

IMPROVEMENT IN DEEP REINFORCEMENT LEARNING
CONTROLLER FOR BUCK-BOOST CONVERTER WITH CONSTANT POWER LOAD

KEVIN KOAY CHEN RONG

UNIVERSITI TEKNOLOGI MALAYSIA

IMPROVEMENT IN DEEP REINFORCEMENT LEARNING CONTROLLER
FOR BUCK-BOOST CONVERTER WITH CONSTANT POWER LOAD

KEVIN KOAY CHEN RONG

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DEDICATION

This thesis is dedicated to my parents, spouse, and friends, who have provided me support, guidance, and wisdom to always be kind and help others.

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ABSTRACT

DC-DC converter has been used in the commercial and industrial sectors to step up and down the DC voltage. The increasing development of renewable energy technology, battery storage, and DC microgrids has stressed the importance of the usage of the DC-DC converter. However, DC-DC converters with constant power load (CPL) have experience instability issues such as voltage and frequency fluctuation. This negative effect is prominent to such an extent that it will cause negative input impedance characteristics that cause destabilize effects in the DC system and sensitive electronic components to be damaged. Many techniques are proposed to mitigate the issue, such as using passive and active damping, but they are limited to cost and physical constraints. Therefore, using an intelligent controller to manage the output of the DC-DC converter is a more attractive solution to the issues. The methods have been implemented in the controller using proportional integral derivative (PID), model predictive control (MPC), machine learning, and deep learning. As the system becomes more complex, methods that used PID and MPC controller have become infeasible to be implemented. Therefore, using machine learning and deep learning is an attractive alternative to solve the control issue. Reinforcement learning (RL) and deep reinforcement learning (DRL) have been used to solve complex control problems such as Proximal Policy Optimization (PPO). This project's purpose is to improve the DRL performance via improving reward function and compare both PPO and AC DRL controllers to analyse the performance during induced CPL by using MATLAB for the simulation. The project has shown that by improving the PPO DRL based long short-term memory (LSTM) network for actor and critic agents with an improved reward system will provide overall all improved performance when compared to the benchmark PID controller. By setting an environment in which the DRL controller is able to train properly, the performance of the buck-boost converter controller by AC and PPO DRL algorithm is compared. PPO DRL showing greater performance in converging to the reference point and a faster training period. Moreover, PPO DRL can demonstrate more robustness and improved voltage stability and settling time of the buck-boost converter without the need to further tune its training parameters.

ABSTRAK

Penukar AT-AT telah digunakan dalam sektor komersial dan perindustrian untuk menaikkan dan menurunkan kadar voltan AT. Perkembangan teknologi dalam bidang tenaga boleh diperbaharui, storan bateri dan mikro grid AT telah memberi fokus terhadap kepentingan penggunaan komponen penukar AT-AT. Walau bagaimanapun, penukar AT-AT dengan nilai Beban Berkuasa Malar (CPL) akan mengalami masalah ketidakstabilan terhadap nilai voltan dan frekuensi yang sentiasa berubah-ubah. Kesan negatif ini amat ketara sehingga ianya akan menghasilkan ciri galangan masukan negatif yang boleh menyebabkan kesan ketidakstabilan dalam sistem AT dan mengakibatkan komponen elektronik yang sensitif akan menjadi rosak. Pelbagai teknik telah dicadangkan bagi mengurangkan masalah yang berkait dengan isu ini seperti menggunakan kaedah penapis pasif dan aktif, tetapi ianya mempunyai nilai kos yang terhad dan kekangan terhadap bentuk fizikal. Oleh yang demikian, salah satu cara penyelesaian yang lebih sesuai terhadap isu dan masalah ini adalah dengan menggunakan peralatan pengawal pintar untuk mengawal nilai output bagi penukar AT-AT ini. Kaedah pengawalan yang telah digunakan adalah dengan melalui cara Berkadar-Kamiran-Terbitan (PID), Model Kawalan Ramalan (MPC), Pembelajaran Mesin dan Pembelajaran Mendalam. Apabila sistem menjadi lebih kompleks, cara yang menggunakan pengawal PID dan MPC akan menjadi lebih sukar untuk dijalankan. Oleh itu, kaedah menggunakan Pembelajaran Mesin dan Pembelajaran Mendalam ini telah menjadi salah satu kaedah alternatif yang menarik dalam menyelesaikan masalah isu pengawalan tersebut. Reinforcement Learning (RL) dan Deep Reinforcement Learning (DRL) telah digunakan bagi menyelesaikan masalah pengawalan yang kompleks seperti penggunaan kaedah Proximal Policy Optimization (PPO). Tujuan projek ini adalah untuk meningkatkan prestasi DRL melalui penambahbaikan fungsi dan membandingkan antara kedua jenis pengawal PPO dan AC DRL dalam menganalisis prestasi dengan memasukkan CPL dalam perisian MATLAB bagi tujuan simulasi. Projek ini telah membuktikan bahawa dengan penambahbaikan terhadap PPO DRL berasaskan panjang rangkaian ingatan jangka pendek atau dikenali sebagai Long Short-Term Memory (LSTM) akan memberikan peningkatan prestasi keseluruhan apabila dibandingkan dengan kawalan PID. Dengan penetapan yang sesuai terhadap pengawalan DRL, perbandingan bagi tahap prestasi pengawal penukar AT-AT di antara algoritma AC dan PPO DRL telah dilakukan. PPO DRL telah menunjukkan prestasi yang lebih baik berbanding nilai rujukan dan mempunyai tempoh yang lebih pantas. Tambahan lagi, PPO DRL adalah lebih kukuh dan stabil serta telah meningkatkan tahap kestabilan voltan dan tempoh penyelesaian masa bagi penukar AT-AT tanpa perlu membuat sebarang penetapan tambahan bagi parameter latihannya.

TABLE OF CONTENTS

	TITLE	PAGE
	DECLARATION	iii
	DEDICATION	iv
	ACKNOWLEDGEMENT	v
	ABSTRACT	vi
	ABSTRAK	vii
	TABLE OF CONTENTS	viii
	LIST OF TABLES	xii
	LIST OF FIGURES	xiv
	LIST OF ABBREVIATIONS	xix
	LIST OF SYMBOLS	xxi
	LIST OF APPENDICES	xxiii
CHAPTER 1	INTRODUCTION	1
1.1	Background of Study	1
1.2	Problem Statement	2
1.3	Research Objectives	2
1.4	Scope of research	3
1.5	Outline of the Thesis	3
CHAPTER 2	LITERATURE REVIEW	5
2.1	Introduction	5
2.2	Overview of DC-DC Converter Controller Stability Improvement	6
2.3	Instability in DC-DC Converter	8
2.4	Buck-Boost Converter	9
2.4.1	Transfer functions of buck-boost converter	12
2.5	Constant Power Load (CPL)	17
2.6	Buck-Boost Controller	18

2.6.1	Proportional Integral Derivative (PID) Controller	18
2.6.2	Reinforcement Learning (RL) Controller	22
2.6.2.1	Proximal Policy Optimization (PPO)	24
2.6.2.2	Actor-Critic (AC)	26
2.7	Recurrent Neural Network (RNN)	29
2.8	Critical Review of Recent Studies	31
2.9	Summary	32
CHAPTER 3	RESEARCH METHODOLOGY	33
3.1	Introduction	33
3.2	Buck-Boost Converter Topology	35
3.3	Feedback Control System Design and Settling Time	36
3.3.1	PID controller	37
3.4	Calibration of PID controller	39
3.5	Deep Reinforcement Learning (DRL) Controller	45
3.5.1	DRL using PPO algorithm and AC algorithm	49
3.5.2	Designing the Observation System for the DRL Agent	50
3.5.3	Designing the Action System for the DRL Agent	52
3.5.4	Designing the Reward Function for the DRL Agent	55
3.5.5	Environment settings and DRL parameter settings algorithm	59
3.5.5.1	Actor and Critic based ANN and RNN Network	60
3.5.5.2	PPO Parameters Settings	65
3.5.5.3	AC Parameters Settings	66
3.5.5.4	Boundary Setup	67
3.5.6	Training process of DRL Algorithm	70
3.6	Experimental Setup	76
3.7	Result Analysis	80
3.8	Summary	81

CHAPTER 4	RESULT AND DISCUSSION	82
4.1	Introduction	82
4.2	Performing the Calculation Buck-Boost Converter	83
4.3	Without Controller	85
4.3.1	Output Voltage of 30 V	85
4.3.2	Output Voltage of 80 V	87
4.4	Benchmark PID Controller	88
4.4.1	Voltage Output 30 V	89
4.4.2	Voltage Output 80 V	92
4.5	Results of Training DRL Algorithm	95
4.5.1	Reward Model Designed	95
4.5.1.1	Model 1 Reward Designed	96
4.5.1.2	Model 2 Reward Designed	98
4.5.1.3	Model 3 Reward Designed	100
4.5.1.4	Model 4 Reward Designed	102
4.5.1.5	Model 5 Reward Designed	104
4.5.1.6	Model 6 Reward Designed	106
4.5.2	Performance Comparison of AC DRL and PPO DRL Controller	108
4.5.2.1	AC DRL Training Evaluation	108
4.5.2.2	PPO DRL Training Evaluation	113
4.5.2.3	Comparison of PPO and AC DRL Training Evaluation	116
4.5.3	PPO Controller	119
4.5.3.1	Voltage Output 30 V	119
4.5.3.2	Voltage Output 80 V	123
4.6	Comparative Results of the PPO and PID Controller	127
4.7	Summary	132
CHAPTER 5	CONCLUSION AND RECOMMENDATIONS	133
5.1	Conclusion	133
5.2	Recommendation and Future Work	134

REFERENCES

135

Appendices A - E

145 - 151

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 3.1	The component of the Buck-Boost converter	35
Table 3.2	Parameter for DRL Observation	51
Table 3.3	List of action range for DRL controller different output voltage	54
Table 3.4	Environment Setting of DRL training	59
Table 3.5	Actor and Critic Neural Network settings	60
Table 3.6	Critic and actor ANN setting for DRL in Simulink.	60
Table 3.7	Critic and actor RNN setting for LSTM for DRL in Simulink.	62
Table 3.8	Description DRL parameter for training	65
Table 3.9	Description of AC DRL parameter for training	66
Table 3.10	Training Parameters for training the DRL	71
Table 3.11	Input and output voltage for buck-boost convert	79
Table 4.1	Buck-boost converter component parameter	84
Table 4.2	Parameter for tuning the PID using PID Tuner	88
Table 4.3	Tuned PID Parameters for 30 V reference voltage	89
Table 4.4	Measurement of PID responds when CPL is connected for 30 V reference voltage	91
Table 4.5	Tuned PID Parameters for 80 V reference voltage	92
Table 4.6	Measurement of PID responds when CPL is connected for 80 V reference voltage	94
Table 4.7	Reward function parameters of reward model 1	96
Table 4.8	Reward function parameters of reward model 2	98
Table 4.9	Reward function parameters of reward model 3	100
Table 4.10	Reward function parameters of reward model 4	102
Table 4.11	Reward function parameters of reward model 5	104
Table 4.12	Reward function parameters of reward model 6	106
Table 4.13	Setting AC DRL parameter for training	116

Table 4.14	Setting PPO DRL parameter for training	116
Table 4.15	Measurement of PPO-LSTM DRL responds when CPL is connected when the reference voltage is 30 V	119
Table 4.16	Measurement of PPO-LSTM DRL responds when CPL is connected when the reference voltage is 80 V	123
Table 4.17	Comparison between PID and PPO algorithm when output at 30 V when CPL is connected	129
Table 4.18	Comparison between PID and PPO algorithm when output at 80 V when CPL is connected	130

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 2.1	Tree diagram of improvement of DC-DC converter voltage and frequency instability	7
Figure 2.2	Buck-boost converter circuit [33]	9
Figure 2.3	Buck-boost converter equivalent circuit [44]	12
Figure 2.4	The buck-boost equivalent circuit for derivation of $G_{vg}(s)$ by setting voltage source to zero [44]	12
Figure 2.5	Manipulating the buck-boost equivalent circuit control by moving the inductor and input voltage through transformer [44]	14
Figure 2.6	By superposition, current source is set to zero [44]	14
Figure 2.7	By superposition, voltage source is set to zero [44]	15
Figure 2.8	V-I curve of constant power load [46]	17
Figure 2.9	A closed-loop feedback system [57]	19
Figure 2.10	Using PID controller to improve power system [58]	19
Figure 2.11	Fuzzy PID controller [62]	21
Figure 2.12	Recurrent neural network [73]	29
Figure 2.13	LSTM architecture [78]	30
Figure 2.14	Detail LSTM block [73]	30
Figure 3.1	Flowchart for implementation of the project	34
Figure 3.2	Buck-boost converter circuit	35
Figure 3.3	A block diagram of closed-loop feedback system [12]	36
Figure 3.4	Sample response time of dynamical control system [80]	36
Figure 3.5	Block diagram of feedback controller using PID controller	37
Figure 3.6	Feedback controller using PID controller in Simulink	37
Figure 3.7	Flowchart for implementation of feedback controller using PID controller	38
Figure 3.8	Buck-boost converter model with CPL and PID controller in Simulink	39

Figure 3.9 Selecting the “Identify New Plant” option under the PID Tuner	40
Figure 3.10 Selecting the “Simulate Data” to enable tuning of PID	40
Figure 3.11 Input the parameters for tuning the PID	41
Figure 3.12 Setting the amplitude of step input specification	41
Figure 3.13 After simulated input and output data of the PID	42
Figure 3.14 Apply the data to the “Plant identification”	42
Figure 3.15 Estimated state-space parameter	43
Figure 3.16 Comparison between identified data and plant	43
Figure 3.17 Tuned parameters of the PID controller’s gains	44
Figure 3.18 The concept of DRL block diagram	45
Figure 3.19 The flow when designing a DRL algorithm	46
Figure 3.20 Flow chart for designing the DRL controller	47
Figure 3.21 DRL algorithm sub-process flow chart	48
Figure 3.22 PPO DRL block diagram.	49
Figure 3.23 AC DRL block diagram	49
Figure 3.24 Block diagram of observation for the DRL agent	50
Figure 3.25 The setup of the observation system in Simulink where the DRL receive the error and V_{out} .	51
Figure 3.26 DRL agent receiving the input signal as an observation of the system in Simulink.	51
Figure 3.27 Action for the DRL agent block diagram	52
Figure 3.28 Action for the DRL agent in Simulink highlighted in the red circle	52
Figure 3.29 PWM period settings	53
Figure 3.30 The action by DRL and PWM output correspond to the period setting of PWM	53
Figure 3.31 DRL has issue converging to the voltage reference at 30V with sudden change in duty input.	54
Figure 3.32 Flow chart for designing the reward system for the DRL controller	55
Figure 3.33 ‘Reward’ subblock connected to the RL Agent Block reward input	56

Figure 3.34 ‘Reward’ subblock internal component	57
Figure 3.35 An example when DRL algorithm is training and achieved its goal. (a) Training of DRL. (b) Agent responds after simulation. (c) Selected episode shows its total reward and training period	58
Figure 3.36 ANN Critic Network	61
Figure 3.37 ANN Actor Network	62
Figure 3.38 RNN Critic Network	63
Figure 3.39 RNN Actor Network	64
Figure 3.40 Check Step Response Characteristics Block circle in red	67
Figure 3.41 Boundary setup using “Check Step Response Characteristics” block. (a) Input the values for each parameter (b) Enable the output assertion signal	68
Figure 3.42 Termination boundaries is highlighted in yellow (a) The output voltage is within the white area (b) Simulation is terminated when the output voltage intercepts the termination boundary	69
Figure 3.43 The training process of the PPO DRL algorithm. (a) The training of PPO DRL, the algorithm will randomly explore to learn and create a policy that enables to achieve the goal. (b) The PPO action able to have the output voltage converge to reference voltage output. (c) V_{out} converge to reference of 30 V with PPO DRL actions will affect PWM.	73
Figure 3.44 The algorithm unable to learn to control the system with the output intercept the termination boundary. (a) The training of PPO DRL with poor training results (b) V_{out} unable to converge to the reference point and it intercept the termination boundary. (c) V_{out} unable to converge due to PPO DRL poor actions.	75
Figure 3.45 Block diagram of closed-loop feedback controller	76
Figure 3.46 Buck-boost converter connected with controller and CPL	76
Figure 3.47 (a) Buck-boost converter connected with DRL controller (b) Buck-boost converter with CPL	77
Figure 3.48 Buck-boost converter parameters settings	78
Figure 3.49 CPL parameters settings	78
Figure 3.50 Flow chart for conducting the experiment	79
Figure 4.1 Buck-boost converter without controller with CPL in Simulink	85

Figure 4.2 Output voltage of 30 V responds buck-boost converter when CPL is connected. (a) 150 W (b) 250 W (c) 350 W	86
Figure 4.3 Output voltage of 80 V responds buck-boost converter when CPL is connected. (a) 150 W (b) 250 W (c) 350 W	87
Figure 4.4 Bench marking the 30 V output voltage responds buck-boost converter with CPL and PID controller (a) 150 W (b) 250 W (c) 350 W	90
Figure 4.5 Bench marking the 80 V output voltage responds buck-boost converter with CPL and PID controller (a) 150 W (b) 250 W (c) 350 W	93
Figure 4.6 System response reward designed model of PPO DRL controller Model 1 reward designed. (a) Episode manager with episode reward per episode (b) Controller response and output voltage	97
Figure 4.7 System response reward designed model of PPO DRL controller Model 2 reward designed. (a) Episode manager with episode reward per episode (b) Controller response and output voltage	99
Figure 4.8 System response reward designed model of PPO DRL controller Model 3 reward designed (a) Episode manager with episode reward per episode (b) Controller response and output voltage	101
Figure 4.9 System response of reward designed model of PPO DRL controller Model 4 reward designed (a) Episode manager with episode reward per episode (b) Controller response and output voltage	103
Figure 4.10 System response reward designed model of PPO DRL controller Model 5 reward designed (a) Episode manager with episode reward per episode (b) Controller response and output voltage	105
Figure 4.11 System response of reward designed model of PPO DRL controller Model 6 reward designed (a) Episode manager with episode reward per episode (b) Controller response and output voltage	107
Figure 4.12 AC DRL with ANN Network	108
Figure 4.13 AC DRL with LSTM based RNN Network	109
Figure 4.14 Poor results when set “num of step look ahead” to default setting of 32	109
Figure 4.15 Improve results when set “num of step look ahead” to 500 with 'Entropy Loss Weight' is 0.01 and 'Discount Factor' is 0.995	110

Figure 4.16 AC DRL when “Entropy Loss Weight” is 0.05 and “Discount Factor” is 0.99	111
Figure 4.17 AC DRL when “Entropy Loss Weight” is 0.08 and “Discount Factor” is 0.992	111
Figure 4.18 AC DRL when “Entropy Loss Weight” is 0.08 and “Discount Factor” is 0.995	112
Figure 4.19 AC DRL when “Entropy Loss Weight” is 0.02 and “Discount Factor” is 0.998	112
Figure 4.20 PPO with ANN Network	113
Figure 4.21 PPO DRL with LSTM based RNN Network	114
Figure 4.22 When the clip factor is 0.1	115
Figure 4.23 When the clip factor is 0.3	115
Figure 4.24 Comparison of training episode between DRL (a) AC (b) PPO	118
Figure 4.25 30V output voltage responds buck-boost converter with CPL rating of 150W and PPO controller (a) Training progress. (b) PPO controller response.	120
Figure 4.26 30V output voltage responds buck-boost converter with 250 W CPL and PPO controller (a) Training progress. (b) PPO controller response	121
Figure 4.27 30V output voltage responds buck-boost converter with 350 W CPL and PPO controller (a) Training progress (b) PPO controller response	122
Figure 4.28 80V output voltage responds buck-boost converter with 150 W CPL and PPO controller (a) Training progress (b) PPO controller response	124
Figure 4.29 80V output voltage responds buck-boost converter with 250 W CPL and PPO controller (a) Training progress (b) PPO controller response	125
Figure 4.30 80V output voltage responds buck-boost converter with 350 W CPL and PPO controller (a) Training progress (b) PPO controller response	126
Figure 4.31 Comparison results of PID and PPO controller performance with output at 30V (a) 150 W (b) 250 W (c) 350 W	127
Figure 4.32 Comparison results of PID and PPO controller performance with output at 80V (a) 150W (b) 250 W (c) 350W	128

LIST OF ABBREVIATIONS

AC	-	Alternating Current
ACRL	-	Actor-Critic Reinforcement Learning
AC DRL	-	Actor-Critic Deep Reinforcement Learning
AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
AT-AT	-	Arus Terus – Arus Terus
CPL	-	Constant power load
CPU	-	Central Processing Unit
DC	-	Direct Current
DDPG	-	Deep deterministic policy gradient
DQN	-	Deep Q network
DRL	-	Deep Reinforcement Learning
FL	-	Fuzzy logic
FSMC	-	Fuzzy Sliding Model Control
GRU	-	Gated Recurrent Unit
IAE	-	Integral absolute error
LSTM	-	Long Short-Term Memory Network
LUS	-	Local Unimodal Sampling
MAE	-	Mean absolute error
MDP	-	Markov decision process
MG	-	Microgrid
MPC	-	Model predictive control
MSE	-	Mean square error
NN	-	Neural Network
PI	-	Proportional-Integral
PID	-	Proportional-Integral-Derivative
PPO	-	Proximal Policy Optimization
PWM	-	Pulse-Width Modulation
SMC	-	Sliding mode control

SISO	-	Single input/single output
SMC	-	Sliding Model Control
TLBO	-	Teaching Learning Based Optimization
ULM	-	Ultra local model
WNN	-	Wavelet Neural Network

LIST OF SYMBOLS

K_p	-	Proportional Gain
K_i	-	Integral Gain
K_d	-	Derivative Gain
T_I	-	Integral Time Constant
T_D	-	Derivative Time Constant
u_t	-	PID control variable
e_t	-	Error value
P	-	Rated power of the CPL (W)
V_{ref}	-	Reference voltage (V)
V_o	-	Output voltage (V)
V_{CPL}	-	Voltage of the CPL (V)
i_L	-	Inductor current (A)
V_C	-	Capacitor voltage (V)
L	-	Inductance (H)
C	-	Capacitance (F)
σ	-	Observer design coefficient
S	-	State space
A	-	Action space
r	-	Reward function
γ	-	Discount factor
G_t	-	Accumulated discounted reward
T_s	-	Sampling Time
T_f	-	Final Time
R	-	Resistor
D	-	Duty Cycle
σ	-	Standard deviation
N	-	the size of the data
μ	-	Mean
x_i	-	Each value from the data
\hat{A}_t	-	Advantage function

π_{θ}	-	Policy parameters
s_t	-	State at time
a_t	-	Action at time
(s_t, a_t)	-	State-action pair
$\pi_{\theta}(a_t s_t)$	-	Policy function
$A^{\pi}(s, a)$	-	Advantage function
Q	-	Action-value function
$V^{\pi}(s)$	-	Value function
$Q^{\pi}(s, a)$	-	Action-value function
π	-	policy
t	-	time
L_c	-	Critic loss function
$\mu(S)$	-	Actor
$V(S)$	-	Critic
t_s	-	Starting time
D_t	-	Advantage function (AC)
$L(\theta)$	-	Surrogate objective function
$r_t(\theta)$	-	Probability Ratio
π_{θ}	-	Policy Parameters
\hat{A}_t	-	Advantage function (PPO)
D_t	-	Advantage function (AC)

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	MATLAB Code PPO DRL Training	145
Appendix B	MATLAB Code AC DRL Training	147
Appendix C	MATLAB Code for Acquiring the Quantitative Measurement	149
Appendix D	Activities listed in the Gantt Chart	150
Appendix E	Summary of Critical Review	151

CHAPTER 1

INTRODUCTION

1.1 Background of Study

Direct Current (DC) power systems have some advantages over Alternating Current (AC) power systems in terms of stability and being applied in DC microgrid and renewable generation system [1]–[4]. In microgrid and renewable generation system, the control schemes have to be able to extract the maximum potential by adjusting the load and regulation of controller to maintain the voltage of the source [3], [5], [6]. The interest to optimize the DC-DC converter have been studied extensively in order to produce a good quality output signal. The DC-DC converter is able to regulate the DC voltage from source and output the DC voltage with its desired setting. A buck converter reduces voltage from the source to the load, whereas a boost converter increases voltage from the source to the load. Furthermore, the output voltage of a buck-boost converter is either less than or more than the source voltage in magnitude.

The destabilizing effects on the circuit limit the potential of DC-DC converters, resulting in severe voltage and frequency oscillations [3], [7], [8]. The issue presented in DC-DC converter with constant power load (CPL) will cause the loss of power, damages to the sensitive component of the system and may cause the occurrence of fault. Therefore, optimising the control system of DC-DC converter for DC microgrid and renewable sources of energy for the production of electrical energy will bring benefit to the industry [5], [9]. To solve this issue, a model-based and model-independent strategies control scheme is presented for DC-DC converter. However, model-based is limited in effectively handling any uncertainties and complex structure. Therefore, the current trend is more toward model-independent strategies control scheme as they are able to adapt to various complex system [8].

1.2 Problem Statement

The application of using buck-boost converters is attractive as it is simple and able to increase or decrease the output voltage depending on the reference voltage. It is instrumental in applications such as battery-powered systems, renewable energy plants, or DC power systems. Still, it has a limitation that causes severe voltage and frequency oscillation when the circuit's constant power load (CPL) is applied. This will cause voltage swell or drop that will affect the power system. Therefore, a feedback control system is needed to manage the buck-boost converter to reduce the voltage in stability and settling time. The standard control techniques include proportional-integral (PI) control, proportional-integral-derivative (PID) control, and model predictive control (MPC) for the buck-boost converters. A sophisticated control technique that uses machine learning or deep learning techniques has provided more opportunities to improve the converter's performance by utilizing reinforcement learning (RL) and deep reinforcement learning (DRL) as the preferred controller. The previous study shows that the voltage stability and settling time of buck-boost converter is improved using DRL with Proximal Policy Optimization (PPO) while comparing benchmark PI controller. However, the study can further expand.

1.3 Research Objectives

The main aim of this work is to develop and validate the deep reinforcement learning algorithm in buck-boost converter controller to reduce the voltage instability and improve settling time. The objectives of the research are:

- (a) To develop the DRL controller to further improve voltage instability and settling time while reaching the desired voltage through simulation by using MATLAB.
- (b) To investigate the performance of the buck-boost controller by AC and PPO algorithm based DRL algorithm.
- (c) To compare different reward design of DRL algorithm.

1.4 Scope of research

The scopes of this research are as follows:

- (a) The DRL algorithms that will focus on this research are PPO and AC only.
- (b) The benchmark to test the performance will be based on a PID controller that is tuned using the MATLAB/Simulink solver.
- (c) The simulation only focuses on the ideal Buck-Boost converter only and voltage output of 30 V and 80 V only and input voltage of 48 V. Non-ideal component is neglected during the simulation of the circuit.

1.5 Outline of the Thesis

The thesis is structured into five chapters. Chapter 1 will consist of the background of the study, problem statement, research objective, and scope of research. In chapter 2, the literature reviews related to the buck-boost converter, PID and DRL are explained. In chapter 3, the designed implementation of the research project is described. In chapter 4, the results and discussion of performance comparison between DRL reward design and buck-boost controller with PID, AC DRL, and PPO DRL controller are presented. Finally, in chapter 5, the conclusion of the study is presented with recommendations for future works for the improvement of the development of DRL.

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