Chapter 2

Literature Review

2.1 Introduction

This chapter presents a thorough examination of pertinent literature, encompassing journal articles, conference papers, theses and internet resources in order to enhance comprehension of the research challenges under investigation. The following sections offer an extensive review of the related research, which forms the foundation for the current thesis. This chapter begins with a discussion on meta-heuristic algorithms which cover well established and newly developed algorithms within the past decade, which have been used for comparative investigation to address the design optimization challenges in renewable energy systems reported in this thesis. The review of recent trends in hybridization of optimization algorithms is also briefly covered. We proceed to introduce the challenge of design optimization involved with DC-DC converters. The methodologies developed for addressing the design optimization problem are discussed in brief along with their limitations. This is followed by discussion on the DC-DC converter interface employed for the MPPT applications in PV systems. Studies on improved circuit configurations and subsequent advantages and disadvantages of non-isolated and isolated converter topologies are discussed. Moreover, a discussion on the various MPPT algorithms as evident in literature and the key areas which present opportunity for exploring possible solutions are highlighted.

This is followed by discussion on the major algorithms that have been employed to address the issues and challenges involved in design optimization of HRES. The complementary nature of renewable energy sources is also established as documented in literature. Furthermore, the major optimization algorithms employed with relation to HRES design optimization based on application of Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Fuzzy Logic Algorithm (FLA) and including recently developed algorithms are discussed briefly.

2.2 Metaheuristic Algorithms

Metaheuristics are common optimization algorithms because they provide realistic time-to-optimal solutions to a variety of nonlinear situations [41, 74, 253]. Compared to derivative-based optimization techniques like Steepest Descent and Newton Method, they have a faster convergence to the optimal solution and lower computing cost [147, 177].These methods have a better degree of accuracy when calculating the global optimum and can avoid the local optimum. Exploration and exploitation are the two search phases that metaheuristic optimization algorithms employ. In order to locate solutions while avoiding local optima, the search space is thoroughly examined in the exploration stage. In the exploitation stage, the algorithms' ability to spot potential solutions is then employed to improve the quality of the solutions in a particular local area [88, 229].

Metaheuristics are typically categorized as being based on evolution, swarm intelligence, and/or physical principles [8]. The idea of evolution in nature serves as the inspiration for evolutionary algorithms. One of the most popular classical optimization techniques based on Darwin's idea of evolution is the Genetic Algorithm (GA)[75, 237]. In this area, there are other approaches based on evolutionary programming [204], differential evolution [40, 95] and evolutionary strategy[73, 82]. Swarm intelligence systems mimic the foraging or movement patterns of diverse animal swarms. The information exchange with other animals throughout the optimization process is the primary characteristic of algorithms in this category [234]. Examples of swarm intelligence-based algorithms include Artificial Bee Colony (ABC)[106], Salp Swarm Algorithm (SSA)[6], Whale Optimization Algorithm (WOA)[154], Ant Lion Optimisation (ALO)[151], Ant Colony Optimisation (ACO)[45], Bat Algorithm (BA)[263], Particle Swarm Optimization (PSO) [112] and Grey Wolf Optimizer (GWO)[156]. Some of the more recently created swarm-based metaheuristics include Artificial Hummingbird Algorithm (AHA) [277], Dragonfly Algorithm (DFA) [148], Harris Hawk's Optimization (HHO) [227], and Moth Flame Optimization (MFO) [152]. The rules of physics or physical phenomena in nature have served as inspiration for the development of physics-based approaches. Simulated annealing (SA)[114] and gravitational search algorithm (GSA)[195] are the two most used algorithms. The big bang big crunch

(BB-BC) algorithm [55], atom search optimization (ASO) [278], equilibrium optimizer (EO) [59], flow direction algorithm (FDA) [108], multi-verse optimizer (MVO) [155], artificial electric field algorithm (AEFA) [258] are recently created, well-known algorithms that belong to this category.

The metaheuristic algorithms that were employed in this research work are broken down into three distinct groups those that are formed on the basis of swarm intelligence, those that are physics based, and those that fall into other categories. The classification under the third category referred to as "Other Algorithms" includes algorithms that are based on evolutionary principles, behavior of humans, and mathematics theorems or principles, respectively [266]. In order to restrict the detailed explanation of methods, a concise explanation of the metaheuristic algorithms is presented. Figure 2.1 gives a pictorial depiction of the algorithms under consideration in the current study. Furthermore, the hybridization of algorithms for formulating improvements in an individual algorithms' performance is also discussed.

2.2.1 Swarm Intelligence Based Algorithms

The introduction of metaheuristic algorithms for the class of swarm intelligence in this section covers the sine cosine algorithm (SCA), ant lion algorithm (ALO), dragonfly algorithm (DFA), artificial bee colony (ABC), harris hawk's optimization (HHO), salp swarm algorithm (SSA), marine predator algorithm (MPA) and artificial hummingbird algorithm(AHA), grey wolf optimizer (GWO), improved grey wolf optimizer (IGWO), moth flame optimizer (MFO), particle swarm optimization (PSO), firefly algorithm (FFA) and whale optimization algorithm (WOA).

2.2.1.1 Sine Cosine Algorithm (SCA)

The population-based SCA method makes use of the mathematical sine and cosine functions [4, 153] to update specific places in the direction of the optimum solution. SCA commences the optimization procedures by utilizing a collection of randomly generated starting solutions. The aim (goal) for all other solutions is to be upgraded to the best-performing solution. With an increasing number of iterations, the SCA may effectively exploit the goal space by adapting the ranges of the sine and cosine functions. The optimization procedure is ended if the maximum number of iterations is achieved.

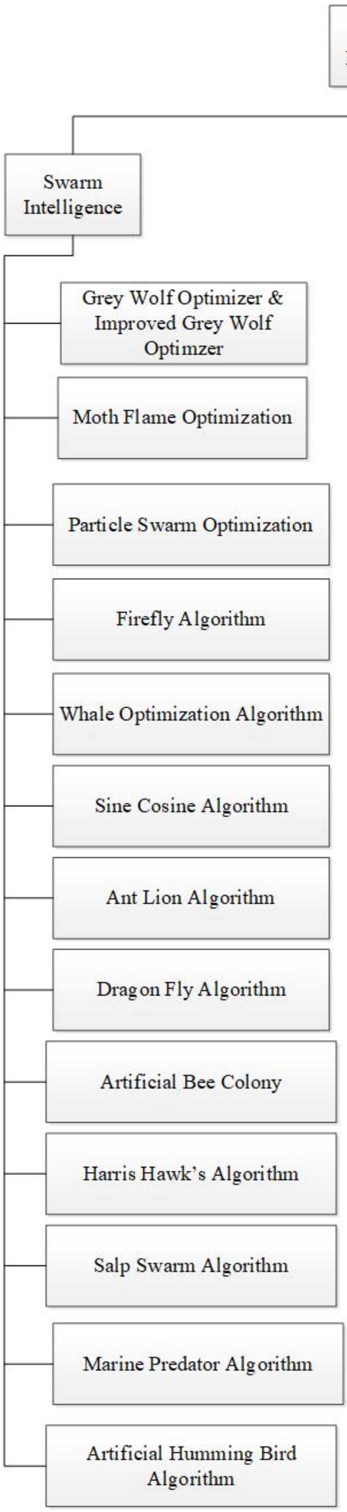

Figure. 2.1: Classification of Metaheuristic Algorithms considered in the study

2.2.1.2 Ant Lion Algorithm (ALO)

ALO mimics how ant lions hunt while they are still in their larvae state [125,151]. The antlion larvae create conical depressions by following a circular path, which function as traps for the prey they pursue inside the ant's environment. An ant lion intentionally moves sand towards the edge of the pit upon spotting prey, resulting in the prey falling down. In order to make room for the next hunt, the ant lion finishes its hunt by consuming its prey. The ant lion, pit, and the ants serve as the fundamental inspiration for the optimization model created for the ALO algorithm. The ALO method solves an optimization issue by using two distinct populations. The initial population consists of ants, who function as potential answers to the optimization problem and exhibit random movement within the search space. The following category consists of ant lions, which can be discovered in different locations of the search area at various times. During the iteration phase, a single antlion is supposed to be picked using a roulette wheel framework, based on its fitness rating, to catch each ant.

2.2.1.3 Dragonfly Algorithm (DFA)

Dragonflies are little flying carnivores that hunt down and consume various microscopic creatures, and their static and dynamic swarming behavior inspired DFA [148]. The DFA model imitates the social behaviors of dragonflies using a combination of exploration and exploitation strategies. It enables the agent to hunt for food, search for resources, and avoid enemies while moving in both static and dynamic environments. Dragonflies engage in long-distance migration, moving in big groups in a single direction to avoid predators. This behavior is known as the exploitation phase. Small colonies of dragonflies move between various places in order to find food and attract gliding prey during the exploration phase. In each iteration, the location of each dragonfly in the swarm is changed based on the key concepts of opposition, alignment, affinity to a feeding spot, and diversion from opponents. Dissociation refers to the deliberate act of avoiding physical contact with others who are in close proximity. Alignment indicates the degree of speed compatibility among the members of an individual's adjacent group. Coherence refers to the inclination of a group to converge towards its central point.

2.2.1.4 Artificial Bee Colony (ABC)

Dervis Karaboga introduced the Artificial Bee Colony (ABC) algorithm in 2005 [107], and its capabilities have subsequently been shown in several real-world applications. This method finds its basis on the intelligent seeking behavior of a bee colony. The approach consists of three main components: food supply placements, nectar quantities, and distinct types of bees [106]. The ABC approach has the benefit of being competitive with other metaheuristic algorithms in numerical comparisons, with the advantage of requiring fewer control parameters to be used. The ABC approach has drawn a lot of attention and has been employed due to its simplicity and convenience of usage to tackle a wide range of real-world optimization problems [205].

Bees are classified into three categories based on their specific tasks. Typically, they represent potential solution locations that, in a metaphorical sense, resemble locales where food may be found. Employing the ABC technique, bees are categorized as worker, observer, or explorer. Worker bees make up 50% of the colony, while the other 50% consists of spectator bees. The population of worker bees in the hive is directly proportional to the amount of accessible food sources. Worker bees forage for food in close proximity to the food source they have stored in their memory and then transmit this information to observation bees. Observer bees have a preference for choosing the most optimal food sources that have not yet been discovered by worker bees. The exploring bees, on the other hand, are inherited from a limited group of worker bees that had previously forsaken their food sources in pursuit of substitutes.

The ABC technique starts by creating a population of potential solutions that are uniformly distributed at random. Following this initialization, the objective function is assessed to identify places that produce suitable solutions. The candidate solutions are altered by the three separate method operators utilizing the values provided by the objective function. If the fitness value fails to demonstrate any improvement after a predetermined number of cycles, the associated food source (position) is discarded and relocated to a randomly selected new place until the termination criteria are satisfied.

2.2.1.5 Harris Hawk's Optimization (HHO)

The hunting strategy of Harris hawks served as the model for the population-based algorithm known as HHO [227]. Harris hawks mimic the sudden jump made by a group of hawks when they gather and begin hunting together. They do this to collectively pursue and attack prey that they have identified, approaching from several directions. In relation to the prey's ability to avoid capture and its behavior, this event may demonstrate a variety of methods used to chase the prey, including many quick dives spanning many minutes toward the direction of the prey. Harris hawks keep a close eye on the fatigue and susceptibility of their identified prey in this manner. The most powerful and experienced falcon seizes the exhausted prey and distributes it among the other members of the group. The HHO method utilizes a vectorized starting population set to represent a collection of hawks, each with a distinct position. Exploration and exploitation stages in the algorithm helps to generate the total population. The solution vector that achieves the highest level of optimization at each iteration is utilized as a reference to ascertain the position of the prey. The aforementioned processes are carried out repeatedly till the maximum iteration number is secured.

2.2.1.6 Salp Swarm Algorithm (SSA)

The foraging and behavior of salps served as the basis for the population-based optimization technique known as SSA [6]. Salps aggregate in deep waters to form salp chains in order to locate food sources. SSA categorizes salps (individuals) as either leaders or followers according to their presence in the command hierarchy. Dominant salps actively seek for the optimal site for their feeding. Conversely, followers go towards the food source while directly or indirectly following the leader, which is the most favorable result up to this point. The salp population is assigned random initial positions using the SSA approach. The most optimal salp, or leader, is chosen based on the evaluation of each salp's fitness. The leader's position is updated and the optimal result for the food source variable is stored. The leader consistently exploits and scrutinizes his environment. The follower salps' spatial arrangement in relation to one another is modified by the algorithm. They do this to prevent being trapped at the local minimum as they gradually move towards the dominant salp.

2.2.1.7 Marine Predator Algorithm (MPA)

The MPA finds its inspiration based on the feeding habits evident in marine predators, which take into consideration the Levy flight and Brownian motion that is observable in nature, characterized in regions having low prey density with plentiful prey [58]. The optimization approach comprises three essential processes, which take into account different speed ratios when modeling the complete lifespan of both predators and prey. The first scenario arises when the prey is moving swiftly or when the predator is surpassing the prey in speed. When the velocity ratio is large (v $\geq$ 10), for the predator, staying still is the best course of action. Both the predator and the prey exhibit a similar or nearly identical velocity ratio in the second stage. That signifies the phase during which they are actively searching for prey. At this moment, the hunter is accountable for 50% of the population's exploration, while the prey bears responsibility for any exploitation associated with the remaining 50%. Traditionally, it is believed that the Brownian motion is the most effective strategy for predators when the prey travels according to a Levy distribution with a velocity ratio close to 1. The ultimate situation involves the predator surpassing the victim in speed. The use of Levy as a hunting method has shown to be highly beneficial for fish catchers, particularly when combined with fish aggregating devices (FADs) that have a low velocity ratio. FADs are regarded as local optima, and they only exert influence inside these specific regions of the search space. The incorporation of these extended jumps in the simulation causes the local optimum to continuously shift (v = 0.1). Environmental issues, such as those resulting from climate change, are an additional determinant of marine predator behavior.

2.2.1.8 Artificial Hummingbird Algorithm (AHA)

AHA imitates hummingbirds' unique foraging habits and flying abilities [277]. The algorithm incorporates axial, transverse, and unidirectional flights, as well as target-hunting, territorial, and migratory feeding approaches, to accurately imitate the flight capabilities of a hummingbird. Hummingbirds are directed towards food sources by a mimicry of their extraordinary memory, which is represented by a visiting table. A hummingbird assesses the quality of each flower's nectar, the rate at which it is filled, and the time that has passed since the last visit in order to choose a suitable source for feeding. The function's fitness value and the solution vector are denoted by the rate at which the nectar is filled in the food supply and the food source, respectively. Every hummingbird possesses a distinct food supply that is found in the exact same spot. A hummingbird monitors the position of the food supply and the pace of nectar accumulation in order to disperse it to other hummingbirds nearby. The temporal duration between successive trips to each of the food sources is likewise maintained in its memory. The frequency at which different hummingbird species visit each food source is tabulated as visitation records. Every level features a timer that shows the elapsed time since the last visit of a certain hummingbird to a specific food source. The hummingbird that is associated with a food source with high number of visitors is given precedence for visits. The preferred food source for each hummingbird is selected by updating the visitation table after each cycle.

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2.2.1.9 Grey Wolf Optimizer (GWO)

Seyedali Mirjalili developed the Grey Wolf Optimizer algorithm [156], which is based on the inspired learning in nature from the behavior of the pack characteristic in grey wolves (*Canis lupus*). This algorithm formulates the leadership and hunting abilities into an optimization framework. On an average a pack of wolves of the species usually have 5-12 members with a dominance hierarchy and the algorithm exploits this trait for the optimization process. The Grey wolves have the Alpha as leader of the pack. The alpha leads the pack and may not always be the strongest member in the pack. It is responsible to guide the pack when they are hunting for a prey. The Beta wolf is usually the second-in-command, follows the Alpha in the pecking order and is responsible for maintaining the hierarchical order in the pack and provide assistance to the Alpha in the form of feedback. The Omega is the wolf having the lowest ranking within the hierarchy. The Delta wolf includes all those members of the pack other than the Alpha, Beta, or Omega. These include the scouts, hunters, caretakers, sentinels, and elders. The figure 2.2 depicts the flowchart of the GWO algorithm.

In this algorithm, the order of preferred solutions is Alpha (α) > Beta (β) > Delta (δ). The remainder of the solutions are considered to be Omega (ω). The ω-wolves are at the bottom of the hierarchy pyramid. The mathematical representation of hunting to encircle the prey is formulated as:

$$\overrightarrow{D} = \overrightarrow{C}.\overrightarrow{X_P}(i) - \overrightarrow{X}(i) \tag{2.1}$$

$$\overrightarrow{X}(i+1) = \overrightarrow{X_P}(i) - \overrightarrow{A}.\overrightarrow{D} \tag{2.2}$$

Where $\overrightarrow{X}$ and $\overrightarrow{X_P}$ indicate the vectors that contain the position of the grey wolf and the prey, i indicates the current iteration count. Coefficient vectors $\overrightarrow{A}$ and

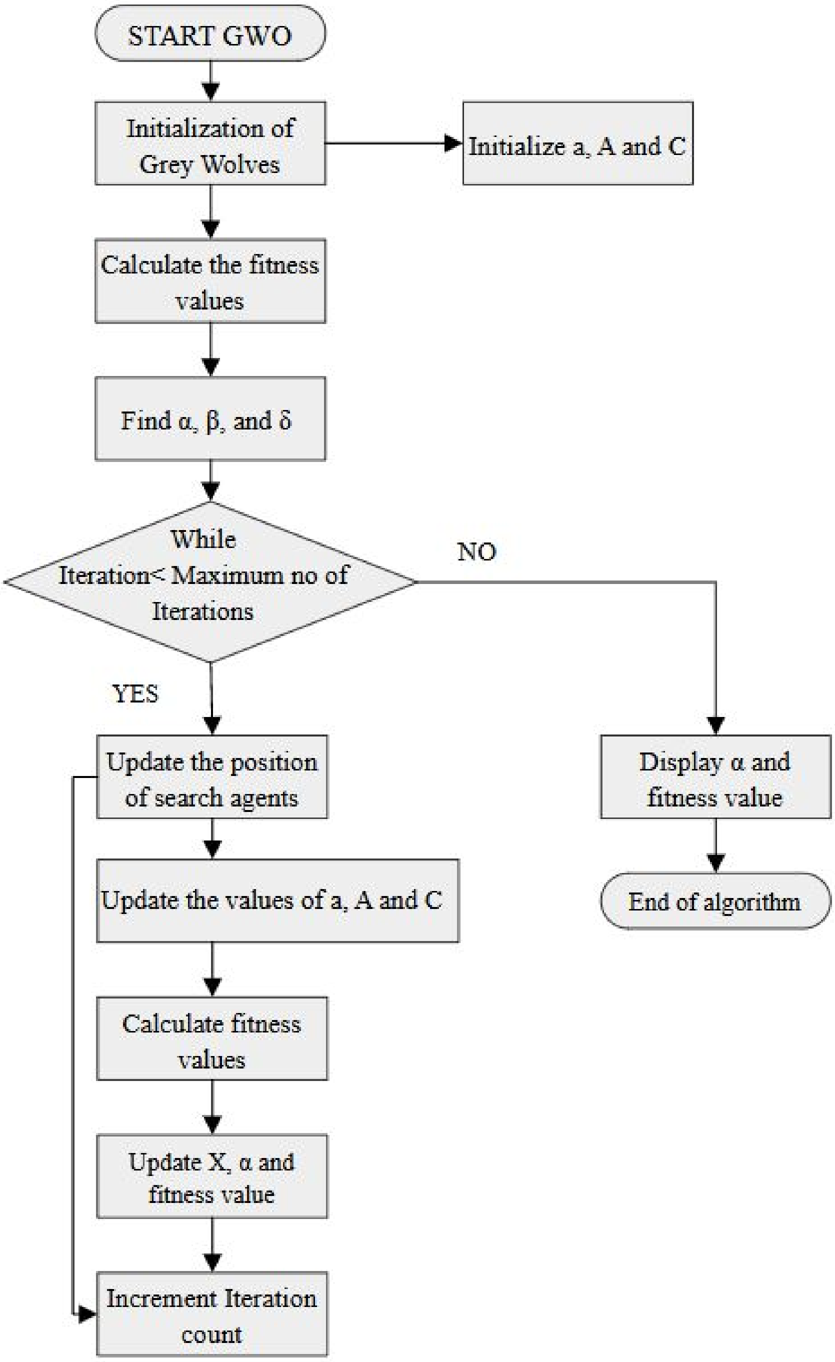

Figure. 2.2: Flowchart of the Grey Wolf Optimizer

$\overrightarrow{C}$ are numerically calculated as:

$$\overrightarrow{A} = 2 \cdot \overrightarrow{a} \cdot \overrightarrow{r_1} - \overrightarrow{a} \tag{2.3}$$

$$\overrightarrow{C} = 2 \cdot \overrightarrow{r_2} \tag{2.4}$$

The vectors r_1 and r_2 are random parameters that have values in the range [0,1] and vector $\overrightarrow{a}$ is linearly decreased from 2 to 0 over the course of iterations. Equations 2.1 and 2.2 mathematically express the positional updating of the pack members around the prey in any random manner. In nature the Alpha grey wolf leads the pack in hunting and others follow its lead. To mathematically formulate this behavior, we assume that prior information on the location of the prey is available to the Alpha and given that knowledge based on where the prey is positioned, the Beta and Delta wolves update their position accordingly. Three best solutions are marked which represent the Alpha, Beta and Delta values, while the remaining search agents in the pack update their position accordingly. This is given as:

$$\begin{aligned}\overrightarrow{D_\alpha} &= \overrightarrow{C_1}.\overrightarrow{X_\alpha} - \overrightarrow{X}\\ \overrightarrow{D_\beta} &= \overrightarrow{C_2}.\overrightarrow{X_\beta} - \overrightarrow{X}\\ \overrightarrow{D_\delta} &= \overrightarrow{C_3}.\overrightarrow{X_\delta} - \overrightarrow{X}\end{aligned} \tag{2.5}$$

The grey wolves adjust their location during hunting, which is given by,

$$\begin{aligned}\overrightarrow{X_1} &= \overrightarrow{X_\alpha} - \overrightarrow{A_1}.(\overrightarrow{D_\alpha})\\ \overrightarrow{X_2} &= \overrightarrow{X_\beta} - \overrightarrow{A_2}.(\overrightarrow{D_\beta})\\ \overrightarrow{X_3} &= \overrightarrow{X_\delta} - \overrightarrow{A_3}.(\overrightarrow{D_\delta})\end{aligned} \tag{2.6}$$

Mathematically the best position or candidate solution in the current iteration acts as a tool for updating the grey wolf's locations is given as:

$$\overrightarrow{X}(i+1) = (\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3})/3 \tag{2.7}$$

The parameter $\overrightarrow{A}$ is responsible for the exploration and exploitation of the algorithm.

2.2.1.10 Improved Grey Wolf Optimizer (IGWO)

Shahraki *et.al.* [167] presented the improved GWO algorithm. The algorithm tackles the issue related to insufficient variation in the wolves population, the tendency of converging on premature basis and also to enhance the algorithms utilization of the exploration and exploitation procedure. Authors introduce the concept of information exchange called dimension learning based hunting (DLH), with focus on sharing information between the neighboring wolves. This is able to balance the diversity in search for local and global solutions. During each iteration, the IGWO algorithm utilizes candidate wolves generated by the DLH strategy as well as position update search techniques to relocate the wolf X_i from its present position to a more optimal position. Furthermore, in each iteration the IGWO incorporates an extra phase for selecting and updating the winning candidate wolf, thereby the position update for the subsequent iteration is realized in the same iteration.

2.2.1.11 Moth Flame Optimization (MFO)

Seyedali Mirjalili introduced the Moth Flame Optimization (MFO) algorithm [152] characterized via moths' technique of navigating at night. The dependence on transverse orientation and the utilization of light from the moon as a guide by which moths navigate in nature is the main inspiration for this optimization technique. This trajectory changes when artificial lights in the form of spotlights or bulbs present as a source, which leads the moths to adjust their transverse flight in regard to the new sources and produce a updated spiral motion to close the distance between them and the source. The MFO emulates this behavior of navigation in moths. The spiral path of the moths is used as an operator to look for the search agents moving in the direction of the solution within the search area. The artificial light source then acts as the local solution while the moths act as the search particle or agent. Thus, the movement of the moths, albeit spiral in nature amounts to the search space's exploration by the moths acting as search agents around the local solution or the flame. A set of moths are used for this purpose where each moth performs the movement indicating the population-based approach of the algorithm. The particles or search agents within the search space correspond to a possible feasible optimum solution which is updated iteratively to find the global optima. Mathematically, the logarithmic model for the spiral path trajectory is represented by:

$$s_i = D_i e^{br} cos(2\pi r) + F_j \tag{2.8}$$

Here, the component D_i is the absolute value of the distance between the particle (or search agent) x_i and the local solution F_j given by:

$$D_i = \left| F_j - x_i \right| \tag{2.9}$$

The parameter b is a constant which is responsible for the shape of the logarithmic spiral and r is a vector equal to the dimension of the problem having values of random nature within the range [-2,1]. It determines the closeness of the updated solution to the local solution and is calculated for each dimension by:

$$r = (a - 1) \cdot rand + 1 \tag{2.10}$$

The parameter a is a convergence constant which dictates the exploitation of the algorithm as the solutions get updated iteratively and its values decreases linearly from -1 to -2, such that at the conclusion of each iteration step, the solutions are closer to the local solution.

2.2.1.12 Particle Swarm Optimization (PSO)

Kennedy and Eberhart [112] presented the Particle Swarm Optimization (PSO) to mimic the behavior of swarms of fish or birds. PSO has become a very popular and widely used swarm intelligence-based algorithm over the years due to its simplicity and flexibility. The algorithm operates to alter the particle trajectories as they look for food to find the objective function. The stochastic and deterministic components of the algorithm act as a guide to ascertain a particle's motion inside the swarm. The particles within the swarm converge towards the global best as well as its own local best position, to allow for random search within the search space, and converges with each iteration as the algorithm searches for the global optimum solution. When a particle locates a place in the search space that is superior to the places already discovered, the position is updated for that particle in the present iteration cycle. The algorithm finds the termination stage when the solutions obtained after a certain number of iteration cycles, no longer gets better. Figure 2.3 demonstrates how particles are moving throughout the search area, indicating the global best as well as the particle best. The directed movement of the particles in the updated iterative stages is also shown. Mathematically the movement of particles is represented by:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{2.11}$$

$$\begin{aligned} v_i^{k+1} = wv_i^k &+ c_1 r_1 (P_{besti} - x_i^k) \\ &+ c_2 r_2 (G_{besti} - x_i^k) \end{aligned} \tag{2.12}$$

Where, x_i^{k+1} gives the position of the i^{th} particle in the $(k+1)^{th}$k+1th iteration step,v_i^{k+1} is the velocity for the i^{th} particle for the iteration step k+1, best value of the particle for the current iteration is given by P_{besti} while the swarms global best value for the current iteration is given by G_{besti}. The parameter w which

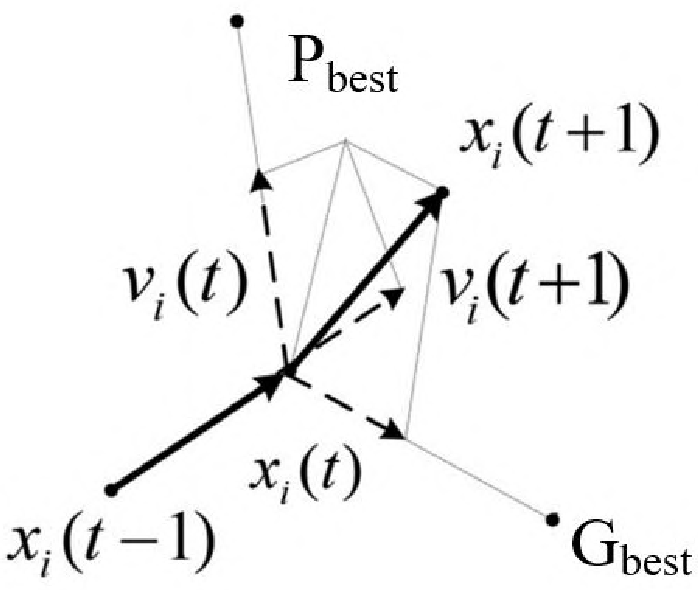

Figure. 2.3: Updating the positions of particles iteratively in PSO algorithm

acts as an inertial weight factor for the velocity to control the convergence speed, c_1, c_2 act as learning parameters and are selected to be equal to 2 while r_1, r_2 are random vectors having values within the range of (0,1)[211].

2.2.1.13 Firefly Algorithm (FFA)

Developed by Xin-She Yang [262], Firefly Algorithm (FFA) finds usage of firefly behavior and flashing patterns. The algorithm tries to model and optimization algorithm based on the firefly's natural flashing patterns that are a form of bio-luminescence that are used to either attract mating partners or prey. It is a known fact that as the distance increases, the light absorption decays exponentially and is governed by inverse square law. Mathematically this variation in the light intensity or attractiveness is modeled as a non-linear term given by:

$$x_i^{t+1} = x_i^t + \beta_o e^{-\gamma r_{ij}^2}(x_j^t - x_i^t) + \alpha\varepsilon \tag{2.13}$$

Where α signifies a scaling factor which is responsible for controlling the step sizes in a random fashion, γ is the parameter regulating the discernability of the fireflies, β_o is the constant that determines the attractiveness between fireflies when the distance between them is zero. The distance between i^{th} and j^{th} fireflies in terms of the Cartesian co-ordinates is given by r_{ij}. The term α is used as the parameter to regulate the overall convergence of the algorithm such that with each iterative step the value changes as:

$$\alpha = \alpha_o \theta^t \tag{2.14}$$

Where θ is the parameter responsible for reduction of the randomness within the values of (0,1). For all practical purposes the initial value of α is taken to be equal to 1, i.e. $\alpha_o = 1$.

2.2.1.14 Whale Optimization Algorithm (WOA)

Developed by Seyedali Mirjalili [154], the Whale Optimization Algorithm(WOA) is a metaheuristic method for optimization that replicates the hunting behavior of humpback whales. Mathematical modeling in the form of an optimization algorithm makes use of the bubble net feeding behavior, which is distinct and unique for the species. This interesting facet involves the foraging behavior or bubble-net feeding method of krill or tiny fish located near to the surface as described in [254]. The algorithm is mainly divided into three parts namely, encircling the prey, feeding movement in the bubble net and exploration in the search space for the prey. It has been reported from the studies on feeding pattern of whales, that whales are able to pinpoint the position of their prey and then move on to close in on them in a circular pattern. This is mathematically represented as being equivalent to the best solution of the candidate for the current step which is near the intended prey or the optimum value. The best position of the search agent is then identified and all other search agents update their position to align in the direction of the best. This is given by:

$$\overrightarrow{D} = \left| \overrightarrow{C} . \overrightarrow{X^*}(t) - \overrightarrow{X}(t) \right| \tag{2.15}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X^*}(t) - \overrightarrow{A} . \overrightarrow{D} \tag{2.16}$$

where $\overrightarrow{X^*}$ and $\overrightarrow{X}$ represent the best solution position vector and position vector respectively. Vectors $\overrightarrow{A}$ and $\overrightarrow{C}$ are the coefficient vectors and are updated as:

$$\overrightarrow{A} = 2 \cdot \overrightarrow{a} \cdot \overrightarrow{r} - \overrightarrow{a} \tag{2.17}$$

$$\overrightarrow{C} = 2 \cdot \overrightarrow{r} \tag{2.18}$$

The $\overrightarrow{r}$ is a random vector in the range [0,1], while the parameter $\overrightarrow{a}$ is responsible for regulating the exploration and exploitation phase. Its value is decreased linearly over the course of the iteration phase from 2 to 0. The modeling of the bubble net attaching of the prey by whales is divided into two further steps. The first of these two steps involves the decreasing of the parameter $\overrightarrow{a}$ which directly leads to the change in the values of the parameter $\overrightarrow{A}$ such that its value lies within [-1,1]. The second stage is maneuvering the whales in a spiral helical pattern around the prey given by:

$$\overrightarrow{X}(t+1) = \overrightarrow{D'} \cdot e^{bl} \cdot cos(2\pi l) + \overrightarrow{X^*}(t) \tag{2.19}$$

Here the parameter $\overrightarrow{D'} = \left|\overrightarrow{X^*}(t) - \overrightarrow{X}(t)\right|$ indicates the whale's and prey's exact distance in the current iteration, the logarithmic spiral's form is governed by b, and l is a random number which has values within [-1,1]. It is to be noted here that the two processes take place simultaneously, i.e. the movement of encircling the prey by the whale in a spiral trajectory which is decreasing as the distance between them gets smaller. Mathematical probability is implemented to model this simultaneous behavior in updating the whale's location iteratively. This is given as:

$$\overrightarrow{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t+1) - \overrightarrow{A} \cdot \overrightarrow{D};\ if \quad p < 0.5 \\ \overrightarrow{D'} \cdot e^{bl} \cdot cos(2\pi l) + \overrightarrow{X^*}(t);\ if \quad p \geq 0.5 \end{cases} \tag{2.20}$$

The range for p is [0,1]. The humpback whales' pursuit of prey indicating the exploration phase of the algorithm is modeled by using the similar approach as used in the variation of $\overrightarrow{A}$. This is modeled mathematically as:

$$\overrightarrow{D} = \left|\overrightarrow{C}.\overrightarrow{X_{rand}} - \overrightarrow{X}\right| \tag{2.21}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X_{rand}} - \overrightarrow{A}.\overrightarrow{D} \tag{2.22}$$

$\overrightarrow{X_{rand}}$ indicates the random vector which is taken from the population.

2.2.2 Physics Inspired Algorithms

These types of algorithms imitate the actions of actual physical phenomena. These algorithms covered under this category used in this study include the equilibrium optimizer (EO), artificial electric field algorithm (AEFA), flow direction algorithm (FDA), atom search optimization (ASO) and the multi-verse optimizer (MVO) [8].

2.2.2.1 Equilibrium Optimizer (EO)

The basis for EO makes use of the equations describing the balance of mass within a confined and control volume, that can ascertain dynamic as well as the equilibrium states [59, 86].To determine a non-reactive component's concentration or location, using the mass balance equation EO takes into account different sources and leakage mechanisms. Each particle (solution) in EO acts as a search agent, with its role determined by its concentration. A notable attribute of search agents is their capacity to adapt their concentrations in a stochastic manner, aligning with the equilibrium number of candidates (best solutions) established at each loop (optimal result), with the aim of achieving the equilibrium state. The evolutionary optimizer (EO) demonstrates superior performance in terms of its ability to explore and exploit, as well as its capacity to avoid local minima, thanks to the utilization of the mass production rate parameter.

2.2.2.2 Artificial Electric Eield Algorithm (AEFA)

Coulomb's electric force law and law of motion served as an inspiration for AEFA [258]. A charged particle is recognized by the algorithm as a potential solution. The electrostatic force between these particles can induce attraction or repulsion, causing movement of the items in the search space in response to this force. The candidate solution refers to the position of the prospective solution in relation to the supplied objective function. The fitness functions associated with the population as well as each individual candidate are utilized to represent burdens. In AEFA, the particle with the highest charge, which attracts all other particles with smaller charges and travels slowly across the search dimension owing to gravity, is defined as the best solution.

2.2.2.3 Flow Direction Algorithm (FDA)

Upon the transformation of rainfall into runoff, the FDA algorithm imitates the direction of flow to the drainage basin outlet having the lowest height [108]. Every flow in the algorithm is characterized by its position and elevation. The flow direction is determined by the slope and it moves towards the direction with the lowest elevation. Put simply, the flow is directed towards the neighbor with the most favorable objective function or lowest elevation. In this method, the drainage pool is originally utilized to produce an initial population (search space).

Afterwards, the flow aims to arrive at the output location with the lowest elevation or moves towards the location with the most favorable response at a lower height.

2.2.2.4 Atom Search Optimization (ASO)

ASO is a molecular dynamics-inspired population-based algorithm [278]. In the context of ASO, each atom's location within the search dimension represents a solution, while its mass serves as a representation of that solution. The solution characteristics of the issues are directly correlated to the mass, where greater masses indicate superior solutions. Similarly, the opposite is also valid. All atoms in the population will either experience attraction or repulsion based on their proximity to one other. The lighter atoms will be compelled to go in the direction of the heavier ones. Heavier atoms tend to search for more favorable solutions in their immediate surroundings due to their slower rate of motion. Conversely, lighter atoms explore the whole search space extensively since they have a fast rate of change of motion.

2.2.2.5 Multi-Verse Optimizer (MVO)

The physics of the multiverse idea served as an inspiration for MVO [155]. The algorithm encompasses the fundamental concepts of the multiverse hypothesis. The genesis of the cosmos is believed to have been mostly driven by a white hole. Black holes exert a very powerful gravitational force on all objects, even beams of light. Multiple cosmological theories posit the existence of wormholes that serve as connections between different realms. Its primary function is to facilitate the transportation of objects between other realities or inside a single universe. The universe is expanding rapidly into space, and the rate of expansion is crucial in shaping the development of planets, stars, and the establishment of physical laws. Wormholes and black and white holes are utilized in MVO to investigate and exploit different dimensions of space and time, respectively. Within the framework of MVO, every potential solution corresponds to a universe that is randomly initialized in the search dimension.

2.2.2.6 Big Bang-Big Crunch Algorithm (BB-BC)

Erol and Eksin devised a metaheuristic algorithm, which is inspired by dissipation of energy change taking place when transitioning from an ordered state to a chaotic or disordered state [55]. The Big Bang-Big Crunch (BB-BC) algorithm is named after the prominent evolutionary hypothesis explaining the beginning of the universe, known as the Big Bang theory. Based on this concept, particles experience attraction towards irregularities during the Big Bang phase, resulting in energy loss. However, they align in a specific direction during the Big Crunch phase. BB-BC, similar to other population-based metaheuristics, starts with the Big Bang phase, which involves generating a set of randomly generated initial potential solutions. The Big Crunch phase occurs prior to each Big Bang phase, with the exception of the initial population, which must be randomly generated inside the search region. Each instance of the Big Bang is succeeded by a Big Crunch, which serves as a convergence operator. Its purpose is to regulate the particles and enable their organization into a structured form in the event that follows the Big Bang phase. In order to assess the effectiveness of the convergence operator, one might choose the mean position of the candidate solutions, taking into account their respective weights. Furthermore, the location of the best possible candidate solution can also be used to determine it. The presence of these two contraction and dispersion phases suggests that the Big Crunch and Big Bang will be repeated in the algorithm until the stopping condition is met, in order to guide the particles towards the global optimum solution.

2.2.3 Other Algorithms

This category contains the teaching-learning-based optimization algorithm (TLBO), which is based on behavioral patterns involving communities and partnerships in humans [102, 248], genetic algorithms (GA) [84] based on genetics and human evolution in nature and arithmetic optimization algorithm (AOA) [8] which is one of the recent additions to the field of optimization.

2.2.3.1 Teaching-Learning-Based Optimization Algorithm (TLBO)

The TLBO algorithm replicates the classroom's teacher-student interaction [191, 248]. The objective is to enhance the students' level of knowledge in the class by rewarding the student who supplied the most exceptional response. There are two main phases that make up TLBO, and they are teaching and learning. The acquisition of knowledge that takes place while the instructor teaches the students is referred to as the teacher stage, while the engagement and participation of the students is referred to as the student stage. The kids' work quality improves, demonstrating an enhancement in the learners' level of competency as the teacher's experience level improves. The student outputs in this scenario function as possible resolutions to the optimization problem. The population of TLBO is made up of the instructor and the pupils in the classroom. The instructor is often acknowledged as the most effective classroom approach.

The goal is to increase the students' knowledge base who gave the best response in the class. Two phases make up TLBO: teaching and learning. The learning that occurs as a result of the instructor's instruction of the pupils is represented by the teacher stage, while student interaction is represented by the student stage. The quality of the work produced by the pupils increases indicating improvement in the learner's degree of proficiency with the improvement of the teacher's expertise level. The student outputs in this case serve as potential solutions to the optimization issue.

2.2.3.2 Genetic Algorithm (GA)

Developed by John Holland [84] and later made famous by Goldberg [149], genetic algorithms (GAs) have been utilized to solve difficult optimization problems, whether they be confined or unconstrained in nature. Engineering and science are two areas where GA is used, and it is often regarded as the best technique for general optimization. The algorithm is referred to as an evolutionary algorithm since it is based on population genetics and natural selection, which modify the population of the person based on evolution. Each stage of the algorithm creates a random starting group of people from a population that are then used as the basis for the algorithm's subsequent iterative phases. Selection, crossover and mutation are the three fundamental processes taking place in the algorithm that causes a fresh set of results to be produced in following cycles.

Based on the theory of natural evolution in species, GA looks for an all-encompassing answer on the basis of the "survival of the fittest" theory for a multi-dimensional search area. In GA, chromosomes are initially formed, which are a collection of individuals chosen at random (potential solutions). Generation refers to each of these actions. To identify the best solution, this phase is repeated until the given termination requirements are met. The initial choice of GA's parameters including size of population, rate of crossover and mutation determine how effective it will be. Two people are selected according to the best fitness function's value. These people first identify the spot that must be crossed before crossing their separated halves. Two new people are acquired as a consequence. In-

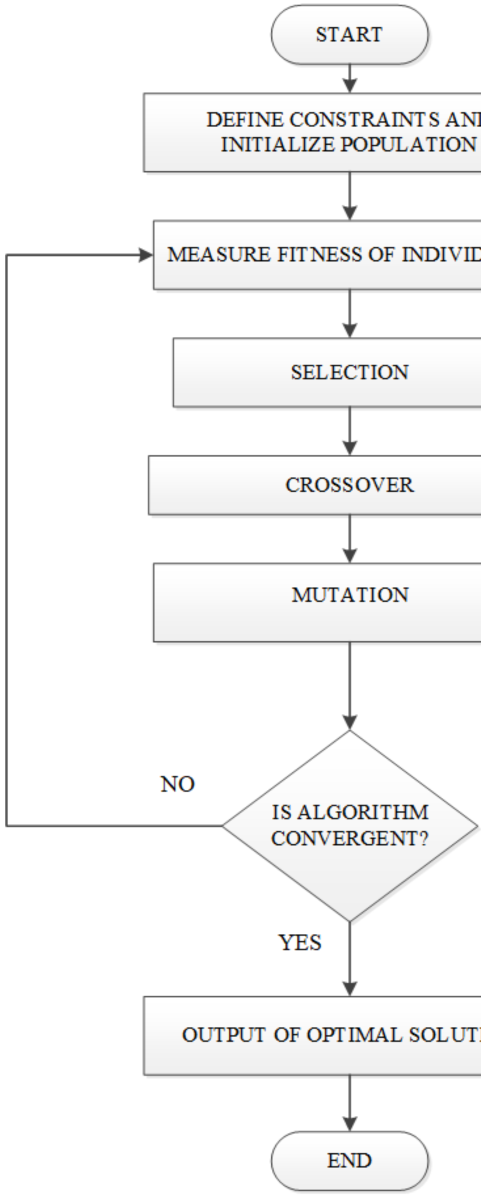

Figure. 2.4: Flowchart of the Genetic Algorithm

dividuals' genes alter throughout the mutation stage. Population variety brought by mutation keeps a solution from just having local optimas. Generation refers to each of these actions. To find the best solution, the algorithm is repeated until the given termination requirements are met. Figure 2.4 demonstrates the procedure for implementing GA.

2.2.3.3 Arithmetic Optimization Algorithm (AOA)

The four operations—multiplication, division, subtraction, and addition—are used by the novel metaheuristic optimization technique known as AOA [5]. In AOA, the optimization process starts by generating candidate solutions randomly. The exploratory search method indicates that the mathematical operations of Division (D) and Multiplication (M), also known as arithmetic operators, yield outcomes that are widely dispersed. Consequently, they are incapable of directly approaching the aim. After several iterations, an exploratory investigation uncovers an almost perfect solution that can be obtained. Mathematical calculations involving the subtraction (S) or addition (A) operations to obtain the desired results that align with the process of searching for exploitable opportunities. Therefore, they find it effortless to approach the aim. After several iterations, the extraction phase of the exploitation stage uncovers an almost perfect answer.

2.2.4 Hybridization of Metaheuristic Algorithms

Several hybrid techniques have been developed that employ meta-heuristic optimization algorithms. Hybridization of GA with stochastic evolution algorithm [143] reported the modification of mutation and crossover operators. Hybrid GA with Simulated Annealing (SA)[42] improved the random population generation for better fitness parameters at the initial stage of GA, while GA with ACO modified the initial ant population using the selection, crossover and mutation operators[137]. GA hybridized with PSO reduced the search domain to a local area before moving on to compute the most optimal location [122]. In another study, to improve the initially generated population diversity, the GA's crossover operators are used to generate a modified starting population to be used by the PSO algorithm [12]. Furthermore, hybridizing GA with PSO resulted in the improvement in PSO's population iteratively [68]. Hybrid algorithms combining two basic algorithms such as SA with WOA [140], ABC with DE [135] and SA with PSO [98] are also reported. In another study, hybridizing ACA with the PSO approach involved initially generating the population using the initial population generation equations of ACA, which was implemented by the PSO algorithm[111]. The adaptive neuro fuzzy inference system (ANFIS) structure was improved using the PSO algorithm to reduce the variation between the ANFIS training outputs and the actual outcomes [71].

GWO has shown successful applications in solving optimization problems related to cryptography algorithms [225], feature subset selection [272], time forecasting [270], optimal power flow problems [48], economic dispatch problems [104], flow shop scheduling problems [118] and optimal design of double layer grids [72]. Numerous algorithms have been developed to enhance the convergence performance of the GWO. These algorithms include techniques involving modification of the GWO by hybridization, parallelization, use of binary version, and use of opposition based learning [52, 158, 180, 232, 233, 274, 279].

While the GWO and SCA have demonstrated superior accuracy compared to other established swarm intelligence optimization approaches, they are not suitable for very complicated functions and may still encounter challenges related to local optimum value. To overcome these restrictions and expand its search capability, a novel hybrid variation that combines the GWO and SCA is suggested as a potential solution for contemporary real-world challenges by Singh and Singh [231]. The researchers enhanced the optimization of the wolves' location changes in the Grey Wolf Optimizer (GWO) algorithm by eliminating the inclusion of random movements of alpha wolves. The hybrid version under consideration is referred to as HGWOSCA. In this specific iteration, update in the alpha wolves position is enhanced by the integration of the SCA. This is represented as:

$$\vec{D}_\alpha = \begin{cases} rand() \times sin(rand()) \times \left|\vec{C}_1 \times \vec{X}_\alpha - \vec{X}\right|, \; rand() < 0.5 \\ rand() \times cos(rand()) \times \left|\vec{C}_1 \times \vec{X}_\alpha - \vec{X}\right|, \; rand() \geqslant 0.5 \end{cases} \tag{2.23}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha) \tag{2.24}$$

By accelerating the search process, this strategy seeks to improve global convergence, exploration, and exploitation performance, rather than letting the variant persist for a number of generations with no appreciable improvement. Empirical evidence confirms that the reported hybrid variant exhibits strong performance as a search algorithm for a wide range of global optimization functions, including standard benchmark functions.

2.3 Optimal Design of DC-DC power converters

An intriguing research challenge is implementation of optimization techniques in the development of power electronic converters [161]. A manual DC-DC converter design takes a lot of effort and money. The initial stage in creating a DC-DC converter is selecting the inductors, capacitors, and switching frequency. The designing procedure must make sure that the electromagnetic interference (EMI) criteria are met, that the device is efficient for a wide variety of loads, and that the bandwidth used in the design guarantees that load and line disturbances are completely eliminated. As a result, designing power electronics converters is a challenging undertaking that frequently requires finding solutions through an iterative process. This paved the way for the application of optimization algorithms for suitable design of a converter topology depending on end utility and to ease the computational time. Electronics advancements in recent years have led to the improvement in the manufacturing of DC-DC converters. Significant design improvements in the energy storage elements have been reported with reduced size and lower associated losses. The improvements in the blocking voltage, transients stress withstand capability and lower operational losses are also significant improvements with respect to device technologies involving power electronic switches. Despite these improvements, choosing the optimal design parameters that give efficient operation under a given set of constraints is still a problem of interest [129].

A review of available literature indicates that the problem of optimal design parameter selection for converters differ in terms of selection of objective functions, the design constraints as well as methodologies implemented for finding the optimized solution. A graphical approach in order to solve the design optimization challenge of monolithic DC-DC converter and loss optimization for envelop tracking in radio frequency (RF) amplifiers was covered in the work [268]. Graphical methods when employed suffer from the limitation of variables to be optimized. At the most two variables can be used simultaneously. As such they are not a viable solution method for design optimization problems with multiple variables and constraints. Authors present an optimization approach involving choice of design to optimize the total weight or total losses resulting in a cost-effective design in [21]. A trade-off between the choice of design parameters in terms of efficiency, weight, optimal power configuration are additional advantages of the proposed computer aided method. In [127] decision factors are included in the study of the monolithic DC-DC buck converter's optimization, which consist of switching frequency, ripple in current and voltage swing in the MOSFET driver circuit. Moreover, the solution to the problems of reduction of EMI and improvement of converter efficiency is also carried out in [197] and [133] respectively. In [220] Lagrangian function is used for the optimization while augmented Lagrangian method was used in [255]. Quadratic programming [37] and Monte Carlo search [171] are also applied for converter design optimization for end applications.

DC-DC converter design optimization with geometric programming (GP) [130,202] applies monomial and posynomial expressions to address the design optimization challenge. Honey Bee Mating Algorithm (HBMA) [184], Particle Swarm Optimization (PSO) [36, 183], Simulated Annealing (SA), Genetic algorithm [239] and Firefly Algorithm (FFA)[211] also find its application in the optimization of converters. In the majority of the cases, it is seen that the optimization approach involves one parameter. These parameters selected are also varying in nature from loss minimization, improvement in efficiency, ripple minimization, voltage swing minimization, optimization of the component weights, EMI minimization among others. Alternate solution techniques employ division of the optimization problem into sequential stages where individual stages solve the problem involving one or two parameters only. This solution methodology has the drawback of not allowing the provision for selection of all the possible constraints for the design optimization process.

2.4 DC-DC converters for maximum power point tracking in PV applications

Photovoltaic (PV) power is one of the major renewable energy sources experiencing rapid expansion. Its development can be attributed, in part owing to the exhaustion of fossil fuels and the pollution in the environment that is changing the climate, as well as to the development of new manufacturing technologies that are associated with PV systems. PV systems rank first among the green energy resources, with a gradual increase in the contribution of the annual production of electricity. By reducing carbon dioxide (CO_2) emissions with opportune energy storage systems, these systems provide hybridization flexibility with other renewable energy sources, thereby improving the margin of the load demand being met [79]. These systems are dependent primarily on varying external atmospheric conditions, specifically solar irradiance and temperature [230]. As solar irradiance incident on PV modules' surface and corresponding ambient temperatures are not constant, environmental conditions are continuously variable. Consequently, the current-voltage (I-V) characteristic curve of a PV cell is nonlinear. This results in time-varying maximums. As such the rated power stated in the data-sheet for PV module is never fully utilized unless a tracking system is present [260]. This disadvantage reduces the cost-effectiveness of any PV system, because of the inherent power that goes unused, which in theory is potentially accessible. The limitations of operating PV however still include a low power output capacity and high associated costs, which has led to the investigation of effective ways to develop a PV converter and its controller that can fulfill the greatest power extraction criterion, thereby accomplishing both objectives of being cost effective and energy competent for PV systems. The application of the DC-DC converters as Power Processing Units (PPUs) is the catalyst for this process. The power processing units (PPU) integrate PV modules' output voltage to the system's specifications, thereby extracting its maximum power [23].

2.4.1 DC-DC converters as PPU's in PV systems for MPPT application

In general, PPU are categorized into two primary groups - Non-isolated DC-DC converters and Isolated DC-DC converters. There are mainly three architectures of such converters namely the buck converters that alleviate voltage values at low values of irradiance. The second category includes the boost converter topologies which aid to aggravate the voltage values at high values of irradiance. The third category of converters cover the buck-boost converters which are employed to augment or decrease voltage values which are indicative of the fluctuating irradiance conditions. A non-isolated DC-DC converter lacks the electrical barrier between the input and output of a device [14, 240].

In the quad input dual output (QIDO) studied in [34], the authors have demonstrated via the designed prototype that by decreasing the components needed for power regulation control of PV system by 56.25%, there is an overall reduction in the total associated cost. The use of a variable inductor instead of a fixed, extends the tracker's operational range, enabling MPPT in circumstances of decreased solar irradiance as reported in [273]. The fourth order buck converter presented in [249], was able to meet the MPP with reduced oscillations, operate at the optimum power point for varying irradiance levels and shortened sample times by a margin on 55% percent when compared to the standard buck converter.

Design improvements in boost converters include gain improvement[50, 116], interleaved configurations [78, 121, 201], reduction of current ripples and enhancing voltage conversion ratio [201], improvement from the basic converter model [113, 187] and multilevel topologies [18]. A buck-boost converter having a single unidirectional switch mode operation is introduced in [43]. The converter has been experimentally tested on a 660 W PV system and has efficiency in the range of 93% to 98%.

In the isolated DC-DC converter a high frequency transformer acts as an electrical barrier between the input and the output [35]. The buck-boost configuration has major complexity of installation, hysteresis and eddy current losses resulting in reduced efficiency. Thus, they are not suitable for PV applications. The simplest configuration of isolated DC-DC converter is the single ended forward converter (SEFC). This circuit model has the disadvantage of suffering from saturation issues [252]. The half bridge configuration makes use of two switches that produce AC waveforms at the transformer's primary side which are symmetrical. The saturation issues are not present in this converter topology as the model stimulates the core flux in both directions and ensures the increase of power rating [226]. The full bridge converter features advantages over the half bridge configuration. Additionally, the converter permits the application of high voltage at the transformer's input [190]. In the push-pull converter, scaling the voltage levels in addition to electrical isolation is achieved by the transformer. The output inductor acts as an energy storage element. The converter's gain is the same as the SEFC but with high power application capabilities [134]. The interleaving concept is utilized in [94] to maximize power while reducing ripple components in the current waveform with 98.08 %. In the half bridge configuration, the input inductance is present in series with the PV panel and the converter implements a center-tapped transformer [128]. The full-bridge converter also called the double ended converter has better utilization of the core material in comparison with the single ended converter [90]. The switched capacitor configuration in the boost converter offers a bi-directional power flow, places the least strain on the transformer, and necessitates a low transformer turns ratio [261]. However, the large number of circuit components makes it less than ideal for implementation in PV systems for peak power point operation.

2.4.2 MPPT Algorithms and DC-DC Converters

A PV system performance is governed by the operating point, which is dependent on external atmospheric conditions of irradiance and temperature and the connected load impedance. The current voltage (I-V) and power-voltage (P-V) characteristic curves of a PV system are dependent on the irradiance and temperature. Changes in the irradiance profile affect the PV output current while the temperature changes affect the PV output voltage. Optimum operating criterion requires that for any given solar irradiance and temperature, the connected load match with the PV module maximum power point resistance (R_{MPP}). Tracking is essential in PV systems to harness the maximum available energy from the sun, either using manual physical tracking or by the electrical Maximum Power Point Tracking (MPPT), which is based on controlling the operating PV voltage, current or power [216]. MPPT involves the use of a control algorithm that regulates the operation of a DC-DC converter interface between the PV module and the load, in order to match the PV module impedance (or the input impedance to the converter) with the load impedance in order for maximum power transfer [51] , i.e., to match the R_{PV} or R_{input} and R_{LOAD}. This impedance matching ensures that the condition for maximum power transfer theorem is satisfied ($R_{PV} = R_{LOAD}$) hence, assuring that the maximum quantity of power is available for use [206,215].

These power point trackers are used with PV systems, to tame the solar operational state to be near the maximum power point (MPP) voltage and current (V_{MPP}/I_{MPP}) in response to varying atmospheric conditions [61]. The functioning is based on the equality of power, i.e. power input P_{in} is equal to the power output P_{out} [97]. Their primary function is controlling the battery charging process, to prevent overcharging and undercharging in addition to meeting the load demand. Additionally, at night when the sun is not available, the array voltage is lower than that of the batteries, the backflow of power from batteries to PV is to be prevented by the system [186]. Likewise, the MPPTs role is paramount in low solar irradiance conditions characterized by cloudy days [44,275].

Figure 2.5 shows the MPPT interfacing the PV and DC-DC converters in the standalone systems. The DC-DC converter portion of MPPT includes active components in the form of inductors and capacitors with frequency sensitive impedance. The algorithm functions to regulate the operating duty ratio (D) in order to match the R_{PV} to the nearest possible value to R_{LOAD}.

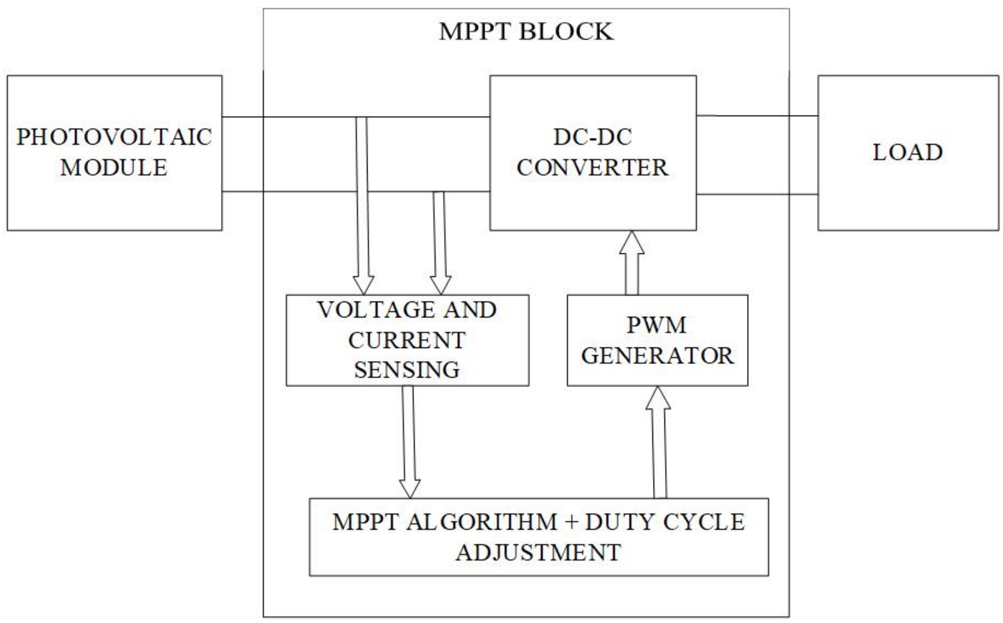

Figure. 2.5: MPPT position with DC-DC converter in standalone PV system

In order to achieve fast tracking and maximum power point location, researchers have developed algorithms based on different techniques which range from perturb and observe (P&O) [28,209], fractional-short circuit (FSC) [115,172], Hill climbing [250, 257], incremental conductance (IC)[136, 146], fractional open circuit voltage (FOCV)[53, 145]. These algorithms are dependent on the uniform irradiance for better utilization of the algorithm to track the MPP. However, they lack the ability to quickly respond to tracking the MPP for partial shading as well as rapidly changing irradiance [20]. Hardware requirements for sensing and implementing these algorithms along with power loss prevent their extensive use for power tracking. To address these issues, many researchers have proposed alternative Soft computing/Evolutionary algorithms which make use of one or more of the aforementioned algorithms to negate their shortfalls. Soft computing techniques have the advantages of handling non-linearity, better exploration of search, ability to reach optimal regions. Popular algorithms include Genetic algorithms [77, 141], Fuzzy logic based techniques [11, 46], Particle Swarm Optimization [20, 93, 150], Artificial Neural Networks (ANN) [189], Differential Evolution [193, 242], Cuckoo Search algorithm [9] and Ant Colony Optimization [99, 238]. Even though these algorithms require the use of high performance and computing facilities, microprocessors, their ability to achieve global MPP tracking at low fluctuation of PV power with high efficiency compensates adequately the calculation and training burden.

Although a majority of algorithms available in literature have focused on development of the algorithms and control strategy for effective tracking of this MPP operation, the combined role of converter topology and algorithm is yet to be explored along with detailed assessment of their individual performance parameters. The converter selection affects the working of the MPPT algorithm, tracking ability as well as the efficiency of meeting the operating point so as to ensure that maximum power is extracted for the given conditions of solar irradiance, temperature and load profile [28, 210]. The effectiveness of the PV module and the converter interface are technology dependent and as such they require a befitting algorithm to match their performance [101]. In the absence of a common test bench for both converter topologies and algorithms, it is difficult to select the best combination of converter and tracking algorithm with a PV system for a connected load. Additionally, it has been observed that there is a broad range in the choice of the algorithm and DC-DC converter interface for implementing the tracking techniques in literature. The widely used converter topology in MPPT studies within the non-isolated category are the buck-boost and boost converters [57, 176, 240]. Measuring the PV current plays a crucial role in the calculation of the MPP. With the buck-boost converter, the discontinuous conduction mode (DCM) of operation makes it difficult to measure the PV current and the MPPT capability decreases [23]. Within the non-isolated converter topologies, boost converter is reported to be the better option to employ as the converter interface in MPPT systems for improved tracking capability.

The rationale for selecting the boost converter as the DC-DC converter for this study is rooted in its fundamental simplicity [23, 28, 54, 101, 139, 161, 199, 235, 240], superior tracking capability [23, 28, 56, 57, 63, 176, 206, 208, 210, 215, 240] compatibility with MPPT algorithms [101, 235, 240] and its established role as an power converter interface in MPPT enabled PV systems [57, 176, 188, 209, 240]. While it is true that more advanced converter topologies exist, their complexity often introduces additional challenges in terms of cost, control and implementation [23, 28, 101, 199, 235, 240]. The boost converter, being a proven and versatile topology, serves as an excellent starting point for exploring the optimization of converter design and its impact on MPPT performance. The study's focus on optimizing this fundamental topology provides valuable insights into minimizing power losses and enhancing MPPT efficiency, while also laying the groundwork for future investigations into more advanced converter designs. Therefore, the optimized boost converter is chosen as the reference converter for the performance analysis of MPPT in this thesis.

2.5 Optimization of Hybrid Renewable Energy Systems (HRES)

An optimal mix of two or more sources with complementary nature are found to be promising and reliable as a renewable energy source and can eliminate the requirement of storage as well. A hybrid renewable energy system, in general, is an energy system that combines two or more renewable sources to deliver energy more economically and reliably [142]. They may operate more or less independently from the grid and can be paired with more traditional power sources, such as diesel generators, for storage and backup. While it has been reported that grid connected systems offer the best solution considering net present cost (NPC) and cost of energy (COE) [19]. However, for remote localities where traditional power production schemes are either unavailable or not economically viable, the use of HRES can serve as an appropriate means of meeting the energy demand.

Hybrid power generation with PV as a major source with distributed generators (DG) enable the system to operate with reduced overall system losses and significant voltage profile improvement when applied using coordinated control

[27]. Investigation of hybrid systems performance in rural settings are reported in [22,173], for techno-economic sizing of renewable energy systems in Oman [10], for the feasibility of standalone hybrid systems in [15], and also in [7] for performance investigation in grid integrated micro-grid systems.

In [32] a Bayesian vector based approach is utilized to evaluate dynamic renewable energy variability and their complementary nature. Their study focused on the importance to understand how climate shocks affect renewable energy generation and whether different types of renewable energy can be used to smooth out production and better match load. The findings demonstrate that hydro power and solar electricity complement each other more generally. In eastern Qinghai Province of China, there is hybrid hydro-PV based power plant. A case study has been done by He Li *et.al.*[132] for long term complimentary operation considering uncertain stream flow and PV output. They found that operationally the hybrid plant performs more satisfactory for long term complimentary than acting as a standalone Hydro PV system. Irregular steam flow and PV output has also improved as a result of complimentary operation. The total generation and total guaranteed rate are improved by 3.18 % and 10.63 % for collaboration period and result for validation period are better that is 6.66% and 22.92%. Kougias *et.al.*[119] tried to find out the complementary relationship between a small hydro power plant system (SHPS) and solar PV systems (SPVS) by using the correlation coefficient and checked whether they can increase the complementary operation by varying the installation parameter and compromising the SPVS output. They got a -66.4% correlation coefficient by compromising 10% SPVS output and keeping their tilt angle at 5° and azimuth is -106 °. Complementary nature in time scale has been studied by Fang-li *et.al.* [131] on Longyangxia hydro/PV hybrid power station. They have developed the multi-objective (NSGA-II) algorithm. With the help of the Pearson-III distribution equation, they have classified the years into extremely wet, wet, normal, dry, extremely dry. The objective function of the multi-objective algorithm is to minimize the output variation and maximize the total output of the plant. Complementary behavior has been found between the system, especially for wet years.

Whenever the power supply by the sources is less than the demand side that is considered as a failure of the system. Beluco *et.al.* [24] came with the concept of the complimentary of the time for hydro and PV system based generating power plants. A computer simulation-based method was proposed to determine the performance limit. One year time is considered for the analysis. It was found that if complementary in the time index increases failure index decreases. It abundantly clear that hydro and PV resources have a clear and unique complementing connection, making them an excellent choice for the main components of an HRES. To achieve the sustainable voltage control of PV-hydro-battery integrated DC microgrid Naik *et.al.* [170] implemented adaptive energy management strategies. Their aim was to mitigate the voltage sustainability problem arising due to sudden change in dynamic load. The work was carried out in MATLAB/Simulink environment coupled with OPAL-RT simulator and oscilloscope. Testing for various types of loads has been carried out resulting in improved voltage sustainability by 53.27 % and reduction in the overall battery stress level.

2.5.1 Applications of Optimization Algorithms

Optimum design of the HRES is often a conflicting optimization problem having solution dependence on economic, environmental and quality performance related issues [105]. GA is utilized for hybrid system control and size optimization [25, 38, 76, 103, 141, 164, 168, 174, 245], optimal economic operation[25, 47, 103, 159, 164] and optimizing parametric models of the PV module [203]. GA serves as a reference for performance comparison studies with Particle Swarm Optimization[217], Differential Evolution[76], Firefly Algorithm [1], Cuckoo Search Algorithm [217], Biogeography Based Optimization [245], Ant Colony Optimization (ACO) and Artificial Immune System (AIS), along with new approaches like the honey bee mating algorithm (HBMA), bacterial food algorithm (BFA) and game playing theory[271]. Successful realization of the objective function using GA has made the use of the algorithm a much sought after optimization technique for its ability to solve high dimensional problems [271].

Review of literature works shows the use of PSO in optimal hybrid system sizing and design [49, 62, 81, 163, 179, 182, 223, 259]. In addition, PSO has been used to evaluate the effectiveness of conventional control techniques as well as novel metaheuristic algorithms [269]. Algorithms like the imperialist competition algorithm (ICA) [163], artificial bee colony (ABC) algorithm [49], cuckoo search (CS) algorithm [26], water cycle algorithm (WCA) [218], mine blast algorithm (MBA) [62] and hybrid big bang-big crunch optimization algorithm(HBB-BCA) [219] utilize PSO as a benchmark to evaluate the capacity to deliver optimum results with improved computing efficiency and resilience in managing competing objectives and operational constraints. This demonstrates that PSO is widely recognized as a popular method for optimizing HRES.

The majority of research on use of novel metaheuristic optimization algorithms in HRES has mostly concentrated on determining the optimal sizing of the system's components [62, 76, 163, 223, 228, 241, 245, 276]. The analysis and design of hybrid systems are also explored to achieve optimum efficiency [49, 69, 70, 76, 105, 217, 241]. Researchers have also addressed the importance of controlling the power management approach in multi-source renewable energy systems [66, 160, 218, 219, 223, 228, 269]. Recent developments also indicate the increasing application of the imperialist competition algorithm (ICA) [163], artificial bee colony (ABC) algorithm [49],cuckoo search (CS) algorithm [26],improved firefly algorithm [276], adaptive modified firefly algorithm (AMFA)[160] , adaptive neuro fuzzy inference system (ANFIS) [66], water cycle algorithm (WCA) [218], mine blast algorithm (MBA) [62], Quasi-Oppositional Harmony Search Algorithm (QOHSA), Teaching Learning Based Optimization (TLBO) [224] and hybrid big bang-big crunch optimization algorithm(HBB-BCA)[219], non-dominated sorting genetic algorithm (NSGA)[105] in the field of HRES.

Although GA and PSO based optimization algorithms are more suitable for tackling high dimension problems, metaheuristic and multi-objective optimization algorithms that utilize bio-inspired algorithms can also effectively address the optimization challenges associated with HRES, as demonstrated by Zahraee et al. (2016) [271]. As the optimization algorithm becomes more complex in terms of constraint handling and the ability to reach an optimized solution with fast computational time with parallel processing, relying solely on these algorithms may not always be the most effective approach to solving the optimization problems. Utilizing a hybrid approach that combines a few algorithms, working together in a coordinated and complimentary manner, applied in a step-by-step fashion, might potentially yield improved outcomes when tackling the optimization challenge at hand.

2.6 Discussion

From the variety of the power electronics converters as discussed in the section 2.4.1 the task of creating a case specific, ideal MPPT solution becomes challenging to be interfaced with a befitting converter configuration. Therefore, some important points are to be considered while selecting a converter topology for MPPT implementation. Firstly, the system designer has to fully consider the irradiance, temperature, and other climatic factors of the atmosphere in which the PV system is to be installed and operated, as well as the presence and absence of precipitation and humidity.

Secondly, design of suitable SMPS appropriate for the implementation of the MPPT algorithm to regulate the PV system optimum performance considering efficiency, reliability, and complexity of operation. The choice of the selected circuit topology to be done to best utilize the system control and operation, fulfilling the MPPT objectives. For the development of a suitable PPU for the tracking algorithm, it is advisable to make use of the non-isolated DC-DC converters against the isolated one. The non-isolated DC-DC converters are devoid of transformers inherently in their design, which naturally solves the issue of current leakage, hysteresis and eddy current loss. The galvanic isolation between the input and the output add a benefit to the isolated topologies; however, they have lower light-load efficiency and increased current stress as well as high circulating power [109]. The design of the non-isolated PPU's is simpler when compared to their isolated counterparts, as they are simple in configuration, have higher reliability, require less space and components, are cost effective as well as have higher efficiencies in voltage conversion and exhibit robust system operation to external disturbances and non-linear aspects [2, 157].

From the detailed assessment of the DC-DC converters used for MPPT in PV systems, it may be stated that the performance of the DC-DC converters cannot be surpassed by linear voltage regulators. This is due to the fact that except for the converters with non-isolated and isolated configurations, other topologies are required to dissipate heat when interfacing PV system. This causes the overall reduction in the conversion efficiency in addition to the requirement of a substantial heat sink for heat dissipation. For isolated converters, the construction is complex when compared to the non-isolated topologies. They require the use of a transformer for the galvanic isolation, which inadvertently leads to hysteresis and eddy current loss, thereby reducing their overall operating efficiency. For the non-isolated converters, the absence of galvanic isolation is overcome by the ease of converter configuration and reduced operating stress on the switching device. They also have a few requirements in terms of circuit element, as such have low power losses.

The review of literature on the HRES gives an overview on the optimization approaches widely implemented like GA, PSO, FLA, ACO, ICA, and others. Important considerations for the design of these hybrid systems include demand side management (DSM), minimized environmental impact, optimal operational costs, and power supply dependability, to mention a few. This study reveals that the popular algorithms used are GA, PSO and the FLA based approach. However recent trends indicate that the use of modified algorithms and new metaheuristic algorithms like Modified Particle Swarm Optimization (MPSO), ACO, ICA, provide improved outcomes in terms of computing effort, resilience, quicker convergence, and the capacity to handle several competing objectives when applied to the optimization problem. In addition, other novel algorithms have been implemented for various additional optimization issues, such as supply chain management, radial power distribution system reliability enhancement, optimum power flow, and optimal load dispatch, to mention a few.

Due to advancements in computing facilities, parallel processing, and hardware and software evolution, there is a growing interest in using soft computing and optimization techniques to solve optimization issues with many competing objectives in the field of HRES. Significant limitations of the optimization methods in real-time assessment include the speed at which the best optimum solution may be found, the rate of convergence, and the number of iterations required. Therefore, it is crucial to select the methods that minimize the above restrictions in order to identify the best settings. Because the best outcome of the chosen algorithms might be significantly impacted by changes in the fitness function of an issue. However, the literature analysis reveals a scarcity of research studies that specifically examine and compare the use and effectiveness of soft computing and optimization methods. There is no existing literature review that provides a comparison of algorithms for a typical benchmark problem related to hybrid energy system design optimization. Significantly, the bulk of studies exhibit variability in the location, hybrid system components, availability of renewable energy sources, formulation of the optimization issue, objectives considered, limitations, and optimization technique employed. Without a shared testing platform, it is not possible to determine if the algorithms are superior than others. Therefore, it is necessary to conduct a comparative analysis of contemporary soft computing approaches for the purpose of design optimization of HRES in order to evaluate the effectiveness of the algorithms being compared.

2.7 Summary

In this chapter, the focus has been to carry out a thorough investigation of available literature in the key areas of design optimization of dc-dc converters, comparison between the dc-dc converters used in MPPT applications with PV applications and application of soft computing as well as optimization approaches in the design of hybrid renewable energy based systems. Analysis of the literature revealed a few gaps which provided opportunities for further exploration and investigation. Some of these issues have been addressed in the current work and can be highlighted as under:

1. The design optimization of DC-DC converters for reduced power loss, though addressed, not much is reported from the point of view of a comparative investigation with respect to established algorithms and proposed in the recent times.

2. Although a lot of work exists in the domain of use of power converter topologies for MPPT applications, research focus has been concentrated on the use of different converter topologies along with improved or hybridized algorithms. A combined investigation into the use of optimally designed power converter topology, i.e. a DC-DC converter designed optimally for MPPT applications in PV systems with an adequate tracking algorithm is yet to be addressed.

3. Optimization of hybrid Renewable Energy sources with PV and Hydro power sources exploring the complementary nature of both solar and hydro-power though addressed, a study on the same is yet to be made for isolated regions in North East, India, where grid integration is still not available or is not a viable economic option.

4. Novel nature inspired algorithms for solving engineering optimization problems have been proposed and various optimization problems have been addressed using such techniques. In order to enhance an algorithms convergence performance, local optima avoidance, improved exploration and exploitation, hybridized algorithms have been reported. In the recent years, GWO algorithm has emerged as a very popular optimization algorithm due to its advantages and GWO based hybridized algorithms with improved performance to address real life optimization problems has been explored in the thesis.