future:

$$\tau_f \frac{d\hat{\ell}(t)}{dt} = \mathbf{P}(t) - \mathbf{P}(t) - \kappa(t)$$

where $\mathbf{P}(t)$ is the original load forecast, $\mathbf{P}(t)$ is the observed load, and $\kappa$ is the estimated forecast error. The expected future load, $\mathbf{P}(t)$, is then given by:

$$\mathbf{P}(t) = \mathbf{P}(t) + \kappa(t)$$

The filter time, $\tau_f$, is taken to be 10 minutes. This low-pass filter screens out the high frequency transients in the load signal which have a magnitude less than 1% of the average signal value. The forecast for incident solar irradiation (insolation) is updated in the same manner.

3. CASE STUDY

The performance of the proposed dispatch strategy is analyzed over a 24 hour period. The microgrid model is built in the Simulink simulation environment. The perturb-and-observe PV controller and E-MPC central controller are programmed in Matlab and implemented in the Simulink model through an Interpreted Matlab Function block. An a posteriori smoothing of the true load and PV forecast is used as the forecast in Simulation 1. Scheduling inputs were chosen based on these forecast values and are shown in Table 2. Two alternative initial forecasts are also considered to ensure that the proposed on-line filtering method is able to effectively reject non-white noise forecasting errors. The different initial forecasts are shown in Fig. 2. Note that the error bias in Simulations 2 and 3 is not constant, e.g. in load forecast 2 the bias is less severe during midday hours. The ambient temperature is assumed to be a constant 25°C.

Fig. 3 shows the 5-minute average power values for each unit in Simulations 1 and 2. The results from Simulation 3 are very similar and are not shown due to space limitations. The proposed on-line filtering method works well for rejecting forecasting errors as evidenced by the similarity in dispatch decisions despite significant differences in forecasting errors among the simulations. In all three simulations, the PV power is never curtailed in the E-MPC solution. In order to prevent curtailment due to under-predicting of insolation, a setpoint signal of 300 kW is sent to the PV controller rather than the value from the optimization.

In all three scenarios, the central controller is able to effectively dispatch units to meet the macrogrid energy exchange goals as shown in Fig. 4. Since the microgrid is billed based on the net energy exchange in each hour and the feed-in tariff is relatively low, the central controller tries to store energy in midday hours (i.e. scheduling hours 11-18) to offset future imports or fuel utilization. This may result in instances when the microgrid is importing power while the battery is charging, but the net exchange in each hour is still very close to zero. This slightly increases the local electricity losses due to the roundtrip efficiency of the battery, but may improve global efficiency by reducing peak load on the macrogrid.

| Scheduling Hour | $x_m$ | $\chi_b$ | $E_{g,1}^{\min}$ | $E_{g,1}^{\max}$ | $SOC_{1}^{\min}$ | $SOC_{1}^{\max}$ |
|-----------------|-------|----------|-----------------|-----------------|-----------------|-----------------|
| 12 – 1 AM       | 1     | 1        | -40             | 20              | 0.25            |
| 1 – 2 AM        | 1     | 1        | 40              | 100             | 0.25            |
| 2 – 3 AM        | 1     | 1        | 30              | 90              | 0.25            |
| 3 – 4 AM        | 1     | 1        | 25              | 85              | 0.25            |
| 4 – 5 AM        | 1     | 1        | 25              | 85              | 0.25            |
| 5 – 6 AM        | 1     | 1        | 35              | 95              | 0.25            |
| 6 – 7 AM        | 1     | 1        | 25              | 85              | 0.25            |
| 7 – 8 AM        | 1     | 1        | 5               | 65              | 0.25            |
| 8 – 9 AM        | 1     | 1        | -15             | 45              | 0.25            |
| 9 – 10 AM       | 1     | 0        | -30             | 30              | 0.25            |
| 10 – 11 AM      | 1     | 0        | -40             | 20              | 0.3             |
| 11 AM – 12 PM   | 1     | 0        | -40             | 20              | 0.4             |
| 12 – 1 PM       | 1     | 0        | -40             | 20              | 0.6             |
| 1 – 2 PM        | 1     | 0        | -40             | 20              | 0.65            |
| 2 – 3 PM        | 1     | 0        | -40             | 20              | 0.65            |
| 3 – 4 PM        | 1     | 1        | -30             | 30              | 0.65            |
| 4 – 5 PM        | 1     | 1        | -30             | 30              | 0.65            |
| 5 – 6 PM        | 2     | 1        | -10             | 50              | 0.5             |
| 6 – 7 PM        | 2     | 1        | 10              | 70              | 0.4             |
| 7 – 8 PM        | 2     | 1        | 30              | 90              | 0.3             |
| 8 – 9 PM        | 2     | 1        | 50              | 110             | 0.25            |
| 9 – 10 PM       | 2     | 1        | 70              | 130             | 0.25            |
| 10 – 11 PM      | 2     | 1        | 85              | 145             | 0.25            |
| 11 PM – 12 AM   | 2     | 1        | 50              | 110             | 0.25            |

Table 1. Parameter values used in the E-MPC

Table 2. Scheduling inputs for the case study
For hours 1 and 24 the realized grid exchange was marginally below the lower bound. In these hours, the central controller sought to exactly meet the lower bound on energy exchange, but slightly undershot the bound due to forecasting errors. The setpoint of local units was reduced to their minimum values during the final few time periods of the scheduling hour in an attempt to meet the bound, but local generation was unable to be backed-off sufficiently. In all 3 simulations, the commitment violation was less than 0.065 kWh in hour 1 and 1.2 kWh in hour 24. In practice, strict adherence to energy exchange bounds could be achieved through shifting of flexible loads (e.g. air conditioning) or the use of a small safety factor in the E-MPC. This could be useful if the penalty is a large, flat fee rather than proportional to the magnitude of the violation.

The central controller is able to keep the battery SOC above the desired level as shown in Fig. 5. Furthermore, the battery temperature does not exceed 30°C in any of the simulations as shown in Fig. 6. As a final note, the mean solution time for the E-MPC problem is ~0.2 seconds, well under the 30 second time slots considered.

4. CONCLUSIONS

An E-MPC formulation for dispatch of microgrid units while subject to hourly constraints on macrogrid energy exchange and battery level was presented in this paper. The central controller is able to effectively manage this sys-
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