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Assessing the Impact of Uncertainty on Demand Response Aggregation Systems

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Outline

- 1 Introduction
- 2 Modeling Framework
- 3 Reliability Assessment
- 4 Case Studies
- 5 Generalizations
- 6 Concluding Remarks

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Background and Motivation

- Demand Response Resources (DRRs) must be aggregated to participate in wholesale electricity markets:
 - ▶ Energy
 - ▶ Capacity
 - ▶ Ancillary services
- DRRs have the potential to contribute a considerable amount of energy and capacity, e.g.,
 - ▶ 10% of peak demand in MISO in 2014
 - ▶ 7% of peak demand in PJM in 2014
- Mechanisms and benefits of coordination of DRRs to provide ancillary services are relatively well understood
- Virtually no work on assessing the impact of uncertain phenomena on the reliability of DRR aggregation systems

Objective

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To develop a reliability assessment framework to evaluate the impact of uncertainty on the capacity of DRR aggregation systems

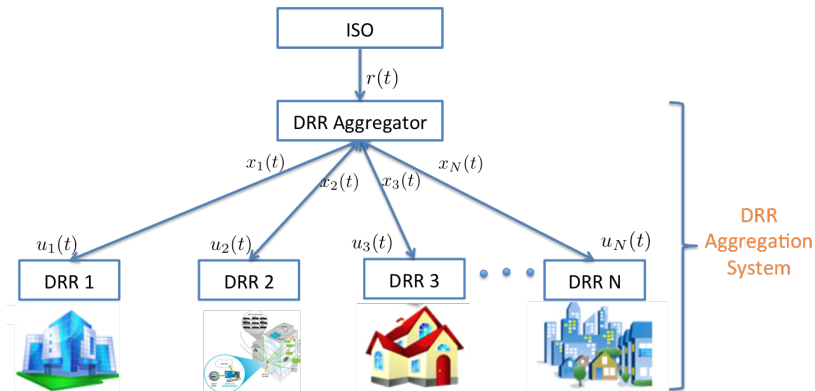
Uncertain phenomena include:

- Packet drops and permanent failures in communication channels between aggregator and DRRs
- Random failures in the processors utilized to implement DRR local control and other hardware
- DRR participants opt out randomly

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DRR Aggregation System Architecture



- The aggregator:
 - ▶ Receives from the ISO a regulation signal, $r(t)$, to be followed
 - ▶ Measures the state of each unit i , $x_i(t)$
 - ▶ Determines the power change from baseline power of each unit i , $u_i(t)$

DRR Individual Dynamics

- Focus on DRRs with the ability to store thermal energy
- Aggregator coordinates response of $1, 2, \dots, N$ DRRs
- Virtual battery model for DRR i :

$$\begin{aligned}\frac{d}{dt}x_i(t) &= -a_i x_i(t) - u_i(t) \\ -C_i &\leq x_i(t) \leq C_i \\ -\underline{n}_i &\leq u_i(t) \leq \bar{n}_i\end{aligned}$$

a_i	Dissipation
C_i	Up/down capacity
$\underline{n}_i, \bar{n}_i$	Discharge/charge rate limits
$x_i(t)$	State of charge
$u_i(t)$	Commanded signal from aggregator

Control Scheme

- Aggregator measures the $x_i(t)$'s and determines the $u_i(t)$'s, so that $\sum_{i=1}^N u_i(t) = r(t)$ as follows:

$$u_i(t) = \frac{C_i}{\sum_j C_j} r(t) + \frac{C_i \sum_{j=1}^N a_j x_j(t)}{\sum_{j=1}^N C_j} - a_i x_i(t)$$

- Closed-loop DRR dynamics:

$$\dot{x}_i(t) = -a_i x_i(t) - u_i(t) = -\frac{C_i}{\sum_{j=1}^N C_j} (r(t) + \sum_{j=1}^N a_j x_j(t))$$

$r(t)$	Regulation signal from ISO/RTO
$x_i(t)$	State of charge
$u_i(t)$	Commanded signal from aggregator

DRR Aggregation System Model

- This control algorithm is a “fair” allocation mechanism:
 - ▶ Participant units reach their energy limit at the same time
 - ▶ Units' state variables are proportional to their energy limits at all times, i.e., $\frac{x_i(t)}{C_i} = \frac{x_j(t)}{C_j} =: z(t), \forall i, j$
- Original N -th order model reduces to a first-order model:

$$\dot{z}(t) = -\frac{\sum_{j=1}^N a_j C_j}{\sum_{j=1}^N C_j} z(t) - \frac{1}{\sum_{j=1}^N C_j} r(t)$$

- We refer to $z(t)$ as the normalized state variable with $-1 \leq z(t) \leq 1$
- In the remainder $r(t) = r$ as focus is on capacity characterization

Incorporating Failure Behavior

- Define an indicator variable characterizing DRR operational status:

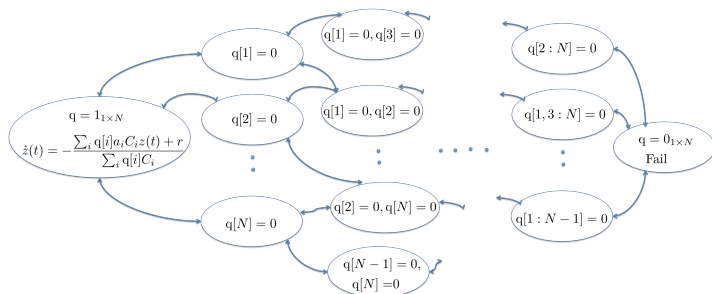
$$\eta_i(t) = \begin{cases} 1, & \text{DRR } i \text{ is functional at time } t \\ 0, & \text{otherwise} \end{cases}$$

- DRR aggregation system dynamics becomes

$$\dot{z}(t) = -\frac{\sum_j \eta_j(t) a_j C_j}{\sum_j \eta_j(t) C_j} z(t) - \frac{1}{\sum_j \eta_j(t) C_j} r$$

- Define $q(t) = (\eta_i(t))_{i=1, \dots, N} \in \mathcal{Q} = \{0, 1\}^N$ to indicate system mode
- Failure/repair process is random:
 - ▶ Failures occur at constant rates, α_i , $i = 1, 2, \dots, N$
 - ▶ Repairs occur at constant rates, β_i , $i = 1, 2, \dots, N$
- The evolution of
 - ▶ $q(t)$ is described by a Markov process, $Q(t)$
 - ▶ $z(t)$ is described by a cont. time cont. state stochastic process, $Z(t)$

DRR Aggregation System Stochastic Model



- The dynamics of $(Q(t), Z(t))$ can be captured by a Stochastic Hybrid System (SHS) model, characterized by
 - S1. A differential equation describing the evolution of $z(t)$ for fixed $q(t)$
 - S2. A collection of transition rate functions defined by component failure and repair rates determining likelihood of transitions among modes

State Statistics

- Choose a set of “test” functions,

$$\psi_i^{(m)}(q, z) := \delta_i(q)z^m = \begin{cases} z^m, & q = i \\ 0, & q \neq i \end{cases}, \forall i \in \mathcal{Q},$$

the expectations of which are the state conditional moments:

$$\mu_i^{(m)}(t) := \mathbb{E}[\psi_i^{(m)}(Q(t), Z(t))]$$

- By using Dynkin's formula:

$$\dot{\mu}_i^{(0)} = - \sum_{j \in \mathcal{O}_i} \lambda_{ij} \mu_i^{(0)} + \sum_{j \in \mathcal{I}_i} \lambda_{ji} \mu_j^{(0)}, \quad i \notin \mathcal{F};$$

$$\begin{aligned} \dot{\mu}_i^{(m)} &= - \frac{mr}{\sum_{k=1}^N i[k]C_k} \mu_i^{(m-1)} - \left(\frac{m \sum_{k=1}^N i[k]a_k C_k}{\sum_{k=1}^N i[k]C_k} \right) \\ &+ \sum_{j \in \mathcal{O}_i} \lambda_{ij} \mu_i^{(m)} + \sum_{j \in \mathcal{I}_i} \lambda_{ji} \mu_j^{(m)}, \quad i \notin \mathcal{F}, m \geq 1 \end{aligned}$$

$$\mathcal{O}_i := \{j \in \mathcal{Q} : \lambda_{ij} \neq 0\}$$

$$\mathcal{I}_i := \{j \in \mathcal{Q} : \lambda_{ji} \neq 0\}$$

$$\mathcal{F}$$

Set of modes to which transitions from mode i occur

Set of modes from which transitions to modes i occur

Set of “fail” modes in which $\sum_{i=1}^N q[i] \bar{n}_i < r$

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Reliability Assessment

Reliability Measure

Probability that the DRR aggregation system can successfully sustain some $r < 0$ for a period of time τ :

$$\begin{aligned} P(r, \tau) &= \Pr\{Z(\tau) > -1 \cap Q(\tau) \notin \mathcal{F}\} \\ &= \sum_{i \notin \mathcal{F}} \Pr\{Z(\tau) > -1 | Q(\tau) = i\} \Pr\{Q(\tau) = i\} \end{aligned}$$

- Using Cantelli's inequality, we have

$$\Pr\{Z(\tau) > -1 | Q(\tau) = i\} > 1 - \frac{\sigma_i^2(\tau)}{\sigma_i^2(\tau) + (-1 - \mu_i(\tau))^2}$$

$\mu_i(\tau)$ Mean of $Z(\tau)$ given $Q(\tau) = i$, equal to $\frac{\mu_i^{(1)}(\tau)}{\mu_i^{(0)}(\tau)}$

$\sigma_i^2(\tau)$ Variance of $Z(\tau)$ given $Q(\tau) = i$, equal to $\frac{\mu_i^{(2)}(\tau)}{\mu_i^{(0)}(\tau)} - \left[\frac{\mu_i^{(1)}(\tau)}{\mu_i^{(0)}(\tau)}\right]^2$

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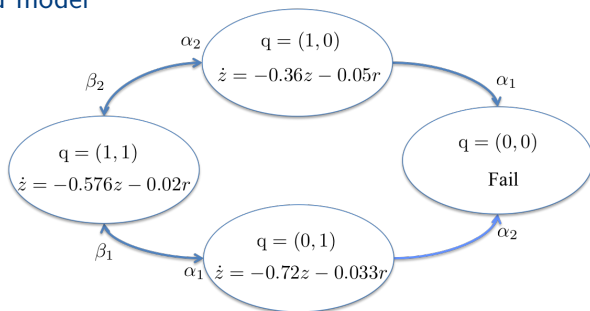
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Two-Unit System

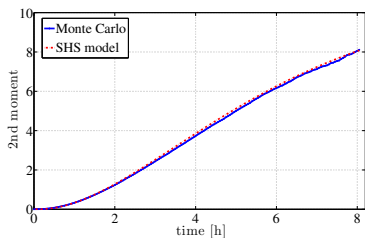
- Unit Parameters

a_1 [h^{-1}]	C_1 [kWh]	α_1 [h^{-1}]	β_1 [h^{-1}]
0.36	20	0.5	6
a_2 [h^{-1}]	C_2 [kWh]	α_2 [h^{-1}]	β_2 [h^{-1}]
0.72	30	0.7	3

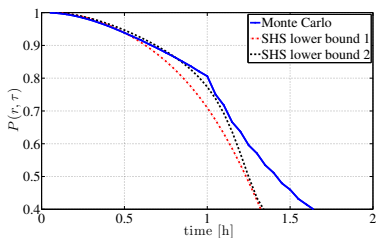
- SHS-based model



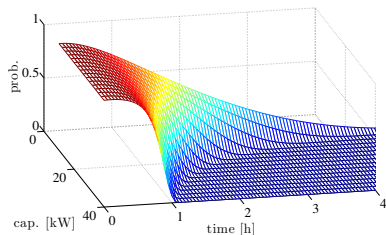
Two-Unit System



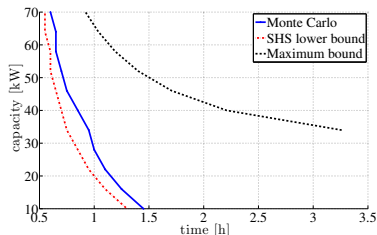
(a) Second moment values



(b) Probability-duration curve



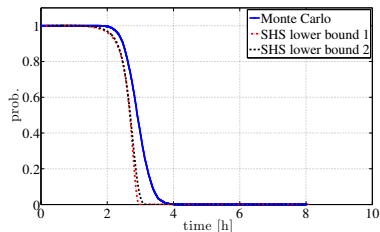
(c) Probability-capacity-duration contour



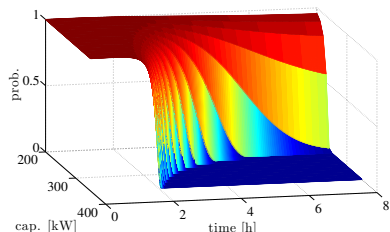
(d) Capacity-duration curve for $p = 0.6$

20-Unit System

- Two identical 10-unit sets
- Units in each set with same parameters as those in two-unit example
- Mode aggregation to form an SHS model with 121 modes



(e) Probability-duration curve



(f) Probability-capacity-duration contour

20-Unit System

- A truncated SHS model with 37 modes yields the same result

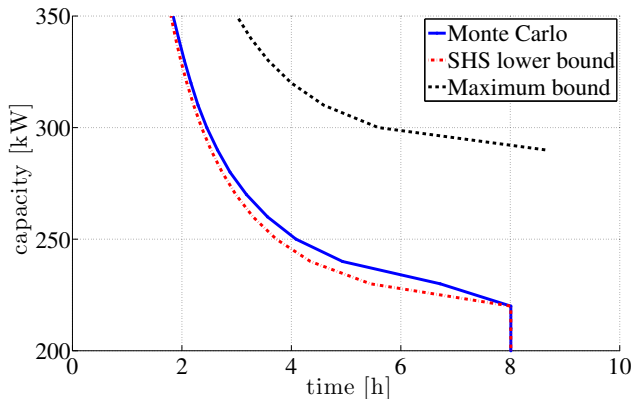


Figure: Capacity-duration curve for $p = 0.95$

1000-Unit System

- Identical units with even-allocation control algorithm
- State space dimension reduction:
 - ▶ Aggregation to form a 1001-mode SHS model
 - ▶ Truncation to form a 100-mode SHS model

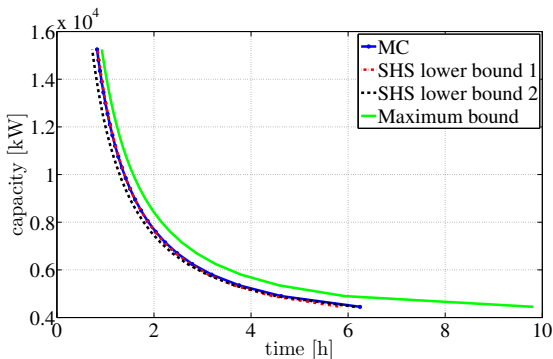


Figure: Capacity-duration curve for $p = 0.95$

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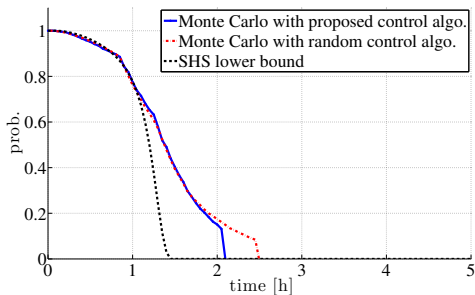
Alternative Allocation Schemes

Lemma ▶ Proof

- Neglect dissipation, i.e., $a_i = 0$
- Assume the failure rate is the same for all units, i.e., $\alpha_i = \alpha_j, \forall i, j$
- Assume units are not repairable, i.e., $\beta_i = 0$

then, the system capacity does not depend on the allocation mechanism

Two-unit system example with $a_1 = a_2 = 0$, $\alpha_1 = \alpha_2 = 0.5$, $\beta_1 = \beta_2 = 0$



Additional Types of DRRs

- Other conventional/interruptible DRRs with no energy limits, e.g.,
 - ▶ Industrial consumers stopping production
 - ▶ Light dimming
- Capacity of the DRR aggregation system is given by

$$\begin{aligned}\Pr\{S^{(\tau)} \geq s\} &= \Pr\{R^{(\tau)} + D \geq s\} \\ &= \int_{-\infty}^{\infty} f_D(v) \cdot F_{R^{(\tau)}}(s - v) dv = f_D \circ F_{R^{(\tau)}}(s)\end{aligned}$$

$S^{(\tau)}$	Total power provided by the overall DRR aggregation system
$R^{(\tau)}$	Power provided by the battery-like DRRs
$F_{R^{(\tau)}}(r)$	Complementary cumulative function of $R^{(\tau)}$
D	Power provided by the conventional DRRs
$f_D(d)$	Probability density function of D

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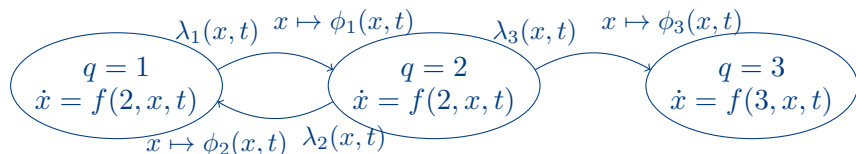
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Concluding Remarks

- We proposed a framework to capture the impact of uncertainty on the capacity of DRR aggregation systems
- We presented a method to evaluate the capacity-duration characteristics of DRR aggregation systems with desired confidence levels
- The computational efficiency and accuracy of this method was illustrated through case studies
- We showed that the method is scalable by reducing the dimension of the SHS state space via mode aggregation and truncation

Backup Slides

Stochastic Hybrid System



- A stochastic differential equation (SDE)
 $dx = f(q, x, t)dt + g(q, x, t)dw$
- A family of m discrete reset maps
 $(q, x) = \phi_l(q^-, x^-, t), \forall l \in 1, \dots, m$
- A family of m transition intensities
 $\lambda_l(q, x, t), \forall l \in 1, \dots, m$

Dynkin's Formula

Thm. Given a function $\psi : \mathcal{Q} \times \mathbb{R}^n \times [0, \infty) \rightarrow \mathbb{R}$ that is twice continuously differentiable w.r.t. its second argument and once continuously differentiable w.r.t. the third argument,

$$\frac{d\mathbb{E}[\psi(q, x, t)]}{dt} = \mathbb{E}[(L\psi)(q, x, t)], \forall (q, x, t) \in \mathcal{Q} \times \mathbb{R}^n \times [0, \infty)$$

where ψ is referred to as a test function, and the operator $\psi \mapsto L\psi$ is called the extended generator of the system and defined as

$$\begin{aligned}(L\psi)(q, x, t) &= \frac{\partial\psi(q, x, t)}{\partial x} f(q, x, t) + \frac{\partial\psi(q, x, t)}{\partial t} \\ &\quad + \sum_{l=1}^m (\psi(\phi_l(q, x, t), t) - \psi(q, x, t)) \lambda_l(q, x, t)\end{aligned}$$

- This gives the moment evolution equations. [◀ Go Back](#)

Proof.

For a given r , let $Q^{(r)}$ indicate the total energy provided by the DRR aggregation system; then,

$$T^{(r)} = \frac{Q^{(r)}}{r}.$$

If no failure has occurred, then the total energy is $\sum_{i=1}^N C_i$. Let L_j indicate the energy loss due to the event that j -th unit in the system fails; then, we have

$$Q^{(r)} = \sum_{i=1}^N C_i - \sum_{k=1}^M L_k,$$

where M indicates the total number of failures during the time that the DRR aggregation system can meet the power regulation request. We show that L_j is independent of the control algorithm used by the aggregator; therefore, the distribution of $T^{(r)}$ is independent of the control algorithm.

Proof.

Take L_1 as an example; the key point is that any control mechanism guarantees that $\sum_{i=1}^N u_i(t) = r$. Let $p_{1,i}$ be the probability that unit i is the first unit that fails. As all the units have the same failure rate, $p_{1,i} = \frac{1}{N}$. Let T_1 be the time that the first unit fails; then, we have that

$$\begin{aligned} L_1 &= \sum_{i=1}^N p_{1,i} (C_i - \int_0^{T_1} u_i(t) dt) = \frac{1}{N} (\sum_{i=1}^N C_i - \int_0^{T_1} \sum_{i=1}^N u_i(t) dt) \\ &= \frac{1}{N} (\sum_{i=1}^N C_i - \int_0^{T_1} r dt) = \frac{1}{N} \sum_{i=1}^N C_i - \frac{r}{N} T_1, \end{aligned}$$

which is independent of $u_i(t)$'s. Then, by setting $T_0 = 0$, expression for L_k is given by

$$L_k = \frac{1}{N} \sum_{i=1}^N C_i - \sum_{j=1}^k \frac{1}{N+1-j} (T_k - T_{k-1}),$$

which again is independent of the control algorithm. Therefore, the distributions of $Q^{(r)}$ and $T^{(r)}$ are independent of the control algorithm. [◀ Go Back](#)