Reliability management of microgrids with renewal energy sources

Koh, Leong Hai

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RELIABILITY MANAGEMENT OF MICROGRIDS WITH RENEWAL ENERGY SOURCES

KOH LEONG HAI
G1000499D

School of Electrical and Electronic Engineering

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Summary

Operational challenges of classical electric utilities, evolutionary changes in the regulatory and the emergence of smaller generating systems (e.g. micro turbines, wind turbines, hydroelectric generators etc.) have unlocked new prospects for distributed generation at site by electricity users. Distributed energy resources (DERs), i.e. small power generating systems which are typically located in the vicinity of end-users, have materialized as a favourable route in meeting the growing electric power needs of end-users and the increasing emphasis on power quality, reliability and energy resilience. DERs are integrated with load demand and energy storage systems (ESSs) providing an opportunity for an entirely new approach in establishing a microgrid. Such a microgrid can provide a lot of benefits to the end-users as it is designed and implemented to meet the immediate power and heat needs of the immediate site. The microgrid can provide uninterrupted power supply, decrease feeder cable losses, enhance local reliability and improve power quality. The energy resources connected to the microgrid include stable sources such as micro turbines, fuel cells and diesel generators; and intermittent energy resources such as photovoltaic system (PVS).

A microgrid can be operated as a stand-alone electrical grid, or grid-tied when connected to the main utility grid. In remote villages, islands, emergency situations (e.g. refugee camps, tsunamis, earthquakes etc.), remote mining operations and military command posts, stand-alone microgrids would be a natural choice to provide electricity.

This thesis serves to establish the probabilistic reliability of hierarchical level I (HL I) of stand-alone microgrid operational adequacy taking into considerations of uncertainties in ESSs, PVSs and conventional generators (CGs). The IEEE Reliability Test System (IEEE-RTS) constant intra-hour load model is modified and used to include a minutely random rapid-ramp microgrid demand model. Instead of using the classical constant intra-hour or intra-day time step, an operating period of one-minute time step to incorporate the effect of fast ramp up (or down) of system components is considered for microgrid operating adequacy due to load and resource variations. The ESS model is proposed with time dependent state-of-charge (SOC) in order to determine the output

power from cell to system level. The PVS reliability is modelled using the basic solar photovoltaic cell to form the PV system in various different configurations and different penetration levels. The interaction between the variability of PVSs and random rapid-ramp demand; and between the variability of PVSs and ESSs are evaluated. The two reliability indices used for the stand-alone microgrid considered are the expected energy not supplied (EENS) and the expected energy not used (EENU).

Table of Contents

Acknowledgements	I
Summary	II
Table of Contents	IV
List of Nomenclature	IX
List of Tables	XXIII
List of Figures.....	XXIII
1 Introduction	1
1.1 Motivation	1
1.2 Objectives.....	4
1.3 Major Contributions	5
1.4 Report Organization	6
2 Literature Review on Reliability Techniques	7
2.1 Introduction	7
2.2 Power System Adequacy Assessment	12
2.2.1 Generation System Studies	12
2.2.2 Composite System Studies	14
2.2.3 Distribution System Studies	15
2.3 Reliability Cost/Worth.....	15
2.4 Adequacy Indices.....	16
2.4.1 Adequacy Indices in HL I Studies.....	17

2.4.2	Adequacy Indices in HL II Studies.....	18
2.4.3	Reliability Worth Indices	19
2.5	Summary	20
3	Energy Resources and Demand Modelling.....	21
3.1	Introduction	21
3.2	Generation System Reliability Model	21
3.2.1	Generator System Model.....	21
3.2.2	Binomial Distribution Technique.....	22
3.2.3	Recursive Algorithm.....	24
3.3	Solar PV Model	26
3.4	Demand Model	30
3.4.1	Constant Load Model.....	31
3.4.2	Time Varying Load Model.....	32
3.4.3	Probabilistic Load Model	34
3.5	Energy Storage Model	37
3.6	Summary	39
4	Impact of Energy Storage and Variability of PV on Power System Reliability	41
4.1	Introduction	41
4.2	Why Investigate the Impact of Energy Storage and Variability of PV on Power System Reliability.....	41
4.3	Models and Proposed Techniques.....	42
4.3.1	Conventional Generator Modelling	43

4.3.2	Time Varying Load Model	44
4.3.3	Solar PV Model.....	44
4.3.4	Energy Storage Model	45
4.3.5	Annual Energy Cost Considerations.....	46
4.4	Results and Discussions.....	48
4.4.1	System Adequacy with addition of PV only.....	48
4.4.2	System Adequacy with addition of PV and ES.....	50
4.4.3	Impact on Electricity Cost.....	55
4.5	Conclusions	56
5	Operational Adequacy Studies of a PV-Based and Energy Storage Stand-Alone Microgrid	57
5.1	Introduction	57
5.2	Why Operational Adequacy Studies for Stand-Alone Microgrid.....	57
5.3	System Modelling	60
5.3.1	Photovoltaic System Model.....	62
5.3.2	Energy Storage System Model.....	65
5.3.3	Load Model.....	67
5.4	Formulation of Stand-Alone Microgrid.....	67
5.4.1	Case 1 Microgrid with CGs	68
5.4.2	Case 2 Microgrid with CGs and PVSs.....	72
5.4.3	Case 3 Microgrid with CGs, PVSs and ESSs	73
5.4.4	Case 4 Generalized Equations	73
5.5	System Studies.....	74

5.5.1	Test System and Parameters	74
5.5.2	Microgrid with only CGs	74
5.5.3	Microgrid with CGs and PVSs.....	77
5.5.4	Microgrid with CGs, PVSs and ESSs	79
5.6	Conclusion.....	81
6	Multistate Reliability Modelling of an Isolated Microgrid	83
6.1	Introduction	83
6.2	Why Multistate Reliability Modelling of Isolated Microgrid	83
6.3	System Modelling: MSS, ESS, PVS, CG and Demand.....	85
6.3.1	Multistate System Model	86
6.3.2	Conventional Generation Modelling	87
6.3.3	Photovoltaic System Modelling	88
6.3.4	Demand Model.....	91
6.3.5	Energy Storage System Modelling.....	92
6.4	Problem Formulation.....	94
6.4.1	Scenario 1 - PVS and CG Multistate Modelling	99
6.4.2	Scenario 2 - ESS, PVS and CG Multistate Modelling.....	101
6.4.3	Scenario 3 - Generalize Equations	103
6.5	System Studies.....	103
6.5.1	Microgrid with Scenario 1	103
6.5.2	Microgrid with Scenario 2.....	106
6.6	Conclusions	109

7	Conclusions and Future Work.....	111
7.1	Conclusion.....	111
7.2	Future Work	115
7.2.1	In-depth Analysis of Monte Carlo Techniques	115
7.2.2	Demand Side Load Management	116
7.2.3	Microgrid Reliability	117
7.2.4	Degradation of System Components	117
	Author's Publications	118
	References	119

List of Nomenclature

Chapter 2:

Variables:

F_i	system state frequency
p_i	system state probability

Abbreviations:

EDNS	expected demand not supplied
EENS	expected energy not supplied
EIC	expected interruption cost
HL I	hierarchical level I
HL II	hierarchical level II
HL III	hierarchical level III
IEAR	interrupted energy assessment rate
ISO	Independent System Operator
LOEE	loss of energy expectation
LOLD	loss of load duration
LOLE	loss of load expectation
LOLF	loss of load frequency
PV	photovoltaic

Chapter 3:

Indices:

i operating period

j time step

Variables:

A unit availability

A_c component c availability

C_i capacity outage of state i for the unit being added

I_λ photon current

I_d Shockley temperature-dependent diode current

I_o output current of single solar PV cell

I_p PV cell leakage current

I_s reverse saturated current of the diode

I_{sc} cell short-circuit current

L variable sunlight intensity

L_s nominal sunlight intensity on a bright clear day on earth

n number of unit states

$P(X)$ cumulative probabilities of the capacity outage of X MW when the subsequent unit are added

$P'(X)$ cumulative probabilities of the capacity outage of X MW when the previous unit are added

P_{Li}^{ave} average load level for period i

P_m	maximum single solar PV cell output power
P_o	single solar PV cell output power
p_i	probability of existence of the unit state i
R_L	load resistance
R_p	parallel resistance across the Shockley diode
U	unit unavailability
U_c	component c unavailability
V_d	diode voltage (volts)
V_o	cell output voltage
V_{oc}	cell open-circuit voltage
λ_c	component c failure rate
μ_c	component c repair rate
η	empirical constant
η_m	conversion efficiency of PV cell for the maximum power generated
σ_{PLi}	standard deviation of P_{Li} .

Constants:

k	Boltzmann constant 1.38047×10^{-23} J/K
q	electron charge 1.60210×10^{-19} C
T	the absolute temperature (K)

Abbreviations:

COPT	capacity outage probability table
ES	energy storage
FOR	forced outage rate
LDC	load duration curve

Chapter 4:

Indices:

i	operating period (subscript)
j	operating state (subscript)

Variables:

$AG_{soc(i)}$	state of charge at time step i
DR	demand response signal
E_{max}	ES maximum storage in MWH
E_{min}	ES minimum storage in MWH
m	PV peak installed capacity ranging from 0~50% of total generation capacity
CD_i	i^{th} interval energy storage (ES) charging / discharging limit
E_{ci} / E_{di}	available energy for charging and required energy for discharging at time step i
k	total interval of reliability simulation
L_c / L_d	charging / discharging limit
L_i	i^{th} interval LDC

n	percentage of demand
R_c / R_d	charging / discharging rate
$R(t)$	reliability as a function of time t
S_i	i^{th} interval PV power from solar irradiance
t_i	duration of time step i
$X\%$	percentage of maximum allowable PV energy to meet load demand with respect to (w.r.t.) the maximum system generation capacity
λ	failure rate
λ_c	failure rate for component c
$\lambda(t)$	time dependent failure rate
μ	repair rate
μ_c	repair rate for component c
η_c / η_d	charging / discharging efficiency
α	annual energy cost in S\$;
β_i	Uniform Singapore Energy Price (USEP) in S\$/MWH;

Abbreviations:

COPT	capacity outage probability table
EMC	Energy Market Company Pte Ltd
ES	energy storage
GHG	greenhouse gases
HL I	Hierarchical level I
HL II	Hierarchical level II

HL III	Hierarchical level III
ISO	Independent System Operator
LOEE	loss of energy expectation
LOLE	loss of load expectation
NEMS	National Electricity Market of Singapore
RPS	renewable portfolio
PV	photovoltaic
SOC	state of charge
USEP	Uniform Singapore Energy Price

Chapter 5:

Indices:

i	operating period (subscript)
j	operating state (subscript)

Variables:

$A_c(t_i)$	reliability of component at time t_i
CG_{ij}	CG capacity at j^{th} state and i^{th} operating period
E_{ci}/E_{di}	available ESS energy for charging and required energy for discharging at i^{th} operating period
ENS_{ij}	energy not supplied at i^{th} operating period j^{th} state
ENU_{ij}	energy not used at i^{th} operating period j^{th} state
I_d	Shockley temperature-dependent diode current

I_{oi}	PV cell current at i^{th} operating period
I_p	PV cell leakage current
I_{ri}	photon current at i^{th} operating period, which depends on the light intensity and its wavelength
I_s	reverse saturated current of the diode
LD_i	load demand
ND_i	net demand
N_{cg}	total number of CG states
N_{es}	total number of ESS states
N_{pv}	total number of PVS states
N_{si}	total number of system operating intervals
N_X	total number of X system component states
P_c/P_d	ESS charging / discharging rate, i.e. power rating of energy storage)
P_{ij}^{cg}	state probability of CGs
P_{il}^{es}	state probability of ESS
P_{ik}^{pvs}	state probability of PVS
P_{im}^X	state probability of X system component
P_{oij}^{sc}	output power of a PV cell
P_{oij}^{es}	output power cell of an energy storage cell
P_{oij}^{ess}	output power cell of an ESS
P_{oij}^{pvs}	output power of the PVS
R_p	parallel resistance across the PV cell

R_s	series resistance between the photon current source and the load across the PV cell terminals
R_i^{elnv}	reliability of energy storage inverter
R_i^{ema}	reliability of energy storage modularized array
R_i^{eis}	reliability of energy storage inverter system
R_i^{es}	reliability of single-cell energy storage
R_i^{ess}	reliability of ESS
R_i^{ma}	reliability of PV modularized array
R_i^{pv}	reliability of PV modularized array
R_i^{pvs}	reliability of PVS
R_i^{slnv}	reliability of PV inverter
R_i^{scell}	reliability of PV cell
R_i^{sis}	reliability of PV inverter system
SOC_i	ESS state of charge
SOC_{max}/SOC_{min}	ESS maximum/minimum state of charge
t_i	duration of i^{th} operating period
$U_c(t_i)$	unreliability of component at time t_i
V_{oc_i}	open-circuit voltage at i^{th} operating period
X_{im}	X system component
λ_c	failure rate for component
λ_{es}	failure rate for single-cell energy storage
λ_{scell}	failure rate for PV cell

η_c/η_d	ESS charging / discharging efficiency
η_g^{es}	ESS g^{th} inverter efficiency
η_g^{pv}	PVS g^{th} inverter efficiency

Constants:

k	the Boltzmann constant
q	the electron charge
V_d	diode voltage (volts)
η	empirical constant
T	the absolute temperature (K)

Abbreviations:

COPT	capacity outage probability table
EENS	expected energy not supplied
EENU	expected energy not used
ESS	energy storage system
FOR	forced outage rate
PL1/2/3	priority loading order 1, 2 or 3
PVS	photovoltaic system
SR	spinning reserve
TCTC	total cross-tied configuration

Chapter 6:

Indices:

i	operating period i
j	operating state j
k	k^{th} component

Variables:

A_k^{cg}	k^{th} component reliability of CG sub-system
A_k^{pvs}	k^{th} component reliability of PVS sub-system
A_k^{ess}	k^{th} component reliability of ESS sub-system
CG_{ij}	CG i^{th} operating period at j^{th} state
$E_{c(t_i)} /$ $E_{d(t_i)}$	depth of charging / discharging and the SOC for t_i
ENS_{ij}	energy not supplied for i^{th} operating period j^{th} state
ENU_{ij}	energy not used for i^{th} operating period j^{th} state
I_d	Shockley temperature-dependent diode current
I_{oi}	solar cell current at i^{th} operating period
I_p	PV cell leakage current
I_{r_i}	photon current at i^{th} operating period
I_s	reverse saturated current of the diode
LD_i	load demand at i^{th} operating period
ND_i	net demand at i^{th} operating period

N_{cg}	total number of CG states
N_{es}	total number of ESS states
N_{pv}	total number of PVS states
N_{si}	total number of system operating intervals
N_X	total number of X system component states
P_c/P_d	ESS charging / discharging rate, i.e. power rating of energy storage
P_{ij}^{cg}	probability of CG sub-system at i^{th} operating interval j^{th} state
P_{ij}^{ess}	probability of ESS sub-system at i^{th} operating interval at j^{th} state
P_{ij}^{pvs}	probability of PVS sub-system at i^{th} operating period j^{th} state
P_{ij}^X	probability of X sub-system at i^{th} operating period j^{th} state
P_{oi}^{sc}	i^{th} operating period output power of solar cell
P_{oi}^{es}	i^{th} operating period single-cell energy storage output power
P_{oi}^{ess}	i^{th} operating period ESS output power
P_{oi}^{pvs}	i^{th} operating period output power of PVS
R_p	parallel resistance across the solar cell
R_s	series resistance between the photon current source and the load across the solar cell terminals
R_i^{elnv}	reliability of energy storage Inverter at i^{th} operating period
R_i^{emod}	reliability of energy storage module i^{th} operating period
R_i^{es}	reliability of energy storage string i^{th} operating period
R_i^{esc}	reliability of single-cell energy storage i^{th} operating period
R_i^{ess}	reliability of energy storage system i^{th} operating period

R_i^{pvs}	reliability of PVS i^{th} operating period
R_i^{slnv}	reliability of solar inverter i^{th} operating period
R_i^{scell}	reliability of solar cell i^{th} operating period
R_i^{smod}	reliability of solar PV module i^{th} operating period
R_i^{str}	reliability of solar PV string i^{th} operating period
$SOC_i /$ SOC_{i-1}	$i^{th}/(i-1)^{th}$ operating period ESS state of charge
$SOC_{max} /$ SOC_{min}	ESS maximum/minimum state of charge
t_i	duration of operating period i
U_k^{cg}	k^{th} component unreliability of CG sub-system
U_k^{pvs}	k^{th} component unreliability of PVS sub-system
U_k^{es}	k^{th} component unreliability of ESS sub-system
V_{oc_i}	i^{th} operating period diode voltage and the open-circuit voltage
X_{ij}	X system component for i^{th} operation period j^{th} state
λ_k^{cg}	k^{th} component failure rate for CG sub-system
λ_k^{es}	k^{th} component failure rate for ESS sub-system
λ_k^{pvs}	k^{th} component failure rate for PVS sub-system
μ_k^{cg}	k^{th} component repair rate for CG sub-system
μ_k^{pvs}	k^{th} component repair rate for PVS sub-system
μ_k^{es}	k^{th} component repair rate for ESS sub-system
η_c/η_d	ESS charging / discharging efficiency

η_h^{es}	ESS h^{th} inverter efficiency
η_g^{pv}	PVS g^{th} inverter efficiency

Constants:

κ	Boltzmann constant
q	electron charge
V_d	diode voltage (volts)
η	empirical constant
T	the absolute temperature (K)

Abbreviations:

COPT	capacity outage probability table
CG	conventional generation
EENS	expected energy not supplied
EENU	expected energy not used
ENS	energy not supplied
ENU	energy not supplied
ESS	energy storage system
FOR	forced outage rate
MSS	multistate system
PL	priority loading order
PV	photovoltaic

PVS photovoltaic system

SR spinning reserve

List of Tables

Table 3-1 Procedure to form COPT using basic probability method	24
Table 3-2 COPT for a generation system with two non-identical units	24
Table 3-3 COPT for a general generation system.....	25
Table 5-1 CG and priority loading order	75
Table 5-2 Impact of CG ramp rate on EENS and EENU	77
Table 6-1 CG reliability data and priority loading order	99
Table 6-2 CG capacity out (MW)	100
Table 6-3 CG state probability.....	100
Table 6-4 PVS capacity out (MW)	101
Table 6-5 PVS state probability	101
Table 6-6 ESS capacity out (MW).....	102
Table 6-7 ESS state probability	102

List of Figures

Figure 2-1 Subdivision of system reliability.....	10
Figure 2-2 Power system hierarchical levels	11
Figure 2-3 Conceptual tasks in generating capacity HL I reliability evaluation	13
Figure 2-4 Conventional system (HL I) model.....	13
Figure 2-5 A sample composite system for HL II studies	14
Figure 2-6 Consumer, utility and total cost as a function of system reliability	16
Figure 3-1 2-state model for a base load generating unit.....	22

Figure 3-2 Equivalent circuit of a single PV Cell.....	26
Figure 3-3 I-V characteristic of a solar cell	27
Figure 3-4 Load profile for a periodic constant load	31
Figure 3-5 IEEE-RTS hourly variable load model	33
Figure 3-6 IEEE-RTS load duration curve (LDC).....	34
Figure 3-7 Normal distribution of load	35
Figure 3-8 A probabilistic hourly variable load model.....	36
Figure 3-9 Batteries' Characteristics	38
Figure 3-10 Energy storage charge / discharge strategy	39
Figure 4-1 Energy Market Company time series year 2010 USEP	47
Figure 4-2 LOLE of PV peak installed capacity (MW) as percentage of system maximum installed capacity	49
Figure 4-3 System LOEE with PV peak installed capacity (MW) as percentage of system maximum generation capacity	50
Figure 4-4 Impact of varying PV peak installed capacity on LOLE (ES = 30%)	51
Figure 4-5 Impact of varying PV peak installed capacity on LOEE (ES = 30%)	52
Figure 4-6 Impact of varying energy storage capacity on LOLE (PV = 30%).....	52
Figure 4-7 Impact of varying energy storage capacity on LOEE (PV = 30%).....	53
Figure 4-8 Impact of varying maximum energy storage charge / discharge hours on LOLE (PV = 30% and ES = 30%)	54
Figure 4-9 Impact of varying maximum energy storage charge / discharge hours on LOEE (PV = 30% and ES = 30%)	55
Figure 4-10 Annual energy cost vs PV peak installed capacity percentage with price information from EMC uniform Singapore energy price	56

Figure 5-1 The equivalent circuit for a photovoltaic cell	61
Figure 5-2 A typical PVS in TCTC with b3 Modularize Arrays	63
Figure 5-3 A typical ESS in TCTC with d3 ES Modularize Arrays.....	66
Figure 5-4 Time varying SOC of an ESS	66
Figure 5-5 The minutely load curve with ramp up (or down)	67
Figure 5-6 Type 1 ENU_{ij} area for both ND and CG ramp down	70
Figure 5-7 Type 2 ENS_{ij} and ENU_{ij} area for ND ramp down and CG ramp up	71
Figure 5-8 Type 3 ENS_{ij} area for both ND and CG ramp up.....	71
Figure 5-9 Type 4 ENS_{ij} and ENU_{ij} area for ND ramp up and CG ramp down	72
Figure 5-10 Impact of spinning reserve on EENS and EENU with PL1, PL2 and PL3 (at base FOR)	76
Figure 5-11 Impact of spinning reserve on EENS and EENU with base FOR and 3 times base FOR.....	77
Figure 5-12 Impact of Spinning Reserve (at PVS=50%) on EENS and EENU with base FOR and 3 times base FOR	78
Figure 5-13 Impact of PVS capacity and CG (at SR=15%) on EENS and EENU with base FOR and 3 times base FOR	79
Figure 5-14 Impact of spinning reserve (at PVS=50% and ESS=50%) on EENS and EENU with base FOR and 3 times base FOR.....	80
Figure 5-15 Impact of ESS (with PVS 50% capacity and CG 15% SR) on EENS and EENU with base FOR and 3 times base FOR.....	81
Figure 6-1 State space diagram for repairable element	87
Figure 6-2 Operational modelling of a CG, (a) Classic constant intra-hour CG, (b) Minute-to-minute ramp up/down CG	88

Figure 6-3 a) The equivalent circuit of a single PV cell, b) module with [a1xb1] solar cell, c) string array with [a2xb2] module, and d) PVS with b3 column String Array System.....	90
Figure 6-4 Minute-to-minute demand curve for a week.....	91
Figure 6-5 ESS SOC in charging or discharging	92
Figure 6-6 Formation of ESS (a) single-cell energy storage, (b) modularized energy storage with [c1xd1] cells, (c) ESS with d2 column String Module System.....	94
Figure 6-7 ENU_{ij} computation for Case 1	96
Figure 6-8 ENS_{ij} and ENU_{ij} computation for Case 2.....	96
Figure 6-9 ENS_{ij} computation for Case 3	97
Figure 6-10 ENS_{ij} and ENU_{ij} computation for Case 4.....	97
Figure 6-11 EENS with multistate PVS and CG	105
Figure 6-12 EENU with multistate PVS and CG.....	105
Figure 6-13 EENS with multistate PVS and CG	106
Figure 6-14 EENU with multistate PVS and CG.....	106
Figure 6-15 EENS with multistate ESS, PVS and CG	107
Figure 6-16 EENU with multistate ESS, PVS and CG.....	108
Figure 6-17 EENS with multistate ESS, PVS and CG	109
Figure 6-18 EENU with multistate ESS, PVS and CG.....	109

1 Introduction

1.1 Motivation

A very comprehensive assessment on greenhouse gas (GHG) emission and mitigation was reported by Inter-governmental Panel on Climate Change (IPCC) Fourth Assessment Report on Climate Change 2007 [1]. The aim is to stabilize GHG concentration emission in atmosphere at a level that will avoid endangering anthropogenic interference with the climate system. This concentration level has to be reached at an appropriate time frame so that the ecosystem has adequate time to adapt naturally to climate change and not adversely impact on food production. Global economic progression can then hopefully be continued in a socially and environmentally sustainable manner.

Power generation and road transport contribute to the largest growth of CO₂ emission, and one of the simplest mitigation techniques is via energy efficiency. The centralized electric power system structure is expensive in infrastructure. It requires long planning lead time, and suffers high losses. Augmentative mechanisms should be adopted in order to meet consumers' growing demand on energy in an effective and efficient manner, yet providing reliable and resilient energy supply. Reference [2, 3] argued that a microgrid has emerged as an augmenting technology with higher resilience, flexibility and efficiency. Isolated microgrids naturally find their applications in islands, remote villages and military command posts [4-7].

Photovoltaic technology has received notable investment for more than a decade due to considerable interests in renewables adoption worldwide. However, deep penetration of intermittent photovoltaic and wind power technology compromises on electric power system reliability, and even more so for an isolated microgrid with low inertia [8-10]. E. Ela and B. Kirby [11] recounted in the February 26, 2008 event where the Electric Reliability Council of Texas (ERCOT) declared a system emergency due to a swift and

enormous ramp down of the output power of the wind turbines. B. Kirby [12] pointed out that generators track load at roughly in one to two-minute interval level and a swift system load fluctuation may cause generators to regulate in the wrong direction. Hence, fast ramp operations and dispatch in isolated microgrids could lead to serious implications and warrant further research.

W. Y. Li and L. Goel [13] articulated the research gap of coordination in adequacy between intermittent sources and random loads; and between intermittent sources and storages. Other researchers have considered large power systems ramp issues in unit commitment and generation economic dispatch [14-19]. Specifically, the impacts of ramp rates of conventional generators on power system reliability have not been investigated in detail. Moreover, operational ramp rate issues in microgrids are more acute because the conventional generators have slower ramp rates than the large power systems and the impacts of fast ramp on microgrid operational adequacy have barely been investigated.

Classical constant intra-hour demand, conventional generators (CGs) and renewable source models have been used in [20-26]. However, the ramp rates of CGs were not considered in these papers. This thesis endeavours to fill this gap by considering the probabilistic 2-state and higher state enumeration methodologies for all the system components such as CGs, PVSs and ESSs with ramp up (or down) operating in a microgrid .

J. V. Milanovic et al. [14] indicated that regular update of load model parameters is crucial for better accuracy in simulation, due to emerging penetration of new non-conventional generation (mostly intermittent sources through power electronics interface) in power systems. Hence, per minute demand model used in this thesis will be of great research value to describe microgrid operation adequacy more accurately.

There have been attempts to connect large solar photovoltaic (PV) farms and energy storage systems (ESSs) at generation and/or transmission level. The cost of such large solar farms and ESSs are prohibitive even for Independent System Operators. However, the general public awareness of global warming and environmental sustainability issues have created a general acceptance of the installation of the rooftop solar PV and the ESSs at the distribution level. The rate of solar PV systems (PVSs) and ESSs installation has increased tremendously for the last two decades at the distribution level. There has been a growing awareness and the need of microgrids that have the options to connect to the larger grid or configure as an isolated microgrid. This has changed the dynamics dramatically of the electric power system where conventional generators will interact with PVSs and ESSs installed at the generation level. The rapid and random change of demand for a small microgrid or isolate microgrid with conventional generators, PVSs and ESSs connected at the distribution level should change the complete dynamics of the microgrid operation. This dynamics of such an interaction in an isolated or small microgrid is completely different from large electric power systems.

Notably, the reliability of all system level components in a microgrid impacts on both its short term and long term viability. Taking PVS and ESS as an example where the system level is made up of hundreds if not thousands of single PV cell and single energy storage (ES) cell respectively. The techniques of connecting all these single cells, the adopted configurations, the manufacturing quality control, application ambient conditions, mean time between failures of each single cell etc. would have an impact on the system level and eventually the microgrid operational adequacy. Hence, it is paramount to investigate and understand the reliability from a single cell component level to the reliability of a complete system level at a distribution level. Furthermore, one or more single PV cell or single ES cell could mal-function prematurely. This will result in a multistate system (MSS) model where performance of the system level component will be derated.

ESS has been widely published in several literatures for many years. The state of charge (SOC) at any point in time has remained a keen research area. In lieu of the hundreds or

thousands of single ES cell, the SOC from single ES cell to ESS level will be time dependent as it interacts with the demand, PVSs and CGs. The research on such time varying SOC of ESSs in the short time analysis will stretch an intriguing scientific value in the operational adequacy of the microgrid.

To fill the research gaps of operational adequacy of microgrids, which are more versatile for load and resource variation, this thesis evaluates the reliability of a stand-alone microgrid with fast demand ramps and high PV penetration. The expected energy not supplied (EENS) and expected energy not used (EENU) have been formulated to represent energy generation / demand corresponding to efficiency and energy surplus in the system operation taking into consideration the effects of the ramp rates of the load, renewable resources and conventional generators. Adequacy coordination among intermittent sources, random demand, generalized PVS reliability model and time varying state of charge (SOC) of ESSs are also considered in the proposed technique. As PVSs and ESSs are made via multiple single PV cells and multiple single ES cells respectively, the multistate system (MSS) model can be applied aptly to study the impact on system level reliability and power output.

1.2 Objectives

This thesis focuses on the stand-alone microgrid operational adequacy studies incorporating energy storage systems (ESSs), photovoltaic systems (PVSs) and conventional generators (CGs). The main objectives of this research are:

- 1) Understand the existing techniques used in conventional power systems and microgrid reliability evaluation; and identify research gaps for operational adequacy in stand-alone microgrids reliability.
- 2) Study the new planning and operation issues due to the integration of intermittent renewable energy sources and energy storage in stand-alone microgrid, while considering uncertainties of all the system components.

- 3) Examine the microgrid operational adequacy due to intermittent PVS generation and random rapid-ramp demand models, in one-minute time step.
- 4) Investigate the microgrid operational adequacy due to intermittent PVS generation and ESS, in one-minute time step.
- 5) Apply probabilistic 2-state and higher state enumeration to cater for the uncertainties of system components, e.g. ESSs, PVSs and CGs.
- 6) Consider the impact of spinning reserve (SR) capacity of CGs, priority loading order, forced outage rate (FOR) and ramp rates on the reliability of stand-alone microgrids.
- 7) Improve the techniques for reliability evaluation of operational adequacy of stand-alone microgrid with integrated of PVSs and ESSs.
- 8) Develop techniques in the selection of the optimal size of ESSs and PVSs.

1.3 Major Contributions

The major contributions of this thesis for microgrid operation adequacy are as follows:

- 1) Introduce ramp up (or down) for ESSs, PVSs, CGs and demand model to determine EENS and EENU due to load and resource variations.
- 2) Consider uncertainties of ESSs, PVSs and CGs at every time step interval such that all contingency states are considered for each system component in the computation of EENS and EENU.
- 3) Deploy probabilistic 2-state and higher state enumeration techniques in random rapid-ramp environment for the system components.
- 4) Formulate reliability modelling and power output of PVS and ESS from the cell level to system level, and identify configuration for better performance over lifetime. The MSS model fits the scenario perfectly as the anomaly of one or more single PV cell and/or single ES cell can be explained nicely via MSS.
- 5) Introduce time varying state-of-charge (SOC) for ESS with uncertainty considerations to determine power output.
- 6) Propose generalize equations to cater for any additional system components with uncertainties to be added to the model.

- 7) Study impact of SR capacity, priority loading order, FOR and ramp rate in rapid-ramp microgrids.
- 8) Enable the system planner to select the type and size of microgrid systems that contain alternative energy sources and energy storage systems.

1.4 Report Organization

This report is organized such that Chapter 2 explains the basic power system and microgrid reliability adequacy, reliability cost / worth and its respective indices. Chapter 3 narrates energy sources, energy storage system and demand modelling. Chapter 4 describes the impact of energy storage and variability of PV on hierarchical level I (HL I) power system reliability evaluation. This is a traditional IEEE-RTS electric power system with conventional generators of 3405MW installed capacity, considering both system reliability and annual cost saving using typical constant intra-hour analytical method. Chapter 5 evaluates the operational adequacy studies of a stand-alone 2.4MW HL I microgrid in per minute ramp analysis with PVS and ESS. Chapter 6 extends the research covered in Chapter 5 to include multistate reliability modelling of the isolated 2.4MW HL I microgrid using per minute ramp technique. Conventional generators, PV systems and energy storage systems are all modelled as multistate system to study the impact on microgrid system adequacy. Finally, Chapter 7 provides the conclusions, and explores the potential of future work to be studied.

2 Literature Review on Reliability Techniques

2.1 Introduction

A modern electric power system is extremely complex due to several reasons. Some of which are sheer physical size, widely dispersed geography, national and international interconnections, flows that do not readily follow the transportation routes as expected by operators but they naturally follow physical laws. The fact that electrical energy cannot be stored efficiently or effectively in large quantities, unpredicted system behaviour at one point of the system can have a major impact on system reliability at long distances from the source of trouble, and many other implications [15].

The fundamental purpose of an electric power system is to supply customers with electricity. It has come to a point where society expects electrical supply to be always available with a reasonable degree of quality. It is neither economically nor technically feasible to build an absolutely reliable power system due to uncontrollable factors, such as the random failures of components. Over-investment can provide high reliability but result in excessive cost. On the other hand, under-investment may cause a large number of power system faults, and therefore leads to much more economic losses. Reliability and economic are competing constraints. This dilemma leads to difficult managerial decisions at both the planning and operating phases.

Deterministic technique has been widely studied and better understood in general. However, electric power systems behaviour is stochastic in nature where deterministic technique cannot account for and shows incongruence. Stochastic electric power systems behaviour will be better studied and explained via probabilistic technique as all input and output event considerations are stochastic variables in nature. Hence, probabilistic techniques can be a better decision supporting tool to resolve the competing constraints between operation, reliability and economic cost.

Reliability is an inherent characteristic of a system or product. It is therefore a design parameter and its assessment should be performed as an integral part of the design process. In order to achieve this, it must be expressed in quantitative term and specified as part of the system objective [16].

Quantitative assessment can be used for two specific applications namely a) evaluation of historical performance, and b) establishment conjecture of future performance. The former can and is frequently done in practice by organizations or individuals that may or may not perform future predictions. The latter, however, requires knowledge of the past in order to predict the future.

In all cases, the system behaviour cannot be defined as deterministic but as stochastic in nature, i.e., it varies randomly with time. Complete assessment of a stochastic process can only be achieved using probability techniques. However, one should note that probability theory alone cannot predict either the reliability or the safety of a system. The system assessment requires a thorough understanding of the system, the manner in which it fails, the method it operates, its design, the stresses and the situation in which it is subjected to. It is in this aspect of reliability evaluation that engineering judgment is paramount and no amount of probability theory can circumvent it [16]. Probability theory is only a tool available to the engineer to transform knowledge of the system into a prediction of its likely behaviour.

The probability of a device carrying out its tenacity sufficiently for the period of time planned under the functioning environments [16] is its reliability. The characterization has four simple portions; 1) adequate performance, 2) operating conditions, 3) time, and 4) probability. Adequate performance, operating conditions and time are all engineering parameters, and probability theory is of no assistance in this part of the assessment. However, the probability portion provides the numerical input for the assessment of reliability and also the first index of system adequacy. In many instances it is the most significant index, however there are many more calculated and used parameters.

Typically, in the initial planning phase to evaluate power system reliability, both probabilistic and deterministic techniques are used [15]. Examples of deterministic techniques are spinning reserves sufficient to cover likely contingencies and planning generation margins equivalent to predetermined margin of forecast peak demand. Similarly, N-1 or N-2 principles are applied as network capacity contingency in case one or more networks are out of order. Hence, deterministic technique suffers from the fact that it cannot anticipate or account for the system behaviour, which is inherently stochastic.

In design, planning and allocation of resources, more consequential information can be derived from probabilistic techniques. The basic aspects of power system reliability evaluation using probabilistic techniques are system security and system adequacy [15, 17] as in Figure 2-1. System adequacy is associated with static conditions, e.g. availability of satisfactory generation, transmission and distribution capability inside the system to meet the demand. System security is related to system dynamics, e.g. capability of the system to react to instabilities appearing within the system. The two methods usually employed to evaluate system performance are simulation techniques and analytical techniques, however this thesis focuses on the latter.

Figure 2-1 Subdivision of system reliability

For all analytical techniques, the system can be described via a mathematical model with direct numerical solutions applied to evaluate the reliability indices. These techniques generally provide expectation indices in a relatively shorter computational time. The analytical model of the system would require assumptions to obtain a simplification of the problem, even more so when modelling complex systems with complex operation procedures.

Reliability evaluation using probabilistic techniques is usually in the field of adequacy assessment. It is important to appreciate that most of the indices available at present are not overall reliability indices but adequacy indices.

Figure 2-2 Power system hierarchical levels

A power system is complex, highly integrated, and very large. It is not necessary to analyse a power system as a whole. The system can be divided into appropriate subsystems, which can be analysed separately. An appropriate method to divide the power system is to use its main purposeful areas, which are a) generation systems, b) transmission systems and c) distribution systems. Reliability evaluation can be shown in each of these purposeful areas in the groupings that give the hierarchical levels. Hierarchical level I (HL I) reliability evaluation is interested only with the generation facilities. Hierarchical level II (HL II) assessment includes both generation and transmission facilities. Hierarchical level III (HL III) evaluation includes all three purposeful areas [15] as in Figure 2-2.

There is considerable interest in using solar photovoltaic (PV) and wind to provide electric power generation due to the global environmental concerns associated with conventional energy sources. Both of these are, however, intermittent and diffused renewable energy resources, however, are intermittent and diffuse energy sources as both are highly variable and site specific. PV and wind behave quite differently from

that associated with conventional energy sources, and therefore the incorporation of these renewable resources will affect the power system reliability in a different manner than the pure conventional energy source system. As power generation from renewable resources at megawatt level are integrated into existing power systems, it becomes particularly important to evaluate the impact of these renewable resource generations on the overall system reliability. Similarly, integrating these renewable resources into an isolated microgrid will impose additional considerations as the microgrid has very low inertia. The intermittency of the power generation from renewable resources could impact the power supply quality and system reliability, which may pose additional concerns.

2.2 Power System Adequacy Assessment

2.2.1 Generation System Studies

All power system planning and operation will require objective determination of the required amount of system generating capacity to ensure an adequate supply [15]. Generation model, load model and risk model as shown in Figure 2-3, are basic approaches to evaluate the adequacy of a particular generation system.

In the reliability evaluation of a HL I generation systems, all the loads are added together to form a total system load and all the generating units are lumped together to form the total system generator, as shown in Figure 2-4. The convolution of system generation and load models will form the appropriate reliability model. The reliability indices can be calculated based on these models. Load modelling will be discussed in the next chapter. In this chapter, the generation system model and reliability indices are introduced.

The elementary approach to evaluating the adequacy of a particular generation configuration consists of three parts as shown in Figure 2-3. The load and generation

models shown in Figure 2-3 are convolved to form the proper risk model. The calculated indices do not normally include transmission constraints or transmission reliabilities, although it has been shown how these constraints can be included, they are therefore overall system adequacy indices. The system representation in a conventional study is shown in Figure 2-4. The calculated indices in this case measure the overall adequacy of the generation system [15].

Figure 2-3 Conceptual tasks in generating capacity HL I reliability evaluation

Figure 2-4 Conventional system (HL I) model

The basic approach for a HL I study is shown in Figure 2-3. Analytical methods and Monte Carlo simulation utilize different techniques to assess generation and load models. The essential concept shown in this figure, however, is basically the same for both techniques.

2.2.2 Composite System Studies

In HL II studies, bulk transmission is included in the simple generation-load model shown in Figure 2-4. This is usually termed composite system or bulk transmission system evaluation for adequacy assessment. An example of a composite system is shown in Figure 2-5. This level assesses the adequacy of a present or planned system including the impact of various strengthening alternatives at evaluating two sets of indices: individual bus (load points) indices and overall system indices.

Figure 2-5 A sample composite system for HL II studies

2.2.3 Distribution System Studies

HL III starts at the generating stations and terminates at the individual consumer load points. It is a very complex system as this level involves all three purposeful areas. The distribution purposeful areas are usually analysed as a separate entity. HL II load-point indices will serve as the input values of HL III indices.

Distribution system adequacy evaluation involves assessment of suitable adequacy indices at the actual consumer load points. There are two basic types of distribution system: meshed and radial configurations. Evaluation methods for meshed distribution systems are conceptually the same as those used for composite systems. The techniques for a radial distribution system are based on failure-mode analysis including considerations of all realistic failure and restoration processes. These techniques also apply to substation adequacy assessment as a substation has similar configurations and failure modes.

2.3 Reliability Cost/Worth

In addition to adequacy studies, the economics of different facilities do have a significant part in the decision making process. A simplified approach is to consider the investment only with different facilities selected. The reliability incremental cost can be computed via the investment cost associated with each alternative facility with increased reliability, in other words it is the cost for a per-unit increase in reliability. The most cost effective solution remains as the lowest incremental cost of reliability. For power system expansion planning to increase system adequacy, this technique can be a useful method when comparing alternatives.

Figure 2-6 Consumer, utility and total cost as a function of system reliability

The basic concept can be illustrated using the cost/worth curves of Figure 2-6. Figure 2-6 shows if higher reliability is required by end-users, then the utility costs will generally increase. On the contrary, end-user costs related with supply interruptions will decrease as the reliability increases. The sum of these two individual costs is the total cost to society. The “optimum” or desired level of reliability is located at the total cost minimum point [17] in Figure 2-6.

2.4 Adequacy Indices

Commonly used adequacy indices are expected values of a random variable. However, in some cases the probability of adequacy indices can be calculated. An adequacy indices entail various inputs such as demand characteristics and uncertainty, system component capacity and availability, system operation conditions and configurations, etc. An expected value is a long-term average of the experience under analysis with stochastic inputs, and hence it is not a deterministic parameter.

2.4.1 Adequacy Indices in HL I Studies

Loss of load duration (LOLD), loss of load frequency (LOLF), loss of energy expectation (LOEE) and loss of load expectation (LOLE) are the four commonly used adequacy indices in generating system adequacy assessment in HL I. These adequacy indices can be represented mathematically by the following equations:

(1) Loss of load duration (LOLD) is represented in (hour/disturbance);

$$LOLD = \frac{LOLE}{LOLF} \quad (2-1)$$

where the expected duration of the deficiencies and the expected frequency of encountering a deficiency is the definition of LOLD. This index provides more information to system planners, as it is sensitive to additional generation system parameters.

(2) Loss of load frequency (LOLF) is described in (occurrence/year);

$$LOLF = \sum_{i \in S} (F_i - f_i) \quad (2-2)$$

where F_i is the frequency of the departing system state i . f_i is the portion of F_i which relates to not going through the boundary wall between the no-loss-of-load state set and the loss-of-load state set.

(3) Loss of energy expectation (LOEE) with units in (MWh/year);

$$LOEE = \sum_{i \in S} 8760 C_i p_i \quad (2-3)$$

where loss of load system state i is described by C_i . All system states associated with the loss of load are represented by S , whereas p_i is the probability of system state i . The expected energy not supplied by the generating system because of the demand exceeding the available generating capacity is LOEE. The duration of loss load, the frequency of loss load, and the severity of the deficiency of loss of load are encompassed within LOEE. Therefore, the likelihood as well as impact of energy shortfalls is evaluated in this adequacy index.

(4) Loss of load expectation (LOLE) with units in (day/year) or (hour/year);

$$LOLE = \sum_{i \in S} p_i T \quad (2-4)$$

where all system states associated with the loss of load is represented by S , whereas p_i is the probability of system state i . The LOLE is the average number of days or hours in a given period, e.g. over a year, in which the daily peak load or hourly load is expected to exceed the available generating capacity. However, a distinction shall be made at this stage that LOLE does not provide information on the duration of the loss load, nor the frequency of loss load, nor the severity of the deficiency of loss of load.

2.4.2 Adequacy Indices in HL II Studies

The adequacy index concepts used in HL I studies can be extended to composite system adequacy assessment. More indices, however, are required to reflect composite system features.

- (1) Expected demand not supplied (EDNS) is expressed in (MW);

$$EDNS = \sum_{i \in S} C_i p_i \quad (2-5)$$

where loss of system state i is described by C_i .

- (2) Expected energy not supplied (EENS) is characterized in (MWh/year);

$$EENS = \sum_{i \in S} C_i F_i D_i = \sum_{i \in S} 8760 C_i p_i \quad (2-6)$$

where at system state i , the duration is D_i . The EENS index in HL II system adequacy assessment is comparable to the LOEE index in HL I studies.

2.4.3 Reliability Worth Indices

Unreliability cost is usually assessed through interruption cost, in order to determine system reliability worth. The reliability worth indices can be explained as follow.

- (1) Expected interruption cost (EIC) is expressed in (k\$/year)

$$EIC = \sum_{i \in V} C_i F_i W(D_i) \quad (2-7)$$

The set of all load loss events is defined by V . At load lost event i , C_i is the load curtailment. The frequency and duration of load loss event i are represented by F_i and D_i , respectively.

(2) Interrupted energy assessment rate (IEAR) is described in (\$/kWh)

$$\text{IEAR} = \text{EIC} / \text{EENS} \quad (2-8)$$

In HL I studies, the LOEE index is normally utilized. In distribution studies, the ENS index is typically deployed. It should be noted that in generation system assessment the EIC and IEAR are system indices, while in composite system and distribution system assessments they can either be system or load point (bus) indices depending on the particular focus of the study.

2.5 Summary

This chapter articulates the importance of probabilistic techniques to study and explain the stochastic behaviour of an electric power system. The system adequacy of the electric power system will be evaluated via analytical technique as this technique generally has a shorter computation time. The hierarchical concept has been introduced and HL I is selected. Though many power system adequacy indices have been introduced in this chapter, the focus of this thesis is on LOLE, LOEE and EENS. A fourth system adequacy index, EENU, will be introduced in chapter 5 and chapter 6. Most of the HL II and HL III adequacy indices have been omitted in this thesis as they are not relevant.

3 Energy Resources and Demand Modelling

3.1 Introduction

It is an important aspect of stand-alone microgrid and power system planning and operation to determine the required amount of system generating capacity to ensure an adequate supply. This can be simplified and categorized into two areas naming; a) static and b) operating capacity requirements. Static capacity typically refers to long-term evaluation of the overall system requirement, whereas operation capacity infers the short-term evaluation of the actual generation capacity required to meet a given demand level. Both these criteria are equally important to evaluate at the planning stage, knowing that once decision has been made, the short-term requirement becomes an operating problem [15].

3.2 Generation System Reliability Model

A generation system usually consists of many generating units. There are many system states when considering random failures of units. The generation system model used for generation adequacy evaluation is known as a capacity outage probability table (COPT), which includes all possible system states, available capacities, capacity outages, individual state probabilities and cumulative state probabilities. This section introduces the different methods that are used to build the COPT of power systems.

3.2.1 Generator System Model

The 2-state reliability model as shown in Figure 3-1 is the fundamental representation of a generator unit. The generation unit can transit from the operating state (or up state) to the failure state (down state) at failure rate (λ). The generation unit can return to the operating state at repair rate (μ) after the unit is repaired.

Figure 3-1 2-state model for a base load generating unit

In static capacity evaluation of generating units, the unit availability (A) and the unit unavailability (U) are two fundamental parameters deployed. The probability of a unit being in the operating state is termed availability (A). The probability of a unit being in the failure state is called unavailability (U) [15]. The unit unavailability is analogous to the unit forced outage rate (FOR) in power system or microgrid reliability. A_c and U_c for component c can be calculated using (3-1) and (3-2).

$$A_c = \frac{\mu_c}{\lambda_c + \mu_c} \quad (3-1)$$

$$U_c = \frac{\lambda_c}{\lambda_c + \mu_c} \quad (3-2)$$

λ_c is the expected failure rate of component c , and μ_c is the expected repair rate of component c .

3.2.2 Binomial Distribution Technique

To evaluate system reliability, a contingency enumeration technique can be used to determine all the possible system states. The generating units with identical capacities and identical probabilities of success and therefore of failure can be deemed as identical generating units. The COPT can be easily obtained using the binomial distribution as shown in (3-3), for n identical generating units. The number of terms in (3-3) represents

the possible system states and the value of each term is the probability of the individual state. The available capacity for a system state can be obtained from the exponent of A_c , e.g. the available capacity of the second term is $(n-1)$ multiplied by the rated capacity of the generating unit.

$$\begin{aligned} (A_c + U_c)^n &= A_c^n + nA_c^{n-1}U_c + \frac{n(n-1)}{2!}A_c^{n-2}U_c^2 + \dots \\ &+ \frac{n(n-1)\dots(n-r+1)}{r!}A_c^{n-r}U_c^r + \dots + U_c^n = 1 \end{aligned} \quad (3-3)$$

The binomial coefficients can be obtained by many methods, such as direct hand evaluation, Pascal's triangle, Stirling's formula and special binomial distribution tables [16]. They all have certain limitations for application. For example, the direct hand evaluation method can only be used when the factorial is small and the special binomial distribution tables can only be used for a certain range of data. With the advance in computer techniques, computer software can provide pre-programmed functions to calculate the binomial coefficients, such as the Matlab software.

If the generating units are not identical, the binomial distribution cannot be used directly to form COPT. A procedure can be used. First, combine together all identical units using the binomial distribution. Second, combine together one at a time these groups of tables by identifying all possible system states and evaluating the probability of each state [15]. The COPT of a generation system with two non-identical generating units is created with this procedure, as shown in Table 3-1 C1 and C2, and FOR_1 and FOR_2 are the capacities and forced outage rates of the two units, respectively.

The final COPT for the generation system with two non-identical units is shown as Table 3-2.

Table 3-1 Procedure to form COPT using basic probability method

State	Capacity in	Individual probability
Step 1: Unit 1 is added		
1	C1	1-FOR ₁
2	0	FOR ₁
Step 2: Unit 2 is added		
1	C1+C2	(1-FOR ₁)·(1-FOR ₂)
2	0+C2	FOR ₁ ·(1-FOR ₂)
3	C1+0	(1-FOR ₁)·FOR ₂
4	0+0	FOR ₁ ·FOR ₂

Table 3-2 COPT for a generation system with two non-identical units

State	Unit 1	Unit 2	Capacity in	Capacity out	Individual probability	Cumulative probability
1	Up	Up	C1+C2	0	(1-FOR ₁)·(1-FOR ₂) ^{#4}	#1+#2+#3+#4
2	Up	Down	C1	C2	(1-FOR ₁)·FOR ₂ ^{#3}	#1+#2+#3
3	Down	Up	C2	C1	FOR ₁ ·(1-FOR ₂) ^{#2}	#1+#2
4	Down	Down	0	C1+C2	FOR ₁ ·FOR ₂ ^{#1}	#1

3.2.3 Recursive Algorithm

If the number of system components increases, the above approach will take a lot of computational time and power. An alternative method is a recursive algorithm in which units are added sequentially to produce the final capacity model [15, 18, 19]. This

technique will work efficiently for both multi-state (with derated states) units as well as 2-state (with no derated states) units. Equation (3-4) shows the cumulative probability $P(X)$ for the case if no derated state is considered.

$$P(X) = (1 - U)P'(X) + (U)P'(X - C) \quad (3-4)$$

$P'(X)$ and $P(X)$ signify the cumulative probabilities of the capacity outage of X MW when the previous and subsequent unit are added, respectively. Equation (3-4) is prepared originally by setting $P'(X) = 1.0$ for $P'(X) = 0$ and $X \leq 0$ otherwise. For the case of derated states considered, the cumulative probability $P(X)$ can be calculated using (3-5):

$$P(X) = \sum_{i=1}^n p_i P'(X - C_i) \quad (3-5)$$

p_i is the probability of existence of the unit state i ; C_i is the capacity outage of state i for the unit being added; and n is the number of unit states. Table 3-3 shows an example of a COPT for a general generation system.

Table 3-3 COPT for a general generation system

State	Capacity in	Individual probability	Cumulative probability
1	C_1	p_1	$P_1 = p_1 + \dots + p_i + \dots + p_{n-1} + p_n$
2	C_2	p_2	$P_2 = p_2 + \dots + p_i + \dots + p_{n-1} + p_n$
:	:	:	:
<i>i</i>	C_i	p_i	$P_i = p_i + p_{i+1} + \dots + p_{n-1} + p_n$
:	:	:	:
<i>n-1</i>	C_{n-1}	p_{n-1}	$P_{n-1} = p_{n-1} + p_n$
<i>n</i>	C_n	p_n	$P_n = p_n$

In Table 3-3, it is assumed that $C_1 > C_2 > \dots > C_i > \dots > C_{n-1} > C_n$ since the values in column “capacity in” are organized in descending order. Due to the potentially large number of states in COPT, this will create a burden in computation. As such cumulative probability, which is less than a specified amount (e.g. 10^{-8}) can be curtailed by omitting these states without compromising on expected indices. This can save considerable computational time.

3.3 Solar PV Model

Figure 3-2 shows an equivalent circuit of a single solar photovoltaic (PV) cell, from where the following equation can be derived [20]. Let I_o be the output current of a single solar PV.

$$I_o = I_\lambda - I_d - I_p \quad (3-6)$$

The photon current, I_λ , depends primarily on the light wavelength (λ) and illumination intensity. I_d represents the Shockley temperature-dependent diode current. I_p describes the PV cell leakage current. Finally, I_o is the output current of single solar PV cell.

Figure 3-2 Equivalent circuit of a single PV Cell

Figure 3-3 I-V characteristic of a solar cell

Figure 3-3 shows the I-V characteristic for a given single solar cell. The cell current is related to both the cell open-circuit voltage, V_{oc} , and the cell short-circuit current, I_{sc} . When the cell output voltage V_o is zero, the short-circuit current may be obtained from the I-V characteristic for a given solar cell, as in Figure 3-3. Similarly, setting $I_o=0$ (no load), for zero output current, will yield the open-circuit voltage.

Let L_s be the nominal sunlight intensity on a bright clear day on earth and $L_s = 1.0$ (or 1 sun) is measured 1000W/m^2 . Let L be the variable sunlight intensity. If $L_s = 1.0$ sun has a prescribed value of $I_{\lambda o}$, the photon current I_λ can be approximated for every other level L through the (3-7).

$$I_\lambda = \frac{L}{L_s} I_{\lambda o} \quad (3-7)$$

The Shockley diode current is given by the classical expression

$$I_d = I_s (e^{qV_d / \eta kT} - 1) \quad (3-8)$$

where

I_s = the reverse saturated current of the diode, typically 100pA for the silicon cell

$k = 1.38047 \times 10^{-23}$ J/K is the Boltzmann constant

$q = 1.60210 \times 10^{-19}$ C is the electron charge

V_d = diode voltage (volts)

η = empirical constant

$T = 273.2 + t_c$ is the absolute temperature given as a function of the temperature ($^{\circ}\text{C}$), t_c , generally taken as $T = 298\text{K}$ (i.e., 25°C)

$q/kT = 38.94452$ C/J for $t_c = 25^{\circ}\text{C}$; or in a more general way, for any temperature, $q/k = 11605.4677^{\circ}\text{C}$

The PV cell converts the sun's rays or photons directly to electrical energy. R_p is the parallel resistance across the Shockley diode, which represents internal losses due to the leakage current. The values of R_p commonly range between 200 and 300 Ω . R_s is a series resistance between the load across the photovoltaic cell terminals and the photon current source, which is normally range between 0.05 to 0.10 Ω . R_s reflects on the manufacturing excellence of the PV cells. As such, (3-6) becomes

$$I_o = I_{\lambda} - I_s (e^{qV_d / kT} - 1) - \frac{V_d}{R_p} \quad (3-9)$$

The diode voltage is $V_d = I_o(R_s + R_L) = V_o(1 + R_s/R_L)$. It can be clearly seen that both load resistance, R_L , and series resistance, R_s , are a function of the diode voltage and play a significant role on the cell output power. Hence, the output current (3-9) can be solved by using V_d from Figure 3-3. The output current is shown below.

$$I_o = \frac{R_p}{R_p + R_s + R_L} [I_{\lambda} - I_s (e^{qV_d / kT} - 1)] \quad (3-10)$$

It is obvious that if the load resistance, R_L , is very much larger than the parallel resistance, R_p , then the output current may become very small from (3-10). In (3-9) or (3-10), the empirical factor, η , in the exponential term serves to adjust the cell output current based on the practical data from the manufacturers as show below.

$$I_o = I_\lambda - I_s(e^{qV_d/\eta kT} - 1) - \frac{V_d}{R_p} \quad (3-11)$$

Or

$$I_o = \frac{R_p}{R_p + R_s + R_L} [I_\lambda - I_s(e^{qV_d/\eta kT} - 1)] \quad (3-12)$$

With reference to Figure 3-3, both the open-circuit voltage, V_{oc} , and the diode voltage, V_d , will vary with the load current. Hence, (3-13) illustrates the single-cell open-circuit voltage when I_o is zero in an illuminated panel.

$$V_{oc} = V_d |_{I_o=0} = (I_\lambda - I_d) R_p = [I_\lambda - I_s(e^{\eta q V_{oc}/kT} - 1)] R_p \quad (3-13)$$

Equation (3-14) shows the logarithmic simplified form of the open-circuit voltage, which is a transcendental equation.

$$V_{oc} = \frac{kT}{\eta q} \ln \left(1 + \frac{I_\lambda}{I_s} - \frac{V_{oc}}{I_s R_p} \right) \quad (3-14)$$

The transcendental equation can be solved using numerical method. Furthermore, R_p is about 200Ω to 300Ω with negative sign and V_{oc} is in the order of $0.6V$, as in (3-15).

$$V_{oc} \cong \frac{kT}{\eta q} \ln \left(\frac{I_\lambda}{I_s} \right) \quad (3-15)$$

If the single-cell PV is shorted, practically the cell current will follow through R_s , as it is in the order 0.1Ω . Hence, the short-circuit current, I_{sc} , can be written as in (3-16).

$$I_{sc} \cong I_\lambda \quad (3-16)$$

Equation (3-17) is the output power, P_o , which is the product of cell output voltage, V_o , and the output current, I_o as shown in (3-12).

$$P_o = \frac{V_o R_p}{R_p + R_s + R_L} [I_\lambda - I_s (e^{qV_o(1+R_s/R_L)/\eta kT} - 1)] \quad (3-17)$$

Differentiating (3-17) with respect to V_o , then setting the derivative equal to zero, (3-18) is the condition to satisfy the maximum output power of the cell with external load voltage V_{om} .

$$I_s e^{qV_{om}(1+R_s/R_L)/\eta kT} = \frac{I_\lambda + I_s}{1 + V_{om} q(1+R_s/R_L)/\eta kT} \quad (3-18)$$

Alternatively, (3-15) can be plotted and locating the maximum voltage V_{om} graphically. Using either technique, the maximum PV cell output power can be obtained by

$$P_m = \frac{V_{om} (I_s + I_\lambda)}{1 + \eta kT / qV_{om} (1 + R_s / R_L)} \quad (3-19)$$

The conversion efficiency of PV cell for the maximum power generated is shown in (3-20) if the incident flux power, P_i , on the cell is known.

$$\eta_m = \frac{P_m}{P_i} = \frac{V_{om} (I_s + I_\lambda)}{P_i (1 + kT / \eta qV_{om}) (1 + R_s / R_L)} \quad (3-20)$$

3.4 Demand Model

Load modelling plays an important role in all microgrid and power system reliability evaluation. A mathematical function can describe a load model, for example load variability with respect to time. In this section, three types of load models for generation system reliability evaluation, constant load models, time varying load models and probabilistic load models, are introduced.

3.4.1 Constant Load Model

The constant load model includes annual constant load model and daily constant load model, in which the load is constant during a year and a day, respectively. In practice, a periodic constant load model is often used, which the energy consumption is relatively constant during a period of hours with very little weather dependent variation [21]. The demand for electrical energy is quite stable from day to day and season to season. The load level changes one, two or three times over 24 hours depending on different shift operation and production. For example, the load profile for a day with three shifts is shown in Figure 3-4.

Figure 3-4 Load profile for a periodic constant load

Large users and many industrial customers belong to the periodic constant load class. This model has relatively high accuracy and can reflect the seasonal and diurnal characteristic of the load in certain level, comparing to the annual constant load model and daily constant load model.

In general, the constant load model is very simple to develop and can save much computation time. The low accuracy and lack of chronological information of the system load are the main disadvantages of the constant load model.

3.4.2 Time Varying Load Model

3.4.2.1 Variable Load Model

It is in the characteristic of the variable load model with load level changing from hour to hour, from minute to minute, and from second to second. [22-28] showed that hourly variable load model is most commonly used. In hourly variable load model, it is assumed that the intra-hour load is constant. The load level for hourly variable load model can be acquired from load forecasting model. Alternatively, IEEE-RTS [29] provides a detail hourly variable load information for a year which is shown in Figure 3-5.

Figure 3-5 IEEE-RTS hourly variable load model

The variable load model over a year from IEEE-RTS (or load forecasting) reflects the chronological characteristic of the system load. This system load characteristic is commonly used in the evaluation of operation reliability. As there are 8760-hours in a year, there will be considerable computation power required to accomplish the evaluation of operation reliability using analytical technique, and much more for Monte Carlo simulation.

3.4.2.2 Load Duration Curve (LDC)

Each hourly data over a defined period from the variable load model in chronological form, either from IEEE-RTS or load forecasting, can be sorted in descending or ascending order. The hourly data sorted in the descending order results in the load duration curve (LDC) [30], as shown in Figure 3-6. The total energy generated by the utility over a defined period is the total area under the LDC.

Figure 3-6 IEEE-RTS load duration curve (LDC)

The take away from Figure 3-6 is that the LDC can be separated into three regions [31]. First is the Base Load which is required all the time over the defined period of the study. Second is the Intermediate Load. Finally third is the Peak Load which may be normally required for only a short period of time in the defined period of the study, depending on the system load characteristic. Hence, understanding the three regions of LDC, it allows system planners to make decision on the types of generating station to be built and determine their operating schedules. Each region of the LDC is generally supplied by different types of generating units.

One major disadvantage of the LDC is the loss of chronological information of the system load and therefore it is not possible to represent some aspects of time dependent by nature, such as the frequency and duration characteristics. In the context of energy supply modelling and utility scheduling, LDCs have to be approximated by some functions, such as the step functions, piecewise functions, and smooth functions [31]. The step and piecewise functions gain accuracy at the expense of simplicity while the smooth functions are quite complex. A trade-off has to be made when using the LDC.

3.4.3 Probabilistic Load Model

Even in the time varying load model, such as the model in Figure 3-5, the load level in an hour is assumed to be constant at a value of the forecasted or statistical average value. However, it is not accurate using these average values due to the load uncertainty. The probability distribution, whose parameters can be estimated from historical experience and forthcoming considerations, is defined as load uncertainty. In practice, adequate past data may not be available in order to determine the distribution type of the system load. Hence, it is common to assume a normal distribution with a given standard deviation to describe the uncertainty of the system load [15]. Hence, load P_{Li} considering uncertainty for load period i can be represented by the normal distribution (3-21).

$$f(P_{Li}) = \frac{1}{\sigma_{P_{Li}} \sqrt{2\pi}} \exp \left(-\frac{(P_{Li} - P_{Li}^{ave})^2}{2\sigma_{P_{Li}}^2} \right) \quad (3-21)$$

P_{Li}^{ave} is the average load level for period i and $\sigma_{P_{Li}}$ is the standard deviation of P_{Li} . Figure 3-7 shows the normal distribution load can be sliced into pre-determined number of approximate steps, which can be used in analytical technique.

Figure 3-7 Normal distribution of load

At time step j , the load level, P_{Li}^j , can be presumed to be constant. Therefore, for operating period i , time step j , the probability of load can be computed via (3-22).

$$P_{Li}^j \approx f(P_{Li}^j)(P_{Li}^{j+1} - P_{Li}^j) \quad (3-22)$$

The constant load model and time varying load model are changed to the probabilistic load model when the load uncertainty is considered. Figure 3-8 is a probabilistic hourly variable load model. The load level at each time step (hour) is a probability distribution, whose parameters can be estimated using historical data. The probability distributions at all steps could be different.

Figure 3-8 A probabilistic hourly variable load model

It is very important to consider the load uncertainty for electric power utilities. Higher accuracy can be achieved when the probabilistic load model is used to evaluate the reliability indices. However, much more computations may be needed, especially when used in Monte Carlo simulations.

The minute-to-minute variable load model similar to Figure 3-5 is used in this current research. In the future works, the load uncertainty will be incorporated to obtain more accurate results.

3.5 Energy Storage Model

Energy storage is a potential resource to solve the uncertainty problem of PV energy variability. The existing energy storage techniques include pump station, flywheel, compressed air energy storage, battery, capacitor, electrolysis hydrogen production device, and heat or cold storage. Energy storage systems can be installed in power systems with PV generation, adding values in a variety of ways, as summarized in [32].

Generally, the short-term energy storage could smooth out the effects of fluctuation of power output from renewable energy resources and so facilitate a higher installed capacity (i.e. penetration level), without exceeding local voltage limits. On the other hand, the long-term energy storage could time-shift power output from renewable energy resources to a time when the local load is higher and, therefore, allow even more generation capacity.

The criteria for selecting suitable energy storage technologies include power and energy capability, response speed, cyclic capability and ramping capability [33]. The competing technologies could also have more credits for high energy density, low maintenance, long life and low cost. The ability to support fast response regulation service also helps to identify suitable technologies. Ease of siting, ability to provide other ancillary services and other specified project requirements are also considered.

Battery techniques are selected to be the energy storage in this research. The main characteristics of several batteries [34] are listed in Figure 3-9, in terms of energy density, cycle life, operating temperature, etc.

Since the charging / discharging efficiencies are assumed to be 100%, the charging and discharging processes are only limited by the charging and discharging rates, as shown in Figure 3-10. The maximum energy in storage is equal to the rated capacity and the minimum energy in storage is equal to 10% of rated capacity.

Type	NiCd	NiMH	Lead Acid	Li-ion	Li-ion polymer	Reusable Alkaline
Parameter						
Gravimetric Energy Density (Wh/kg)	45-80	60-120	30-50	110-160	100-130	80
Internal Resistance (mΩ)	100 to 200 6V pack	200 to 300 6V pack	<100 12V pack	150 to 250 7.2V pack	200 to 300 7.2V pack	200 to 2000 6V pack
Cycle Life (number of cycle)	1500	300 to 500	200 to 300	500 to 1000	300 to 500	50 (to 50%)
Fast Charge Time (hour)	1h typical	2-4h	8-16h	2-4h	2-4h	2-3h
Overcharge Tolerance	moderate	low	high	very low	low	moderate
Cell Voltage (Nominal)	1.25V	1.25V	2V	3.6V	3.6V	1.5V
Load Current (peak)	20C	5C	5C	>2C	>2C	0.5C
Operating Temperature (discharge only)	-40 to 60°C	-20 to 60°C	-20 to 60°C	-20 to 60°C	0 to 60°C	0 to 65°C
Commercial Use since	1950	1990	1970	1991	1999	1992

Figure 3-9 Batteries' Characteristics

Figure 3-10 Energy storage charge / discharge strategy

3.6 Summary

The generator system model has been introduced. The 2-state reliability model, COPT and recursive algorithm will form the basis of the analytical technique in this thesis. A time independent single-cell solar PV model has been presented in this chapter. However, chapter 5 and chapter 6 will take into consideration the time dependency of the single-cell solar PV model.

The IEEE-RTS hourly variable load model and the load duration curve have been presented. This will be used in chapter 4 to evaluate the reliability of an electric power system. However, the IEEE-RTS hourly variable load model will be modified to per minute variable load model to suit the research objectives in chapter 5 and chapter 6.

Finally, the energy storage system selected for this thesis is utilizing the battery technique. The minimum ES level, maximum ES level, maximum ES charge / discharge duration, ES charge / discharge rates and ES charge / discharge efficiency are key parameters in the modelling of the energy storage system.

4 Impact of Energy Storage and Variability of PV on Power System Reliability

4.1 Introduction

The variability of renewable sources has high impact on power system reliability, e.g. photovoltaic (PV), has high impact on power system reliability and integrating this with energy storage (ES) is one of several options for better grid reliability [35-37]. This chapter serves to establish power system reliability of hierarchical level I (HL I) using analytical techniques. The IEEE Reliability Test System (IEEE-RTS) generation model and load model are applied to convolute a system risk model. Incorporating PV improves system reliability but the variability of PV power output compromises on PV capacity credit. ES is included into the system risk model to enhance system reliability performance. System adequacy indices are investigated to show the system reliability performance. Impact on system generation cost, via variation of PV and ES capacities are presented. Actual Singapore PV irradiance data and Energy Market Company price information are incorporated in this study. This analytical technique can help Independent System Operators (ISO) to evaluate the potential of PV to benefit system reliability and find ways to improve its potentials.

4.2 Why Investigate the Impact of Energy Storage and Variability of PV on Power System Reliability

The power systems' three main functional sub-systems have been articulated in Section 2.1 [15, 38-44]. Similarly, the challenges and opportunities of solar photovoltaic (PV) have been stated. ISOs are responsible for complying with requirements for renewable portfolio standards (RPS), energy conservation measures, mitigation of greenhouse gases (GHG) and environmental issues. RPS mechanism places an obligation on ISOs to have a minimum percentage of their electricity from an approved renewable energy source. The impact of the variability of renewable sources, e.g. photovoltaic (PV) on power system reliability has been widely reported, as this is of great importance to grid

reliability, especially when dealing with an aging infrastructure [35, 45, 46]. Energy storage (ES) is one of several options available to increase reliability.

System behaviour is mostly stochastic and changes randomly with time, while a probability based approach for a stochastic problem will give a comprehensive assessment. However a probability based approach towards a stochastic problem is by no means the only methodology that can be adopted in determining the safety or the reliability of a system. Additional understanding of the system, the way it operates, the way it malfunctions, its environment, its design and the stresses imposed on the system are equally important. Probability is only an enhancement of knowledge in predicting the expected behaviour of the system.

The basic approach of this chapter is use Figure 2-2 to evaluate the adequacy of a particular generation system requires the integration of a generation model with a load model and a risk model using HL I. These calculated indices, do not reflect generation deficiencies at any particular customer load point but measure the overall adequacy of the generation system [15].

Section 4.2 describes the motivation behind the research studies and also serves as an introduction. Section 4.3 presents the modelling and techniques used in this research. Section 4.4 illustrates system adequacy sensitivity study results and discussion. Finally, Section 4.5 presents the conclusions reached.

4.3 Models and Proposed Techniques

Practitioners for electric power systems usually associate reliability evaluation by using probability distributions. This is understandable as not all components will fail at the same time, but will fail at different times according to their own probability of failure function. Hence, time-to-failure obeys a probability distribution which depicts the

probability of a component failing within a certain specific time. There are two commonly used distributions, namely *Continuous* and *Discrete*. Continuous distributions include Gaussian (or Normal), gamma, Weibull, Rayleigh and exponential distributions, whereas Discrete distributions are Poisson and Binomial distributions. The probability of surviving that period of time, $R(t) = e^{-\int_0^t \lambda(t)dt}$, without assuming any specific form of functions and is equally applicable to all probability distributions used in reliability evaluations, where the failure rate $\lambda(t)$ is time dependent [36]. $R(t) = e^{-\int_0^t \lambda(t)dt}$ applies equally well to all failure distributions as there are no distributional assumptions in the derivation of the equation. That is this is a general equation which is applicable for all types of failure distributions. During the useful life of a component, λ can be assumed constant and independent of time. $R(t) = e^{-\int_0^t \lambda(t)dt}$ can then be simplified to $R(t) = e^{-\lambda t}$ and thus treated as an exponential distribution. This is a special case of failure rate as it is a constant. For an n-component time dependent probability series system, with hazard rate $\lambda_i(t)$, the probability of surviving is expressed as $R_s(t) = \prod_{i=1}^n e^{-\int_0^t \lambda_i(t)dt}$. For n-component time independent probability series system when $\lambda_i(t)$ is known and integrated, $R_s(t)$ can be expressed as $R_s(t) = \exp(-\sum_{i=1}^n \lambda_i t)$. The total reliability for a n-component time independent series system is simply the summation of each component failure rate.

4.3.1 Conventional Generator Modelling

A conventional generating unit can be represented by a 2-state reliability. Section 3.2 has elaborated the generating unit moving from the operating state to failure state at failure rate (λ) and returning to operating state at repair rate (μ) after the unit is repaired. In section 3.2.1, (3-1) and (3-2) have A_c and U_c for component c defined via λ_c and μ_c .

The above approach can be extended to a recursive algorithm in which units are added sequentially to produce the final capacity model as described in [15, 18, 19]. This algorithm can be used for multi-state (with derated states) units as well as 2-state (with

no derated states) units. Using IEEE-RTS generation model, the capacity outage probability table (COPT) is generated using this technique for up to 1871 states, with other states omitted where cumulative probability is less than a specified amount, e.g. 10^{-8} .

Hierarchical level I (HL I) basic adequacy indices in generating system adequacy assessment are loss of load expectation (LOLE), loss of energy expectation (LOEE) and can be calculated using (2-4) and (2-3). The LOLE does not indicate the severity of the deficiency nor the frequency or the duration of the loss of load. The LOEE incorporates the severity of deficiencies in addition to the number of occasions and their duration, and therefore the impact of energy shortfalls as well as their likelihood is evaluated. The LOEE index is the expected energy not supplied by the generating system due to the load demand exceeding the available generating capacity.

4.3.2 Time Varying Load Model

The variable load may change its load level from hour to hour, from minute to minute and from second to second. In practice, an hourly variable load model is usually used. It is assumed that the load level within an hour is constant in this load model, which the load level can be obtained from the load forecast. The load information provided in IEEE-RTS [29] is a typical hourly variable load for a year. The hourly variable load model can reflect the chronological characteristic of the system load and is usually used in operational reliability evaluation.

4.3.3 Solar PV Model

The Solar Photovoltaic (PV) model provides hourly solar irradiance data collected from the roof top of the School of Electrical and Electronic Engineering (EEE), Nanyang Technological University (NTU) during 2010. The original high resolution per minute

data has been averaged to per hour data, normalized and scaled as PV power hourly output for ease of analytical computation.

Using the risk modelling concept, the hourly solar irradiance data can be scaled as a relative percentage of the IEEE-RTS system generation capacity, yielding PV peak installed capacity in mega-watts. The PV peak installed capacity can be incorporated as generation model or negative load model, where the latter was chosen to compute system adequacy indices.

4.3.4 Energy Storage Model

For reliability evaluation, four parameters are usually used to characterise a battery energy storage unit [47-50]. They are storage capacity, charging / discharging rate (R_c / R_d) (i.e. the power rating of energy storage), charging / discharging efficiency (η_c / η_d) and charging / discharging limit (L_c / L_d) (i.e. maximum/minimum capacity of energy storage). The available energy remaining in the energy storage is the state of charge (SOC), where $AG_{soc(i)}$ is the state of charge at time step i ; t_i is the duration of time step i ; and E_{ci} and E_{di} are the available energy for charging and required energy for discharging at time step i , respectively.

The boundary conditions used in (4-1) are $\{L_d \cdot t_i \leq AG_{soc(i)} \leq L_c \cdot t_i\}, \{0 \leq E_{ci} \leq R_c \cdot t_i\}$ and $\{0 \leq E_{di} \leq R_d \cdot t_i\}$.

$$AG_{soc(i)} = \begin{cases} AG_{soc(i-1)} + \eta_c \cdot E_{ci}, & \text{in charging states} \\ AG_{soc(i-1)} - \frac{1}{\eta_d} \cdot E_{di}, & \text{in discharging states} \end{cases} \quad (4-1)$$

In the charging states, the available PV energy E_{ci} for charging may not be equal to the produced PV energy since some PV energy may be used to supply the system load. Only

the excess PV energy is available to charge the energy storage (batteries). The excess PV energy is limited by the charging rate and charging efficiency when charging the batteries. In the discharging states, the energy left in the batteries is discharged with the limits of the discharging rate and discharging efficiency. In any state, the energy left in the batteries must be within the maximum and minimum capacities, i.e. the charging and discharging limits. The charging / discharging efficiencies are set to be 100% for this study. For the sensitivity study the maximum energy in storage (i.e. ES rated capacity) is equal to a pre-determined percentage of installed generation capacity, and the minimum energy in storage is equal to 10% of ES rated capacity.

4.3.5 Annual Energy Cost Considerations

Singapore is the first liberalised electricity market in Asia, where the wholesale electricity market is operated by the Energy Market Company Pte Ltd (EMC). The National Electricity Market of Singapore (NEMS) opened for trading on 1-January-2003. Modelling for the annual energy price is taken from the time series of the Uniform Singapore Energy Price (USEP) in Singapore dollar per mega-watt (\$/MWH) for the year 2010 shown in Figure 4-1. USEP is the energy purchase paid by retailers. It is the weighted average of energy prices at all the off-take nodes on Singapore's electricity network. The statistics for year 2010 time series USEP are depicted in Figure 4-1, peaked at 3235 \$/MWH on the 73rd day of the year, 1100 hour [51].

Figure 4-1 Energy Market Company time series year 2010 USEP

$\alpha(S_i, X\%, L_i)$ is the annual energy cost in S\$; β_i is the Uniform Singapore Energy Price (USEP) in S\$/MWh; DR is the demand response signal; E_{c_i} is the i^{th} interval of ES charge; E_{d_i} is the i^{th} interval of ES discharge; E_{max} is the ES maximum storage in MWh; E_{min} is the ES minimum storage in MWh; m is the PV peak installed capacity ranging from 0~50% of total generation capacity; S_i is the i^{th} interval PV power from solar irradiance; $X\%$ is the percentage of maximum allowable PV energy to meet load demand with respect to (w.r.t.) the maximum system generation capacity; L_i is the i^{th} interval LDC; CD_i is the i^{th} interval energy storage (ES) charging / discharging limit; k is the total interval of reliability simulation; and n is the percentage of demand. The 2010 USEP time series can be convolved into the IEEE-RTS time varying demand model, conventional and solar power generation, energy storage (ES) time series, as shown in (4-2) to yield the expected annual energy cost. That is at each time interval, there is known demand level from IEEE-RTS time vary load model, conventional and solar power generation and the SOC of ES. The EMC publishes the Singapore peak demand profile which typically occurs in the day. As such, the DR will turn on within this fixed interval in the day catering to the Singapore peak demand duration. Hence, depending

on the PV power from solar irradiance there are two conditions to be considered in each i^{th} interval, that is $(S_i \leq X\% * L_i)$ and $(S_i > X\% * L_i)$ as described in (4-2), to be considered in each i^{th} interval. In the event when $(S_i > X\% * L_i)$, the remaining excess PV power from solar will be stored in the ES within the limitation of E_{max} .

$$\alpha(S_i, X\%, L_i) = \begin{cases} \sum_{(S_i)_{max=0}}^m \sum_{X\%=0}^n \sum_{i=1}^k \beta_i \{L_i - S_i - E_{d_i}\}, & DR = On \text{ \& } (S_i \leq X\% * L_i) \\ \sum_{(S_i)_{max=0}}^m \sum_{X\%=0}^n \sum_{i=1}^k \beta_i \{L_i - X\% * L_i - E_{d_i}\}, & DR = On \text{ \& } (S_i > X\% * L_i) \\ \sum_{(S_i)_{max=0}}^m \sum_{X\%=0}^n \sum_{i=1}^k \beta_i \{L_i - X\% * L_i + E_{c_i}\}, & DR = Off \end{cases}$$

$$E_{c_i} \Big|_{E_{min}}^{E_{max}} = \sum_{n=1}^k \{E_{c_{i-1}} + (S_i - X\% * L_i) \Big|^{CD_i}\}, \quad DR = On$$

$$E_{d_i} \Big|_{E_{min}}^{E_{max}} = CD_i, \quad DR = On \quad (4-2)$$

$$E_{c_i} \Big|_{E_{min}}^{E_{max}} = \sum_{n=1}^k \{E_{c_{i-1}} + CD_i\}, \quad DR = Off$$

4.4 Results and Discussions

This section describes the system sensitivity studies using system adequacy indices, LOLE and LOEE. This provides insights of the impact to power system adequacy due to variation of peak PV installed capacity; energy storage (ES) installed capacity, maximum ES charging / discharge hours, and finally the impact on the annual cost of energy due to PV and ES.

4.4.1 System Adequacy with addition of PV only

Figure 4-2 shows that once PV peak installed capacity reaches 30% of IEEE-RTS system generation capacity, i.e. $3405\text{MW} * 30\% = 1201\text{MW}$, LOLE improves marginally with no major gain in benefit on system adequacy. Further increases in PV peak installed capacity yields diminishing return on system adequacy.

The NTU EEE scaled PV peak installed capacity varied from 0~50% of IEEE-RTS system generation capacity formed as part of the negative load model to arrive at the risk model as shown in Figure 4-3.

Figure 4-2 LOLE of PV peak installed capacity (MW) as percentage of system maximum installed capacity

Figure 4-3 System LOEE with PV peak installed capacity (MW) as percentage of system maximum generation capacity

Again, LOEE in Figure 4-3 shows diminishing improvement once PV peak installed capacity exceeds 30% of the system generation capacity, i.e. $3405\text{MW} * 30\% = 1021\text{MW}$. It is worthy to highlight that system adequacies relationship improve positively with increase in Peak PV Installed Capacity.

4.4.2 System Adequacy with addition of PV and ES

Figure 4-4 and Figure 4-5 show the results of using (4-2) by keeping all the parameters constant except the PV peak installed capacity which varies from 0~50% of the installed generation capacity. Clearly, both LOLE and LOEE improved. Consideration of both PV and ES in the computation yielded a significant positive outcome on system

adequacy, which is clearly evident from beyond the 15% generation capacity.

Figure 4-4 Impact of varying PV peak installed capacity on LOLE (ES = 30%)

Figure 4-5 Impact of varying PV peak installed capacity on LOEE (ES = 30%)

The results of varying the energy storage capacity from 0~50% of installed generation capacity in (4-2) whilst maintaining the other parameters constant are shown in Figure 4-6 and Figure 4-7. Again both the LOLE and LOEE improve with increasing energy storage capacity. With both PV and ES taken in the computation, the results show that they yield a relatively positive outcome on system adequacy.

Figure 4-6 Impact of varying energy storage capacity on LOLE (PV = 30%)

Figure 4-7 Impact of varying energy storage capacity on LOEE (PV = 30%)

Similarly, with all parameters being kept constant except the energy storage maximum charge / discharge hours varying from 5~10-hours the results of using (4-2) are shown in Figure 4-8 and Figure 4-9. The energy storage maximum charge / discharge hours is defined as in Figure 3-10. LOLE and LOEE improve with increasing maximum energy storage charge / discharge hours. However, it can be observed from Figure 4-8 and Figure 4-9 that once the maximum energy storage charge / discharge hours exceed 8 hours, the system adequacy indices yield diminishing returns. Considering both PV and ES in the computation yielded a more positive outcome on system adequacy than simply considering ES only.

Figure 4-8 Impact of varying maximum energy storage charge / discharge hours on LOLE (PV = 30% and ES = 30%)

Figure 4-9 Impact of varying maximum energy storage charge / discharge hours on LOEE (PV = 30% and ES = 30%)

4.4.3 Impact on Electricity Cost

Figure 4-10 shows the impact of PV peak installed capacity on annual energy cost and annual cost saving using the USEP time series for the year 2010. In this case, the ES percentage of maximum system generation capacity and ES maximum charge / discharge hours are prefixed at 30% and 10 hours respectively. The PV peak installed capacity variation has a positive linear relationship on annual energy cost saving. Once the PV peak installed capacity exceeds 10% of installed generation capacity, the positive energy cost saving becomes obvious. At 30% PV peak installed capacity of the installed generation capacity, the additional cost saving of PV and ES combination is S\$131M per annum. Note that the capital and operation costs of PV and ES are not included in this cost saving computation.

Figure 4-10 Annual energy cost vs PV peak installed capacity percentage with price information from EMC uniform Singapore energy price

4.5 Conclusions

Analytical techniques with numerical solutions used in conventional power system reliability evaluation, e.g. capacity outage probability table (COPT), has been presented using the IEEE-RTS generation and load model. Intermittent PV energy and the crucial supporting role of energy storage (ES) on improving system adequacy have been shown. Optimal ES Capacity and the PV peak installed capacity for better electric power system adequacy assessment and annual energy cost saving have been demonstrated. Applying USEP from EMC for the year 2010 time series data provides some understanding on annual energy cost and cost saving, with implementation of PV and ES at various capacities.

5 Operational Adequacy Studies of a PV-Based and Energy Storage Stand-Alone Microgrid

5.1 Introduction

This chapter presents a probabilistic approach in the modelling of stand-alone microgrids to predict their operational adequacy performance by considering uncertainties of energy storage system (ESS), photovoltaic system (PVS) and conventional generator (CG). Instead of using the daily or hourly time step, an operating period at one-minute time step is considered to incorporate the effect of fast ramp up/down of system components. This is used to study the microgrid operating adequacy due to load and resource variation through the use of expected energy not supplied (EENS) and expected energy not used (EENU). A time varying state of charge (SOC) model is proposed to determine the power output of an ESS in reliability modelling. The reliability of a PVS is modelled in detail based on the total cross-tied configuration (TCTC) of photovoltaic (PV) cells. TCTC configuration has been reported with higher efficiency and operational life cycle [60]. The proposed technique and indices will be useful for system planners to select the type and size of microgrid systems that contain alternative energy sources and storages.

5.2 Why Operational Adequacy Studies for Stand-Alone Microgrid

This chapter evaluates the reliability of a stand-alone microgrid system via operational adequacy and efficiency of energy usage, with fast ramp up/down rate of demand, and high PVS penetration. Expected energy not supplied (EENS) has impact on system operational adequacy, whereas expected energy not used (EENU) reflects the energy generation/demand matching efficiency and energy surplus in the system. Adequacy in the coordination of intermittent sources and random demand, and intermittent sources with ESS, with different forced outage rate (FOR) and spinning reserve (SR) are evaluated. Section 5.2 gives an introduction on literature review, research gaps and

motivation of this study. Section 5.3 narrates the system modelling approach for each system component and Section 5.4 describes the formulation of the system components. Section 5.5 dwells on the detail system studies and finally, Section 5.6 concludes this chapter.

As the penetration of renewable energy in isolated microgrids continues to increase globally, the impact of random intermittency of renewable sources on operation reliability and efficiency is becoming evident. The reliability challenges faced by system operator during system operation are power shortages and surplus due to the rapid changes in the renewable power source and load. Ramping of power production and load is a notable characteristic in a typical power system time series associated with drastic change in values in a set of consecutive time steps. AWS Truewind, on January 28, 2008 reported [11] that the Electric Reliability Council of Texas (ERCOT) can expect an amount of less than 2.8GW, 30-minute drop in wind output (93MW/minute) per year with the 15GW wind fleet. Two to four 1.3GW, 30-minute increase or decrease of 43MW/minute can be expected. E. Ela and B. Kirby [11] reported a rapid and large ramp-down event occurred in the ERCOT operation area on February 26, 2008, which forced ERCOT to declare an emergency. B. Kirby [12] revealed that the rapid system load fluctuations typically measured at 2-second intervals by utility control centres cannot be tracked by generator. B. Kirby indicated that generator tracks load at roughly 1 to 2-minute interval level. Hence, if ramps in microgrid operation and dispatch are not investigated, it could lead to serious problems such as high costs and additional risks incurred.

W. Y. Li and L. Goel [13] articulated that “adequacy evaluation of generation, transmission, distribution and microgrids with random intermittent sources has been investigated for decades. However, coordination in adequacy between intermittent sources and random loads; and between intermittent sources and storages shall be investigated too”. The ramp issues have been considered in unit commitment and generation economic dispatch of large power systems [52-57]. Moreover, the reliability problems of power systems caused by the ramp rates of conventional generators have

not been investigated in detail. On the contrary, the ramp rate issues are more critical in the operation of microgrids because the system has lower ramp rates compared with those of the large systems. The impacts of fast minute-to-minute ramp on operation adequacy have hardly been investigated.

Y.A. Katsigiannis [22] argued that the reliability evaluation of small isolated power system with renewable energy sources cannot be implemented using the traditional deterministic and analytical methods. Renewables power sources increase the complexity of the power system as their power output are non-dispatchable, seasonal and highly intermittent. This is aggravated and more challenging by the large number of design options and the uncertainties in key parameters. E. S. Gavanidou [23] proposed a multi-objective planning under uncertainty in the design of a stand-alone system with renewable energy sources consisting wind, solar and storage battery. The load and wind time series information at the site of study is assumed to be available. P. Arun [24] considered the uncertainty of solar insolation to optimally sized photovoltaic battery systems through a design space approach. The time series simulation of the entire system is proposed using the design space approach so as to incorporate resource uncertainties. R. Karki [25] used Monte Carlo simulation technique for adequacy study on variability of wind, hydro energy storage with conventional generators (CGs). The IEEE 4-state model was adopted to simulate the irregular operation of the hydro units. Anindita Roy [58] considered the uncertainty of wind speed only to size a wind-battery system for isolated applications. The paper used pre-determined reliability parameters and time series simulation of the entire system to arrive at a deterministic corresponding energy balance equation. E.S. Sreeraj [59] considered a wind-PV-battery system for isolated renewable hybrid power systems. It capitalized on the availability of renewable resources and load to find the minimum size of battery capacity. Bagen [26] used probabilistic evaluation based on the well-being concept for small stand-alone power systems with wind, solar, diesel and energy storage. The paper argued why probabilistic techniques can overcome the drawback of deterministic criteria because of customer demands, system behaviour and inherent random nature of the site resources. C.V. Cabral [27] applied Markov Chain as stochastic analysis to study stand-alone photovoltaic system sizing. The author presented why stochastic analysis is more reliable and the results more realistic compared to Sandia's deterministic method. F.M.

Safie [28] used Markov Chain theory to present a probabilistic approach to model stand-alone PV-battery power system for a radio repeater. The paper presented the significant advantages of probabilistic approach as the technique can analyse the system performance and battery subsystem performance over a long period. This will also allow the designers and developers to determine the system design requirements which will meet a specified service performance level. The hourly constant load and renewable source models have been used in most of these papers. The ramp rates of CGs have not been considered in these papers. It is one of the motivations for this study to deploy the probabilistic 2-state enumeration approach to all system components such as CG, PVS and ESS, with minute-to-minute ramp up/down demand in a microgrid environment.

J. V. Milanović et al. [14] established a working group to identify the current international industry practice on load modelling for static and dynamic power system studies, and indicated that regular update of load model parameters is essential to ensure accurate simulation results. Hence, the per-minute load model used in this study will be of great research value to come. The impact on the minute-to-minute ramp rates can be more accurately investigated using per-minute load and resource model.

To fill the research gaps of operational adequacy of microgrids, which are more versatile for load and resource variation, this study evaluates the reliability of a stand-alone microgrid considering fast ramps in load demand and high PV penetration. Expected energy not supplied (EENS) and expected energy not used (EENU) have been formulated considering the effects of ramp rates of load, renewable resources and conventional generators to represent energy generation / demand matching efficiency and energy surplus in system operation. Adequacy coordination among intermittent sources, random demand, generalized PVS reliability model and time varying SOC of energy storage systems (ESSs) are considered in the proposed technique.

5.3 System Modelling

A microgrid consists of conventional generators (CGs), ESSs and photovoltaic systems (PVSs). Reliability models of the subsystems are presented in this section. The reliability of subsystem like PVS is determined by many system contingency states and considering component failures using probabilistic techniques [15]. All possible states of a subsystem are determined using contingency enumeration technique based on the states of components. The 2-state component reliability model is used in this study to find the system states. The reliability and unreliability of component c and period i can be calculated using the following equations (5-1) to (5-3) while ignoring the repair rate.

$$U_c(t_i) = 1 - e^{-\lambda_c t_i} \quad (5-1)$$

$$U_c(t_i) \approx \lambda_c t_i \quad (5-2)$$

$$A_c(t_i) = 1 - U_c(t_i) \quad (5-3)$$

The reliability of a sub-system with conventional generators (CGs) has been well developed. This section focuses on PVS and ESS reliability modelling.

Figure 5-1 The equivalent circuit for a photovoltaic cell

5.3.1 Photovoltaic System Model

A basic equivalent circuit model of a PV cell consists of a real diode in parallel with an ideal current source and resistor, and a series resistor, as shown in Figure 5-1. The PV cell converts the sun's rays or photons directly to electrical energy. A parallel resistance R_p represents the internal losses, or leakage current. R_s is the equivalent source series resistance connected between the photon current source and the load across the photovoltaic cell terminals. The current-voltage (I-V) and power characteristic of a PV cell is described by (5-4)~(5-7).

$$I_{o_i} = I_{r_i} - I_d - I_p \quad I_d = I_s (e^{qV_d/\eta kT} - 1) \quad (5-4)$$

$$I_{o_i} = \frac{R_p}{R_p + R_s + R_L} \left[I_{r_i} - I_s (e^{qV_d/\eta kT} - 1) \right] \quad (5-5)$$

$$V_{oc_i} = \frac{kT}{\eta q} \ln \left(1 + \frac{I_{r_i}}{I_s} - \frac{V_{oc_i}}{I_s R_p} \right) \quad (5-6)$$

$$P_{o_{ij}}^{sc} = \frac{V_{oc_i} R_p}{R_p + R_s + R_L} [I_{r_i} - I_s (e^{qV_{oc_i}(1+R_s/R_L)/\eta kT} - 1)] \quad (5-7)$$

The reliability and output of a PVS are modelled in detail based on the total cross-tied configuration (TCTC) of PV cells, and arrays as shown in Figure 5-2. The TCTC can increase the operation life of an array by 30% with higher efficiency [60]. The reliability of a cell R_i^{scell} can be calculated based on its failure rate λ_{scell} using similar equation as (5-3). An array is constructed with $a1$ rows and $b1$ columns of PV cells. The PV cells are connected in TCTC within an array. A modularized array (MA) consists of $a2$ rows and $b2$ columns of arrays in TCTC. The reliability R_i^{ma} of a MA is as defined in (5-8). A MA and the corresponding inverter are connected in series as shown in Figure 5-2. The total reliability of a MA and the corresponding inverter R_i^{sis} can be calculated based

on R_i^{slnv} and R_i^{ma} using (5-9). A PVS consists of b_3 modularized arrays and corresponding inverters connected in parallel. The reliability R_i^{pvs} of a PVS for period i can be calculated by (5-10). The output power of a PVS can be calculated using (5-11) by considering the inverter efficiency, η_g^{pv} , and the reliability of the PV cells.

Figure 5-2 A typical PVS in TCTC with b_3 Modularize Arrays

$$R_i^{ma} = \prod_{g=1}^{a_2} \left\{ 1 - \prod_{f=1}^{b_2} \left\{ 1 - \prod_{e=1}^{a_1} \left\{ 1 - \prod_{d=1}^{b_1} \left[1 - R_{i_{defg}}^{scell} \right] \right\} \right\} \right\} \quad (5-8)$$

$$R_i^{sis} = R_i^{ma} R_i^{slnv} \quad (5-9)$$

$$R_i^{pvs} = 1 - \prod_{d=1}^{b_3} \left[1 - R_{i_d}^{sis} \right] \quad (5-10)$$

$$P_{o_{ij}}^{pvs} = \sum_{g=1}^{b_3} \eta_g^{pv} \sum_{f=1}^{b_2} \sum_{e=1}^{a_2} \sum_{d=1}^{b_1} \sum_{c=1}^{a_1} P_{o_{ij}}^{sc} \quad (5-11)$$

It should be noted that the power output of a PV array depends on the control of the grid tied inverter. There are many maximum power point tracking (MPPT) techniques that have been used in practical grid-tied inverters to harness maximum power in PVSs. It is assumed in this study that the inverters can always be controlled to obtain the maximum power from a PVS. The power output from (5-11) is the total maximum power from a PVS.

$$SOC_{min} \leq SOC_i \leq SOC_{max} \quad (5-12)$$

$$SOC_i = \begin{cases} SOC_{i-1} + \eta_c \cdot E_{ci}, & \text{In charging states} \\ SOC_{i-1} - \frac{1}{\eta_d} \cdot E_{di}, & \text{In discharging states} \end{cases} \quad (5-13)$$

$$(0 \leq E_{ci} \leq P_c \cdot t_i) \quad (5-14)$$

$$(0 \leq E_{di} \leq P_d \cdot t_i) \quad (5-15)$$

$$R_i^{ema} = \prod_{g=1}^{c_2} \left\{ 1 - \prod_{f=1}^{d_2} \left\{ 1 - \prod_{e=1}^{c_1} \left\{ 1 - \prod_{d=1}^{d_1} [1 - R_i^{es}] \right\} \right\} \right\} \quad (5-16)$$

$$R_i^{eis} = R_i^{ema} R_i^{elnv} \quad (5-17)$$

$$R_i^{ess} = 1 - \prod_{d=1}^{d_3} [1 - R_i^{eis}] \quad (5-18)$$

$$P_{o_{ij}}^{ess} = \sum_{g=1}^{d_3} \eta_g^{es} \sum_{f=1}^{c_2} \sum_{e=1}^{d_2} \sum_{d=1}^{c_1} \sum_{c=1}^{d_1} P_{o_{ij}}^{es} \quad (5-19)$$

5.3.2 Energy Storage System Model

Four important parameters usually employed to characterize a battery energy storage unit [47-50] in operational reliability evaluation are: storage capacity, charging / discharging rate (P_c/P_d), charging / discharging efficiency (η_c/η_d) and charging / discharging capacity limit (SOC_{max}/SOC_{min}). Unlike conventional generators, the available generation capacity and output of an ESS changes with time based on the system resource and load conditions. Therefore a time varying SOC model is proposed to represent the output of an ESS, as shown in Figure 5-4. The real-time state-of-charge at the end of each operating period and corresponding limitations are determined by (5-12) and (5-13). Capacity limitations are determined by (5-14) and (5-15) to protect the ESS from over charged and discharged, respectively. The reliability of an ESS is determined based on the battery cell reliability taking into consideration the configuration of cells. The configuration of the ESS is shown in Figure 5-3, where the operation life time can increase by 30% [60]. Each single-cell energy storage (ES) has reliability and failure rate of R_i^{es} and λ_{es} , respectively. An ES array is constructed with $c1$ rows and $d1$ columns of energy storage (ES) cells. An ES modularized array with reliability R_i^{ema} , is formed via $c2$ rows and $d2$ columns of ES arrays. Finally, $d3$ columns of ES inverters are connected to their respective ES modularized arrays to form an ESS with reliability R_i^{ess} . Hence, (5-16)~(5-19) can be applied. The efficiency of ESS charging / discharging (η_c/η_d) cycle is assumed to be 75%.

Figure 5-3 A typical ESS in TCTC with d3 ES Modularize Arrays

Figure 5-4 Time varying SOC of an ESS

5.3.3 Load Model

The load may change its level from day to day, hour to hour, minute to minute and second to second. Figure 5-5 shows the modified IEEE-RTS [61] hourly load curve over the simulation period. In this study, per minute variable load model is adopted. It is assumed that the load level within each minute is ramping upward (or downward) in this load model. The IEEE-RTS hourly variable load information has been modified with per minute resolution at 1.85MW peak demand. The per minute variable load model can reflect the chronological characteristics of the system load and can be used in operational reliability evaluation.

Figure 5-5 The minutely load curve with ramp up (or down)

5.4 Formulation of Stand-Alone Microgrid

Considering the rapid changes in the demand and resource, CGs and energy storage systems (ESSs) have to ramp up (or ramp down) to meet the energy deficiency (or energy surplus). Two indices are formulated to determine the operation reliability and energy utilization efficiency of isolated microgrids under different resource and load conditions. The expected energy not supplied (EENS) can be due to the slow ramp up rate of CG, and/or slow rate of PVS solar irradiance change. Similarly, the expected energy not used (EENU) is the impact of slow ramp down rate of CG, and/or fast rate of PVS solar irradiance change. EENS and EENU also depend on priority loading order of CGs. ENS_{ij} and ENU_{ij} for operating period i under different load and resource

conditions for different types of microgrids are formulated in the following three cases. It is imperative to note that in each i^{th} operating period, there are various probability states for ESS, PVS and CG. Each system component probability state is considered using their respective capacity outage probability table (COPT), in the computation of ENS_{ij} and ENU_{ij} .

5.4.1 Case 1 Microgrid with CGs

In this case, a microgrid comprises CGs only to meet load demand. CGs include diesel generator, micro-turbine and fuel cell (FC) unit. Figure 5-6 shows the formulation of ENU_{ij} for state j operating period i with duration t_i when load decreases from ND_{i-1} to ND_i . Type 1(a) and Type 1(b) show two scenarios where the committed CGs have slow and fast ramp down rates, respectively. The ENU_{ij} can be computed by (5-20) and (5-21) for ramp down rate Type 1(b) and Type 1(a) respectively. Equation (5-20) illustrates Type 1(a) where CG'_i do not meet ND_i at time t_i in Figure 5-6. The ENU_{ij} can be calculated using parallelogram formula as in (5-20). However, in the event if CG'_i do not meet ND_i at time t_i , then this is a Type 1(b) situation as in Figure 5-6. Then ENU_{ij} can be calculated using triangle formula as in (5-21).

$$ENU_{ij} = \frac{1}{2}t_i \{ (CG_{i-1} + CG'_i) - (ND_{i-1} + ND_i) \} \quad (5-20)$$

$$ENU_{ij} = \frac{1}{2}t_i \{ CG_{i-1} - ND_{i-1} \} \quad (5-21)$$

$$ENS_{ij} = \frac{1}{2}t_i \{ ND_{i-1} - CG_{i-1} \} \quad (5-22)$$

$$ENU_{ij} = \frac{1}{2}t_i \{ CG_i - ND_i \} \quad (5-23)$$

$$ENS_{ij} = \frac{1}{2}t_i \{ (ND_{i-1} + ND_i) - (CG_{i-1} + CG'_i) \} \quad (5-24)$$

$$ENS_{ij} = \frac{1}{2} t_1 \{ND_{i-1} - CG_{i-1}\} \quad (5-25)$$

$$ENU_{ij} = \frac{1}{2} t_1 \{CG_{i-1} - ND_{i-1}\} \quad (5-26)$$

$$ENS_{ij} = \frac{1}{2} t_2 \{ND_i - CG_i\} \quad (5-27)$$

Figure 5-7 shows a Type 2 scenario where ND is ramping down and CG ramping up, where ENS_{ij} and ENU_{ij} can be computed by (5-22) and (5-23), respectively. Figure 5-7 shows $CG'_i = ND'_i$ at time t_1 where ENS_{ij} and ENU_{ij} can be computed using triangle formula via (5-22) and (5-23) respectively. Note that ENS_{ij} and ENU_{ij} are computed using t_1 and t_2 in (5-22) and (5-23) respectively.

Figure 5-8 shows that both the ND and CG are ramping up, where ENS_{ij} can be computed by (5-24) and (5-25) for Type 3(a) and Type 3(b) respectively. Note that Type 3(a) is applying parallelogram formula whereas Type 3(b) is using triangle formula. If CG'_i do not meet ND_i as the CG ramp is too slow at time t_i , then the parallelogram formula (5-24) applies. However, if $CG'_i = ND_i$ or CG ramp is faster than ND_i at time t_1 , then the triangle formula (5-25) applies.

Figure 5-9 shows a Type 4 scenario where ND_{i-1} is ramping up and CG_{i-1} ramping down. Once CG'_i meets ND'_i at the end of t_1 , depending on the ramp rate of the committed CG, the CG_i could be ramp limited and yields non-zero ENS_{ij} at end of interval t_2 . Figure 5-9 Type 4 ENU_{ij} and ENS_{ij} can be calculated using the same triangle formula in (5-26) and (5-27) respectively. The values of ENU_{ij} and ENS_{ij} will depend on the point where $CG'_i = ND'_i$ meet which changes t_1 and t_2 .

To cater for all contingency states of CGs from 1 to N_{cg} , considering all operating periods from 1 to N_{si} , the system EENS and EENU can be calculated using (5-28) and

(5-29). The contingency enumeration technique [15] has been used to determine all the possible system states and the related probabilities.

It should be noted that the major difference between the conventional reliability techniques and the proposed technique for EENS and EENU formulation is with and without considering the ramp rates of CGs for load and resource change. The conventional techniques usually use constant load for long period (such as an hour) without considering the ramp rates of conventional generators when the load and resource changes. Therefore the results from the conventional techniques will be smaller than those obtained from the proposed technique. As shown in Figure 5-6~5-8, there will be no ENS_{ij} and ENU_{ij} if the CGs can follow the load change immediately.

$$EENS = \sum_{i=1}^{N_{st}} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENS_{ij}(CG_{ij}, LD_i) \quad (5-28)$$

$$EENU = \sum_{i=1}^{N_{st}} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENU_{ij}(CG_{ij}, LD_i) \quad (5-29)$$

Figure 5-6 Type 1 ENU_{ij} area for both ND and CG ramp down

Figure 5-7 Type 2 ENS_{ij} and ENU_{ij} area for ND ramp down and CG ramp up

Figure 5-8 Type 3 ENS_{ij} area for both ND and CG ramp up

Figure 5-9 Type 4 ENS_{ij} and ENU_{ij} area for ND ramp up and CG ramp down

5.4.2 Case 2 Microgrid with CGs and PVSs

Case 2 microgrid consists of CGs and PVSs to meet demand. PVS is treated as a negative demand as illustrated in (5-30). The analytic concept is the same as that in Case 1, where Figure 5-6 to Figure 5-9 can be applied. However, the net demand (ND_i) in Case 2 will have influence from the intermittency of P_{oij}^{pvs} , as shown in (5-30). It is worthy to note from (5-30) that for $(LD_i - P_{oij}^{pvs}) < 0$, the excess energy of PVS has no storage in this case. Similarly, each contingency state j of CG and state k of PVS is described via (5-31) and (5-32) to compute EENS and EENU, respectively.

$$ND_i = LD_i - P_{oij}^{pvs} \quad (5-30)$$

$$EENS = \sum_{i=1}^{N_{st}} \sum_{k=1}^{N_{pv}} P_{ik}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENS_{ij} \left(P_{oij}^{pvs}, CG_{ij}, LD_i \right) \quad (5-31)$$

$$EENU = \sum_{i=1}^{N_{st}} \sum_{k=1}^{N_{pv}} P_{ik}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENU_{ij} \left(P_{oij}^{pvs}, CG_{ij}, LD_i \right) \quad (5-32)$$

5.4.3 Case 3 Microgrid with CGs, PVSs and ESSs

Case 3 microgrid comprises CGs, PVSs and ESSs. Again, the PVS is treated as a negative demand as illustrated in (5-30). Similarly, when $(LD_i - P_{oij}^{pvs}) < 0$, the excess energy of PVS will reduce the ENS_{ij} and the additional energy will be stored in the ESS within the charging limits. Each contingency state of CG, PVS and ESS are catered in the analysis by computing EENS and EENU as shown in (5-33) and (5-34) respectively. Each ESS contingency state l from 1 to N_{ess} is catered for in the analysis as shown in (5-33) and (5-34) for each operating period i in addition to the PVS and CG contingency states.

$$EENS = \sum_{i=1}^{N_{sj}} \sum_{l=1}^{N_{es}} P_{il}^{es} \sum_{k=1}^{N_{pv}} P_{ik}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENS_{ij} \left(P_{oij}^{ess}, P_{oij}^{pvs}, CG_{ij}, LD_i \right) \quad (5-33)$$

$$EENU = \sum_{i=1}^{N_{sj}} \sum_{l=1}^{N_{es}} P_{il}^{es} \sum_{k=1}^{N_{pv}} P_{ik}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENU_{ij} \left(P_{oij}^{ess}, P_{oij}^{pvs}, CG_{ij}, LD_i \right) \quad (5-34)$$

There are many papers published on strategies of ESS interacting with the system. The strategy applied in this study is primarily to transfer the CG and PVS excess (or inadequate) energy, into ESS through charging (or discharging) when there is surplus (or deficiency) of energy to meet the net demand (ND), as illustrated in Figure 5-4.

5.4.4 Case 4 Generalized Equations

In lieu of the technique used in the EENS and EENU analysis above, (5-35) and (5-36) provide a generalized method which allows system planners to study stand-alone microgrid operational adequacy for any additional system components to be added with uncertainty considerations. The additional system components can be represented by P_{im}^X as used in (5-35) and (5-36).

$$EENS = \sum_{i=1}^{N_{si}} \sum_{m=1}^{N_X} P_{im}^X \sum_{l=1}^{N_{es}} P_{il}^{es} \sum_{k=1}^{N_{pv}} P_{ik}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENS_{ij} \left(X_{ij}, \dots, P_{o_{ij}}^{ess}, P_{o_{ij}}^{pvs}, CG_{ij}, LD_i \right) \quad (5-35)$$

$$EENU = \sum_{i=1}^{N_{si}} \sum_{m=1}^{N_X} P_{im}^X \sum_{l=1}^{N_{es}} P_{il}^{es} \sum_{k=1}^{N_{pv}} P_{ik}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENU_{ij} \left(X_{ij}, \dots, P_{o_{ij}}^{ess}, P_{o_{ij}}^{pvs}, CG_{ij}, LD_i \right) \quad (5-36)$$

5.5 System Studies

5.5.1 Test System and Parameters

The system study is based on a stand-alone microgrid with 2.4MW CG capacity and a per minute variable load model with 1.85MW peak load modified from the IEEE-RTS demand profile. The CGs comprises diesel generators, micro-turbines and fuel cell (FC) units with priority loading order as shown in Table 5-1. The per-minute time series information from Nanyang Technological University roof top solar irradiance measurement in year 2010 is used in the modelling of the PVS.

5.5.2 Microgrid with only CGs

In this case, the microgrid consists of only CGs. Figure 5-10 shows the system EENS and EENU for different SRs under different unit commitment orders using the given FORs of CGs. Figure 5-10 shows the impacts of different priority orders of the unit commitment and SRs on EENS and EENU. It can be seen that priority loading order 1 (PL1) has the lowest EENS and EENU for the same SR. Using Table 5-1 with priority loading order 2 (PL2), decreasing the base ramp rate to 10% of its original value (i.e. 0.1 times base rate) will have 57% and 244% increase in both EENS and EENU, respectively, as shown in Table 5-2.

Table 5-1 CG and priority loading order

<i>kW</i>	<i>Qty</i>	<i>FOR^{#1}</i>	<i>kW per min^{#2}</i>	<i>Type</i>	<i>PL1</i>	<i>PL2</i>	<i>PL3</i>
400	1	0.060	80	Diesel	1	3	1
200	2	0.045	40	Diesel	2-3	4-5	2-3
200	2	0.045	40	Micro-turbine	4-5	6-7	4-5
50	2	0.030	10	Micro-turbine	6-7	10-11	10-11
400	2	0.090	20	FC	8-9	1-2	6-7
200	1	0.075	10	FC	10	8	8
100	1	0.060	10	FC	11	9	9

^{#1}Base FOR

^{#2}Base ramp rate (kW/min) for CG

With reference to Table 5-1, there are 3 types of CG priority loading orders defined which are stipulated using various sorting criteria. It is interesting to note that PL2 criteria will experience reduced EENS and EENU with increased CG spinning reserve (SR) as shown in Figure 5-10. PL1 and PL3 have insignificant increased EENS with increased SR, but EENU does not show significant reduction with varying SR. However, it is important to note that among the 3 priority loading orders, PL1 has the lowest EENS and EENU for SR variation from 0% to 25%. The demand curve in the simulation has 1.85MW, 0.63MW, 1.13MW and 0.28MW for maximum, minimum, mean and standard deviation respectively. From Table 5-1 and adding via priority loading order sequence, PL2 can be observed to load all the biggest CGs first whereas PL1 and PL3 do not. The number of CGs and the loading in and out of CGs change will be more for PL1 and PL3 compared to PL2, at the 1.13MW mean of demand curve. As such, Figure 5-10 shows an increasing EENS for PL1 and PL3.

Figure 5-10 Impact of spinning reserve on EENS and EENU with PL1, PL2 and PL3 (at base FOR)

In Figure 5-11, the CG base FOR and 3 times base FOR are considered in the study. It is evident that with PL2 sorting the size of CG, the quantity and FOR order has positive impact on the reduction of EENS and EENU with an increase in SR. EENS with 3 times base FOR is up to 128% more than that base FOR as shown in Figure 5-11. Hence, EENS is more pessimistic with increasing FOR. Conversely, EENU with 3 times base FOR is up to 19% less than the one with base FOR. Therefore, increasing base FOR gives EENU a more optimistic consideration.

Figure 5-11 Impact of spinning reserve on EENS and EENU with base FOR and 3 times base FOR

Table 5-2 Impact of CG ramp rate on EENS and EENU

MW-Min / Month	Base ramp rate	0.1 times base ramp rate
EENS	1,717	2,696
EENU	695	2,388

5.5.3 Microgrid with CGs and PVSs

This section attempts to address the reliability issue of microgrid with intermittent source and rapid random load for different SRs and FORs. Five PVSs are added to the test system installations with 0.01 FOR each. Figure 5-12 shows the system EENS and EENU under different system reliability conditions. It can be seen that for the same SR, EENS increases to 106% and EENU reduces to 16% when CGs FOR increases 3 times from the base FOR.

Comparing Figure 5-12 with Figure 5-11, the EENS and EENU increase up to 10% and 73% more, respectively. The addition of rapid intermittent resources through PVSs introduction will generally increase EENS and EENU, which indicates the need of energy storage.

Figure 5-13 shows that EENS with 3 times base FOR is increased up to 113% more than that with base FOR. EENS results in more pessimistic outcome with increased FOR. Conversely, EENU with 3 times base FOR is decreased up to 18% less than that of base FOR which results in more optimistic outcome.

Figure 5-12 Impact of Spinning Reserve (at PVS=50%) on EENS and EENU with base FOR and 3 times base FOR

Figure 5-13 Impact of PVS capacity and CG (at SR=15%) on EENS and EENU with base FOR and 3 times base FOR

5.5.4 Microgrid with CGs, PVSs and ESSs

This section investigates the impacts of the intermittent source with ESS; and the intermittent source with rapid random load. A system level ESSs is made up of four energy storage devices with 0.02 FOR each. Figure 5-14 shows EENS with 3 times base FOR is increased up to 203% more than EENS with base FOR. It results in more pessimistic outcome with increased FOR. Conversely, EENU with 3 times base FOR is decreased up to 14% less than EENU with the base FOR, which results in more optimistic outcome.

Comparing Figure 5-14 with Figure 5-11, the EENS and EENU are reduced by up to 76% and 65%, respectively. This is due to the positive impact of ESS. Whereas comparing Figure 5-14 and Figure 5-12, the EENS and EENU are reduced up to 78% and 78%, respectively. Hence, it can be observed that the addition of PVSs and ESSs

into CGs results in lower EENS and EENU in general where the major contribution is from the ESS.

Figure 5-14 Impact of spinning reserve (at PVS=50% and ESS=50%) on EENS and EENU with base FOR and 3 times base FOR

Figure 5-15 shows that the EENS with 3 times base FOR is increased up to 177% more than the EENS with base FOR. Increased FOR shows a more pessimistic EENS results. Conversely, the EENU with 3 times base FOR is reduced down to 16% lower than the EENU with base FOR showing more optimistic results. It is worth noticing that the EENU does not improve further once the ESS capacity exceeds 50%. Comparing both Figure 5-11 and Figure 5-12 with Figure 5-14 it is evidently shown that once ESS is implemented, both the EENS and EENU reduced significantly with base FOR and 3 times base FOR. This explains the significance of energy storage system. It can be seen from Figure 5-15 that the EENU becomes almost constant when the ESS capacity increases to 50%. The further increase of ESS capacity cannot reduce EENU. However, the EENS can still reduce when the EES capacity is over 50%. The final size of ESS can be simply determined by the required EENS or/and EENU levels. However, the size of an ESS should be determined using optimization technique based on the balance

between the benefits of reliability improvement and reduction of energy spilled taking into consideration the cost of the ESS.

Figure 5-15 Impact of ESS (with PVS 50% capacity and CG 15% SR) on EENS and EENU with base FOR and 3 times base FOR

5.6 Conclusion

A probabilistic approach to model stand-alone microgrids and predict their operational adequacy performance by considering the uncertainties of the energy storage system (ESS), photovoltaic system (PVS) and conventional generator (CG) has been proposed in this paper. The per minute load and resource models have been considered to incorporate the effect of fast ramp up/down of system components on microgrid operating adequacy through expected energy not supplied (EENS) and expected energy not used (EENU) due to load and resource variation. Time varying state-of-charge (SOC) model and TCTC-based PVS model are proposed. The proposed technique, models and indices have been applied to the modified IEEE-RTS. The results clearly show the impact of ramp rates of CGs on system reliability and energy utilization efficiency. Sensitivity studies of EENS and EENU for different FOR, SR, PVS capacity and ESS capacity clearly indicate the positive impact of ESS in improving microgrid operational reliability and energy utilization efficiency with intermittent source and

rapid random demand. The generalized equations allow system planners to analyse the uncertainty, operational adequacy and energy utilization efficiency of microgrids with other different resource components.

6 Multistate Reliability Modelling of an Isolated Microgrid

6.1 Introduction

This chapter proposes a new technique for evaluating the probabilistic reliability of an isolated microgrid incorporating energy storage system (ESS), photovoltaic system (PVS) and conventional generator (CG), using multistate system (MSS) modelling technique with minute to minute ramp up (or down). PVS is well suited to the MSS model due to the random variations of solar radiation, cloud shading, solar cell failure etc. Microgrid scale ESS for power system applications using super capacitor, lithium ion batteries and redox flow batteries are made up of series-parallel combination of single-cell energy storage, and are apt for the MSS model analysis. The uncertainty of ESS is implemented in tandem with time dependent state-of-charge (SOC) techniques. Microgrid CG can function at different levels of capacity due to outages of several auxiliaries, such as water pumps, fans etc., and can also be evaluated using the MSS technique. The study presents a MSS probabilistic reliability method considering the uncertainties of each of the system components. The isolated microgrid operational adequacy studies are expressed using the expected energy not supplied (EENS) and expected energy not used (EENU).

6.2 Why Multistate Reliability Modelling of Isolated Microgrid

This study investigates the operational adequacy of isolated microgrid reliability due to the interactions between intermittent source and random-rapid load demand; and between intermittent source and ESS. Multistate system (MSS) technique and uncertainties are employed for the ESS, intermittent PVS and CG. EENS and EENU are two probabilistic reliability indices to determine quantitatively the operational adequacy of the isolated microgrid reliability. The spinning reserve (SR) amount chosen which impacts the isolated microgrid reliability is studied. Different sizes of PVS and ESS are examined using the MSS technique to emphasize the exemplary contribution of ESS to

microgrid operational adequacy, regardless of the increase in the number of states in the MSS. Section 6.2 details the motivation in studying multistate modelling of an isolated microgrid operational adequacy. Section 6.3 describes the MSS technique, ESS, PVS, CG and demand modelling. Section 6.4 features problem formulation to compute the EENS and EENU for various scenarios, and arrives at a set of generalized formulae for these two indices. Section 6.5 focuses on the system sensitivity studies with scenarios narrated in Section 6.4, where a 2-state model is used as base case for comparing with higher state MSS models. Finally, Section 6.6 concludes this study summarizing the research findings of the isolated microgrid operational adequacy with MSS modelling of the ESS, PVS and CG.

Environmental issues (for example extreme weather and rising sea level) and the depletion of fossil fuels have been a major concern for several decades. Hierarchical electric power systems have served the industry well in the past. However, there remain many challenges which the traditional electric power systems pose, example extraordinary cost of capital equipment, extremely long planning leading time, high losses in systems etc. Microgrids emerge as a very promising system architecture which could overcome some of the challenges in large electric power systems. The microgrid with integration of distributed generation, renewable energy generation and energy storage system; bring both generation and demand closer to one another making a significant contribution to higher system energy efficiency, resilience and flexibility. An isolated microgrid becomes even more attractive to remote villages, islands, disaster zones or military command posts [4-7]. There have been considerable interests in renewable adoption worldwide and photovoltaic (PV) technology has received great attention with remarkable investments. However, high penetration of PV with intermittent output impacts the microgrid system reliability and ESS can serve as a good augmentation [62-64].

Kirby and Milligan [65] examined the energy imbalances, hourly energy, load following and regulation to understand how restructured power systems accommodate and value inter-hour ramps. Kirby and Hirst [12] described rapid system load fluctuation that was

measured at 2-second interval. The conventional generators (CGs) which do not track these high speed load changes and generating units assigned to this regulation service can be a regulating issue. References [12, 65] clearly state that rapid changing system loads can be a problem in power system reliability. However, microgrid operational adequacy with CGs operating in fast ramp up (or down) following random-rapid load demand ramp changes has seldom been investigated. Moreover, typical publications approach the issue with constant intra-hour demand and seldom consider intra-minute random ramp load demand. With the integration of more PVS with intermittent output, the intra-minute random ramp demand analysis becomes more acute.

The merits of MSS based on COPT technique for power system applications have been reported [66-69]. However, these papers did not study microgrid or isolated microgrid MSS in the research. Li and Goel [13] articulated the significant research gaps in operational adequacy in the coordination between different intermittent sources and random loads; between intermittent sources and storages, and that system adequacy would call for new ideas, models, methods, and computing tools. These are some of the motivations to study the system adequacy of microgrid with rapid intra-minute random demand considerations, using MSS models for the ESS, PVS and CG.

EENS and EENU are two indices employed to determine microgrid operational adequacy for two scenarios namely (a) microgrid with PV and CG, (b) microgrid with ESS, PV and CG. The intra-minute analysis will result in better correlation between PVS intermittency and random demand ramp analysis, taking into consideration the uncertainties of the ESS, PVS and CG. Finally, a 2-state probabilistic analysis is used as the base case to compare with other MSSs.

6.3 *System Modelling: MSS, ESS, PVS, CG and Demand*

The multistate system coupled with probabilistic analytical technique can be employed to investigate the interactions between PVS intermittency and random demand; between

the ESS and PVS intermittency; and between the ESS and random demand. The isolated microgrid operational adequacy is determined through expected energy not supplied (EENS); and generation / demand matching efficiency via expected energy not used (EENU). EENS arises due to slow CG ramp up rate, slow ramp up rate of solar PV output, and/or random-rapid demand ramp up. EENU in the microgrid system comes from the slow CG ramp down rate, fast ramp up rate of PVS output, and/or rapid demand ramp down.

6.3.1 Multistate System Model

Some technical systems are designed to carry out their intended tasks in a given environment with various distinguished levels of efficiency, or commonly known as performance rates. A system with a finite number of performance rates is known as multistate system (MSS). Or rather the different states of the system correspond to the different performance rates of the system. At any point in time, each performance rate is a discrete state continuous time stochastic process. For instance, each CG unit can perform at a different level of capacity. CG is a complex assembly, which comprises many parts. There exists a probability that failure of different parts may lead to a scenario where CG continues to function, but at a reduced capacity and this can be modelled as MSS as shown in Figure 6-1. Some examples of CG auxiliaries' outages include failure of fans, pumps, sensors etc. A PVS suffers the same performance rates like other systems where it is subjected to environmental stresses from both predictable sources and unpredictable sources such as fallen foreign objects, bird dropping, cloud cover and hail impacts. Each PVS performance rate is also a discrete state which can be represented by the MSS model. An ESS comprises many single-cell energy storage connected in series-parallel configuration. An ESS in hot ambient temperature, degradation of the ESS materials, over charging, deep discharge, fast discharge, vibration etc. reduces the reliability of ESS prematurely. A MSS model would naturally describe each discrete state of the ESS degradation, as shown in Figure 6-1.

Figure 6-1 State space diagram for repairable element

6.3.2 Conventional Generation Modelling

SR evaluation using the probabilistic method to study unit commitment risks was proposed in the Pennsylvania-New Jersey-Maryland (PJM) interconnected system [70]. In the midst of lead time, if a sudden load increase unexpectedly, the operator is prohibited to replace any committed units which fail or start other units, till the elapse of the lead time. Assuming failures and repairs are exponentially distributed, then (6-1) ~ (6-3) can be applied.

$$U_k^{cg}(t_i) = 1 - e^{-\lambda_k^{cg} t_i} \quad (6-1)$$

$$U_k^{cg}(t_i) \approx \lambda_k^{cg} t_i \quad (6-2)$$

$$A_k^{cg}(t_i) = 1 - U_k^{cg}(t_i) \quad (6-3)$$

Classical CG modelling has constant intra-hour model or constant intra-daily model, as shown in Figure 6-2(a). In reality, CG output ramps up (or down) to meet demand [12]. In order to understand the interaction between random-rapid demand change and CG output ramp, minute to minute CG ramp is considered, as shown in Figure 6-2(b).

Figure 6-2 Operational modelling of a CG, (a) Classic constant intra-hour CG, (b) Minute-to-minute ramp up/down CG

6.3.3 Photovoltaic System Modelling

Figure 6-3(a) shows the equivalent circuit of a single photovoltaic (PV) cell that includes the parallel leakage resistance R_p , series resistance R_s , an ideal current source I_{r_i} and a parallel diode. The output current I_{o_i} , output voltage V_{oc_i} and output power $P_{o_i}^{sc}$ at any i^{th} operating interval can be described by equations (6-4)~(6-7). As I_{o_i} and V_{oc_i} are transcendental functions, the maximum power point transfer can be solved by numerical method to get the maximum $P_{o_i}^{sc}$. This algorithm can be implemented in the solar inverter.

$$I_{o_i} = I_{r_i} - I_d - I_p \quad I_{r_i} = \frac{L}{L_s} I_{\lambda O} \quad I_d = I_s (e^{qV_d/\eta kT} - 1) \quad (6-4)$$

$$I_{o_i} = \frac{R_p}{R_p + R_s + R_L} \left[I_{r_i} - I_s (e^{qV_d/\eta kT} - 1) \right] \quad (6-5)$$

$$V_{oc_i} = \frac{kT}{\eta q} \ln \left(1 + \frac{I_{r_i}}{I_s} - \frac{V_{oc_i}}{I_s R_p} \right) \quad (6-6)$$

$$P_{o_i}^{sc} = \frac{V_{o_i} R_p}{R_p + R_s + R_L} [I_{r_i} - I_s (e^{qV_{o_i}(1+R_s/R_L)/\eta kT} - 1)] \quad (6-7)$$

Figure 6-3 a) The equivalent circuit of a single PV cell, b) module with $[a1 \times b1]$ solar cell, c) string array with $[a2 \times b2]$ module, and d) PVS with $b3$ column String Array System

Figure 6-3(b) shows a module comprises $[a1 \times b1]$ (row x column) solar cells, Figure 6-3(c) shows a string array with $[a2 \times b2]$ modules and Figure 6-3(d) shows a $a3$ rows of string array connected to their respective string array inverter labelled here as string array system (SAS). The PVS is made up of $b3$ columns of SAS in parallel. As the PV cells are connected in series-parallel configuration, this results in equation (6-8), (6-9) and (6-10) which follow Figure 6-3(c) and Figure 6-3(d) respectively. Each reliability defined will have its corresponding failure rate and repair rate, e.g. R_i^{pvs} , λ_k^{pvs} and μ_k^{pvs} . Equation (6-11) narrates the reliability and unreliability of k^{th} PVS while equation (6-12) sums the individual solar cells power output taking into consideration the efficiency of each solar inverter efficiency η_g^{pv} (assumed at 0.95) to yield total PVS output.

$$R_i^{smod} = \left\{ 1 - \prod_{d=1}^{b1} \left(1 - \prod_{c=1}^{a1} R_{i_{cd}}^{scell} \right) \right\} \quad (6-8)$$

$$R_i^{str} = \left\{ 1 - \prod_{f=1}^{b2} \left(1 - \prod_{e=1}^{a2} R_{i_{ef}}^{smod} \right) \right\} \quad (6-9)$$

$$R_i^{pvs} = \left\{ 1 - \prod_{h=1}^{b3} \left(1 - R_{i_h}^{sInv} \prod_{g=1}^{a3} R_{i_{gh}}^{str} \right) \right\} \quad (6-10)$$

$$A_k^{pvs} = \frac{\mu_k^{pvs}}{\lambda_k^{pvs} + \mu_k^{pvs}} \quad U_k^{pvs} = \frac{\lambda_k^{pvs}}{\lambda_k^{pvs} + \mu_k^{pvs}} \quad (6-11)$$

$$P_{o_i}^{pvs} = \sum_{h=1}^{b3} \eta_g^{pv} \sum_{g=1}^{a3} \sum_{f=1}^{b2} \sum_{e=1}^{a2} \sum_{d=1}^{b1} \sum_{c=1}^{a1} P_{o_{icdefgh}}^{sc} \quad (6-12)$$

6.3.4 Demand Model

Classic variable load model deployed by most papers are usually day to day or hour to hour, where the load profile remains constant within the intra-period, similar to Figure 6-2(a). Figure 6-4 illustrates a weekly variable load model with a different approach, where minute to minute variations of load cater for random-rapid demand change in the form of ramp up (or down) within intra-minute, similar to Figure 6-2(b). The hourly demand profile of the IEEE reliability test system (RTS) [61] is modified to minute to minute demand profile with randomly generated demand in the time series.

Figure 6-4 Minute-to-minute demand curve for a week

Figure 6-5 ESS SOC in charging or discharging

6.3.5 Energy Storage System Modelling

ESS are characterized by its charging / discharging rate (P_c / P_d), charging / discharging efficiency (η_c / η_d), equation (6-13) charging / discharging capacity limit (SOC_{max} / SOC_{min}) and storage capacity. Equation (6-14) depicts the real time state of charge at the i^{th} operating interval considering η_c and η_d at 75%, illustrated in Figure 6-5 with the duration of time step t_i . Equations (6-15) and (6-16) are the ESS energy boundary conditions for charging and discharging within each time step t_i . Figure 6-6(a) shows a single-cell energy storage, whereas Figure 6-6(b) and equation (6-17) depict the reliability of energy storage module configuration with $[c1 \times d1]$ [row x column] cells. An ESS with $c2$ rows of modules connected to a string module inverter is named as String Module System (SMS) shown in Figure 6-6(c). The ESS consists of $d2$ columns of SMS. Equations (6-18) and (6-19) articulate the reliability of the energy storage string and ESS, respectively. The reliability and un reliability of the k^{th} ESS is given in equation (6-20). The ESS output power is determined by equation (6-21) taking into

considerations that of ESS with $d2$ columns of SMS with each of the inverter having an efficiency, η_h^{es} , of 75%.

$$SOC_{min} \leq SOC_i \leq SOC_{max} \quad (6-13)$$

$$SOC_i = \begin{cases} SOC_{i-1} + \eta_c \cdot E_{c(t_i)}, & \text{In charging states} \\ SOC_{i-1} - \frac{1}{\eta_d} \cdot E_{d(t_i)}, & \text{In discharging states} \end{cases} \quad (6-14)$$

$$\left(0 \leq E_{c(t_i)} \leq P_c \cdot t_i \right) \quad (6-15)$$

$$\left(0 \leq E_{d(t_i)} \leq P_d \cdot t_i \right) \quad (6-16)$$

$$R_i^{emod} = \left\{ 1 - \prod_{f=1}^{dl} \left(1 - \prod_{e=1}^{cl} R_{i_{ef}}^{esc} \right) \right\} \quad (6-17)$$

$$R_i^{es} = \left\{ R_i^{eInv} \prod_{e=1}^{c2} R_{i_e}^{emod} \right\} \quad (6-18)$$

$$R_i^{ess} = \left\{ 1 - \prod_{f=1}^{d2} \left(1 - R_{i_f}^{eInv} \prod_{e=1}^{c2} R_{i_{ef}}^{emod} \right) \right\} \quad (6-19)$$

$$A_k^{es} = \frac{\mu_k^{es}}{\lambda_k^{es} + \mu_k^{es}} \quad U_k^{es} = \frac{\lambda_k^{es}}{\lambda_k^{es} + \mu_k^{es}} \quad (6-20)$$

$$P_{o_i}^{ess} = \sum_{h=1}^{d2} \eta_h^{es} \sum_{g=1}^{c2} \sum_{f=1}^{dl} \sum_{e=1}^{cl} P_{o_{i_{efgh}}}^{es} \quad (6-21)$$

Figure 6-6 Formation of ESS (a) single-cell energy storage, (b) modularized energy storage with [c1xd1] cells, (c) ESS with d2 column String Module System

6.4 Problem Formulation

There exist j contingency states for CG, PVS and ESS SOC, respectively at each i^{th} operating period as shown in Figure 6-7, Figure 6-8, Figure 6-9 and Figure 6-10. The EENS and EENU can be determined by summing each i^{th} operating interval of the ENS_{ij} and ENU_{ij} . The interaction between PVS intermittent output and random-rapid changing demand; between PVS intermittent output and ESS; and between ESS and random-rapid changing demand can be evaluated.

Each i^{th} operating interval PVS output is considered as negative load to arrive at net demand. With random-rapid changing demand, the CG has to meet the demand with the four different cases namely Case 1, Case 2, Case 3 and Case 4 shown in Figure 6-7, Figure 6-8, Figure 6-9 and Figure 6-10. Unlike traditional power systems analysis with hourly data, this study considers randomly rapid changing demand in per minute, i.e. t_i is in one-minute, to understand the interaction of each of the system components before arriving at the microgrid operation adequacy.

Figure 6-7 and Figure 6-8 show that when the net demand is ramping down at the i^{th} operating period, CG_{i-1} could be ramping down as in Case 1(a) or Case 1(b), or CG_{i-1} could be ramping up as in Case 2. Case 1(a) is based on equation (6-22), whereas Case 1(b) uses equation (6-23), and lastly Case 2 deploys equations (6-24) and (6-25). The ENS_{ij} and ENU_{ij} can be determined for the i^{th} operating period, before taking into consideration the next possible j^{th} contingency states for the respective CG, PVS and SOC of ESS.

Figure 6-9 and Figure 6-10 show the cases when the net demand is ramping up at the i^{th} operating period with CG_{i-1} ramping up as in Case 3(a) or Case 3(b), or CG_{i-1} ramping down as in Case 4. Case 3(a) applies equation (6-26), whereas Case 3(b) uses equation (6-27), and finally Case 4 deploys equations (6-28) and (6-29). The ENS_{ij} and ENU_{ij} can be determined for the i^{th} operating period, before taking into consideration the next possible j^{th} contingency states for the respective CG, PVS and SOC of ESS.

Figure 6-7 ENU_{ij} computation for Case 1

Figure 6-8 ENS_{ij} and ENU_{ij} computation for Case 2

Figure 6-9 ENS_{ij} computation for Case 3

Figure 6-10 ENS_{ij} and ENU_{ij} computation for Case 4

$$ENU_{ij} = \frac{I}{2}t_i \{ (CG_{i-1} + CG'_i) - (ND_{i-1} + ND_i) \} \quad (6-22)$$

$$ENU_{ij} = \frac{I}{2}t_1 \{ CG_{i-1} - ND_{i-1} \} \quad (6-23)$$

$$ENS_{ij} = \frac{I}{2}t_1 \{ ND_{i-1} - CG_{i-1} \} \quad (6-24)$$

$$ENU_{ij} = \frac{I}{2}t_2 \{ CG_i - ND_i \} \quad (6-25)$$

$$ENS_{ij} = \frac{I}{2}t_i \{ (ND_{i-1} + ND_i) - (CG_{i-1} + CG'_i) \} \quad (6-26)$$

$$ENS_{ij} = \frac{I}{2}t_1 \{ ND_{i-1} - CG_{i-1} \} \quad (6-27)$$

$$ENU_{ij} = \frac{I}{2}t_1 \{ CG_{i-1} - ND_{i-1} \} \quad (6-28)$$

$$ENS_{ij} = \frac{I}{2}t_2 \{ ND_i - CG_i \} \quad (6-29)$$

Table 6-1 CG reliability data and priority loading order

<i>kW</i>	<i>Qty</i>	<i>FOR</i>	<i>kW per min</i>	<i>Type</i>	<i>Priority Loading</i>
400	1	0.060	80	Diesel	3
200	2	0.045	40	Diesel	4-5
200	2	0.045	40	Micro-turbine	6-7
50	2	0.030	10	Micro-turbine	10-11
400	2	0.090	20	FC	1-2
200	1	0.075	10	FC	8
100	1	0.060	10	FC	9

6.4.1 Scenario 1 - PVS and CG Multistate Modelling

Scenario 1 considers both the PVS and CG in the MSS model in order to investigate the interactions between intermittent source and random-rapid changing demand. The CG is arranged with priority loading while the other technical parameters are given as per Table 6-1. Equation (6-30) illustrates that the PVS output is treated as negative demand in the net demand, ND_i . Applying Case 1 to Case 4 for each i^{th} operating interval by considering all contingency states over a 30-day period, the EENS and EENU can be determined from equation (6-31) and (6-32). In this scenario, an energy surplus is possible if a low demand with high PVS penetration without ESS is in place. MSS models for 2, 3, 4 and 5-states are considered in the analysis for EENS and EENU. Table 6-2, Table 6-3, Table 6-4 and Table 6-5 illustrate a 5-state table with CG capacity out in MW, CGs state probability, PVSs capacity out in MW and PVS state probability respectively.

Table 6-2 CG capacity out (MW)

PL=2	State	1	2	3	4	5
CG Capacity Out (MW)	CG1	0	0.37	0.38	0.39	0.4
	CG2	0	0.37	0.38	0.39	0.4
	CG3	0	0.37	0.38	0.39	0.4
	CG4	0	0.185	0.19	0.195	0.2
	CG5	0	0.185	0.19	0.195	0.2
	CG6	0	0.185	0.19	0.195	0.2
	CG7	0	0.185	0.19	0.195	0.2
	CG8	0	0.185	0.19	0.195	0.2
	CG9	0	0.0925	0.095	0.0975	0.1
	CG10	0	0.04625	0.0475	0.04875	0.05
	CG11	0	0.04625	0.0475	0.04875	0.05

Table 6-3 CG state probability

PL=2	State	1	2	3	4	5
CG State Probability	CG1	0.97	0.00225	0.0015	0.00075	0.0255
	CG2	0.97	0.00225	0.0015	0.00075	0.0255
	CG3	0.98	0.0015	0.001	0.0005	0.017
	CG4	0.985	0.001125	0.00075	0.000375	0.01275
	CG5	0.985	0.001125	0.00075	0.000375	0.01275
	CG6	0.985	0.001125	0.00075	0.000375	0.01275
	CG7	0.985	0.001125	0.00075	0.000375	0.01275
	CG8	0.975	0.001875	0.00125	0.000625	0.02125
	CG9	0.98	0.0015	0.001	0.0005	0.017
	CG10	0.99	0.00075	0.0005	0.00025	0.0085
	CG11	0.99	0.00075	0.0005	0.00025	0.0085

Table 6-4 PVS capacity out (MW)

PL=2	State	1	2	3	4	5
PVS Capacity Out (MW)	PVS1	0	0.222	0.228	0.234	0.24
	PVS2	0	0.222	0.228	0.234	0.24
	PVS3	0	0.222	0.228	0.234	0.24
	PVS4	0	0.222	0.228	0.234	0.24
	PVS5	0	0.222	0.228	0.234	0.24

Table 6-5 PVS state probability

PL=2	State	1	2	3	4	5
PVS State Probability	PVS1	0.99	0.00075	0.0005	0.00025	0.0085
	PVS2	0.99	0.00075	0.0005	0.00025	0.0085
	PVS3	0.99	0.00075	0.0005	0.00025	0.0085
	PVS4	0.99	0.00075	0.0005	0.00025	0.0085
	PVS5	0.99	0.00075	0.0005	0.00025	0.0085

$$ND_i = LD_i - P_{oij}^{pvs} \quad (6-30)$$

$$EENS = \sum_{i=1}^{N_{si}} \sum_{j=1}^{N_{pv}} P_{ij}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENS_{ij} \left(P_{oij}^{pvs}, CG_{ij}, LD_i \right) \quad (6-31)$$

$$EENU = \sum_{i=1}^{N_{si}} \sum_{j=1}^{N_{pv}} P_{ij}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENU_{ij} \left(P_{oij}^{pvs}, CG_{ij}, LD_i \right) \quad (6-32)$$

6.4.2 Scenario 2 - ESS, PVS and CG Multistate Modelling

Scenario 2 considers the ESS, PVS and CG in the MSS model in order to investigate the interactions between intermittent source and random-rapid changing demand; and ESS and intermittent source. Again, the PVS is treated as negative demand in equation (6-30) to arrive at the net demand, ND_i . However, any surplus energy in Scenario 2 can be

stored in the ESS unless it exceeds the SOC_{max} . Again, applying Case 1 to Case 4 for each i^{th} operating interval over a 30-day period, the EENS and EENU can be determined with equations (6-33) and (6-34) with all the contingency states of the ESS, PVS and CG taken into consideration. Once again, the MSS models for 2, 3, 4 and 5-states are considered in the analysis for EENS and EENU. Table 6-2 to Table 6-7 illustrate the 5-state capacity out in MW and state probability of CGs, PVSs and ESS.

Table 6-6 ESS capacity out (MW)

PL=2	State	1	2	3	4	5
ESS Capacity Out (MW)	ESS1	0	0.2775	0.285	0.2925	0.3
	ESS2	0	0.2775	0.285	0.2925	0.3
	ESS3	0	0.2775	0.285	0.2925	0.3
	ESS4	0	0.2775	0.285	0.2925	0.3

Table 6-7 ESS state probability

PL=2	State	1	2	3	4	5
ESS State Probability	ESS1	0.99	0.00075	0.0005	0.00025	0.0085
	ESS2	0.99	0.00075	0.0005	0.00025	0.0085
	ESS3	0.99	0.00075	0.0005	0.00025	0.0085
	ESS4	0.99	0.00075	0.0005	0.00025	0.0085

$$EENS = \sum_{i=1}^{N_{si}} \sum_{j=1}^{N_{es}} P_{ij}^{ess} \sum_{j=1}^{N_{pv}} P_{ij}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENS_{ij} \left(P_{o_{ij}}^{ess}, P_{o_{ij}}^{pvs}, CG_{ij}, LD_i \right) \quad (6-33)$$

$$EENU = \sum_{i=1}^{N_{si}} \sum_{j=1}^{N_{es}} P_{ij}^{ess} \sum_{j=1}^{N_{pv}} P_{ij}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENU_{ij} \left(P_{o_{ij}}^{ess}, P_{o_{ij}}^{pvs}, CG_{ij}, LD_i \right) \quad (6-34)$$

6.4.3 Scenario 3 - Generalize Equations

Scenario 3 combines the approaches in Section 6.4.1 and Section 6.4.2, resulting in a set of generalized equations being formulated given by equations (6-35) and (6-36) where any other types of system elements can be added into the isolated microgrid for system planners. This method can cater for both the uncertainties and MSS models of each of the system elements.

$$EENS = \sum_{i=1}^{N_{si}} \sum_{j=1}^{N_X} P_{ij}^X \dots \sum_{j=1}^{N_{es}} P_{ij}^{ess} \sum_{j=1}^{N_{pv}} P_{ij}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENS_{ij} \left(X_{ij}, \dots, P_{o_{ij}}^{ess}, P_{o_{ij}}^{pvs}, CG_{ij}, LD_i \right) \quad (6-35)$$

$$EENU = \sum_{i=1}^{N_{si}} \sum_{j=1}^{N_X} P_{ij}^X \dots \sum_{j=1}^{N_{es}} P_{ij}^{ess} \sum_{j=1}^{N_{pv}} P_{ij}^{pvs} \sum_{j=1}^{N_{cg}} P_{ij}^{cg} ENU_{ij} \left(X_{ij}, \dots, P_{o_{ij}}^{ess}, P_{o_{ij}}^{pvs}, CG_{ij}, LD_i \right) \quad (6-36)$$

6.5 System Studies

The total installed CG capacity of the isolated microgrid system in this study is 2.4MW as per Table 6-1. The IEEE reliability test system (RTS) [61] hourly demand profile is modified with randomly generated per minute microgrid demand while maintaining peak demand, mean demand and minimum demand at 1.85MW, 1.13MW and 0.63MW, respectively.

6.5.1 Microgrid with Scenario 1

Five sets of the PVS with 0.01 FOR are deployed. Figure 6-11 and Figure 6-12 show the impact of SR on the EENS and EENU, respectively, by considering the MSS models of both PVS and CG from 2-state to 5-state. The results show that both the EENS and EENU decrease linearly with increasing SR. This shows that increasing the SR capacity

improves the isolated microgrid operational adequacy, as shown by the EENS and EENU trends.

From Figure 6-11, using the 2-state model as a base case, the EENS using MSS models differs by 0.2 to 10.4MW-Min/Month with SR varying from 0 to 25%. 2-state model for both the PV and CG gives slightly more pessimistic results for EENS compared to the more accurate results obtained using MSS. The EENU using the MSS models differs by 0 to 0.2MW-Min/Month over the same range of SR from Figure 6-12. The difference is insignificant.

Figure 6-13 and Figure 6-14 show the impact of the PVS capacity on the EENS and EENU for MSS models with 2-state, 3-state, 4-state and 5-states. Both the EENS and EENU increase with increasing PVS capacity. However the EENS stops increasing after 70% PVS capacity and even shows slight decline as shown in Figure 6-13. The impact of increasing the PVS capacity compromises on microgrid reliability as seen by the increasing EENS and EENU. Hence, increasing PVS capacity in the presence of CG capacity only is detrimental to microgrid operational adequacy.

Again using the 2-state model as a base case, the EENS differs by 0.2 to 10.8MW-Min/Month as shown in Figure 6-13 with the MSS models, i.e. MSS gives slightly more pessimistic EENS results. Similarly, the EENU differs by 0 to 0.4MW-Min/Month as shown in Figure 6-14, and their difference is insignificant.

Figure 6-11 EENS with multistate PVS and CG

Figure 6-12 EENU with multistate PVS and CG

Figure 6-13 EENS with multistate PVS and CG

Figure 6-14 EENU with multistate PVS and CG

6.5.2 Microgrid with Scenario 2

Four sets of ESS with 0.01 FOR are added in Scenario 2. Figure 6-15 and Figure 6-16 show the impact of SR on the EENS and EENU, by considering the MSS models for all

the system components such as the ESS, PVS and CG. The EENS stays practically constant with increasing SR as shown in Figure 6-15. However, Figure 6-16 shows the EENU decreases linearly with increasing SR. The impact of increasing SR on the EENS and EENU with the presence of ESS is more favourable compared with Figure 6-11 and Figure 6-12. As compared to Scenario 1, the absolute values of the EENS and EENU reduce by a factor of four and five, respectively. This demonstrates a very significant improvement in operational adequacy with the contribution attributed to ESS.

Using the 2-state model as a base case, the EENS with MSS models differs by 5.6 to 11.9MW-Min/Month as shown in Figure 6-15. Using the MSS models, the EENS shows a slight optimistic result compared to that of the base case. The EENU, however, differs by 0 to 0.1MW-Min/Month which is practically insignificant.

Figure 6-15 EENS with multistate ESS, PVS and CG

Figure 6-16 EENU with multistate ESS, PVS and CG

Figure 6-17 and Figure 6-18 show the impact of increasing ESS capacity on the EENS and EENU, respectively, with 2-state, 3-state, 4-state and 5-state MSS models. Both the EENS and EENU decrease exponentially with increasing ESS capacity. The impact of increasing ESS capacity favours the EENS and EENU as it improves the isolated microgrid operation adequacy. Comparing Figure 6-17 and Figure 6-13 with PVS capacity set at 50%, the EENS reduces favourably from 1.7 to 12.5 times. Similarly comparing Figure 6-18 and Figure 6-14 with the same PVS capacity setting, the EENU reduces favourably from 2.2 to 4.4 times. All these three observations are attributed to the positive contribution of the ESS in the isolated microgrid improving the operational adequacy.

Again using the 2-state as a base case, the EENS differs by 0 to 6.6MW-Min/Month from Figure 6-17. The EENU using the MSS models differs by 0 to 0.1MW-Min/Month from Figure 6-18, which is insignificant. Different MSS models selected did not show any significant impact on the EENS and EENU.

Figure 6-17 EENS with multistate ESS, PVS and CG

Figure 6-18 EENU with multistate ESS, PVS and CG

6.6 Conclusions

Both Scenario 1 and Scenario 2 support the notion of better isolated microgrid operational adequacy with increasing SR. In Scenario 1, increasing SR has the impact

of reducing EENS and EENU, whereas Scenario 2 shows a significant reduction in the absolute value of the EENS and EENU by four to five times. In general, the results show that when the MSS model changes from a 2-state to a 5-state model, the EENS is slightly more optimistic whereas the EENU appears indifferent.

Scenario 1 supports the perception that increasing the PVS capacity alone will have detrimental effect on the isolated microgrid operational adequacy. The inclusion of ESS in Scenario 2 improves the isolated microgrid operational adequacy significantly and at the same time mitigates the impact of the states on the MSS model.

7 Conclusions and Future Work

7.1 Conclusion

First, this thesis started by conveying electric power system HL I reliability evaluation with PVS, ESS, IEEE-RTS conventional generators (CGs) and demand model using constant intra-hour analytical techniques. Loss of load expectation (LOLE) and loss of energy expectation (LOEE) are the two indices to narrate power system adequacy. The system sensitivity studies include various PV peak installed capacity, energy storage (ES) installed capacity, maximum ES charging / discharging hours and impact on annual cost of energy. Some key points arising from this research in chapter 4 are as follow:

1. For CG and PV combination, system adequacy will improve with increase PV peak installed capacity. LOLE and LOEE will taper off when PV peak installed capacity is about 30% (or greater) of installed CG capacity.
2. For CG, PV and ES combination, system adequacy improved by about one third or more. ES plays a significant role in the electric power system reliability and reducing annual cost of energy when intermittent PV generation is incorporated with CGs.
3. The study pointed that a cost saving of S\$131M per annual is possible if PV and ES combination were used, with ES capacity at 30% of the installed CG capacity.

Second, stand-alone microgrid reliability evaluation using analytical technique considering uncertainties for all system components under minutely rapid-ramp, has been presented in this thesis using the modified IEEE-RTS generation and load model. Two system adequacy indices, expected energy not supplied (EENS) and expected energy not used (EENU), have been incorporated to articulate the operational adequacy of microgrid. The EENS and EENU have helped in analysing the selection of optimal

ESS capacity and PVS capacity for better microgrid reliability. These indices have been instrumental in explaining the operational adequacy of microgrid between intermittent PVS and rapid-random demand; and between ESS and intermittent PVS. Each time interval of CGs will have intra-minute ramp to meet rapid-random demand ramp and intermittent PVS generation. In addition, the contingency states of each system component at each time interval have been considered in the computation of EENS and EENU. The intermittent PVS energy source and the crucial supporting role of energy storage system (ESS) on improving system adequacy have been shown. The fundamental outcomes from chapter 5 are as follow:

1. All PVS and ESS comprise of many single solar PV cell and single ES cell. The impact of these single cells manufacturing and assembly process control, premature aging of components under operation, extreme environmental conditions etc., would lead to system reliability issues. Hence, the modelling from single solar PV cell and single ES cell to PVS and ESS respectively in an isolated microgrid environment is a practical and realistic approach. The total cross-tied configuration (TCTC) will increase the operation life of the array by 30% with higher efficiency. The reliability and conversion efficiency of PVS and ESS inverters are included in this analysis. These considerations will have the notion to increase the isolated microgrid operational adequacy.
2. Traditional electric power system relies on constant intra-hour analysis for variable resources, CGs and ESSs. The Singapore solar irradiance fluctuates rapidly within the minute due to tropical weather conditions etc., which contravenes the traditional constant intra-hour analysis. A per-minute time step analysis considering ramp up / down and including uncertainties considerations of each microgrid system component is a practical approach to aid ISO with a decision supporting tool for isolated microgrid operational adequacy. Though chapter 5 only narrate CGs, PVSs and ESSs in the study, the formulation can include any other additional microgrid system components, e.g. wind generators, tidal generators etc.
3. CGs with slower ramp rates will compromise on microgrid system adequacy from 1.5 to 3.4 times as shown in Table 5-2.

4. For CGs and PVSs combination only, when CGs' FOR increases three times (PVS at 50%) the EENS increases 106% whereas EENU reduces 16%.
5. Incorporating ESSs into CGs and PVSs combination, the isolated microgrid operational adequacy improves more than 65%. The positive impact of having ESSs can be clearly seen by comparing the absolute EENS and EENU before and after installation of ESSs.

Furthermore, by considering the multistate system (MSS) modelling of each of the system components (ESS, PVS and CG) has provided additional insights to the microgrid operation adequacy with different priority loading, spinning reserves, FOR and ramp rates. Incorporating ESS into a stand-alone microgrid will improve operational adequacy and mitigate the impact on MSS. Chapter 6 results can be summarized as follow:

1. As PVS and ESS comprise of many single solar PV cell and single ES cell in series-parallel combination, the potential for getting into a derated state is high. The study of MSS model for CGs, PVSs and ESSs is extremely relevant and useful. The study attempts to compare 2-state, 3-state, 4-state and 5-state MSS model in an isolated microgrid.
2. For CGs and PVSs combination (Scenario 1) with increasing SR, EENS differs up to 10.8MW/month on the pessimistic side with MSS whereas EENU variation is not significant.
3. For CGs, PVSs and ESSs combination (Scenario 2), the absolute values of EENS and EENU reduce by a factor of four and five respectively. This is due to the positive impact of ESSs on isolated microgrid operational adequacy. The EENS differs up to 6.6MW/month favourably comparing 2-state model to MSS model, whereas EENU differs insignificantly.

This thesis will find potential applications for the distribution level, where PVSs and ESSs can be connected incrementally at the precinct level, district level or city level. Diesel generators have been prevalently installed in the precinct traditionally and a

microgrid infrastructure can be formed naturally. In the last two decades, the public awareness of environmental sustainability has increased tremendously. The entry of fuel cells and micro-turbines installation will accelerate distribution level connections of dispatchable generation. Also, the gradual increase in installed capacity of PVSs at the distribution level, the quality of supply of microgrid can be compromised. The quick change in solar irradiance has been widely reported to take place within minutes or seconds. Similarly, more rapid load change is another real challenge to a small microgrid infrastructure. This is aggravated by the fact that the current cost price of ESS is still relatively high, even if it is at the distribution level. Hence, the ramp characteristics of each system level component shall be considered as it will impact on the overall system adequacy and shall not be taken lightly. The detailed analysis of EENS and EENU within a microgrid for higher operational system adequacy will be an important topic to investigate and minimize the impact on system reliability.

Each system level component, example PVS and ESS, comprises of hundreds to thousands of single cell components connected in series-parallel configuration internally. The type of connection, interconnecting techniques, different mean time before failure, manufacturing and assembly quality control, extreme ambient conditions etc. impose severe challenges to the reliability of each system component. In this thesis, multiple single solar PV cell and single ES cell are formulated with different configuration to arrive at a system level PVSs and ESSs respectively. The reliability and power output formulation of many single cell components to the system level component(s) is one of the realistic issues in practical applications of microgrid reliability considerations. Furthermore, the impact on time varying SOC of the ESSs has been investigated to understand its potential contributions to isolated microgrid operational adequacy. By and large, ESSs improve on the isolated microgrid operational adequacy. These research hypotheses are clearly demonstrated in chapter 5 and chapter 6 contributions. System owners will appreciate the detailed reliability and power output analysis of the PVSs and the ESSs proposed and find them meaningful for their design, implementation, maintenance and decommissioning.

7.2 Future Work

Though several aspects of system adequacy indices and annual energy cost saving impact have been presented, there exist more avenues and considerations for improving the current techniques, and understanding of system reliability and cost worth. Section 7.2.1 and Section 7.2.2 present some of these opportunities for future work.

7.2.1 In-depth Analysis of Monte Carlo Techniques

It has been presented in this thesis that analytical techniques interpret an electric power system and stand-alone microgrid via a mathematical model and compute the reliability indices from this model with a direct numerical method. An analytical technique will yield reliability indices within a relative fast computational time, but assumptions are normally required to simplify the model and arrive at a simplified analytical model. This is even more so when modelling complex systems where the outcome could be compromised. Hence, an in-depth analysis with Monte Carlo simulation (MCS) should be employed [71-76].

Simulation techniques can simulate the real process and stochastic effect of an electric power system to yield the reliability indices. It could simulate the process like a series actual experiments. Simulation techniques could take into consideration of all aspects and contingencies inherent in the planning, design and operation of an electric power system. Hence, if the simulation is extended over a long period of time it can exhibit a closer behaviour on the type of mal-function which the system could run into. Expected values of reliability indices and their respective frequency distributions can be studied, and provide a thorough understanding of the system reliability. Riding on the knowledge gained leading to this thesis, MCS will provide a better understanding on the detail study of system reliability.

7.2.2 Demand Side Load Management

Demand side load management (DSL_M) infers reduction in electricity consumption by end-use customers in response to power grid needs, economic signals from a special retail rates or competitive wholesale market. DSL_M plays a key role especially in a congested power grid. DSL_M endeavours to provide an operation of robust, transparent, efficient, and non-discriminatory electricity market, and reliable operation of the bulk power transmission grid. The system operators have another means to maintain system reliability through DSL_M. System operators will provide financial incentives to end-use customers who own or control physical resources, which follow instructions from DSL_M signals to take actions to increase reliability.

With the advent of energy intensive loads like plug-in hybrid electric vehicles (PHEVs), data centres, building air-conditioning mechanical ventilation (ACMV) system etc., these demands present ample opportunity for DSL_M as they could potentially be shifted from the peak load period to increase system reliability. A green garage of PHEVs and data centres within a cluster of commercial buildings fully powered with ACMV on an extremely hot day, will pose good potentials for demand respond management applications. The wide adoption of smart energy meters embedded with the ZigBee communication protocol, direct load control (DLC) [77, 78] provide opportunities for energy intensive loads to be explored.

A finer point worth understanding is to segregate industrial, commercial and residential loads for DSL_M studies with cost / worth analysis. Finally, a quantitative cost-benefit analysis can be performed through MCS on DSL_M for finding a global optimum solution.

7.2.3 Microgrid Reliability

It has become evident that the fundamental architecture of today's electricity grid, which is based on top-down topology on transmission system providing energy flow in one direction from a large electricity generating source, needs rethinking. Microgrids have become a vital concept due to proliferation of distributed energy generation (DEG) near vicinity at site of use. A microgrid with distributed energy resources (DER), could operate as a single or autonomous grid, either stand alone or in parallel with an existing utility grid infrastructure [79]. It is crucial to study the system adequacy of microgrid with DER and DSLM optimized for maximum cost / worth. Hence, MCS and solvers could be deployed to realize global optimum solutions in a microgrid environment. In addition, choosing the right size PVSs and ESSs considering an optimum cost / worth analysis would play a significant role too. In addition, the fast changing operation factors and market conditions in dynamic microgrids can be incorporated in further studies.

7.2.4 Degradation of System Components

As the PVSs and ESSs comprise many single-cell components to form a complete system level, it is imperative to have high reliability in the manufacturing and assembly of each single-cell component. However, due to extreme ambient conditions, abnormal cyclic loading on each system level component, inappropriate thermal management of system components, incorrect manufacturing practices etc., could lead to premature failure of PVSs and ESSs over time. A comprehensive literature review, modelling and simulation of PVSs and ESSs can be formulated as part of the formulation in chapter 5 and chapter 6 for future work, so as to understand the impact on time dependent degradation of system components on system adequacy.

Author's Publications

Journal Publications

- [1] L. H. Koh, P. Wang, K. J. Tseng, Z. Y. Gao, and B. H. Puttgen, "Multistate Reliability Modelling Of An Isolated Microgrid," *IEEE Transactions on Sustainable Energy (under review)*, 2015.
- [2] L. H. Koh, P. Wang, F. H. Choo, K. J. Tseng, Z. Y. Gao, and H. B. Puttgen, "Operational Adequacy Studies of a PV-Based and Energy Storage Stand-Alone Microgrid," *IEEE Transactions on Power Systems*, vol. PP, pp. 1-9, 2014.
- [3] L. H. Koh, G. Z. Yong, P. Wang, and K. J. Tseng, "Impact of Energy Storage and Variability of PV on Power System Reliability," *Energy Procedia*, vol. 33, pp. 302-310, 2013.
- [4] I. McLoughlin, K. Narendra, L. H. Koh, Nguyen, Q. N., B. Seshadri, *et al.*, "Campus mobility for the future: the electric bicycle," *Journal of Transportation Technologies, Vol. 1 No. 5, Jan. 2012*, vol. 1, p. 12, 2012.

Conference Publications

- [1] L. H. Koh, P. Wang, F. H. Choo, K. J. Tseng, Z. Y. Gao, and H. B. Puttgen, "Operational Adequacy Studies of a PV-Based and Energy Storage Stand-Alone Microgrid," *IEEE PES General Meeting, Denver, Colorado (Accepted)*, 2015.
- [2] L. H. Koh, P. Wang, K. J. Tseng, and Z. Y. Gao, "Reliability Evaluation of Electric Power Systems with Solar Photovoltaic & Energy Storage," in *Probabilistic Methods Applied to Power Systems (PMAPS), 2014 IEEE International Conference on*, ed, 2014.
- [3] L. H. Koh, Y. K. Tan, P. Wang, and K. J. Tseng, "Renewable energy integration into smart grids: Problems and solutions; Singapore experience," in *Power and Energy Society General Meeting, 2012 IEEE*, 2012, pp. 1-7.
- [4] L. H. Koh, Y. K. Tan, Z. Z. Wang, and K. J. Tseng, "An energy-efficient low voltage DC grid powered smart LED lighting system," in *IECON 2011 - 37th Annual Conference on IEEE Industrial Electronics Society*, 2011, pp. 2883-2888.

References

- [1] IPCC. (2007, 16-Mar). *Inter-governmental Panel on Climate Change (IPCC) Climate Change 2007 (AR4): Mitigation of Climate Change (. ed.)*. Available: http://www.ipcc.ch/publications_and_data/publications_ipcc_fourth_assessment_report_wg3_report_mitigation_of_climate_change.htm
- [2] K. Ravindra, B. Kannan, and N. Ramappa, "Microgrids: A Value-Based Paradigm: The need for the redefinition of microgrids," *Electrification Magazine, IEEE*, vol. 2, pp. 20-29, 2014.
- [3] D. Quiggin, S. Cornell, M. Tierney, and R. Buswell, "A simulation and optimisation study: Towards a decentralised microgrid, using real world fluctuation data," *Energy*, vol. 41, pp. 549-559, 5// 2012.
- [4] R. H. Lasseter, "Smart Distribution: Coupled Microgrids," *Proceedings of the IEEE*, vol. 99, pp. 1074-1082, 2011.
- [5] B. Kroposki, R. Lasseter, T. Ise, S. Morozumi, S. Papatlianassiou, and N. Hatziargyriou, "Making microgrids work," *Power and Energy Magazine, IEEE*, vol. 6, pp. 40-53, 2008.
- [6] J. Mitra and M. R. Vallem, "Determination of Storage Required to Meet Reliability Guarantees on Island-Capable Microgrids With Intermittent Sources," *Power Systems, IEEE Transactions on*, vol. 27, pp. 2360-2367, 2012.
- [7] S. Abu-Sharkh, R. J. Arnold, J. Kohler, R. Li, T. Markvart, J. N. Ross, *et al.*, "Can microgrids make a major contribution to UK energy supply?," *Renewable and Sustainable Energy Reviews*, vol. 10, pp. 78-127, 2006.
- [8] R. H. Lasseter, "MicroGrids," in *Power Engineering Society Winter Meeting, 2002. IEEE*, 2002, pp. 305-308 vol.1.
- [9] W. Gu, Z. Wu, R. Bo, W. Liu, G. Zhou, W. Chen, *et al.*, "Modeling, planning and optimal energy management of combined cooling, heating and power

- microgrid: A review," *International Journal of Electrical Power & Energy Systems*, vol. 54, pp. 26-37, 1// 2014.
- [10] Q. Bin, L. Yilu, C. Eng Kiat, and L. L. J. Cao, "LAN-based control for load shedding," *Computer Applications in Power, IEEE*, vol. 14, pp. 38-43, 2001.
 - [11] E. Ela and B. Kirby, *ERCOT event on February 26, 2008: Lessons learned*: National Renewable Energy Laboratory, 2008.
 - [12] B. Kirby and E. Hirst, "Generator response to intrahour load fluctuations," *Power Systems, IEEE Transactions on*, vol. 13, pp. 1373-1378, 1998.
 - [13] W. Li and L. Goel, "Foreword: Special Section on Adequacy in Power Systems With Intermittent Sources," *Power Systems, IEEE Transactions on*, vol. 27, pp. 2295-2296, 2012.
 - [14] J. V. Milanovic, K. Yamashita, S. Martinez Villanueva, S. Z. Djokic, and L. M. Korunovic, "International Industry Practice on Power System Load Modeling," *Power Systems, IEEE Transactions on*, vol. 28, pp. 3038-3046, 2013.
 - [15] R. A. Billinton, Ronald N., *Reliability evaluation of power systems*: New York : Plenum Press, 1996. 2nd ed., 1996.
 - [16] R. A. Billinton, Ronald N., *Reliability evaluation of engineering systems : concepts and techniques*: New York : Plenum Press, c1992. 2nd ed., 1992.
 - [17] R. Billinton and W. Li, *Reliability assessment of electric power systems using Monte Carlo methods*: New York : Plenum Press, c1994., 1994.
 - [18] A. K. Ayoub and A. D. Patton, "A frequency and duration method for generating system reliability evaluation," *Power Apparatus and Systems, IEEE Transactions on*, vol. 95, pp. 1929-1933, 1976.
 - [19] R. Billinton, C. L. Wee, and G. Hamoud, "Digital Computer Algorithms for the Calculation of Generating Capacity Reliability Indices," *Power Apparatus and Systems, IEEE Transactions on*, vol. PAS-101, pp. 203-211, 1982.
 - [20] F. A. Farret and M. G. Simões, *Integration of Alternative Sources of Energy [electronic resource]*: Hoboken : John Wiley & Sons, Inc., 2006., 2006.

- [21] A. Sankarakrishnan, "Composite system reliability evaluation using sequential Monte Carlo simulation," PhD, Universit of Saskatchewan, Saskatoon, Canada.
- [22] Y. A. Katsigiannis and P. S. Georgilakis, "Effect of customer worth of interrupted supply on the optimal design of small isolated power systems with increased renewable energy penetration," *IET Generation, Transmission and Distribution*, vol. 7, pp. 265-275, 2013.
- [23] E. S. Gavanidou and A. G. Bakirtzis, "Design of a stand alone system with renewable energy sources using trade off methods," *Energy Conversion, IEEE Transactions on*, vol. 7, pp. 42-48, 1992.
- [24] P. Arun, R. Banerjee, and S. Bandyopadhyay, "Optimum sizing of photovoltaic battery systems incorporating uncertainty through design space approach," *Solar Energy*, vol. 83, pp. 1013-1025, 7// 2009.
- [25] R. Karki, H. Po, and R. Billinton, "Reliability Evaluation Considering Wind and Hydro Power Coordination," *Power Systems, IEEE Transactions on*, vol. 25, pp. 685-693, 2010.
- [26] Bagen and R. Billinton, "Incorporating well-being considerations in generating systems using energy storage," *Energy Conversion, IEEE Transactions on*, vol. 20, pp. 225-230, 2005.
- [27] C. V. T. Cabral, D. O. Filho, A. S. A. C. Diniz, J. H. Martins, O. M. Toledo, and L. d. V. B. Machado Neto, "A stochastic method for stand-alone photovoltaic system sizing," *Solar Energy*, vol. 84, pp. 1628-1636, 9// 2010.
- [28] F. M. Safie, "Probabilistic modeling of solar power systems," in *Reliability and Maintainability Symposium, 1989. Proceedings., Annual*, 1989, pp. 425-430.
- [29] "IEEE reliability test system," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-98, pp. 2047-54, 1979.
- [30] H. L. Willis, *Spatial Electric Lad Forecasting*, 2 ed. New York: Marcel Dekker, 2002.

- [31] J. Monette, "A mathematical model of an electrical utility's load-duration curve," *Omega*, vol. 10, pp. 94-6, 1982.
- [32] J. P. Barton and D. G. Infield, "Energy storage and its use with intermittent renewable energy," *IEEE Transactions on Energy Conversion*, vol. 19, pp. 441-8, 2004.
- [33] Y. Bo, Y. Makarov, J. Desteese, V. Viswanathan, P. Nyeng, B. McManus, *et al.*, "On the use of energy storage technologies for regulation services in electric power systems with significant penetration of wind energy," in *Electricity Market, 2008. EEM 2008. 5th International Conference on European*, 2008, pp. 1-6.
- [34] F. Youcef Ettoumi, A. Mefti, A. Adane, and M. Y. Bouroubi, "Statistical analysis of solar measurements in Algeria using beta distributions," *Renewable Energy*, vol. 26, pp. 47-67, 2002.
- [35] P. Hu, R. Karki, and R. Billinton, "Reliability evaluation of generating systems containing wind power and energy storage," *Generation, Transmission & Distribution, IET*, vol. 3, pp. 783-791, 2009.
- [36] Y. Sun, P. Wang, L. Cheng, and H. Liu, "Operational reliability assessment of power systems considering condition-dependent failure rate," *Generation, Transmission & Distribution, IET*, vol. 4, pp. 60-72, 2010.
- [37] P. Wang, Y. Ding, and L. Goel, "Reliability assessment of restructured power systems using optimal load shedding technique," *Generation, Transmission & Distribution, IET*, vol. 3, pp. 628-640, 2009.
- [38] A. Akhavein, M. Fotuhi-Firuzabad, R. Billinton, and D. Farokhzad, "Adequacy equivalent development of composite generation and transmission systems using network screening," *Generation, Transmission & Distribution, IET*, vol. 5, pp. 1141-1148, 2011.
- [39] R. Allan and R. Billinton, "Probabilistic assessment of power systems," *Proceedings of the IEEE*, vol. 88, pp. 140-162, 2000.

- [40] R. N. Allan and R. Billinton, "Probabilistic methods applied to electric power systems-are they worth it?," *Power Engineering Journal*, vol. 6, pp. 121-129, 1992.
- [41] R. N. Allan, R. Billinton, I. Sjarief, L. Goel, and K. S. So, "A reliability test system for educational purposes-basic distribution system data and results," *Power Systems, IEEE Transactions on*, vol. 6, pp. 813-820, 1991.
- [42] R. Billinton and L. Goel, "Overall adequacy assessment of an electric power system," *Generation, Transmission and Distribution, IEE Proceedings C*, vol. 139, pp. 57-63, 1992.
- [43] R. Billinton, S. Kumar, N. Chowdhury, K. Chu, K. Debnath, L. Goel, *et al.*, "A reliability test system for educational purposes-basic data," *Power Systems, IEEE Transactions on*, vol. 4, pp. 1238-1244, 1989.
- [44] R. Billinton, S. Kumar, N. Chowdhury, K. Chu, L. Goel, E. Khan, *et al.*, "A reliability test system for educational purposes-basic results," *Power Systems, IEEE Transactions on*, vol. 5, pp. 319-325, 1990.
- [45] Z. Y. Gao and P. Wang, "Reliability evaluation of power systems with WTGs and energy storage," in *IPEC, 2010 Conference Proceedings*, 2010, pp. 654-659.
- [46] Z. Y. Gao, P. Wang, and W. Jianhui, "Impacts of energy storage on reliability of power systems with WTGs," in *Probabilistic Methods Applied to Power Systems (PMAPS), 2010 IEEE 11th International Conference on*, 2010, pp. 65-70.
- [47] A. Chowdhury and D. Koval, *Power distribution system reliability : practical methods and applications / by Ali Chowdhury, Don Koval*: Oxford : Wiley-Blackwell, 2009., 2009.
- [48] J. Mitra, "Reliability-Based Sizing of Backup Storage," *IEEE Transactions on Power Systems*, vol. 25, pp. 1198-9, 2010.
- [49] A. Oudalov, R. Cherkaoui, and A. Beguin, "Sizing and optimal operation of battery energy storage system for peak shaving application," in *Power Tech 2007, 1-5 July 2007*, Piscataway, NJ, USA, 2008, pp. 1731-5.

- [50] Bagen and R. Billinton, "Impacts of energy storage on power system reliability performance," in *2005 Canadian Conference on Electrical and Computer Engineering, 1-4 May 2005*, Piscataway, NJ, USA, 2006, pp. 494-7.
- [51] EMC. (2010). *Energy Market Company, Uniform Singapore Energy Prices*. Available: <http://www.emcsg.com/marketdata/priceinformation>
- [52] D. Simopoulos and S. Kavatza, "Consideration of ramp rate constraints in unit commitment using simulated annealing," in *Power Tech, 2005 IEEE Russia*, 2005, pp. 1-7.
- [53] M. K. C. Marwali, M. Haili, S. M. Shahidehpour, and K. H. Abdul-Rahman, "Short term generation scheduling in photovoltaic-utility grid with battery storage," *Power Systems, IEEE Transactions on*, vol. 13, pp. 1057-1062, 1998.
- [54] A. J. Svoboda, T. Chung-Li, C. Li, and R. B. Johnson, "Short-term resource scheduling with ramp constraints [power generation scheduling]," *Power Systems, IEEE Transactions on*, vol. 12, pp. 77-83, 1997.
- [55] C. Wang and S. M. Shahidehpour, "Effects of ramp-rate limits on unit commitment and economic dispatch," *Power Systems, IEEE Transactions on*, vol. 8, pp. 1341-1350, 1993.
- [56] C. Wang and S. M. Shahidehpour, "Ramp-rate limits in unit commitment and economic dispatch incorporating rotor fatigue effect," *Power Systems, IEEE Transactions on*, vol. 9, pp. 1539-1545, 1994.
- [57] C. Ferreira, J. Gama, V. Miranda, and A. Botterud, "Probabilistic Ramp Detection and Forecasting for Wind Power Prediction," in *Reliability and Risk Evaluation of Wind Integrated Power Systems*, R. Billinton, R. Karki, and A. K. Verma, Eds., ed: Springer India, 2013, pp. 29-44.
- [58] A. Roy, S. B. Kedare, and S. Bandyopadhyay, "Optimum sizing of wind-battery systems incorporating resource uncertainty," *Applied Energy*, vol. 87, pp. 2712-2727, 8// 2010.

- [59] E. S. Sreeraj, K. Chatterjee, and S. Bandyopadhyay, "Design of isolated renewable hybrid power systems," *Solar Energy*, vol. 84, pp. 1124-1136, 7// 2010.
- [60] N. K. Gautam and N. D. Kaushika, "Reliability evaluation of solar photovoltaic arrays," *Solar Energy*, vol. 72, pp. 129-141, 2002.
- [61] C. Grigg, P. Wong, P. Albrecht, R. Allan, M. Bhavaraju, R. Billinton, *et al.*, "The IEEE Reliability Test System-1996. A report prepared by the Reliability Test System Task Force of the Application of Probability Methods Subcommittee," *Power Systems, IEEE Transactions on*, vol. 14, pp. 1010-1020, 1999.
- [62] T. Xisheng, D. Wei, and Q. Zhiping, "Investigation of the Dynamic Stability of Microgrid," *Power Systems, IEEE Transactions on*, vol. 29, pp. 698-706, 2014.
- [63] X. Tan, Q. Li, and H. Wang, "Advances and trends of energy storage technology in Microgrid," *International Journal of Electrical Power & Energy Systems*, vol. 44, pp. 179-191, 1// 2013.
- [64] R. Zamora and A. K. Srivastava, "Controls for microgrids with storage: Review, challenges, and research needs," *Renewable and Sustainable Energy Reviews*, vol. 14, pp. 2009-2018, 2010.
- [65] B. Kirby and M. Milligan, "A Method and Case Study for Estimating the Ramping Capability of a Control Area or Balancing Authority and Implications for Moderate or High Wind Penetration," *Conference Paper NREL/CP-500-38153*, May 2005 2005.
- [66] P. Wang and R. Billinton, "Implementation of nonuniform reliability in a deregulated power market," in *Electrical and Computer Engineering, 2001. Canadian Conference on*, 2001, pp. 857-861 vol.2.
- [67] P. Wang, R. Billinton, and L. Goel, "Unreliability cost assessment of an electric power system using reliability network equivalent approaches," *Power Systems, IEEE Transactions on*, vol. 17, pp. 549-556, 2002.

- [68] A. Mehrtash, P. Wang, and L. Goel, "Reliability Evaluation of Power Systems Considering Restructuring and Renewable Generators," *Power Systems, IEEE Transactions on*, vol. 27, pp. 243-250, 2012.
- [69] B. Zhaohong, Z. Peng, L. Gengfeng, H. Bowen, M. Meehan, and W. Xifan, "Reliability Evaluation of Active Distribution Systems Including Microgrids," *Power Systems, IEEE Transactions on*, vol. 27, pp. 2342-2350, 2012.
- [70] L. T. Anstine, R. E. Burke, J. E. Casey, R. Holgate, R. S. John, and H. G. Stewart, "Application of Probability Methods to the Determination of Spinning Reserve Requirements for the Pennsylvania-New Jersey-Maryland Interconnection," *Power Apparatus and Systems, IEEE Transactions on*, vol. 82, pp. 726-735, 1963.
- [71] R. N. Allan, R. Billinton, A. M. Breipohl, and C. H. Grigg, "Bibliography on the application of probability methods in power system reliability evaluation: 1987-1991," *Power Systems, IEEE Transactions on*, vol. 9, pp. 41-49, 1994.
- [72] R. N. Allan, R. Billinton, A. M. Breipohl, and C. H. Grigg, "Bibliography on the application of probability methods in power system reliability evaluation," *Power Systems, IEEE Transactions on*, vol. 14, pp. 51-57, 1999.
- [73] R. N. Allan, R. Billinton, and S. H. Lee, "Bibliography on the Application of Probability Methods in Power System Reliability Evaluation 1977-1982," *Power Apparatus and Systems, IEEE Transactions on*, vol. PAS-103, pp. 275-282, 1984.
- [74] R. Billinton, "Bibliography on the Application of Probability Methods In Power System Reliability Evaluation," *Power Apparatus and Systems, IEEE Transactions on*, vol. PAS-91, pp. 649-660, 1972.
- [75] R. Billinton, M. Fotuhi-Firuzabad, and L. Bertling, "Bibliography on the application of probability methods in power system reliability evaluation 1996-1999," *Power Systems, IEEE Transactions on*, vol. 16, pp. 595-602, 2001.

- [76] M. T. Schilling, A. M. Leite da Silva, R. Billinton, and M. A. El-Kady, "Bibliography on power system probabilistic analysis (1962-88)," *Power Systems, IEEE Transactions on*, vol. 5, pp. 1-11, 1990.
- [77] W. Qiuwei, P. Wang, and L. Goel, "Direct Load Control (DLC) Considering Nodal Interrupted Energy Assessment Rate (NIEAR) in Restructured Power Systems," *Power Systems, IEEE Transactions on*, vol. 25, pp. 1449-1456, 2010.
- [78] P. Wang, J. Y. Huang, Y. Ding, P. Loh, and L. Goel, "Demand side load management of smart grids using intelligent trading/metering/ billing system," in *PowerTech, 2011 IEEE Trondheim*, 2011, pp. 1-6.
- [79] A. Ipakchi and F. Albuyeh, "Grid of the future," *Power and Energy Magazine, IEEE*, vol. 7, pp. 52-62, 2009.