Chapter 2

Energy Management: Frameworks and Solution Approaches

2.1 Introduction

A large number of controllable DERs, such as DG units, EVs and D-BESS, and demand responsive loads, require effective and efficient control schemes for DNO to operate and exchange information with local operators (MGO or/and other aggregators). In the new scenario, consumers now play an important role in energy trading because of their demand-response characteristics and they can also act as seller due to the excess of energy generated from RES installed in their premises or stored in battery storage. Therefore, to fulfill the above trading arrangement, optimal pricing scheme would be required. This chapter gives an overview of the energy management frameworks reported in the subsequent chapters. The management frameworks are in context of distribution system with multiple operating agents. First, the energy scheduling problem is described with the coordination schemes that can be implemented via the EMS interface. Later, the chapter presents the solution methodologies that will be followed in the simulation studies carried out in the subsequent chapters.

2.2 Energy Management Frameworks

The main function of EMS is to optimally balance load and supply to achieve the given objectives. This work presents the integrated scheduling of different DERs (dispatchable generators, RESs, PHEVs, D-BESSs, and consumer loads with demand response) controlled by different operators/aggregators, taking into account the restructuring of the distribution network and the active involvement of multiple operating agents with some conflicting and some non-conflicting goals. Different technical and economic objectives, such as cost minimization, GHG reduction, real power loss minimization, bus voltage profile improvement, and optimal power exchange with main grid are considered in the proposed framework. Three different energy management frameworks are examined based on the ownership and control of the DERs by different operating agents. Energy management frameworks can be described as follows.

2.2.1 Centralized energy management framework

In this framework, the central controller such as Distribution Utility (DU) is responsible for scheduling and controlling the flow of electricity from energy producers to consumers. It is assumed that the central controller is empowered to operate and control all DERs. To optimize all DERs and supply power to consumers, the central controller accumulates all the information, such as RESs generation availability, consumer demand, parameters related to PHEVs (arrival time, departure time, owner energy requirement), SOC level of D-BESS, cost functions of dispatchable generator, electricity tariff. The solution of the scheduling problem depends on the certain objectives considered in the proposed framework. The centralized energy management framework is depicted in Figure 2.1.

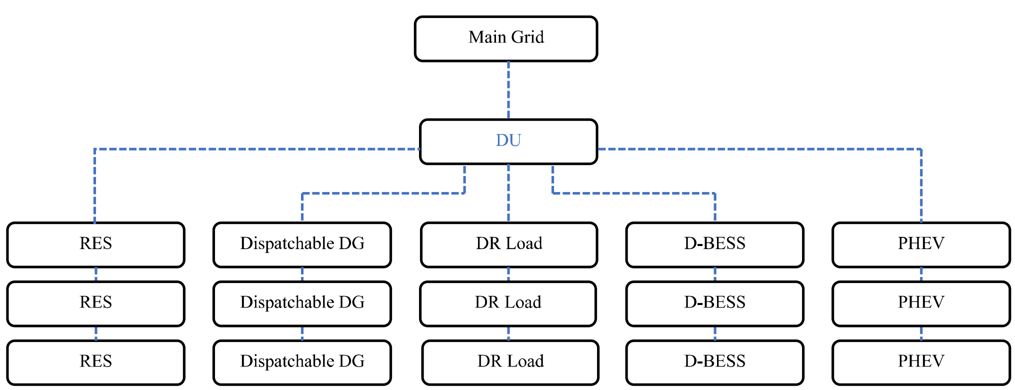

Figure 2.1: Centralized energy management framework

A two-way communication link must exist between central controller and DERs. The central controller sends the controlling signals to all the resources and consumers. This framework needs a large amount of information exchange.

2.2.2 Distributed energy management framework with multiple operating agents

Aggregation and communication infrastructure of distributed energy management system is depicted in Figure 2.2.

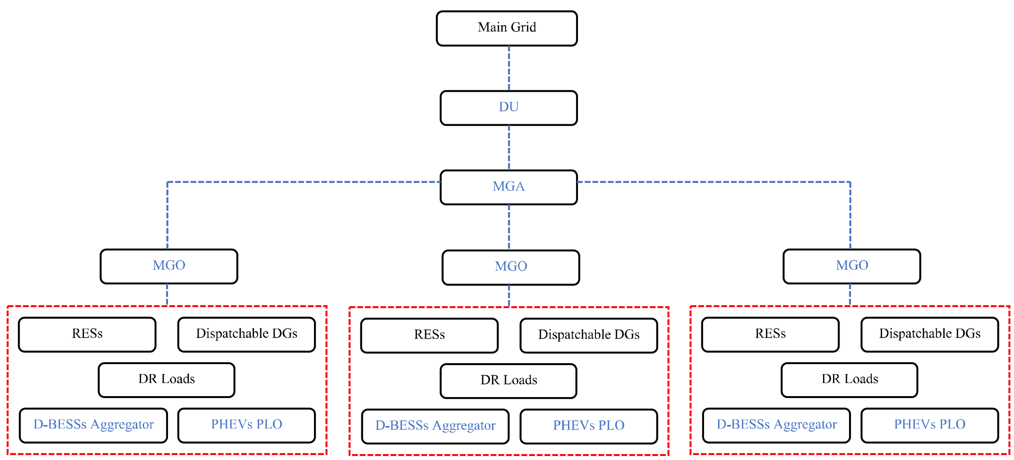

Figure 2.2: Energy management framework with multiple operating agents

In this framework, the various DERs are aggregated by a controller usually called as MGO, which is treated as a single entity. The MGO has autonomy to control and operate the DERs in its designated domain. Multiple network-connected MGs are considered in this framework. All MGOs operate in a cooperative manner to collectively act as a single entity in relation to Distribution Utility (DU). This co-operation is enabled by an entity called as MGs aggregator (MGA). The DU imposes certain power exchange limits and provides information regarding electricity tariff to the MGA. The MGA is regarded as an intermediary between the MGOs and the DU, and is responsible for power allocation among MGs and generates a price signal for power trading among the MGOs. All MGOs schedule their assets independently with some power exchange constraints and they are coordinated via price signal for economic benefits. Therefore all the MGOs can operate in a decentralized manner to optimize MGO-owned energy resources and prosumers with minimum mandatory information sharing. The proposed framework eliminates the joint scheduling of all MGs for cooperative operations. Further, PHEVs and D-BESSs are aggregated by PL operators and D-BESS aggregators within a MG. MGO uses time-varying tariffs to coordinate the PL operators and D-BESS aggregators, and to encourage the flexibility and contribution of PLs and D-BESSs in MG's energy management. The aggregation (of different agents) and decentralized scheduling reduces the amount of information exchange required and addresses some privacy issues.

2.2.3 Hierarchical energy management framework

The Integrated Energy Management Framework based on hierarchical decision making for ADNs with network-connected MGs is depicted in Figure 2.3.

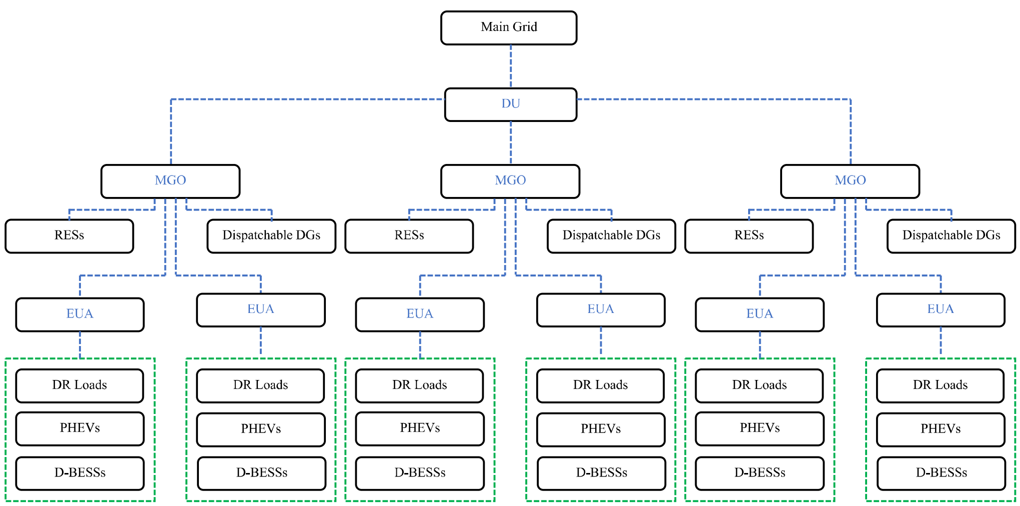

Figure 2.3: Hierarchical energy management framework

The different levels of this hierarchical model in order of hierarchy are DU, MGOs and EUAs. In this energy management framework with multiple operating agents, the objectives of different agents may or may not be same. However, the decisions of all the agents are inter-related with each other. The optimization problem of the leader agent consists of nested optimization that corresponds to the optimization problem of the follower agent. For example, the DU optimization contains the optimality conditions of the MGO optimization problem and similarly MGO optimization includes the optimality conditions of the EUA. In this framework, the leader makes the first move, and then the follower reacts optimally to the leader's action. For the interaction between different leader-follower stages, the framework uses a game-theoretic dynamic pricing strategy to make use of the follower's flexibility to improve the technical and economic aspects.

2.3 Methodologies

Energy management frameworks examined in this thesis are introduced in the previous section. Depending on the objectives, coordination schemes and operational constraints of different operating agents, there is a need for dedicated solution approaches. The basic concepts of the methods implemented to develop the solution approaches for energy management framework are as follows.

2.3.1 Dantzig-Wolfe decomposition method

Dantzig–Wolfe Decomposition (DWD) method is a technique for efficient solution of linear and integer programming problems, with embedded substructures, in a decentralized manner [118, 119]. The DWD method can be used to divide the original problem into sub-problems and a master problem. The master problem, which is equivalent to the original problem in some respects, coordinates the sub-problems and ensures the satisfaction of the coupling constraints. As the problems of different operating agents are associated with certain constraints (coupling constraints), the optimal solution for the original problem cannot be achieved independently. Therefore, the DWD method can be adopted to deal with such optimization problems without the need to share privacy data. The basic mathematical structure of DWD method can be described as follows.
Consider the original problem as

$$min\ \{\mathbf{c}^T\mathbf{x}\ :\mathbf{A}\mathbf{x}=\mathbf{b},\ \mathbf{x}\geq\mathbf{0}\}, \tag{2.1}$$

where, constraint matrix $\mathbf{A}\mathbf{x}=\mathbf{b}$ has structure as follows.

$$\begin{bmatrix} \mathbf{A}_o & \mathbf{A}_{a_1} & \dots & \mathbf{A}_{a_N} \\ \mathbf{0} & \mathbf{B}_{a_1} & \dots & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{B}_{a_N} \end{bmatrix} \begin{bmatrix} \mathbf{x}_o \\ \mathbf{x}_{a_1} \\ \vdots \\ \mathbf{x}_{a_N} \end{bmatrix} = \begin{bmatrix} \mathbf{b}_o \\ \mathbf{b}_{a_1} \\ \vdots \\ \mathbf{b}_{a_N} \end{bmatrix}. \tag{2.2}$$

Here, $\mathbf{c}=\begin{bmatrix}\mathbf{c}_o & \mathbf{c}_{a_1} & \dots & \mathbf{c}_{a_N}\end{bmatrix}^T$ is the vector of cost coefficients. The column vectors $\mathbf{c}_o$ and $\mathbf{c}_{a_n}$ are the cost coefficients of main operating agent (i.e., MGO or DU) and the a_n^{th} operating agent (i.e., PHEVs, D-BESSs, or end-users), respectively. Similarly, the vectors $\mathbf{x}_o$ and $\mathbf{x}_{a_n}$ are associated with the variables of main operating agent and a_n^{th} operating agent, respectively. The dimension of the matrices and the sub-matrices given in Equations (2.1) and (2.2) are as follows.

$\mathbf{b} = number\ of\ constraints\ in\ original\ problem \times 1$

$\mathbf{x} = number\ of\ variables\ in\ original\ problem \times 1$

$\mathbf{A} = number\ of\ constraints \times number\ of\ variables\ in\ original\ problem$

$\mathbf{A}_o = number\ of\ coupling\ constraints \times variables\ associated\ with\ main\ operating\ agents$

$\mathbf{A}_{a_n} = number\ of\ coupling\ constraints \times variables\ associated\ with\ a_n^{th}\ operating\ agents$

$\mathbf{B}_{a_n} = number\ of\ constraints \times variables\ associated\ with\ a_n^{th}\ operating\ agents$

From the above said dimension, $\mathbf{B}_{a_n}\mathbf{x}_{a_n} = \mathbf{b}_{a_n}$ represents the set of constraints for the a_n^{th} operating agent, while $\mathbf{A}_o\mathbf{x}_o + \mathbf{A}_{a_1}\mathbf{x}_{a_1} + \cdots + \mathbf{A}_{a_N}\mathbf{x}_{a_N} = \mathbf{b}_o$ represents the set of coupling constraints. According to DWD method, the original problem can be decomposed into a master problem and a_N subproblems in the following manner.

The Master-problem contains restructured objective function, all the coupling constraints and constraints associated with only main operating agent. The Master-problem can be written as[1]

$$min\ \mathbf{c}_o^T\mathbf{x}_o + \sum_{a_n=1}^{a_N}\sum_{w=1}^{W}(\mathbf{c}_{a_n}^T\mathbf{x}_{a_n,w})u_{a_n,w}, \tag{2.3}$$

subject to

$$\mathbf{A}_o\mathbf{x}_o + \sum_{a_n=1}^{a_N}\sum_{w=1}^{W}(\mathbf{A}_{a_n}\mathbf{x}_{a_n,w})u_{a_n,w} = \mathbf{b}_o \qquad \boldsymbol{\lambda}, \tag{2.4}$$

$$\sum_{w=1}^{W} u_{a_n,w} = 1 \qquad \boldsymbol{\sigma_{a_n}}\ \ for\ \ a_n = 1, 2, ...a_N, \tag{2.5}$$

[1]Expression (2.3) can be expanded as,

$$min\ \begin{bmatrix} c_{o1} & c_{o2} & \dots & c_{op} \end{bmatrix}\begin{bmatrix} x_{o1} \\ x_{o2} \\ \vdots \\ x_{op} \end{bmatrix} + \begin{bmatrix} c_{a_1 1} & c_{a_1 2} & \dots & c_{a_1 q} \end{bmatrix}\begin{bmatrix} x_{a_1 1,1} & \dots & x_{a_1 1,w} & \dots & x_{a_1 1,W} \\ x_{a_1 2,1} & \dots & x_{a_1 2,w} & \dots & x_{a_1 2,W} \\ \vdots & \dots & \vdots & \dots & \vdots \\ x_{a_1 q,1} & \dots & x_{a_1 q,w} & \dots & x_{a_1 q,W} \end{bmatrix}\begin{bmatrix} u_{a_1,1} \\ \vdots \\ u_{a_1,w} \\ \vdots \\ u_{a_1,W} \end{bmatrix}$$

$$+ \dots + \begin{bmatrix} c_{a_N 1} & c_{a_N 2} & \dots & c_{a_N r} \end{bmatrix}\begin{bmatrix} x_{a_N 1,1} & \dots & x_{a_N 1,w} & \dots & x_{a_N 1,W} \\ x_{a_N 2,1} & \dots & x_{a_n 2,w} & \dots & x_{a_N 2,W} \\ \vdots & \dots & \vdots & \dots & \vdots \\ x_{a_N r,1} & \dots & x_{a_N r,w} & \dots & x_{a_N r,W} \end{bmatrix}\begin{bmatrix} u_{a_N,1} \\ \vdots \\ u_{a_N,w} \\ \vdots \\ u_{a_N,W} \end{bmatrix},$$

$$u_{a_n,w} \geq 0. \tag{2.6}$$

Here, variables $u_{a_n,w}$ assign weights to the w^{th} proposal of a_n^{th} operating agents. $\boldsymbol{\lambda}$ and $\boldsymbol{\sigma_{a_n}}$ are the dual variables. The coupling constraints are enforced by Equation (2.4) and convexity constraints are represented by Equation (2.5).

The Sub-problems (Pricing problems) enforce the constraints associated with individual operating agents and are solved independently by operating agents considering the dual values of master-problem. One of such sub-problem can be written as

$$min\ (\mathbf{c}_{a_n}^T - \boldsymbol{\lambda}^T \mathbf{A}_{a_n})\mathbf{x}_{a_n} - \sigma_{a_n}, \tag{2.7}$$

subject to

$$\mathbf{B}_{a_n}\mathbf{x}_{a_n} = \mathbf{b}_{a_n}, \tag{2.8}$$

$$\mathbf{x}_{a_n} \geq \mathbf{0}. \tag{2.9}$$

Whenever the objective value of the sub-problem (Equation (2.7)) is negative the proposal $\mathbf{x}_{a_n}^*$ (optimum solution of (2.7)) is added to the Master-problem, otherwise no master problem variable exists to improve the current solution. The schematic of DWD method is shown in Figure 2.4 [120] and the basic algorithm of DWD method is depicted in flow chart of Figure 2.5. If there is no optimal solution to any problem at any stage, the process will be aborted at that stage.

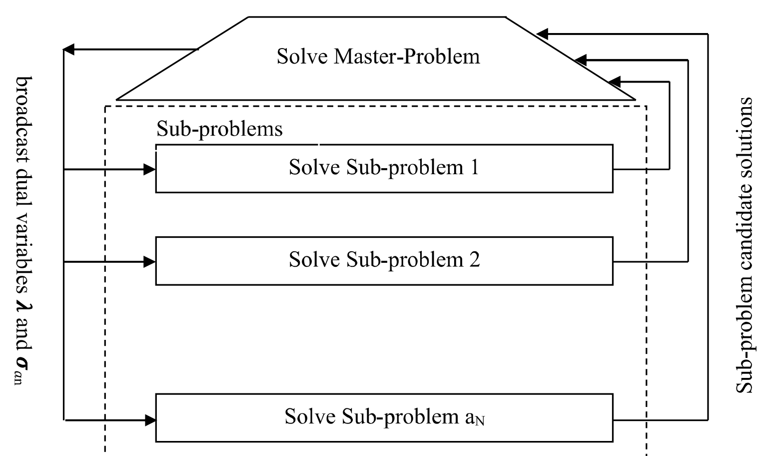

Figure 2.4: Schematic of Dantzig-Wolfe decomposition method

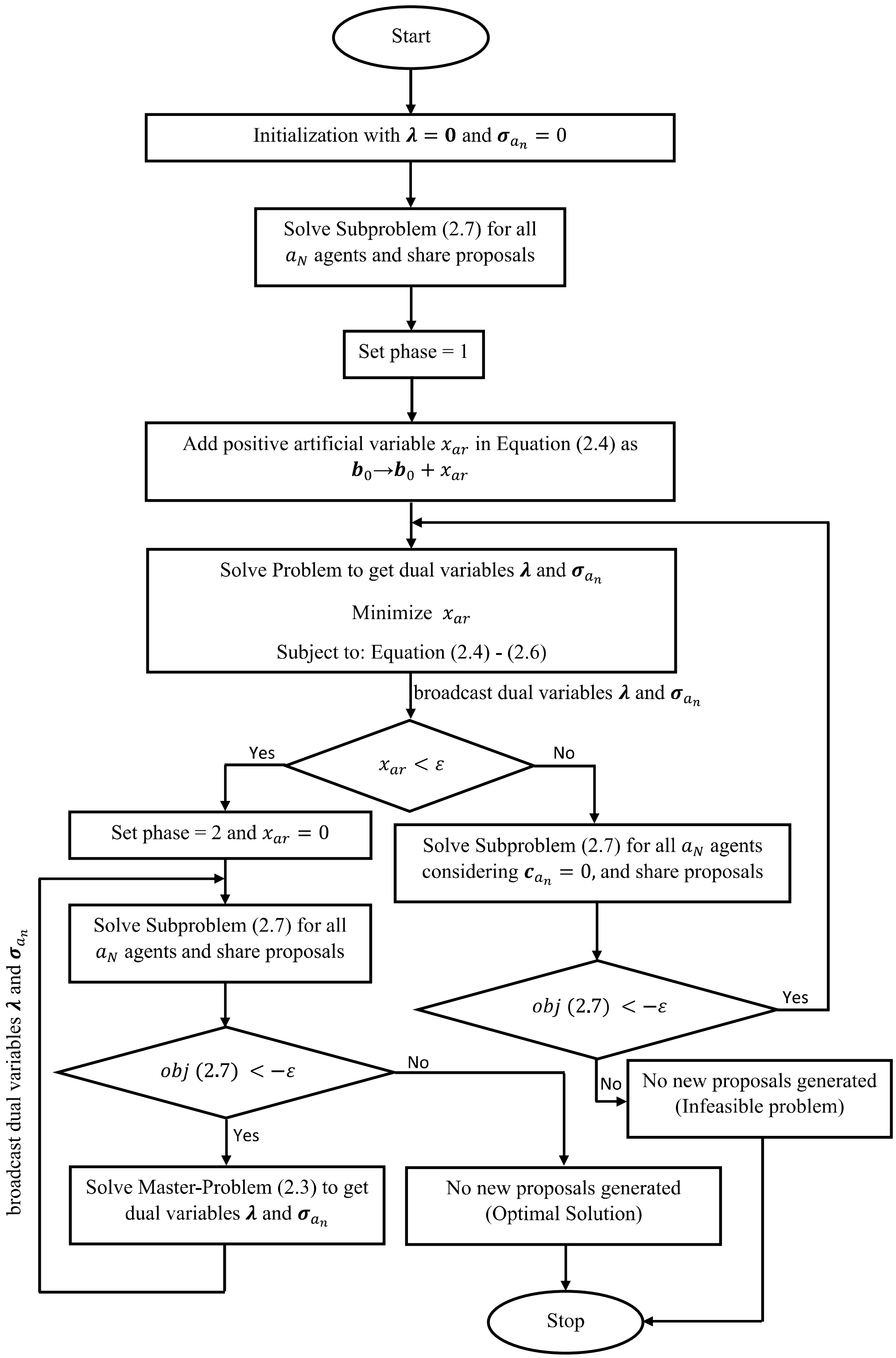

Figure 2.5: Basic algorithm for Dantzig-Wolfe Decomposition Method

2.3.2 ε-constraint method

In multi-objective optimization, optimal solution corresponding to a single objective cannot optimize all the objectives simultaneously. In contrast to a single optimal solution, the most preferred decision needs to be made in the presence of trade-offs between two or more conflicting objectives. The ε-constraint method is a technique to deal with multi-objective optimization problems [121]. In the ε-constraint method, there is no need to scale the objective functions on a common scale. The ε-constraint method can be described as follows.

Assume the following multi-objective problem

$$min(f_1(x), f_2(x), ..., f_p(x)), \tag{2.10}$$

subject to,

$$x \in S.$$

Here, x is the decision vector, $f_1(x)$, $f_2(x)$,....,$f_p(x)$ are p objective functions to be minimized, and S is feasible region.

In ε-constraint method, one of the objective function is optimized and other $(p-1)$ objective functions are considered as inequality constraints along with other constraints of the problem. Now, the problem can be redefined as

$$min f_1(x), \tag{2.11}$$

subject to,

$$f_2(x) \leq \varepsilon_2, ..., f_n(x) \leq \varepsilon_n, ..., f_p(x) \leq \varepsilon_p,$$

$$x \in S,$$

where,

$$\varepsilon_n = max(f_n) - [max(f_n) - min(f_n)] \times \left(\frac{\beta_n}{\alpha - 1}\right). \tag{2.12}$$

Here, α is a user defined integer parameter and possible values of β_n are 0,1,2,.....$(\alpha - 1)$.

To find max(f_n) and min(f_n), each function is optimized "individually" and a pay-off table is constructed, as shown in Equation (2.13).

$$\begin{bmatrix} f_1^*(x_1^*) & f_2(x_1^*) & \dots & f_n(x_1^*) & \dots & f_p(x_1^*) \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ f_1(x_n^*) & f_2(x_n^*) & \dots & f_n^*(x_n^*) & \dots & f_p(x_n^*) \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ f_1(x_p^*) & f_2(x_p^*) & \dots & f_n(x_p^*) & \dots & f_p^*(x_p^*) \end{bmatrix} \tag{2.13}$$

In pay-off table given by Equation (2.13), x_n^* is the optimal value of x when $f_n(x)$ is considered as an objective function to be optimized in problem (2.10). $f_n^*(x_n^*)$ represent the optimum value of f_n and $f_p(x_n^*)$ is the value of f_p when n^{th} function is optimized individually.

2.3.3 Shapley value method

The Shapley Value Method (SVM) is an appropriate solution concept used in cooperative game theory to fairly distribute profits/costs to multiple players working in coalition [122, 123]. The Shapley value primarily applies to situations where each player works in a coalition with unequal contributions to obtain a gain/payoff. The SVM defines the importance and contribution of the each player in the coalition. For a coalitional game (ψ, N), the Shapley value, $\phi^i(\psi)$, of the i^{th} player can be obtained as

$$\phi^i(\psi) = \sum_S \left(\frac{(n- \mid S \mid)!(\mid S \mid -1)!}{n!} \right) \left(\psi(S) - \psi(S - \{i\}) \right). \tag{2.14}$$

Here, N is the set of n players, ψ is the characteristic function and $|S|$ is the number of players in coalition S. $\psi(S)$ is the total profit/cost of coalition S and $\psi_t(S - \{i\})$ is profit/cost of coalition S without participation of i^{th} player.

2.4 Summary

An overview of different energy management frameworks for a distribution system with multiple operating agents and coordination schemes has been described in this chapter. The basic concepts of three methods viz. Dantzig-Wolfe decomposition, ε-constraint method, and Shapley value method has also been described in this chapter. These methods will be used in the subsequent chapters to develop the problem specific solution approaches for energy management frameworks.