INL/CON-16-39650
PREPRINT

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Sustech 2016

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April 2017

The INL is a
U.S. Department of Energy
National Laboratory
operated by
Battelle Energy Alliance

Idaho National Laboratory

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Dispatch Control with PEV Charging and Renewables for Multiplayer Game Application

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***Abstract*— This paper presents a demand response model for a hypothetical microgrid that integrates renewable resources and plug-in electric vehicle (PEV) charging systems. It is assumed that the microgrid has black start capability and that external generation is available for purchase while grid connected to satisfy additional demand. The microgrid is developed such that in addition to renewable, non-dispatchable generation from solar, wind and run of the river hydroelectric resources, local dispatchable generation is available in the form of small hydroelectric and moderately sized gas and coal fired facilities. To accurately model demand, the load model is separated into independent residential, commercial, industrial, and PEV charging systems. These are dispatched and committed based on a mixed integer linear program developed to minimize the cost of generation and load shedding while satisfying constraints associated with line limits, conservation of energy, and ramp rates of the generation units. The model extends a research tool to longer time frames intended for policy setting and educational environments and provides a realistic and intuitive understanding of beneficial and challenging aspects of electrification of vehicles combined with integration of green electricity production.**

***Index Terms*—Plug-in electric vehicle, demand response, real time dispatch, gamification.**

I. INTRODUCTION

The introduction of charging stations for plug-in electric vehicles (PEVs) is intended to decrease greenhouse emissions by relying on bulk power generation rather than internal combustion engines for short to medium length commutes. This will inherently increase the load on the power grid and has the potential to stress existing distribution feeders, but can be beneficial if the charging cycles are scheduled during off peak hours. This is supported by studies that suggest that load leveling is positively impacted if residential charging occurs during the off-peak hours from midnight to 6:00 AM. [4] The impact of publicly accessible direct current fast charging systems (DCFC) is less well understood but they are anticipated to be used on the reverse commute and, as a result, increase the burden on the power grid during peak-load hours. To further complicate the issue, renewable generation from photovoltaic and wind technologies are inherently intermittent and, without storage, cannot be relied upon for demand response.

In this regard, various authors have developed models to solve the dispatch and commitment problems for PEV charging systems and renewable resources when considered in isolation [2-3]. However, there is a need to develop a demand response model that incorporates these elements while providing reliable dispatch to satisfy the energy balance equation.

This paper proposes a model formulated as a mixed integer linear program that incorporates generation from renewable and dispatchable resources, energy from contract markets and grid scale storage, and load shedding decisions for distribution feeders servicing residential, commercial, and industrial loads. While PEV charging systems have been aggregated into these loads in some studies, the model described in this paper integrates them separately and discretely with the assumption that they can be remotely curtailed for load shedding purposes. The model defines the objective function as a cost function associated with unit dispatch and commitment of local generation and load resources while satisfying the constraints associated with energy conservation and equipment rating limitations. This model is used to demonstrate the dynamic response of the system to variability of the renewable generation and the increased demand on the system by the PEV charging systems. These are then aggregated into the energy balance equation and used to minimize the cost of the dispatchable resources for the current time step. This model is applied to extend a multiplayer game simulation of microgrids [1] to extended time frames for exploration of greater transportation electrification.

This paper is arranged as follows. Section II specifies the scope and assumptions of the proposed work. It is followed in Section III by a description of the model development. Section IV provides a summary of the results followed by the conclusion in Section V.

II. SCOPE

The model presented in this paper is limited to a single hypothetical microgrid acting independent of surrounding utilities. External generation may be purchased on spot markets from polluting and non-polluting sources which are represented by infinite buses constrained only by the contract amount. The generation and load models were developed from historical and stochastic sources in order to demonstrate the dynamic behavior of the demand response model for determining the optimal dispatch of the local resources. Further, the simulation has been developed with the flexibility to allow for system faults but has not integrated them at this time. Finally, in order to demonstrate the challenges associated with renewable resource integration into power systems, the renewables are assumed to be non-curtailable and therefore are always connected to the microgrid after installation. Finally, to allow for adequate fidelity and compatibility with DCFC system charge times, the simulation is developed for a medium time scale simulation that uses a time step of 15 minutes to represent the primary loading periods of the day in order to approximate the response of the model to variable renewable generation and PEV charging systems.

III. Model Development

The objective of the study is to develop a demand response model that can be used to determine the optimal dispatch of the local dispatchable generation resources and perform load shedding as needed to maintain energy balance when renewable generation variation is non-curtailable. To accomplish this, the model allows for grid-scale energy storage and for purchase decisions from spot markets. In order to achieve these objective, three primary aspects were developed to demonstrate this principle:

A. The generation model

The generation model considers three primary contributions to total generation. These include local renewable generation, local dispatchable generation and energy purchased and imported from spot markets. Each generation resource is assigned an operation cost, a fuel cost, and a ramping cost. Local renewable generation cannot be curtailed and represents distributed generation within the microgrid. The costing structure assigns no fuel or ramping cost to renewable resources, but assigns high operating costs, which, in this case, is used to represent the capital and regulatory contract costs. The three types of renewable generation include solar, wind, and run of the river hydro-electric. The solar generation model uses normalized normal incident radiation data collected by the Renewable Resource Data Center (RREDC) at the National Renewable Energy Laboratory (NREL) [5]. This dataset was selected because it accounted for output variations as a result of climatic, geographic and seasonal characteristics. The wind generation model uses hourly wind speed datasets from the System Advisory Model (SAM) developed at NREL [6] which was interpolated to satisfy the desired time step selected for the model. The energy output produced from the wind resources was defined using the characteristics of the Vestas V110 2MW turbine [7]. The run of the river hydroelectric generation model was developed by normalizing historical volumetric Snake River flow rate data sampled at 15 minute intervals provided by Idaho Falls Power [9] and interpolating for the simulation time step, as required.

The renewable energy generation for each resource, expressed in units of MWhrs, is expressed in (1).

$$G_{RS}(n\Delta t) = N_s P_s \Delta t \frac{H_s(n\Delta t)}{\max(H_s)} \qquad (1a)$$

$$G_{RW}(n\Delta t) = \begin{cases} N_W P_W \Delta t \dfrac{v_w(n\Delta t) - 3}{9} & 3 < v(n\Delta t) \leq 12 \\ N_W P_W & 12 < v(n\Delta t) \leq 20 \\ 0 & otherwise \end{cases} \qquad (1b)$$

$$G_{RH}(n\Delta t) = N_H P_H \Delta t \frac{Q_H(n\Delta t)}{\max(Q_H)} \qquad (1c)$$

Where:

$G_{R\{S,W,H\}}$ → $Generated\ Renewable\ energy\ (MWhr)$
$N_{\{S,W,H\}}$ → $Total\ number\ of\ units$
$P_{\{S,W,H\}}$ → $Peak\ Power\ output\ (MW)$
H_S → $Solar\ Irradiance\ \left(\frac{W}{m^2}\right)$
v_w → $Wind\ Speed\ \left(\frac{m}{s}\right)$
Q_H → $Volumetric\ Flow\ Rate\ \left(\frac{m^3}{s}\right)$
Δt → $timestep\ (s)$
n → $index$

Note: a linear approximation of wind generation from minimum to name plate (maximum) power from the cut in wind speed of 3m/s to peak generation wind speed of 12m/s for the Vestas turbine. The cut off speed at which the turbine shuts down operation is 20m/s.

Local dispatchable generation is assumed to exist within the microgrid and represents fixed assets that can be dispatched at any level between 0 and 100%. The costing structure for dispatchable resources includes operational, fuel, and ramping costs. In addition, asymmetric ramp up and ramp down rates are associated with each dispatchable resource to realistically limit the rate at which the resource can respond to load changes. The three types of dispatchable generation include coal fired generation, gas fired generation, and hydroelectric generation. Coal fired generation incurs the highest ramp cost and lowest ramp rate while hydro-electric resources incurring the lowest ramp cost, no fuel cost and highest ramp rate. For the purpose of this paper, limits on the availability of feedstock (e.g. coal, natural gas, and stored water) are not considered.

Energy purchased from spot markets is limited to a predefined upper boundary defined by the purchased contract. The energy is assumed to be delivered from an infinite bus and therefore is not constrained by ramp rate restrictions. Since energy purchased from spot markets is assumed to be external to the microgrid, it is subject to transmission line limits and losses. While not implemented at this time, future implementations will allow for day ahead energy contracts. For this reason, any amount of energy may be purchased on each timestep within the predefined limits. However, because of restrictive pricing associated with the spot markets, preference is always given to fully utilize the local dispatchable resources before utilizing spot markets. Variable pricing in the spot market can be implemented given a specification of a model of the market or multiplayer game interaction.

The peak energy capacity of local dispatchable generation resources and spot market contracts are similarly modeled and are of the form:

$$\left|G_{D\{C,G,H\}}\right| = N_{\{C,G,H\}}P_{\{C,G,H\}}\Delta t \qquad (2a)$$
$$\left|G_{SM}\right| = N_{SM}P_{SM}\Delta t \qquad (2b)$$

It follows then that the energy generated per timestep is a function of the peak energy capacity and the dispatch level as determined by the mixed integer linear program described by (3).

$$G_{D\{C,G,H\}}(n\Delta t) = \left|G_{D\{C,G,H\}}\right| d_{\{C,G,H\}}(n\Delta t) \qquad (3a)$$
$$G_{SM}(n\Delta t) = \left|G_{SM}\right| d_{SM}(n\Delta t) \qquad (3b)$$

Where:

$G_{D\{C,G,H\}}, G_{SM}$ → *Generated Dispatchable energy* $(MWhr)$
$N_{\{C,G,H,SM\}}$ → *Total number of units*
$P_{\{C,G,H,SM\}}$ → *Peak Power output* (MW)
$d_{\{C,G,H,SM\}}$ → *Dispatch level*
Δt → *timestep* (s)
n → *index*

B. A load model with PEV charging system

The load model is composed of residential, commercial, and industrial loads. The residential and commercial loads are modeled from load profiles, normalized by dividing by the maximum value, from the System Advisory Model[7]. The industrial load profile for the model was developed with normalized historical load profiles from Idaho Falls Power [9]. Each of the normalized load profiles were scaled by a user defined Peak Power Demand factor and the number of units for each type of load to allow variations of load magnitude and mix to be applied.

$$L_{\{R,C,I\}}(n\Delta t) = N_{\{R,C,I\}}P_{\{R,C,I\}}\Delta t \frac{Y_{\{R,C,I\}}(n\Delta t)}{\max\left(Y_{\{R,C,I\}}\right)} \qquad (4a)$$

Where:

$L_{\{R,C,I\}}(n\Delta t)$ → *Load demand* $(MWhr)$
$N_{\{R,C,I\}}$ → *Total number of units*
$P_{\{R,C,I\}}$ → *Peak Power demand* (MW)
$Y_{\{R,C,I\}}(n\Delta t)$ → *Data source value*
Δt → *timestep* (s)
n → *index*

In addition, PEV charging systems associated with residential based slow charging systems and commercially available DC fast charging systems are included as separate controllable loads. The simulation currently assigns the charging load using uniformly distributed variables to represent the PEV charging systems. Future integration of the residential PEV slow charging model developed by Scoffield and Kunz [4] into the simulation is planned to approximate the charging cycle that predominantly contributes to the load during the evening and morning hours (6:00 PM to 6:00 AM). Since the literature review did not provide evidence that a model has been developed for DC fast chargers, a uniformly distributed variable was similarly used. Extending the statistical residential charging model to fast charging stations for the time periods that are expected to predominantly contribute to the load in the late afternoon (6:00 PM to 12:00 AM), is left to future work.

C. The Storage Model

Grid-level storage was integrated into the simulation in order to demonstrate the benefits of such technology when used in conjunction with intermittent renewable resources. In order to account for the energy transferred to or from the grid-level storage, the storage model was developed as a coupled sink and source system. Using this approach, the storage sink behaved as a load element while the storage source element behaved as generation with constraints limiting only one to be active at a time. Initial approaches introduced non-linearity in the objective function which was resolved by modifying the cost structure of the storage prior to evaluation of the MILP based on the current level of charge. The storage model was integrated into the cost function defined in (5) and modeled as a change in change of the grid storage.

$$\Delta ST = ST_{sink} - ST_{source} \qquad (5a)$$

$$ST_{SOC} = ST_{SOC} + \Delta ST \qquad (5b)$$

where ΔST is the change in state of charge of the storage element, ST_{sink} and ST_{source} are the sink and source variables for power supplied to or take from the grid, and ST_{SOC} tracks the state of charge in energy units. It is noted that this approach does not currently account for losses in the storage system.

D.Dispatch and commitment model

The dispatch and unit commitment model is similar in nature to the Robust Energy and Reserve Dispatch model presented in [3]. It is formulated as an optimization problem that minimizes the cost of dispatch of the local resources subject to the energy conservation, energy production levels, and physical constraints associated with resources defined in (6).

Objective function:

$$\min C = \sum C_{rt} W_{rt} \qquad (6a)$$

Constraints:

$$\sum W_g = \sum W_l \qquad (6b)$$

$$0 \leq P_{da} + P_{rt} \leq P_{max} \qquad (6c)$$

Where:

C	$\rightarrow$	*Dispatch cost*
C_{rt}	$\rightarrow$	*Price per MWhr for real time dispatch*
W_{rt}	$\rightarrow$	*Energy produced through real time dispatch*
W_g	$\rightarrow$	*Total energy generated*
W_l	$\rightarrow$	*Total energy requirement of load*
P_{da}	$\rightarrow$	*Power allocated by day ahead dispatch*
P_{rt}	$\rightarrow$	*Power allocated by real time dispatch*
P_{max}	$\rightarrow$	*Maximum power available from resource*

This approach was extended such that the initial formulation of the objective function accounted for the cost of energy purchased on the spot market, the cost of generation and the cost of load shedding. The formulation was later extended to include grid level storage. In order to account for costs associated with ramping the local dispatchable generation, the ramping costs were determined using the change in dispatch level from the previous timestep and was evaluated separately from the operations and fuel costs of the unit. The inclusion of the ramping term as a function of the change in dispatch level was included for clarification during the objective function formulation, and was later simplified as seen in (8). In addition, the load commitment flags were integrated into the objective function using Boolean negation. While these practices clarified the objective function formulation, they also resulted in a sub-optimal formulation as seen in (7).

Objective function:

$$\min C = \sum \left[\left(C_{op} + C_f\right)_i d_i + C_j\left(d_i(n) - d_i(n-1)\right) \right] G_i + \sum p_j\left(1 - d_j\right) L_j + C_{sm} G_{sm} + C_{st}\left(ST_{Source} + ST_{Sink}\right) \qquad (7)$$

To optimize the objective function, constant terms were eliminated which resulted in the simplified objective function in (8). This resulted in the elimination of both the $d_i(n-1)$ term of the ramping term as well as the negation term of the load curtailment penalty terms.

$$\min C = \sum \left(C_{op} + C_f + C_r\right)_i d_i G_i - \sum p_j d_j L_j + C_{sm} G_{sm} + C_{st} |\Delta \mathrm{ST}| \qquad (8)$$

The constraints were similarly extended to account for the ramp rate restrictions placed on the dispatchable generation sources, the storage limits, the dispatch levels all treated as continuous on the interval [0,1] and the load commitment flag as treated as discreet in the set {0,1}. The authors aware of the simplification of a static ramping cost that should be considered as a function of the ramp rate. However, this introduces a non-linearity, which eliminates the possibility of using straightforward linear programing. For the purpose of the initial gamification with a tractable time to solve, the solution is left sub-optimal.

Constraints:

$\sum d_i G_i + d_{sm} G_{sm} - \sum d_j L_j = 0\,,$	*Energy balance constraint*
$\sum [d_i G_i(n) - d_i(n-1) G_i(n-1)] \leq \sum G_{ri}$	*Ramp rate constraint*
$ST_{Source} - ST_{Sink} + ST_{SOC} \leq \max(ST)$	*Upper storage limit*
$ST_{Source} - ST_{Sink} + ST_{SOC} \geq 0$	*Lower storage limit*
$d_i \in [0,1]$	*Generation dispatch level*
$d_j \in \{0,1\}$	*Load Commitment flag*

The constraints above were then reformulated in terms of the decision variables which resulted in:

$\sum d_i G_i + d_{sm} G_{sm} - \sum d_j L_j = 0\,,$	*Energy balance constraint*
$\sum d_i G_i(n) \leq \sum [G_{ri} + d_i(n-1) G_i(n-1)]$	*Ramp rate constraint*
$ST_{Source} - ST_{Sink} \leq \max(ST) - ST_{SOC}$	*Upper storage limit*
$-ST_{Source} + ST_{Sink} \leq ST_{SOC}$	*Lower storage limit*
$d_i \in [0,1]$	*Generation dispatch level*
$d_j \in \{0,1\}$	*Load Commitment flag*

Where:

C_{op}	$\rightarrow$	*Operation cost of generation (USD/MWhr)*
C_f	$\rightarrow$	*Fuel cost of generation (USD/MWhr)*
C_r	$\rightarrow$	*Ramp up/down cost of generation (USD/MWhr)*
d	$\rightarrow$	*Dispatch level*
G	$\rightarrow$	*Generation capacity (MWhr)*
p	$\rightarrow$	*Penalty for load shedding (USD/MWhr)*
L	$\rightarrow$	*Load (MWhr)*

The simulation was implemented in a Matlab script using the mixed-integer linear programming function, intlinprog(), to compute the minimum solution to the cost function applying the applicable constraints at each time step.

IV. Results

To evaluate the effectiveness of the dispatch model, simulations were performed utilizing varying levels of renewable generation and PEV charging system penetration in the microgrid. Each simulation evaluated the model for 35,040 time steps which represents one year's worth of data. Four simulations were performed which include:

- Baseline Case
    - Peak Generation Capacity: 175 MW
    - Peak Load: 140 MW
    - No Renewable Generation
    - No PEV Charging systems
- Case 2:
    - Peak Generation Capacity: 470 MW
    - Peak Load: 334.3 MW
    - No Renewable Generation
    - Peak PEV Charging Load: 9.1 MW
- Case 3:
    - Peak Generation Capacity: 410 MW
    - Peak Load: 350 MW
    - Peak Renewable Capacity: 200 MW
    - No PEV Charging systems
- Case 4:
    - Peak Generation Capacity: 410 MW
    - Peak Load: 370 MW
    - Peak Renewable Capacity: 200 MW
    - Peak PEV Charging Load: 40 MW

Table I summarizes the results of the four test cases described above.

TABLE I: Summary of Test Case Feasibility

	TOTAL NUMBER OF NON-FEASIBLE SOLUTIONS	FEASIBLE SOLUTION CONVERGENCE RATE
CASE 1:	22	99.94%
CASE 2:	11	99.97%
CASE 3:	85	99.76%
CASE 4:	79	99.77%

As illustrated, the results from all four test cases show a high feasible solution convergence rate. This indicates that the linear program converged to a solution for the objective function while satisfying the constraints. The first two test cases which did not include any renewable generation produced the fewest number of infeasible solutions while the latter two cases produced the highest number of infeasible solutions.   This suggested that the feasible solution convergence rate was influenced by the renewable generation penetration in the microgrid. This was supported by observations when it was noted that the non-feasible solutions occurred during instances for which the microgrid was not importing power from the spot market contracts and was relying only on local dispatchable and renewable generation. During these instances, sudden significant decreases in load or increases in renewable generation resulted in non-feasible solutions that failed to satisfy the energy balance constraint. In both of these cases, the down ramp rate restricted the dispatchable generation from spinning down quick enough to achieve equilibrium. This resulted in instances of overproduction when non-feasible solutions were encountered. The "price" of over production becomes energy that is provided to the connect transmission system without compensation, burned off as heat, or creation of a frequency instability.

V. Conclusion

As described in Section IV, the dispatch and commitment model was generally able to determine a feasible solution. The test cases demonstrated that the model was more likely to converge to a feasible solution in the absence of renewable generation. Further, the model showed no sensitivity to increased penetration of PEV charging systems. This was observed to be the result of the limitations placed on the ramp down rate for the dispatchable generation in instances when no power is imported from spot markets. The dispatch model appears to be a feasible, albeit suboptimal, mechanism to explore time frames in a game context that will allow players to experience the effects of increased number of PEVs connected to the electricity grid. It is suggested that future work investigate the impact of curtailment of renewable resources to the feasible solution convergence rate. More optimal dispatch algorithms could be introduced given computationally tractable solutions for variable ramp rates can be implemented in future work.

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