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Intelligent Secondary Control for energy management in a Micro-grid by using Multi-Agent System

By

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To my parents

Heidar Selseleh Jonban

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Abstract

Nowadays, distributed energy resources are widely used to supply demand in micro grids especially in green buildings. These resources are usually connected by using power electronic converters, which act as actuators, to the system and make it possible to inject desired active and reactive power, as determined by smart controllers. The overall performance of a converter in such system depends on the stability and robustness of the control techniques. This thesis presents two bottom-up smart control approaches to manage energy in DC microgrids that split the demand among several generators. Firstly, an energy management system (EMS) based on multi-agent system (MAS) controllers is developed to manage energy, control the voltage and create balance between supply and demand in the system with the aim of supporting the reliability characteristic. In the proposed approach, a reconfigured hierarchical algorithm is implemented to control interaction of agents, where a CAN bus is used to provide communication among them. This framework has the ability to control system, even if a failure appears into decision unit.

The second research approach presents an energy management system based on multi-agent system under the supervision of a smart contract with a bottom-up approach for a grid connected DC micro-grid that is equipped with solar photovoltaic panels (PV), wind turbine (WT) and micro-turbine (MT) and battery energy storage (BES). In the presented approach, each unit controls and manages through a distributed decision structure. The BES agent is managed by an intelligent structure based on a reinforcement learning model. Since charging and discharging the battery is a stepwise process, in this research, a Markov decision process is trained by using a Q-learning algorithm. The rest of the agents are controlled and managed by heuristic algorithms. To create interaction and coordination among agents, a tendering process is used wherein each agent under its supervised control structure presents its

offer to the tendered item at each time period. The tendering organization allocates the requested power through first price sealed-bid algorithm between bidders to optimize energy cost in the MG.
The two proposed approaches present online intelligent systems that can guarantee fault-tolerance, stability and reliability in the MG especially in green houses and smart cities.

Keywords
Energy management system, multi-agent system, self-healing, fault-tolerance, artificial intelligence, subsumption architecture, smart contract, tendering process, first-price sealed-bid algorithm, reinforcement learning, Markov decision process, c-means algorithm, Q-learning algorithm.

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Acronyms

CANopen	Controller Area Network-open
CEMS	Centralized energy management system
DEMS	Distributed energy management system
EMS	Energy management system
MAS	Multi-agent system
PV	Photovoltaic
RES	Renewable energy system
SC	Super-capacitor
DER	Distributed energy resource
BES	Battery energy storage
FPSB	First-price sealed-bid algorithm
MT	Micro-turbine
WT	Wind turbine
MDP	Markov decision process
RL	Reinforcement learning

Nomenclature

Δt	Total delay in the system
ΔV	Maximum oscillation voltage at the DC bus
C_{bus}	Capacitor of DC bus
i_{Bat}	Injected current of battery
$i_{batchar}$, $i_{batdchar}$	Charging/ discharging current of battery
i_{grid}, i_{pv}, i_{sc}	Injected current of grid/ PV/ SC
i_{scchar}, $i_{scdchar}$	Charging/ Discharging current of SC
i_{total}	Total injected current to the DC bus
L	inductance
m	Binary variable, m=1 boostmode, m=0 Buck mode
P_{Bat}, P_{grid}, P_{pv}, P_{SC}	Injected Power of battery/ grid/ PV/ SC
A^{PV}	Aperture area of PV module (m^2)
$\overline{b}^{MT}$	Maximum offered price of MT ($/kWh)
$\overline{E}^{BES}$, $\underline{E}^{BES}$	Maximum and minimum stored energy in BES (kWh)
n	Life time of unit
$\overline{P}^{BES+}, \overline{P}^{BES-}$	Maximum discharge and charge rate of BES (kW)
$\overline{P}^{GR-}$, $\overline{P}^{GR+}$	Maximum injected power to/ by the grid (kW)
$\overline{P}^{i}, \underline{P}^{i}$	Maximum and minimum generated power by agent i (kW)
r	Interest rate
R_L, R_H	Ramp up and down limit (kW)
$T^{MT,on/off}$	Turn on and turn off time (min)
$\underline{v}, \overline{v}$	Maximum and minimum wind speed for WT (m/s)
μ^{MT}	MT efficiency (%)
π_t^{ES}	Binary variable of ES
Δt	Time step (h)
$C^{i,inv}$	Investment cost of generator i ($)
$C^{i,o\&m}$	Operation and maintenance cost of generator i ($)
$C^{PV,ins}$	Installation cost of PV ($)
$C^{PV,pan}$	Solar panel cost ($)
$C^{MT,fu}$	Fuel cost ($)

$C^{MT,st}$	Start up cost ($)
CF^{WT}	Capacity factor of WT
E_t^{BES}	Stored energy in BES at time t (kWh)
F_t^{MT}	Fuel consumption rate
I_t	Solar radiation at time t (W/m^2)
P_t^T	Requested power by the Tenderer (kW)
$\hat{P}^{WT}$, $\hat{v}^{WT}$	WT rated power (kW) and wind speed (m/s)
$SPOT_t$	selling price of the electricity to the grid at t (USD/kWh)
TOU_t	time-of-use price at t (USD/kWh)
v_t	Wind speed (m/s)
ζ_t^{MT}	Discount applied by MT at time t (%)
b_t^i	Offered price by bidder i at time t ($/kWh)
C^i	Cost to purchase energy
p_t^{BES+}, p_t^{BES-}	Discharging/Charging power of BES at time t (kW)
p_t^{GR-},p_t^{GR+}	Injected power to/by the grid at time t
p_t^{MT}	Offered power by bidder MT at time t
R_t^i	Revenue gained by bidder i at time t ($)

Chapter 1

Introduction

This chapter presents the subject of the proposed work in the thesis. The state of the art, hypothesis and objective are included in this chapter. Finally, thesis outline is presented at the end of this chapter.

CONTENTS:

1.1 Research topic

Utilization of renewable energy systems (RES) such as wind and solar power is increasing due to their environmental friendly and cost-effective operation. However, intermittent generation from RES and unpredictable changes in demand profiles cause concerns regarding supply-demand balance and the stability and reliability of power systems. For example, in a building with engaged renewable energy resources, voltage stability and reliability of system could be significant as well as supporting supply-demand balance [1, 2]. Energy storage systems could be used in such system to guarantee these features [3]. However, by aggregating BES (usually of small scale) in a micro-grid, power control and energy management become more challenging. Multi-agent systems (MASs) are introduced to solve such control problems in EMSs, where individual system components are distributed and control is decentralized and autonomous [4, 5, 6, 7]. In the MAS, each component acts as an agent and operates in a dynamic environment, where it has the freedom to either join or leave the system whenever required. The agents in MASs are able to perceive environmental changes and decide based on their own decision structure and change the environment with proper actions [8]. Consequently, the overall challenge and objective in the EMS is divided into a set of small tasks that could be controlled either integrated or distributed [9]. It is important to mention that, by autonomous and decentralized control, the response time and control delays are minimized, thus increasing the reliability of grid connected RES [10].

The energy management system for distributed energy sources can be divided into centralized energy management system (CEMS) and distributed energy management system (DEMS) [11, 12, 13]. In both cases, the aim is to achieve a balance between supply and demand; the difference lies in the control architecture and decision type [14, 15, 16, 17, 18]. In CEMSs, associated controllable devices are directly connected to a central control unit, so that it efficiently monitors the whole system taking into consideration the various factors such as the energy balance and cost functions [19, 20, 21, 22, 23, 24]. The control unit receives measured variable and sends suitable control signals based on certain restrictions and set points [25, 26, 27, 28]. The DEMS, on the other hand, works on small networks and use distributed processing and control units for regulating the entire system [29]. Each part in the DEMS has its own decision unit and based on a specific predefined control structure, it participates in the process of EMS [30, 31, 32]. In order to implement the DEMS, the MAS can be used to provide maximum independence to the individual energy systems. In fact, each decision part, acting as an agent, communicates and offers a robust control over the distributed energy sources [33]. This type of control presents many benefits as compared to the CEMS, such as, the scalability and redundancy [34].

1.2 Research problem

Recently, several studies have been done to present a suitable control system for MGs. Some of studies focused on day-ahead optimal scheduling wherein by prediction of generation and demand response were tried to control and manage MG [35, 36, 37]. For instance, in [38], an uncertainty-aware day-ahead optimal scheduling tool was presented for a grid connected microgrids based on information gap decision theory wherein additional constraints were used to bound the demand response signals to decrease the harmful effects of response fatigue. To lighten the peak load, in [39], a hybrid robust-stochastic model was introduced to schedule day-ahead for plug-in electric vehicle parking lots by considering the inherent uncertainties. In [40], with respect to the uncertainty of wind power and electricity price, aiming to maximize income of wind farms in day-ahead market, a quantum genetic algorithm was proposed to assign an optimal stored energy for each wind farm.

Newly, multi-agent systems (MASs) are introduced as flexible framework to control and manage energy in the power system [41, 42, 43]. In this system, each agent can individually perceive the environment by its sensors, make decision and act through its actuators [8]. Generally, distributed or centralized decision making are used for controlling MAS. In both cases, the aim is to achieve a balance between supply and demand; the difference lies in the control architecture and decision type [14, 15, 16, 17, 18]. In centralized decision making, agents are controlled through a central intelligent unit [44] and in distributed control, each agent independently acts into the MAS [45]. Various algorithms are presented to control MASs such as, hierarchical architecture [46, 47], heuristic algorithm [48, 49] and recently, machine learning (ML) [50, 51]. For instance, in [52], a multi-party energy management was presented to manage energy in multiple smart buildings based on non-cooperative theory wherein each building as a player in the game tried to decrease energy cost by considering DGs and demand response. A hierarchical and decentralized energy management system in [53] was introduced to reduce household energy cost by exchanging energy between prosumers and coordinating the operation of energy resources and shiftable home appliances. A controllable structure based on reinforcement learning was presented in [54] for electric vehicles charging scheduling to optimize the operating cost in electric vehicles.

Although MASs are formed by numerous independent units that could be effective for controlling large-scale systems, but implementation and management of their action are very challengeable. Basically, controlling MAS needs a framework wherein interaction among agents are clarified. Each agent in this framework, can independently act so that it persuades the system to the global aim. Implementing such framework allows user to have parallel processing, in the other word, it could be possible to implement various controlling units in which each part is controlled, separately. This framework will bring the following advantages to a power system [55]:

- fault tolerance, stability and reliability as the system can continue its operation if some agents fail
- scalability and flexibility due to capacity of adding and removing agents
- response time reduction and efficiency improvement thanks to asynchronous and parallel computing
- cost reduction in the sense that development cost of some small systems may be less than that of a large complex system
- redevelopment and reusability as the components of MAS may be applicable in new setups

Besides, MASs have capability to present an online operation to user so that, each agent operates without requirement to any prediction and at time makes suitable decision. In such system, agents should independently decide through artificial intelligence algorithm and as well, a framework is needed to create interaction among agents.

Generally, two approaches exist for implementing MASs; top-down approach and bottom-up approach. In top-down approach, user seeks to implement the rules in the system that cause the desired behavior between agents. In this approach agent has less discretion [56]. In bottom-up approach, user seeks the specific abilities for agents which create interaction in the whole system. In this approach, agents have more discretion in choosing actions. In other words, agent in the bottom-up approach could be utility-based agent that pursues its own greedy aims instead of the global aim so that, the results of these aims lead to the social benefits in the whole system [57]. The challenge that exists in bottom-up approach is to implement an intelligent algorithm for each agent in a way that beside of guarantee the individual profits, it obligates performance of agents to achieve the global aim. The following shortcomings have recognized in the previous studies:

- Absence of an online intelligent system to control distributed energy resources at MGs. In fact, majority of presented studies are focused on prediction based energy management [58, 59, 60, 61].
- In most of studies, proposed energy management systems is implemented as central control approach in which agent is not the decision maker and set points adjusted by central unit who optimizes and processes [62, 63, 64, 65].
- Non-existence of an intelligent framework to create interaction among agents. Most of the studies as energy management in MGs, or the control structure is in the form of central optimization [66, 67, 68], or implementation a management system for a generator without considering the control of the rest [69, 70, 71]. Absence of study in this section decreases stability and reliability in smart systems especially, by high penetration of RESs.
- In the online smart control of microgrids by using MAS, communication could be used to avoid collapse in faced with failure in decision parts and increases reliability and stability of system but it was ignored [72, 73, 74].

1.3 Hypotheses

In order to implement a smart energy management on a system, the following hypotheses have been adjusted for this research:

- A system with high penetration of RESs can be modeled as a MASs.
- It is possible to have smart secondary control on generators by using MASs.
- It is possible to implement mechanism based on MASs as a framework so that generators operate in it.
- Communication among agents will allow to decrease blackouts in the system.
- By implementing MAS over a MG and controlling agents with artificial intelligence algorithm, stability and reliability could be achieved and system would be fault tolerance.

1.4 Aim and objective

In order to address the research problem and test the research hypotheses, the main objective of this thesis is design and implement artificial intelligence approaches capable of controlling set points of providers to achieve balance between supply and demand. Such control structure should support stability, reliability and fault tolerance in the MG. For this purpose, the following steps will be developed.

- **Modelling of the MG**
  To model the MG following sections should be considered:
  - Generators such as RESs, BES, MT and the grid
  - Converters and inverters
  - Voltage and current controller
  - AC and DC loads
- **Modelling of smart control units**
  In order to design and implement smart control structures on the generators, the following sections are taken into account:
  - Determining a structure of MASs for controlling generators
  - Defining a type of smart control approach
  - Creating a communication structure between agents
- **Controlling the MG**
  To control and allocate tasks among agents in the MAS, the following section should be taken into account:
  - Clarifying and implementing a framework for controlling the MAS
  - Defining and implementing smart distributed decision unit for each agent

1.5 Thesis outline

To cover the exposed objective, this thesis is organized as follows:

Chapter 2 presents the implementation methods of electrical power systems in smart grid. Control models and constraints of providers in this chapter will be explained.

Chapter 3 introduces the intelligent control energy management systems that proposed in this thesis. Two different approaches will be designed to control MGs.

Chapter 4 investigates the results and performance of proposed intelligent energy management systems.

Chapter 5 evaluates the performance of implemented smart energy management systems on MGs based on fault tolerance.

Chapter 6 presents the general conclusions and future work of this research.

Chapter 7 presents the thesis disseminations and published articles as a result of the investigation collaborations around this thesis.

Chapter 2

Problem formulation, modeling and control structure of the micro-grid

To validate and evaluate the proposed control method, two different power systems have been implemented in this thesis. In this section, the implementation of electrical power system modeling methods in smart grids are explained. Then, control models and constraints of each distributed generator (DG) are presented in two separated sections. Also, in this section, the connection model of DGs to the demand and their mathematical models are presented.

CONTENTS:

In smart grids, to evaluate a smart control method, power system can be modeled in two different ways. Considering that the presented control method in this thesis is a new smart online method based on multi-agent system (MAS), therefore, in order to accurately evaluate the proposed methods, both models have been implemented, simulation model for a green building and mathematical model for smart city. Therefore, in this thesis, we model different power systems in two different models. Each system has different smart control mechanism that will be described in the next chapter. As a result, in this thesis, each chapter has two different studied systems that are examined and controlled separately from each other. In the following, simulated model of grid connected DC micro-grid for the green building is presented.

2.1 Simulation model for green building

In case study I, a simple model of DC micro-grid as a green building is depicted in figure 2.1, which is similar to the system in [55, 75]. This electrical system contains a Photovoltaic (PV), battery, SC and the gird those are supplying a DC active load through a DC bus.

2.1.1 Mathematical Model

The mathematical formulation of the green building is presented in this subsection. Eqs. (2.1)-(2.4) describe the average model of converters which is obtained by applying the Kirchhoff rules on circuit shown in figure 2.2 [76].

$$di_{sc}/dt = 1/L_1 * (V_{sc} - U_{12}V_{dc} - R_1 i_{sc}) \tag{2.1}$$

$$di_2/dt = 1/L_2 * (U_{43}V_{Bat} - V_{dc} - R_2 i_2) \tag{2.2}$$

$$di_3/dt = 1/L_3 * (U_5 V_{PV} - V_{dc} - R_3 i_3) \tag{2.3}$$

$$di_4/dt = 1/L_4 * (U_5 V_{grid} - V_{dc} - R_4 i_4) \tag{2.4}$$

where, R and L are resistance and inductance of converters, respectively. U is the duty cycle, where as U_{12} and U_{34} are defined in Eqs.(2.5) and (2.6), respectively.

$$U_{12} = m(1 - U_1) + (1 - m)U_2 \tag{2.5}$$

$$U_{43} = m(1 - U_4) + (1 - m)U_3 \tag{2.6}$$

where, m is binary variable defined as following:

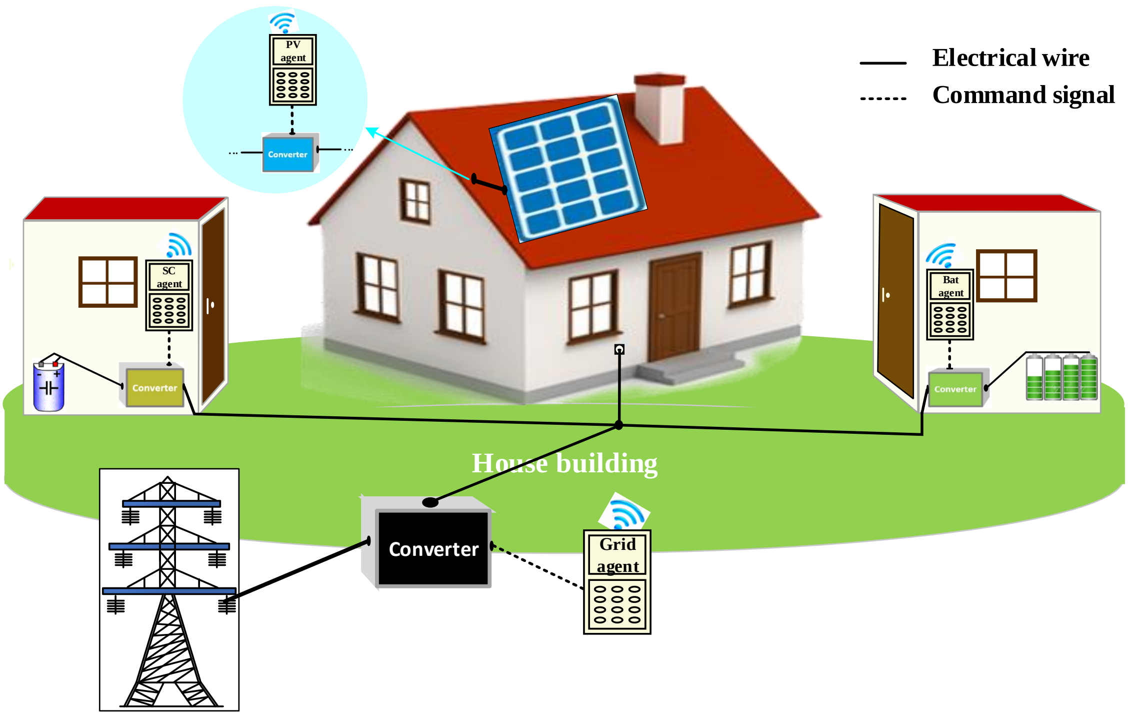


Figure 2.1: Simplified Model of a DC green building (microgrid)

$$m = \begin{cases} 1 & if\ Boostmode \\ 0 & if\ Buckmode \end{cases} \tag{2.7}$$

The voltage at DC bus is equal to the sum of injected currents to the DC bus and is given by Eq.(2.8).

$$V_{bus}(t) = 1/C_{bus} \int i_{total} dt + V_{bus}(t_0) \tag{2.8}$$

where, C_{bus} is the capacity of capacitor connected to the bus. Eq. (2.8) can be rewritten as Eq. (2.9).

$$V_{bus}(t) - V_{bus}(t_0) = 1/C_{bus} \int i_{total} dt \tag{2.9}$$

The total injected current i_{total} to the DC bus can be calculated by Eq. (2.10).

$$i_{total} = \sum i = i_{1_{dchar}} - i_{1_{char}} + i_{2_{dchar}} - i_{2_{char}} + i_3 + i_4 \tag{2.10}$$

where, $\sum i$ is the sum of injected current to the DC bus by individual converters and it can be calculated by Eq. (2.11).

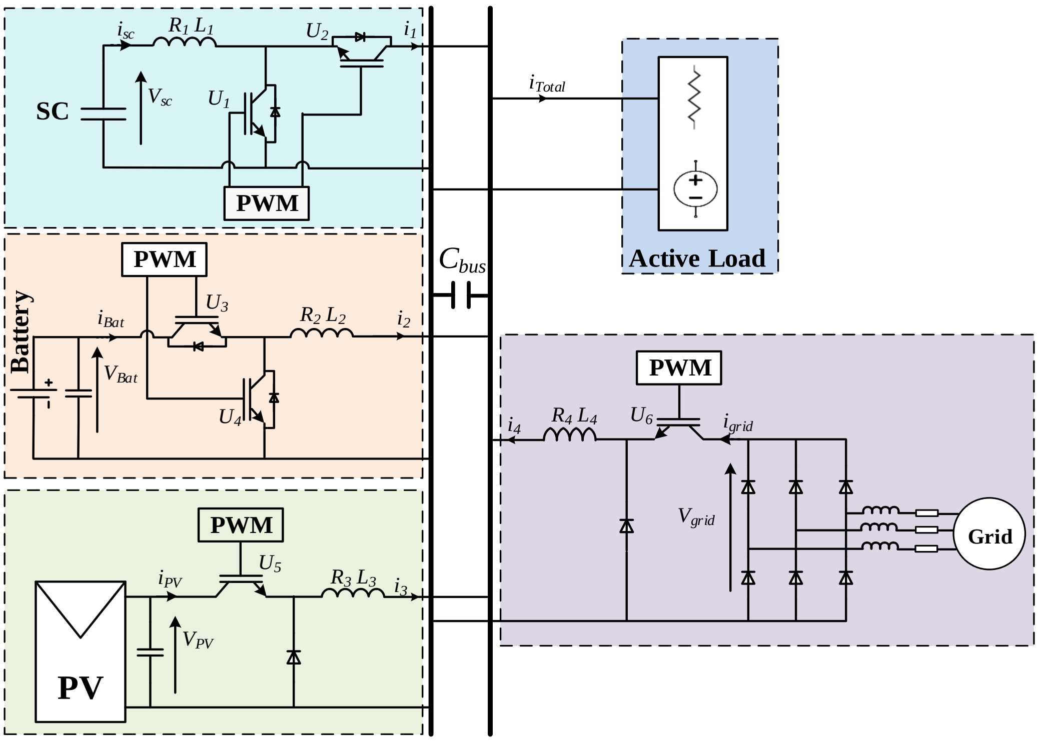


Figure 2.2: Realisation mode of Microgrid

$$i_{total} = \sum \begin{cases} i_{1_{dchar}} = \eta_1 P_{sc}/V_{bus} = \eta_1 V_{sc} i_{sc}/V_{bus} \\ i_{1_{char}} = V_{sc} i_{sc}/\eta_1 V_{bus} \\ i_{2_{dchar}} = \eta_2 P_{Bat}/V_{bus} = \eta_2 V_{Bat} i_{Bat}/V_{bus} \\ i_{2_{char}} = V_{Bat} i_{Bat}/\eta_2 V_{bus} \\ i_3 = \eta_3 P_{pv}/V_{bus} = \eta_3 V_{PV} i_{PV}/V_{bus} \\ i_4 = \eta_4 P_{grid}/V_{bus} = \eta_4 V_{grid} i_{grid}/V_{bus} \end{cases} \tag{2.11}$$

where, η is efficiency of converter, and i_1, i_2, i_3 and i_4 respectively represent the currents for super-capacitor, battery, PV and the grid. Consequently, the total injected current in Eq. (2.10) can be expressed as Eq. (2.12).

$$\begin{aligned} i_{total}(t) = 1/V_{bus}\big(&\eta_1 V_{sc} i_{sc}(t) - V_{sc} i_{sc}(t)/\eta_1 + \eta_2 V_{Bat} i_{Bat}(t) \\ &- V_{Bat} i_{Bat}(t)/\eta_2 + \eta_3 V_{PV} i_{PV}(t) + \eta_4 V_{grid} i_{grid}(t)\big) \end{aligned} \tag{2.12}$$

By substituting Eq. (2.12) in Eq. (2.9), it can be rewritten.

$$\begin{aligned} V - bus(t) - V_{bus}(t_o) = 1/C_{bus}V_{bus} \int \big(& \eta_1 V_{sc} i_{sc}(t) - V_{sc} i_{sc}(t)/\eta_1 \\ & + \eta_2 V_{Bat} i_{Bat}(t) - V_{Bat} i_{Bat}(t)/\eta_2 \\ & + \eta_3 V_{PV} i_{PV}(t) + \eta_4 V_{grid} i_{grid}(t) \big) dt \end{aligned} \tag{2.13}$$

Eq. (2.13) shows voltage oscillation on the DC side, thus, a proper control strategy is needed to avoid voltage fluctuations at the DC bus. The corresponding control strategy is applied to the system by transmitting set points through the individual agents. In order to calculate capacity of capacitance, in DC bus, the following voltage constraint can be assumed:

$$V_{nom} - \Delta V \leq V_{bus} \leq V_{nom} + \Delta V \tag{2.14}$$

where V_{nom} is the nominal voltage and ΔV signifies the maximum oscillation voltage at the DC bus that can be controlled by the DC bus capacitor. Eq. (2.15) shows the relationship between the current and voltage of capacitor.

$$dV(t) = 1/C_{bus} * i_{total}(t)dt \tag{2.15}$$

Eq. (2.15) can further be modified to find the optimal value of capacitance for a certain value of Δ, as

$$C_{bus} = I_{total}\Delta t/\Delta V \tag{2.16}$$

The Δt in Eq. (2.16) represents the total time delay in the system and calculated by Eq. (2.17).

$$\Delta t = t_d + t_p + t_m + t_s + t_c \tag{2.17}$$

where t_d is the time delay for the power electronic devices such as the delay in switching of converters, t_p is related to the delay involved in the processing of individual agent, t_m indicates the delay in sending and receiving messages on a communication port, t_s represents the measurement delay caused by sensors and t_c is time delay associated with the controllers. For instance, in the system with 0.2 ms as a total time delay and 20 A as total current; if 2% voltage oscillation is desired, a capacitor with 2 mF should be used.

2.1.2 Control structure

Figure 2.3 shows the control structure of converters which are used to control the voltage and current [77]. Each element in this topology is controlled by an agent. In this control structure, agent based on measured value that could be output voltage of PV panel or SOC of SC or battery, and also communication signal that comes

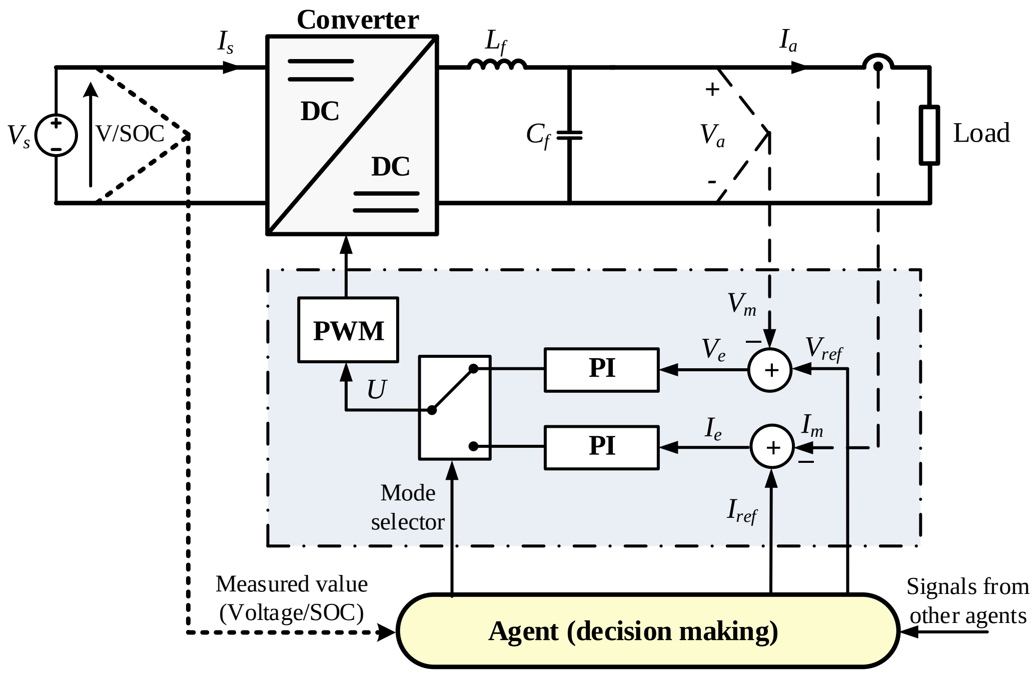


Figure 2.3: The control structure for a dc-dc converter

from other agents, generates suitable set points. These set points include mode selector, voltage and current reference. Mode selector is used to determine that a converter is in voltage mode or in current mode. Voltage mode is considered to maintain output voltage of converter in constant value, consequently, voltage of DC bus will be preserved in desired value. Current mode is expected to supply shared current by other agents. It is clear that one agent can be used to regulate the voltage and others just participate in the current control. In order to enable a smooth switching, to maximise the optimum use of resources and to help protecting storage devices, agents share current in the system. In this control structure, error signal that is difference between voltage/currnt reference, V_{ref} (or I_{ref}), and measured voltage/current, V_m (or I_m), applied to the P.I control. The out put of the P.I control is applied to the pulse width modulation (PWM) in order to generate proper signal for switching MOSFET in the converter.

2.2 Mathematical formulation model for smart city

In the case study II, it is assumed a micro-grid as a smart city equipped with renewable energy generations via solar PV panels and WT, has a BES system and MT and is connected to the grid to meet the electricity demand. As shown in Fig. 2.4, at each time period t, the energy generated by the PV and WT is given priority to meet demand. The demand beyond the PV and WT power generation can be supported by BES, MT and the grid. These providers (BES, MT and the grid) are considered to be controlled by smart control units. Each provider via a controllable converter is connected to the DC load. Set point of any generator is regulated by a smart unit that can sense signal from a central unit, measure available power in the generator and based on proper policy changes set point to meet the demand. As well based on BES agent policy, BES is supported to be charged from renewable energy generations at off-peak times when extra energy is available in the MG and discharged when needed to support the demand at on-peak times. The problem is formulated on the discretized planning horizon of one-day with 24 one-hour periods based on the daily cyclic pattern for parameters. In the following, the mathematical model and constraints of component in the micro-grid are described.

2.2.1 Economic dispatch

In this study, as shown in Eq. (2.18), the general objective is to find the optimum operating policy for allocating the total demand between various providers.

$$min \sum_{t \in T} (C_t P_t), \ T = \{1, 2, ...\} \tag{2.18}$$

2.2.2 Energy Balance constraint

The deterministic equivalent model can be formulated as a linear programming problem where the total provided power should be equal to the total consumed power as shown in Eq. (2.19).

$$P_t^{PV} + P_t^{WT} + P_t^{ES-} + P_t^{MT} + P_t^{gr-} = P_t^{ES+} + P_t^{L} + P_t^{gr+} \tag{2.19}$$

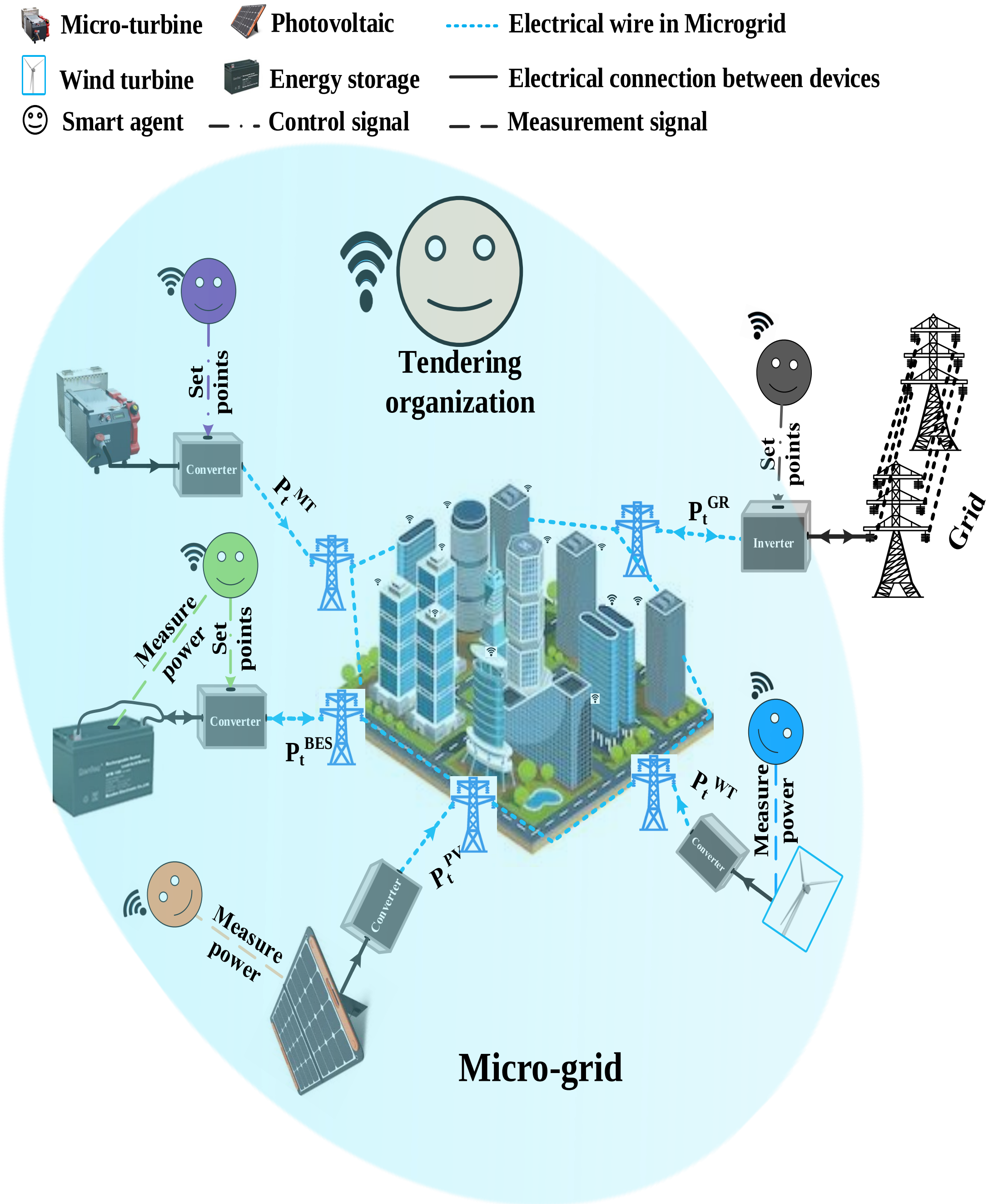


Figure 2.4: Simplified Model of smart city (micro-grid)

2.2.3 WT constraints

The drawn power from WT depends on the wind speed and could be calculated by Eq. (2.20). It can oscillate between minimum and maximum power provided by turbine as shown in Eq. (2.21).

$$P_t^{WT} = \begin{cases} \underline{P}^{WT} = 0 & if \quad v_t \leq \underline{v} \ or \ \overline{v} \leq v_t \\ (v_t - \underline{v})/\hat{v}^{WT} - \underline{v}) * \hat{P}^{WT} & if \quad \underline{v} \leq v_t \leq \hat{v}^{WT} \\ \overline{P}^{WT} = \hat{P}^{WT} & if \quad \hat{v}^{WT} \leq v_t \leq \overline{v} \end{cases} \tag{2.20}$$

$$\underline{P}^{WT} \leq P_t^{WT} \leq \overline{P}^{WT} \tag{2.21}$$

2.2.4 PV constraints

The power generated by PV depends on the solar radiation on PV module and could be calculated via Eq.(2.22), where β is cell efficiency of PV system. Further, the variation in PV power could be done between minimum and maximum values as shown in Eq. (2.23).

$$P_t^{PV} = \beta^{PV} A^{PV} I_t \tag{2.22}$$

$$\underline{P}^{PV} \leq P_t^{PV} \leq \overline{P}^{PV} \tag{2.23}$$

2.2.5 MT constraints

Constraints in MT could be considered as turn on/ turn off constraints as shown in Eqs. (2.24-2.26).

$$\pi_t^{MT} - \pi_{t-1}^{MT} - \epsilon_t^{MT} + \alpha_t^{MT} = 0 \tag{2.24}$$

$$\alpha_t^{MT} + \sum_{k=t}^{\delta_{t1}} \epsilon_t^{MT} \leq 1, \quad \delta_{t1} = min\{t + T^{MT,on}, T\} \tag{2.25}$$

$$\epsilon_t^{MT} + \sum_{k=t}^{\delta_{t2}} \alpha_t^{MT} \leq 1, \quad \delta_{t2} = min\{t + T^{MT,off}, T\} \tag{2.26}$$

π_t^{MT} is a binary variable that indicates on/off situation at time t. It allocates one when the unit is on, otherwise its value will be zero. α_t^{MT} and ϵ_t^{MT} are binary variables whose condition depends on the unit exploitation conditions change. Eq. (2.27) shows Ramp up and down constraints in MT [78].

$$R_L \leq (P_t^{MT} - P_{t-1}^{MT}) \leq R_H \tag{2.27}$$

Output power in MT is limited between minimum and maximum power generation, as shown in Eq. (2.28). Moreover, fuel consumption by MT depends on its efficiency and could be calculated by Eq. (2.29).

$$\pi_t^{MT}.\underline{P}^{MT} \leq P_t^{MT} \leq \pi_t^{MT}.\overline{P}^{MT}, \quad \pi_t^{MT} \in \{0,1\} \tag{2.28}$$

$$F_t^{MT} = P_t^{MT}/\mu^{MT} \tag{2.29}$$

2.2.6 ES constraints

As shown by Eq. (2.30), the energy stored in BES could not exceed the minimum and maximum capacity. Accordingly, its state of charge (SOC) could be calculated via Eq. (2.31).

$$\underline{E}^{BES} \leq E_t^{BES} \leq \overline{E}^{BES} \tag{2.30}$$

$$SOC_t^{BES} = SOC_{t-1}^{BES} + (E_t^{BES-} - E_t^{BES+})/\overline{E}^{BES} \tag{2.31}$$

Energy level in BES at any time period Δt is dynamically updated by Eq. (2.32), where π_t^{BES} is a binary variable that remarks charge and discharge mode.

$$E_t^{BES} = E_{t-1}^{BES} + (\pi_t^{BES}.P_t^{BES-} + (1-\pi_t^{BES}).P_t^{BES+}) * \Delta t, \quad \pi_t^{BES} \in \{0,1\} \tag{2.32}$$

The stored power in BES could not exceed the maximum charge rate, when BES is in charging mode ($\pi_t^{BES} = 1$), and in discharging mode ($\pi_t^{BES} = 0$), the injected power by BES could not pass the maximum discharge rate as shown in Eq. (2.33, 2.34).

$$(1-\pi_t^{BES}).P_t^{BES+} \leq \overline{P}^{BES+}, \quad P_t^{BES+} \geq 0 \tag{2.33}$$

$$\pi_t^{BES}.P_t^{BES-} \geq \overline{P}^{BES-}, \quad P_t^{BES-} \leq 0 \tag{2.34}$$

2.2.7 Grid constraints

The exchange power between external grid and MG could not exceed the minimum and maximum exchange power of the inverter as shown in Eq.(2.35-2.37).

$$\overline{P}^{GR-} \leq P_t^{GR} \leq \overline{P}^{GR+} \tag{2.35}$$

$$(1-\pi_t^{GR}).P_t^{GR-} \geq \overline{P}^{GR-}, \quad \overline{P}^{GR-} < 0 \tag{2.36}$$

$$\pi_t^{GR}.P_t^{GR+} \leq \overline{P}^{GR+}, \quad \overline{P}^{GR+} > 0 \tag{2.37}$$

2.3 Conclusions

In this chapter, the implementation of two different power systems was presented with two different models; simulation model for green building and mathematical model for smart city. In the simulation model, real behavior of the converters connected to the DC bus was investigated and the mathematical equations and the implemented circuit model were investigated. In the mathematical model, the generation resources were analyzed in the form of mathematical equations based on power exchange. The control mechanisms used in each power system and constraints of the systems were presented, which should be considered in the implementation a smart grid through the MAS. In this chapter, the main constraints of each system were introduced. For green building, the goals were to maintain voltage of the DC bus in constant value, and in smart city, the aims were to optimize the total cost of electricity consumed in the MG and create balance between supply and demand. In general, this chapter presented methods of implementing power systems for smart control by artificial intelligence algorithms, which can be a suitable guidance for researches in the field of smart grids.

Chapter 3

Energy management system

In order to manage energy of the power systems presented in the previous chapter, two bottom-up approaches are presented in this thesis. In this section, the presented control approaches are introduced. Two types of control systems are considered for energy management. In first section, energy management based on subsumption architecture is explained for managing green building, and then tendering process is fully introduced in the second part to control in smart city.

CONTENTS:

3.1 Subsumption architecture for managing energy in green building

In this research, the aim is to fix the voltage of DC bus and supply demand in the green building. At any time, only one agent controls the voltage in system and shares current based on its own constrains. This request is applied by a signal shared through the communication port. In most previous research (mentioned earlier), the objective is to enable energy management in a system without considering any fault in the management unit [79, 80]. This may threaten the reliability and stability of smart grids. In this research, a bottom-up approach is developed to manage energy in a system similar to that presented in [55, 75] and results are compared especially when decision part is under fault. Results show that the proposed approach is more fault tolerant as compared to the method presented in [55, 75], where the whole system would collapse if CEMS faced a failure or agent carries token fails, respectively. In the proposed mechanism, when the agent is in normal operation, sets in a layer of subsumption architecture and with sending 5 bits signal via the communication bus clarifies its cooperation in the system. When that agent faces failure, its signal will not be received by others and hierarchical algorithm reconfigures itself. In general, the main contributions of this research are:

- An online smart energy management framework is proposed to support supply-demand balance in a DC microgrid. The framework is easy to implement in a large-scale system due to simple behavioural if-then rules.
- A multi-agent based energy management scheme is proposed to monitor generators interaction. The proposed solution has high reliability and is easy to implement.
- A low bandwidth communication is used engage agents in order to transmit their operating conditions and status in the smart system. By implementing it on the smart system, characteristic of fault tolerance will be added to the system.

3.1.1 Decision algorithm

As it was mentioned that there are two decision-making structures in order to control the agents in multi-agent systems; the CEMS and the DEMS. In this study, the DEMS is used to manage and control the energy among various available sources,

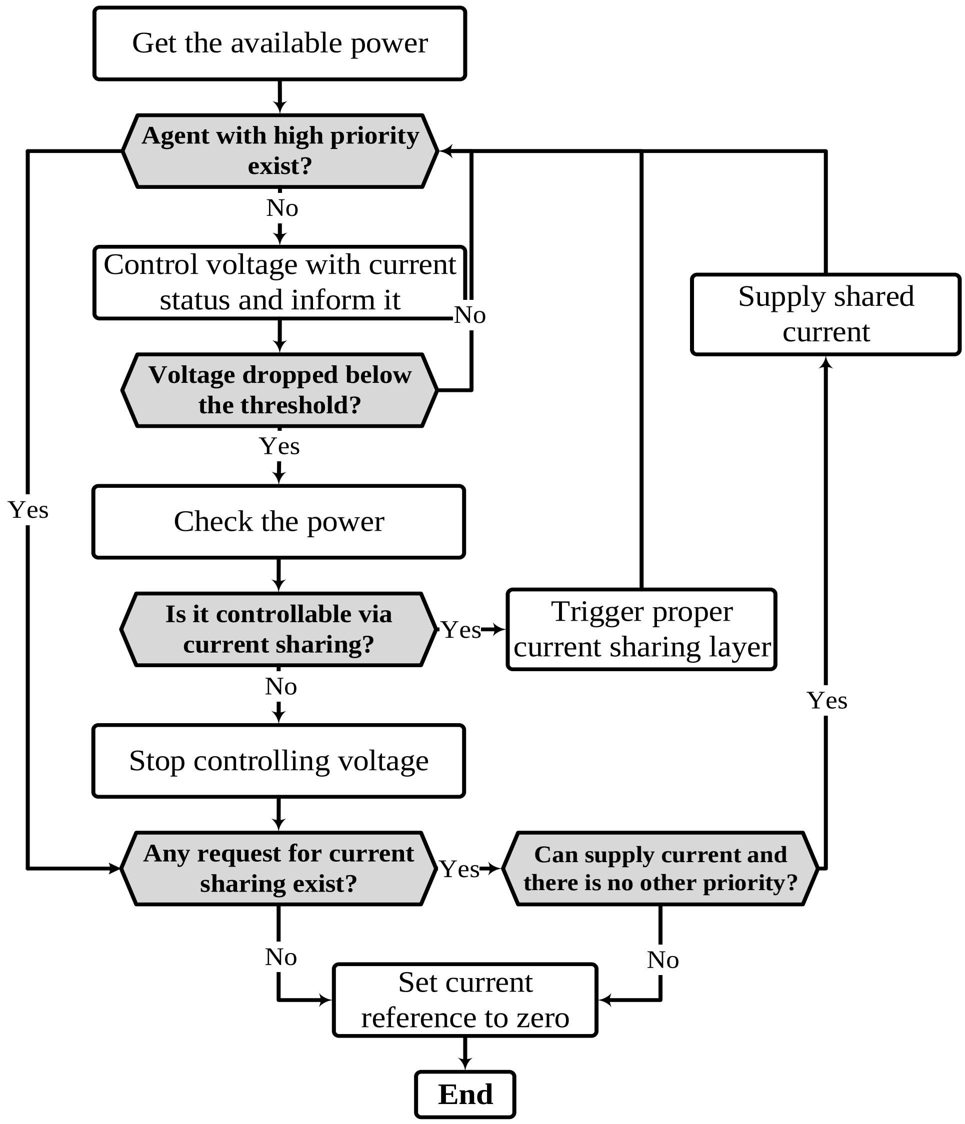


Figure 3.1: The flowchart of agent's decision

where each energy source is controlled through an agent. The first step for the agents is to check the available power from the generator. Subsequently, based on the hierarchal algorithm given in figure 3.1, agents will choose the control mode that is either voltage mode or current mode. If the voltage control mode is chosen, agent will control DC bus voltage and can share current based on its current sharing layer (Section 3.4). In this case, shared current is supplied by another one (as will be discussed in section (3.1.4)).

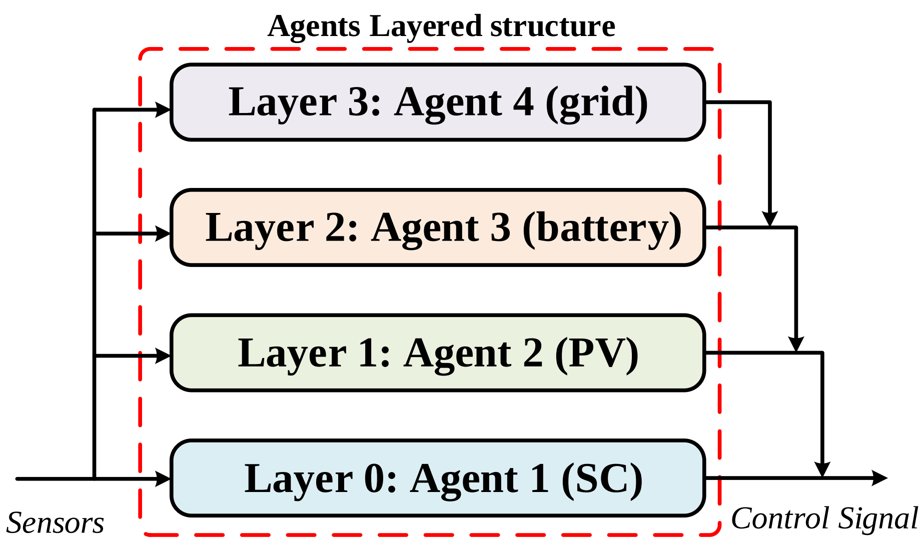


Figure 3.2: Brooks's subsumption architecture for our case study

3.1.2 Priority mechanism

In order to manage and control MASs, it is essential to utilize a robust intelligent algorithm to allocate tasks between agents. Subsumption architecture is proposed as a reactive structure to organize and define principle among agents. In this architecture, any agent has priority in the system. Each agent takes place in one layer and the lowest layer has the highest priority. Brooks developed this structure in 1986 to control robot's behaviours, wherein any behaviour is organized in a layered architecture based on a priority as shown in figure 3.2 [81]. For example, layer 1 has priority over layer 2 and 3 but if layer 0 is activated, it can be disregarded. With this approach, the main challenge of energy management in a system is divided into a set of simple challenges which can be implemented by some simple if and then rules.

subsumption architecture designed by Brooks includes a hierarchy of competence for layers. Accordingly, a layer without any communication can override the remaining of its higher layers at any time and control the system as long as it is necessary [82]. It means that there is a rigid separation among the layers and it is impossible for an agent to disregard this hierarchy any time even if a failure exists in the decision part. Thus, when a fault occurs in a decision layer, the entire system collapses. In order to have a robust control on the system, in this study, a mechanism similar to the classic subsumption will be implemented but there is a communication between agents that enables it to change priorities. This architecture is developed to control the voltage of DC bus.

As the main objective of energy management is to reduce the use of conventional energy sources, thus, the external grid is located in the highest layer. Despite an active load in the system, SC is considered in the lowest layer in order to store energy when the load is in generation mode and supply power as soon as the load turns to demand mode. Hence, SC has given the highest priority in suggested architecture by allocating it the lowest layer. PV is next agent that has high priority to make room for energy saving and maximum exploitation of its energy. Finally, battery is located in layer 2 and when SC and PV are unable to control the voltage, it could be controlled by the battery. As it is obvious, grid has the lowest priority and when SC, PV, and battery could not control the voltage of DC bus, the grid will be switched in for maintaining the system operation.

In the proposed approach, there is a distributed decision unit where agents make their own decisions and carry out tasks independently, and in comparison with ref. [55], communication between agents makes system robust. In order to better understand, assume in [55], agent A is in voltage mode, if a fault occurs in the central unit, the entire system will collapse, because all the set points are appointed by the central unit. However, in the proposed mechanism, when an agent collapses, system is reconfigured and rest of system controls and manages energy.

3.1.3 Communication mechanism

To have proper reaction in the system, status of agent is transferred by a communication link. In the following, the communication between agents is explained.

3.1.3.1 Communication protocol

In order to use multi-agent systems, especially in DEMSs as depicted in figure 3.3, it is essential to have frequent communication among the agents. For this purpose, Controller Area Network-open (CANopen) can be used as a communication protocol to transmit instructions between the agents [83]. The CAN bus is a fast field bus control system having the possibility to transmit instructions in 0.2 ms between various CAN stations and is used for decentralization, intelligence and network control [84, 85]. Despite of CANbus does not need to support high data traffic in this application; it has been selected due to its wide availability and comparatively low price.

3.1.3.2 Digital message

In the proposed approach, agents communicate through CAN bus and transmit 5 bits to clarify their states. By using this data, each agent can have appropriate reaction in the system. This data as status signal is defined as follows:

Bit 2^0 shows current control mode of agents. If it is 1, that means agent just supplies shared current. For example, in figure 3.3, agent 2 supplies requested current by agent 1. Bit 2^1 shows voltage control mode and when its value is 1, it means agent is involved in controlling the voltage of DC bus. For instance, agent 1 in figure 3.3 is in voltage control mode. Bit 2^2 and 2^3 show the level of current sharing. When bit 2^2 is 1, it means that agent shares current as defined by level 1, and when bit 2^3 is 1 it implies that level 2 of the current sharing is activated. Further, when bit 2^2 and 2^3 is activated simultaneously, it means that current is shared based on level 3. For example, in figure 3.3, agent 1 shares layer 2 of its subsumption architecture with others. In next subsection, subsumption architecture for current sharing will be explained.

Bit 2^4 shows failure status of the agent. If it is 1, agent is in normal performance and when it is 0, agent is under fault. For example, in figure 3.3, agent 3 is collapsed and others are operating in normal state.

3.1.4 Current sharing mechanism

For optimal use of RESs and to eliminate voltage ripple on the switching, Brooks' subsumption mechanism is implemented to share current between the available sources. Thus, when agent wants to share current, it sends a binary code through the CAN bus wherein agent clarifies about the shared current. Based on priority and capability, other agents can reply to the request. In order to decrease transmitted data in sharing, maximum three levels for each agent are considered. In this case only the agent that is on voltage control mode can make the request. The complete mechanism of current sharing is explained below.

3.1.4.1 Current sharing in SC

Assume SC is in voltage control mode, therefore, it can share current based on its charge according to subsumption architecture shown in figure 3.4 (a). The following set of instructions will be passed over the layers.

1. Layer 0: SC will set bit 2^2 if its SOC is in level 1.

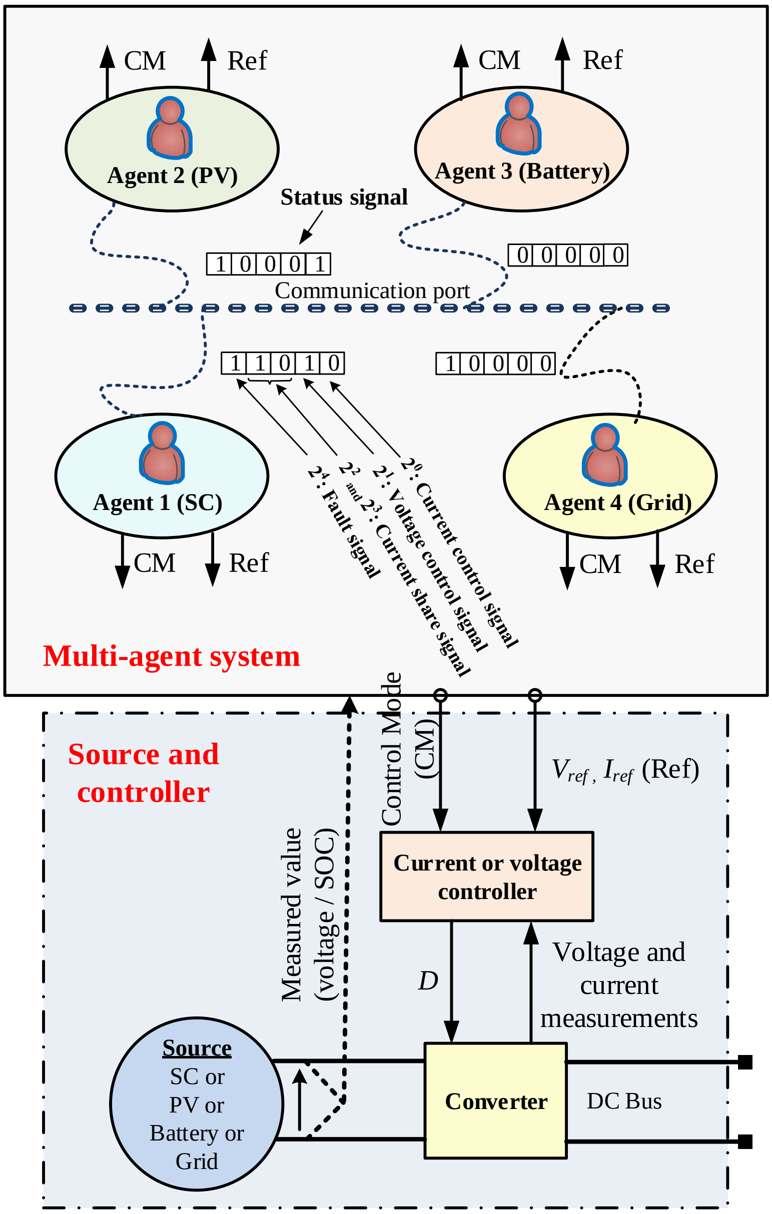


Figure 3.3: Structure of communication between agents

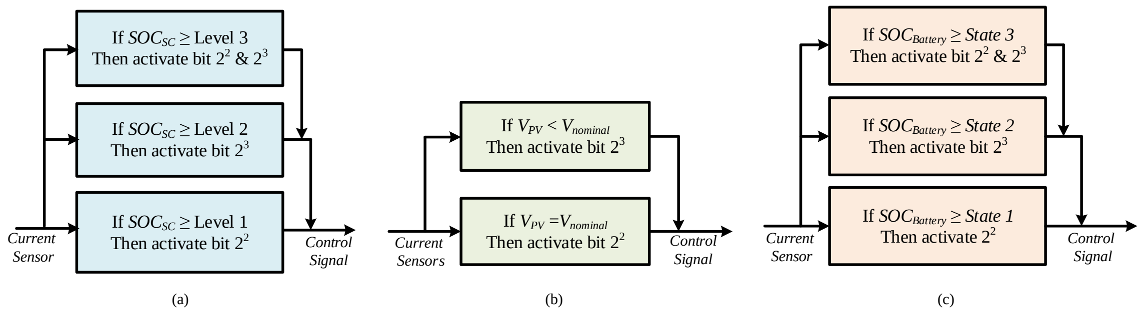


Figure 3.4: The subsumption architecture for current sharing by (a) the SC agent, (b) the PV agent and (c) by the battery agent

2. Layer 1: When its charge reaches to level 2, it triggers the bit 2^3.

3. Layer 2: SC activates bit 2^2 and 2^3 when its SOC is in level 3.

3.1.4.2 Current sharing in PV

Similar to SC, current sharing in PV is carried out by a hierarchy approach. As it is shown in figure 3.4 (b), when PV agent controls voltage of DC bus; it shares current in two states.

1. Layer 0: When terminal voltage of PV is nominal, it activates bit 2^2.

2. Layer 1: When terminal voltage of PV is dropped from nominal value, bit 2^3 is set by PV agent until it loses the voltage control.

3.1.4.3 Current sharing in battery

According to hierarchy algorithm, battery controls voltage when SC and PV are out of service. In this case, if battery has enough stored charge, it will supply to fulfil the demand and share current in three levels with the grid as shown in figure 3.4 (c).

1. Layer 0: When SOC of battery is level 1, battery agent triggers bit 2^2.

2. Layer 1: Battery agent sets bit 2^3 when its charge is in level 2.

3. Layer 2: When its charge drops to level 3, before moving out of the voltage control, battery agent activates bits 2^2 and 2^3.

When an agent is unable to supply shared current, it informs the other by activating bits 2^0 and 2^1.

3.2 Markov decision process in a smart contract for managing energy in smart city

In this study, a multi-agent system is implemented to manage energy at distributed energy resources. Each DG is controlled and managed by intelligent agent. The tendering process as a smart contract is implemented for controlling and managing MAS. In this smart contract, an agent is considered as tendering organization which puts the requested power of consumers as a tendered item between DG agents. Each DG agent as a bidder presents its offer price for supplying power to the tendering organization. The tenderer chooses the lowest offer price as the winner bid based on first price sealed-bid. The tendering organization iterates tendering process while whole demand shared between DG agents and satisfied balance between supply and demand. Since power system environment is a dynamic, utility-based agent is used in the proposed model that set of decisions to converge the whole system to the optimum value. In the proposed model, agents operate greedily in a way that, each agent tries to select an action which results in more benefits. In this study, a separated decision algorithm is considered for each agent which presents power to the system through the smart contract. Since BES agent should store extra energy of RESs during off-peak time and support demand during on-peak time, Markov decision process could be a suitable selection as a decision framework to control BES's set point. This framework allows BES to choose appropriate action to move from state s to $s^{'}$ at each time period by considering future rewards. For this purpose, BES should learn to perform the best action in each state. To train BES in Markov decision process, Q-learning algorithm is used. BES agent is trained by Q-learning algorithm based on historical data and participates in the tender at each time period depending on located state by selecting an action. The learning method for BES is based on rewards and penalties that agent receives by performing an action at each state. The rest of agents are controlled by heuristic algorithms wherein agents try to operate greedily. The proposed mechanism in this study, provides a new approach in smart energy management system which if implemented on MGs, will bring the following advantages:

- An online intelligent management system for controlling MGs without any prediction.
- Given that decision-making in the proposed mechanism is online, it is not necessary to consider uncertainty, unlike the scheduling management systems.

- The system is designed in such a way that agents make the optimum decision at each time period and the tendering organization minimizes the electricity cost of consumer by choosing the minimum offer price.
- Since BES agent uses reinforcement learning therefore, it stores power at off-peak price and presents it to the consumer at on-peak price.
- In the proposed model, power is shared through the tendering process so, at on-peak price, the grid bidder does not inject any power to the MG due to high offer price.
- The presented mechanism has overlapping responsibilities so that if an agent could not share power at each time period, it would not be participated in the tendering process. Consequently, the proposed approach could present fault tolerance, high stability and reliability to MGs.

3.2.1 Tendering process

Distributed decision making in a MAS lets user create a superior management and as well provides balance between supply and demand in isolated and grid-connected mode. In this study, each provider is controlled via smart unit called agent except PV and WT which directly share their power with the MG. BES, MT and the grid have their own smart control units which can sense signal in the system, decide based on individual algorithm and regulate set points. In this structure, in order to control agents, a control structure is implemented over the system that applies a smart contract among agents called tendering process.

The tendering process can be assumed as a smart contract on the MAS that power rather being allocated by user among generators, could be allocated by a small amount of code [86]. In a tendering process, bidders via their bid express how much they prefer to participate in a particular contract. A tendering organization as an upstream agent supervises contracts and allocates tasks based on bids. The tendering framework is generally utilized by companies and governments to allocate services [87], along with in robotic industry [88, 89, 90] to devote tasks among robots, and recently to create smart contracts in block-chain [91, 92, 93]. According to figure 3.5, in order to create a smart contract, an agent named tendering organization is used which is responsible for creating balance between supply and demand. In fact, the tendering organization takes demand from consumers and spreads the requested power on generating agents. The proposed framework creates a structure that makes possible for EMS to pass any failure appeared in

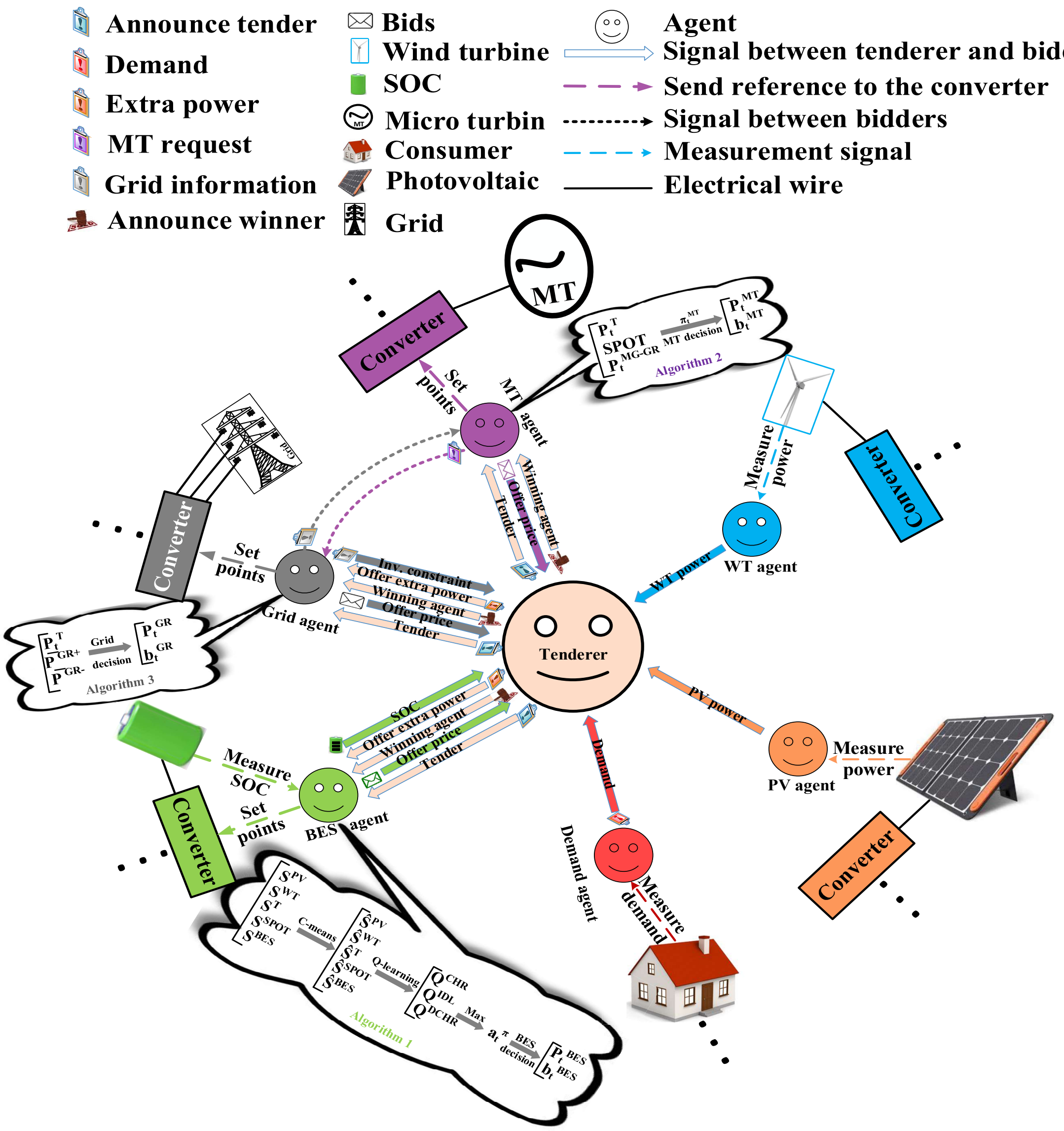


Figure 3.5: General schematic of the tendering process

the MAS. Any failure that occurs in one of the producers would result the measured power by the agent being zero, or if it happens in the agent, it would lead to non-participation in the tender. As a result, the presented structure will be fault tolerant against any failure in energy providers. In the presented framework, the roles of the tendering organization is to arrange an online control, manage energy and create cooperation between the bidders. To create smart contract and allocate demand among generating agents, tendering organization uses FPSB algorithm.

3.2.2 First-Price Sealed-Bid algorithm

In the tendering process, FPSB algorithm is implemented by the tendering organization to allocate power among bidders [94]. In this algorithm, at the beginning, consumer agent sends demand to the tendering organization. The tendering organization subtracts generated power by PV and WT from demand, and sets it as a requested power and holds tender among bidders. As shown in figure 3.6 agents present offer price and power as bidders based on their evaluation and decision structures. After evaluating and sending bids, the tenderer sorts them and chooses the lowest offer price as the winning bid based on FPSB algorithm. The winner shares its offered power with MG by regulating its set points. Tenderer based on Eq.(3.1) in each tender considers supply-demand balance. If extra power exist in the MG, at first, it will be offered to the BES. If the BES is full, it will be injected to the grid. Iteration would be stopped, if balance condition is satisfied. Figure 3.7 shows the flow chart of FPSB algorithm that is described in the following:

1. At each discrete one-hour period, demand P_t^D, available power in PV P_t^{PV} and wind P_t^{WT} are sent to the tendering organization.
2. The tendering process calculates the net demand P_t^T and present it as a new tender.
3. The bidders who can support demand, send their available power and offer price to the tendering organization.
4. The tender organization sorts bids based on agents and calls select winner function which here is the lowest presented price.
5. The tendering organization subtracts the supplied power of winner from demand, if total demand is supplied, the tendering process will be finished else it will be iterated that Eq.(3.1) is satisfied and whole demand supplied by generating agents.

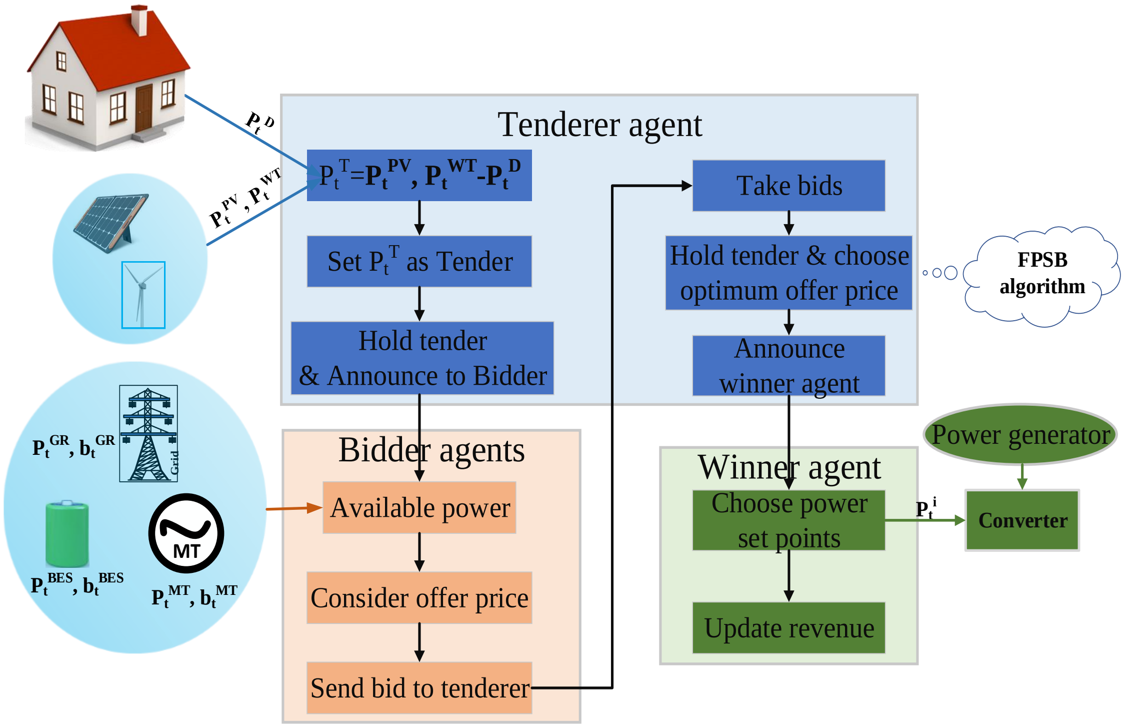


Figure 3.6: General schematic of the tender framework

$$\sum_i P_t^{win_i} - P_t^T = 0 \, ; \quad i = number\ of\ iteration \tag{3.1}$$

3.2.3 Markov decision process for BES control

To manage energy in BES, a sequential decision framework is used that allows agent to choose appropriate actions by considering available parameters at each time period. In this study, Markov decision process (MDP) has been used to model the sequential decision problem. MDP is a type of reinforcement learning (RL) that deals with a set of state space $s \in S$, action space $a^\pi \in A$, transition function $T(s, a, s^{'})$ and reward function $R(s, a, s^{'})$ [95]. The transition function gives the probability of landing on state s' from s by choosing action a. In this study, the planning horizon is defined as one-day consisting of 24 equal time slots. The provided power by PV, wind, requested power by the tenderer, electricity price and stored energy by BES are defined as state variables $\{S_t^{PV}, S_t^{WT}, S_t^T, S_t^{SPOT}, S_t^{BES}\} \in S$. The decision-making space a_t^π shows the possible action of BES that could be charging, idle, and discharging action where policy π chooses an action for each state [96]. In the proposed system, all system variables are assumed to be constant during each discrete-time period and it is supposed at time step t, BES agent does

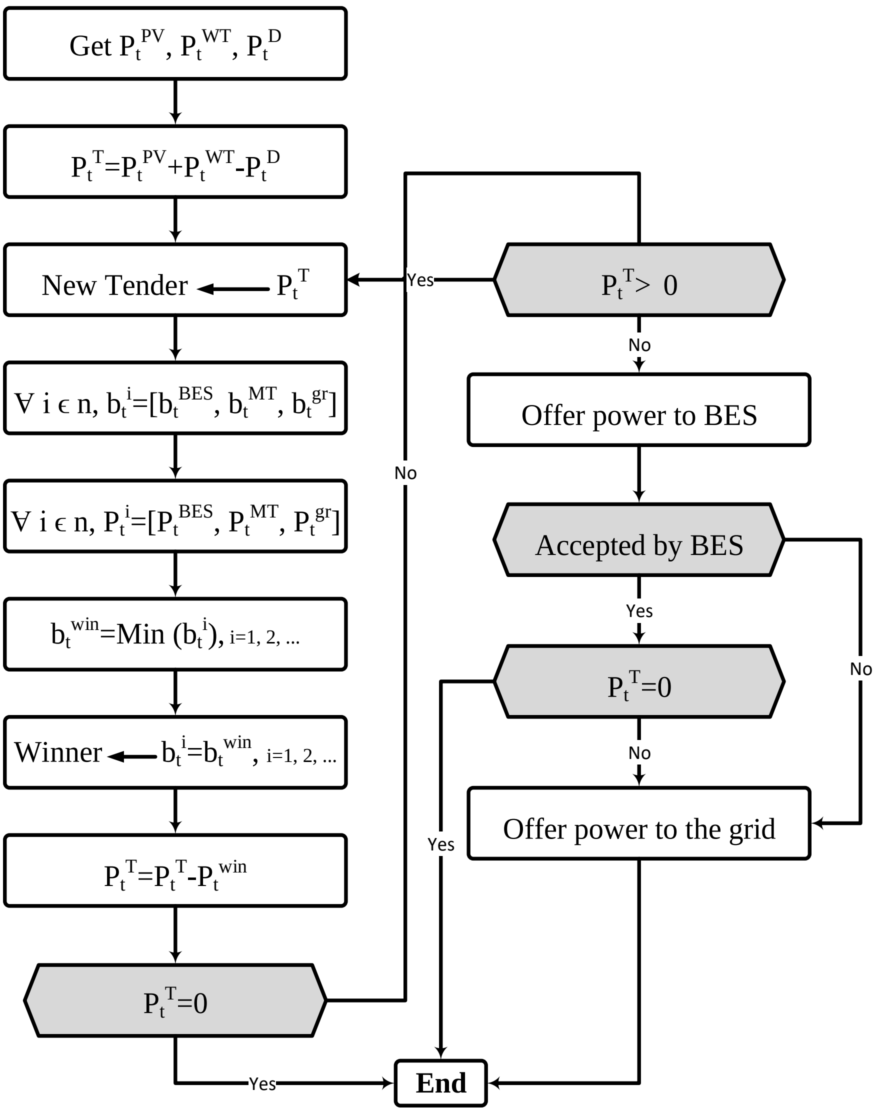


Figure 3.7: The flow chart of FPSB algorithm

not have any preliminary information about PV and wind generation, demand, electricity price from time step $t+1$. Therefore, the transition probability between states always remains unknown.

In this study, Q-learning algorithm is implemented as a RL algorithm to train BES agent. Because state variables in this study are continuous, so there are infinite samples, which makes it complicated to learn by Q-learning. In order to solve this problem, continuous state variables are discretized by c-means algorithm. By discretization of state space, the number of samples would be finite, and consequently, learning accuracy would be increased.

3.2.3.1 System state space

A state is a mathematical description of system condition that provides necessary information for agent to make a suitable decision. Data included in state space for modeling MDP consist of continuous variables of generated power by PV and wind, requested power by the tendering organization, electricity price and energy level of BES. To normalize the state variables, first, historical data $\{S_t^{PV}, S_t^{WT}, S_t^{T}, S_t^{SPOT}, S_t^{BES}\}$ is presented to c-means algorithm. C-means is a point-based clustering algorithm that begins with the cluster centers initially placed at arbitrary positions [97]. Then, data is allocated to the nearest center. In this algorithm, by moving the cluster centers tried to minimize the sum of the squared Euclidean distances between data X_i and the centroid m_i as shown in Eq.(3.2) [98].

$$E(m_1, ..., m_k) = \sum_{j=1}^{k} \sum_{i=1}^{n} ||X_i - m_j||^2 \tag{3.2}$$

The proposed approach could map the historical data, provided power by PV, wind, requested power by the tenderer, electricity price to the discrete spaces. Each variable set is divided into three clusters wherein each data is allocated to a center. Any cluster supports a certain range of power or price, and the center of that cluster is known as cluster representative. In fact, c-means algorithm maps each data to a center. In this mapping approach, cluster centers are considered as state spaces and during training Q-learning algorithm, they are used as discrete variables. So, the output of c-means algorithm is discrete-time variable space as defined in Eq.(3.3).

$$\hat{S}_t = \{\hat{S}_t^{PV}, \hat{S}_t^{WT}, \hat{S}_t^{T}, \hat{S}_t^{SPOT}, \hat{S}_t^{BES}\} \tag{3.3}$$

In this study, variables are divided into three clusters, i.e., charging, discharging and idle mode area. The cluster centers for each data set are utilized as discrete state space in MDP for training Q-learning algorithm. After training c-means algorithm, once a data is inserted to the algorithm as input, one of these three cluster determines at the output. As well, in this study, to normalize BES energy level the following approach is applied:

- If $10\% \geq SOC_t^{BES} \geq 0$, the first cluster that BES could just have charging operation.
- If $90\% \geq SOC_t^{BES} > 10\%$, the second cluster where BES could operate in idle, charging or discharging mode.
- If $100\% \geq SOC_t^{BES} > 90\%$, the third cluster where BES just operate in discharging mode.

3.2.3.2 Action policy

According to state space, BES agent can select an optimal action policy a_t^{π} at each time period to minimize the drawn power from the grid and consequently, electricity cost. As shown in Eq.(3.4), BES agent can select three actions at each time period. The policies that BES agent can choose based on various situations are described in the following:

- At off-peak price pireod, agent can just select the charging acion, unless it is fully charged.
- While electricity price is between off-peak and on-peak time, BES agent can choose one of charging, discharging and idle actions.
- At on-peak time, if a tender is held, BES can participate and perform discharging action.
- If it is full, BES agent can not select charging action even it is at off-peak price.
- BES agent could not preform discharging action and participate in a tender, when it is empty.

Consequently, action policy for BES agent is based on requested power in a tender and its stored energy could be considered as shown in Eq.(3.5)

$$A = \{Charge, Idle, Discharge\} \tag{3.4}$$

$$A_{s_t}^{\pi} = \begin{cases} Charging & if\ \hat{S}_t^{SPOT} = \text{Off\_peak time } \&\ E_t^{BES} < E_t^{BES} \\ Idle, charging, discharging & if\ \hat{S}_t^{SPOT} \neq \text{Off/On \_peak time } \&\ \underline{E}_t^{BES} < E_t^{BES} < \overline{E}_t^{BES} \\ Discharging & if\ \hat{S}_t^{SPOT} = \text{On\_peak time } \&\ \underline{E}_t^{BES} < E_t^{BES} \end{cases} \tag{3.5}$$

BES agent gradually learns how to react in different state without any information about the next period by using Q-learning algorithm. Consequently, BES agent at each time period could update its energy level by performing actions according to Eq.(3.6).

$$P_{t+1}^{BES} = \begin{cases} 1/\eta^{Ch}[min\{(|P_t^T| + P_t^{BES}), (\overline{P}_t^{BES} - P_t^{BES})\}] & \text{Charging mode} \\ P_t^{BES} & \text{Idle mode} \\ \eta^{Dis}[min\{(P_t^{BES} - |P_t^T|), (P_t^{BES} - \underline{P}_t^{BES})\}] & \text{Discharging mode} \end{cases} \tag{3.6}$$

3.2.3.3 Cost function for BES control

At each time period, state of BES agent is transferred from $\hat{s}$ to $\hat{s}'$ by performing an action and depending on the action, it receives reward or penalty. As shown in figure. 3.8, the agent in state s performs an action on the environment based on its action policy to moves to state s′ and gains related reward or penalty. Eq.(3.7) shows the reward or penalty of BES agent at time t.

$$f_t(\hat{s}_t, a_t, \hat{s}_t') = \eta^{R/P} C(\hat{s}_t, a_t, \hat{s}_t') p(\hat{s}_t, a_t, \hat{s}_t'), \quad \forall\ \hat{s}_t \in \hat{S}, a_t \in A_{\hat{s}_t}^{\pi} \tag{3.7}$$

where $p(\hat{s}_t, a_t, \hat{s}_t')$ is the amount of power that BES receives or transmits to move from state $\hat{s}$ to $\hat{s}'$ by acting a_t. $C(\hat{s}_t, a_t)$ shows the cost of kilowatt hours of electricity. $\eta^{R/P}$ is reward or penalty factor that is considered a small amount for the reward and a large amount for the penalty. The large amount penalty causes agent learns that wrong action at state s will result a heavy fines. Therefore, when BES agent lies in a same situation, makes the best choice. It is clear that BES at each time tends to maximize its profit. By implementation the proposed cost function, the agent learns which state is the best state for charging, discharging and idle.
By choosing the proper action policy, BES agent finds the profit that finally, the sum of these actions lead to reach the maximum profit. Based on Eq.(3.8), by selecting the appropriate action, BES agent could calculate the total profits that would gain in the future.

$$F_t^{\pi}(\hat{s}_t, a_t, \hat{s}_t') = f_t(\hat{s}_t, a_t, \hat{s}_t') + \sum_{i=1}^{\infty} \Gamma^i [f_t(\hat{s}_{t+1}, a_{t+1}, \hat{s}_{t+1}')], \quad \forall\ \hat{s} \in \hat{S}, a \in A_{\hat{s}_t}^{\pi} \tag{3.8}$$

where Γ implies the future discount factor. When Γ=0 the current profit is very critical, and Γ=1 implies that the future profits are as important as the current profit.

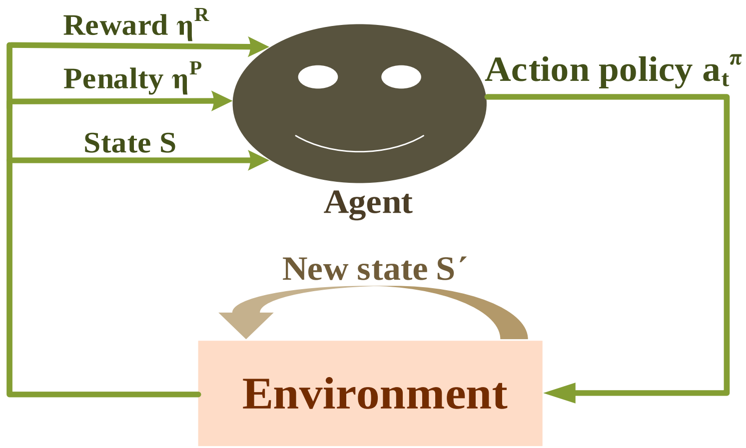


Figure 3.8: The agent-environment interaction layout of RL

3.2.3.4 Q-learning algorithm

To solve sequential decision, Q-learning algorithm is a suitable selection. The optimization problem becomes complicated when the number of states and actions increases, especially while the system is unpredictable. Therefore, in this type of EMS, it is critical to use an algorithm not only to manage the system, but also to increase its performance. MDP presents a mathematical framework where agent could transfer from state $\hat{s}$ to $\hat{s}'$ by action a with probability function $T(\hat{s}, a, \hat{s}')$ and gain profit F. In order to implement this problem based on MPD, utility function of agent at state $\hat{s}$ could be updated based on Bellman Eq.(3.9).

$$u_{t+1}(\hat{s}) = F(\hat{s}) + \gamma \max_{a} \sum_{s'} T(\hat{s}, a, \hat{s}') U_t(\hat{s}') \tag{3.9}$$

Considering that calculating the values of utility function and transition probability function could be challenging so, in this study, Q-learning algorithm is used that is a model-free RL algorithm in which instead of calculating utility function and transition probability function returns Q-value for each state-action pair, as shown in Eq.(3.10).

$$\begin{aligned} Q_{t+1}(\hat{s}_t, a_t) \longleftarrow (1-\alpha)Q_t(\hat{s}_t, a_t) + \alpha(f_t(\hat{s}_t, a_t, \hat{s}'_t) + \gamma \max_{a'} Q_t(\hat{s}'_t, a'_t)), \\ \forall\ \hat{s}_t, \hat{s}'t \in \hat{S} \ and\ a_t, a't \in A \end{aligned} \tag{3.10}$$

In this algorithm, a Q-value is defined for each state-action pair that BES agent updates it based on rewards and penalties gained by acting various actions in the system. In each exploration, Q-values are stored in a lookup table. α is the learning rate that if α=0, BES agent more attends to use previous information and, while α=1, agent would like to explore and learn against to use its knowledge. To escape from local optima, ϵ-greedy policy is used to provide trade-off between exploration and exploitation. By generating ϵ as a random number, agent selects an arbitrary action with probability ϵ and with 1-ϵ probability, agent selects the action that is faced with high profit in the system environment. Algorithm 1 shows the structure of Q-learning algorithm that is implemented to control and manage energy in BES.

Algorithm 1: Q-learning algorithm for controlling BES

Training process:
Initialize $Q_0(\hat{s}, a) = 0, \forall \hat{s} \in \hat{S}, a \in A$
Initialize learning parameters: $\eta^R = 1$ $\eta^P = 200$, $\gamma = .95$, $\alpha = .5$, $\epsilon = .2$
while $t = 1, 2, ...$ **do**
    Normalize S =$\{S^{PV}, S^{WT}, S^T, S^{SPOT}, S^{BES}\}$ by c-means algorithm
    Determine $\hat{S} = \{\hat{S}^{PV}, \hat{S}^{WT}, \hat{S}^T, \hat{S}^{SPOT}, \hat{S}^{BES}\}$
    Generate random number β
    if $\beta < \epsilon$ **then**
        Select random action $a \in A$ and gain $f_t(\hat{s}_t, a_t, \hat{s}'_t)$ ▷ exploration
    else
        Select action a_t^π (optimal policy) and gain $f_t(\hat{s}_t, a_t, \hat{s}'_t)$ ▷ exploitation
    end
    $Q_{t+1}(\hat{s}_t, a_t) \longleftarrow (1-\alpha)Q_t(\hat{s}_t, a_t) + \alpha(f_t(\hat{s}_t, a_t, \hat{s}'_t) + \gamma \max_{a'} Q_t(\hat{s}'_t, a'_t))$
    $t \longleftarrow t+1$
end

Testing process:
for *t=1:24* **do**
    if *Existing a tender* **then**
        Normalize S =$\{S^{PV}, S^{WT}, S^T, S^{SPOT}, S^{BES}\}$ by c-means algorithm
        Determine $\hat{S} = \{\hat{S}^{PV}, \hat{S}^{WT}, \hat{S}^T, \hat{S}^{SPOT}, \hat{S}^{BES}\}$
        Select action $a_t^\pi \in A$ with maximum Q-value
        Update P_t^{BES} based on Eq.(3.6)
    end
    C_t^{BES}= C_{t-1}^{BES}+1/$|\eta^{R/P}| * f_t(\hat{s}_t, a_t, \hat{s}'_t)$
end

At any given state, in addition to the Q-value, the BES agent should consider its capacity to choose an action $a_t \in A$. So that if at time t, the BES agent is placed on charging mode according to the Q-value, it will perform the charging action on the condition that its level of stored energy is less than the maximum energy that can be charged. As the same way, when it is placed on discharge mode based on the Q-value, it will choose the discharging action provided that its energy is more than the minimum stored energy. In each tender, the BES agent updates its offer price based on Eq.(3.11) after taking charging action, and also its revenue according to

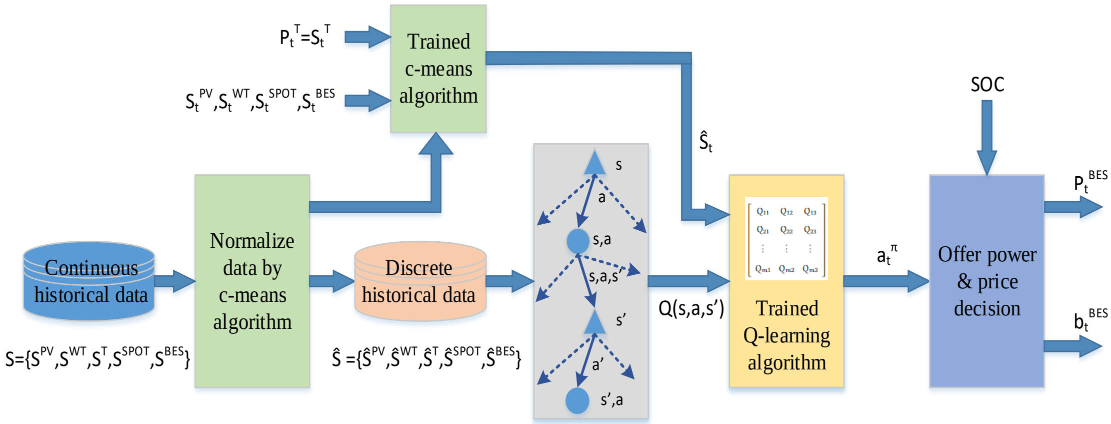


Figure 3.9: Overview of the proposed decision approach on BES agent

Eq.(3.12) at the end of any tender.

$$b_{t+1}^{ES} = (P_{t-1}^{ES}.b_t^{ES} + (\phi_t^{ES} + \zeta^{ES}.\phi_t^{ES}).P_t^{ES-})/P_t^{ES} \tag{3.11}$$

$$R_t^{ES} = R_{t-1}^{ES} + \pi_t^{ES}.\phi_t^{ES}.P_t^{ES-} + (1 - \pi_t^{ES}).b_t^{ES}.P_t^{ES+} \tag{3.12}$$

Figure 3.9 shows the general overview of the proposed decision approach on BES agent. In this structure, at first, continuous historical data as input data is applied to c-means algorithm to be normalized and transformed into discrete data. Discrete data then, is used to train Q-learning algorithm. After training both algorithms, the structure is prepared to manage energy in BES. When a tender is held, at the beginning, data set as state space is applied to the trained c-means to be normalized then normalized state space is presented to Q-learning algorithm to clarify the optimal action policy. While action policy is clarified, BES agent according to SOC assigns supply power and offer price. At the end, BES agent regulates set point of converter.

3.2.4 Structure of decision in MT agent

Heuristic decision making algorithm is used to control set point of MT in the system. As shown in algorithm 2, MT agent based on its situation in previous state chooses various offer prices to gain profit and satisfies on/off constraints. Its offer price could be calculated based on Eq. (3.13). MT agent during various period, based on its policy action as shown in Eq. (3.14), selects different set point. During on-peak price, by considering grid constraint, MT agent can inject power to the grid to gain more profit. While it is selected as winning agent, MT agent changes set point of micro turbine and then, based on its offer price updates its revenue as shown in Eq. (3.15). If it was not selected or not cooperated in a tender, it would not inject power to the system.

$$b_t^{MT} = C^{MT,fu} + C^{MT,o\&m} + C^{MT,st} + C^{MT,inv} \tag{3.13}$$

$$\pi_t^{MT} = \begin{cases} P_t^{MT} = 0 & if\ off - peak\ price \\ P_t^{MT} = \underline{P}^{MT} & if\ (TOU_t - b_t^{MT}) \leq \varepsilon\ \&\ \mathrm{P}_{t-1}^{MT} \neq 0 \\ P_t^{MT} = \overline{P}^{MT},\ P_t^{MT} = P_t^{T} & if\ on - peak\ price \end{cases} \tag{3.14}$$

$$R_t^{MT} \leftarrow (R_{t-1}^{MT} + b_t^{MT}.P_t^{MT} + SPOT_t.P_t^{MT-GR}) \tag{3.15}$$

Algorithm 2: Decision structure of MT agent

Input:
$X = [t = \{1, 2, ..., 24\}, P_t^T, TOU_t, \overline{P}^{MT}, \underline{P}^{MT}, SPOT_t, P^{MG-GR}]$
Output:
Y=[Offer price and power by MT, Revenue gained by MT, set point of converter]
if *Existing tender* ($P_t^T > 0$) **then**
  if *MT is on at previous time* ($P_{t-1}^{MT} \neq 0$) **then**
    $b_t^{MT} \leftarrow \overline{b}^{MT}$ ▷ **Offer maximum bid**
  else
    $b_t^{MT} \leftarrow (\overline{b}^{MT} - \zeta_t^{MT}.\overline{b}^{MT})$ ▷ **Use discount**
  end
  if *It is on-peak time* **then**
    Select action based on π_t^{MT} in on_peak price (Eq.(3.14))
    $P_t^{MT} \leftarrow (p_t^{MT} + P_t^{MG-GR})$
  else
    Select action based on π_t^{MT} in off_peak price (Eq.(3.14))
  end
  Wait for holding the tender
  if *Win?* $b_t^{MT} = b_t^{win}$ **then**
    Regulate set point
    Update revenue based on Eq.(3.15)
  end
else
  $P_t^{MT} \leftarrow 0$ ▷ **Non-cooperation**
end

3.2.5 Structure of decision in Grid agent

To control the connected inverter to the grid, a decision making algorithm is proposed as shown in algorithm 3. At each time period, grid agent presents its offer price to the tendering organization and according to existing constraints of inverter and requested power, can send power to the MG. Once extra power exists in the MG, grid agent can absorb it as much as its constraints allow. After holding a tender, grid agent depending on winning or losing in the tender, can regulate set point of inverter and then updates its revenue by using Eq.(3.16).

$$R_t^{GR} = R_{t-1}^{GR} + b_t^{GR}.P_t^{GR} \tag{3.16}$$

Algorithm 3: Decision structure of the grid agent

```
Input:
X=[t={1, 2, ..., 24}, P_t^T, TOU_t, \overline{P}^{GR}]
Output:
Y=[Offer price and power by the grid, Revenue gained, set point of converter]
if Existing tender P_t^T > 0 then
    b_t^{GR} ← SPOT_t                                         ▷ Offer price
    Based on demand, offer P_t^{GR} ← (\overline{P}^{GR+}, |P_t^T|)   ▷ Offer power based on
      requested power and constraint
    Wait for holding the tender
    if Extra power is available in the MG then
        P_t^{GR} ← (\overline{P}^{GR-}, |P_t^T|)              ▷ Absorb the extra power
    end
    Regulate set point
    Update revenue based on Eq.(3.16)
else
    Wait for a new tender
end
```

3.3 Conclusions

In this chapter, two intelligent control systems based on the bottom-up approach were presented to control and manage energy in MGs. In the first section, an approach with distributed decision-making was presented, in which the agents tried to control the DC bus and supply the demand by using subsumption architecture and sharing information through the data bus. In the second section, an energy management system based on multi-agent system under supervising a smart contract with a bottom-up approach was presented to control a grid connected DC micro-grid. In the proposed mechanism, in order to have a robust control structure for BES, Markov decision process is considered as a mathematical control framework, which is trained by Q-learning algorithm to clarify BES's action policy. Heuristic algorithms were introduced for the rest of agents in MAS to manage energy. In the presented structure, agents are utility-based agents who are only trying to maximize their own profit. The structure is implemented in such a way that set of decisions and actions of these agents maximizes the final benefit of the system. As a general conclusion, the proposed approach in this thesis creates a very robust coordination in the MAS, which makes the system performance better in normal operation and in fault-facing.

Chapter 4

Results and Discussion

In this chapter, performance of the presented energy management systems is examined and analysed on the green building and smart city, separately. The simulation is done in such a way that agents can online measure, decide and act in the system without prediction.

CONTENTS:

4.1 Results of energy management by using subsumption architecture

The green building as shown in figure 2.1, includes an active load and a grid connected PV with two storage devices. The details are:

- 1 kW PV generator with a voltage of 190 V
- The electrical grid with a voltage of 380 V (phase to phase)
- SC with a capacity of 10 F having a nominal voltage of 75 V
- Two batteries each having a voltage of 144 V and a capacity of 60 AH

All the elements are connected to an active load through a 100 V DC bus. The active load can be operated as a motor or generator. A current rectifier and 230/100 V buck converter is used to connect the grid to the DC bus. The SC and batteries are connected to the load through bidirectional converter and buck converter, respectively.

At first, the proposed EMS is implemented on a simulation model with a scenario of 30 s while all the converters act with real behaviour. The converters are modeled to present real behaviour and not just as a voltage source converter. For this reason, inevitable oscillation appears in profiles.

4.1.1 Result of Energy Management

To implement the proposed mechanism on the system, some parameters have been defined as shown in table 4.1. In order to have a suitable comparison, these parameters are obtained from [55]. Initially, it is assumed that SC and battery is fully charged and all the agents are in normal mode, and therefore, bit 2^4 for all of them is set to 1.

Table 4.1: The level of constraints for agents and respective shared currents.

Agent	Level of constraints	Constraints	Shared current (A)
SC	Level 1	$85\% < SOC_{SC}$	0
	Level 2	$70 < SOC_{sc} \leq 85\%$	6
	Level 3	$55\% < SOC_{SC} \leq 70\%$	12
PV	Level 1	$V_{PVnom} \geq 190$	0
	Level 2	$V_{PVnom} < 190$	15
Battery	Level 1	$13\% \leq SOC_{Bat}$	0
	Level 2	$10\% \leq SOC_{Bat} < 13\%$	8
	Level 3	$7\% < SOC_{Bat} < 10$	16

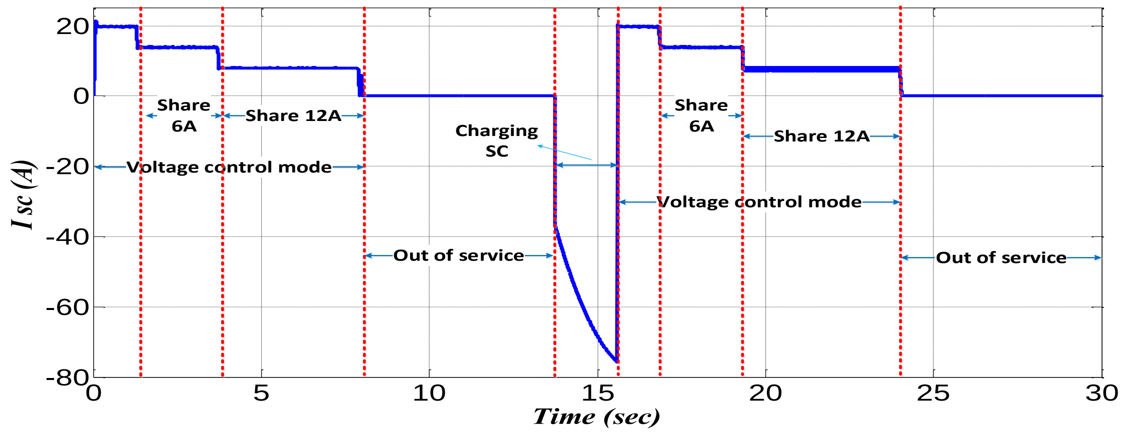


Figure 4.1: The injected current by SC under different time periods of decision making

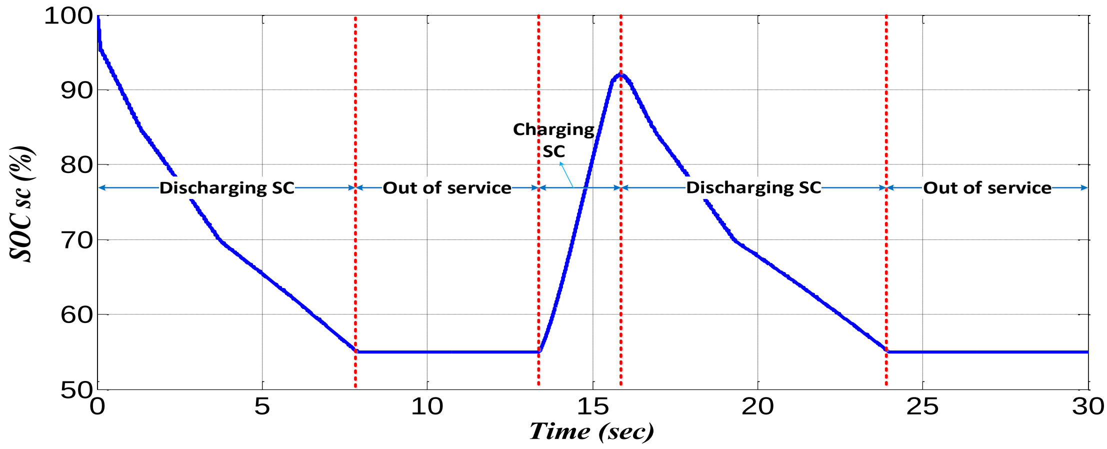


Figure 4.2: The state of charge of SC

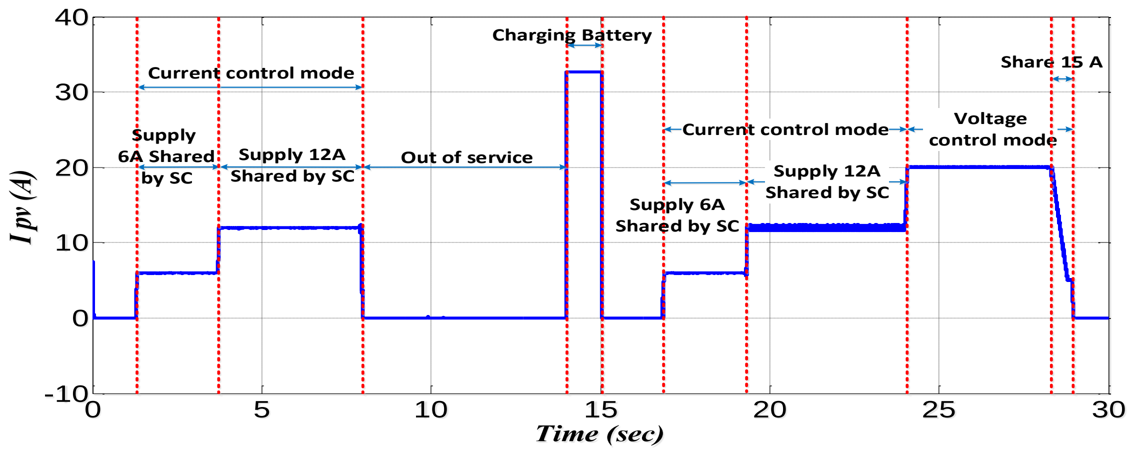


Figure 4.3: The injected currents by PV under different time sections of the decision making

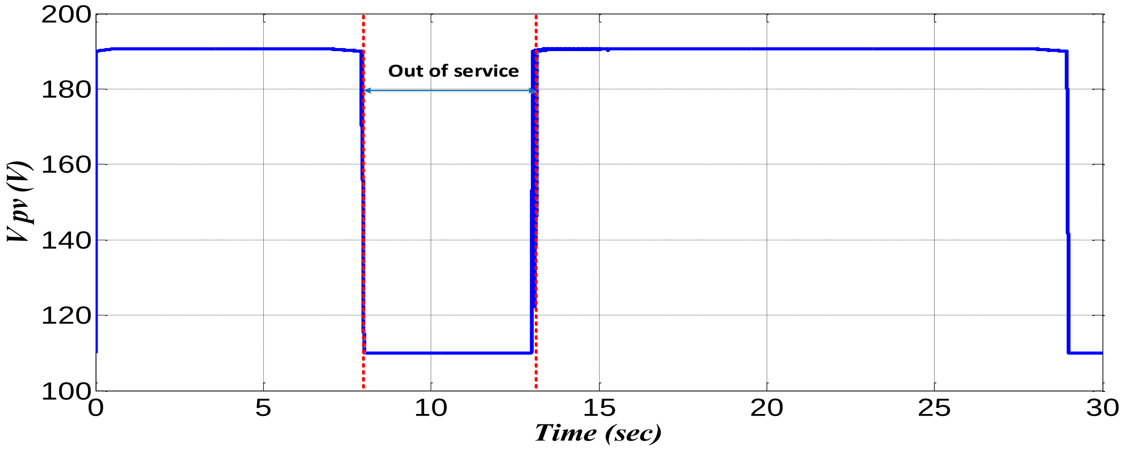


Figure 4.4: The evolution of the PV output voltage

Control voltage by SC: In the start, all the agents check for the available power and based on subsumption architecture, SC agent overrides all requests and takes control of DC bus and supplies the energy demand. Consequently, it sets bit 2^1 and, sends [10110] as signal to the communication port. It means that SC agent is in normal mode and shares current with level 1 of its current constraint as shown in figure 4.1. At t=1.3 s, its charge is dropped to 85% (figure 4.2) and SC enters to second level of current constrain, so activates 2^3 bit, [11010], to request for sharing current. Based on section 3.4, PV has high priority to share current with SC. Subsequently, PV agent accepts to supply shared current, by activating bit 2^0 ([10001]). The PV supplies 6A of demand as shown in Figure 4.3. At t=3.7s, as the SOC of SC drops below 70%. PV increase the share to 12 A. Therefore, the communication signal by SC is changed to [11110], and PV supplies a total of 12 A. If PV cannot supply shared current, battery and grid can do it based on their priority.

Control voltage by battery: When charge of SC drops to 55% (t=7.9 s), SC agent based on its voltage constraint in subsumption architecture cannot supply the demand. So, the voltage control transferred completely to the agent placed in the next layer (which was supposed to be PV). However, at t=7.9 s, terminal voltage of PV is also dropped such that it is out of service (figure 4.4). Thus, based on figure 4.5, battery has enough charge to supply the requested demand, and by sending [10110] as a data signal, it controls the DC bus. Further, based on the SOC of battery, the battery agent shares current in three levels with the grid agent, as shown in figure 4.6 and figure 4.7.

Control voltage by grid: After cooperating in three levels of current share by battery as shown in figure 4.7, at t=11 s the grid takes the control of voltage at

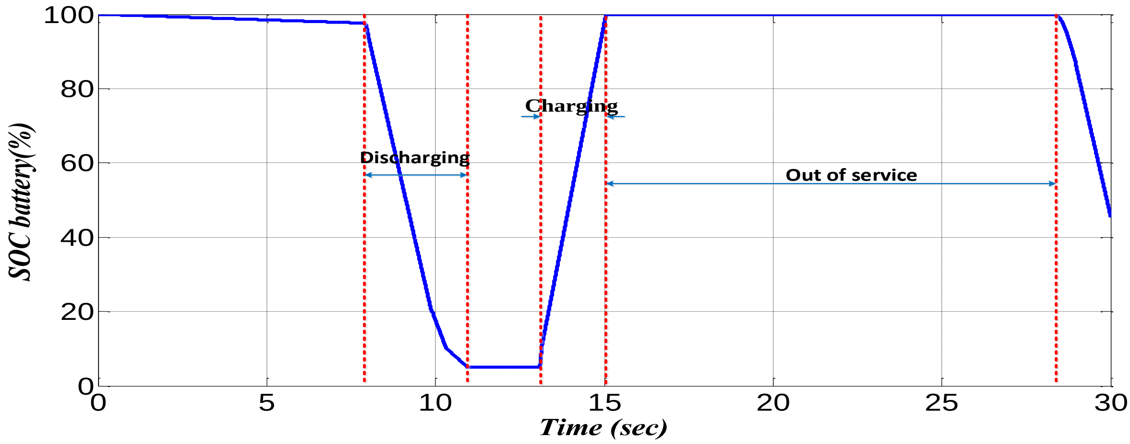


Figure 4.5: The state of charge of battery

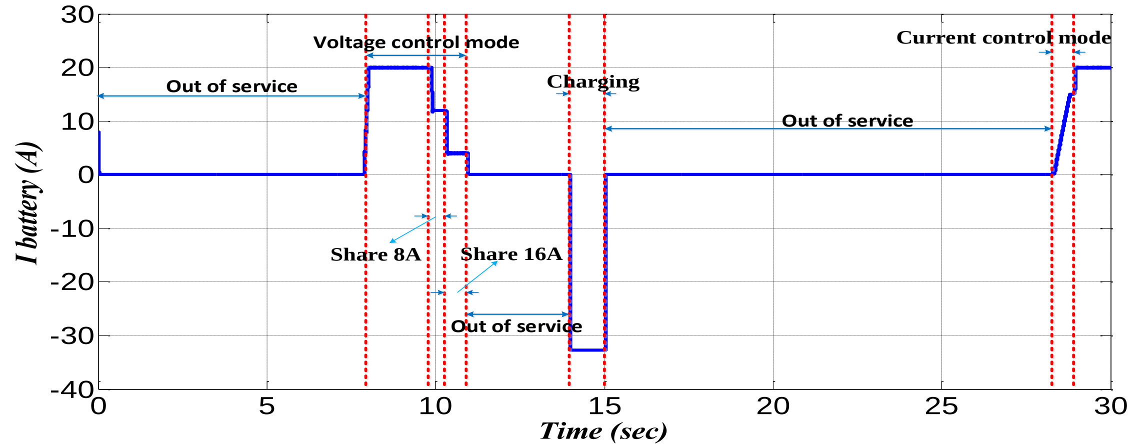


Figure 4.6: The injected current by battery under different time span of decision making

DC bus by sending [10010] over the communication port. If any agent with high priority exists with sufficient power to share, it can override the grid's request. However, the grid has the ability to keep it for a long time without sharing current until one of the agents with high priority overrides its precedence.

As there is an active load in the system thus, it can provide energy in generator mode (see figure 4.8). At t=13 s, load generates power and SC stores it. Therefore, SC takes voltage control until t=15.6 s. During this time, the terminal voltage of PV is also increased. The energy generated by PV is absorbed by the battery since it is already discharged. When the SOC of battery is reached to 100%, it is disconnected from the PV. Once the load finished generating energy, the SC is charged enough to keep the control of DC bus by sending request [10110]. The other agents cannot override its competence because it is in the lowest layer with high priority.

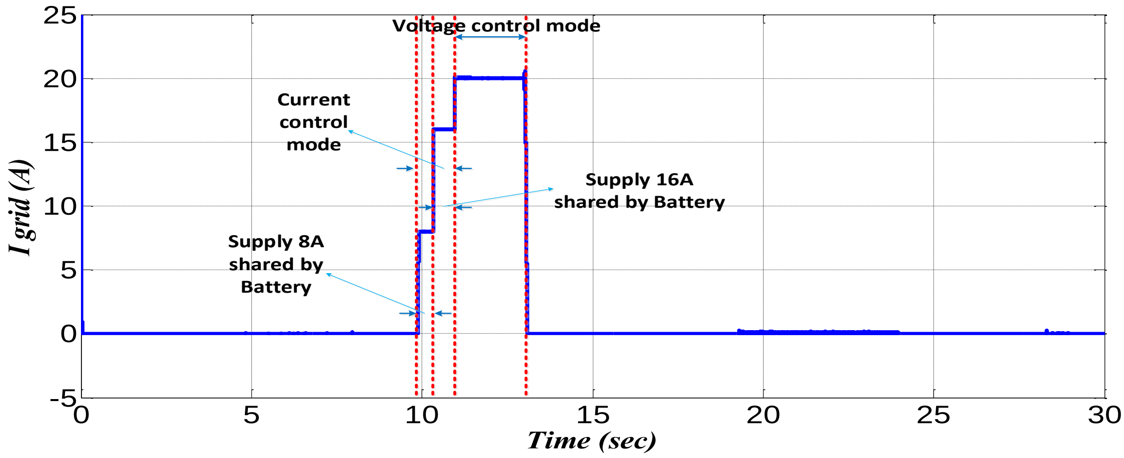


Figure 4.7: The injected current by grid under different time section of decision making

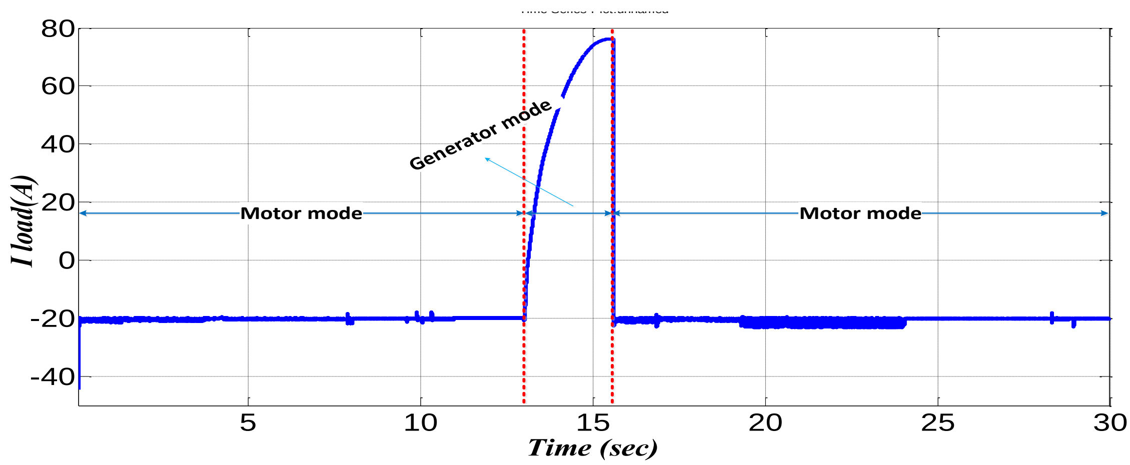


Figure 4.8: The waveform for the load current variation

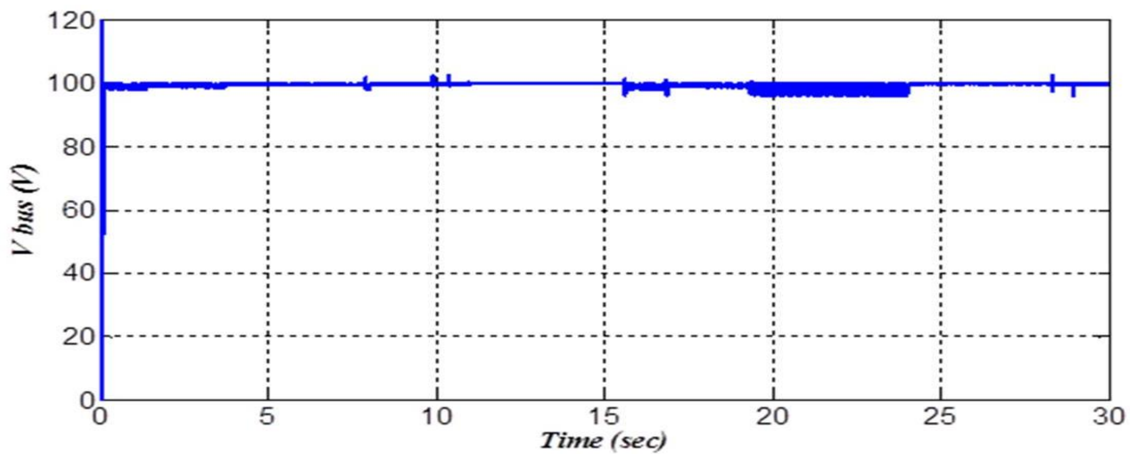


Figure 4.9: The voltage at the DC bus

The SC agent during voltage control of DC bus shares current with PV in two steps by sending signals [11010] and [11110] over the communication network. After the SOC of SC drops to a critical percentage, the PV with high priority based on hierarchical algorithm takes voltage control of DC bus. It is obvious that when PV controls the voltage of DC bus, others can just participate in sharing the current. It is worth mentioning that only the agent with high priority (here SC) can take voltage control back. The PV agent will supply load until there is sunshine. To conclude, all the interactions among the agents are assigned by a communication signal. Agents just by reading the 5 bits signal can sense variations in the system and take a proper control action. Figure 4.9 shows how agents control DC bus without any fluctuation in switching.

4.2 Analysis of energy management based on smart contract

To evaluate the effectiveness, hourly data information and parameter settings of the MG in a 24 one-hour period are applied as inputs to the proposed approach. The data set includes demand, solar and wind power generation, electricity price, and initial charge of battery. The BES capacity is considered 30 percent at the beginning and maximum discharging and charging rates are assumed to be 10 and 90 percent of total BES capacity, respectively. The MG is connected to the grid through a 20 kW inverter. A summary of data information and parameters are presented in tables 4.2-4.4.

Table 4.2: Constraints of PV and WT agents

$\underline{P}^{PV}$	$\overline{P}^{PV}$	$\overline{P}^{WT}$	$b_t^{PV,WT}$
0 kW	20 kW	25 kW	0.13 USD

Table 4.3: Constraints of ES agent

$\underline{E}^{ES}$	$\overline{E}^{ES}$	$\underline{P}^{ES}$	$\overline{P}^{ES}$	ζ^{ES}
0 kWh	10 kWh	1 kW	9 kW	%30

Table 4.4: Constraints of MT agent

$\underline{P}^{MT}$	$\overline{P}^{MT}$	$\overline{b}^{MT}$	ζ_t^{MT}
2.5 kW	10 kW	0.18 USD	%15

4.2.1 Result and discussion

In this study, the idea is online control and manage a MG. At the beginning of each time period, it is assumed all the renewable energy resources present their available power and consumer agent submits its requested power to the tendering organization. Figure 4.10 shows provided power by PV and WT as well, requested power by consumer. The tender organization after calculating net demand (P_t^T), presents it as a tender among BES, MT and the grid to achieve balance between supply and demand.

While a tender is held, each agent presents offer price and power based on its smart control units. BES agent, at the beginning of simulation, applies continuous

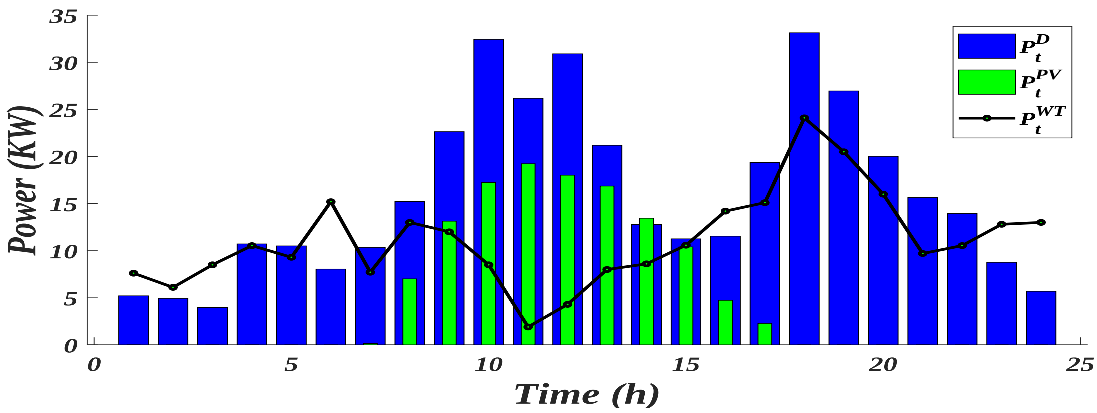


Figure 4.10: Demand and supplied power by PV and WT (TOU_t, $SPOT_t$)

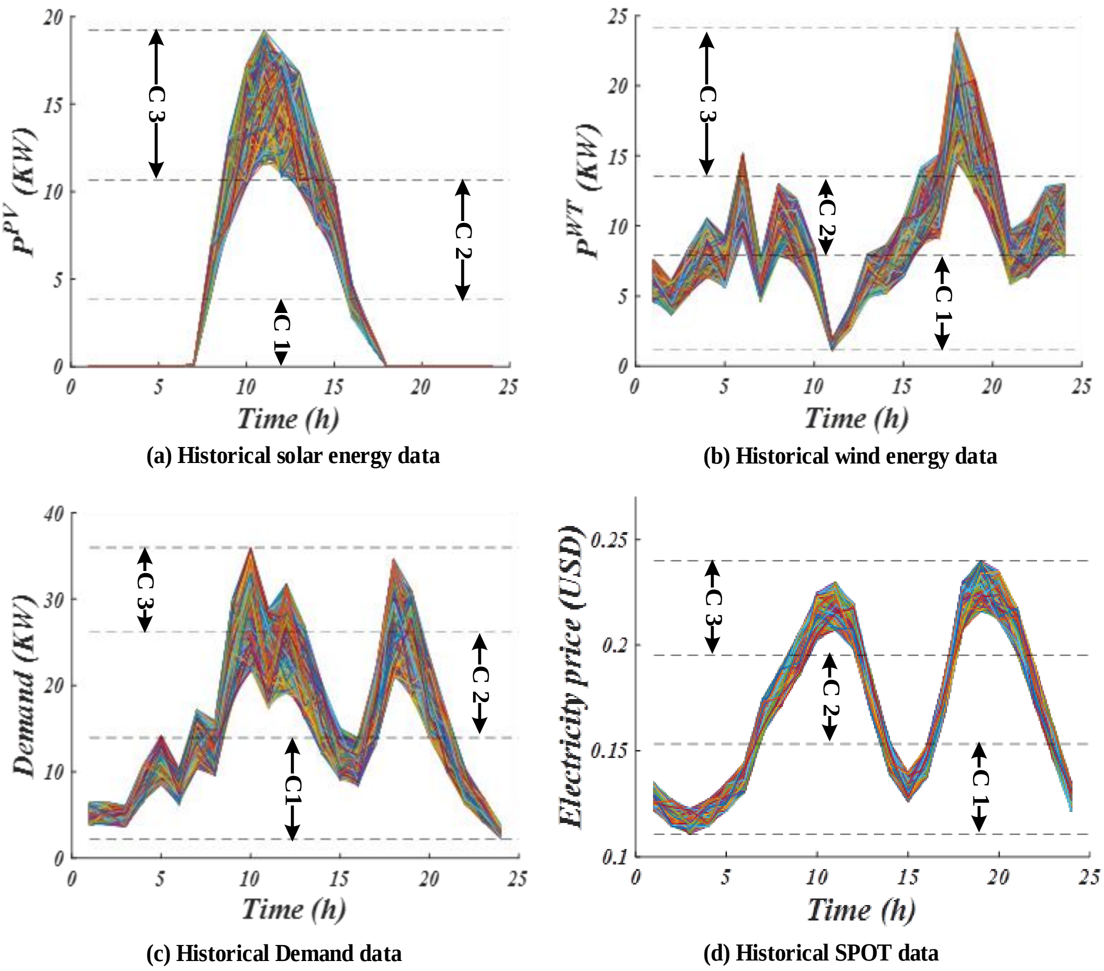
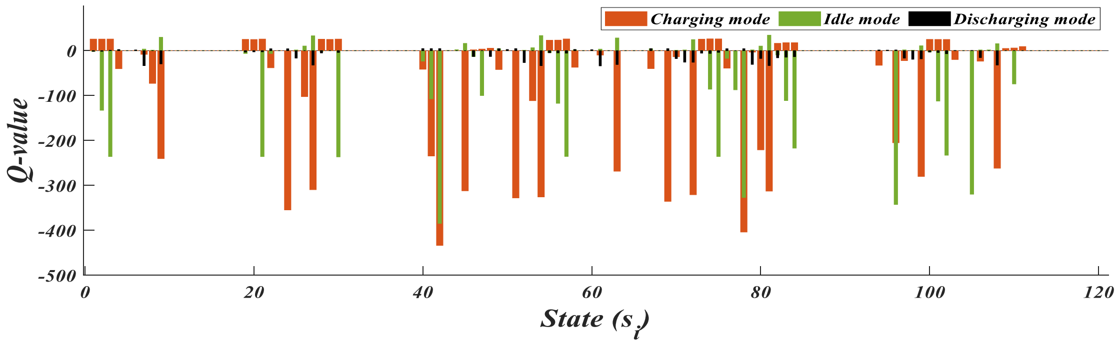
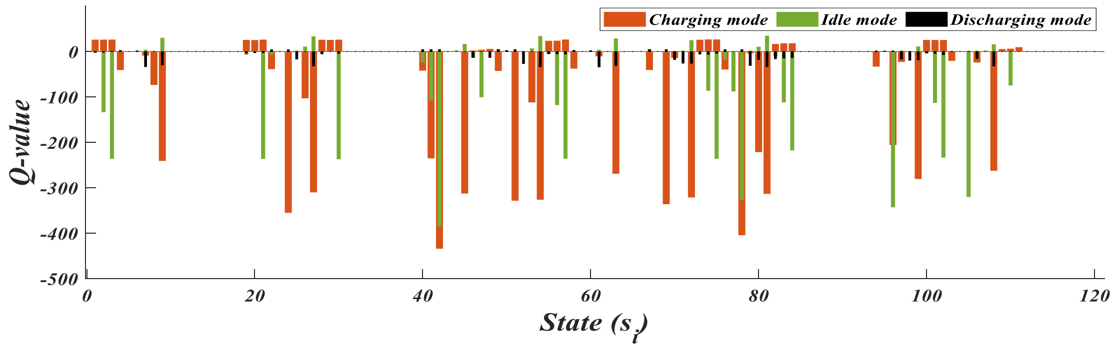


Figure 4.11: Discretization of the state space



(a) Q-value of state-action pair for s_1 to s_{120}



(b) Q-value of state-action pair for s_{121} to s_{240}

Figure 4.12: Q-value of BES for state-action pair obtained by Q-learning algorithm

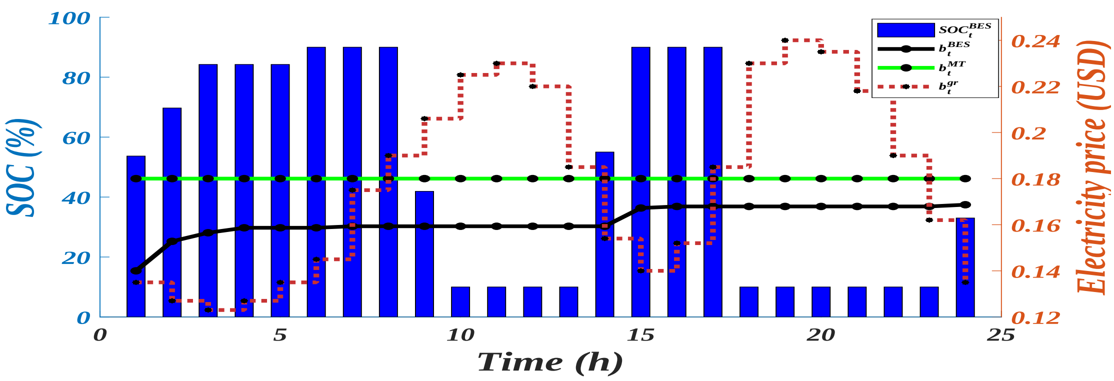


Figure 4.13: SOC of BES and offer price of agents

Table 4.5: Center and range of clusters created by c-means algorithm

	Center of cluster 1	Center of cluster 2	Center of cluster 3	Range of cluster 1	Range of cluster 2	Range of cluster 3
PV	0.2408	7.4173	13.9367	[0 3.8284]	(3.8284 10.6763]	(10.6763 19.23]
WT	5.6873	10.2224	16.811	[1.14 7.9546]	(7.9546 13.5153]	(13.5153 24.1]
Demand	6.7947	15.2947	26.1126	[2.2511 13.9352]	(13.9352 26.178]	(26.178 35.9448]
SPOT	0.1313	0.1752	0.2156	[0.1107 0.1532]	(0.1532 0.1954]	(0.1954 0.24]

Table 4.6: State, Q-value and action policy of BES during 24-hour

t	1	2	3	4	5	6	7	8
PV	0	0	0	0	0	0	0.115	5.757
WT	7.574	6.541	5.416	8.509	6.632	14.165	5.706	10.128
Demand	5.206	4.938	3.963	10.715	10.503	8.046	10.351	15.225
SPOT	0.1255	0.1264	0.1189	0.1156	0.1344	0.1431	0.173	0.1756
BES	53.68	69.71	84.24	84.24	84.24	90	90	90
$\hat{s}_i$	[1 1 1 1 2]	[1 1 1 1 2]	[1 1 1 1 2]	[1 3 1 1 2]	[1 1 1 1 2]	[1 2 1 1 3]	[1 1 1 3 3]	[2 3 3 3 3]
Q_i^{CHR}	25.78	25.69	25.69	23.36	25.78	25	-240.08	-327.7
Q_i^{IDL}	-132.63	-132.63	-132.63	-117.1	-132.63	0	29.7	35.39
Q_i^{DCHR}	-1.42	-1.42	-1.42	-4.88	-1.42	0	-29.3	-30.72
Action	CHR	CHR	CHR	CHR	CHR	CHR	IDL	IDL

t	9	10	11	12	13	14	15	16
PV	8.546	15.207	15.329	16.608	11.817	10.898	9.386	3.705
WT	9.276	5.103	2.725	7.212	2.936	6.391	8.297	9.674
Demand	22.632	32.437	26.178	30.897	21.192	12.787	11.256	11.542
SPOT	0.1995	0.2182	0.2232	0.2017	0.1692	0.1445	0.1396	0.1506
BES	41.9	10	10	10	10	55.02	90	90
$\hat{s}_i$	[2 3 2 2 2]	[3 1 2 2 1]	[3 1 3 2 1]	[3 1 2 2 1]	[3 1 2 3 1]	[3 1 3 1 2]	[2 3 3 1 3]	[1 3 3 1 3]
Q_i^{CHR}	-401.8	-97.04	-38.3	-38.78	-18.24	0.56	23.37	26.19
Q_i^{IDL}	-363	-168.48	-14.07	-18.04	3.41	-25.5	-104.01	-235.46
Q_i^{DCHR}	1.55	4.26	4.29	4.25	-32.23	-25.4	-8.74	-3.7
Action	DCHR	DCHR	DCHR	DCHR	IDL	CHR	CHR	CHR

t	17	18	19	20	21	22	23	24
PV	2.048	0	0	0	0	0	0	0
WT	12.818	18.766	17.521	13.403	7.565	8.594	10.355	7.993
Demand	19.355	33.132	26.954	20.018	15.634	13.935	8.765	5.692
SPOT	0.1731	0.2135	0.2215	0.2118	0.2132	0.1797	0.1606	0.1332
BES	90	10	10	10	10	10	10	33
$\hat{s}_i$	[1 3 3 3 3]	[1 2 2 2 1]	[1 2 2 2 1]	[1 3 3 2 1]	[1 1 3 2 1]	[1 3 1 3 1]	[1 3 1 3 1]	[1 3 1 1 2]
Q_i^{CHR}	-312.49	-433.35	-41.27	-38.8	-37.9	-9.7	-9.7	23.13
Q_i^{IDL}	34.4	-384.4	-23.28	-17.08	-6.29	3.35	3.35	-117.11
Q_i^{DCHR}	-33.06	4.5	4.5	4.31	4.16	-33.78	-33.78	-4.61
Action	IDL	DCHR	DCHR	DCHR	DCHR	IDL	IDL	CHR

state space to c-means algorithm. As shown in Figure (4.11), c-means algorithm divides data set to three clusters and maps each cluster to a center. In table 4.5 center of cluster, range of power and price in each cluster are shown. After normalizing, the discrete data is applied to Q-learning algorithm. The Q-learning algorithm calculates a Q-value for each action in a state. Selecting an action that has a higher Q-value in a special state, will result in more profit for BES agent. Figure (4.12a) and figure (4.12b) show Q-value of each state-action pair that obtained through Q-learning algorithm. As shown there are three actions that each one has especial Q-value. The maximum Q-value in each state indicates the action which should be chosen through BES agent to make the best decision in the tender. In table 4.6,

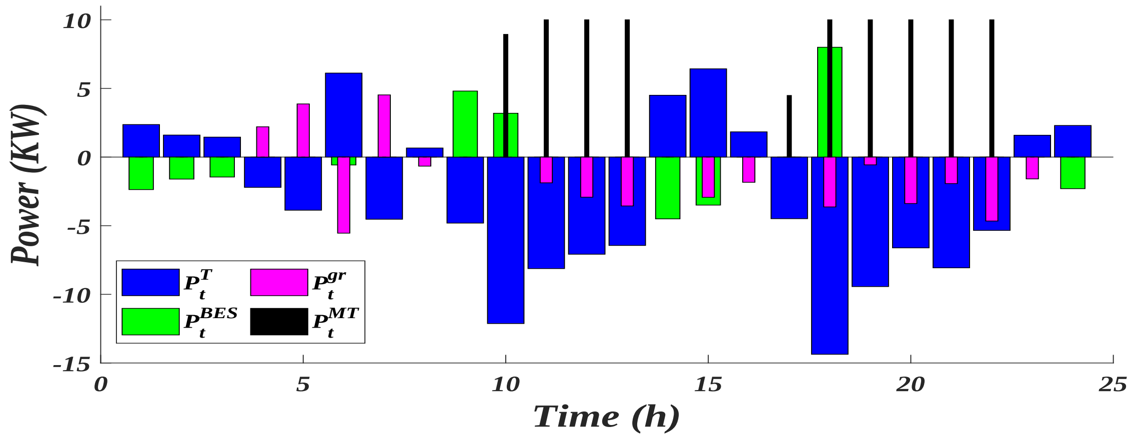


Figure 4.14: Operation results of BES, MT and grid agents

Q-values and states are presented that during 24 one-hour, BES agent is located in. BES agent at each tender based on located state and Q-value chooses one of actions, charging, discharging and idle. Taking the action in each state based on the optimal control policy, push agent to achieve more reward in the system. As it is obvious in figure (4.13), BES agent stores energy while extra power exist in the MG and also policy is charging. While balance in the MG is negative and policy is to take discharging action, BES injects power if its SOC is more than minimum defined SOC.

It can be seen in figure (4.13) that BES agent charge battery while electricity price is low and in on-peak price, based on requested power by tendering organization supports the MG. Also, BES agent at some states take idle action that means agent does not have any tendency to participate in the tender for instance, $t = 7, 8, 13, 17$ s. In fact, BES agent based on trained Q-learning, just participates in a tender when it is on-peak time or off-peak time. As it is clear in figure (4.14), at off-peek price, BES agent chooses charging action and stores energy, and during on-peak price, it takes discharging action and supports MG. During charging modes, BES agent calculates its offer price based on Eq.(2.31) in order to present to the tendering organization in the next tender as shown in figure (4.13). As it is clear at whole time periods, BES offer price is less than rest and it shows BES agent charges battery while it is off-peak price.

MT and grid agent uses heuristic algorithms to participate in a tender. As shown in figure (4.14), MT agent injects power to the MG while it is on-peak time. In fact during these time periods, it can gain more profit due to the highest requested energy through the system. As it is clear during off-peak time, MT offer

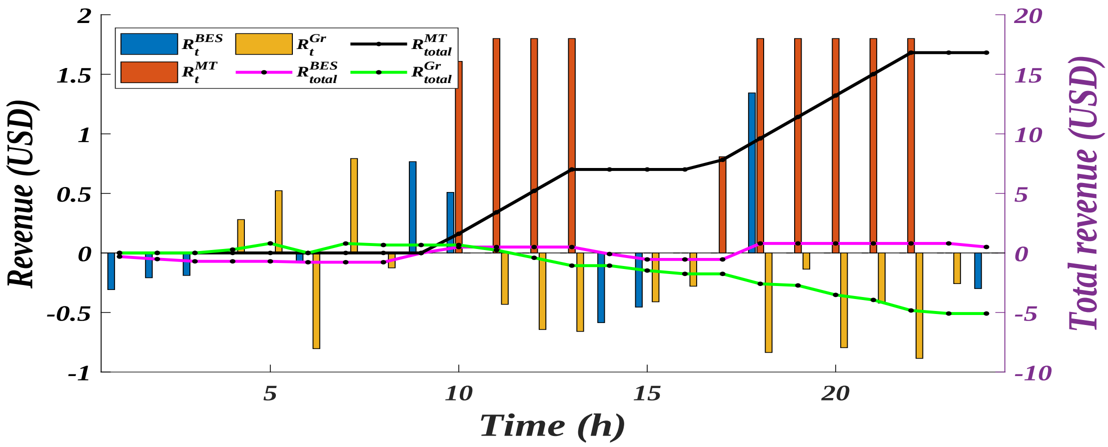


Figure 4.15: Revenue and total revenue of agents

price is more than the grid, so MT agent makes micro-turbine off. Therefor, MT agent can just be as winner when its offer price is less than grid offer price, otherwise, the tendering organization selects the grid as the winner. Based on MT heuristic algorithm, during on-peak price, MT can present power to the grid to gain more profit.

Figure (4.15) shows revenue of each agent in participating in tenders during each time period. As shown, grid agent inject energy to the MG during off-peak price and absorbs energy while extra power exists in it especially, in on-peak price. So, by passing time, its total revenue would decrease. Since MT agent just at on-peak price injects power to the MG and grid, gains more profits and along time its total revenue would increase. BES agent at off-peak time period stores energy and at on-peak time period injects energy to the MG, its total revenue would generally increase.

4.3 Conclusions

In this chapter, the results of implementation of the presented control approaches in this thesis were examined. In the first section, subsumption architecture was used to control DC bus and supply demand, in which the agents were responsible for supplying power according to the existed priority in the control structure. In order to increase the reliability in the system, the agents interacted with each other through a communication bus, wherein each agent shared its status with the rest of agents by using a 5-bit signal. The simulation results showed that the agents share power well under the proposed approach in the green building.

In the second section, the results of controlling power in the smart city were presented by using smart contract. The simulation results show that the presented control framework accurately allocates power between agents and creates coordination them. On the other hand, in this framework, BES was controlled by Markov decision process framework. The results show that BES stores power during off-peak time and injects power to the MG during on-peak time. The presented approach decreases electricity price in the MG and increases reliability and stability in the system.

In general, both of the presented methods manage the energy in the system well, and it leads to create balance between supply and demand, as well as stability in the power system.

Chapter 5

Result of fault tolerance

One of the main advantages of MAS is fault tolerance. In fact, when MASs face a fault, they should be able to guarantee the stability of the system. In this section, we will evaluate the performance of presented smart control systems in this thesis against faults. It is assumed that BES agent will face a fault in both proposed structures.

CONTENTS:

5.1 Fault tolerance in subsumption architecture

In this section, the system is simulated for 10 s in order to evaluate the operation of EMS in a fault-facing at the decision part. As mentioned in section 3.1.3.2, agents transfer 5 bits to the communication port wherein bit 2^4 describes about the failure status of an agent. Assuming at the beginning that the battery agent (decision part of battery) suffered from a breakdown. Subsequently, the signal from the battery over the data bus will be [00000]. In this case, hierarchy in layers is reconfigured only with sub-behaviours of SC, PV, and grid agents without considering the battery agent. This is one of the main advantages of MASs known as fault tolerance and high reliability. It enables a system to continue its operation while even some parts stop working.

At first, SC agent completely controls the voltage and after sharing 6 A and 12 A by sending [11010] and [11110] to the data bus, respectively, PV agent takes the control of DC bus voltage, as shown in figure 5.1. The PV supplies demand until t=6.3 s, this time it shares current by sending signal [11011] to the data bus. Although battery has high the priority rather than the grid, however, the detected signal from battery on the communication port is [00000], due to its fault. Consequently, the grid agent supplies the shared current. At t=6.9 s, the grid controls voltage of DC bus by sending [10010] signal. This situation stays until one of the agents is able to supply the demand.

The battery failure is resolved at t=9 s, so it sets 2^4 bit to 1. By this signal, the configuration among the agents is changed to 4 agents and the voltage control of DC bus is handed over to the battery agent. Figure 5.2 shows the changes in the DC bus voltage. It is obvious that despite of failure in battery agent, there is no oscillation in the voltage profile and energy management is carried out smoothly among the generators.

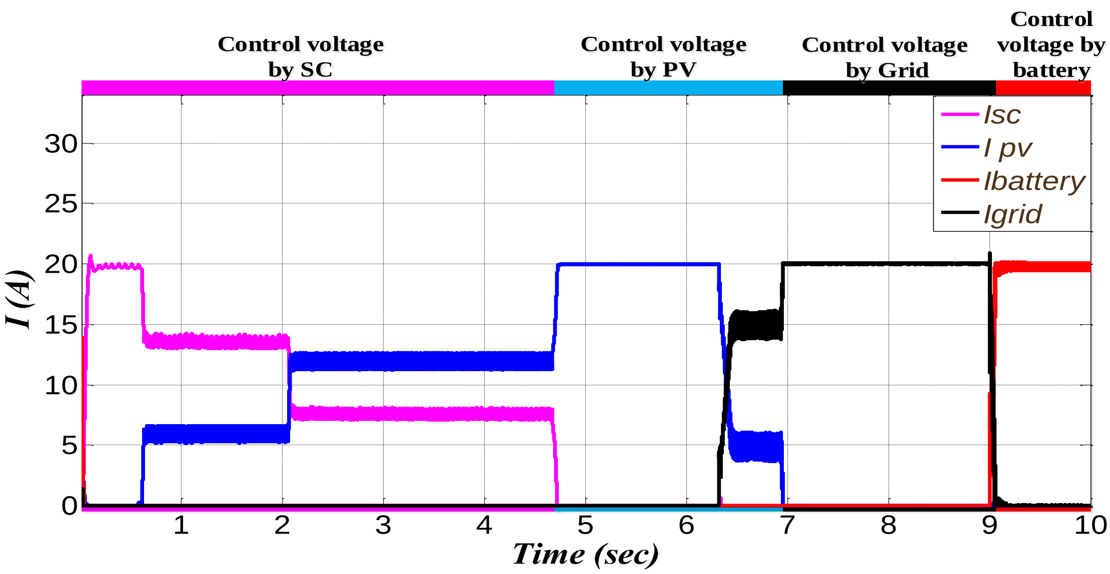


Figure 5.1: The injected current of SC, PV, battery and grid under different time periods of fault tolerance test

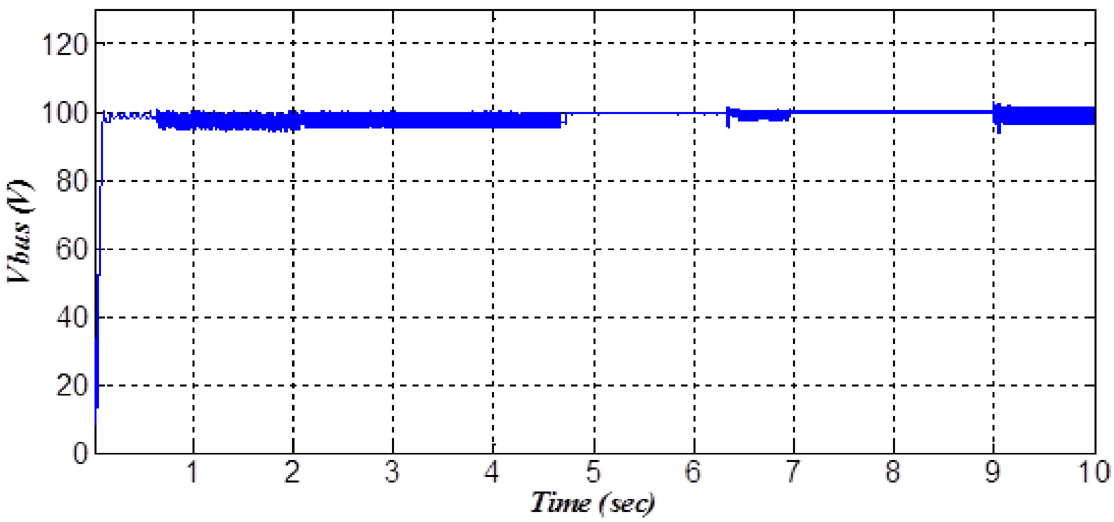


Figure 5.2: The voltage of the DC bus during fault tolerance test

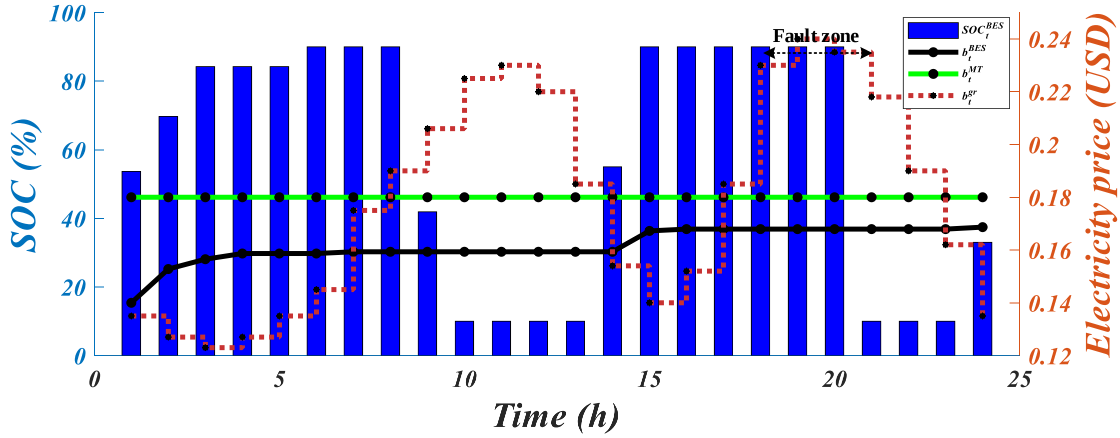


Figure 5.3: SOC of BES and offer price of agents during fault tolerance test

5.2 Fault tolerance in smart contract

To evaluate the performance of the presented approach in a fault-facing, it is assumed that the battery agent is not able to inject power to the MG at times 18-20 due to the fault in the power part. Therefore, when a tender is held during these times, according to figure (5.3), although BES agent stored energy and could win the tender by submitting an offer price, but due to the fault, it is unable to inject power. Therefore, it is excluded and the tender is held among the rest of agents. As it is obvious in figure (5.4), during these times, demand is supplied by MG and the grid. Although, as shown in figure (5.5), the presented approach can increase the cost of MG energy supply at on-peak time due to fault-facing (the demand may be supplied through the grid), but it prevents blackouts and system instability. This is one of the main advantages of MASs known as fault tolerance and high reliability. It enables a system to continue its operation while even some parts stop working. At t=21, when the fault in the battery is resolved, BES agent is included in the tender and can share its stored power with MG. As a result, the proposed structure has the ability to control stability in fault-facing.

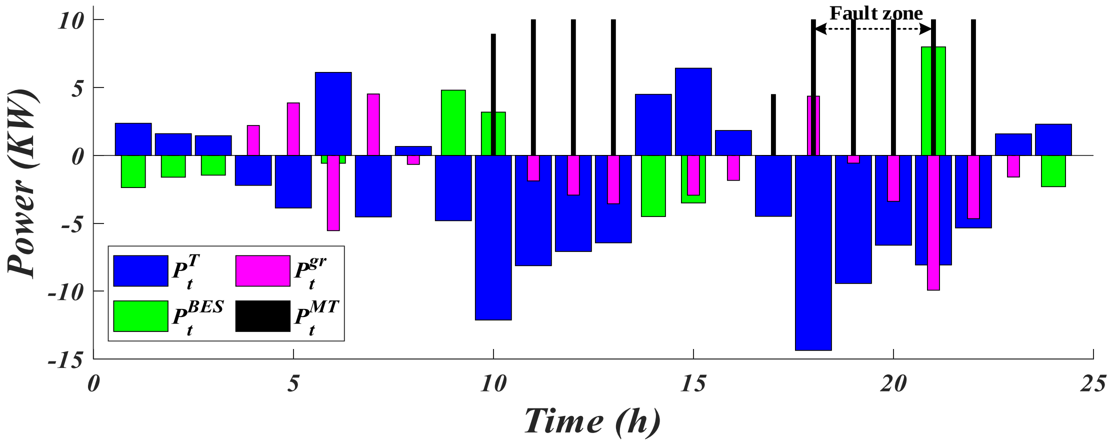


Figure 5.4: Operation results of BES, MT and grid agents during fault tolerance test

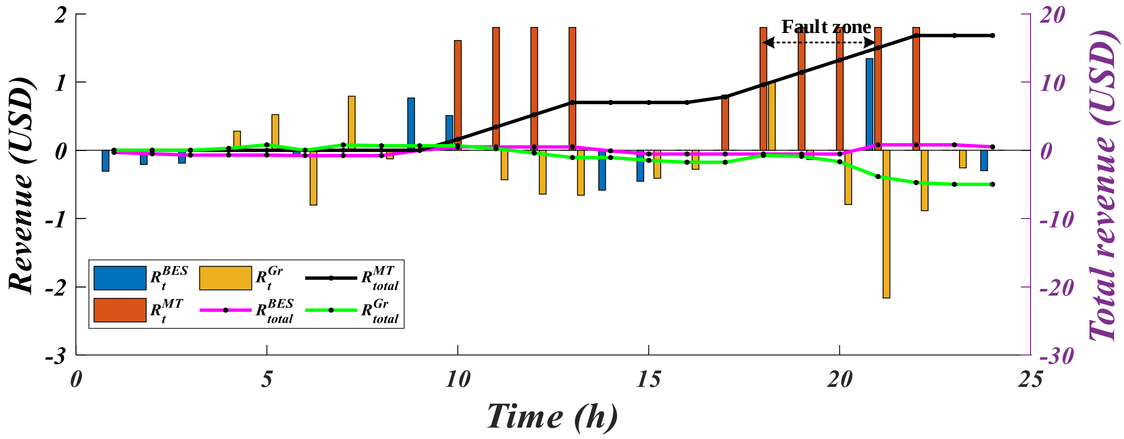


Figure 5.5: Revenue and total revenue of agents during fault tolerance test

5.3 Conclusions

In this chapter, the performance of presented control approaches in the thesis was investigated in fault-face . In the first section, it was observed that when BES agent faced a fault and could not able to send its status signal to the data bus, presented subsumption architecture by changing the priority, changed the configuration between the agents and prevented blackouts in the system. In fact, this adds a self-healing feature to the smart control system, which presents fault-facing ability to the system.

In the second section, when the battery agent faced a fault, considering that the tender structure was implemented in such a way that the agent had to present the offer price to the tendering organization, therefore BES agent was not able to send any signal to participate in the tender and demand was met by the rest.

In general, the simulation results show both of the presented control structures have ability to face fault and can avoid blackouts in the system. As a result, the presented approaches increase stability and reliability in the system in addition to optimal allocation of power. But, the second approach is more complex and is useful in a highly disturbed electrical systems, as well it is more scalable and flexible to add and remove a provider.

Chapter 6

Overall conclusion and future works

General conclusions of the thesis are presented in this chapter. At the beginning, conclusions of the proposed approaches according to the research problem, hypotheses and objectives will be described, and in the following, approaches will be proposed to show the direction of future researches in this field.

CONTENTS:

6.1 Thesis conclusion

In this thesis, two fault tolerant bottom-up approaches have been presented to control and manage energy in the MG. In the first approach, a multi-agent based distributed energy management system with a low bandwidth communication bus has been proposed to control the voltage of DC bus and supply-demand balance in a micro-grid. In the proposed system, any agent can control the voltage and current through the set points using subsumption architecture and is supported by a communication link. The proposed architecture provides flexibility, high speed in decision-making, adaptability after redevelopment and fault tolerance. The fault ride through capability enables smooth and reliable operation of the entire system if local controllers develop faults. To achieve these objectives, agents in this framework cooperates through a communication link wherein allocated tasks such as voltage and current control are conveyed. The communication between agents improves the reliability of the system, especially in mitigating the failure state by re-configuring the sequence of agents. The proposed control for voltage and power is validated for normal operation and in failure state. Overall, the proposed framework presents the following advantages:

1. Online smart control of micro-grid
2. Flexible and easy implementation, even for large-scale systems
3. Require low communication bandwidth and low sized transmission data (5 bits)
4. High reliability and fault tolerance
5. Easy redevelopment by reassigning the priorities

In the second approach, an online smart energy management system based on multi-agent system has been implemented wherein agents managed energy in a MG under supervision of a smart contract with a bottom-up approach. In order to control agents into the MAS, a tendering process as a smart contract has been used that shared requested power as a tendered item between DGs in each time period. Each agent separately presents its offer price to the tendering organization to supply demand. The tendering organization allocates power between bidders based on FPSB algorithm. In the proposed approach, each agent makes online decision by using AI algorithm and at each time period, participates in the tendering process depending on the electricity price and demand. In the presented mechanism, in addition to the energy price at each time period, the tendered power is also considered in decision making of bidders to allocate optimum power in the MG. The proposed structure presented a new approach with online distributed decision to allocate power in MGs that implementing this approach on power systems has following advantages:

1. It does not require any prediction and uncertainty consideration thanks to online data processing
2. Automated power allocation among DGs via smart contract without user's participation
3. High reliability due to having distributed structure in decision making and online processing as well
4. The presented approach guarantees supply-demand balance at each time period and thus the system would be stable
5. The proposed approach optimizes the electricity cost in MGs thanks use of reinforcement learning for BES and the tendering process for the MAS
6. Quick response time due to the asynchronous and parallel computing
7. BES lifetime would be increased because it just activates at on-peak price and off-peak price.
8. Easy redevelopment by reprogramming agents due to distributed decision structures in the proposed approach
9. Flexible and scalable to add or remove generation devices into the system
10. Easy implementation including large-scale systems
11. If one of agents is failed, the rest of system are able to supply demand and control stability of the system.

Therefore, the thesis has demonstrated the capacity of the MAS to control a microgrid with high flexibility, reliability, and fault tolerance, without using excessive communication resources between the different agents involved in the control. The developed controls are easily scalable and can be implemented in real systems without excessive cost.

6.2 Future works

This research presented a robust intelligent control structure with significant results, which in addition to providing a distributed smart structure for generators, also provides an optimal framework for users, which can guarantee stability, reliability and fault tolerance in smart systems. The presented control structure is designed for intelligent control in the generation side. As a future work, a control framework can be developed in the demand side to control the demand in the microgrid as a demand response. Therefore, in the future, we would like to add an artificial intelligence algorithm to the presented intelligent system in demand side, which can improve the stability and reliability of the system for any sudden change. Such a structure can replace user-assisted controlled systems. Another future line of research could be the development of MAS controls for hybrid DC/AC microgrids, including active and reactive energy transfers, and also the development of stability studies of the resulting hybrid system, as well as the analysis of the sensitivity of the MAS system to combined faults in the DC and AC network.

Chapter 7

Thesis results disseminations

This chapter presents a list of articles published in international journals that resulted from this research, and well as, an article related to the collaboration with Northumbria University, Newcastle, United Kingdom.

CONTENTS:

7.1 Derived publications from this thesis work

7.1.1 Journal papers

1. Mansour Selseleh Jonban, Jose Luis Romeral Martinez, Adel Akbarimajd, Zunaib Ali, Seyedeh Samaneh Ghazimirsaeid, Mousa Marzband, Ghanim Putrus, ”Autonomous Energy Management System with Self-Healing Capabilities for green buildings (Microgrids),” Journal of Building Engineering, Volume 34, February 2021, 101604.
   Impact factor: 7.144

2. Mansour Selseleh Jonban, Jose Luis Romeral Martinez, Mousa Marzband, ”Intelligent fault tolerant energy management system using first-price sealed-bid algorithm for microgrids,” Journal of Sustainable Energy, Grids and Networks. **Under review**.
   Impact factor: 5.405

3. Mansour Selseleh Jonban, Jose Luis Romeral Martinez, Mousa Marzband, ”Flexible smart energy management system through an online tendering process framework for microgrids”, Journal of Electric Power Systems Research, **Under review**.
   Impact factor: 3.818

4. Mansour Selseleh Jonban, Jose Luis Romeral Martinez, Mousa Marzband, ”A reinforcement learning approach with Markov decision process for controlling battery energy storage in a smart contract framework”, **Draft version completed, internal review**.

7.2 Resulting publication from additional collaboration related with this work

1. Seyedeh Samaneh Ghazimirsaeid, Mansour Selseleh Jonban, Manthila Wijesooriya Mudiyanselage, Mousa Marzband, Jose Luis Romeral Martinez, ”Multi-agent-based Energy Management of multiple Grid-connected green buildings,” Journal of Building Engineering. **Revised with minor changes and preparing the pre-printed version**.
   Impact factor: 7.144

References

[1] S. Khemakhem, M. Rekik, L. Krichen, A collaborative energy management among plug-in electric vehicle, smart homes and neighbors' interaction for residential power load profile smoothing, Journal of Building Engineering 27 (2020) 100976.

[2] V. Aryanpur, M. S. Atabaki, M. Marzband, P. Siano, K. Ghayoumi, An overview of energy planning in iran and transition pathways towards sustainable electricity supply sector, Renewable and Sustainable Energy Reviews 112 (2019) 58–74.

[3] S. Aznavi, P. Fajri, R. Sabzehgar, A. Asrari, Optimal management of residential energy storage systems in presence of intermittencies, Journal of Building Engineering 29 (2020) 101149.

[4] H. R. Gholinejad, A. Loni, J. Adabi, M. Marzband, A hierarchical energy management system for multiple home energy hubs in neighborhood grids, Journal of Building Engineering 28 (2020) 101028.

[5] P. Chen, Y. Wu, L. Zou, Distributive pv trading market in china: A design of multi-agent-based model and its forecast analysis, Energy 185 (2019) 423–436.

[6] R. K. Chauhan, K. Chauhan, Building automation system for grid-connected home to optimize energy consumption and electricity bill, Journal of Building Engineering 21 (2019) 409–420.

[7] L. Ju, Q. Zhang, Z. Tan, W. Wang, H. Xin, Z. Zhang, Multi-agent-system-based coupling control optimization model for micro-grid group intelligent scheduling considering autonomy-cooperative operation strategy, Energy 157 (2018) 1035–1052.

[8] J. Ferber, G. Weiss, Multi-agent systems: an introduction to distributed artificial intelligence, Vol. 1, Addison-Wesley Reading, 1999.

[9] J. B. Almada, R. P. S. Leão, R. F. Sampaio, G. C. Barroso, A centralized and heuristic approach for energy management of an ac microgrid, Renewable and Sustainable Energy 60 (2016) 2884–2894.

[10] T. Wang, D. O'Neill, H. Kamath, Dynamic control and optimization of distributed energy resources in a microgrid, *IEEE Transactions on Smart Grid*, 6 (6) (2015) 2884–2894.

[11] M. S. S. Danish, T. Senjyu, A. M. Ibrahimi, M. Ahmadi, A. M. Howlader, A managed framework for energy-efficient building, Journal of Building Engineering 21 (2019) 120–128.

[12] H. Zhou, T. Bhattacharya, D. Tran, Composite energy storage system involving battery and ultracapacitor with dynamic energy management in microgrid applications, IEEE Transactions on Power Electronics 26 (3) (2011) 923–930.

[13] M. Latif, A. Nasir, Decentralized stochastic control for building energy and comfort management, Journal of Building Engineering 24 (2019) 100739.

[14] B. Li, R. Roche, D. Paire, A. Miraoui, A price decision approach for multiple multi-energy-supply microgrids considering demand response, Energy 167 (2019) 117–135.

[15] M. Nazari-Heris, M. A. Mirzaei, B. Mohammadi-Ivatloo, M. Marzband, S. Asadi, Economic-environmental effect of power to gas technology in coupled electricity and gas systems with price-responsive shiftable loads, Journal of Cleaner Production 244 (2020) 118769.

[16] A. Q. Santos, R. M. Monaro, D. V. Coury, M. Oleskovicz, A new real-time multi-agent system for under frequency load shedding in a smart grid context, Electric Power Systems Research 174 (2019) 105851.

[17] D. Stimoniaris, T. Kollatou, D. Tsiamitros, M. Zehir, A. Batman, M. Bagriyanik, A. Ozdemir, E. Dialynas, Demand-side management by integrating bus communication technologies into smart grids, Electric Power Systems Research 136 (2016) 251–261.

[18] M. Marzband, E. Yousefnejad, A. Sumper, J. L. Domínguez-García, Real time experimental implementation of optimum energy management system in

standalone microgrid by using multi-layer ant colony optimization, International Journal of Electrical Power & Energy Systems 75 (2016) 265–274.

[19] D. E. Olivares, C. A. Cañizares, M. Kazerani, A centralized energy management system for isolated microgrids, IEEE Transactions on smart grid 5 (4) (2014) 1864–1875.

[20] M. Marzband, M. Ghadimi, A. Sumper, J. L. Domínguez-García, Experimental validation of a real-time energy management system using multi-period gravitational search algorithm for microgrids in islanded mode, Applied energy 128 (2014) 164–174.

[21] M. Jadidbonab, B. Mohammadi-Ivatloo, M. Marzband, P. Siano, Short-term self-scheduling of virtual energy hub plant within thermal energy market, IEEE Transactions on Industrial Electronics (2020) 1–1.

[22] M. A. Mirzaei, A. Sadeghi-Yazdankhah, B. Mohammadi-Ivatloo, M. Marzband, M. Shafie-khah, J. ao P.S. Catalão, Integration of emerging resources in igdt-based robust scheduling of combined power and natural gas systems considering flexible ramping products, Energy 189 (2019) 116195.

[23] M. Pourakbari-Kasmaei, M. Lehtonen, M. Fotuhi-Firuzabad, M. Marzband, J. R. S. Mantovani, Optimal power flow problem considering multiple-fuel options and disjoint operating zones: A solver-friendly MINLP model, International Journal of Electrical Power Energy Systems 113 (2019) 45–55.

[24] N. Gholizadeh, G. Gharehpetian, M. Abedi, H. Nafisi, M. Marzband, An innovative energy management framework for cooperative operation management of electricity and natural gas demands, Energy Conversion and Management 200 (2019) 112069.

[25] C. Wang, Y. Liu, X. Li, L. Guo, L. Qiao, H. Lu, Energy management system for stand-alone diesel-wind-biomass microgrid with energy storage system, Energy 97 (2016) 90–104.

[26] R. Das, Y. Wang, G. Putrus, R. Kotter, M. Marzband, B. Herteleer, J. Warmerdam, Multi-objective techno-economic-environmental optimisation of electric vehicle for energy services, Applied Energy 257 (2020) 113965.

[27] M. Hong, X. Yu, N.-P. Yu, K. A. Loparo, An energy scheduling algorithm supporting power quality management in commercial building microgrids, IEEE Transactions on Smart Grid 7 (2) (2014) 1044–1056.

[28] A. Mondal, S. Misra, M. S. Obaidat, Distributed home energy management system with storage in smart grid using game theory, IEEE Systems Journal 11 (3) (2015) 1857–1866.

[29] Y. Xu, W. Zhang, G. Hug, S. Kar, Z. Li, Cooperative control of distributed energy storage systems in a microgrid, IEEE Transactions on smart grid 6 (1) (2014) 238–248.

[30] B. M. Radhakrishnan, D. Srinivasan, A multi-agent based distributed energy management scheme for smart grid applications, Energy 103 (2016) 192–204.

[31] Q. Shafiee, J. M. Guerrero, J. C. Vasquez, Distributed secondary control for islanded microgrids—a novel approach, IEEE Transactions on power electronics 29 (2) (2013) 1018–1031.

[32] Y. F. Eddy, H. B. Gooi, S. X. Chen, Multi-agent system for distributed management of microgrids, IEEE Transactions on power systems 30 (1) (2014) 24–34.

[33] A. Kulmala, M. Alonso, S. Repo, H. Amaris, A. Moreno, J. Mehmedalic, Z. Al-Jassim, Hierarchical and distributed control concept for distribution network congestion management, IET Generation, Transmission & Distribution 11 (3) (2017) 665–675.

[34] I.-Y. Chung, S.-J. O. Cheol-HeeYoo, Distributed intelligent microgrid control using mul-ti-agent systems, Engineering 5 (01) (2013) 1.

[35] B. Kandpal, P. Pareek, A. Verma, A robust day-ahead scheduling strategy for ev charging stations in unbalanced distribution grid, Energy 249 (2022) 123737.

[36] J. Zhang, X. Kong, J. Shen, L. Sun, Day-ahead optimal scheduling of a standalone solar-wind-gas based integrated energy system with and without considering thermal inertia and user comfort, Journal of Energy Storage 57 (2023) 106187.

[37] T. Zhang, N. Hanousek, M. Qadrdan, R. Ahmadian, A day-ahead scheduling model of power systems incorporating multiple tidal range power stations, IEEE Transactions on Sustainable Energy (2022).

[38] M. Tostado-Véliz, S. Kamel, H. M. Hasanien, R. A. Turky, F. Jurado, Uncertainty-aware day-ahead scheduling of microgrids considering response fatigue: An igdt approach, Applied Energy 310 (2022) 118611.

[39] A. H. Mobaraki, P. Salyani, A. Safari, A. Quteishat, M. A. Younis, A hybrid robust-stochastic optimization model for planned outage based day-ahead scheduling of a plug-in electric vehicles parking lot, Sustainable Energy Technologies and Assessments 54 (2022) 102831.

[40] X. Yang, L. Fan, X. Li, L. Meng, Day-ahead and real-time market bidding and scheduling strategy for wind power participation based on shared energy storage, Electric Power Systems Research 214 (2023) 108903.

[41] T. Wu, J. Wang, X. Lu, Y. Du, Ac/dc hybrid distribution network reconfiguration with microgrid formation using multi-agent soft actor-critic, Applied Energy 307 (2022) 118189.

[42] M. S. Jonban, L. Romeral, A. Akbarimajd, Z. Ali, S. S. Ghazimirsaeid, M. Marzband, G. Putrus, Autonomous energy management system with self-healing capabilities for green buildings (microgrids), Journal of Building Engineering 34 (2021) 101604.

[43] H. K. Nunna, A. M. Saklani, A. Sesetti, S. Battula, S. Doolla, D. Srinivasan, Multi-agent based demand response management system for combined operation of smart microgrids, Sustainable Energy, Grids and Networks 6 (2016) 25–34.

[44] V. Stennikov, E. Barakhtenko, G. Mayorov, D. Sokolov, B. Zhou, Coordinated management of centralized and distributed generation in an integrated energy system using a multi-agent approach, Applied Energy 309 (2022) 118487.

[45] Q.-Q. Zhang, R.-J. Wai, Distributed secondary control of islanded micro-grid based on adaptive fuzzy-neural-network-inherited total-sliding-mode control technique, International Journal of Electrical Power & Energy Systems 137 (2022) 107792.

[46] I. Jendoubi, F. Bouffard, Multi-agent hierarchical reinforcement learning for energy management, Applied Energy 332 (2023) 120500.

[47] J. Zhao, W. Wang, C. Guo, Hierarchical optimal configuration of multi-energy microgrids system considering energy management in electricity market environment, International Journal of Electrical Power & Energy Systems 144 (2023) 108572.

[48] M. Blonsky, K. McKenna, J. Maguire, T. Vincent, Home energy management under realistic and uncertain conditions: A comparison of heuristic, deterministic, and stochastic control methods, Applied Energy 325 (2022) 119770.

[49] S. Yelisetti, V. K. Saini, R. Kumar, R. Lamba, A. Saxena, Optimal energy management system for residential buildings considering the time of use price with swarm intelligence algorithms, Journal of Building Engineering 59 (2022) 105062.

[50] S. Abedi, S. W. Yoon, S. Kwon, Battery energy storage control using a reinforcement learning approach with cyclic time-dependent markov process, International Journal of Electrical Power & Energy Systems 134 (2022) 107368.

[51] Q. He, M. Wu, C. Liu, D. Jin, M. Zhao, Management and real-time monitoring of interconnected energy hubs using digital twin: Machine learning based approach, Solar Energy 250 (2023) 173–181.

[52] L. Ma, N. Liu, L. Wang, J. Zhang, J. Lei, Z. Zeng, C. Wang, M. Cheng, Multi-party energy management for smart building cluster with pv systems using automatic demand response, Energy and Buildings 121 (2016) 11–21.

[53] M. Elkazaz, M. Sumner, D. Thomas, A hierarchical and decentralized energy management system for peer-to-peer energy trading, Applied Energy 291 (2021) 116766.

[54] K. Park, I. Moon, Multi-agent deep reinforcement learning approach for ev charging scheduling in a smart grid, Applied Energy 328 (2022) 120111.

[55] M. Selseleh Jonban, A. Akbarimajd, J. Javidan, Intelligent fault tolerant energy management system with layered architecture for a photovoltaic power plant, Journal of Solar Energy Engineering 137 (1) (2015).

[56] S. Vaisi, M. Firouzi, P. Varmazyari, Energy benchmarking for secondary school buildings, applying the top-down approach, Energy and Buildings 279 (2023) 112689.

[57] M. Monfared, M. Rezazadeh, Z. Alipour, Road networks reliability estimations and optimizations: A bi-directional bottom-up, top-down approach, Reliability Engineering & System Safety 222 (2022) 108427.

[58] X. Kang, X. Wang, J. An, D. Yan, A novel approach of day-ahead cooling load prediction and optimal control for ice-based thermal energy storage (tes) system in commercial buildings, Energy and Buildings 275 (2022) 112478.

[59] A. Z. G. Seyyedi, E. Akbari, M. H. Atazadegan, S. M. Rashid, A. Niazazari, S. Shahmoradi, A stochastic tri-layer optimization framework for day-ahead scheduling of microgrids using cooperative game theory approach in the presence of electric vehicles, Journal of Energy Storage 52 (2022) 104719.

[60] T. Ouyang, M. Zhang, W. Wu, J. Zhao, H. Xu, A day-ahead planning for multi-energy system in building community, Energy 267 (2023) 126399.

[61] R. Sabzehgar, D. Z. Amirhosseini, M. Rasouli, Solar power forecast for a residential smart microgrid based on numerical weather predictions using artificial intelligence methods, Journal of Building Engineering 32 (2020) 101629.

[62] Y. Li, N. Bonyadi, A. Papakyriakou, B. Lee, A hierarchical decomposition approach for multi-level building design optimization, Journal of Building Engineering 44 (2021) 103272.

[63] S. Ahmadi, A. H. Fakehi, A. Vakili, M. Moeini-Aghtaie, An optimization model for the long-term energy planning based on useful energy, economic and environmental pollution reduction in residential sector: A case of iran, Journal of Building Engineering 30 (2020) 101247.

[64] J. Jurasz, M. Guezgouz, P. E. Campana, A. Kies, On the impact of load profile data on the optimization results of off-grid energy systems, Renewable and Sustainable Energy Reviews 159 (2022) 112199.

[65] A. A. Ewees, M. A. Al-qaness, L. Abualigah, M. Abd Elaziz, Hbo-lstm: Optimized long short term memory with heap-based optimizer for wind power forecasting, Energy Conversion and Management 268 (2022) 116022.

[66] A. Fathy, T. M. Alanazi, H. Rezk, D. Yousri, Optimal energy management of micro-grid using sparrow search algorithm, Energy Reports 8 (2022) 758–773.

[67] F. Zhou, Y. Li, W. Wang, C. Pan, Integrated energy management of a smart community with electric vehicle charging using scenario based stochastic model predictive control, Energy and Buildings 260 (2022) 111916.

[68] L.-N. Liu, G.-H. Yang, Distributed optimal energy management for integrated energy systems, IEEE Transactions on Industrial Informatics 18 (10) (2022) 6569–6580.

[69] A. O. Ali, A. M. Hamed, M. M. Abdelsalam, M. N. Sabry, M. R. Elmarghany, Energy management of photovoltaic-battery system connected with the grid, Journal of Energy Storage 55 (2022) 105865.

[70] S. Rai, H. Mathur, R. C. Bansal, Optimal energy management of nanogrid using battery storage system, Sustainable Energy Technologies and Assessments 55 (2023) 102921.

[71] W. Li, H. Cui, T. Nemeth, J. Jansen, C. Uenluebayir, Z. Wei, L. Zhang, Z. Wang, J. Ruan, H. Dai, et al., Deep reinforcement learning-based energy management of hybrid battery systems in electric vehicles, Journal of Energy Storage 36 (2021) 102355.

[72] H. Fallahzadeh-Abarghouei, S. Hasanvand, A. Nikoobakht, M. Doostizadeh, Decentralized and hierarchical voltage management of renewable energy resources in distribution smart grid, International Journal of Electrical Power & Energy Systems 100 (2018) 117–128.

[73] M. S. Golsorkhi, D. J. Hill, H. R. Karshenas, Distributed voltage control and power management of networked microgrids, IEEE Journal of Emerging and Selected Topics in Power Electronics 6 (4) (2017) 1892–1902.

[74] M. R. B. Khan, R. Jidin, J. Pasupuleti, Multi-agent based distributed control architecture for microgrid energy management and optimization, Energy Conversion and Management 112 (2016) 288–307.

[75] J. Lagorse, D. Paire, A. Miraoui, A multi-agent system for energy management of distributed power sources, Renewable energy 35 (1) (2010) 174–82.

[76] A. Tahri, H. El Fadil, F. Belhaj, K. Gaouzi, A. Rachid, F. Giri, F. Chaoui, Management of fuel cell power and supercapacitor state-of-charge for electric vehicles, Electric Power Systems Research 160 (2018) 89–98.

[77] R. Teodorescu, M. Liserre, P. Rodriguez, Grid converters for photovoltaic and wind power systems, Vol. 29, John Wiley & Sons, 2011.

[78] M. Marzband, H. Alavi, S. S. Ghazimirsaeid, H. Uppal, T. Fernando, Optimal energy management system based on stochastic approach for a home microgrid with integrated responsive load demand and energy storage, Sustainable cities and society 28 (2017) 256–264.

[79] T. Logenthiran, R. T. Naayagi, W. L. Woo, V.-T. Phan, K. Abidi, Intelligent control system for microgrids using multiagent system, IEEE Journal of Emerging and Selected Topics in Power Electronics 3 (4) (2015) 1036–1045.

[80] G. Artale, A. Cataliotti, V. Cosentino, D. Di Cara, S. Guaiana, N. Panzavecchia, G. Tinè, Real-time power flow monitoring and control system for microgrids integration in islanded scenarios, IEEE Transactions on Industry Applications 55 (6) (2019) 7186–7197.

[81] R. Brooks, A robust layered control system for a mobile robot, IEEE journal on robotics and automation 2 (1) (1986) 14–23.

[82] G. Schouten, J. Steckel, A biomimetic radar system for autonomous navigation, IEEE Transactions on Robotics 35 (3) (2019) 539–548.

[83] H. Boterenbrood, Canopen high-level protocol for can-bus, Nikhef, Amsterdam 20 (2000).

[84] M. Esro, A. A. Basari, S. Kumar, M. Sadhiqin, Z. Syariff, Controller area network (can) application in security system, World Academy of Science, Engineering and Technology 35 (2009).

[85] Y. Zhu, F. Zhuo, L. Xiong, Communication platform for energy management system in a master-slave control structure microgrid, in: Proceedings of The 7th International Power Electronics and Motion Control Conference, Vol. 1, IEEE, 2012, pp. 141–145.

[86] D. Han, C. Zhang, J. Ping, Z. Yan, Smart contract architecture for decentralized energy trading and management based on blockchains, Energy 199 (2020) 117417.

[87] P. Petrou, M. A. Talias, Price determinants of the tendering process for pharmaceuticals in the cyprus market, Value in Health Regional Issues 7 (2015) 67–73.

[88] J. Terán, J. Aguilar, M. Cerrada, Integration in industrial automation based on multi-agent systems using cultural algorithms for optimizing the coordination mechanisms, Computers in Industry 91 (2017) 11–23.

[89] N. Hooshangi, A. A. Alesheikh, Agent-based task allocation under uncertainties in disaster environments: An approach to interval uncertainty, International journal of disaster risk reduction 24 (2017) 160–171.

[90] M. S. Jonban, A. Akbarimajd, M. Hassanpour, A combined auction mechanism for online instant planning in multi-robot transportation problem, Advances in robotics research 2 (3) (2018) 247.

[91] T. Nodehi, A. Zutshi, A. Grilo, B. Rizvanovic, Ebdf: The enterprise blockchain design framework and its application to an e-procurement ecosystem, Computers & Industrial Engineering 171 (2022) 108360.

[92] V. Hassija, V. Chamola, D. N. G. Krishna, N. Kumar, M. Guizani, A blockchain and edge-computing-based secure framework for government tender allocation, IEEE Internet of Things Journal 8 (4) (2020) 2409–2418.

[93] A. Tezel, P. Febrero, E. Papadonikolaki, I. Yitmen, Insights into blockchain implementation in construction: models for supply chain management, Journal of management in engineering 37 (4) (2021) 04021038.

[94] B. Elyakime, J. J. Laffont, P. Loisel, Q. Vuong, First-price sealed-bid auctions with secret reservation prices, Annales d'Economie et de Statistique (1994) 115–141.

[95] M. L. Puterman, Markov decision processes, Handbooks in operations research and management science 2 (1990) 331–434.

[96] D. M. Roijers, P. Vamplew, S. Whiteson, R. Dazeley, A survey of multi-objective sequential decision-making, Journal of Artificial Intelligence Research 48 (2013) 67–113.

[97] A. Likas, N. Vlassis, J. J. Verbeek, The global k-means clustering algorithm, Pattern recognition 36 (2) (2003) 451–461.

[98] K. P. Sinaga, M.-S. Yang, Unsupervised k-means clustering algorithm, IEEE access 8 (2020) 80716–80727.