A Thesis for the Degree of Doctor of Philosophy

Hybrid Energy Optimization Algorithms Based on Energy Consumption Prediction in IoT Environment

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Dedicated to my parents and family,

for their immense support and

encouragement.

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List of Abbreviation

T	Temperature
L	Illumination
A	Air-quality
USP	User Set Parameters
AP	Adjusted Power
CP	Consume Power
RP	Required Power
Ω	No of generations
μ	Few successive generations
$\beta_{1,} \beta_{2,} \beta_3$	User defined factors [0, 1]
e_T, ce_T, e_L, e_A	Error in (Temperature, Change in Temperature, Illumination, Air-quality)
T_{set}, L_{set}, A_{set}	(User set parameters for temperature, illumination and air-quality)
J_1, J_2, J_3	Small values between '0' and '1'
$P\ (k)$	Sum of required power

Abstract

Intelligent optimized energy management and prediction model in residential buildings received attraction of the researchers in last couple of years. Various techniques and models have been proposed in the literature for optimized energy management and prediction, but the trade-off between occupant comfort index and energy consumption is still a great challenge to the research community. Previously we have proposed power consumption optimization and prediction models based on particle swarm optimization (PSO) and genetic algorithm (GA). Our proposed models accomplished good performance results up to some extent, but still there is room for more improvements. In this thesis we proposed hybrid optimization of energy management and power control models based on preprocessing mechanisms for occupants comfort index, energy saving and energy consumption. The focus of our proposed hybrid optimized and prediction models is to increase occupant's comfort index and reduce energy consumption using hybrid optimization, power prediction and preprocessing of power consumption data. The proposed single and multi-preprocessing hybrid optimization based power control models provides energy efficient environment by reducing power consumption and improving occupant's comfort index as compared to GA and PSO based power prediction models.

Our proposed hybrid energy optimization based prediction models are simple and maintains better user's comfort index and minimized the energy consumption without compromising the occupants comfort index. User set parameters plays a vital role in deciding the occupants comfort index. In [23, 26-30], user is not involved to determine the occupants

comfort index, while our proposed models consider user set parameters to decide the occupants comfort index. So our proposed models are user friendly. In [23, 31, 32], the energy efficiency is not addressed, while our proposed models gives attention to energy savings and our models are energy efficient by reducing energy consumption. In [29, 30], the occupants comfort index is not considered while our proposed approach addressed occupants comfort index. So the bottom line is, our proposed hybrid energy optimized models based on prediction and preprocessing addressed energy efficiency, occupants comfort index and user set parameters, while other approaches mentioned above either provides energy efficiency or occupants comfort index without considering user set parameters.

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1. Introduction

1.1. Research background

Energy consumption management and user's comfort index are two foremost design objectives in forthcoming energy efficient building models. The fundamental reason is that, power consumption increases day by day while its sources of generations are limited and expensive as well. On the other side users wants is to consume minimum power without compromising the occupants comfort index. This prerequisite of minimum power consumption without compromising users comfort index is an interesting problem to the research community to cope with. This leads to the trade-off between energy consumption and user comfort index [1-4]. To address this trade-off, an intelligent and optimized control model is needed to maintain both energy consumption and occupants' comfort index.

1.1.1. What is Energy management system (EMS)?

An energy management system (EMS) is a computer-aided tool used by machinists of electric smart grids to monitor, control, optimize and predict the performance of the generation and/or transmission system. EMS is a vital module of the smart grid to insure smooth operation of the electricity and smart grid.

1.1.2. Why we need energy efficient system?

An energy efficient system is needed to avoid extra consumption of energy. The basic aim of energy efficient systems is to satisfy occupants comfort index without consumption of extra energy. This will help in smooth operation of the smart grid and it will also put a positive impact on the energy generation companies.

1.2. Proposed idea

In this section proposed idea of hybrid energy optimization methodologies for users comfort index and energy saving is described. Proposed techniques address both energy savings and occupants comfort index simultaneously. Proposed hybrid techniques integrates in its fitness function the indoor occupants' comfort index and the corresponding energy consumption. The proposed hybrid energy optimization techniques also targets to satisfy the occupant's requirement along with minimal energy consumption. A range of user set parameters (temperature, illumination, air-quality) which constitute occupants' comfort index [5] in building are selected and then optimized using proposed hybrid energy optimization algorithms according to the user's comfort index.

The error difference of optimal parameters and real environmental parameters is input to the fuzzy controller. The output of the fuzzy controller is the minimum required power according to the user's comfort index. Coordinator agent takes as input required power and optimal parameters. The coordinator agent adjusts the input power of the building on the basis of available power, required power and user comfort index. The adjusted power is compare with the required power to get the actual consume power. The consumed power is input to the Kalman filter and ARIMA prediction algorithms to predict consume power. The predicted consume power is used by the actuators.

Proposed hybrid energy optimization based prediction models are simple and maintains better user's comfort index, and minimized the energy consumption without compromising the occupants comfort index. User set parameters plays a vital role in deciding the occupants comfort index. In [23, 26-30], user is not involved to determine the occupants comfort index while proposed models are user friendly and consider user set parameters to decide the occupants comfort index. In [23, 31, 32], the energy efficiency is not addressed while proposed models give attention to energy efficiency by reducing energy consumption. In [29, 30], the occupants comfort index is not considered while proposed approach addressed occupants comfort index. So the bottom line is, proposed hybrid energy optimization models based on prediction and preprocessing addressed energy efficiency, occupants comfort index and user set parameters while other approaches mentioned above either provides energy efficiency or occupants comfort index without considering user set parameters.

Major components of proposed models included sensors data; single preprocessing, multi-preprocessing, hybrid energy optimization, fuzzy logic controllers, coordinator, comparator, energy consumption predictions and post-processing. Figure 1.1 shows the proposed hybrid energy optimization and prediction simulated model.

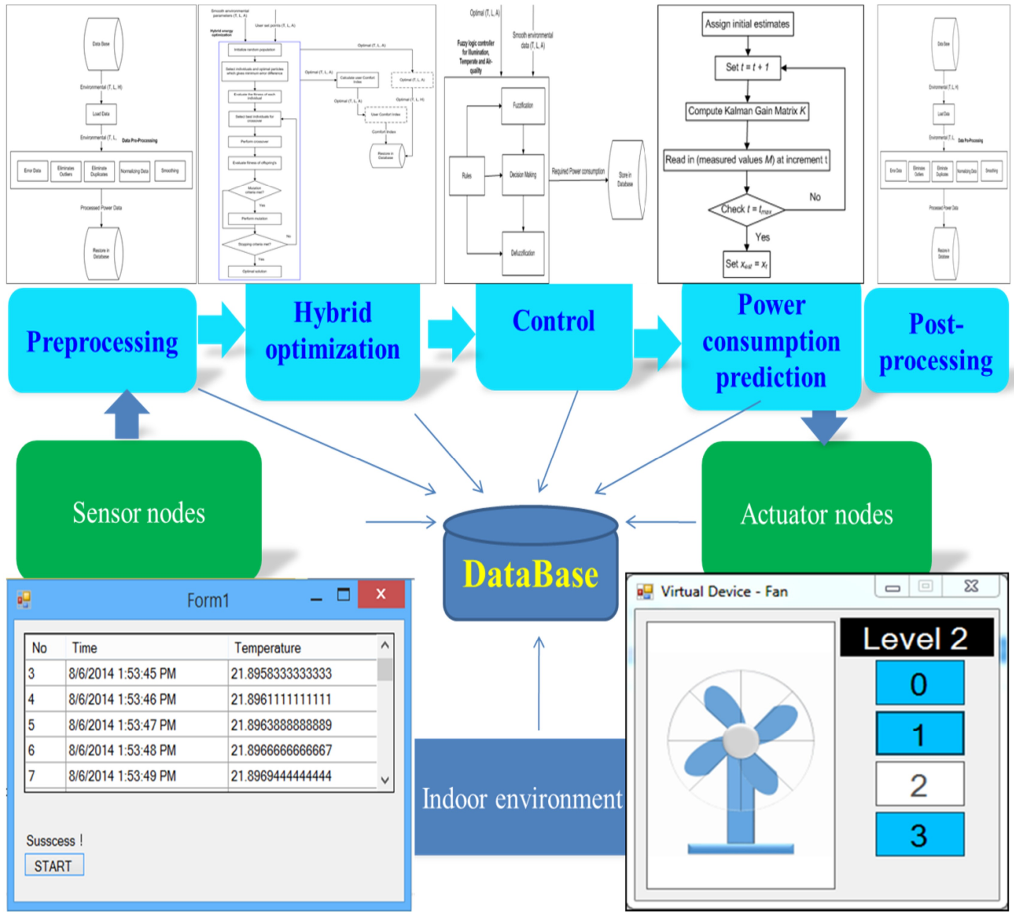

Figure 1.1. Proposed hybrid energy optimization and prediction simulation model

Before discussing each component of the proposed hybrid energy optimization and prediction models we first discuss conceptual model and building model.

1.2.1 Conceptual model

In this section we are going to described conceptual model of the energy consumption reduction and increase of occupants comfort index. Figure 1.2 shows the conceptual configuration of the building energy management system, where the comfort index of the user increases and consumed power decreases. Although these two concepts are opposite to each other, but using optimization we maintained both parameters simultaneously. Temperature, illumination and air-quality of the building calculated using sensor devices. Illumination is the visual display (subjective) inside the building and air-quality is the CO_2 emission inside the building. CO_2 concentration is used as an index to measure the air-quality in the building environment.

Figure 1.2. Conceptual model

1.2.2. Building model

In this section we presented the building model Figure 1.3. The building model is classified into different comfortable zones. Each comfortable zone named room space1 and room space2 up-to room space n. Each room space installed sensors and actuators. Installed sensors are temperature sensor, illumination sensor and air-quality sensor. Each of these sensors is responsible to collect respective environmental temperature, illumination and air-quality data for each individual room space. Four actuators are considered for each room space in the building. Building actuators are the devices which actually use the power inside the building. The actuators considered here are AC (Air-condition) used for cooling the room space and Boiler used for heating room space, and light for lighting system (visual comfort) and fan for providing air-quality comfort. Each of these actuators receives message information to turn on/off during different hours of the day.

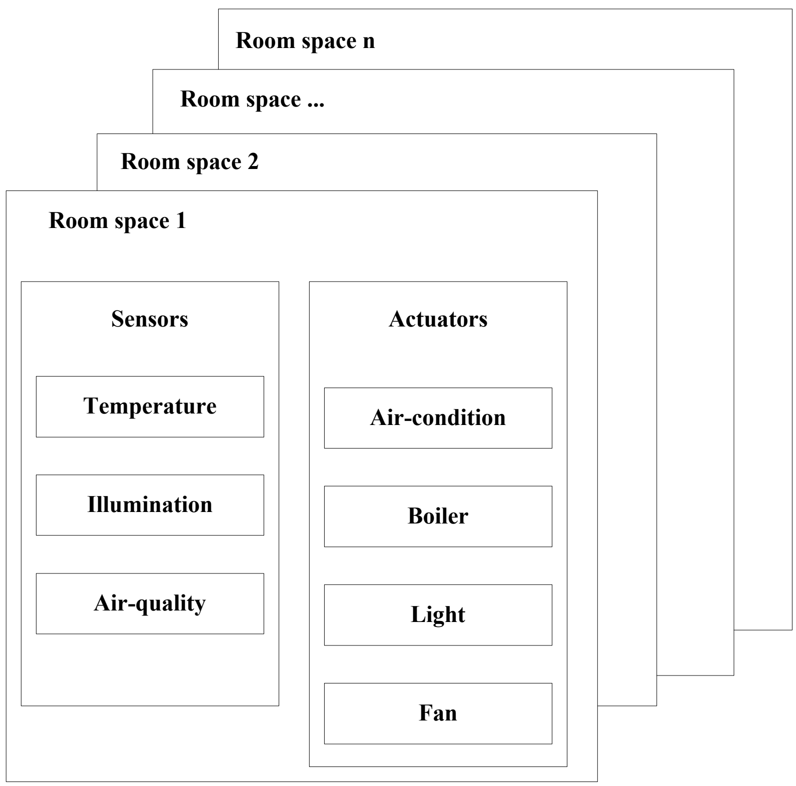

Figure 1.3. Building model

1.2.3. Sensor data

The sensors data considered to be included in proposed models are Temperature, Illumination and Air-quality. These three sensors data are selected to satisfy users comfort index with respect to the thermal, visual and air-quality comfort. These three parameters jointly defined the occupants comfort index.

1.2.4. Single preprocessing

Three out of six proposed models are based on single preprocessing mechanisms. In single preprocessing only sensing data are smooth. The sensing data is also checked against the noise of outlier, zero cell data, standard form and normalization. If the data is found to be noisy then simply removes the outlier's data, zero cell data and bring the data into the standard form. When the data becomes processed and in the standard form, it is then input to the optimization component.

1.2.5. Multi-preprocessing

Other three proposed models are based on multi-preprocessing mechanisms. In multi-preprocessing each major component is preprocessed using smoothing. The sensing data is also checked against the noise of outlier, zero cell data, standard form and normalization. If the data is found to be noisy then simply removes the outlier's data, zero cell data and bring the data into a standard form. When the sensing data becomes processed and in the standard form, it is then input to the optimization component. After optimization smoothing is again applied to smooth the optimal parameters but this time conditional smoothing is applied. Conditional smoothing means, if the parameters to be smooth results in degrading occupants comfort index then those parameters are not candidates for smoothing. Otherwise the parameters are smooth when it results in increase of occupants comfort index. After smoothing optimal parameters, the updated optimal parameters results in improved occupants comfort index. The error difference between updated optimal parameters and smooth environmental data is input to the fuzzy controllers.

1.2.6. Comfort index

In residential buildings, the important parameters which manage occupant's quality of lives are thermal comfort, visual comfort and air-quality [5]. Temperature identifies the thermal comfort of the occupant's in a residential building. The heating or cooling system is used to preserve the temperature in building's comfortable zone. The illumination level is used to identify the visual comfort of the occupants in the residential building [6]. The electrical lighting system is used to accomplish the visual comfort. CO_2 concentration is used as an index to measure the air-quality in the building. Ventilation system is utilized to keep low CO_2 concentration [7]. So the combination of these three parameters serves as occupant's comfort index in the residential building. We considered these three parameters to assess the occupant's comfort index and energy savings in residential buildings.

We have calculated comfort index using Eq. (1.1).

$$\text{Comfort} = \beta_1\,[1-(err_T/T_{set})^2] + \beta_2\,[1-(err_L/L_{set})^2] + \beta_3\,[1-(err_A/A_{set})^2] \quad (1.1)$$

Where "Comfort" is the objective function and the aim is to maximize this function. It denotes the overall comfort level (temperature, illumination and air-quality) of the user. The range of comfort index is between [0, 1]. The comfort index varies between '0' and '1'. '0' means lowest or minimum comfort index and '1' means highest or maximum comfort index. $\beta 1$, $\beta 2$, $\beta 3$ are the user defined factors which solve any possible conflict between the three comfort factors (temperature, illumination and air-quality). At any time $\beta 1+\beta 2+\beta 3 = 1$. In (Eq. 1.1) e_T is the error difference between optimal parameter of hybrid energy optimization (temperature in this case) and actual sensor temperature. The minimum error difference, the maximum will be the comfort index. So we can say there is an inverse relationship between comfort index and error difference of the parameters (temperature, illumination and air-quality). As the error difference is the input to the fuzzy controller which confirms, the minimum error difference, the minimum will be the consumed power.

So in this aspect comfort index also has inverse relationship with power consumption. The minimum consume power, the highest will be the comfort index. So the comfort index is depended on the error difference for each of the temperature, illumination and air-quality parameters. If the error difference for each of the parameters minimize, the maximum will be the comfort index and vice versa. This fulfills our basic design objectives to minimize the power consumption and maximize the comfort index.

err_L is the error difference between optimal parameter of hybrid energy optimization (illumination in this case) and actual sensor illumination. err_A is the error difference between optimal parameter of hybrid energy optimization (air-quality in this case) and actual sensor air-quality. T_{set}, L_{set}, A_{set} are the user set parameters of temperature, illumination and air-quality.

1.2.7. Hybrid energy optimization

Based on serial and parallel hybrid energy optimization algorithms, three hybrid energy optimization algorithms in two different models (single preprocessing and multi-preprocessing) are described in this section. First hybrid energy optimization algorithm is based on PSO and GA. This hybrid energy optimization is the parallel hybrid energy optimization algorithm. This algorithm is applied in both single preprocessing and multi-preprocessing model. In single preprocessing hybrid parallel energy optimization, PSO and GA optimizes user set parameters. When both GA and PSO finished optimization, then both the optimization solutions PSO and GA are combined to get the best solution. After getting best solutions, the next iteration population included individuals of both PSO and GA. The process is continued until we get optimal solutions. The optimal solution of hybrid parallel energy optimization based on PSO and GA is used to calculate the occupant's comfort index. The error difference between these optimal parameters and environmental parameters is input to the fuzzy controllers.

In multi-preprocessing hybrid parallel energy optimization, PSO and GA optimizes user set parameters. When both GA and PSO finished optimization then both the optimization solutions are combined to get the best solution from both PSO and GA. After getting best solution, the next iteration population included individuals of both PSO and GA. The process is continued until we get optimal solution. The optimal solution of hybrid parallel energy optimization based on PSO and GA is used to calculate the occupant's comfort index. The optimal parameters are preprocessed using smoothing to smooth the optimal parameters and improve the occupants comfort index. After smoothing, the optimal parameters are updated. The comfort index is recalculated based on the updated optimal parameters to get the improved occupants comfort index. The updated optimal parameters are then used along with environmental parameters to calculate the error difference. The resultant error difference is then input to the fuzzy controllers.

Second hybrid energy optimization algorithm is based on PSO and GA. This hybrid energy optimization is the serial hybrid energy optimization algorithm. This algorithm is applied in both single preprocessing and multi-preprocessing models.

In single preprocessing hybrid serial energy optimization, PSO optimizes user set parameters. When PSO finished optimization then GA algorithm starts optimization of user set parameters with respect to the environmental parameters along with optimal parameters of PSO to get the best solution. After getting best solution, the next iteration population for GA included individuals of its own and optimal parameters of PSO. The process is continued until we get optimal solution. The optimal solution of hybrid serial energy optimization based on PSO and GA is used to calculate the occupant's comfort index. The error difference between these optimal parameters and environmental parameters is input to the fuzzy controllers.

In multi-preprocessing hybrid serial energy optimization, PSO optimizes user set parameters. When PSO finished optimization then GA algorithm starts optimization of user set parameters with respect to the environmental parameters along with optimal parameters of PSO to get the best solution. After getting best solution, the next iteration population for GA contains individuals of its own and optimal parameters of PSO. The process is continued until we get optimal solution. The optimal solution of hybrid serial energy optimization based on PSO and GA is used to calculate the occupant's comfort index.

These optimal parameters are preprocessed using smoothing to smooth the optimal parameters and improve the occupants comfort index. After smoothing, the optimal parameters are updated. The comfort index is recalculated based on the updated optimal parameters to get the improved comfort index. The updated optimal parameters are then used along with environmental parameters to calculate the error difference. The resultant error difference is then input to the fuzzy controllers.

Third hybrid energy optimization algorithm is based on PSO and MIGA. This hybrid energy optimization is the serial hybrid energy optimization algorithm. This algorithm is applied in both single preprocessing and multi-preprocessing model. In single preprocessing hybrid serial energy optimization, PSO optimizes user set parameters. When PSO finished optimization then MIGA algorithm starts optimization of user set parameters with respect to the environmental parameters along with optimal parameters of PSO to get the best solution. After getting best solution, the next iteration population for MIGA contains individuals of its own and optimal parameters of PSO. The process is continued until we get optimal solution. The optimal solution of hybrid serial energy optimization based on PSO and GA is used to calculate the occupant's comfort index. The error difference between these optimal parameters and environmental parameters is input to the fuzzy controllers.

In multi-preprocessing hybrid serial energy optimization, PSO optimizes user set parameters. When PSO finished optimization then MIGA algorithm starts optimization of user set parameters with respect to the environmental parameters along with optimal parameters of PSO to get the best solution of MIGA. After getting best solution, the next iteration population for MIGA contains individuals of its own and optimal parameters of PSO. The process is continued until we get optimal solution. The optimal solution of hybrid serial energy optimization based on PSO and MIGA is used to calculate the occupant's comfort index.

These optimal parameters are preprocessed using smoothing to smooth the optimal parameters and improve the occupants comfort index. After smoothing, the optimal parameters are updated. The comfort index is recalculated based on the updated optimal parameters to get the improved comfort index. The updated optimal parameters are then used along with environmental parameters to calculate the error difference. The resultant error difference is then input to the fuzzy controllers.

1.2.7.1. Hierarchy of energy optimization and prediction algorithms

In this section we are going to introduce the conceptual and detailed hierarchy of the optimization algorithms applied to energy consumption optimization. Figure 1.4 shows the conceptual hierarchy of the proposed hybrid energy optimization algorithms. The basic optimization algorithms applied to energy optimization is divided into two types of optimization models. One is single energy optimization and prediction models and second is hybrid optimization and prediction models. As the names describes, the former one uses single optimization technique to optimize the user set parameters while the latter one uses combination of two techniques to form a hybrid optimization algorithms. The latter one is further divided into two types of optimization and prediction models. One is single preprocessing optimization and prediction models and second one is multi-preprocessing optimization and prediction models.

The earlier one uses preprocessing of the environmental data while second one uses preprocessing at multiple stages in the model i.e. before each of optimization, fuzzy control and prediction components. Similarly post-processing is applied only at the end of the single preprocessing optimization and prediction models while for the multiple preprocessing optimization and prediction models it is applied after each stage of the model. Preprocessing involves smoothing of the data while post-processing involves analysis, results communication with the users and visualization of the results for each part (Optimization, Fuzzy control and Prediction) of the model.

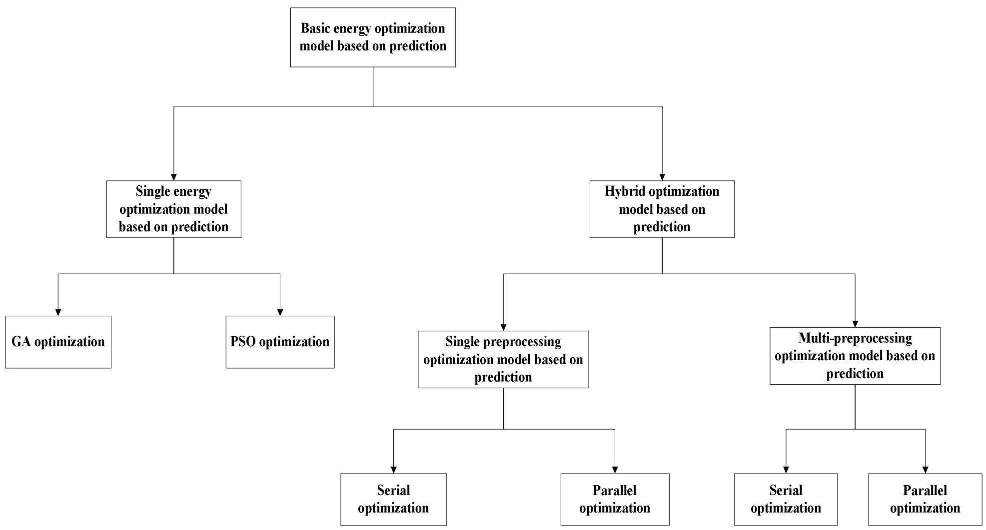

Figure 1.4. Conceptual hierarchy of optimization algorithms

Figure 1.5 shows the detailed hierarchy of the proposed hybrid energy optimization algorithms. In single energy optimization model based on prediction, two kinds of optimization algorithms have been used. PSO based optimization and GA based optimization of parameters. Proposed hybrid energy optimization is divided into two parts, single preprocessing and multi-preprocessing. Single preprocessing optimization models use three scenarios of optimizations. One is (PSO and GA based parallel hybrid optimization), second is (PSO and GA based serial hybrid optimization) and third is (PSO and MIGA based serial hybrid optimization).

In PSO and GA based parallel hybrid optimization, initially PSO particle's positions and velocities along with GA individuals is populated. The size of initial population is 100. In the next step, the particles and individuals are evaluated against the fitness function defined in (Eq. 1.1). In the next step, particles local best fitness and local best position is defined. Individuals are selected for recombination based on the rank based selection method. In the next step, global best fitness is initialized with local best fitness. In the next step, particles position and velocities are updated using (Eq. 3.1 and Eq. 3.2). Crossover is performed for the individuals to get create offspring's. In the next step, fitness of particles and individuals is evaluated using (Eq. 1.1). In the next step, a mutation criterion is checked and if it met then mutation is performed by creating a random individual. If the mutation criterion does not met then combined updated particles and updated individuals to select the best solution. If the current best fitness is bad than the combined fitness, then update particles position and velocities along with creation of off-springs using crossover. If this is not the case and current fitness is best than the global fitness then assigned current best to the global best fitness. In the next step if the stopping criterion met then stop the evaluation of the algorithm and we get optimal solution otherwise update particles position and velocities along with creation of off-springs using crossover until stopping criterion is met.

In PSO and GA based serial hybrid optimization, initially GA individuals are randomly populated. The size of initial population is 100. In the next step, individual from initial population of GA and PSO optimal solutions is selected based on the minimum error difference against the environmental parameters. In the next step, individuals are evaluated against the fitness function defined in (Eq. 1.1). In the next step, individuals are selected for recombination based on the rank based selection method.

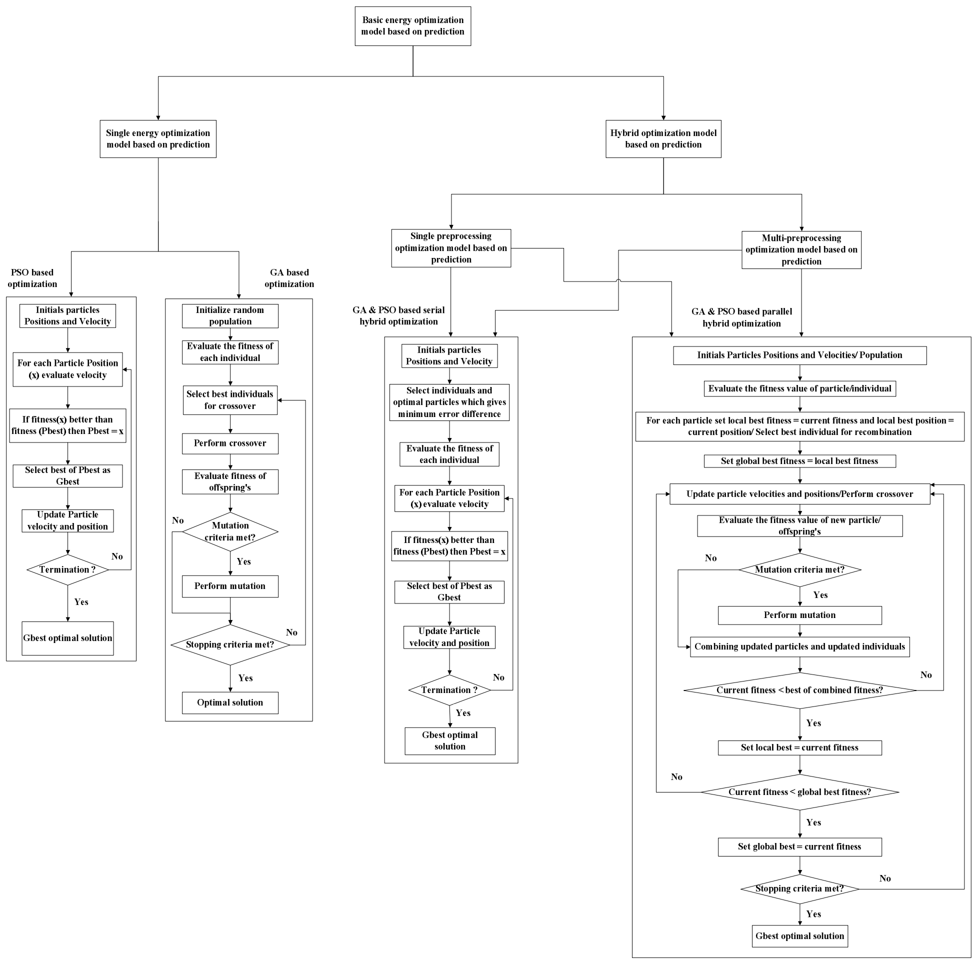

Figure 1.5. Detailed hierarchy of optimization algorithms

In the next step, crossover is performed for the individuals to create offspring's. In the next step, individuals are evaluated using (Eq. 1.1). In the next step, a mutation criterion is checked and if it met then mutation is performed by creating a random individual. If mutation criterion is met then perform mutation by creating a random individual otherwise check stopping criterion. If stopping criterion arises then stop evaluation of algorithm and we will get optimal solution, otherwise create off-springs using crossover until stopping criterion is met.

PSO and MIGA based serial hybrid optimization; initially GA individuals are randomly populated. The size of initial population is 100. In the next step, individual from initial population of MIGA, and PSO optimal solutions is selected based on the minimum error difference against the environmental parameters.

In the next step, the population is divided into two islands. In the next step, individuals of both islands are evaluated against the fitness function defined in (Eq. 1.1). In the next step, individuals from each island are selected for recombination based on the rank based selection method. In the next step, crossover is performed for the individuals of each island to create offspring's. In the next step, individuals of each island are evaluated using (Eq. 1.1). In the next step, migration and mutation criterion is checked and if it met then migrations and mutation is performed by migrating individuals between the islands and randomly creating individual respectively. If migration and mutation criterion does not is met then check stopping criterion. If stopping criterion arises then stop evaluation of algorithm and we will get optimal solution, otherwise create off-springs using crossover until stopping criterion is met.

1.2.7.2. Algorithms complexity

Most evolutionary algorithms (EA) have, at each iteration, a complexity of O(n*p + Cof*p), where n is the dimension of the problem and p is the population size and Cof is the cost of the objective function, CM is the crossover and mutation O(CM), S is the Selection of parents O(S), PV is the particle and velocities updates O(PV), U is the update of optimal parameters and comfort index (T, L, A). The complexity of objective functions are of O(n).

Furthermore, EA usually perform FEs/p iterations, where FEs is the maximum amount of function evaluations allowed. Thus, the complexity cost becomes O (n*FEs + Cof*FEs). Once again, the second term tends to determine the time complexity and this complexity is determined by the cost of evaluating the objective function and the amount of evaluations we perform. That's why in EA, the quality of an algorithm is frequently measured by the amount of evaluations it performs. Eq (1.2 to 1.11) shows the complexities of each of the model algorithm.

Where n = 3, FEs = 1, Cof = 9, p = 100, CM = PV = 100 * 3, S = O (p*0.9) = 100 * 0.9 = 90 and U = Update optimal parameters = 3, (T, L, A) and update comfort (T, L, A) = 3

1. PSO based model complexity/Algorithm 1

O (n*FEs + Cof*Fes + PV) (1.2)

= 3 * 1 + 9 * 1 + 100 * 3 = 312

2. GA based model complexity/Algorithm 2

$$O\ (n*FEs + Cof*FEs + CM + S) \tag{1.3}$$

$$= 3 * 1 + 9 * 1 + 100 * 3 + 90 = 402$$

3. PSO and GA based single preprocessing parallel based algorithm complexity

$$O\ (n*FEs + Cof*FEs + PV + CM + S) \tag{1.4}$$

$$= 3 * 1 + 9 * 1 + 100 * 3 + 100 * 3 + 90 = 702$$

4. PSO and GA based single preprocessing serial algorithm complexity

$$O\ ((n*FEs + Cof*FEs + PV) + (n*FEs + Cof*FEs + CM + S)) \tag{1.5}$$

$$= 3 * 1 + 9 * 1 + 100 * 3 + 3 * 1 + 9 * 1 + 100 * 3 + 90 = 714$$

5. PSO and MIGA based single preprocessing serial algorithm complexity

$$O\ ((n*FEs + Cof*FEs + PV) + ((n*FEs + Cof*FEs + (CM + S + S)) \tag{1.6}$$

$$= 3 * 1 + 9 * 1 + 100 * 3 + 3 * 1 + 9 * 1 + 100 * 3 + 90 + 90 = 802$$

6. PSO based multi-preprocessing algorithm complexity

$$O\ (n*FEs + Cof*Fes + PV + U*n) \tag{1.7}$$

$$= 3 * 1 + 9 * 1 + 100 * 3 + 3 * 3 = 321$$

7. GA based multi-preprocessing algorithm complexity

$$O\ (n*FEs + Cof*FEs + CM + S + U*n) \tag{1.8}$$

$$= 3 * 1 + 9 * 1 + 100 * 3 + 90 + 3 * 3 = 411$$

8. PSO and GA based multi-preprocessing parallel algorithm complexity

$$O\ (n*FEs + Cof*FEs + PV + CM + S + U*n) \tag{1.9}$$

$$= 3 * 1 + 9 * 1 + 100 * 3 + 100 * 3 + 90 + 3 * 3 = 711$$

9. PSO and GA based multi-preprocessing serial algorithm complexity

$$O\ ((n*FEs + Cof*FEs + PV) + (n*FEs + Cof*FEs + CM + S)) + U \quad (1.10)$$

$$= 3 * 1 + 9 * 1 + 100 * 3 + 3 * 1 + 9 * 1 + 100 * 3 + 90 + 3 * 3 = 723$$

10. PSO and MIGA based multi-preprocessing serial algorithm complexity

$$O\ ((n*FEs + Cof*FEs + PV) + ((n*FEs + Cof*FEs + (CM + S + S)) + U \quad (1.11)$$

$$= 3 * 1 + 9 * 1 + 100 * 3 + 612 + 90 + 90 + 3 * 3 = 1113$$

The complexity and performance (energy consumption) graph is shown in Figure 1.6. In graph each model algorithms complexity and performance is analyzed with respect to the energy consumption. Algorithm 1 and 2 are the PSO based model and GA based model complexities, algorithm 3, 4 and 5 are the single preprocessing hybrid optimization models complexities, algorithm 6 and 5 are the PSO and GA based multi-preprocessing model algorithms and algorithm 8 to 10 are the multi-preprocessing hybrid energy optimization model complexities.

In Figure 1.6 GA based model (algorithm 2) has higher complexity as compared to PSO based model (algorithm 1). GA based model algorithm consumed less power as compared to PSO based model algorithm. The performance of GA based algorithm is much better than PSO based model algorithm as far as power consumption reduction is concerned. PSO & GA based hybrid parallel model with single preprocessing (algorithm 3), PSO & GA based hybrid serial model with single preprocessing (algorithm 4), and PSO & MIGA hybrid serial model with single preprocessing (algorithm 5) has higher complexities as compared to algorithm 1 and algorithm 2 but consumed less power as compared to algorithm 1 and algorithm 2. The performance of algorithms 3, 4 and 5 which are the single preprocessing hybrid energy model algorithms, are much better than PSO based model algorithm and GA based model algorithm with respect to the power consumption reductions.

PSO based multi-preprocessing model (algorithm 6) and GA based multi-preprocessing model (algorithm 7) has higher complexities as compared to algorithm 1 and algorithm. Although complexities of algorithms 6 and 7 are higher than algorithm 1 and 2 but consumed less power as compared to algorithm 1 and 2.

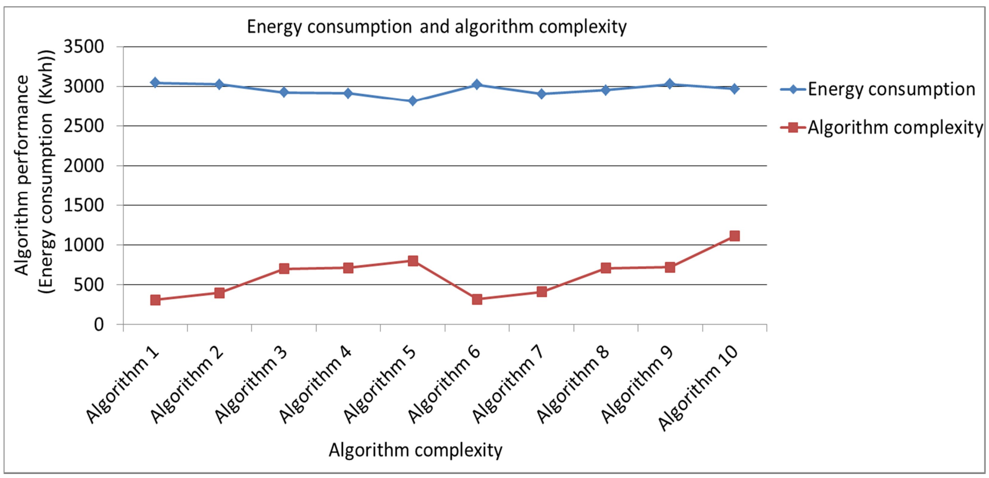

Figure 1.6. Algorithm’s complexity and performance graph

The performance of algorithms 6 and 7 are much better than PSO based model algorithm and GA based model algorithm with respect to the power consumption reductions. PSO & GA based hybrid parallel model with multi-preprocessing (algorithm 8), PSO & GA based hybrid serial model multi-preprocessing (algorithm 9), and PSO & MIGA hybrid serial model multi-preprocessing (algorithm 10) has higher complexities as compared to algorithm 1 and algorithm 2 but consumed less power as compared to algorithm 1 and algorithm 2. Although the complexities of the multi-preprocessing hybrid energy model algorithms 8, 9 and 10 are high but the performance are much better than PSO based model algorithm and GA based model algorithm with respect to the power consumption reductions.

Table 1.1 shows the performance of each model's algorithm for temperature, illumination, air-quality and total power consumption. It also shows the complexity values of each model's algorithm. 'Yes' means that respective algorithm perform well with respect to the power consumption reductions and comfort index as compared to basic model algorithms.

PSO based model algorithm complexity is 312 and its corresponding total power consumption is 3047KWh. GA based model algorithm complexity is 402 while its total power consumption is 3026KWh. GA based model complexity is high than PSO based model complexity but it perform well in terms of power consumption reduction and comfort index improvements.

PSO & GA based hybrid parallel with single preprocessing model algorithm complexity is 702 and its corresponding total power consumption is 2922KWh. PSO & GA hybrid serial with single preprocessing model algorithm complexity is 714 while its total power consumption is 2914KWh. PSO & MIGA hybrid serial with single preprocessing model algorithm complexity is 802 while its performance with respect to total power consumption is 2812KWh.

Table 1.1. Algorithm's complexity and performance with respect to the power consumption reduction and comfort index

<table>
<tr><td colspan="3"></td><td colspan="4">Predicted Power Consumption</td><td></td><td></td><td colspan="4" rowspan="2">System performance</td></tr>
<tr><td>Model</td><td>Scenario</td><td>Algo</td><td>T</td><td>L</td><td>A</td><td>Total</td><td>Algorithm complexity</td><td>Complexity value</td></tr>
<tr><td rowspan="2">Basic model</td><td>PSO based prediction</td><td>PSO & K</td><td>601</td><td>1707</td><td>738</td><td>3047</td><td>O (n*FEs + Cof*Fes + PV)</td><td>312</td><td colspan="2">Power consumption reduction</td><td colspan="2">Comfort Index Improvement</td></tr>
<tr><td>GA based prediction</td><td>GA & K</td><td>581</td><td>1704</td><td>739</td><td>3026</td><td>O (n*FEs + Cof*FEs + CM + S)</td><td>402</td><td>Compared to Basic Model PSO</td><td>Compared to Basic Model GA</td><td>Compared to Basic Model PSO</td><td>Compared to Basic Model GA</td></tr>
<tr><td rowspan="3">Hybrid optimization single preprocessing</td><td>Scenario 1 Parallel</td><td>GA in PSO and K</td><td>518</td><td>1665</td><td>738</td><td>2922</td><td>O (n*FEs + Cof*FEs + PV + CM + S)</td><td>702</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>Scenario 2 Serial</td><td>PSO & GA and K</td><td>532</td><td>1641</td><td>739</td><td>2914</td><td>O ((n*FEs + Cof*FEs + PV)
+ (n*FEs + Cof*FEs + CM + S))</td><td>714</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>Scenario 3 Serial</td><td>PSO & MIGA and</td><td>507</td><td>1599</td><td>705</td><td>2812</td><td>O ((n*FEs + Cof*FEs + PV)
+ ((n*FEs + Cof*FEs +</td><td>802</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
</table>

		ARIMA					(CM + S + S))					
PSO based multi-preprocessing	Scenario 1	PSO Serial K & A	586	1679	756	3022	O (n*FEs + Cof*Fes + PV + U*n)	321	Yes	Yes	Yes	Yes
GA based multi-preprocessing	Scenario 2	GA Parallel K ARIMA	537	1659	707	2904	O (n*FEs + Cof*FEs + CM + S + U*n)	411	Yes	Yes	Yes	Yes
Hybrid optimization multi-preprocessing	Scenario 1 Parallel	GA in PSO and K	551	1659	742	2953	O (n*FEs + Cof*FEs + PV + CM + S + U*n)	711	Yes	Yes	Yes	Yes
	Scenario 2 Serial	PSO & GA and K	610	1679	738	3028	O ((n*FEs + Cof*FEs + PV) + (n*FEs + Cof*FEs + CM + S)) + U	723	Yes	Almost same power consumption	Yes	Yes
	Scenario 3 Serial	PSO & MIGA &ARIMA & K	572	1667	729	2968	O ((n*FEs + Cof*FEs + PV) + ((n*FEs + Cof*FEs + (CM + S + S)) + U	1113	Yes	Yes	Yes	Yes

Note. - Algo = Algorithm. T = Temperature. L = Illumination. A = Air-quality

Compared to PSO based model algorithm and GA based model algorithm, single preprocessing hybrid energy optimization algorithm's complexity is high but performs well in terms of power consumption reduction and comfort index improvements. PSO based multi-preprocessing model algorithm complexity is 321 and its corresponding total power consumption is 3022KWh. GA based multi-preprocessing model algorithm complexity is 411 while its total power consumption is 2904KWh. Compared to PSO based model algorithm and GA based model algorithm, multi-preprocessing energy optimization algorithm's complexity is high but perform well as afar as total power consumption reduction and comfort index improvements is concern.

PSO & GA based hybrid parallel with multi-preprocessing model algorithm complexity is 711 and its corresponding total power consumption is 2953KWh. PSO & GA based hybrid serial with multi-preprocessing model algorithm complexity is 723 while its total power consumption is 3028KWh. PSO & MIGA based hybrid serial with multi-preprocessing model algorithm complexity is 113 while its performance with respect to total power consumption is 2968KWh. Compared to PSO based model algorithm and GA based model algorithm, multi-preprocessing hybrid energy optimization algorithm's complexity is high but perform well in terms of power consumption reduction and comfort index improvements.

1.2.7.3. Proposed hybrid energy optimization algorithms

In this section we are going to explain our proposed parallel and serial based optimization methods and with the help of flow charts. Figure 1.7 shows the step by step procedure of hybrid parallel optimization algorithm based on PSO and GA.

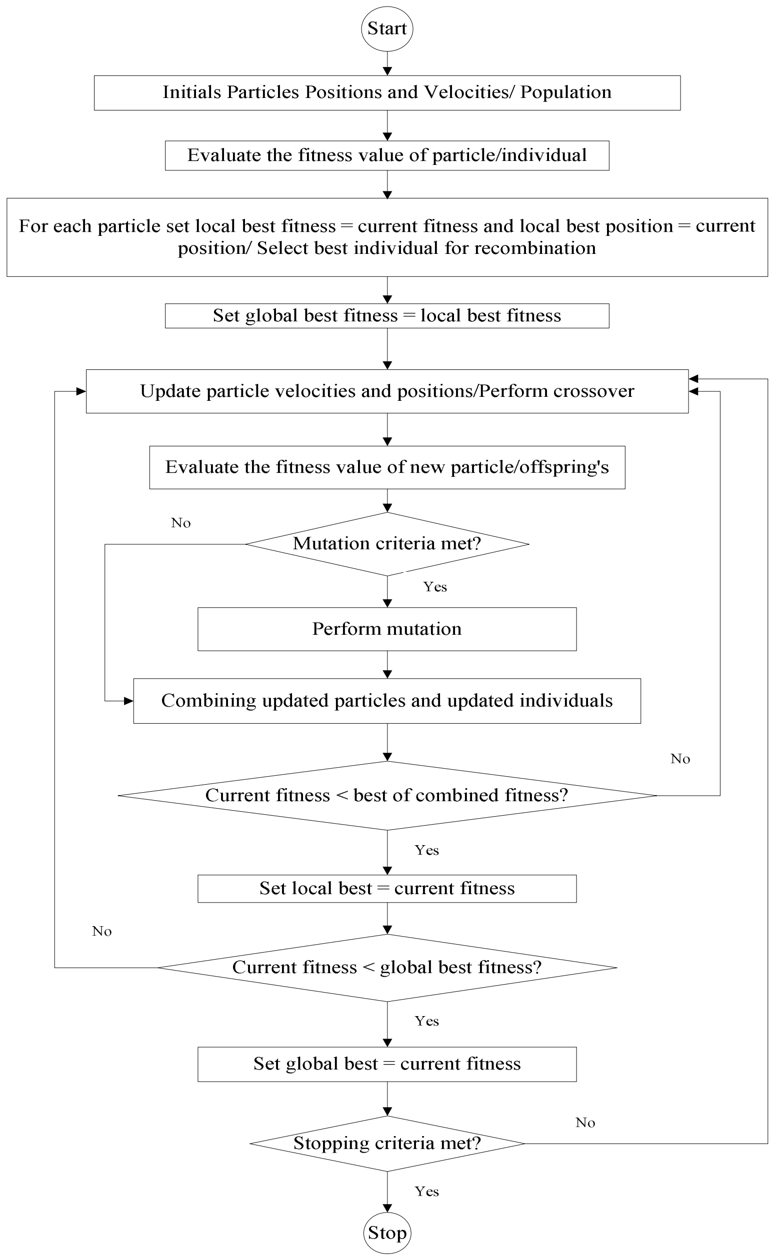

Figure 1.7. Parallel hybrid energy optimization algorithms flow chart

Initially random population of individuals and particles is initialized. Then the individuals and particles are evaluated using fitness function (Eq. 1.1). For each particles the local best fitness and local best position is set. Similarly for recombination of individuals the best fitted chromosomes are selected. Then the global best fitness is also initialized using local best fitness. The new particles and offspring's are evaluated using fitness function (Eq. 1.1). If mutation criteria meet then apply mutation. Combining updated particles and updated individuals.

If current fitness is less than best of all combined solutions then set local best as current otherwise updated particle velocities, positions and perform crossover. If current fitness is less than global best fitness then set global best as current fitness otherwise updated particle velocities, positions and perform crossover. If stopping criteria met then stop and we get optimal solution otherwise updated particle velocities, positions and perform crossover. Figure 1.8 shows the step by step procedure of hybrid serial optimization algorithm based on PSO and GA. Initially random population of individuals is initialized. Then select individuals and optimal particles give the minimum error difference with respect to environmental parameters. Then the selected individuals are evaluated using fitness function (Eq. 1.1). Then select best fitted individuals for recombination as parents. Perform 'variable two point' crossover and evaluate fitness of each offspring using fitness function (Eq. 1.1). If mutations criteria meet then perform mutation otherwise check stopping criteria. After mutation check stopping criteria if yes then stop otherwise select best individuals for crossover and continue until stopping criteria arises.

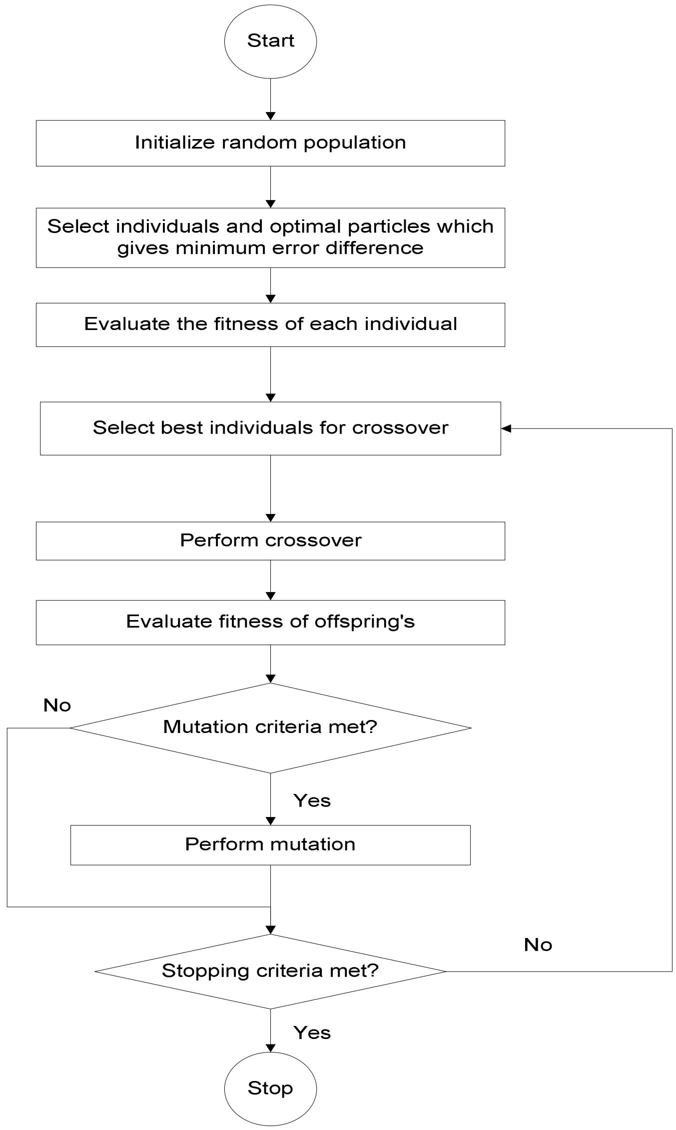

Figure 1.8. Serial hybrid energy optimization algorithms flow chart

1.2.7.4. Which approach is good in which situation?

In this section we are going to described which proposed approach is good in which situation.

1. In situation where we want to provides the highest level of occupants comfort

index, then multi-preprocessing hybrid energy optimization with prediction is much suitable than single preprocessing.

2. In situation where we want to provide a better comfort index without compromising energy consumption, then single preprocessing hybrid energy optimization with prediction is suitable as compared to GA/PSO with prediction and multi-preprocessing hybrid energy optimization with prediction.
3. In situation where we want to implement and proposed simple model without compromising the design objectives then single preprocessing hybrid energy optimization with prediction models are better and simpler than complex models of multi-preprocessing hybrid energy optimization with prediction.

1.2.8. Energy consumption predictions

Single preprocessing hybrid parallel energy optimization based on PSO and GA model uses Kalman filter to predict the energy consumption. Hybrid serial energy optimization based on PSO and GA model also used Kalman filter to predict energy consumption. Third model of single preprocessing hybrid energy optimization uses hybrid energy consumption prediction. Hybrid energy prediction uses both Kalman filter and ARIMA model to predict the energy consumption. In hybrid energy prediction, ARIMA model predict the energy consumption and then the predicted energy consumption is again input to the Kalman filter to predict it again. Then the average of the two predictions gives the predicted energy consumption. The predicted consume power is given to the actuators for usage. The predicted consume power is the power to be consumed in the building.

In multi-preprocessing hybrid energy optimization and prediction models, the consumed power is preprocessed to smooth the consumed power before it is given to the prediction component of the model. After smoothing, the consumed power is updated, and revised consumed power is input to the prediction component. Multi-preprocessing uses the Kalman filter, ARIMA model and hybrid energy consumption prediction based on the two prediction algorithms (Kalman filter and ARIMA model) to predict the energy consumption.

1.2.9. Actuators

Building actuators are the devices which actually use the power inside the building. The actuators considered for simulation here are AC used for cooling, heater for heating the residential building, and light for visual comfort and fan for providing air-quality comfort. Each of these actuators receives message information to turn on/off.

1.2.10. Indoor environment

When actuators received message information the status of the actuators changes accordingly. When actuators start running, the indoor environment gets change and updated with respect to the optimal parameters. The indoor environment gets improve gradually based on the message information received by actuators.

1.3. Contributions

In this section the work contributed to the research of energy management in future energy efficient building environment is described. All the work discussed in the related work did not consider these contributions.

1. Proposed idea of preprocessing based on single preprocessing and multi-preprocessing mechanism did not covered by the previous approaches.
2. Proposed models uses hybrid energy optimization algorithms to optimized user set parameters instead of single optimization.
3. Energy consumption is predicted using hybrid prediction algorithms used by the actuators of the building.
4. Proposed idea of energy management deals with energy consumption reduction and occupants comfort index simultaneously as compared to other approaches.
5. In [29, 30], the user occupants comfort index is not addressed while proposed models gives attention to the occupants comfort index.
6. In [23, 26-30], the user set parameters are not considered in deciding occupants comfort index. User set parameters plays a vital role in deciding occupants comfort index. So these models are not user friendly while proposed hybrid energy optimization based on prediction and preprocessing considers user set parameters in deciding occupants comfort index.

7. In [23, 31-32], the energy efficiency is not addressed while proposed models addressed energy efficiency.

2. Related works

2.1. Energy consumption optimization

In this section we are going to explore the related work of optimization algorithms applied to energy management previously.

2.1.1. Optimization

A series of steps used (usually by a computer program) to find an optimal solution to a problem. An optimization algorithm consists of maximizing or minimizing a real function by systematically choosing input values from within an allowed set and computing the value of the function. Optimization includes finding "best available" values of some objective function given a defined domain, including a variety of different types of objective functions and different types of domains.

Despite its name, optimization does not necessarily mean finding the optimum solution to a problem, since it may be unfeasible due to the characteristics of the problem, which in many cases are included in the category of NP-hard problems. Yet, for optimization problems that are NP-hard, no polynomial time algorithm exists, i.e. the algorithms used might need exponential computation time in the worst case to obtain the optimum, which leads to computation times that are too high for practical purposes.

As a result, in recent decades many authors have proposed approximate methods, including heuristic approaches and artificial neural networks, to solve these problems instead of using traditional optimization methods, such as linear-programming), nelder–mead simplex method, lagrangian relaxation and quadratic programming etc. Heuristic methods can be seen as simple procedures that provide satisfactory, but not necessarily optimal, solutions to large instances of complex problems rapidly. Meta-heuristics are generalizations of heuristics in the sense that they can be applied to a wide set of problems, needing few modifications to be adapted to a specific case. In some cases, the complexity of the problems to solve is so high that even heuristic and meta-heuristic methods are not able to obtain accurate solutions in reasonable runtimes.

2.1.2. Energy optimization

The two important parameters in energy management are user set preference parameters and environmental parameters. User set parameter is the required comfort level of the occupants in building environment, while environmental parameter is the environmental conditions. User set parameters and environmental parameters consists of temperature, illumination and air-quality. In our proposed model, the input to the fuzzy controller is the error difference between user set parameters and environmental parameters. The minimum error difference, the minimum will be the power consumption. Here the aim of optimization is to minimize the error difference between users set parameters and environmental parameters which results in minimizing the energy consumption. So energy optimization is carried out to ensure minimum power consumption and increase occupants comfort index. The user set parameters are optimized using hybrid optimization algorithms to minimize the error difference between optimal user set parameters (optimal parameters) and environmental parameters. After calculating the error difference between optimal parameters and environmental parameters we concluded that error difference between optimal parameters and environmental parameters is less than error difference between user set parameters and environmental parameters.

2.1.3. Particle swarm optimization (PSO)

PSO algorithm was first described as a new modern heuristic algorithm in 1995 [8]. It is introduced as a stochastic operator-based, population-based and self-adaptive computer algorithm simulated based on birds social behaviors. PSO is being widely used for various engineering applications and has turned out to be a powerful optimizer. PSO is a directed search algorithm because it keeps local best position and global best position of all the particles and particle fly according to the information's it currently have. Compare to GA [9] it is not computationally expensive. So it produced results quickly. Like other evolutionary algorithms such as GA, PSO also randomly generates a number of solutions called initial population, and then finds the optimal solution by updating generations iteratively. Each potential solution in PSO is called a particle, which follows the current local best solution to fly through the whole solution space for approaching the global best solution. An objective function is used to evaluate the quality of each candidate solution with respect to a given problem. In PSO, each particle represents a possible solution involving two vectors, which are the position vector and velocity vector. The step by step PSO algorithms is discussed in section 3.1.2.

2.1.4. Genetic algorithm (GA)

GA is evolutionary, search and optimization algorithm based on the principles of natural selection and genetics. The principals of GA technique are given [9]. GA has been deployed to solve wide range of optimization problems where search space is too much large. GA evolves a population of initial individuals to a population of high quality individuals, where each individual represents a solution of the problem to be solved. Each individual is called chromosome, and is composed of a predetermined number of genes. The quality of fitness of each chromosome is measured by a fitness function described earlier in section 1.6.

Determination of the following factors has the crucial impact on the efficiency of the algorithm: selection of fitness function, representation of individuals and the values of GA parameters (crossover and mutation rate, and size of population). Determination of the above factors usually depends on the application. In our implementation we used the crossover rate as 0.9% and mutation rate as 0.1%. The rate of crossover and mutation were set after a long run of the GA algorithm. After completion of the iterations, GA output the optimal parameters with respect to the sensor data. Figure 2.1 shows the flow cycle of the GA. First of all, initial population of chromosome is created. Then it is evaluated by using some fitness function, in our case we used equation (Eq. 1.1) for evaluation of chromosomes. Then selection of parent candidates is carried out for modification (crossover). In our case we used rank based selection to select parent candidates. Then after modification of parent chromosomes we got new chromosomes as modified off-springs, also called child chromosomes.

We used "variable two point crossover" method for modifications of parent chromosomes. After getting child chromosomes we evaluated them against the fitness function that is equation (Eq. 1.1). Then after evaluation of child chromosomes some best chromosomes are selected for next generation and remaining weak chromosomes are deleted. The modification process also involved another method called "mutation". After some fixed iterations the algorithm performs mutation in which case the genes of the chromosomes are randomly perturbed. This enables GA to avoid getting stuck in local optima. Hence GA searches for the best solution in multiple directions. This process of modification using "crossover" and "mutation" is continuing until the GA algorithm converged to the optimal solution or number of desired iterations completed.

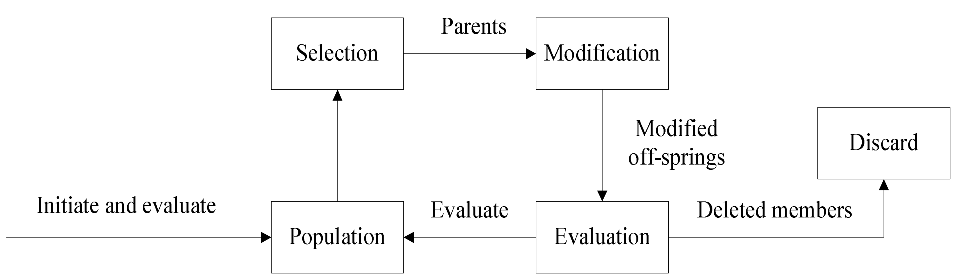

Figure 2.1. Genetic algorithm flow cycle

2.1.5. Multi-Island genetic algorithm (MIGA)

A Multi-Island Genetic Algorithm, or MIGA, is a variant of GA. Basically it consists of distributed GA. The outstanding features of this method are that the population in one generation is divided into several sub-populations called Islands, and the genetic operations are performed independently on each sub-population. This independency enables MIGA to avoid converging partial optimal solutions. An exchange of individual information, named a migration, is carried out periodically among sub-populations. Figure 2.2 shows the operational diagram of a MIGA.

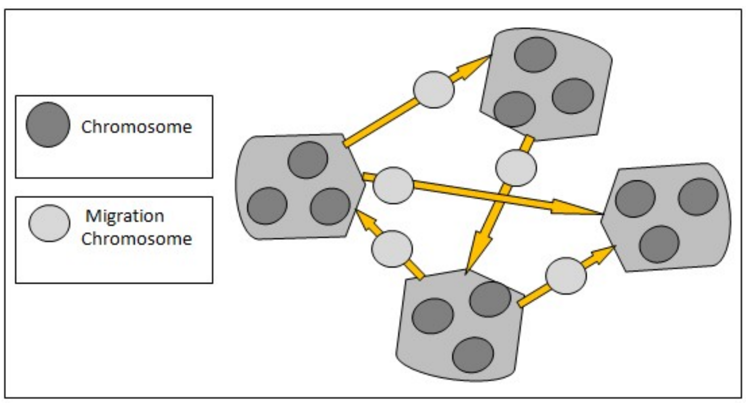

Figure 2.2. Operational diagram of Multi-Island Genetic Algorithm

Previously many approaches have been proposed for energy optimization. GA has been applied for energy management in many ways, like GA adopted for heating, ventilation and air-conditioning (HVAC) control problems [10]. This method also being applied to the control problems of energy systems consisting fuel cells, thermal storage, and heat pumps [11]. Another author applied GA [12] to investigate multi-objective (building energy cost and occupant thermal discomfort) problems to identify the optimal pay-off characteristic. One of the authors applied GA to mixed integer and nonlinear programming problems in an energy plant in Beijing and made a detailed economic investigation by changing the economic and environmental legislative contexts [13]. Application of GA for the optimization of the control parameters in parallel to hybrid electric vehicles (HEV) described in [14]. The optimization problem was formulated for an electric assistant control strategy (EACS) in order to meet the minimum fuel consumption and emissions while maintaining the vehicle performance requirements. Another work proposed integrated algorithm based on GA, simulated-based GA, time series and DOE (ANOVA and DMLT) to forecast electricity energy consumption [15]. A method which demonstrates the application of GP to learn occupancy behavioral rules that predict the presence and absence of an occupant in a single-person office was proposed in [16]. An optimum scheduling strategy of cold water supply system in an intelligent building has been proposed in [17]. An integrated GA and artificial neural network (ANN) to estimate and predict electricity demand using stochastic procedures has been proposed in [18].

Optimal control strategies of variable air volume and air-conditioning system has been proposed in [19]. The control strategies included a base control strategy of fixed temperature set point and two advanced strategies for insuring comfort and indoor air-quality (IAQ). The optimization problem for each control strategy was formulated based on the cost of energy consumption and constrained by system and thermal space transient models. They used GA to solve the problem of optimization. Supervisory control for hybrid solar vehicles proposed in

[20], and some beginning tests have been performed on the road. An optimal design method for energy system of single building has been developed for the first time by establishing optimal design method for distributed energy system [21].

2.2. Energy consumption control

In the literature many works have been presented in the area of energy savings and some valuable energy management control systems have been proposed. Approaches based on conventional control systems have been introduced in prior works [22, 23]. These conventional controllers consist of classical controllers [22]. The classical controller has the temperature overshoot problem. The other problem with this approach is that, it does not consider user set parameters and the model is not user friendly. It also does not address the energy efficiency and the model was not energy efficient. To overcome the overshoot problem designer proposed PID controllers [23]. These controllers improve the situation, but the improper choice of the gains in PID controllers could make the system unreliable and unstable. Therefore designers give attention to the optimal controller and adaptive controller respectively [24, 25]. The problems of conventional controllers are addressed in the optimal and adaptive controls. Optimal controller based approach improves the thermal comfort. Adaptive controllers have the capability to adapt to the environmental conditions. It is reported as most promising controllers in the context of adaptation to the climate conditions. Although optimal and adaptive controllers addressed the problems of classical controllers, but these approaches also have problems. These approaches need building model which makes it difficult to implement for each and every building. The use of elements of bioclimatic architecture confuses the process of minimization of the cost function and if such a minimization is acquired, the results are not valid in practice. Another problem with techniques is that, they don't consider occupants comfort index. These approaches are also not user friendly because they did not consider user set parameters. The last and most important point is that, these approaches don't consider energy efficiency and consumed more energy.

A comparison of different control mechanisms for energy consumption and occupants comfort index in building environment is carried out in [26]. During comparisons user set parameters were not considered. So the main disadvantage of their work is that, their models are not user friendly because users are not involved in deciding the occupants comfort index. A control strategy is proposed in [27] to maintain energy consumption and occupants comfort index, but user set parameters does not considers in deciding occupants comfort index. User set parameters plays a vital role in deciding occupants comfort index. In one of the previous work attention is made towards the occupants comfort index [28]. This work also did not considered the user participation in deciding occupants comfort index. Predictive and adaptive controllers using artificial neural network to allow the adaptation of the control model to the environmental conditions, building characteristics and user behaviors is proposed in [29]. This approach not only lack of user set parameters but also did not consider occupants comfort index. Another predictive control strategy using a system method for overall system environment and energy performance to the changes of control settings of VAV air-conditioning system is proposed and developed in [30]. To optimize the parameters GA algorithm has been used. This system also lack of user set points and occupants comfort index. The approach only considers energy efficiency in the building.

A reinforcement learning controller to achieve occupants comfort index with minimal energy consumption is described in [31]. The method succeeded in accomplishing occupants comfort index but failed to provide energy efficiency. Another robust reinforcement learning control for building power systems is proposed in [32]. The main drawback of this system is energy efficiency because the system could not achieved the desired results to minimized energy consumption.

An optimized fuzzy controller applied for the control of environmental parameters at the building zone level has been proposed in [33]. In this method the occupants' preferences are monitored via a smart card unit. Other proposals in this connection are predictive control approaches [34, 35], where weather predictions has been applied to heating, ventilating and air-conditioning system. A multi-agent control system with information fusion has been devised in [36]. The author's proposed a building indoor energy and comfort management model based on information fusion using ordered weighted averaging (OWA) aggregation. They achieved a high level of comfort with minimum power consumption.

Perceived comfort in office buildings is strongly influenced by several personal, social and building factors. The relationship between these factors are complex, so to get a better understanding of the relationships between these factors a proposal has been presented in [37]. A method presented in [38] proposed a comfort classification indexes suitable for both single environment and whole buildings. The methodology allows evaluation of both energy consumption and polluting impacts and takes into account comfort conditions of indoor environment and outdoor climate. An approach based on artificial network for energy management and control has been proposed in [39]. The artificial neural network based energy management and controller provides efficient and effective operation of wind, solar, and hydrogen energy-based hybrid renewable stand-alone structure.

2.2.1. Fuzzy logic control

Fuzzy logic was introduced by Lotfi Zadiah in 1965 [40] to deal with vague and imprecise concepts. In classical set theory, elements either belong to a particular set or not. The concept of partial membership does not exist in classical set theory. However, in fuzzy set theory the association of an element with a particular set lies between 0 and 1 which is called its degree of association or membership degree. In our daily life, we find many vague statements like hot water, cold weather, dark night, high danger etc. We cannot quantify exactly about the severity of the danger or hotness. The fuzzy set theory adds generalization concept in classical set theory and makes it diverse enough to represent imprecise boundaries like hot, tall, low speed, high risk etc.

The input to the fuzzy controller for temperature is the error difference between optimal parameters and real environmental parameters. For efficient control, both the error difference e_T and change in error ce_T (difference between current and previous error) are used. The input/output membership functions for temperature are shown in Figure 2.3.

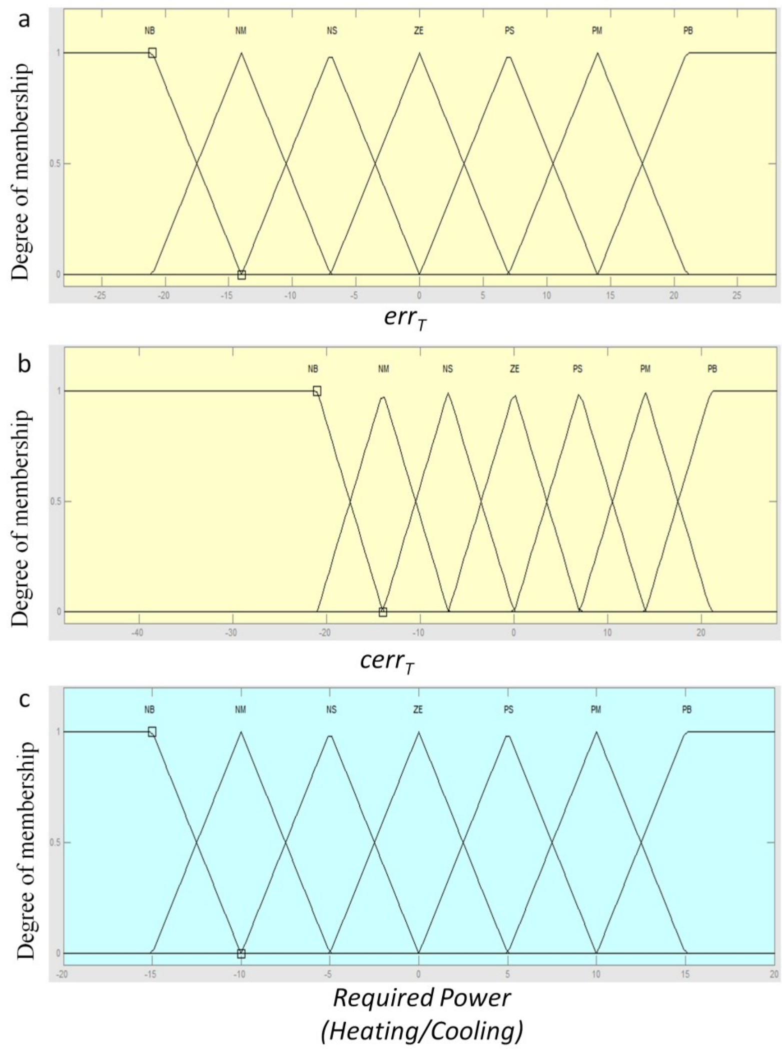

Figure 2.3. Input and output membership functions for temperature. (a) Input membership function of e_T, (b) Input membership function of ce_T, (c) Output membership function.

Table 2.1 shows the fuzzy controller rules for temperature control. It is a 7x7 matrix.

Each entry in the table is the error difference err_T and change in error $cerr_T$. The required power is the power to fulfill the user requirements inside the building. In Table 2.2 the terms NB, NM, NS, ZE, PS, PM, and PB have been abbreviated for negative big, negative medium, negative small, zero, positive small, positive medium, and positive big, respectively.

The input to the fuzzy controller for illumination is the error difference between the optimal parameter and real environmental illumination parameter. The input membership/output membership functions for illumination are shown in Figure 2.4.

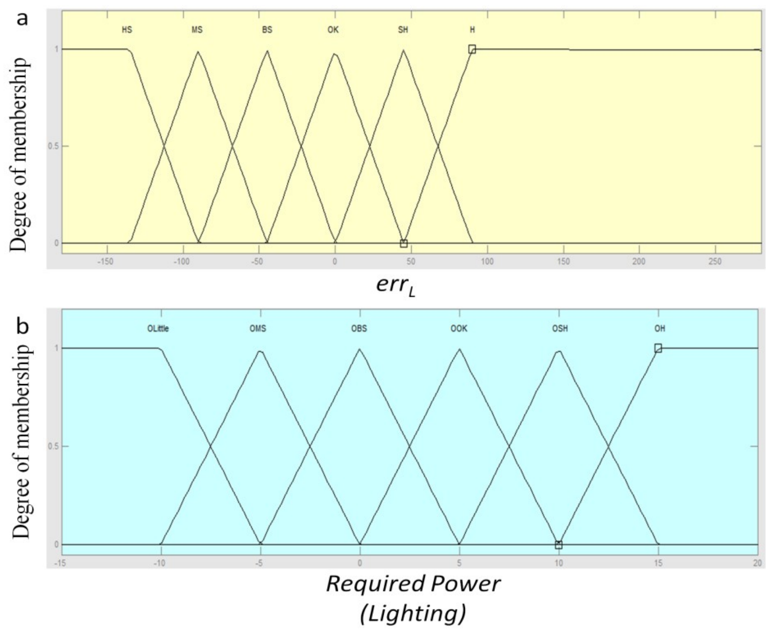

Figure 2.4. Input and output membership functions for illumination. (a) Input membership function of err_L (b) Output membership function

The input membership function is for the error err_L which is the only input. Table 2.2 shows fuzzy controller rules for illumination control. If the input error is High Small the required output power would be OLittle. For error Medium Small (MS) the output power would be OMS. For Basic Small (BS) the required power would be OBS. For OK the output power would be OOK. For SH the required output power is OSH while for High, the required power is OH.

The input to the fuzzy controller for air-quality is the error difference between optimized air-quality parameter and real environmental air-quality parameter. The input/output membership functions for air-quality are shown in Figure 2.5.

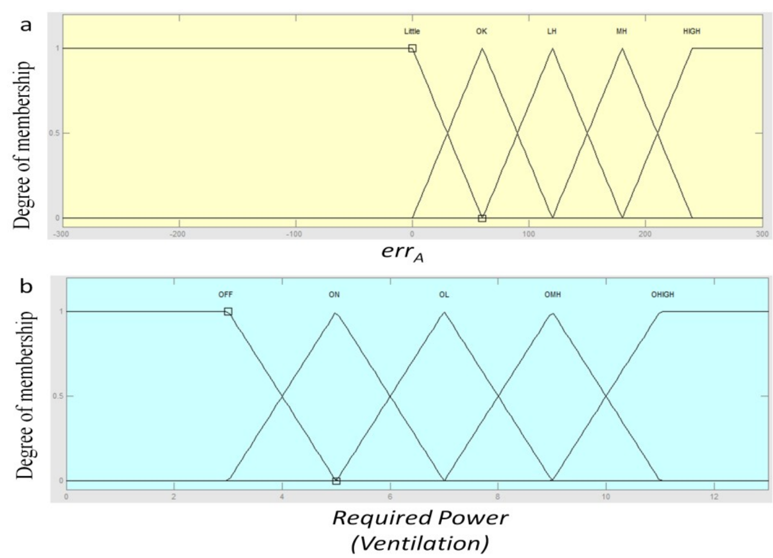

Figure 2.5. Input and output membership functions for air quality. (a) Input membership function of e_A (b) Output membership function

The input membership function is for the error err_A which is the only input to the air quality fuzzy controller. Table 2.3 shows the fuzzy controller rules for air quality control. If the input error is little, the required output power would be OFF. For OK, the output power would be ON. For LH the required power will be OL. For MH, the required power would be OMH, and for HIGH the required would be OHIGH.

The output of the fuzzy controllers is the required power for each of the temperature, illumination and air-quality. The required power is input to the coordinator agent and comparator components.

Table 2.1. Fuzzy controller rules for temperature controller

Required Power		err_T						
		NB	NM	NS	ZE	PS	PM	PB
$cerr_T$	NB	NB	NS	PS	PB	PB	PB	PB
	NM	NB	NM	ZE	PM	PM	PB	PB
	NS	NB	NM	NS	PS	PM	PB	PB
	ZE	NB	NM	NS	ZE	PS	PM	PB
	PS	NB	NB	NM	NS	PS	PM	PB
	PM	NB	NB	NM	NM	ZE	PM	PB
	PB	NB	NB	NB	NB	NS	PS	PB

Table 2.2. Fuzzy controller rules for illumination control

Error	HS	MS	BS	OK	SH	H
Required Power	OHS	OMS	OBS	OOK	OSH	OH

Table 2.3. Fuzzy controller rules for air-quality control

Error	Little	OK	LH	MH	HIGH
Required Power	OFF	ON	OL	OMH	OHIGH

2.3. Energy consumption prediction

Power consumption prediction and forecasting has become one of the main areas of interest to the researchers and practitioners in energy markets due to the fluctuation of energy price. This leads to the requirement of accurate and efficient energy price prediction methodology. All the stakeholders including market players and regulators wage more attention to the power consumption evolution. Energy consumption prediction is vital information to organize energy price bidding strategies and maximize their benefits and profits. Furthermore, it can also help customers minimize their electricity costs. The smart grid will be operated smoothly and efficiently with the satisfactory level of consumers' needs and power generation companies.

The energy consumption prediction techniques can be generally classified into two classes. One is time series techniques. The other kind of energy consumption forecasting and prediction techniques is Artificial Neural Networks (ANNs). The ANN's technique that keeps excellent strength and error tolerance is an effective way to solve the complex nonlinear problems. ANN's has received attention of researchers due to its clear model, easy implementation and good performance in solving nonlinear problems. So it is successful to model and predict changing complicated power system using ANN techniques. ANN has been applied to forecast electricity prices in many markets [41–46]. To increase the forecasting accuracy, it has been performed using supervised neural learning techniques [47, 48].

These works frequently apply neural network model, which contains many parameters. These parameters are continuously judged by experience and the model become hard to be established [49]. So it is difficult to establish a model using ANN. Moreover, it has been perceived that while the neural network (NN) gives small error during training the patterns, the error for testing patterns is usually of a larger order [50], in other words, when this technique is applied to practical system, the prediction accuracy is not good. Moreover, this algorithm is required to transform the characters of all the problems into numbers and change all the inferences into numerical calculation. Nevertheless, it definitely cause the loss of information which degrade the prediction accuracy. Although ANN based price forecasting techniques can also be used for energy prediction, but its disadvantages reported above for price forecasting restrict its application for energy consumption prediction.

Stationary time series prototypes such as autoregressive (AR) [51], Dynamic Regression (DR), Transfer Function (TF) [52], non-stationary time series models like Autoregressive Integrated Moving Average (ARIMA) [53] have been devised to forecast electricity price in the recent time. In most modest energy markets the series of prices describes the following features: high frequency, non-constant mean and variance, daily and weekly, monthly, seasonality, calendar effect on weekend and public holidays, high volatility and high percentage of unusual prices [54]. It is not easy to forecast electricity price accurately, therefore, it has to require special dealing in case of estimating price changes. In this connection a hybrid method to forecast day-ahead electricity price is proposed in [55]. The hybrid method is based on wavelet transform, Auto-Regressive Integrated Moving Average (ARIMA) models and Radial Basis Function Neural Networks (RBFN). A price forecasting system for electric market participants to reduce the risk of price volatility is proposed in [56]. The method combines the Probability Neural Network (PNN) and Orthogonal Experimental Design (OED) to propose an Enhanced Probability Neural Network (EPNN). Another work proposed a new combination of a Feature Selection (FS) technique based Mutual Information (MI) technique and Wavelet Transform (WT) in [57]. Other proposed approaches in this connection are short-term load forecasting for micro-grids [58] and iterative strategy [59]. The iterative strategy approach is the combination of the ARIMA, wavelet transform and non-linear neural network. In this thesis we proposed for our model the energy power consumption prediction using Kalman filter, ARIMA model and hybrid prediction model based on Kalman filter and ARIMA model. In hybrid prediction we take the average of the two energy prediction algorithms (Kalman filter and ARIMA) and predict the energy consumption.

2.3.1. Kalman filter

A Kalman filter is an optimal estimator. It gathers parameters of interest from indirect, inaccurate and uncertain observations. It is recursive so that new measurements can be processed as they arrive. The Kalman filter addresses the general problem of trying to estimate the state $x \in R^n$ of a discrete-time controlled process that is governed by the linear stochastic difference equation.

$$X_t = A_{x(t-1)} + B_{u(t-1)} + p_{(t-1)} \tag{2.1}$$

$$z \in R^n \tag{2.2}$$

$$Z_t = H_{x(t-1)} + m_{(t-1)} \tag{2.3}$$

$$P(p) \sim N(0, Q) \tag{2.4}$$

$$P(m) \sim N(0, R) \tag{2.5}$$

The matrix *A* in the difference equation (Eq. 2.1) relates the state at the previous time step *t – 1* to the state at the current step *t*, in the absence of either a driving function or process noise. In general *A* might change with each time step. In this case the value of *A* is set to 0.90 after empirical analysis. When we increase this value and set to 1, 2 or 3…, 10 then it affects the prediction value and produced inaccurate prediction results. The matrix *B* relates the optional control input to the state *x*. The matrix *H* in the measurement equation (Eq. 2.3) relates the state to the measurement z_t. Normally *H* might change with each time step or measurement. In our case the value of *H* is set to 1 after empirical analysis. When we increase or decrease value of *H* from 1 then it affects the prediction process and hence results in inaccurate prediction. Similarly, the value of *R* in our case is set to 0.10. When we increase this value from 0.10 and set to 1, 2, 3 or 4…, 10 then the prediction process disturbed and inaccurate values are predicted. If the value of *R* is set to 1 then it may results in over-fitting. So after empirical analysis we found that *R* value must be less than 1 depending on the data, but the optimal value for R is 0.10 for all kinds of data trends. Equations (2.4 and 2.5) are the standard normal distribution functions for each of the random variables p and m respectively. The process noise covariance Q and measurement noise covariance R matrices are change with each time step or measurement. In our case the value of Q is set to 1 after empirical analysis. When we increase this value from 1 to 2 or 3…., 10 then it affects the prediction and results in inaccurate prediction.

2.3.2. ARIMA model

ARIMA (0, 1, 1) model is one of the variations of ARIMA (p, d, q) model. The ARIMA (p, d, q) model is the common class of model for forecasting a time series data which can be stationaries by using some sort of transformations like differencing and logging. In fact, one of the easiest way to think about ARIMA models is as fine-tuned types of random-walk and random-trend models, the fine-tuning contains of adding lags of the differenced series and lags of the forecast errors to the prediction equation, as required to eliminate any last traces of autocorrelation from the forecast errors. In ARIMA (p, d, q) model p is the number of autoregressive terms, d is the number of non-seasonal differences, and q is the number of lagged forecast errors in the prediction equation. Where $Y_{(t)}$ is the forecasting, β is the coefficient of the lagged forecast error, $e_{(t-1)}$ denotes the error at time period $t-1$, α value varies between [0, 1].

$$Y(k) = \mu + Y(k-1) - \beta \times e(k-1) \tag{2.6}$$

$$\mu = Y_k - Y_{k-1} \tag{2.7}$$

$$\beta = 1 - \alpha \tag{2.8}$$

2.4. Coordinator agent

Coordinator agent takes the required building power from fuzzy controller and optimal parameters according to the user comfort index as input. It adjusted the building power on the basis of available power, required power and optimal parameters of comfort index. The adjusted building power is compared with the required power to get the actual consume power. The consumed power is input to the Kalman filter to predict consume power. The predicted consume power is given to the actuators for usage. The predicted consume power is the power to be consumed in the building.

In Eqs (2.9), (2.10), and (2.11) $P\ (k)$ is the required power, which is the sum of power demands from temperature, illumination and air-quality. $P_{required}$, is the total energy source (outside grid-power or internal local power source). $P_{max}\ (k)$ is the maximum input power either from the power grid or from the local micro sources to the building.

$$P_T(k+1) = P_T(k) \tag{2.9}$$

$$P_L(k+1) = P_L(k) \tag{2.10}$$

$$P_A(k+1) = P_A(k) \tag{2.11}$$

$$P_T(k)+P_L(k)+P_A(k)=P_{required}(k) \tag{2.12}$$

$$P_{required}(k) \leq P_{available}(k) \tag{2.13}$$

$P_{available} \leq P_{max}$ (2.14)

2.5. Preprocessing

Smoothing is applied to environmental data as a preprocessing mechanism. The aim behind application of smoothing to environmental data is to reduce and bring the data in to smoother form. The data points which are higher or lower than the adjacent data points are decreases or increases to become smooth.

2.6. Post-processing

Post-processing evolved to analyze the output data after each step in the proposed models. The aim of post-processing applied after optimization is to analyze optimal parameters and comfort index. Communicating optimal parameters and comfort index results with the users. Also the optimal parameters and comfort index results are visualized for user understanding and analysis.

3. Proposed hybrid energy optimization algorithms based on prediction in IoT environment

3.1. Basic energy optimization model based on prediction

3.1.1. Genetic algorithm based energy optimization prediction

3.1.1.1. Proposed architecture

Figure 3.1 shows optimized system diagram for the energy management. Environmental parameters (temperature, illumination and air-quality) and user set points are input to the GA optimizer for optimization. Then optimized parameters are used as user comfort index to calculate the occupant's comfort index. Three fuzzy logic based controllers are used to control temperature, illumination and air-quality. Coordinator Agent adjusted the power according to the optimized required power from the fuzzy controllers and available power from the external power grid or internal local power sources. Coordinator agent performs the function of coordination among the three fuzzy controllers based on the required power and available power. It also provides maximum comfort index according to the user requirements and available power. Building actuators are the devices which actually utilizes the power.

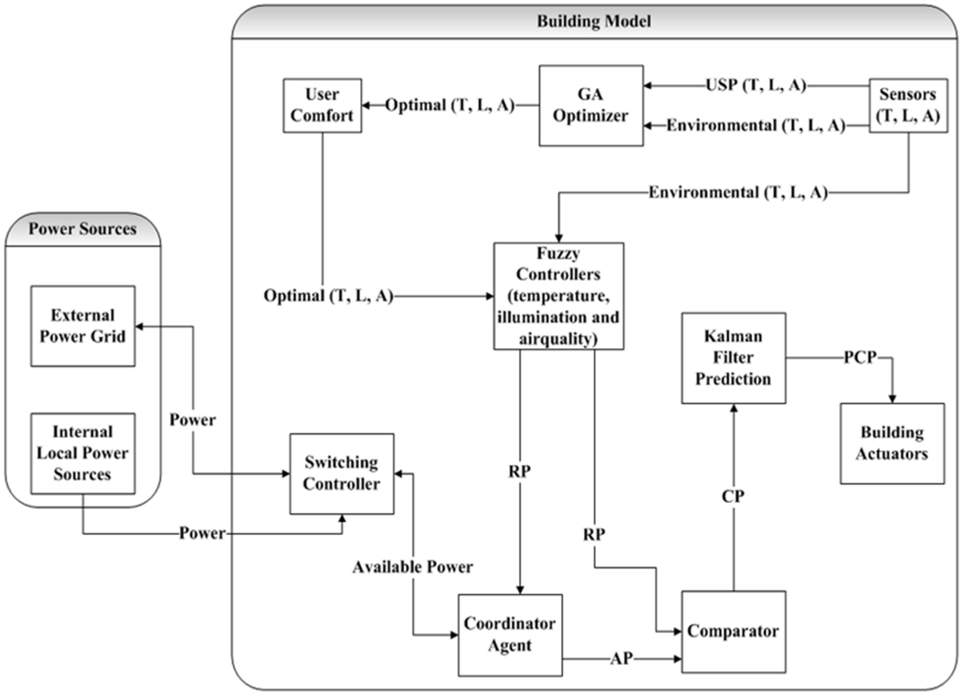

Figure 3.1. System diagram of a residential building energy management

3.1.1.2. Optimization algorithm using GA

GA steps for parameters optimizations and comfort index are:

1) Initial random population
2) Calculate fitness function for user comfort using Eq. (1.1)
3) Select best individuals using any of three selection criteria (Rank, Roulette wheel or Tournament selection), we used rank based selection
4) Perform 'variable two point' crossover of the selected individuals
5) After crossover, we get off-springs
6) Now calculate comfort for the off-springs

7) Combining populations of step (3) and (5)

8) If mutation criteria meet, then perform mutation

9) Repeat above eight steps until termination criteria arise or objective function does not improve.

10) Then after arrival of termination criteria select best fitted chromosome.

These parameters were selected after running the algorithm for λ times to get optimal results. GA stops either when the maximum number of generation's Ω met, or no significant change is observed in the fitness for μ (few successive) generations. The maximum population size selected is 100. The variable two point crossover is performed with the probability of 0.9 and mutation rate of 0.1. GA parameters (population size, crossover rate and mutation rate) have been set after running GA for number times. The experimentations are performed using Latitude D620 laptop of 2.00 GHz with 2GB RAM. The C # 2008 is used for the simulation. When GA evaluation process finishes, best fitted chromosome is to be selected to get optimal parameters and comfort index.

3.1.2. Particle swarm optimization based energy optimization prediction

3.1.2.1. Proposed architecture

Figure 3.2 shows the block diagram of the proposed energy management and prediction model for building environment using fuzzy controllers and Kalman filter. Environmental parameters (temperature, illumination and air-quality) are input to the comfort index. Then comfort parameters were used to calculate the occupant's comfort index. Coordinator Agent adjusted the power according to the user comfort index and predicted power in conjunction with available source power from outside power grid or inside local energy sources. Fuzzy controllers control the temperature, illumination and air quality. Actuators are the devices which actually utilizes the output power of fuzzy controller. Coordinator agent basically performs the function of coordination between comfort index and power prediction to provide maximum comfort index according to the user requirements while keeping energy consumption as minimum as possible.

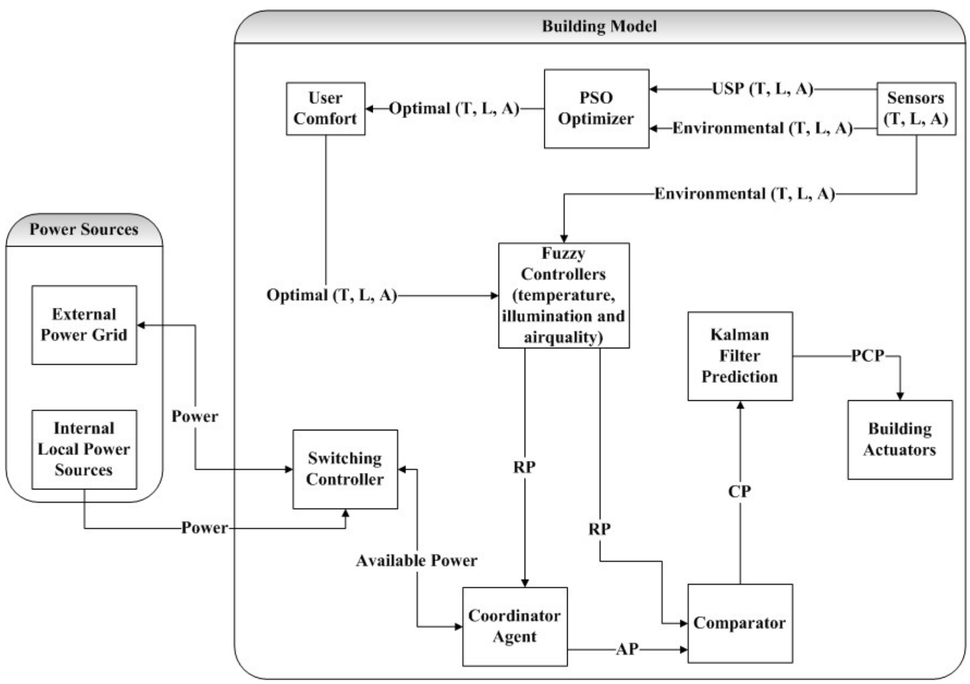

Figure 3.2. System diagram of a residential building energy management

3.1.2.2. Optimization algorithm using PSO

For optimization we used PSO. PSO steps for parameters optimizations and comfort calculations are:

1. Initialize

   a) Set constants $k_{\max}, c_1, c_2, r_1, r_2 w_0$

   b) Randomly initialize particle positions $x_i \in D$ in R^n for $= 1 \ldots \ p$

   c) Randomly initialize particle velocities $0 \le v_0^i \le v_0^{\max}$ for $= 1 \ldots \ p$

   d) Set K = 1

2. Optimize

   a) Evaluate f_k^i for particle $\mathbf{x}_k^i$

   b) If $f_k^i \le f_{best}^i$ then $f_{best}^i = f_k^i, p^i = x_k^i$

   c) If $f_k^i \le f_{best}^g$ then $f_{best}^g = f_k^i, p^g = x_k^i$

   d) If stopping condition is satisfied then go to step 3

   e) Update particle velocity vector v_{k+1}^i by equation (3.1)

   f) Update particle position vector x_{k+1}^i by equation (3.2)

   g) Increment i (index for particles). If $i > pop$ then increment k (index for iterations), and set $= 1$

   h) Go to 2 (a)

3. Report results

4. Terminate

Where $k_{\max}$ determines the maximum change one particle can take during one iteration.

The parameters w_0, c_1 and c_2 ($0<=w_0<= 1.2$, $0<=c_1<=2$, and $0<=c_2<=2$) are user-supplied coefficients.

The values r_1 and r_2 ($0<=r_1<=1$ and $0<=r_2<= 1$) are random values regenerated for each velocity update.

The variable x_k^i represents the best ever position of particle i up till time k (the cognitive contribution to the search vector)

At the initialization time step $k = 0$, the particle velocities v_0^i are initialized to random values within the limits $0 \le v_0 \le v_0^{\max}$

The domain R^n of f is referred to as the search space (or parameter space). Each element of R^n is called a candidate solution in the search space. The value n denotes the number of dimensions of the search space, and thus the number of parameters involved in the optimization problem. The function f is called the objective function, which maps the search space to the function space.

Since a function has only one output, this function space is usually one-dimensional. The function space is then mapped to the one-dimensional fitness space, providing a single fitness value for each set of parameters. This single fitness value determines the optimality of the set of parameters for the desired task. In most cases, including the one discussed in this work, the function space can be directly mapped to the fitness space.

The best ever fitness value of a particle at design coordinates x_k^i is denoted by f_{best}^i and the best ever fitness value of the overall swarm at coordinates x_k^g is denoted by f_{best}^g, pop means number of populations and k is the time variable.

$$V_i(k+1) = \alpha V_i(k) + m_1 r_1 [P_{best(i)}(k)] + m_2 r_2 [G_{best}(k) - x_i(k)] \quad (3.1)$$

$$X_i(k+1) = x_i(k) + V_i(k+1) \quad (3.2)$$

3.2. Hybrid energy optimization model based on prediction

3.2.1. Single preprocessing hybrid optimization model based on prediction

3.2.1.1. Hybrid energy optimization and predicted power control model

3.2.1.1.1. Proposed architecture

In Figure 3.3 we show hybrid optimized power control model for the energy management and efficiency. Initially, the environmental parameters are passed to smoothing component for preprocessing. After smoothing, the smoothed environmental parameters and user set points are passed to hybrid optimization component of the model to get optimal parameters. Then optimized parameters are used as user comfort index to calculate the occupant's comfort index. Three controllers based on fuzzy logic are used to control temperature, illumination and air-quality. Coordinator agent adjusted the power according to the optimized required power from the fuzzy controllers and available power from the external power grid or internal local power sources. Coordinator agent performs the function of coordination among the three fuzzy controllers based on the required power and available power. The consumed power is passed to Kalman filter model to predict power consumption. The predicted power is input to the building actuators. At the end the results are analyzed, visualized and communicated with the users. Actuators received message information's (MI) to turn ON/OFF.

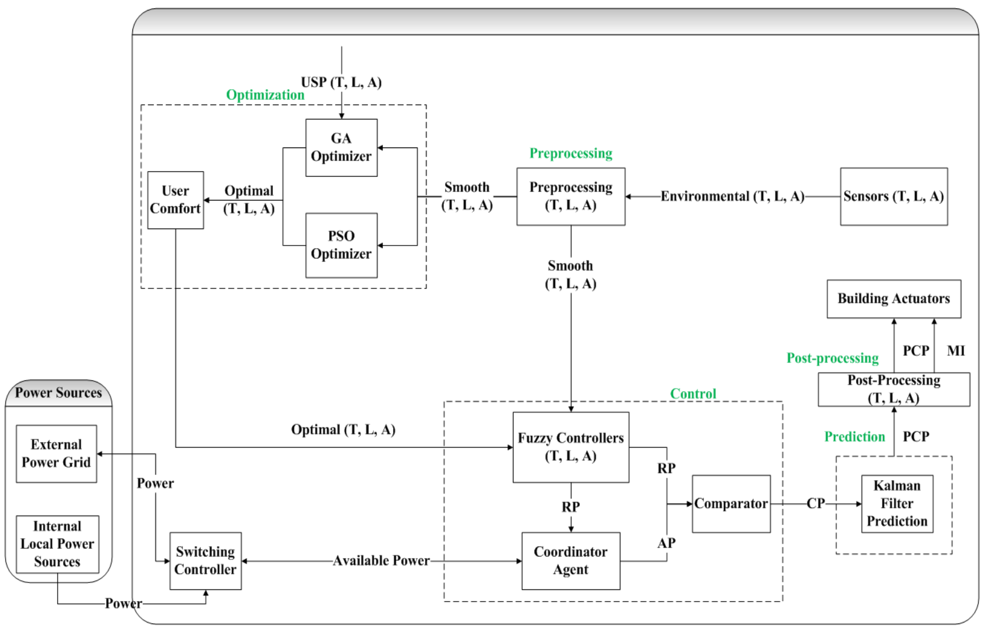

Figure 3.3. Hybrid optimization algorithm based on PSO and GA parallel

3.2.1.1.2. Optimization algorithm based on PSO and GA parallel

Hybrid optimization steps for parameters optimizations and comfort index based on GA and PSO are:

1) Initial random population/particles

2) Calculate fitness function for user comfort using Eq. (1.1)

3) Select best parent individuals using any of three selection criteria (Rank, Roulette wheel or Tournament selection), we used rank based selection

4) Perform 'variable two point' crossover of the selected individuals

5) Update particle positions using Eq. (3.1).

6) Update particle velocities using Eq. (3.2).

7) After step 3 and 4, we get off-springs.

8) After step 5 and 6 we get new positions and velocities of the particles.

9) Now calculate comfort for the off-springs and comfort for the new particles.

10) Combining populations of step (3) and (7)

11) If mutation criteria meet, then perform mutation

12) Combining updated particles from step (8) and updated chromosomes from step (10)

13) Selecting best individuals from combined population in step (12)

14) Repeat above 13 steps until termination criteria arise or fitness function does not improve.

15) Then after arrival of termination criteria select best fitted individual.

These parameters were selected after running the hybrid algorithm for λ times to get optimal results. Hybrid optimization stops either when the maximum number of generation's

Ω met, or no significant change is observed in the fitness for μ (few successive) generations. The maximum population size selected is 100. The variable two point crossover is performed with the probability of 0.9 and mutation rate of 0.1. GA parameters (population size, crossover rate and mutation rate) have been set after running GA for number of times. The experimentations are performed using Intel(R) Core(TM)i3-2130 3.40 GHz with 8GB RAM. The C # 2012 is used for the simulation. When hybrid optimization evaluation process finishes, best fitted individual is selected to get optimal parameters and comfort index.

3.2.1.2. A hybrid approach to optimization of energy and power control prediction

3.2.1.2.1. Proposed architecture

In Figure 3.4 we show hybrid optimized power control model for the energy management and efficiency. Initially, the environmental parameters are passed to smoothing component for preprocessing. After smoothing, the smoothed environmental parameters and user set points are passed to PSO optimization component of the model to get optimal parameters. The PSO based optimal parameters are then again optimized using GA based optimizer to get finally optimized parameters. Then optimized parameters are used as user comfort index to calculate the occupant's comfort index. Three controllers based on fuzzy logic are used to control temperature, illumination and air-quality. Coordinator agent adjusted the power according to the optimized required power from the fuzzy controllers and available power from the external power grid or internal local power sources. Coordinator agent performs the function of coordination among the three fuzzy controllers based on the required power and available power.

The consumed power is passed to Kalman filter model to predict power consumption. The predicted power is input to the building actuators. At the end the results are analyzed, visualized and communicated with the users. Actuators received message information's (MI) to turn ON/OFF.

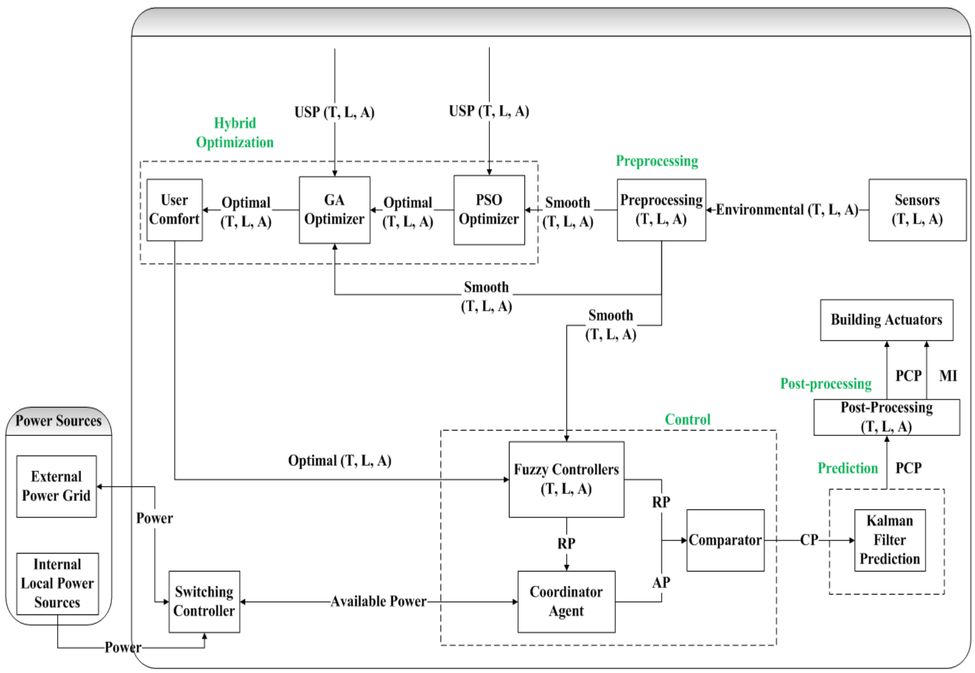

Figure 3.4. Hybrid optimization algorithm based on PSO and GA serial

3.2.1.2.2. Optimization algorithm based on PSO and GA serial

Serial based PSO and GA steps for parameters optimizations and comfort index are:

1. Initialize
   a) Set constants k max, c_1, c_2, r_1, r_2, w_0
   b) Randomly initialize particle positions $x_i \in D$ in R^n *for* $i = 1 \ldots p$
   c) Randomly initialize particle velocities $0 <= v_0^i <= v_0^{max}$ for $i = 1 \ldots p$
   d) Set k = 1
2. Optimize
   a) Evaluate f_k^i for particle X^i_k
   b) If $f^i_k <= f^i_{best}$ then $f^i_{best} = f^i_k$, $p^i = x^i_k$
   c) If $f^i_k <= f^g_{best}$ then $f^g_{best} = f^i_k$, $p^g = x^i_k$
   d) If stopping condition is satisfied then go to step 3
   e) Update particle velocity vector v^i_{k+1} Eq. (3.1)
   f) Update particle position vector x^i_{k+1} Eq. (3.2)
   g) Increment *i* (index for particles). If $i > pop$ then increment *k* (index for iterations), and set $i = 1$
   h) Go to 2 (a)
3. Report Results
4. Terminate PSO optimization and getting optimal parameters.
5. Initial random population for GA
6. Updating initial random population of GA by combining with optimal PSO based parameters
7. Selecting best individuals from combined populations of step (6) as an initial population of GA
8. Calculate fitness function for user comfort using Eq. (1.1)
9. Select best parent individuals using any of three selection criteria (Rank, Roulette

wheel or Tournament selection), we used rank based selection

10. Perform ‘variable two point’ crossover of the selected individuals
11. After crossover, we get off-springs
12. Now calculate comfort for the off-springs
13. Combining populations of step (9) and (11)
14. If mutation criteria meet, then perform mutation
15. Repeat steps from 5 to 14 until termination criteria arise or algorithm does not improve.
16. Then after arrival of termination criteria select best fitted chromosome.

These parameters were selected after running the algorithm for λ times to get optimal results. GA stops either when the maximum number of generation’s Ω met, or no significant change is observed in the fitness for μ (few successive) generations. The maximum population size selected is 100. The variable two point crossover is performed with the probability of 0.9 and mutation rate of 0.1. GA parameters (population size, crossover rate and mutation rate) have been set after running GA for number times. The experimentations are performed using Intel(R) Core(TM)i3-2130 3.40 GHz with 8GB RAM. The C # 2012 is used for the simulation. When GA evaluation process finishes, best fitted chromosome is to be selected to get optimal parameters and comfort index.

3.2.1.3. Hybrid optimization energy management and predicted power control model

3.2.1.3.1. Proposed architecture

In Figure 3.5 we show hybrid optimized power control model for the energy management and efficiency. Initially, the environmental parameters are passed to smoothing component for preprocessing. After smoothing, the smoothed environmental parameters and user set points are passed to hybrid optimization component of the model to get optimal parameters. Then optimized parameters are used as user comfort index to calculate the occupant's comfort index. Three controllers based on fuzzy logic are used to control temperature, illumination and air-quality. Coordinator agent adjusted the power according to the optimized required power from the fuzzy controllers and available power from the external power grid or internal local power sources. Coordinator agent performs the function of coordination among the three fuzzy controllers based on the required power and available power. The consumed power is passed to the ARIMA model and Kalman filter to predict the consumed power in serial fashion. First the consumed power is passed to ARIMA model to predict the power consumption and then the predicted power is input to the Kalman filter model. At the end we take the average of the prediction results to get final prediction of power consumption. The average predicted power is input to the building actuators. At the end the results are analyzed, visualized and communicated with the users. Actuators received message information's (MI) to turn ON/OFF.

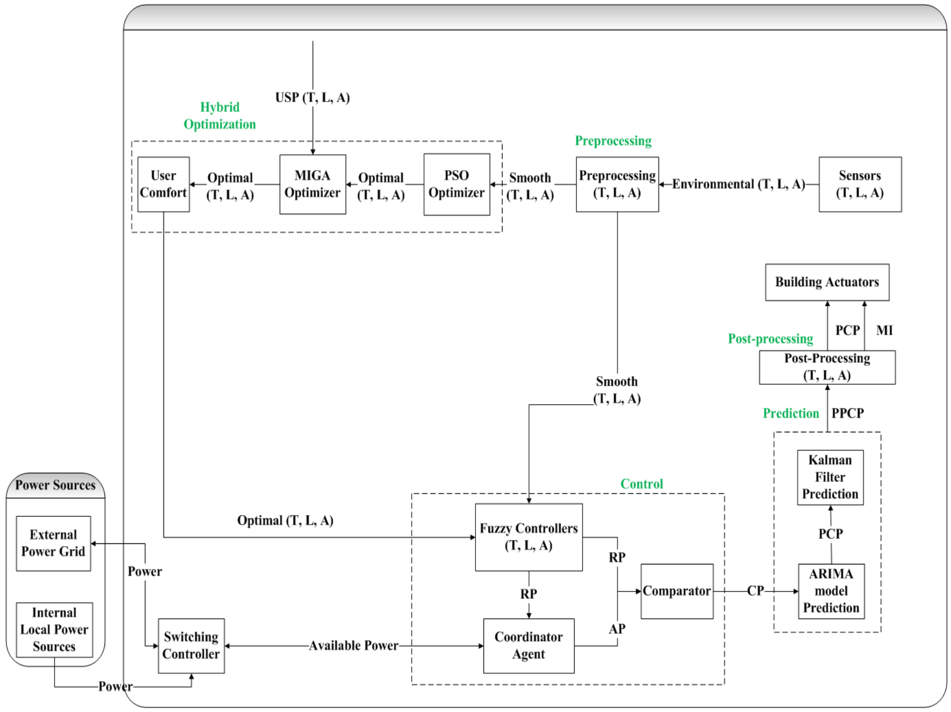

Figure 3.5. Hybrid optimization algorithm based on PSO and MIGA serial

3.2.1.3.2. Optimization algorithm based on PSO and MIGA serial

Serial based PSO and MIGA steps for parameters optimizations and comfort index are:

1. Initialize

   a) Set constants k max, c_1, c_2, r_1, r_2, w_0

   b) Randomly initialize particle positions $x_i \in D$ in R^n *for i = 1…p*

   c) Randomly initialize particle velocities $0 <= v_0^i <= v_0^{max}$ for i = 1…p

   d) Set k = 1

2. Optimize

   a) Evaluate f_k^i for particle X^i_k

   b) If $f^i_k <= f^i_{best}$ then $f^i_{best} = f^i_k$, $p^i = x^i_k$

c) If $f^i_k <= f^g_{best}$ then $f^g_{best} = f^i_k$, $p^g = x^i_k$

d) If stopping condition is satisfied then go to step 3

e) Update particle velocity vector v^i_{k+1} Eq. (3.1)

f) Update particle position vector x^i_{k+1} Eq. (3.2)

g) Increment i (index for particles). If $i > pop$ then increment k (index for iterations), and set $i = 1$

h) Go to 2 (a)

3. Report results
4. Terminate PSO optimization and getting optimal parameters.
5. Initial random population for MIGA
6. Updating initial random population of MIGA by combining with optimal PSO based parameters
7. Selecting best individuals from combined populations of step (6) as an initial population of MIGA
8. Divide initial population in step (7) into multiple Islands
9. Perform Step (4) to Step (9) for each of the Island
10. Calculate fitness function for user comfort using equation Eq. (1.1)
11. Select best individuals using any of three selection criteria (Rank, Roulette wheel or Tournament selection), we used rank based selection
12. Perform 'variable two point' crossover of the selected individuals
13. After crossover, we get off-springs
14. Now calculate comfort for the off-springs.
15. Combining populations of step (5) and (7).
16. If mutation criteria meet, then perform mutation

17. If migration criteria meet, then perform migration
18. Repeat steps from 5 to 14 until termination criteria arise or algorithm does not improve.
19. Then after the arrival of termination criteria select best fitted chromosomes from each island.

These parameters were selected after running the hybrid algorithm for λ times to get optimal results. Hybrid optimization stops either when the maximum number of generation's Ω met, or no significant change is observed in the fitness for μ (few successive) generations. The maximum population size selected is 100. The variable two point crossover is performed with the probability of 0.9 and mutation rate of 0.1. MIGA parameters (population size, crossover rate and mutation rate, migration rate) have been set after running MIGA for number of times. The experimentations are performed using Intel(R) Core(TM)i3-2130 3.40 GHz with 8GB RAM. The C # 2012 is used for the simulation. When hybrid optimization evaluation process finishes, best fitted individual is selected to get optimal parameters and comfort index.

3.2.2. Multi-preprocessing hybrid optimization model based on prediction

3.2.2.1. Energy efficient hybrid optimization and predicted power control model

3.2.2.1.1. Proposed architecture

In Figure 3.6 we show hybrid optimized power control model for the energy management and efficiency. Initially, the environmental parameters are passed to smoothing component for preprocessing. After smoothing, the smoothed environmental parameters and user set points are passed to hybrid optimization component of the model to get optimal parameters. Then optimized parameters are used as user comfort index to calculate the occupant's comfort index. In post-processing the results are analyzed, published and communicated with the users. Then the optimal parameters are again preprocessed before it can be forwarded to the fuzzy controllers. The aim behind smoothing as preprocessing at this level is to improve the optimal parameters and occupants comfort index. So the occupants comfort index is calculated again using updated optimal parameters to get updated occupants comfort index. This improves the occupants comfort index. Three controllers based on fuzzy logic are used to control temperature, illumination and air-quality. Each fuzzy controller accepts as input, the error difference between smoothed environmental parameters and updated optimal parameters. Coordinator agent adjusted the power according to the optimized required power from the fuzzy controllers and available power from the external power grid or internal local power sources. Coordinator agent performs the function of coordination among the three fuzzy controllers based on the required power and available power. The consumed power is then post-processed to published and communicate results with users.

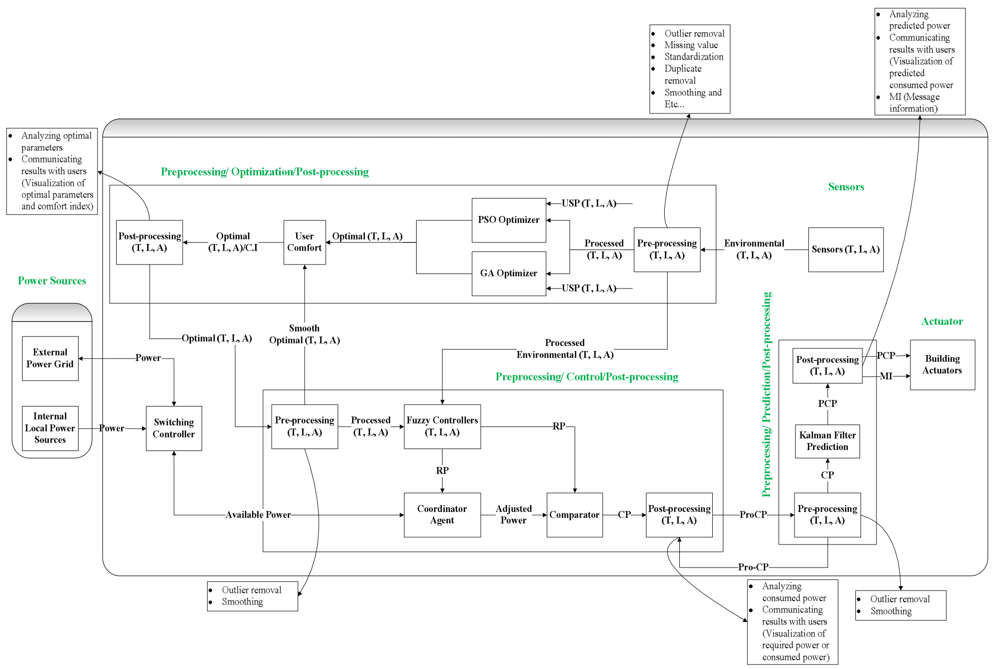

Figure 3.6. Hybrid optimization algorithm based on PSO and GA parallel with multi-preprocessing

The consumed power is preprocessed before it can be passed on to the prediction component. At this level of preprocessing smoothing is performing to remove any outliers. After preprocessing the consumed power is updated with new revised and smoothed power consumption. Then the updated consumed power is passed to the Kalman filter model to predict power consumption. At the end we again applied post-processed the predicted power consumption by analyzing the results and communicate these results with the users. Actuators received message information's (MI) to turn ON/OFF.

3.2.2.1.2. Optimization algorithm based on PSO and GA parallel

Hybrid optimization steps for parameters optimizations and comfort index based on GA and PSO are:

1. Initial random population/particles
2. Calculate fitness function for user comfort using Eq. (1.1)
3. Select best parent individuals using any of three selection criteria (Rank, Roulette wheel or Tournament selection), we used rank based selection
4. Perform 'variable two point' crossover of the selected individuals
5. Update particle positions using Eq. (3.1).
6. Update particle velocities using Eq. (3.2).
7. After step 3 and 4, we get off-springs.
8. After step 5 and 6 we get new positions and velocities of the particles.
9. Now calculate comfort for the off-springs and comfort for the new particles.
10. Combining populations of step (3) and (7)
11. If mutation criteria meet, then perform mutation
12. Combining updated particles from step (8) and updated chromosomes from step (10)

13. Selecting best individuals from combined population in step (12)
14. Repeat above 13 steps until termination criteria arise or fitness function does not improve.
15. Then after arrival of termination criteria select best fitted individual.
16. Update optimal parameters after smoothing to get updated parameters
17. Update comfort index using updated parameters

These parameters were selected after running the hybrid algorithm for λ times to get optimal results. Hybrid optimization stops either when the maximum number of generation's Ω met, or no significant change is observed in the fitness for μ (few successive) generations. The maximum population size selected is 100. The variable two point crossover is performed with the probability of 0.9 and mutation rate of 0.1. GA parameters (population size, crossover rate and mutation rate) have been set after running GA for number of times. The experimentations are performed using Intel(R) Core(TM)i3-2130 3.40 GHz with 8GB RAM. The C# 2012 is used for the simulation. When hybrid optimization evaluation and smoothing process finishes, best fitted individual is selected to get updated optimal parameters and comfort index.

3.2.2.2. Energy efficient hybrid optimization and power control prediction model

3.2.2.2.1. Proposed architecture

In Figure 3.7 we show hybrid optimized power control model for the energy management and efficiency. Initially, the environmental parameters are passed to smoothing component for preprocessing. After smoothing, the smoothed environmental parameters and user set points are passed to PSO optimization component of the model to get optimal parameters. The PSO based optimal parameters are then again optimized using GA based optimizer to get finally optimized parameters. Then optimized parameters are used as user comfort index to calculate the occupant's comfort index. In post-processing the results are analyzed, published and communicated with the users. Then the optimal parameters are again preprocessed before it can be forwarded to the fuzzy controllers. The basic purpose of smoothing before control part of the model is to improve the optimal parameters and occupants comfort index of GA based optimization. The GA based occupants comfort index is calculated again using updated optimal parameters to get updated occupants comfort index. This improves the occupants comfort index. In control part of the model, three controllers based on fuzzy logic are used to control temperature, illumination and air-quality respectively. The fuzzy controllers received as input, the error difference between smoothed environmental parameters and updated optimal parameters. The coordinator agent adjusted the power according to the optimized required power from the fuzzy controllers and available power from the external power grid or internal local power sources. The consumed power is then post-processed to published and communicate consumed power results with users. The consumed power is preprocessed before it can be passed on to the prediction component. At this level of preprocessing smoothing is applied to normalized data and remove outliers. After preprocessing, the consumed power is revised with new updated and smoothed power consumption. Then the updated consumed power is passed to the Kalman filter model to predict power consumption. Finally, we again post-processed the predicted power consumption by analyzing the results and communicate these results with the users. Actuators received message information's (MI) to turn ON/OFF.

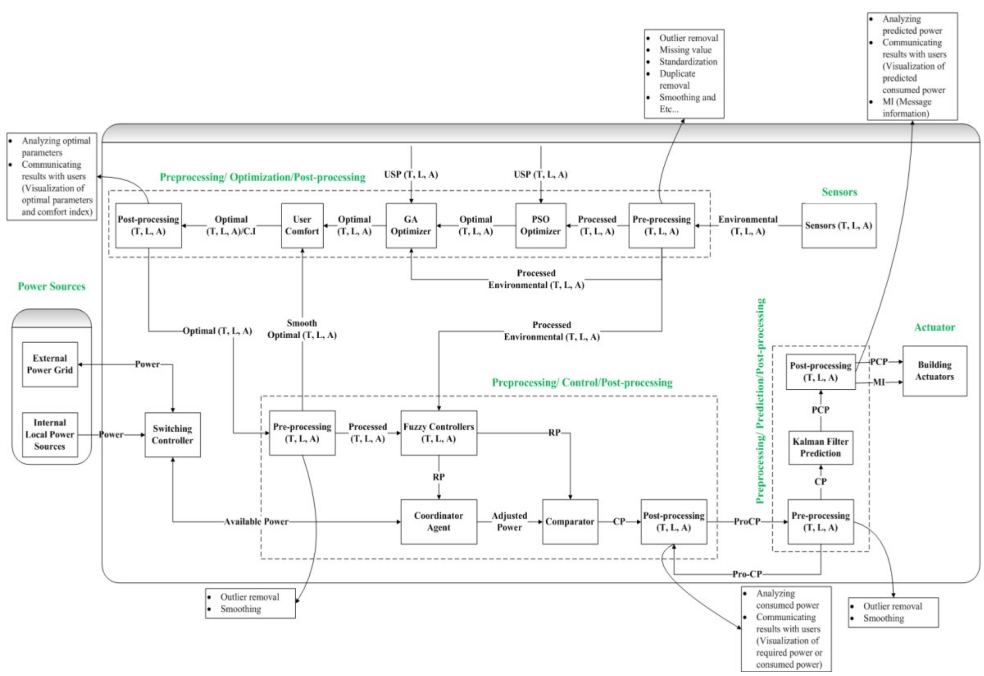

Figure 3.7. Hybrid optimization algorithm based on PSO and GA serial with multi-preprocessing

3.2.2.2.2. Optimization algorithm based on PSO and GA serial

Serial based PSO and GA steps for parameters optimizations and comfort index are:

1. Initialize
   a) Set constants k max, c_1, c_2, r_1, r_2, w_0
   b) Randomly initialize particle positions $x_i \in D$ in R^n *for* $i = 1 \ldots p$
   c) Randomly initialize particle velocities $0 <= v_0^i <= v_0^{max}$ for i = 1…p
   d) Set k = 1
2. Optimize
   a. Evaluate f_k^i for particle X^i_k
   b. If $f^i_k <= f^i_{best}$ then $f^i_{best} = f^i_k$, $p^i = x^i_k$
   c. If $f^i_k <= f^g_{best}$ then $f^g_{best} = f^i_k$, $p^g = x^i_k$
   d. If stopping condition is satisfied then go to step 3
   e. Update particle velocity vector v^i_{k+1} Eq. (3.1)
   f. Update particle position vector x^i_{k+1} Eq. (3.2)
   g. Increment *i* (index for particles). If $i > pop$ then increment *k* (index for iterations), and set $i = 1$
   h. Go to 2 (a)
3. Report Results
4. Terminate PSO optimization and getting optimal parameters.
5. Initial random population for GA
6. Updating initial random population of GA by combining with optimal PSO based parameters
7. Selecting best individuals from combined populations of step (6) as an initial

population of GA

8. Calculate fitness function for user comfort using Eq. (1.1)
9. Select best parent individuals using any of three selection criteria (Rank, Roulette wheel or Tournament selection), we used rank based selection
10. Perform 'variable two point' crossover of the selected individuals
11. After crossover, we get off-springs
12. Now calculate comfort for the off-springs
13. Combining populations of step (9) and (11)
14. If mutation criteria meet, then perform mutation
15. Repeat steps from 5 to 14 until termination criteria arise or algorithm does not improve.
16. Then after arrival of termination criteria select best fitted chromosome
17. Update optimal parameters after smoothing to get updated parameters
18. Update comfort index using updated parameters

These parameters were selected after running the algorithm for λ times to get optimal results. GA stops either when the maximum number of generation's Ω met, or no significant change is observed in the fitness for μ (few successive) generations. The maximum population size selected is 100. The variable two point crossover is performed with the probability of 0.9 and mutation rate of 0.1. GA parameters (population size, crossover rate and mutation rate) have been set after running GA for number times. The experimentations are performed using Intel(R) Core(TM)i3-2130 3.40 GHz with 8GB RAM. The C # 2012 is used for the simulation. When hybrid optimization evaluation and smoothing process finishes, best fitted individual is selected to get updated optimal parameters and comfort index.

3.2.2.3. Hybrid Energy Optimization and Prediction Based on PSO and MIGA Serial

3.2.2.3.1. Proposed architecture

In Figure 3.8 we show hybrid optimized power control model for the energy management and efficiency. Initially, the environmental parameters are passed to smoothing component for preprocessing. After smoothing, the smoothed environmental parameters and user set points are passed to hybrid optimization component of the model to get optimal parameters. Then optimized parameters are used as user comfort index to calculate the occupant's comfort index. In post-processing the results are analyzed, published and communicated with the users. Then the optimal parameters are again preprocessed before it can be forwarded to the fuzzy controllers. The fundamental purpose of smoothing before control part of the model is to improve the optimal parameters and occupants comfort index of MIGA based optimization. The MIGA based occupants comfort index is calculated again using updated optimal parameters to get updated occupants comfort index. This improves the occupants comfort index. In control part of the model, three controllers based on fuzzy logic are used to control temperature, illumination and air-quality respectively. The fuzzy controllers received as input, the error difference between smoothed environmental parameters and updated optimal parameters. The coordinator agent adjusted the power according to the optimized required power from the fuzzy controllers and available power from the external power grid or internal local power sources. The consumed power is then post-processed to published and communicate consumed power results with users. The consumed power is preprocessed before it can be passed on to the prediction component. At this level of preprocessing smoothing is applied to normalized data and remove outliers.

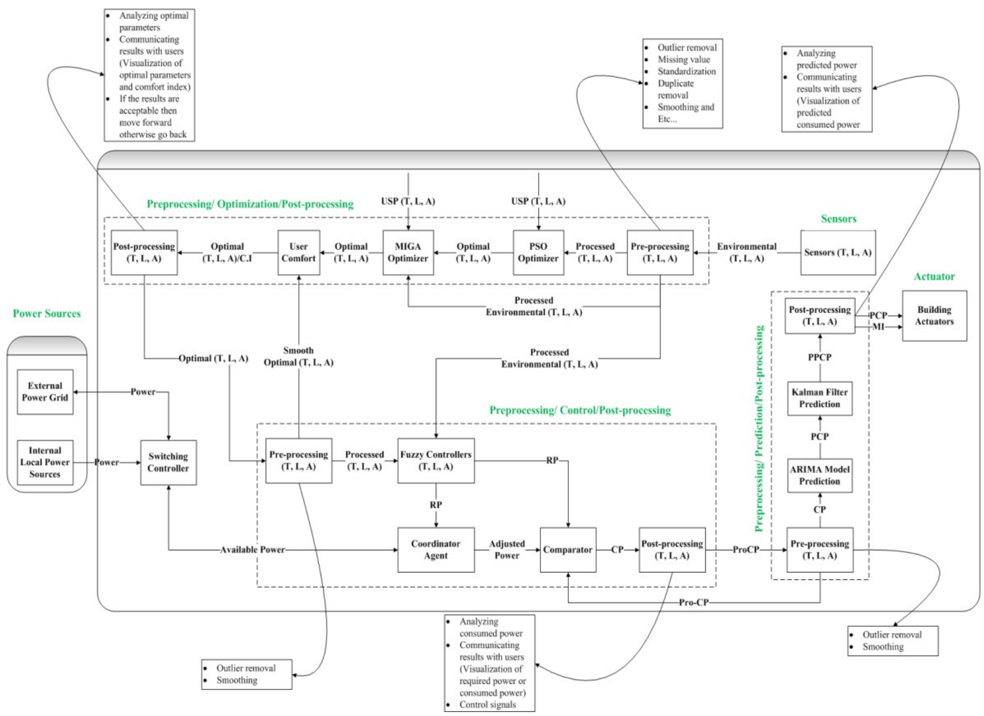

Figure 3.8. Hybrid optimization algorithm based on PSO and MIGA serial with multi-preprocessing

After preprocessing, the consumed power is revised with new updated and smoothed power consumption. Then the updated consumed power is passed to the hybrid prediction part of the model to predict power consumption. Initially the consumed power is passed to the ARIMA prediction model to predict power consumption and then the predicted power consumption is again passed to the Kalman filter to predict the power consumption. Then finally we took the average of the too predictions to get the predicted power consumption. At the last we again post-processed the predicted power consumption by analyzing the results and communicate these results. Actuators received message information's (MI) to turn ON/OFF.

3.2.2.3.2. Optimization algorithm based on PSO and MIGA serial

Serial based PSO and MIGA steps for parameters optimizations and comfort index is:

1. Initialize
   a) Set constants k max, c_1, c_2, r_1, r_2, w_0
   b) Randomly initialize particle positions $x_i \in D$ in R^n *for* $i = 1 \ldots p$
   c) Randomly initialize particle velocities $0 <= v_0^i <= v_0^{max}$ for $i = 1 \ldots p$
   d) Set $k = 1$
2. Optimize
   a) Evaluate f_k^i for particle X^i_k
   b) If $f^i_k <= f^i_{best}$ then $f^i_{best} = f^i_k$, $p^i = x^i_k$
   c) If $f^i_k <= f^g_{best}$ then $f^g_{best} = f^i_k$, $p^g = x^i_k$
   d) If stopping condition is satisfied then go to step 3
   e) Update particle velocity vector v^i_{k+1} Eq. (3.1)
   f) Update particle position vector x^i_{k+1} Eq. (3.2)
   g) Increment *i* (index for particles). If $i > pop$ then increment *k* (index for iterations), and set $i = 1$
   h) Go to 2 (a)

3. Report results
4. Terminate PSO optimization and getting optimal parameters.
5. Initial random population for MIGA
6. Updating initial random population of MIGA by combining with optimal PSO based parameters
7. Selecting best individuals from combined populations of step (6) as an initial population of MIGA
8. Divide initial population in step (7) into multiple Islands
9. Perform Step (4) to Step (9) for each of the Island
10. Calculate fitness function for user comfort using equation (1.1)
11. Select best individuals using any of three selection criteria (Rank, Roulette wheel or Tournament selection), we used rank based selection
12. Perform 'variable two point' crossover of the selected individuals
13. After crossover, we get off-springs
14. Now calculate comfort for the off-springs.
15. Combining populations of step (5) and (7).
16. If mutation criteria meet, then perform mutation
17. If migration criteria meet, then perform migration
18. Repeat steps from 5 to 14 until termination criteria arise or algorithm does not improve.
19. Then after the arrival of termination criteria select best fitted chromosomes from each island.
20. Update optimal parameters after smoothing to get updated parameters
21. Update comfort index using updated parameters

These parameters were selected after running the hybrid algorithm for λ times to get optimal results. Hybrid optimization stops either when the maximum number of generation's Ω met, or no significant change is observed in the fitness for μ (few successive) generations. The maximum population size selected is 100. The conventional single point crossover is performed with the probability of 0.9 and mutation rate of 0.1. MIGA parameters (population size, crossover rate and mutation rate, migration rate) have been set after running MIGA for number of times. The experimentations are performed using Intel(R) Core(TM)i3-2130 3.40 GHz with 8GB RAM. The C # 2012 is used for the simulation. When hybrid optimization evaluation process finishes, best fitted individual is selected to get optimal parameters and comfort index.

4. Simulation and analysis

4.1. Single preprocessing hybrid optimization model based on prediction

4.1.1. Optimization algorithm based on PSO and GA parallel

4.1.1.1. Simulation environment

Real environment is difficult to implement. For the demonstration of our thesis work we carried out simulations in C# 2012. User preference set parameters range is T_{set} = [18, 24] (C), L_{set} = [720, 880] (lux) and A_{set} = [700, 880] (ppm) for simulator.

The environmental configuration remains the same for all the experiments. The uniform configuration helps in the comparison of results with existing techniques. We developed the simulator by using .Net programming environment with the configuration shown in Table 4.1.

To evaluate the hybrid energy optimization and power consumption prediction algorithms and actuator control, we developed a smart IoT simulator using .Net programming environment with the modules and its configuration shown in Table 4.1. Each of these modules for each of the applied algorithms is discussed in next successive sections.

Table 4.1. Simulation environment

Module	Hardware	Software	Remark
Virtual sensing data for	Intel(R) Xeon(R) CPU	Microsoft	C#

temperature, illumination and air-quality	W3503 @2.4GHz 2.39GHz 4GB RAM	Visual Studio	Windows 7
Preprocessing	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Optimization of user set parameters (temperature, illumination and air-quality)	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Temperature, illumination and air-quality control	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Prediction of power consumption for temperature, illumination and air-quality	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Message information for Actuators	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7

Figure 4.1 shows the simulated energy management model for evaluation of hybrid energy optimization and predictions. Each part of the model is shown with its corresponding data or

results. Virtual environment data for air-quality is sensing data obtained from the virtual sensor emulator. Similarly temperature and illumination emulators provide the virtual environment data for the temperature and illumination. The virtual sensing data is then preprocessed to get the processed data. The preprocessed data is then input to the hybrid energy optimization component to get the optimized values for each of the temperature, illumination and air-quality parameters. The optimal parameter for air-quality is also shown in the Figure 4.1.

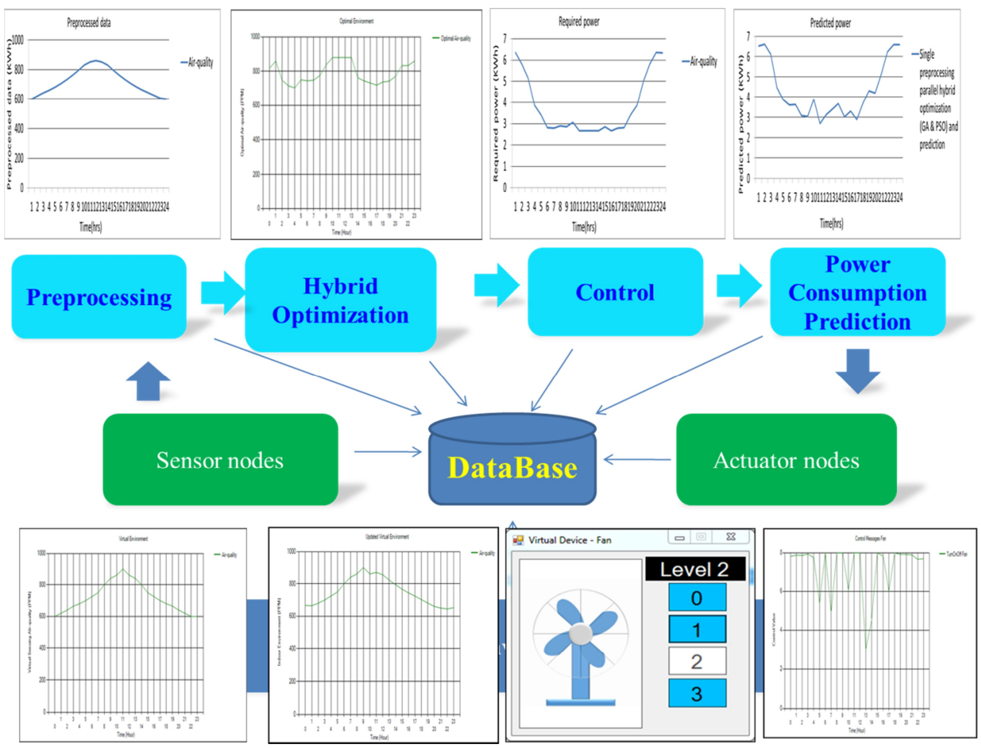

Figure 4.1. Simulated environment of hybrid energy optimization and prediction model

Control component uses fuzzy logic to provide the required power. This component accepts error difference between optimal parameters and processed (smooth) environmental parameters to provide required power. The required power for air-quality is shown in Figure

4.1. Power consumption prediction result for air-quality is also shown in Figure 4.1. The power is predicted using Kalman filter, ARIMA model or combination of both. Message information for air-quality is also depicted in Figure 4.1. These messages describe the different messages received by the Fan actuator as input to change its states from on to off and vice versa. When actuators states changes the indoor environment is changes and updated according to the optimal parameters. The process is continued until the indoor environment gets updated completely.

Table 4.2 shows the detailed emulator and simulation environment. Real environment system consists of temperature sensor emulator, illumination sensor emulator, air-quality sensor emulator, air-conditioned emulator, boiler emulator, light emulator and fan emulator. Temperature sensor emulator, illumination sensor emulator and air-quality sensor emulator are used to build and create temperature, illumination and air-quality sensing environment. The sensing data for temperature, illumination and air-quality is generated by the temperature, illumination and air-quality emulators for each hour of the day. The created environment is the virtual sensing environment for each of the temperature, illumination and air-quality sensing. VirTemperatureController, VirIlluminationController and VirAirQualityController are the names of the programs to create virtual temperature, illumination and air-quality sensing environment. The virtual temperature, virtual illumination environment and virtual air-quality environment is shown in Figure 4.2, Figure 4.3 and Figure 4.4 respectively. The virtual sensing environment shows for 24 hours of the day. Each one point represents one hour of the day. In case of temperature the unit is centigrade, for illumination the unit of measurement is lux and for air-quality, the measurement unit is ppm. GetCurrTmp(), AffectTmp(), GetCurrLux(), AffectLux(), GetCurrAq(), AffectAq(), SetLbp(), HandleLbp1() and UpdateDataUi() functions are used to get current temperature, current illumination and current air-quality of the environment. Affected temperature, affected illumination and affected air-quality are the new temperature, new illumination and new air-quality caused by the change of states of the air-conditioned, boilers, and light and fan actuators. The actuators changes its states by receiving the optimized message information and this is done by setting the affected temperature with respect to the optimal temperature. Then the environment is updated based on the change of states of the actuators levels. Form1HPpsogaM1, Form1HPpsogaM2, Form1HSpsogaM1, Form1HSpsogaM2, Form1HSpsomigaM1 and Form1HSpsomigaM2 are the program names used for optimization of user set parameters (temperature, illumination and air-quality) and virtual sensing temperature, illumination and air-quality data. The functions used by these programs for optimizations are callPSO() and callGA(). FuzzyLogicLibrary is used to calculate required power for temperature, illumination and air-quality control. KalmanRun() function is used to predict the consumed power for each of the temperature, illumination and air-quality.

Air-conditioned emulator, boiler emulator, light emulator and fan emulators are used to control the indoor environment. Air-conditioned emulator is used to control the indoor cooling environment, boiler emulator is used for heating the indoor environment, light emulator is used to control indoor lighting and fan emulator is used to control indoor air-quality. Each emulator received message information to change its current state. Setoff(), SetLevel1(), SetLevel2(), SetLevel3(), ReceiveController(), SendController(), SendData(), StartSend(), SendTmpData(), SendMsgToAc() are the functions used by these actuators to received message information and change their levels. There are four states defined for these actuator emulators, turn off, turn on at level1, turn on at level 2 and turn on at level3. When these emulator actuators received message information then the corresponding state is change to affect the indoor environment. SendMsgToAc() sends message information's to corresponding emulator actuator. If the control message information is zero then corresponding actuator is turn OFF. If control message information results in value between 0 and 3 then respective actuator is turn ON at level1 i.e. low speed. If control message information results in value between 3 and 6 then respective actuator is turn ON at level2 i.e. medium speed. If value is more than 6 then corresponding actuator is turn ON at level3 i.e. high speed. All the four actuators used during simulation of this work are shown in Figure 4.12.

Table 4.2. Detailed emulator and simulation environment

Real environment system	**Simulation environment system**	**Program name**	**Library name and functions**
Temperature sensor emulator	Virtual Temperature	VirTemperatureController, Form1HPpsogaM1, Form1HPpsogaM2, Form1HSpsogaM1, Form1HSpsogaM2,	GetCurrTmp(), AffectTmp(), SetLbp(), HandleLbp1(), UpdateDataUi()

		Form1HSpsomigaM1, Form1HSpsomigaM2, Clskalmanfilter	callSensingData(), callPSO(), callGA(), FuzzyLogicLibrary, KalmanRun(),
Illumination sensor emulator	Virtual Illumination	VirIlluminationController, Form1HPpsogaM1, Form1HPpsogaM2, Form1HSpsogaM1, Form1HSpsogaM2, Form1HSpsomigaM1, Form1HSpsomigaM2, Clskalmanfilter	GetCurrTmp(), AffectTmp(), SetLbp(),HandleLbp1(), UpdateDataUi(), callSensingData(), callPSO(), callGA(), FuzzyLogicLibrary, KalmanRun(),
Air-quality sensor emulator	Virtual Air-quality	VirAirQualityController, Form1HPpsogaM1, Form1HPpsogaM2, Form1HSpsogaM1, Form1HSpsogaM2, Form1HSpsomigaM1, Form1HSpsomigaM2, Clskalmanfilter	GetCurrTmp(), AffectTmp(), SetLbp(),HandleLbp1(), UpdateDataUi(), callSensingData(), callPSO(), callGA(), FuzzyLogicLibrary, KalmanRun(),
Air-condition emulator	Control signals/Message information	DeviceAirCon, Form1HPpsogaM1, Form1HPpsogaM2, Form1HSpsogaM1, Form1HSpsogaM2, Form1HSpsomigaM1, Form1HSpsomigaM2	Setoff(), SetLevel1(), SetLevel2(), SetLevel3(), ReceiveController(), SendController(), SendData(), StartSend(), SendTmpData(), SendMsgToAc()
Boiler emulator	Control signals/Message information	DeviceBoiler, Form1HPpsogaM1, Form1HPpsogaM2, Form1HSpsogaM1, Form1HSpsogaM2, Form1HSpsomigaM1, Form1HSpsomigaM2	Setoff(), SetLevel1(), SetLevel2(), SetLevel3(), ReceiveController(), SendController(), SendData(), StartSend(), SendTmpData(), SendMsgToBoiler()
Light	Control	DeviceLight,	Setoff(), SetLevel1(),

emulator	signals/Message information	Form1HPpsogaM1, Form1HPpsogaM2, Form1HSpsogaM1, Form1HSpsogaM2, Form1HSpsomigaM1, Form1HSpsomigaM2	SetLevel2(), SetLevel3(), ReceiveController(), SendController(), SendData(), StartSend(), SendLuxData(), SendMsgToLight()
Fan emulator	Control signals/Message information	DeviceFan, Form1HPpsogaM1, Form1HPpsogaM2, Form1HSpsogaM1, Form1HSpsogaM2, Form1HSpsomigaM1, Form1HSpsomigaM2	Setoff(), SetLevel1(), SetLevel2(), SetLevel3(), ReceiveController(), SendController(), SendData(), StartSend(), SendAqData(), SendMsgToFan(CAA)

4.1.1.2. Simulation analysis

4.1.1.2.1. Virtual environment

In this section we are presenting virtual sensing environment for temperature, illumination and air-quality. The virtual sensing environment shows here for 24 hours of the day. Each one point represents one hour of the day. In case of temperature the unit is centigrade, for illumination the unit of measurement is lux and for air-quality, the measurement unit is ppm. Figures 4.2, 4.3 and 4.4 respectively show the virtual sensing environment for temperature, illumination and air-quality. The virtual environment shows the change in temperature, illumination and air-quality throughout a day.

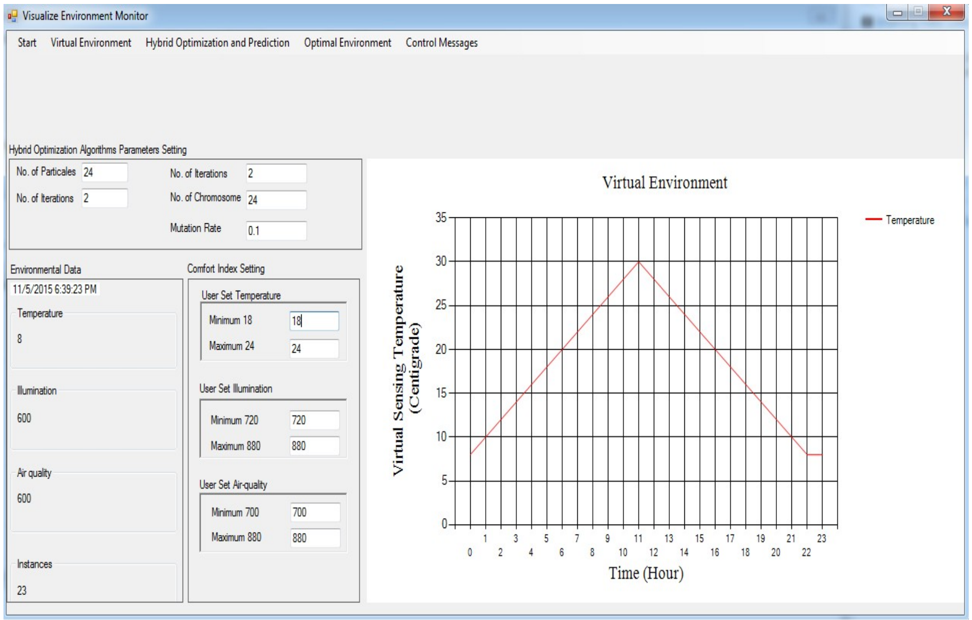

Figure 4.2. Virtual sensing environment for temperature

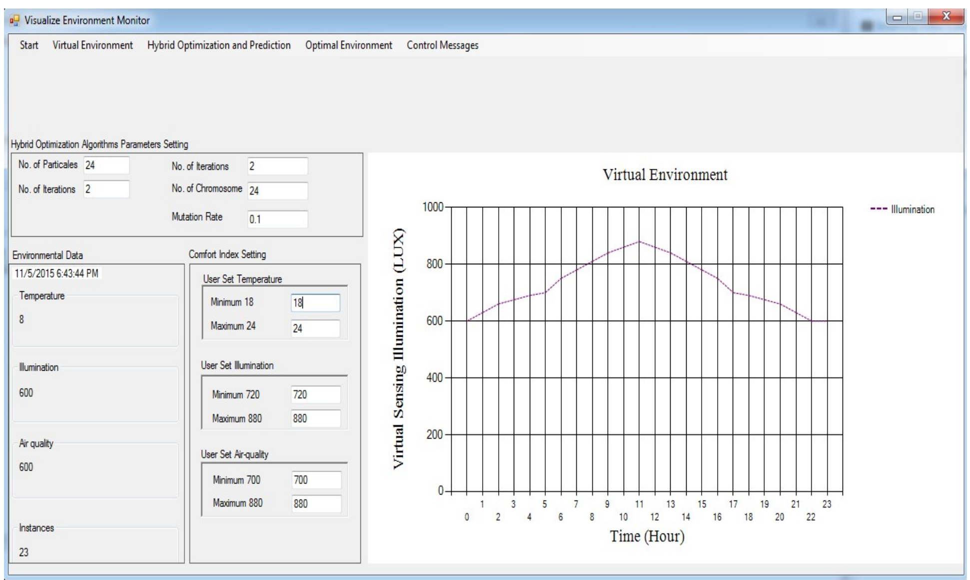

Figure 4.3. Virtual sensing environment for illumination

Temperature environment starts from 8^{o} degree centigrade and reaches 30^{o} at 11 o'clock of the day, it then decreases and reaches almost 8^{o} centigrade. Similarly the change in illumination and air-quality starts from 600lux and 600ppm respectively and reaches 900lux and 900ppm at 11 o'clock. Again it decreases and reaches at 600 each at 23 O'clock.

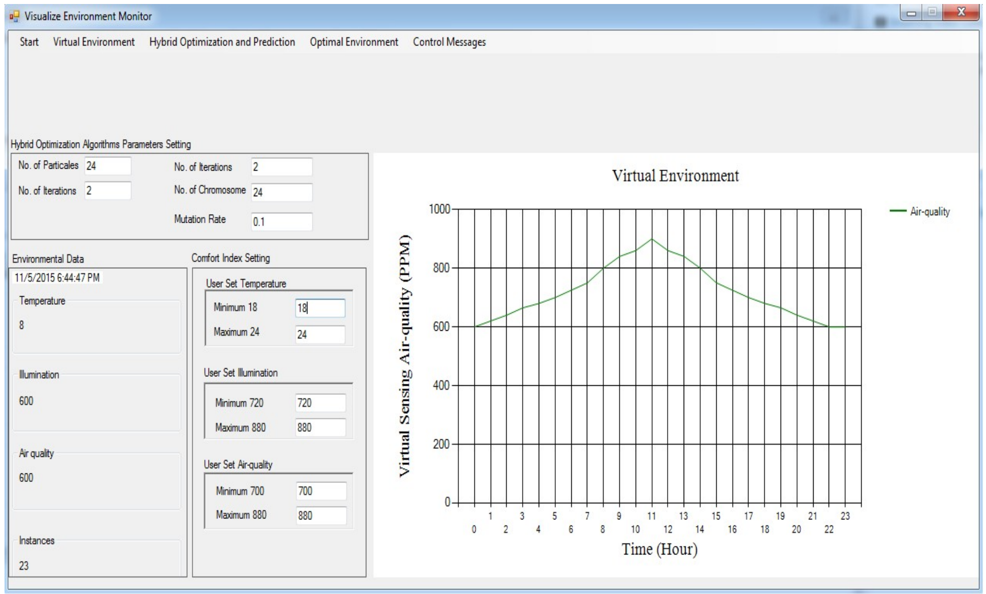

Figure 4.4. Virtual sensing environment for air-quality

4.1.1.2.2. Optimization

Figures 4.5, 4.6 and 4.7 show the optimal environmental parameters for each of the temperature, illumination and air-quality. In case of optimal temperature Figure 4.5, the optimal temperature changes between 18^o to 24^o centigrade as compare to virtual sensing environment temperature Figure 4.2. The user set points are optimized to [18, 24]. The users feel comfortable if the temperature level is between [18, 24]. So we can say that using hybrid parallel optimization based on GA and PSO the user set parameters for temperature optimized to achieve optimal temperature. In case of optimal illumination Figure 4.6, the illumination parameters changes between 720^o to 880^o lux as compare to virtual sensing environment illumination Figure 4.3. The user set points are optimized to [720, 880]. The users feel comfortable if the illumination level is between [720, 880].

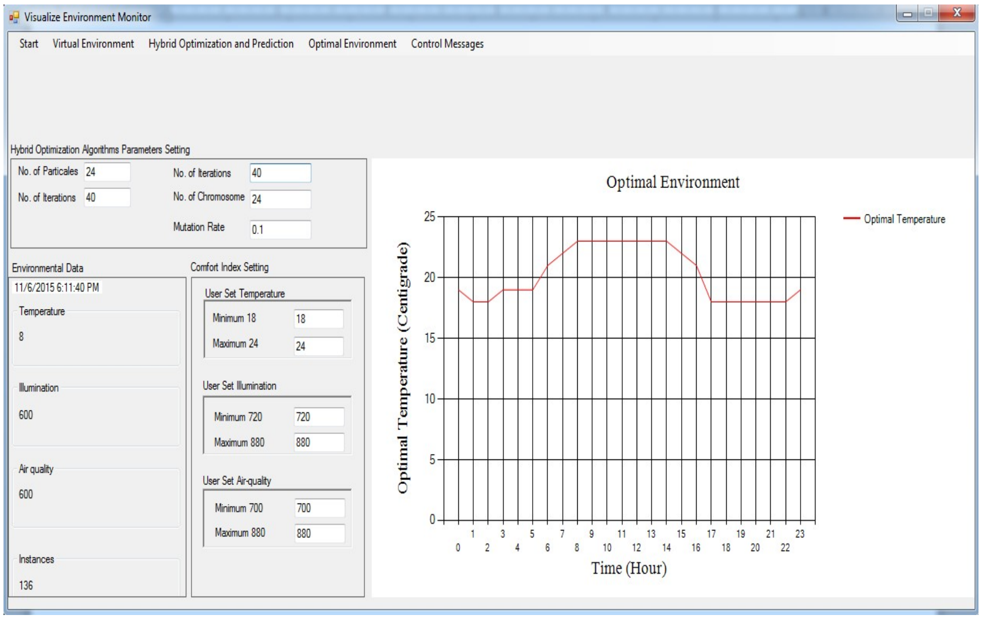

Figure 4.5. Optimal parameters for temperature (Based on PSO and GA parallel)

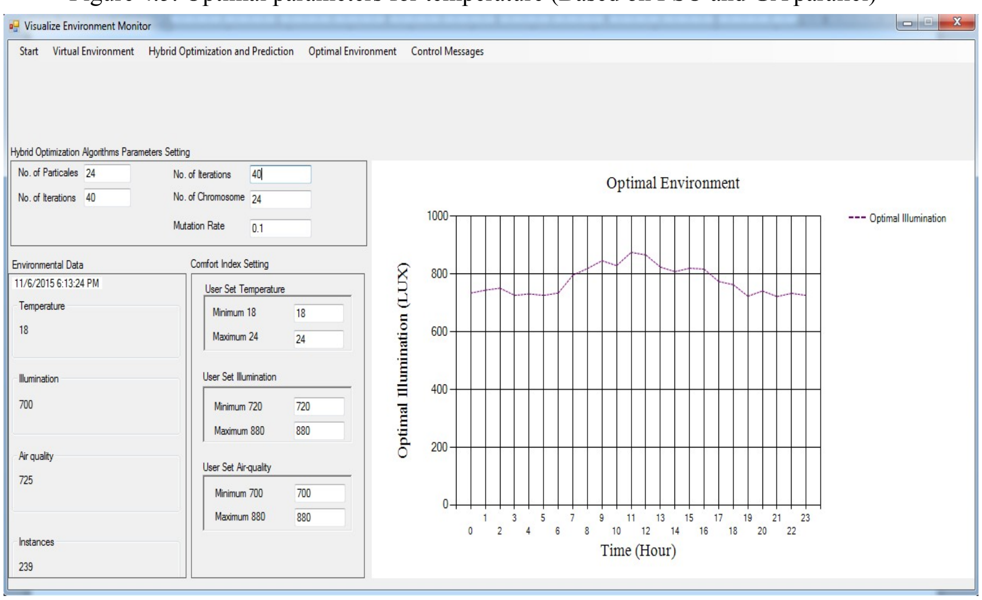

Figure 4.6. Optimal parameters for illumination (Based on PSO and GA parallel)

So we can say that using hybrid parallel optimization based on GA and PSO, the user set parameters for illumination are optimized to achieve optimal illumination. In case of optimal air-quality Figure 4.7, the air-quality parameters changes between 700^{o} to 880^{o} ppm as compare to virtual sensing environment air-quality Figure 4.4. The user set points for air-quality are optimized to [700, 880]. The users feel comfortable when the air-quality level is between [700, 880]. So we can say that using hybrid parallel optimization based on GA and PSO, the user set parameters for air-quality are optimized to achieve optimal air-quality.

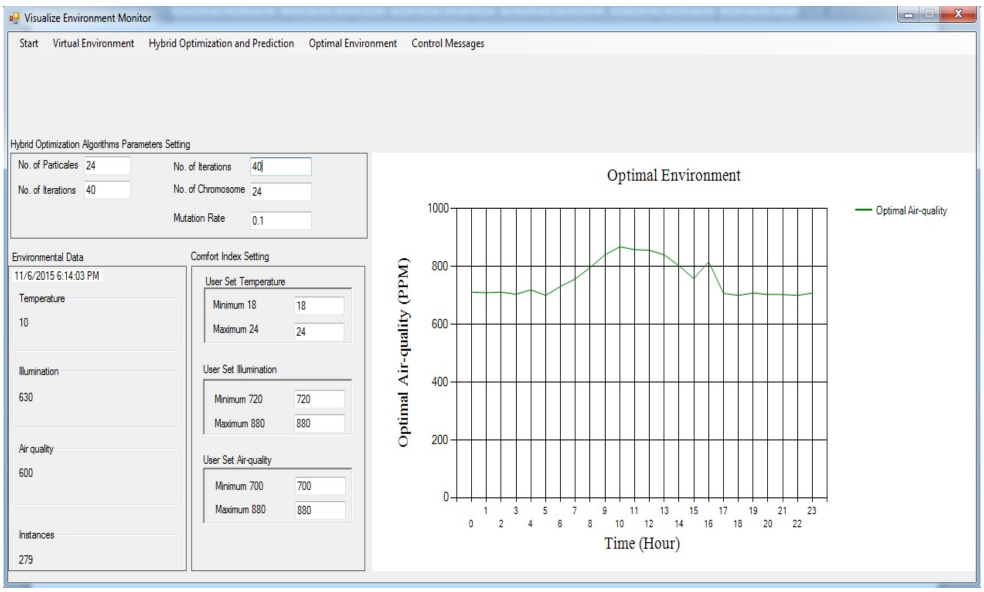

Figure 4.7. Optimal parameters for air-quality (Based on PSO and GA parallel)

4.1.1.2.3. Control messages

Figure 4.8 shows control messages to turn ON/OFF air-condition. If the control message value is zero then its means that virtual sensing environment temperature and optimal temperature is same and air-condition should be turn OFF. If control message value results in value between 0 and 3 then AC will be turn ON slow. If control message value results in value between 3 and 6 then AC will be Turn ON Medium. If value is more than 6 then AC will be turn ON in high speed. But for air-con we can see that the message information value does not exceeds 6 so the air-con is run at level 1 and 2 most of the time and turn OFF at time 7hrs and 15hrs . While between 0hrs to 6hrs and between 16hrs to 23hrs the air-con remains Turn OFF due to running of boiler.

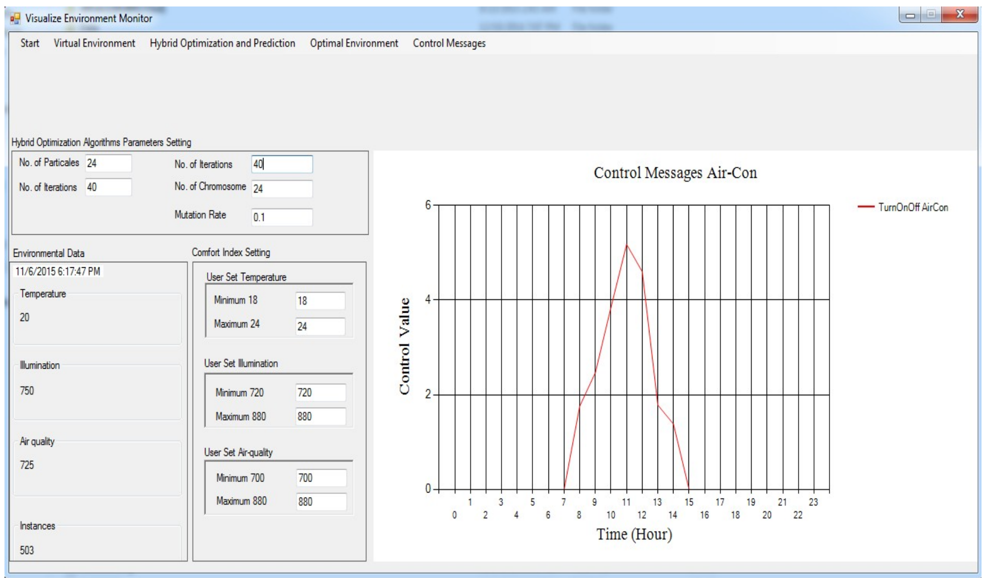

Figure 4.8. Control messages for Air-con (Based on PSO and GA parallel)

Figure 4.9 shows control messages to Turn ON/OFF boiler. If the control message value is zero then its mean that virtual sensing environment temperature and optimal temperature is same and boiler should be turn OFF (level 0). If control message value results in value between 0 and 3 then the boiler will be turn ON slow (level 1). If control message value results in value between 3 and 6 then boiler will be turn on Medium (level 2). If value is more than 6 then boiler will be turn ON in high speed (level 3). But for boiler we can see that the message information value results in zero between 8hrs and 16hrs and turn OFF. While between 0hrs to 7hrs and between 16hrs to 23hrs the boiler is turn ON for all of its levels.

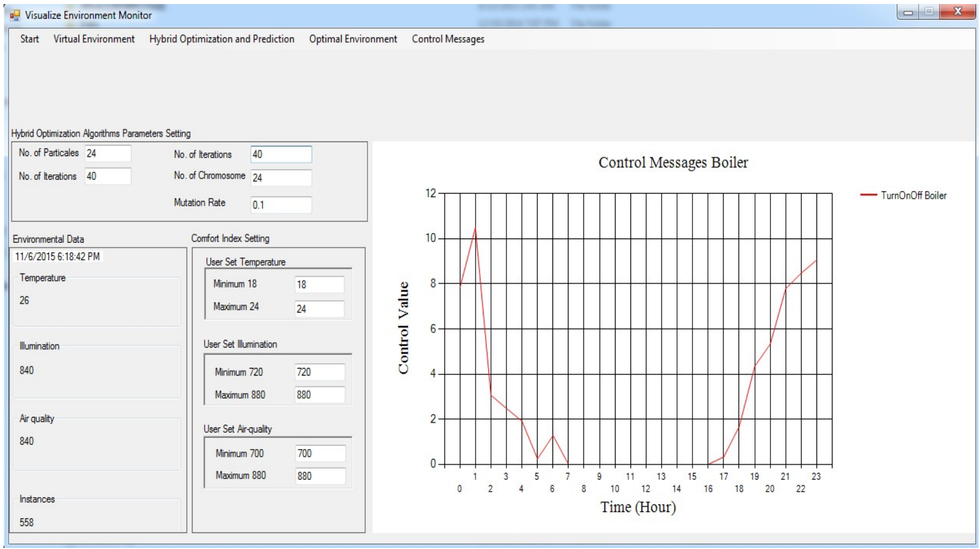

Figure 4.9. Control messages for Boiler (Based on PSO and GA parallel)

Figure 4.10 shows control messages to turn ON/OFF Light. If the control message value is zero then its means that virtual sensing environment illumination and optimal illumination is same and light should be turn OFF. If control message value results in value between 0 and 3 then light will be turn ON slow. If control message value results in value between 3 and 6 then light will be Turn ON Medium. If value is more than 6 then light will be turn ON in full mode (level 3). Here we can see that the message information values results in between 1 and 18 which means that light is turn ON for all of its levels during 24hrs. The light consumption decreases as the day time arrives and increase again as the day time finishes. Figure 4.11 and Figure 4.12 shows control messages to turn ON/OFF FAN and the four actuators used during IoT simulator implementation to turn them ON/OFF. If the control message value is zero then its means that virtual sensing environment air-quality and optimal air-quality is same and

FAN should be turn OFF.

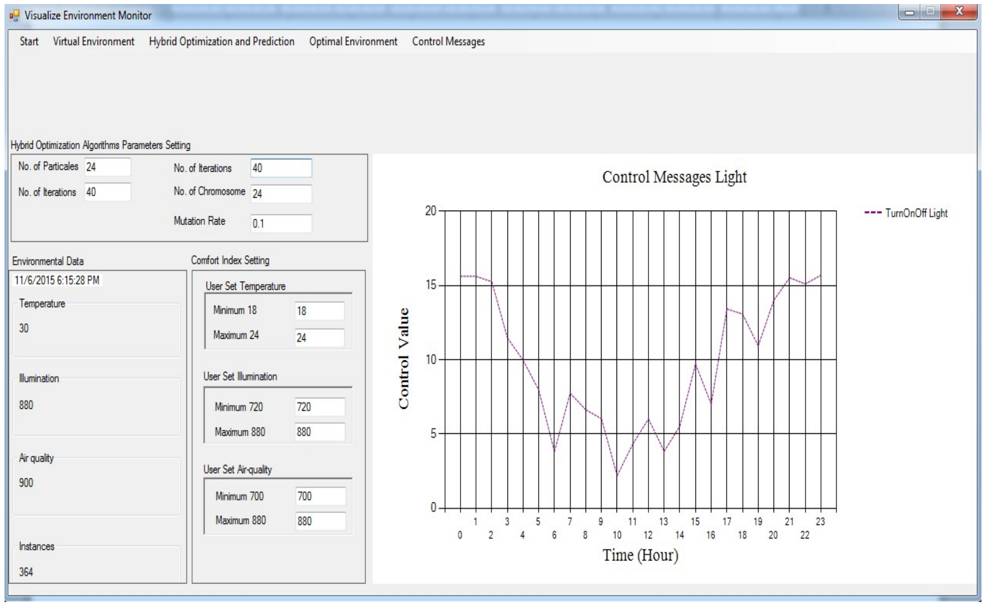

Figure 4.10. Control messages for Light (Based on PSO and GA parallel)

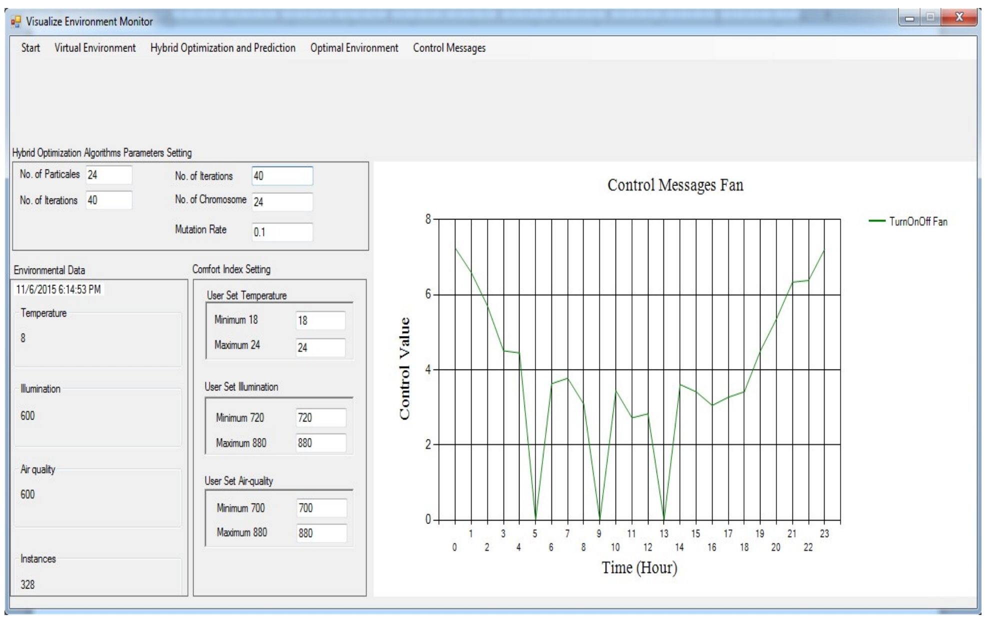

Figure 4.11. Control messages for Fan (Based on PSO and GA parallel)

If control message value result in value between 0 and 3 then FAN will be turn ON slow. If control message value results in value between 3 and 6 then FAN will be turn ON Medium. If value is more than 6 then light will be turn ON in high speed. Here we can see that the message information values results in more than 6 so the FAN is turn ON for all of its levels, while during some specific hours of the day FAN is turn OFF.

4.1.1.2.4. Actuator emulators

The four actuator emulators we considered are shown in Figure 4.12. In case of hybrid energy optimization based on prediction using GA and PSO with single preprocessing model these actuator emulators received signals shown in Figure 4.8, 4.9, 4.10 and 4.11. Each actuator has four levels as shown in Figure 4.12. Level 0, level 1, level 2 and level 3 represents turn OFF, turn ON slow, turn ON Medium and turn ON high respectively. Each emulator received message information to change its current state. When these actuator emulators received message information then the corresponding state is change to affect the indoor environment. Control signals defined in previous section used as message information's to affect corresponding emulator actuator. If the control message information is zero then corresponding emulator actuator is turn OFF. If control message information results in value between 0 and 3, then respective emulator actuator is turn ON at level1 i.e. low speed. If control message information results in value between 3 and 6 then respective actuator is turn ON at level2 i.e. medium speed. If value is more than 6 then corresponding actuator is turn ON at level3 i.e. high speed. Here air-con actuator used signals shown in Figure 4.8. Air-con actuator changes its states according to these signals. From these signals, we can see that the message information values results values which cause the air-con actuator to be turn OFF between 0 to 6 hours and 16 to 23 hours.

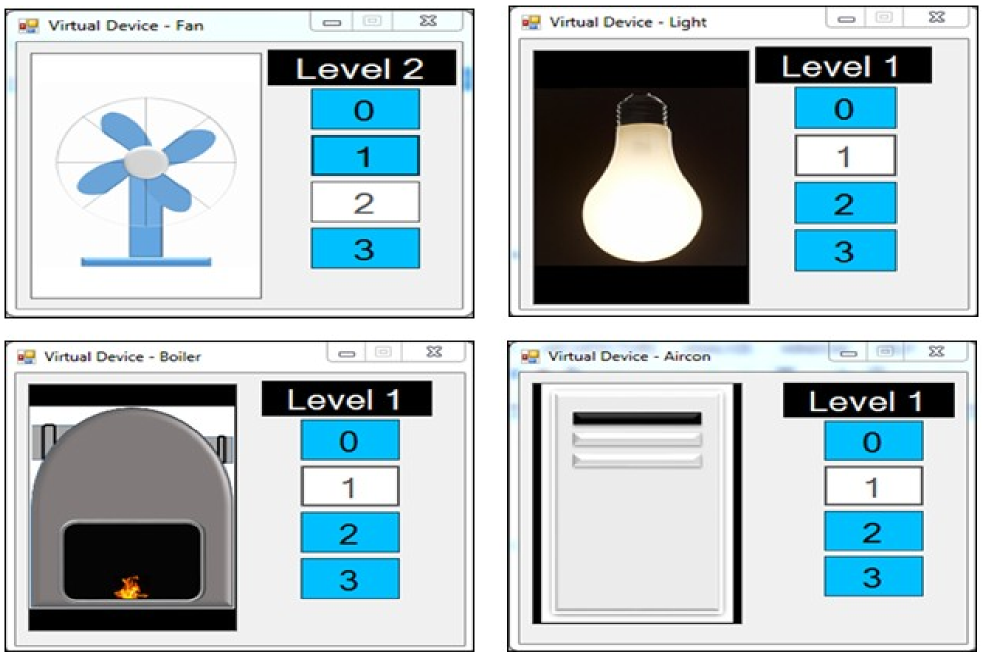

Figure 4.12. Actuators

During this time boiler is running to heat the indoor environment. Boiler actuator uses signals shown in Figure 4.9. Boiler actuator state changes according to these signals. Here for boiler actuator we can see that the message information value results in zero between 8hrs and 16hrs, and the boiler remains turn OFF, while between 0hrs to 7hrs and between 16hrs to 23hrs the boiler is turn ON for all of its levels. Light actuator used signals shown in Figure 4.10. Light is turn ON/OFF according to these signals. Here we can see that the message information values results in between 1 and 18 which means that light is turn ON for all of its levels during 24hrs. The light consumption decreases as the day time arrives and increase again as the day time finishes. Similarly, fan actuator received signals shown in

Figure 4.11 to operate and change state accordingly. Here we can see that the message information values results in more than 6 so the FAN is turn ON for all of its levels, while during some specific hours of the day FAN is turn OFF.

4.1.2. Optimization algorithm based on PSO and GA serial

4.1.2.1. Simulation environment

The simulation environment is kept same for each of the algorithm. The simulation environment is discussed in detailed in section 4.

4.1.2.2. Simulation analysis

4.1.2.2.1. Virtual environment

The simulation virtual environment is kept same for each of the algorithm. The virtual environment for each of the virtual sensor temperature, illumination and air-quality is discussed in detailed in section 4.1.1.2.1.

4.2.1.2.2. Optimization

Figures 4.13, 4.14 and 4.15 show the optimal environmental parameters for each of the temperature, illumination and Air-quality. In case of optimal temperature Figure 4.13, the optimal temperature changes between 18^{o} to 24^{o} centigrade as compare to virtual sensing environment temperature Figure 4.2. The user set points are optimized to [18, 24]. The users feel comfortable if the temperature level is between [18, 24]. From the Figure 4.13, we can see that using hybrid serial optimization based on GA and PSO the user set parameters for temperature optimized to achieve optimal temperature. In case of optimal illumination Figure 4.14, the illumination parameters changes between 720^{o} to 880^{o} lux as compare to virtual sensing environment illumination Figure 4.3. The user set points are optimized to [720, 880]. The users feel relax and comfortable if the illumination level varies between [720, 880]. Here we can conclude that using hybrid serial optimization based on GA and PSO, the user set parameters for illumination are optimized to achieve optimal illumination level. In case of optimal air-quality Figure 4.15, the air-quality parameters changes between 700^{o} to 880^{o} ppm as compare to virtual sensing environment air-quality Figure 4.4.

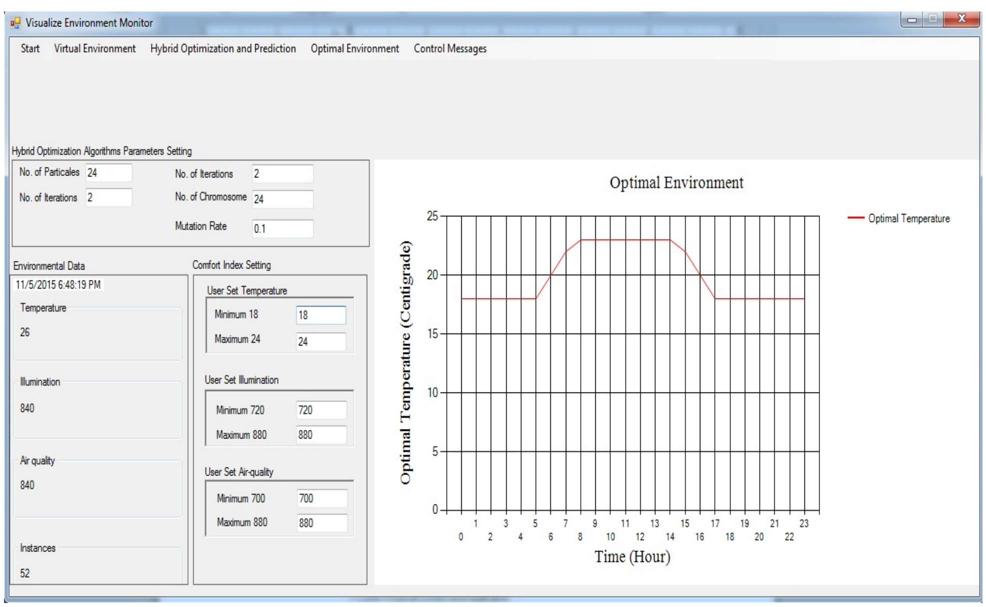

Figure 4.13. Optimal parameters for temperature (Based on PSO and GA serial)

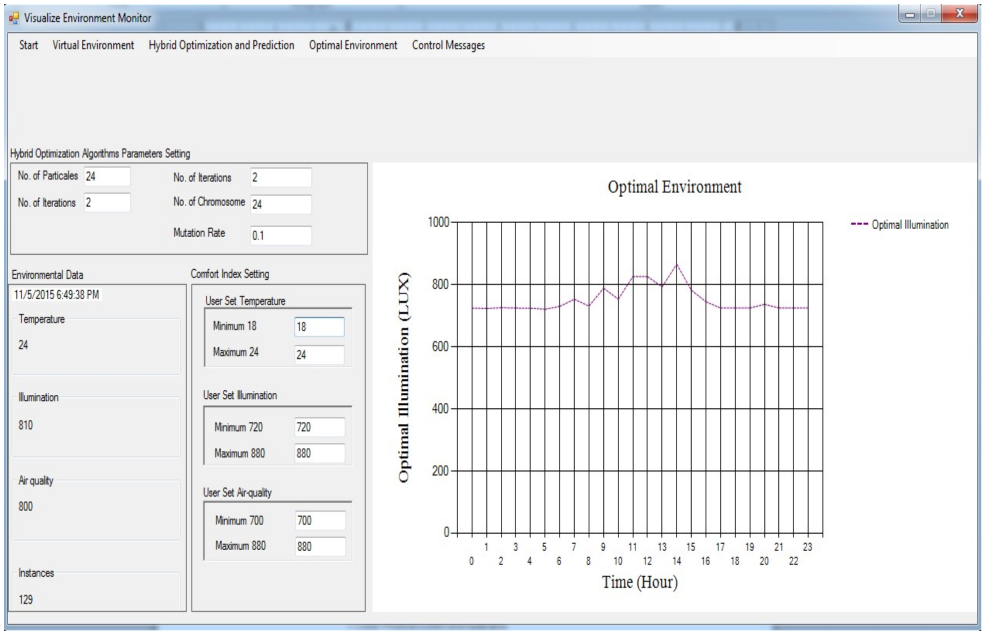

Figure 4.14. Optimal parameters for illumination (Based on PSO and GA serial)

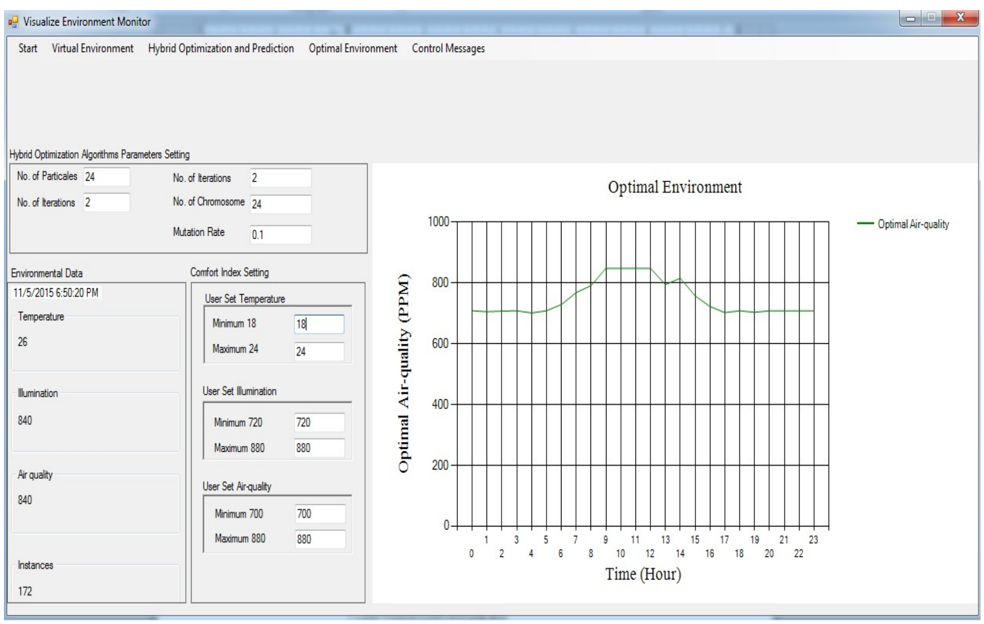

Figure 4.15. Optimal parameters for air-quality (Based on PSO and GA serial)

The user set points for air-quality are optimized to [700, 880] using hybrid optimization algorithm based on PSO and GA serial. The users feel happy when the air-quality level is between [700, 880] as defined by user set parameters. From this we can conclude that using hybrid serial optimization based on GA and PSO, the user set parameters for air-quality are optimized to accomplish optimal air-quality.

4.2.1.2.3. Control messages

In Figures 4.16, 4.17, 4.18 and 4.19 shows the control messages information for hybrid optimization algorithm based on PSO and GA serial. Figure 4.16 shows control messages to turn ON/OFF air-condition. The same turn ON/OFF mechanism is used here. That is, if the control message information results in zero then its means that virtual sensing environment for temperature and optimal temperature is same and air-condition should be turn OFF. If control message value results in value between 0 and 3 then AC will be turn ON slow. If control message value results in value between 3 and 6 then AC will be Turn ON Medium. If value is more than 6 then AC will be turn ON in high speed. Here we can see that message information's for air-con results in values more than 6, so the air-con in this case is turn ON for all of the levels between 7hrs to 15hrs, while for the rest of the time air-con remains turn OFF.

Figure 4.17 shows control messages to Turn ON/OFF boiler. If the control message value is zero then its mean that virtual sensing environment temperature and optimal temperature is same and boiler should be turn OFF. If control messages information results in values between 0 and 3 then boilers will be turn ON slow. If control message value results in value between 3 and 6 then boiler will be turn on Medium. If value is more than 6 then boiler will be turn ON in high speed. Here we can see that boiler is turn ON between 0hrs to 5hrs and 17hrs to 23hrs.

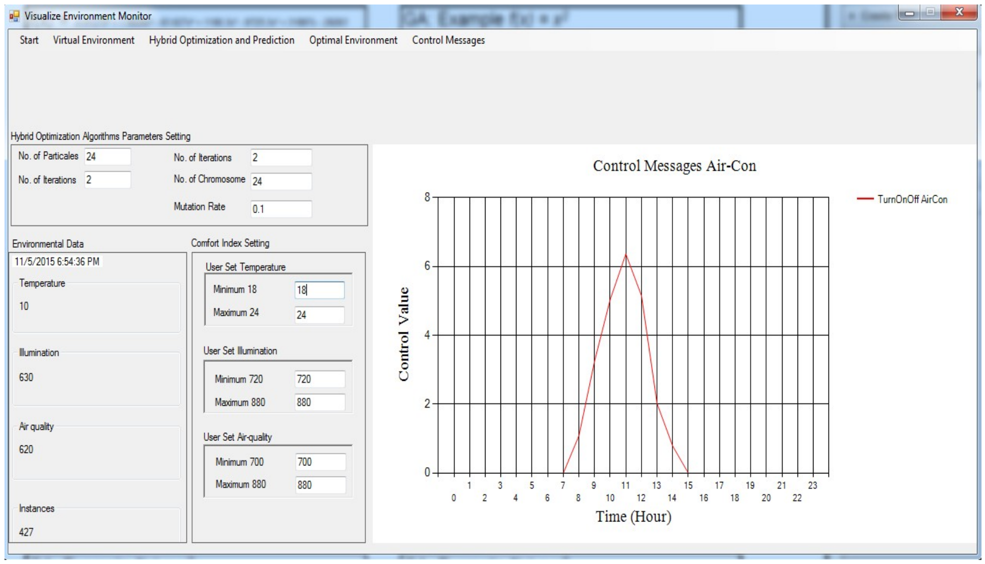

Figure 4.16. Control messages for Air-con (Based on PSO and GA serial)

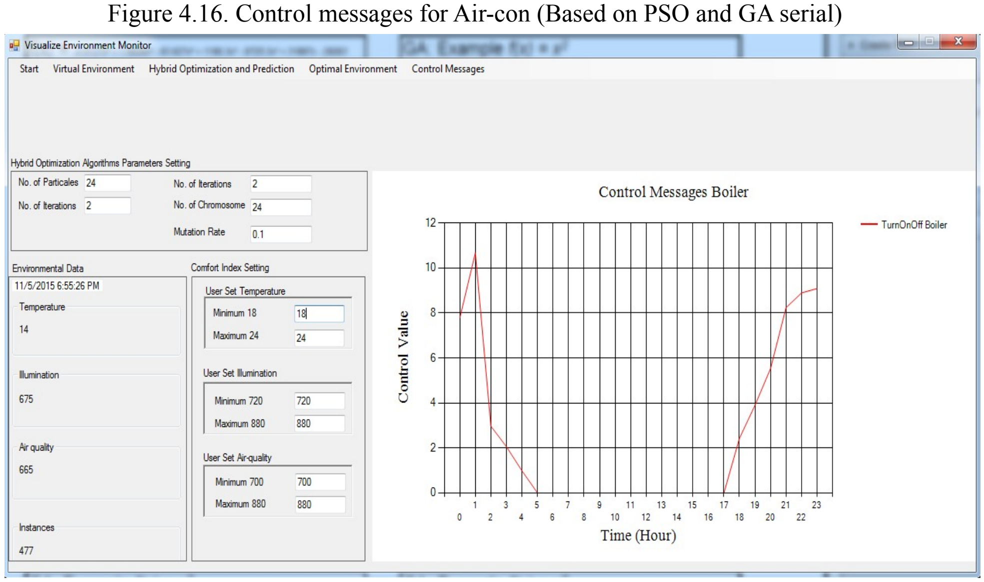

Figure 4.17. Control messages for Boiler (Based on PSO and GA serial)

For the rest of the time it is turn OFF due to either running of air-con or environmental parameters and optimal parameters remain same.

Figure 4.18 shows control messages to turn ON/OFF Light. If the control message value is zero then its means that virtual sensing environment illumination and optimal illumination is same and light should be turn OFF. If control message value results in value between 0 and 3 then light will be turn ON slow. If control message value results in value between 3 and 6 then light will be Turn ON Medium. If value is more than 6 then light will be turn ON in full mode. Here we can see that light is turning ON for all of its levels during 24hrs of the day. The power consumption for illumination varies as the day progresses to night and vice versa. Figure 4.19 shows control messages to turn ON/OFF FAN. If the control message value is zero then its means that virtual sensing environment air-quality and optimal air-quality is same and FAN should be turn OFF.

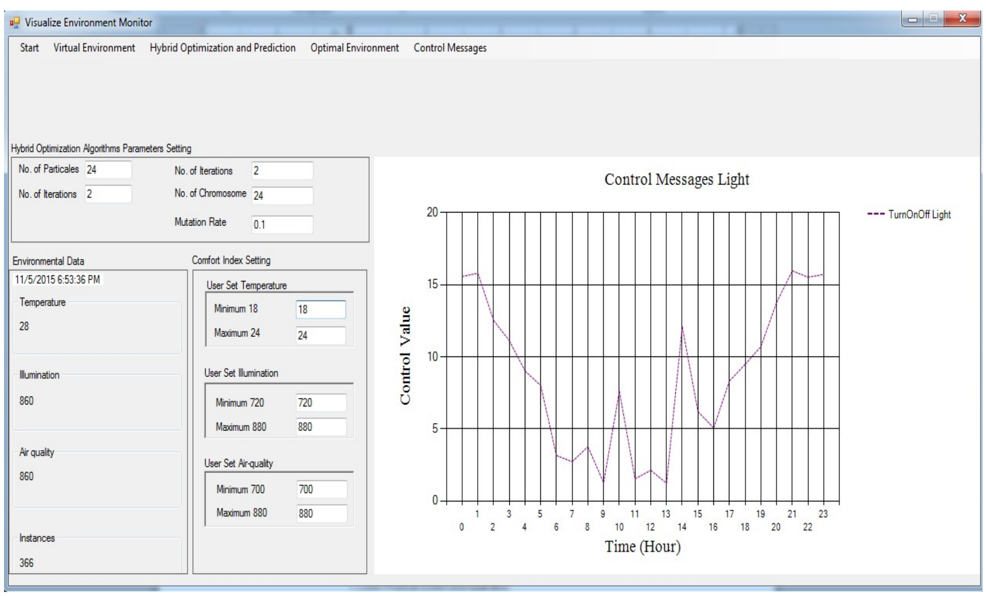

Figure 4.18. Control messages for Light (Based on PSO and GA serial)

If control message value result in value between 0 and 3 then FAN will be turn ON slow. If control message value results in value between 3 and 6 then FAN will be turn ON Medium. If value is more than 6 then FAN will be turn ON in high speed. Here we can see that FAN is turn ON for all of its levels during 24hrs of the day. Most of the time, FAN is running at level 2 and level 3.

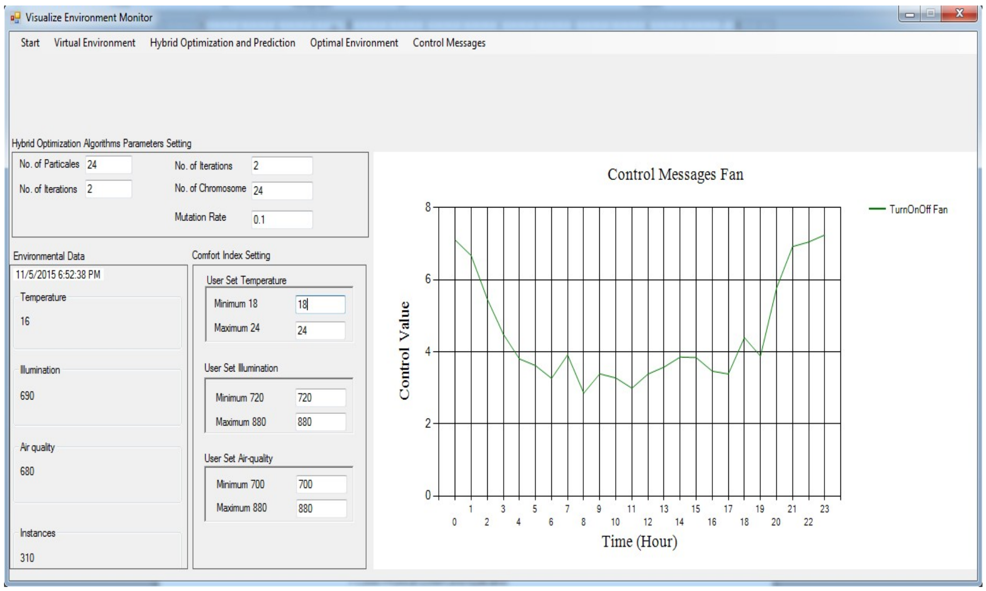

Figure 4.19. Control messages for Fan (Based on PSO and GA serial)

4.2.1.2.4. Actuator emulators

In case of hybrid energy optimization based on prediction using GA and PSO serial with single preprocessing model the actuator emulators received signals shown in Figure 4.16, 4.17, 4.18 and 4.19. The control signals shown in Figure 4.16, 4.17, 4.18 and 4.19 shows the signals created by the hybrid energy optimization algorithm based on PSO and GA serial algorithm. From Figure 4.16, we can see that message information's for air-con actuator results in values more than 6, so the air-con in this case is turn ON for all of the levels between 7hrs to 15hrs, while for the rest of the time air-con remains turn OFF. From Figure 4.17, we can see that boiler actuator is turn ON between 0hrs to 5hrs and 17hrs to 23hrs. For the rest of the time it is turn OFF due to either running of air-con or environmental parameters and optimal parameters remain same. From Figure 4.18, we can see that light actuator is turning ON for all of its levels during 24hrs of the day. The power consumption for illumination varies as the day progresses to night and vice versa. From Figure 4.19, we can see that FAN actuator is turn ON for all of its levels during 24hrs of the day. Most of the time, FAN is running at level 2 and level 3.

4.1.3. Optimization algorithm based on PSO and MIGA serial

4.1.3.1. Simulation environment

The simulation environment is kept same for each of the algorithm. The simulation environment is discussed in detailed in section 4.

4.1.3.2. Simulation analysis

4.1.3.2.1. Virtual environment

The simulation virtual environment is kept same for each of the algorithm. The virtual environment for each of the virtual sensor temperature, illumination and air-quality is discussed in detailed in section 4.1.1.2.1.

4.1.3.2.2. Optimization

Figures 4.20, 4.21 and 4.22 show the optimal environmental parameters for each of the temperature, illumination and air-quality. In case of optimal temperature Figure 4.20, the optimal temperature changes between 18^{o} to 24^{o} centigrade as compare to virtual sensing environment temperature Figure 4.2. The user set points are optimized to [18, 24] using hybrid serial optimization based on PSO and MIGA. The users feel comfortable if the temperature level is between [18, 24].

From Figure 4.20, we can see that using hybrid serial optimization based on PSO and MIGA the user set parameters for temperature optimized to achieve optimal temperature. In case of optimal illumination Figure 4.21, the illumination parameters changes between 720^{o} to 880^{o} lux as compare to virtual sensing environment illumination Figure 4.3. The user set points are optimized to [720, 880]. The users feel relax and comfortable if the illumination level varies between [720, 880]. Here we can conclude that using hybrid serial optimization based on PSO and MIGA, the user set parameters for illumination are optimized to achieve optimal illumination level.

In case of optimal air-quality Figure 4.22, the air-quality parameters changes between 700^{o} to 880^{o} ppm as compare to virtual sensing environment air-quality Figure 4.4. The user set points for air-quality are optimized to [700, 880] using hybrid serial optimization based on

PSO and MIGA.

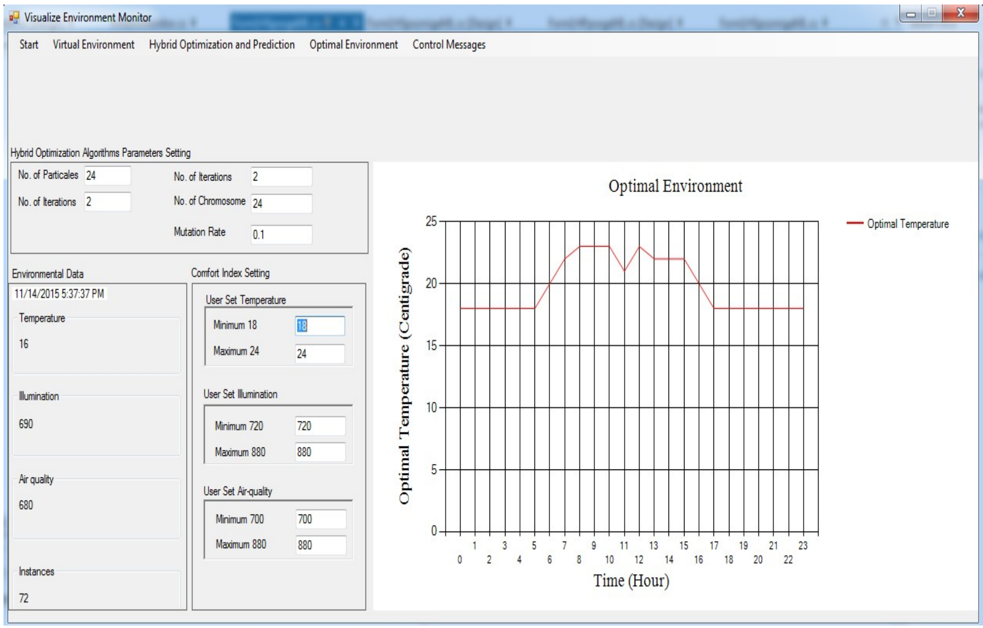

Figure 4.20. Optimal parameters for temperature (Based on PSO and MIGA serial)

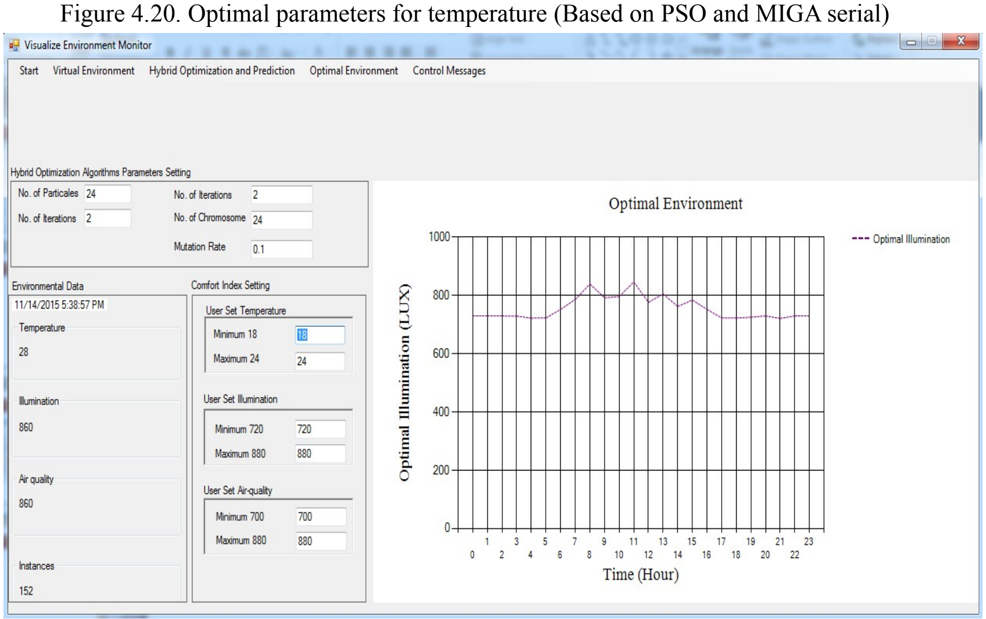

Figure 4.21. Optimal parameters for illumination (Based on PSO and MIGA serial)

The users feel happy when the air-quality level is between [700, 880] as defined by user set parameters. From this we can conclude that using hybrid serial optimization based on PSO and MIGA, the user set parameters for air-quality are optimized to accomplish optimal air-quality.

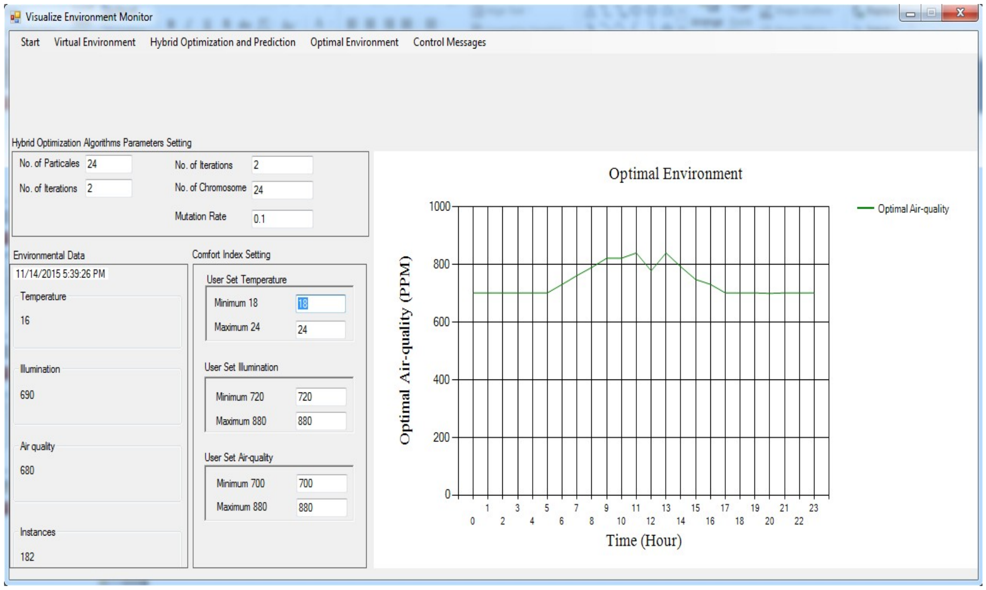

Figure 4.22. Optimal parameters for air-quality (Based on PSO and MIGA serial)

4.1.3.2.3. Control messages

In Figures 4.23, 4.24, 4.25 and 4.26 shows the control messages information for hybrid optimization algorithm based on PSO and GA serial. Figure 4.23 shows control messages to turn ON/OFF air-condition. The same turn ON/OFF mechanism is used here. That is, if the control message information results in zero then its means that virtual sensing environment for temperature and optimal temperature is same and air-condition should be turn OFF. If control message value results in value between 0 and 3 then AC will be turn ON slow. If control message value results in value between 3 and 6 then AC will be Turn ON Medium. If value is more than 6 then AC will be turn ON in high speed. Here we can see that message information's for air-con results in values more than 6, so the air-con in this case is turn ON for all of the levels between 7hrs to 15hrs, while for the rest of the time air-con remains turn OFF.

Figure 4.24 shows control messages to Turn ON/OFF boiler. If the control message value is zero then its mean that virtual sensing environment temperature and optimal temperature is same and boiler should be turn OFF. If control messages information results in values between 0 and 3 then boilers will be turn ON slow. If control message value results in value between 3 and 6 then boiler will be turn on Medium.

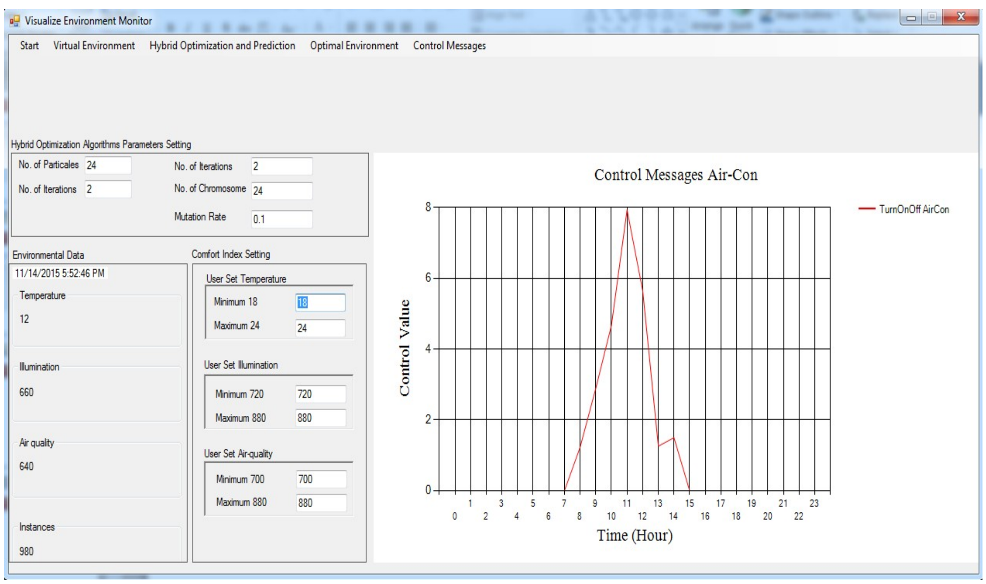

Figure 4.23. Control messages for Air-con (Based on PSO and MIGA serial)

If value is more than 6 then boiler will be turn ON in high speed. Here we can see that boiler is turn ON between 0hrs to 5hrs and 17hrs to 23hrs. For the rest of the time it is turn OFF due to either running of air-con or environmental parameters and optimal parameters remain same.

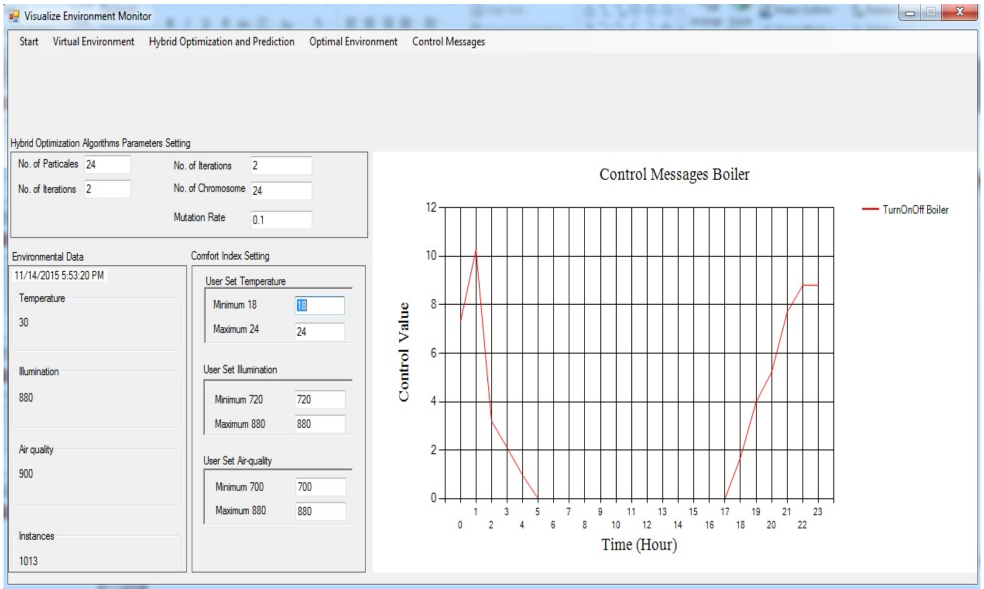

Figure 4.24. Control messages for Boiler (Based on PSO and MIGA serial)

Figure 4.25 shows control messages to turn ON/OFF Light. If the control message value is zero then its means that virtual sensing environment illumination and optimal illumination is same and light should be turn OFF. If control message value results in value between 0 and 3 then light will be turn ON slow. If control message value results in value between 3 and 6 then light will be Turn ON Medium. If value is more than 6 then light will be turn ON in full mode. Here we can see that light is turning ON for all of its levels during 24hrs of the day. The power consumption for illumination varies as the day progresses to night and vice versa. Figure 4.26 shows control messages to turn ON/OFF FAN. If the control message value is zero then its means that virtual sensing environment air-quality and optimal air-quality is same and FAN should be turn OFF.

If control message value result in value between 0 and 3 then FAN will be turn ON slow. If control message value results in value between 3 and 6 then FAN will be turn ON Medium. If value is more than 6 then FAN will be turn ON in high speed. Here we can see that FAN is turn ON for all of its levels during 24hrs of the day. Most of the time, FAN is running at level 2 and level 3.

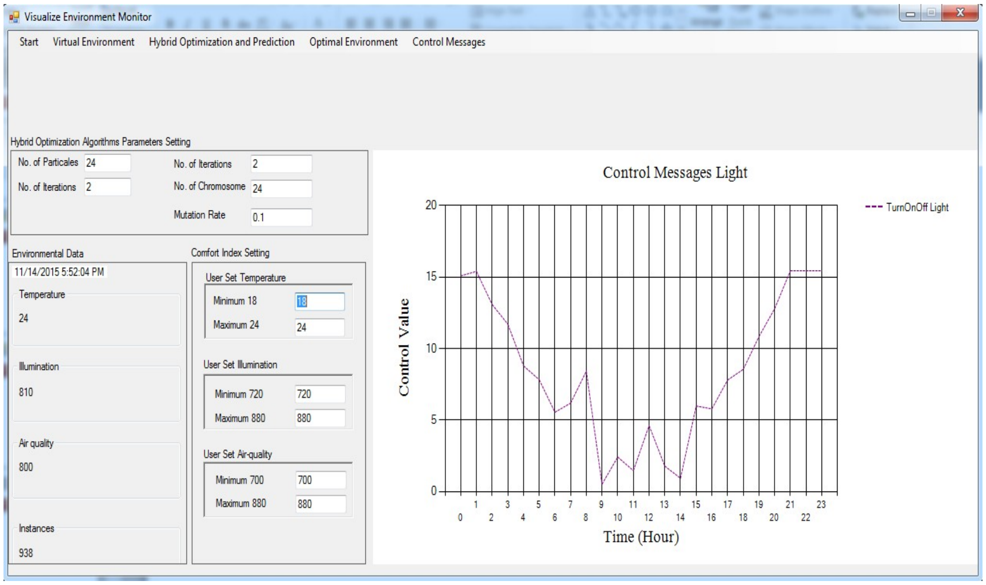

Figure 4.25. Control messages for Light (Based on PSO and MIGA serial)

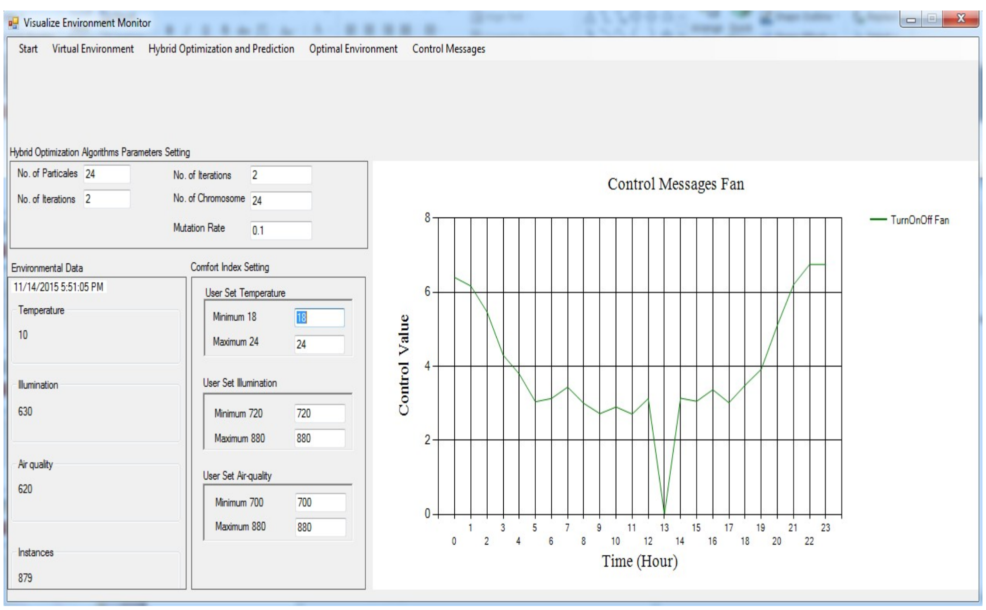

Figure 4.26. Control messages for Fan (Based on PSO and MIGA serial)

4.1.3.2.4. Actuator emulators

In case of hybrid energy optimization based on prediction using MIGA and PSO with single preprocessing model the actuator emulators received signals shown in Figure 4.23, 4.24, 4.25 and 4.26. Hybrid energy optimization algorithm based on PSO and MIGA serial algorithm creates control signals described in Figure 4.23, 4.24, 4.25 and 4.26 respectively. From Figure 4.23, we can see that message information's for air-con actuator results in values more than 6, so the air-con emulator in this case is turn ON for all of the levels between 7hrs to 15hrs, while for the rest of the time air-con remains turn OFF. From Figure 4.24, we can see that boiler actuator is turn ON between 0hrs to 5hrs and 17hrs to 23hrs. For the rest of the time it is turn OFF due to either running of air-con emulator or environmental parameters and optimal parameters remain same. From Figure 4.25, we can see that FAN actuator is turn ON for all of its levels during 24hrs of the day. Most of the time FAN emulator will be in running mode and switching between level 2 and level 3. From Figure 4.26, we can see that light actuator is turning ON for all of its levels during 24hrs of the day.

4.2. Multi-preprocessing hybrid optimization model based on prediction

4.2.1. Optimization algorithm based on PSO and GA parallel

4.2.1.1. Simulation environment

The simulation environment is kept same for each of the algorithm. The simulation environment is discussed in detailed in section 4.

4.2.1.2. Simulation analysis

4.2.1.2.1. Virtual environment

The simulation virtual environment is kept same for each of the algorithm. The virtual environment for each of the virtual sensor temperature, illumination and air-quality is discussed in detailed in section 4.1.1.2.1.

4.2.1.2.2. Optimization

Figures 4.27, 4.28 and 4.29 show the optimal environmental parameters for each of the temperature, illumination and air-quality using hybrid optimization algorithm based on PSO and GA parallel with multi-preprocessing. In case of optimal temperature Figure 4.27, the optimal temperature changes between 18^{o} to 24^{o} centigrade as compare to virtual sensing environment temperature Figure 4.2. The user set points are optimized to [18, 24] using hybrid optimization algorithm based on PSO and GA parallel with multi-preprocessing. The users feel comfortable when the temperature varies between [18, 24]. We can say that using hybrid parallel optimization based on GA and PSO with multi-preprocessing, the user set parameters for temperature optimized to achieve optimal temperature.

In case of optimal illumination Figure 4.28, the illumination parameters changes between 720^o to 880^o lux as compare to virtual sensing environment illumination Figure 4.3. The user set points are optimized to [720, 880]. The users feel comfortable when the illumination level is between [720, 880]. So we can say that using hybrid parallel optimization based on GA and PSO with multi-preprocessing, the user set parameters for illumination are optimized to achieve optimal illumination.

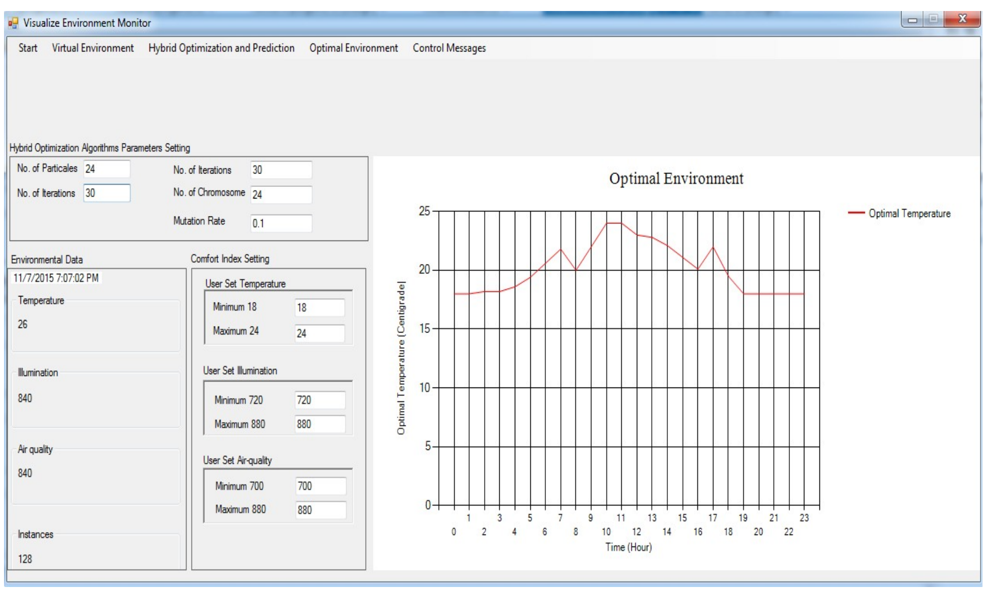

Figure 4.27. Optimal parameters for temperature (Based on PSO and GA parallel with multi-Preprocessing)

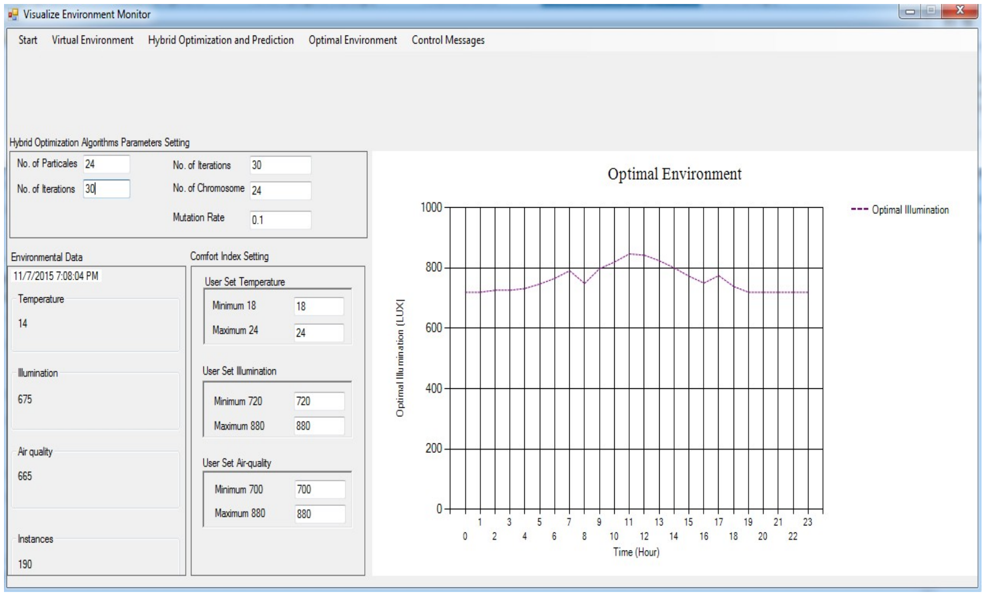

Figure 4.28. Optimal parameters for illumination (Based on PSO and GA parallel with multi-Preprocessing)

In case of optimal air-quality Figure 4.29, the air-quality parameters changes between 700^o to 880^o ppm as compare to virtual sensing environment air-quality Figure 4.4.

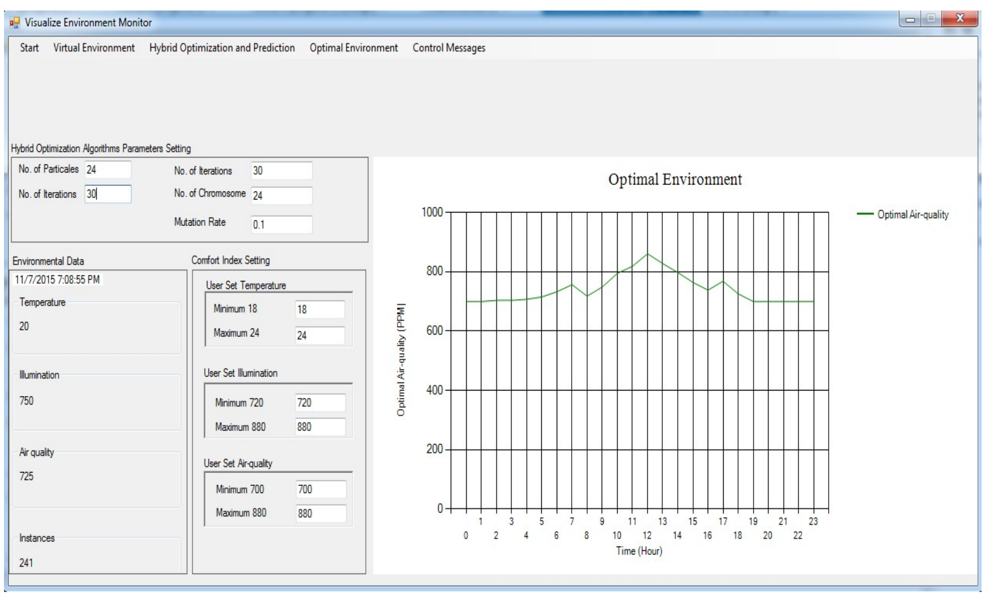

Figure 4.29. Optimal parameters for air-quality (Based on PSO and GA parallel with multi-Preprocessing)

The user set points for air-quality are optimized to [700, 880] using hybrid parallel optimization based on GA and PSO with multi-preprocessing. The users feel comfortable when the air-quality level is between [700, 880]. So we can say that using hybrid parallel optimization based on GA and PSO with multi-preprocessing, the user set parameters for air-quality are optimized to accomplish optimal air-quality.

4.2.1.2.3. Control messages

Figure 4.30, Figure 4.31, Figure 4.32 and Figure 4.33 shows the control messages information's using hybrid parallel optimization based on GA and PSO with multi-preprocessing approach. Figure 4.30 shows control messages to turn ON/OFF air-condition.

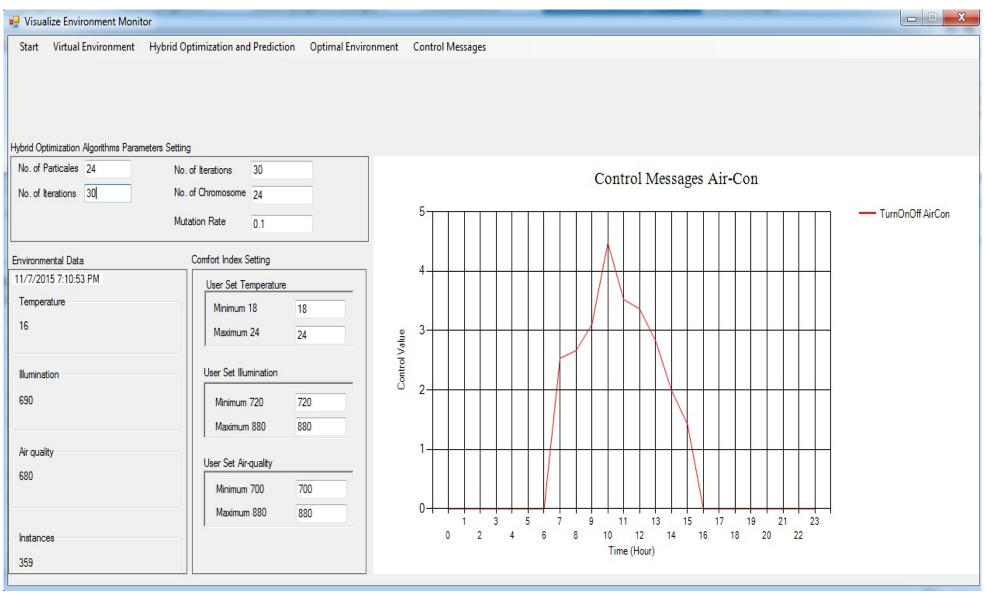

Figure 4.30. Control messages for Air-con (Based on PSO and GA parallel with multi-Preprocessing)

When the control message value is zero then its means that virtual sensing environment temperature and optimal temperature is same and air-condition should be turn OFF. When control message value results in value between 0 and 3 then AC will be turn ON slow. If control message value results in value between 3 and 6 then AC will be Turn ON Medium. If value is more than 6 then AC will be turn ON in high speed. Here we can see that message information's for air-con varies between 0 and 5. So air-con is turn ON for level 1 and level 2 only. From 0hrs to 6hrs and from 16hrs to 23hrs the air-con remains turn OFF.

Figure 4.31 shows control messages to Turn ON/OFF boiler. When the control message value is zero then its mean that virtual sensing environment temperature and optimal temperature is same and boiler should be turn OFF.

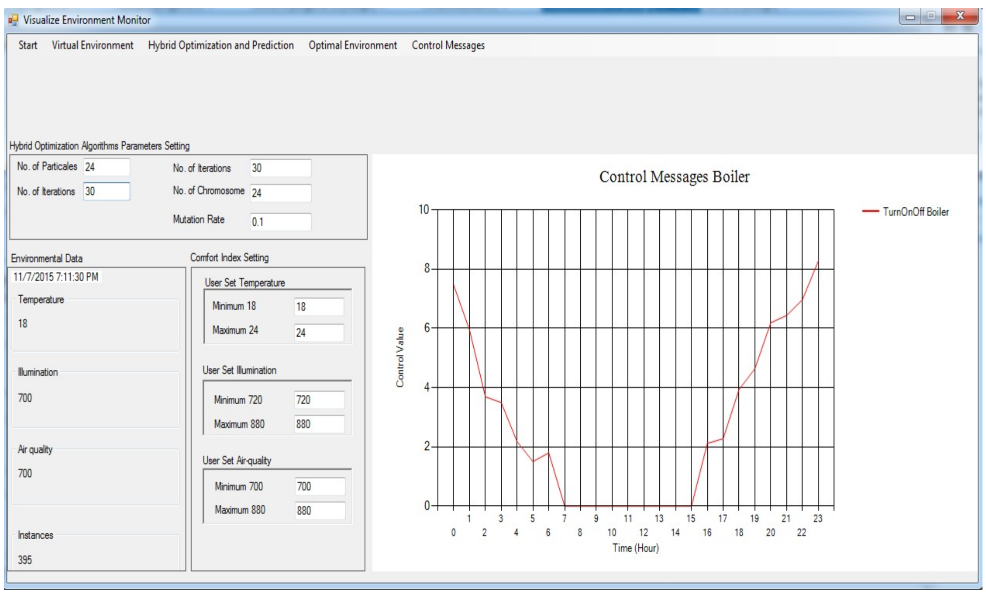

Figure 4.31. Control messages for Boiler (Based on PSO and GA parallel with multi-Preprocessing)

When control message value results in value between 0 and 3 then boilers will be turn ON slow. If control message value results in value between 3 and 6 then boiler will be turn on Medium. If value is more than 6 then boiler will be turn ON in high speed. Here we can see that boiler remains turn OFF during 7hrs to 15hrs, while turn ON at different levels between

0hrs to 7hrs and 15hrs to 23hrs. Figure 4.32 shows control messages to turn ON/OFF Light. When the control message value is zero then its means that virtual sensing environment illumination and optimal illumination is same and light should be turn OFF.

When control message value results in value between 0 and 3 then light will be turn ON slow. When control message value results in value between 3 and 6 then light will be Turn ON Medium. If the message information value is more than 6 then light will be turn ON in full. Here we can see that the light is turn ON for all of its levels. The power consumption for light varies during each hour of the day.

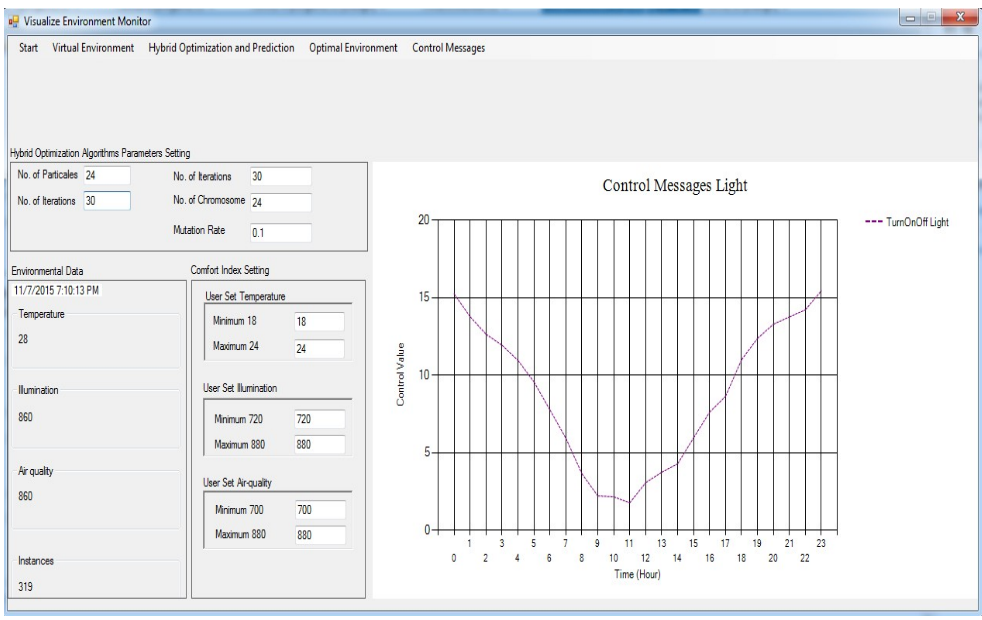

Figure 4.32. Control messages for Light (Based on PSO and GA parallel with multi-Preprocessing)

Figure 4.33 shows control messages to turn ON/OFF FAN. When the control message value is zero then its means that virtual sensing environment air-quality and optimal air-quality is same and FAN should be turn OFF. When control message value result in value between 0 and 3 then FAN will be turn ON slow. When control message value results in value between 3 and 6 then FAN will be turn ON Medium. When value is more than 6 then FAN will be turn ON in high speed. Here we can see that FAN is running during 24hours of the day. Each hour different power is consumed by the FAN.

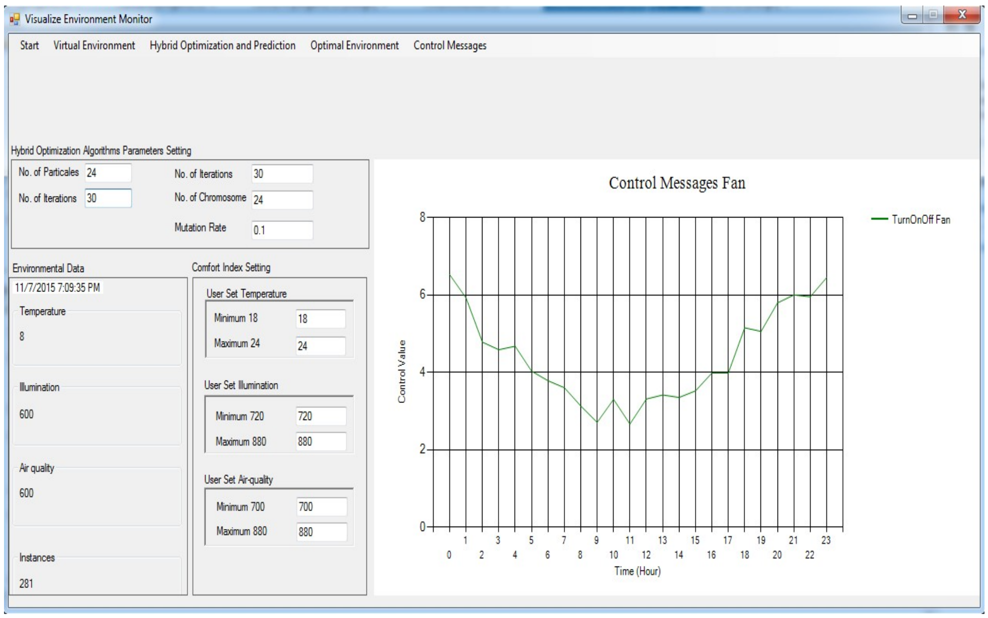

Figure 4.33. Control messages for Fan (Based on PSO and GA parallel with multi-Preprocessing)

4.2.1.2.4. Actuator emulators

In case of hybrid energy optimization based on prediction using GA and PSO with multi-preprocessing model the actuator emulators received signals shown in Figure 4.30, 4.31, 4.32 and 4.33. Hybrid energy optimization algorithm based on PSO and GA and multi-preprocessing model creates control signals presented in Figure 4.30, 4.31, 4.32 and 4.33 respectively. From Figure 4.30, we can see that message information's for air-con actuator varies between 0 and 5. So air-con is turn ON for level 1 and level 2 only. From 0hrs to 6hrs and from 16hrs to 23hrs the air-con remains turn OFF. From Figure 4.31, we can see that boiler actuator remains turn OFF during 7hrs to 15hrs, while turn ON at different levels between 0hrs to 7hrs and 15hrs to 23hrs. From Figure 4.32, we can see that the light emulator is turn ON for all of its levels. The power consumption for light varies during each hour of the day. From Figure 4.33, we can see that FAN actuator is running during 24hours of the day. Each hour different power is consumed by the FAN according to the control signals it received.

4.2.2. Optimization algorithm based on PSO and GA serial

4.2.2.1. Simulation environment

The simulation environment is kept same for each of the algorithm. The simulation environment is discussed in detailed in section 4.

4.2.2.2. Simulation analysis

4.2.2.2.1. Virtual environment

The simulation virtual environment is kept same for each of the algorithm. The virtual environment for each of the virtual sensor temperature, illumination and air-quality is discussed in detailed in section 4.1.1.2.1.

4.2.2.2.2. Optimization

Figures 4.34, 4.35 and 4.36 show the optimal environmental parameters for each of the temperature, illumination and air-quality using hybrid serial optimization based on GA and PSO with multi-preprocessing. In case of optimal temperature Figure 4.34, the optimal temperature changes between 18^o to 24^o centigrade as compare to virtual sensing environment temperature Figure 4.2. The user set points are optimized to [18, 24] using hybrid serial optimization based on GA and PSO with multi-preprocessing.

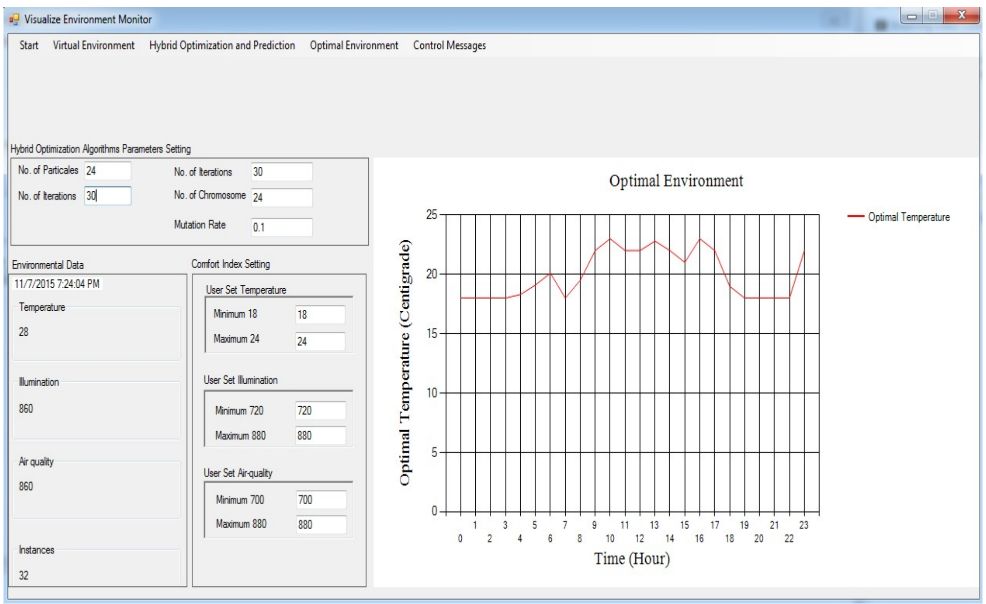

Figure 4.34. Optimal parameters for temperature (Based on PSO and GA serial with multi-Preprocessing)

The users feel relax and happy when the temperature level is varies between [18, 24]. So we can say that using hybrid parallel optimization based on GA and PSO with multi-preprocessing the user set parameters for temperature optimized to achieve optimal temperature. In case of optimal illumination Figure 4.35, the illumination parameters changes between 720° to 880° lux as compare to virtual sensing environment illumination Figure 4.3. The user set points are optimized to [720, 880] using hybrid serial optimization based on GA and PSO with multi-preprocessing. The users feel comfortable when the illumination level is between [720, 880].

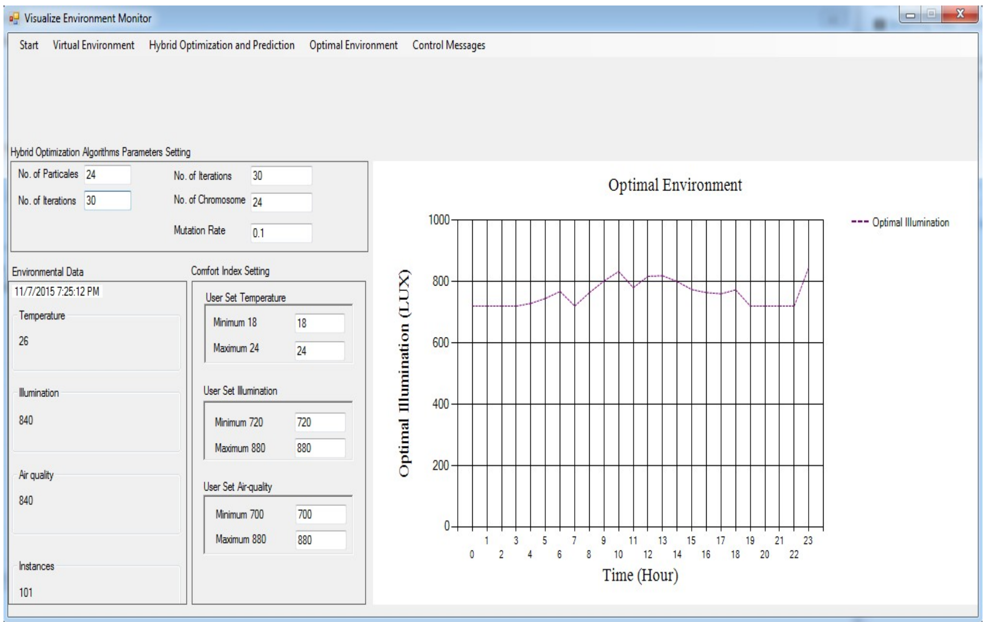

Figure 4.35. Optimal parameters for illumination (Based on PSO and GA serial with multi-Preprocessing)

So we can say that using hybrid parallel optimization based on GA and PSO with multi-preprocessing, the user set parameters for illumination are optimized to achieve optimal illumination. In case of optimal air-quality Figure 4.36, the air-quality parameters changes between 700° to 880° ppm as compare to virtual sensing environment air-quality Figure 4.4. The user set points for air-quality are optimized to [700, 880] using hybrid serial optimization based on GA and PSO with multi-preprocessing. The users feel comfortable and happy when the air-quality level is between [700, 880]. So we can conclude that using hybrid serial optimization based on GA and PSO with multi-preprocessing, the user set parameters for air-quality are optimized to achieve optimal air-quality.

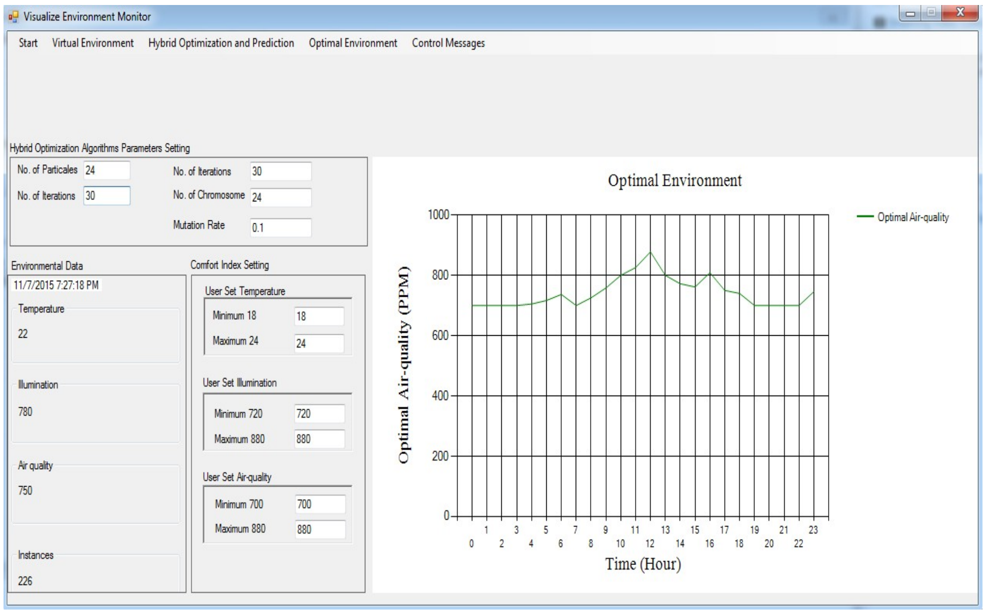

Figure 4.36. Optimal parameters for air-quality (Based on PSO and GA serial with multi-Preprocessing)

4.2.2.2.3. Control messages

Figure 4.37 shows control messages to turn ON/OFF air-condition. If the control message value is zero then its means that virtual sensing environment temperature and optimal temperature is same and air-condition should be turn OFF. If control message value results in value between 0 and 3 then AC will be turn ON slow. If control message value results in value between 3 and 6 then AC will be Turn ON Medium. If value is more than 6 then AC will be turn ON in high speed. Here we can see that air-con is turn ON at different levels during 6hrs to 16hrs. The air-con remains turn OFF between 0hrs to 6hrs and between 16hrs to 23 hrs.

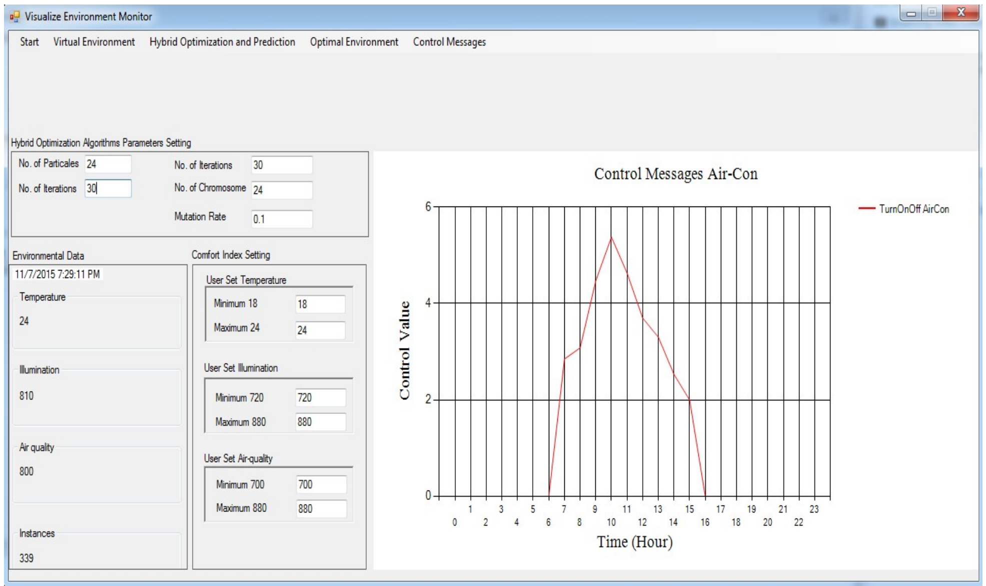

Figure 4.37. Control messages for Air-con (Based on PSO and GA serial with multi-Preprocessing)

Figure 4.38 shows control messages to Turn ON/OFF boiler. If the control message value is zero then its mean that virtual sensing environment temperature and optimal temperature is same and boiler should be turn OFF. When control message value results in value between 0 and 3 then boilers will be turn ON slow. If control message value results in value between 3 and 6 then boiler will be turn on Medium. If value is more than 6 then boiler will be turn ON in high speed. Here we can see that boiler is turn OFF between 7hrs to 15hrs and turn ONN between 0hrs to 7hrs and between 15hrs to 23 hrs.

Figure 4.39 shows control messages to turn ON/OFF Light. When the control message value is zero then it means that virtual sensing environment illumination and optimal illumination is same and light should be turn OFF. If control message value results in value between 0 and 3 then light will be turn ON slow. If control message value results in value between 3 and 6 then light will be Turn ON Medium. If value is more than 6 then light will be turn ON in fully. Here we can see that light is turning ON for all of its levels. The power consumption for light decreases as the day time arrives and increases as the night time arrives.

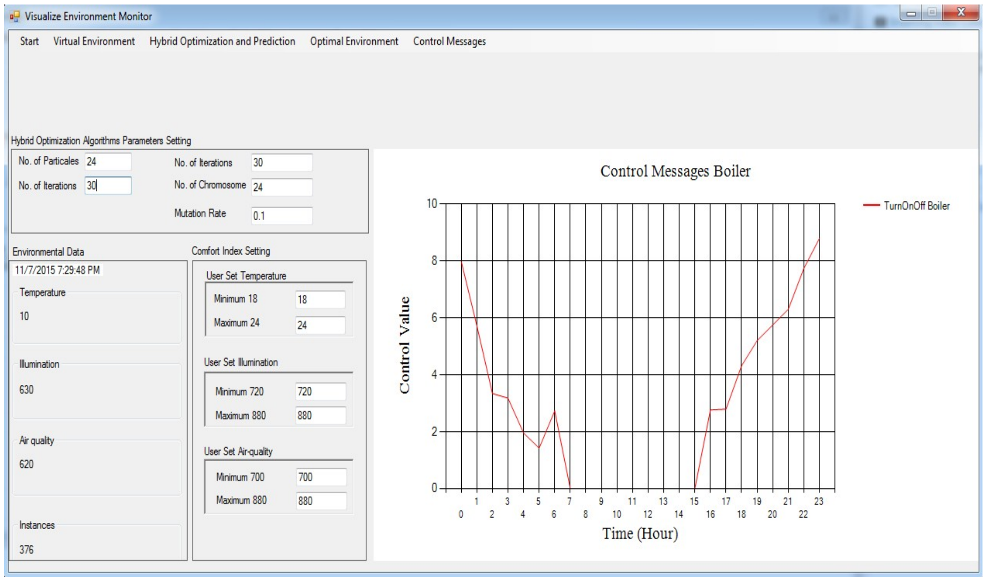

Figure 4.38. Control messages for Boiler (Based on PSO and GA serial with multi-Preprocessing)

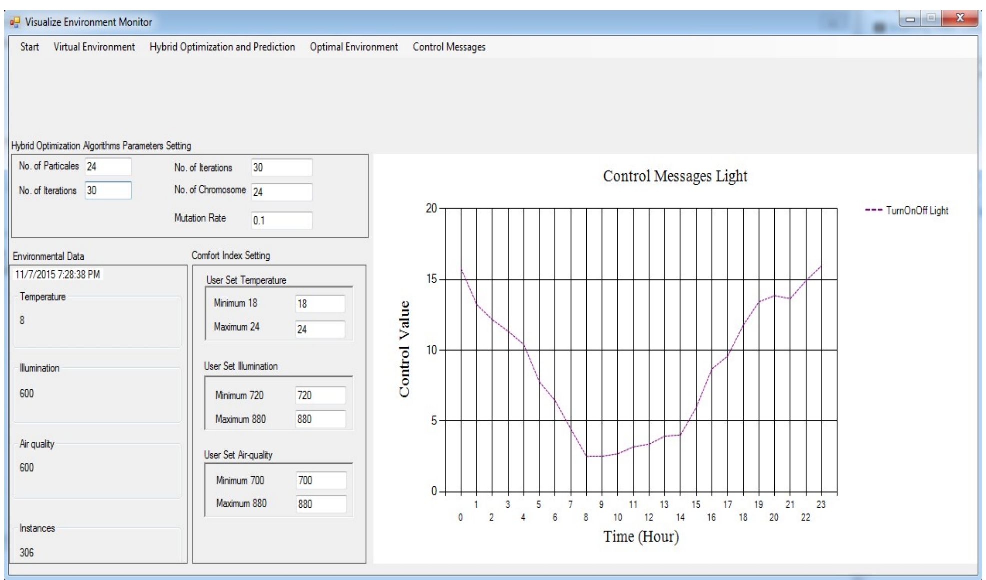

Figure 4.39. Control messages for Light (Based on PSO and GA serial with multi-Preprocessing)

Figure 4.40 shows control messages to turn ON/OFF FAN. If the control message value is zero then its means that virtual sensing environment air-quality and optimal air-quality is same and FAN should be turn OFF. If control message value result in value between 0 and 3 then FAN will be turn ON slow. If control message value results in value between 3 and 6 then FAN will be turn ON Medium. If value is more than 6 and then FAN will be turn ON in high speed. Here we can also see that FAN remains turn ON during 24 hours of the day with different levels.

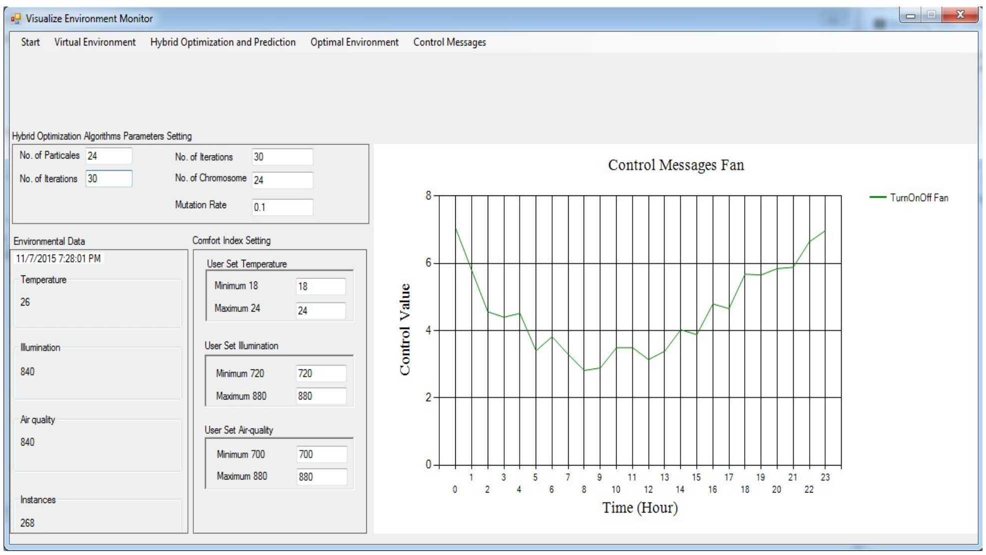

Figure 4.40. Control messages for Fan (Based on PSO and GA serial with multi-Preprocessing)

4.2.2.2.4. Actuator emulators

In case of hybrid energy optimization based on prediction using GA and PSO serial with multi-preprocessing model the actuator emulators received signals presented in Figure 4.37, 4.38, 4.39 and 4.40. Hybrid serial energy optimization algorithm based on PSO and GA and multi-preprocessing model creates control signals described in Figure 4.37, 4.38, 4.39 and

4.40 respectively. From Figure 4.37, we can see that air-con actuator is turn ON at different levels during 6hrs to 16hrs. The air-con remains turn OFF between 0hrs to 6hrs and between 16hrs to 23 hrs. From Figure 4.38, we can see that boiler emulator is turn OFF between 7hrs to 15hrs and turn ONN between 0hrs to 7hrs and between 15hrs to 23 hrs. From Figure 4.39, we can see that light emulator is turning ON for all of its levels. The power consumption for light decreases as the day time arrives and increases as the night time arrives. From Figure 4.40, we can also see that FAN remains turn ON during 24 hours of the day with different levels.

4.2.3. Optimization algorithm based on PSO and MIGA serial

4.2.3.1. Simulation environment

The simulation environment is kept same for each of the algorithm. The simulation environment is discussed in detailed in section 4.

4.2.3.2. Simulation analysis

4.2.3.2.1. Virtual environment

The simulation virtual environment is kept same for each of the algorithm. The virtual environment for each of the virtual sensor temperature, illumination and air-quality is discussed in detailed in section 4.1.1.2.1.

4.2.3.2.2. Optimization

Figures 4.41, 4.42 and 4.43 show the optimal environmental parameters for each of the temperature, illumination and air-quality using hybrid serial optimization based on MIGA and PSO with multi-preprocessing. In case of optimal temperature Figure 4.41, the optimal temperature changes between 18^{o} to 24^{o} centigrade as compare to virtual sensing environment temperature Figure 4.2. The user set points are optimized to [18, 24] using hybrid serial optimization based on MIGA and PSO with multi-preprocessing. The users feel relax and happy when the temperature level is varies between [18, 24]. So we can say that using hybrid parallel optimization based on MIGA and PSO with multi-preprocessing the user set parameters for temperature optimized to achieve optimal temperature.

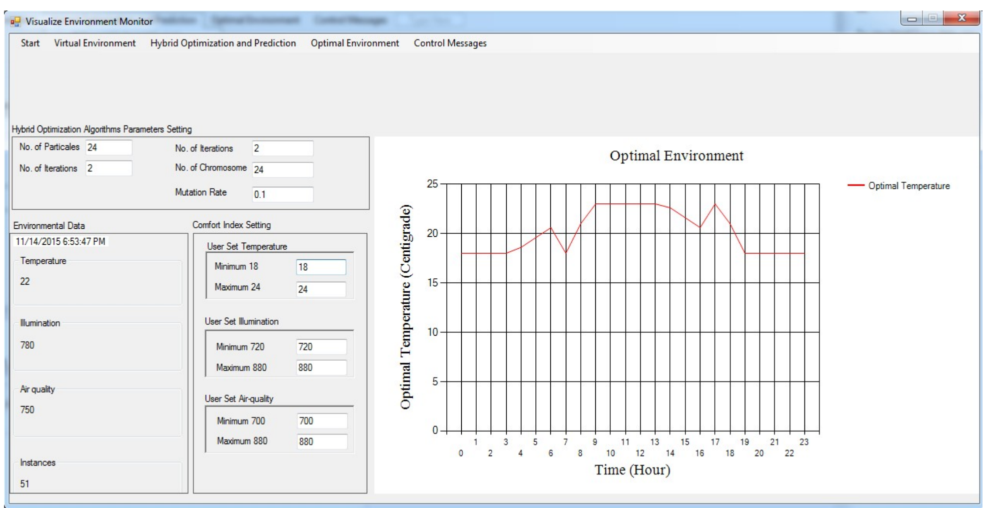

Figure 4.41. Optimal parameters for temperature (Based on PSO and MIGA serial with multi-Preprocessing)

In case of optimal illumination Figure 4.42, the illumination parameters changes between 720^o to 880^o lux as compare to virtual sensing environment illumination Figure 4.3. The user set points are optimized to [720, 880] using hybrid serial optimization based on MIGA and PSO with multi-preprocessing. The users feel comfortable when the illumination level is between [720, 880]. So we can say that using hybrid parallel optimization based on MIGA and PSO with multi-preprocessing, the user set parameters for illumination are optimized to achieve optimal illumination.

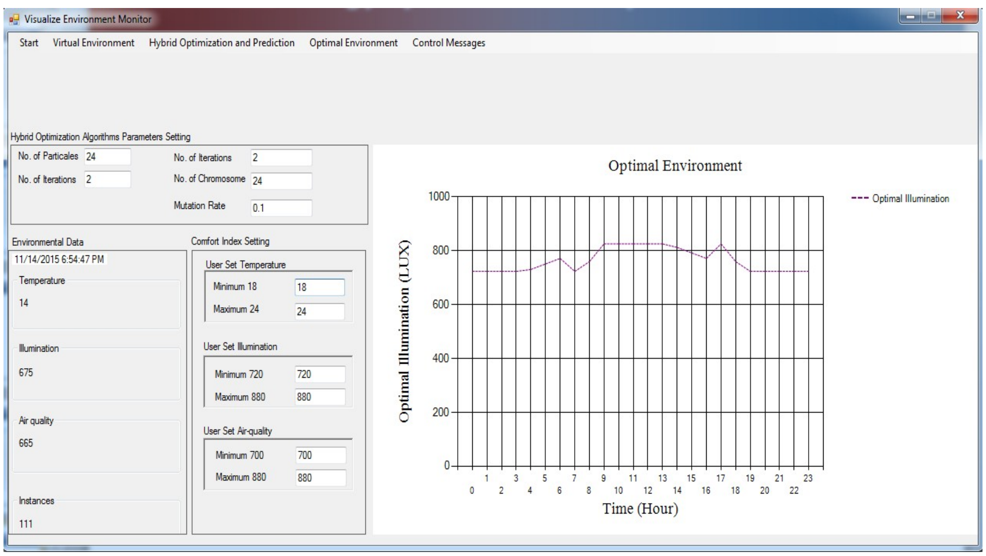

Figure 4.42. Optimal parameters for illumination (Based on PSO and MIGA serial with multi-Preprocessing)

In case of optimal air-quality Figure 4.43, the air-quality parameters changes between 700^o to 880^o ppm as compare to virtual sensing environment air-quality Figure 4.4. The user set points for air-quality are optimized to [700, 880] using hybrid serial optimization based on MIGA and PSO with multi-preprocessing. The users feel comfortable and happy when the air-quality level is between [700, 880].

So we can conclude that using hybrid serial optimization based on MIGA and PSO with multi-preprocessing, the user set parameters for air-quality are optimized to achieve optimal air-quality.

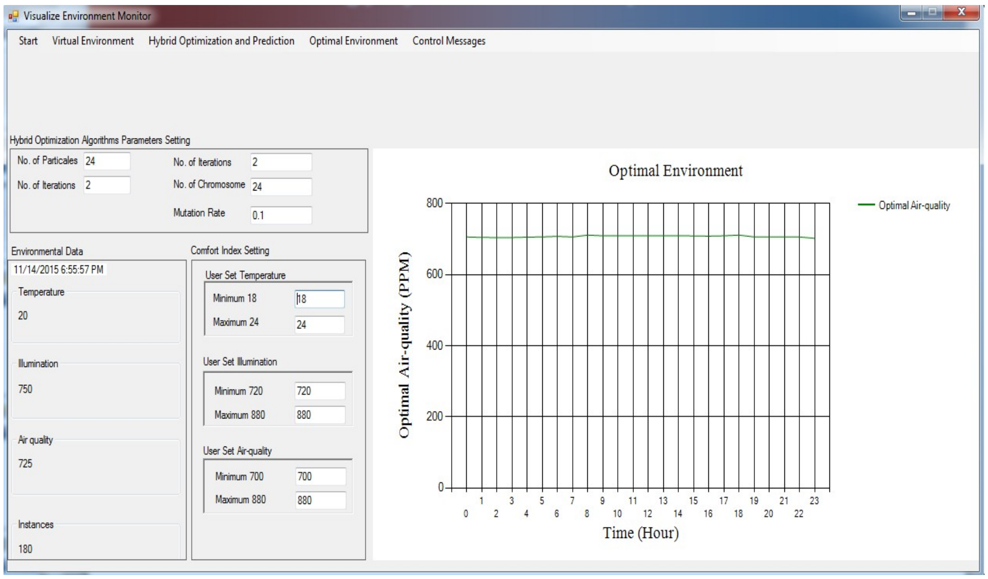

Figure 4.43. Optimal parameters for air-quality (Based on PSO and MIGA serial with multi-Preprocessing)

4.2.3.2.3. Control messages

Figure 4.44 shows control messages to turn ON/OFF air-condition. If the control message value is zero then its means that virtual sensing environment temperature and optimal temperature is same and air-condition should be turn OFF. If control message value results in value between 0 and 3 then AC will be turn ON slow. If control message value results in value between 3 and 6 then AC will be Turn ON Medium. If value is more than 6 then AC will be turn ON in high speed. Here we can see that air-con is turn ON at different levels during 6hrs to 16hrs. The air-con remains turn OFF between 0hrs to 6hrs and between 16hrs to 23 hrs.

Figure 4.45 shows control messages to Turn ON/OFF boiler. If the control message value is zero then its mean that virtual sensing environment temperature and optimal temperature is same and boiler should be turn OFF. When control message value results in value between 0 and 3 then boilers will be turn ON slow.

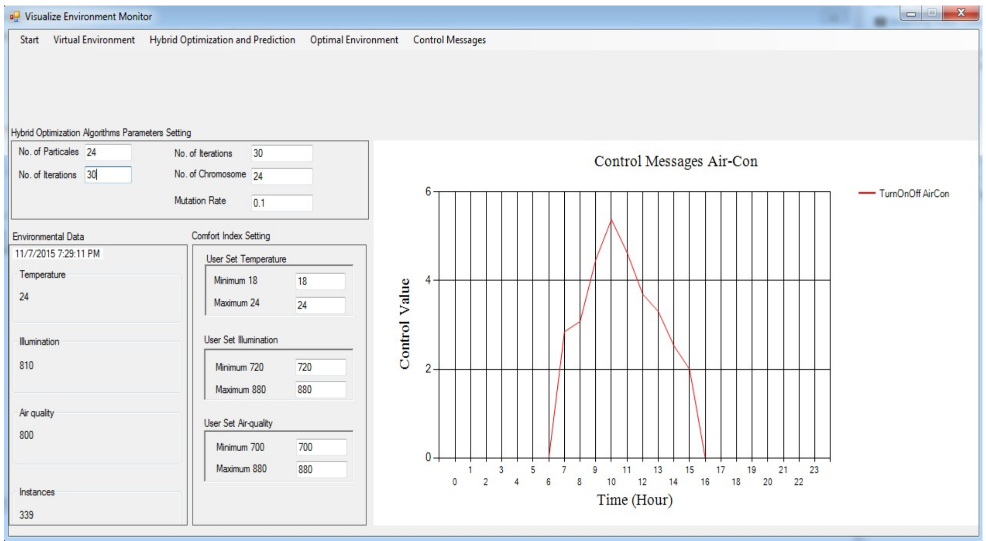

Figure 4.44. Control messages for Air-con (Based on PSO and MIGA serial with multi-Preprocessing)

If control message value results in value between 3 and 6 then boiler will be turn on Medium. If value is more than 6 then boiler will be turn ON in high speed. Here we can see that boiler is turn OFF between 7hrs to 15hrs and turn ONN between 0hrs to 7hrs and between 15hrs to 23 hrs. Figure 4.46 shows control messages to turn ON/OFF Light. When the control message value is zero then it means that virtual sensing environment illumination and optimal illumination is same and light should be turn OFF. If control message value results in value between 0 and 3 then light will be turn ON slow. If control message value results in value between 3 and 6 then light will be Turn ON Medium.

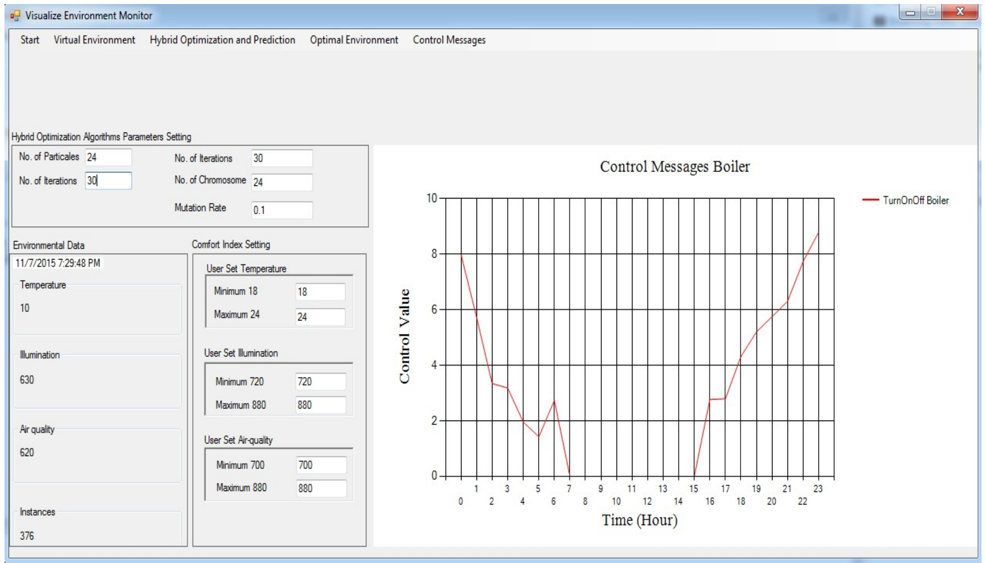

Figure 4.45. Control messages for Boiler (Based on PSO and MIGA serial with multi-Preprocessing)

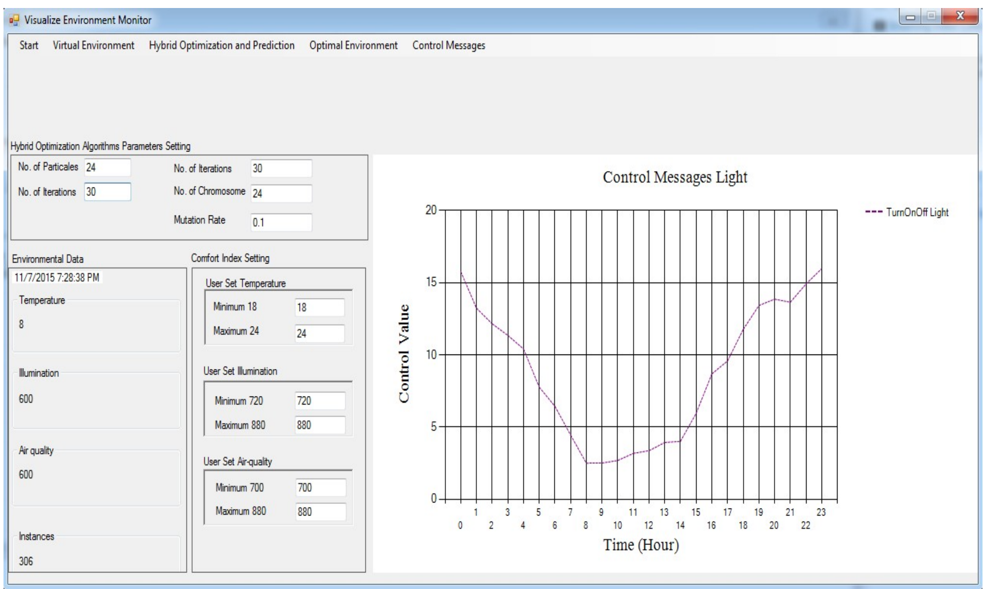

Figure 4.46. Control messages for Light (Based on PSO and MIGA serial with multi-Preprocessing)

If value is more than 6 then light will be turn ON in fully. Here we can see that light is turning ON for all of its levels. The power consumption for light decreases as the day time arrives and increases as the night time arrives. Figure 4.47 shows control messages to turn

ON/OFF FAN. If the control message value is zero then its means that virtual sensing environment air-quality and optimal air-quality is same and FAN should be turn OFF. If control message value result in value between 0 and 3 then FAN will be turn ON slow.

If control message value results in value between 3 and 6 then FAN will be turn ON Medium. If value is more than 6 and then FAN will be turn ON in high speed. Here we can also see that FAN remains turn ON during 24 hours of the day with different levels.

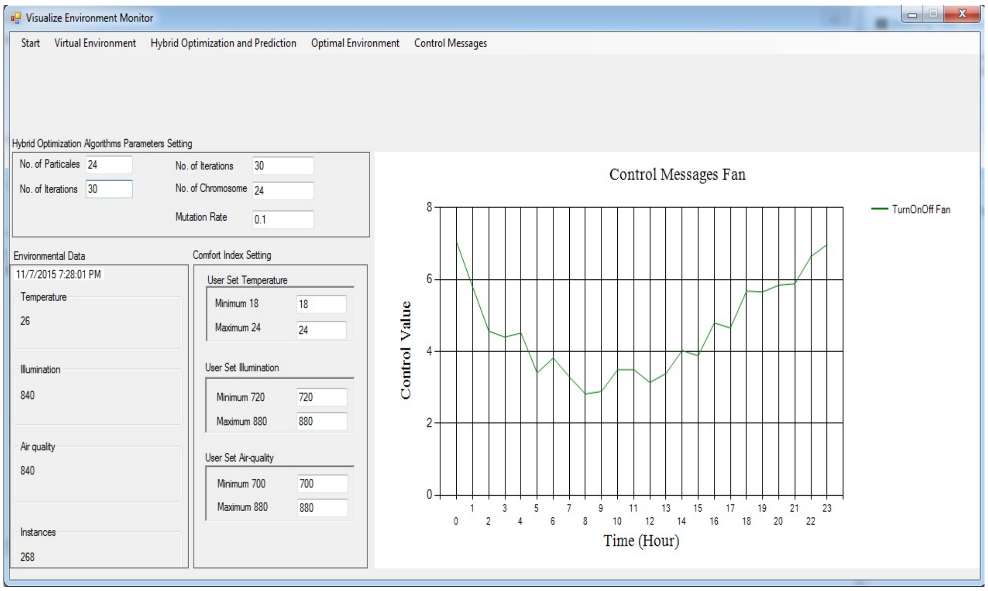

Figure 4.47. Control messages for Fan (Based on PSO and MIGA serial with multi-Preprocessing)

4.2.3.2.4. Actuator emulators

In case of hybrid energy optimization based on prediction using MIGA and PSO with multi-preprocessing model the actuator emulators received signals shown in Figure 4.44, 4.45, 4.46 and 4.47. Hybrid serial energy optimization algorithm based on PSO and MIGA and multi-preprocessing model creates control signals shown in Figure 4.44, 4.45, 4.46 and

4.47 respectively. From Figure 4.44, we can see that air-con emulator is turn ON at different levels during 6hrs to 16hrs. The air-con remains turn OFF between 0hrs to 6hrs and between 16hrs to 23 hrs. From Figure 4.45, we can see that boiler emulator is turn OFF between 7hrs to 15hrs and turn ONN between 0hrs to 7hrs and between 15hrs to 23 hrs. From Figure 4.46, we can see that light emulator is turning ON for all of its levels. The power consumption for light decreases as the day time arrives and increases as the night time arrives. From Figure 4.47, we can also see that FAN remains turn ON during 24 hours of the day with different levels.

5. Performance comparisons and analysis

5.1. Basic energy optimization model based on prediction

5.1.1. Optimized power control methodology using GA and PSO

5.1.1.1. Comparisons of power consumption prediction results

Figure 5.1, 5.2, 5.3 and 5.4 shows the comparisons of power consumption. X-axis shows the time in house while Y-axis shows the predicted power consumption in kilowatts and comfort index between 0.0 and 1.0 is the minimum and maximum comfort index respectively. From the results of Figure 5.1 it can be evident, that in case of power consumption for temperature, system with GA based prediction method consumes less power as compared to the system with PSO based prediction. This is due to the fact that GA based optimized parameters are more optimal than PSO based optimized parameters. So when environmental disturbance occur GA based predicted method consume less power as compare to PSO based predicted method. Less power consumption is ensured by controllers using optimized parameters of GA. Similarly for illumination as shown in Figure 5.2, GA based predicted method confirmed to consume less power as compared to the PSO based prediction method.

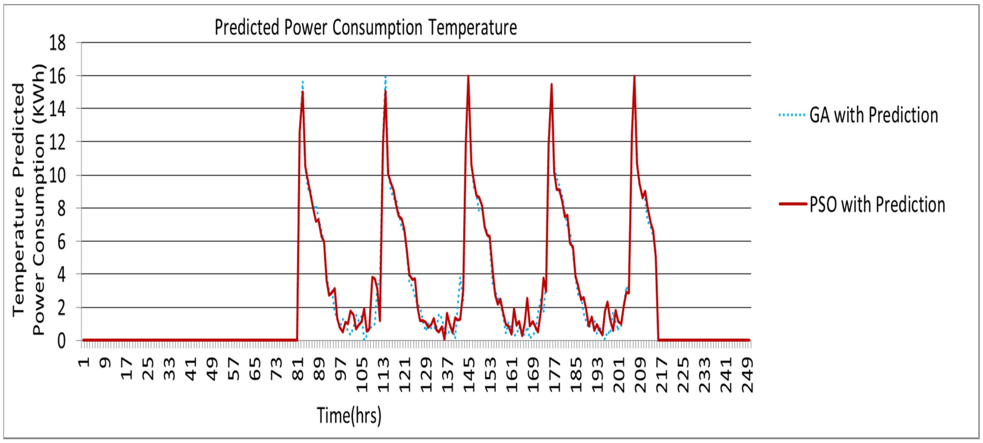

Figure 5.1. Comparison of predicted power consumption for temperature with GA based system and PSO based system

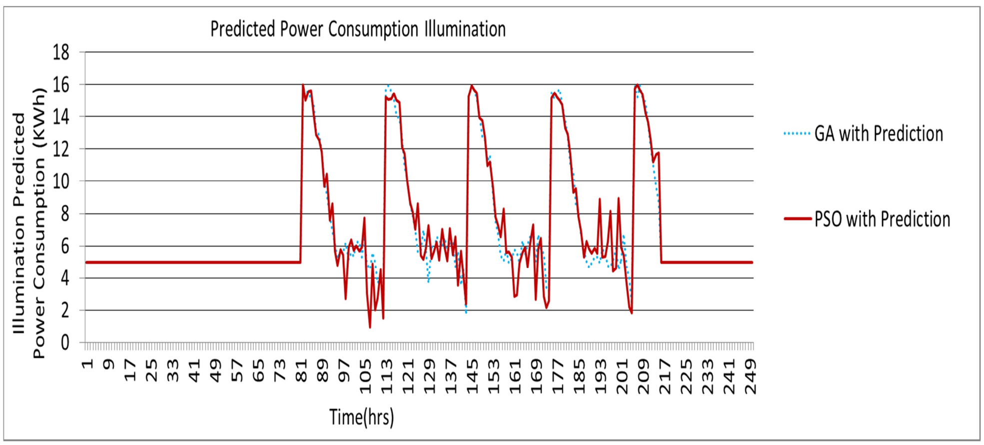

Figure 5.2. Comparison of predicted power consumption for illumination with GA based system and PSO based system

Figure 5.3 shows the results for the air-quality control. Here we can see that GA based predicted system consumed almost same power as compared to its counterpart PSO based prediction system. Figure 5.4 shows the total predicted power consumption in case of GA based optimized system and PSO based optimized system. The total power consumption of GA based system is less than PSO predicted system.

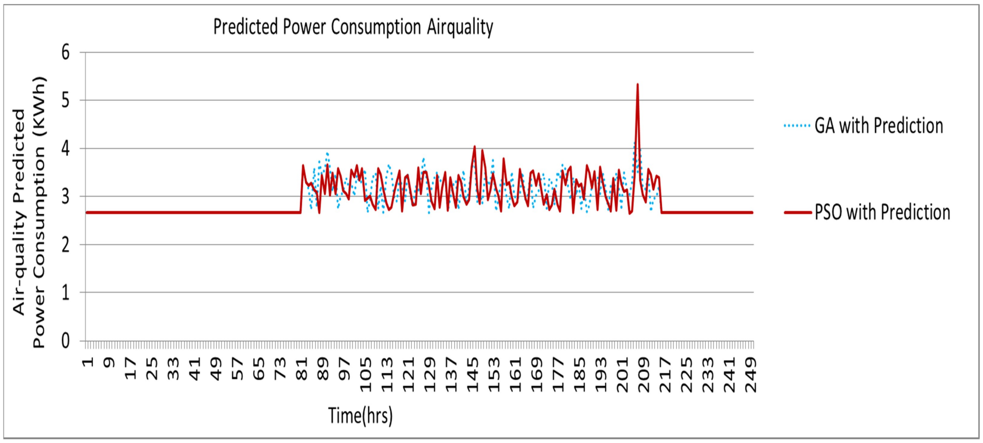

Figure 5.3. Comparison of predicted power consumption for air-quality with GA based system and PSO based system

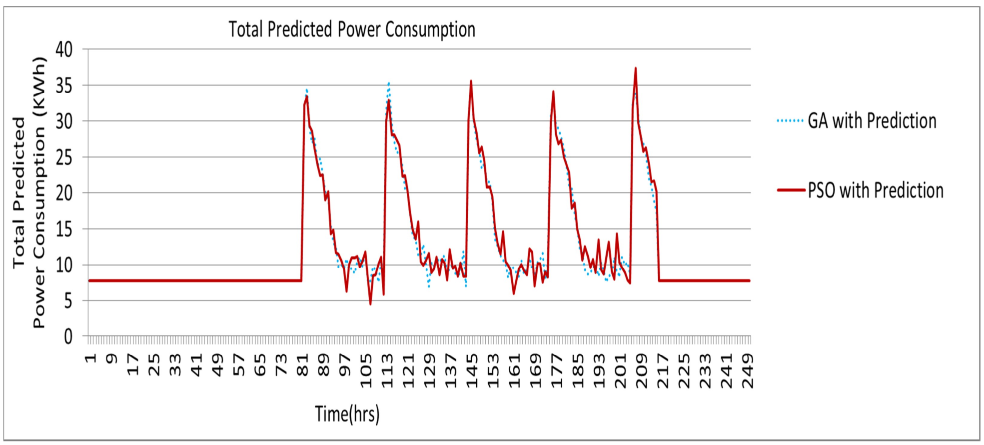

Figure 5.4. Comparison of total predicted power consumption with GA based system and PSO based system

5.1.1.2. Comparisons of occupants comfort index results

Figure 5.5 shows the results of user comfort index in case of GA based prediction system and PSO based prediction system.

Here we can see occupants comfort index improving and degraded couple of times during different hours. This is due to the multiple environmental disturbances. We have created this multiple environmental disturbances to check the efficiency of the energy optimization algorithms. First time the environmental disturbance occurs at time 82hrs, second disturbance arises at time 115hrs, and third, fourth and fifth environmental disturbance occurs at time 146hrs, 177hrs and 208hrs respectively. In rest of all the comfort index results, the environmental disturbances occur in the same way.

Comfort index is varied between '0' and '1'. '0' means lowest or minimum occupants comfort index and '1' means highest or maximum occupants comfort index. The degradation in occupants comfort index experienced when there is an environmental disturbance, and improvement in the comfort index achieved when optimization is done. So when environmental disturbance occurs then optimization gets started to improve the occupants comfort index. Initially comfort index is '1' from time '1hr' to time '81hrs', then at time 82hrs first environmental disturbance occurs. At this time comfort level of GA based prediction system and PSO based predicted system both degraded and goes down from '1' to 0.970. AT this time optimization gets started to improve the occupants comfort index. When the system gets optimized then occupants comfort index starts improving. As we can see both the systems recover soon. When second time power disturbance arises, comfort index of PSO based predicted system degraded before the GA based predicted system. So during second time disturbance GA based predicted system perform well as compared to the PSO based predicted system. During the entire disturbances except for the first one where both the predicted systems degraded at the same time, PSO based predicted system degraded early than GA based predicted system. So whenever there is an environmental disturbance, GA based prediction system degraded slowly as compared to its counterpart PSO based predicted system. With GA based estimated power consumption, user comfort index is improved as compare to the PSO based prediction system. So if there are multiple environmental disturbances, GA based predicted system perform well to handle them as compared to PSO based predicted system. Although in GA based prediction system less power is consume as compare to that of PSO based prediction system, but still it achieved improved occupants comfort level.

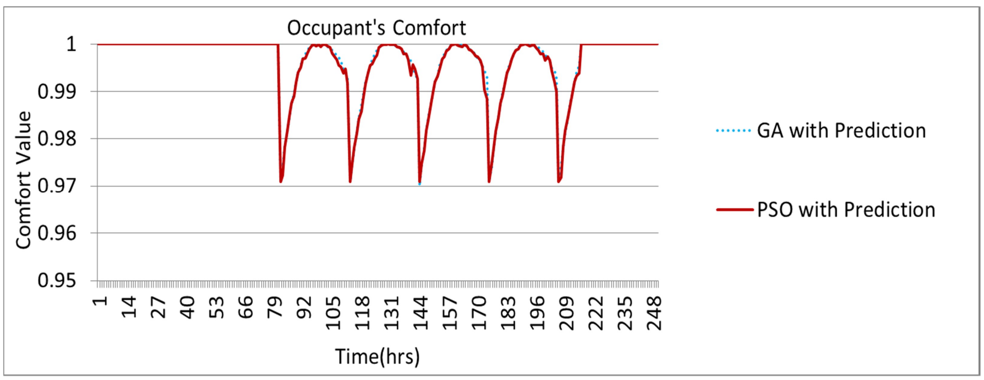

Figure 5.5. Comparison of predicted GA and PSO based comfort index

5.2. Hybrid energy optimization model based on prediction

5.2.1. Single preprocessing hybrid optimization model based on prediction

5.2.1.1. Optimization algorithm based on PSO and GA parallel

5.2.1.1.1. Comparisons of power consumption prediction results

Figure 5.6, 5.7, 5.8 and 5.9 shows the comparisons of power consumption. X-axis shows the time in hours while Y-axis shows the predicted power consumption in kilowatts, and comfort index between 0.0 and 1.0 is the minimum and maximum comfort index respectively. From the results of Figure 5.6 it can be observed that in case of power consumption for temperature, proposed parallel hybrid optimization and prediction based on Kalman filter and preprocessing model consumed less power as compared to the GA based system with no hybrid optimization and preprocessing. When environmental intermission occur, parallel hybrid optimization, prediction and preprocessing model consumed less power as compared to GA based predicted model where no hybrid optimization and preprocessing involved. Less power consumption is ensured by controllers using optimized parameters. For illumination as shown in Figure 5.7, parallel hybrid optimization and prediction with preprocessing model consumed minimum power as compared to GA based predicted model. Figure 5.8 shows the results for the air-quality control.

Here we can see that parallel hybrid optimization and prediction model consumed almost less power as compared to its equivalent GA based predicted system. Figure 5.7 shows the total predicted power consumption in case of proposed parallel hybrid optimization model and GA based predicted model with no hybrid prediction and preprocessing involved.

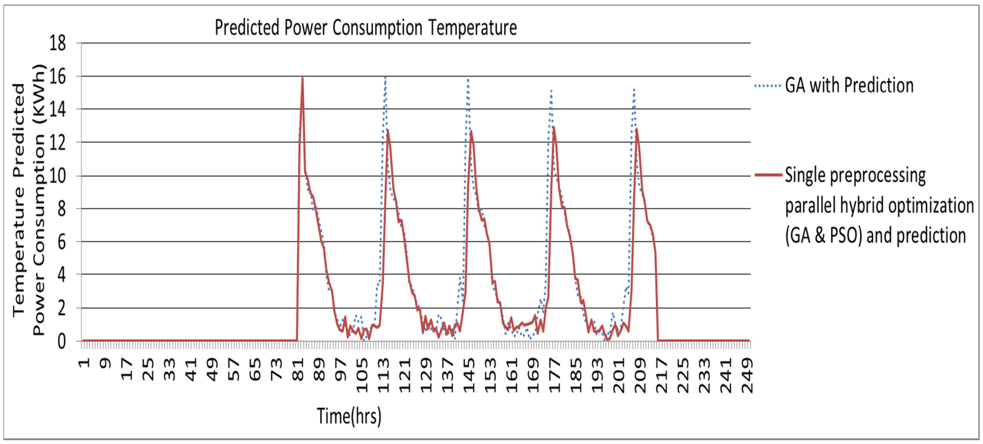

Figure 5.6. Comparison of predicted power consumption for temperature with GA based predicted system and parallel hybrid optimization and prediction

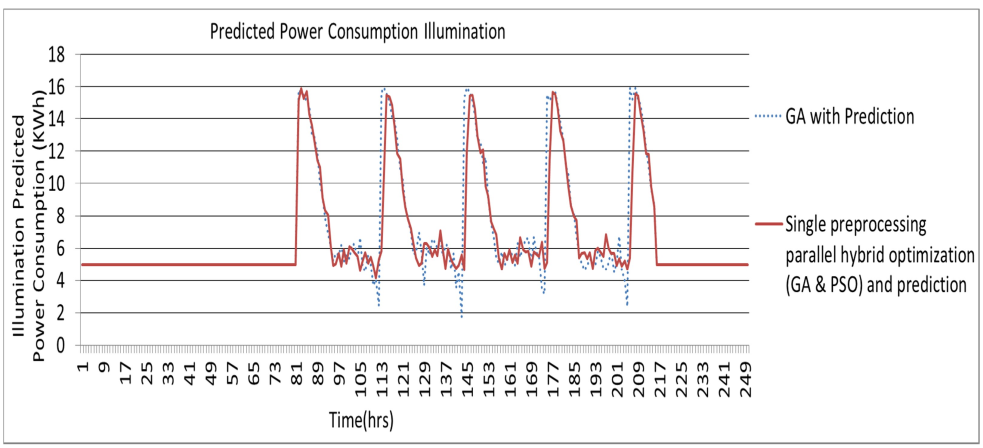

Figure 5.7. Comparison of predicted power consumption for illumination with GA based predicted system and parallel hybrid optimization and prediction

The total predicted power consumption of parallel hybrid optimization and prediction model with preprocessing consumed less power than its counterpart GA based prediction system with no hybrid prediction and preprocessing. The power disturbance first time arises at 82hrs. At this time comfort level of hybrid optimization based proposed system with prediction and preprocessing goes down to 0.970 almost same as to GA based predicted system with no hybrid prediction and preprocessing.

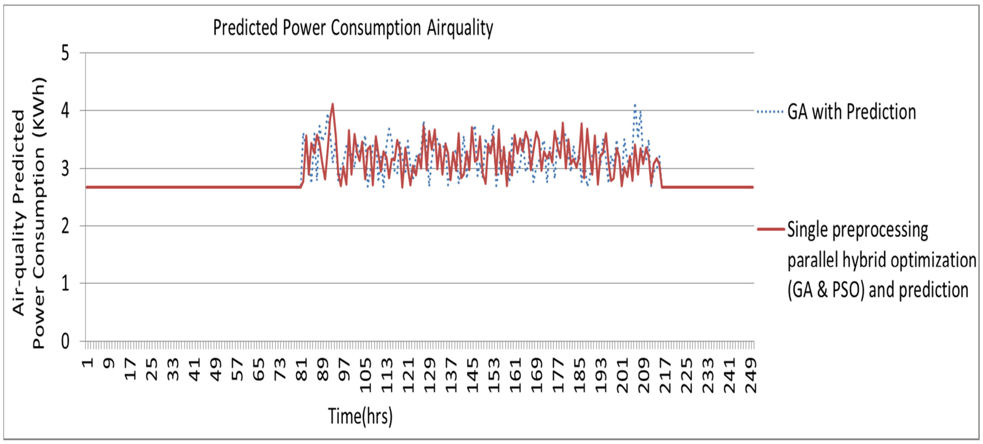

Figure 5.8. Comparison of predicted power consumption for air-quality with GA based predicted system and parallel hybrid optimization and prediction

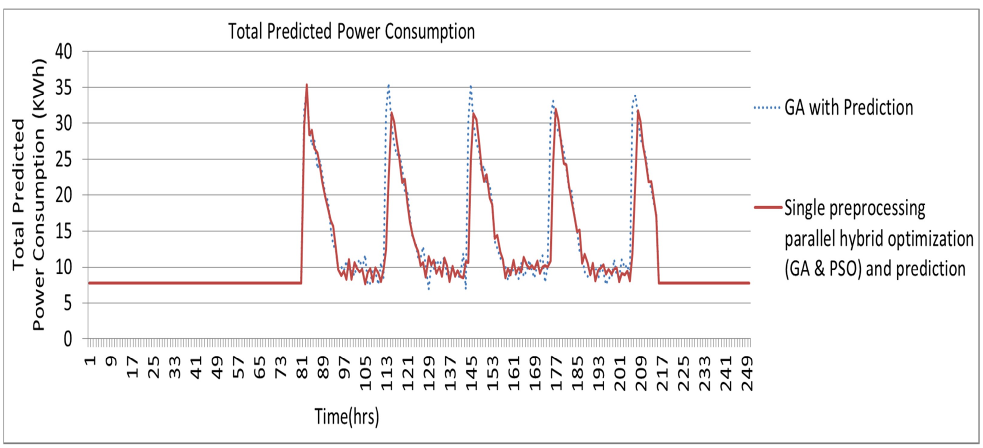

Figure 5.9. Comparison of total predicted power consumption with GA based predicted system and parallel hybrid optimization and prediction

When second time power disturbance occurs, the comfort index of GA based predicted system immediately goes down as compared to proposed hybrid optimization based prediction and preprocessing model. When second time power disturbance arises proposed parallel hybrid optimization model degraded to almost 0.998 as compared to 0.967 of GA based prediction model with no preprocessing. Similarly in all cases of degradation the proposed hybrid optimization based predicted with preprocessing system provides improved comfort index as compared to GA based predicted system where no preprocessing applied. So whenever there is an environmental disturbance, hybrid optimization based prediction and preprocessing system provides better comfort index as compared to its counterpart GA based predicted system.

5.2.1.1.2. Comparisons of occupants comfort index results

Figure 5.10 shows the results of user comfort index in case of proposed hybrid optimization based prediction with preprocessing model and GA based prediction system.

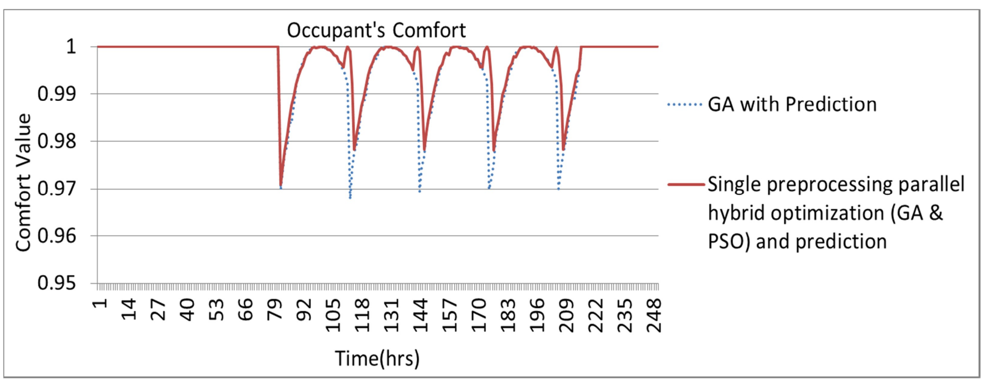

Figure 5.10. Comparison of comfort value/index with GA based predicted system and parallel hybrid optimization and prediction

From the comfort index it is clear that parallel hybrid optimization based prediction and preprocessing model provides better and improved comfort index as compared to GA based prediction model [3]. Although in parallel hybrid optimization based prediction and preprocessing model less power is consumed as compare to that of GA based prediction system, but still proposed model achieved improved and better comfort index as compared to GA and based predicted system.

5.2.1.2. Optimization algorithm based on PSO and GA serial

5.2.1.2.1. Comparisons of power consumption prediction results

Figure 5.11, 5.12, 5.13 and 5.14 shows the comparisons of power consumption. X-axis shows the time in hours while Y-axis shows the predicted power consumption in kilowatts, and comfort index between 0.0 and 1.0 is the minimum and maximum comfort index respectively. From the results of Figure 5.11 it can be observed that in case of power consumption for temperature, proposed serial hybrid optimization and prediction based on Kalman filter and preprocessing model consumed less power as compared to the GA based system with no hybrid optimization and preprocessing. When environmental intermission occur, serial hybrid optimization, prediction and preprocessing model consumed less power as compared to GA based predicted model where no hybrid optimization and preprocessing involved. Less power consumption is guaranteed by controllers using optimized parameters. For illumination as shown in Figure 5.12, serial hybrid optimization and prediction with preprocessing model consumed minimum power as compared to GA based predicted model.

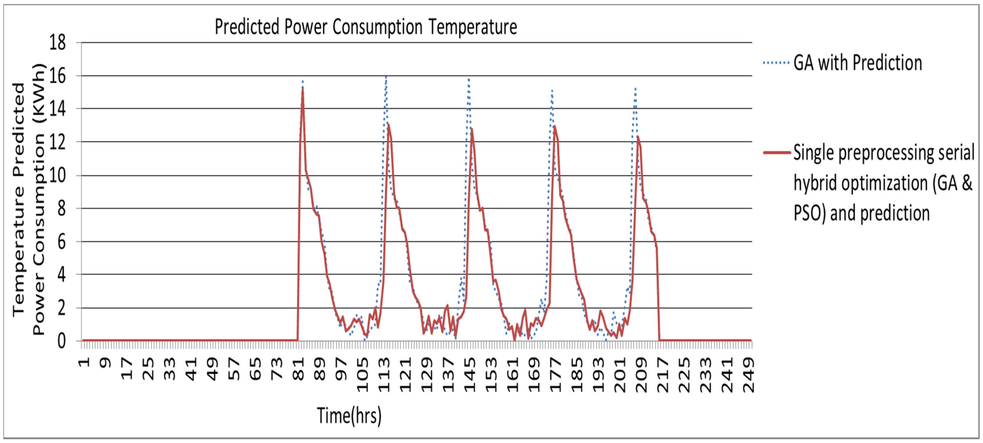

Figure 5.11. Comparison of predicted power consumption for temperature with GA based predicted system and serial hybrid optimization and prediction

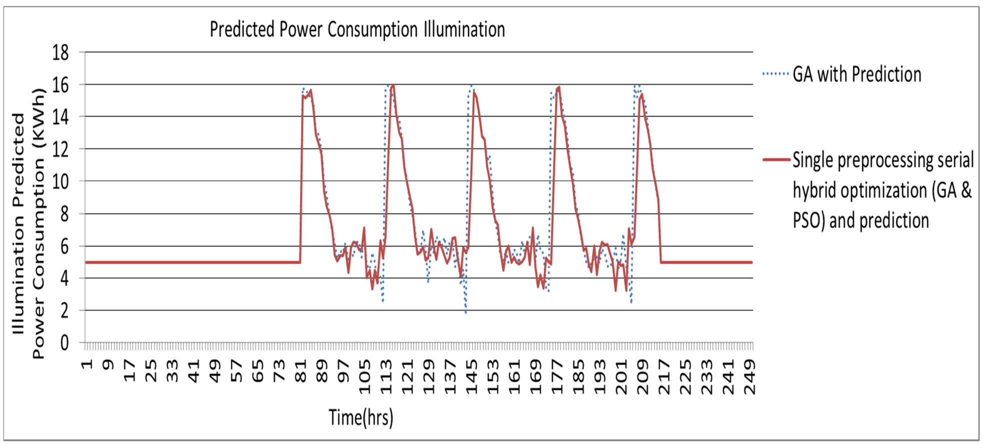

Figure 5.12. Comparison of predicted power consumption for illumination with GA based predicted system and serial hybrid optimization and prediction

Figure 5.13 shows the results for the air-quality control. Here we can see that serial hybrid optimization and prediction model consumed same power as compared to its equivalent GA based predicted system. Figure 5.14 shows the total predicted power consumption in case of proposed serial hybrid optimization model and GA based predicted model with no hybrid prediction and preprocessing/ involved. The total predicted power consumption of serial hybrid optimization and prediction model with preprocessing is less than its counterpart GA based prediction system with no hybrid optimization and preprocessing.

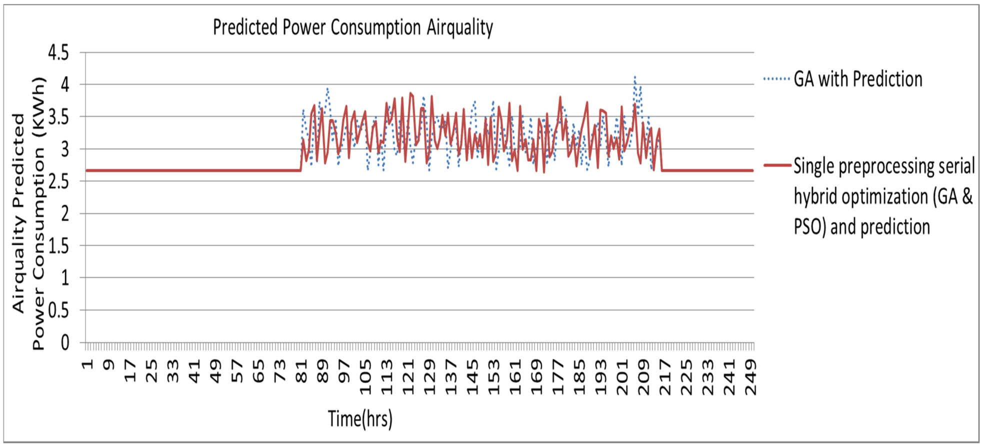

Figure 5.13. Comparison of predicted power consumption for air-quality with GA based predicted system and serial hybrid optimization and prediction

The power disturbance first time occurs at 82hrs. At this time comfort level of hybrid optimization based proposed system with prediction and preprocessing goes down to 0.970 same as to GA based predicted system with no hybrid prediction and preprocessing. But when second time power disturbance occurs, the GA based predicted system immediately goes down as compared to proposed hybrid optimization based prediction and preprocessing model. When second time power disturbance arises proposed hybrid serial optimization model degraded to 0.978 as compared to 0.970 of GA based prediction model with no preprocessing. Similarly in all cases of degradation of comfort index, the proposed hybrid serial optimization based prediction with preprocessing system provides improved comfort index as compared to GA based predicted system where no preprocessing applied. So whenever there is an environmental disturbance, hybrid serial optimization based prediction and preprocessing system provides better comfort index as compared to its counterpart GA based predicted system.

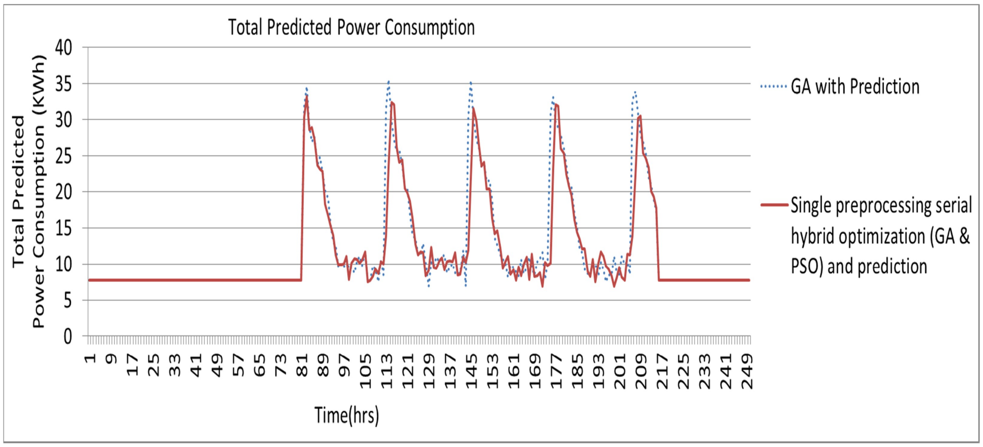

Figure 5.14. Comparison of total predicted power consumption with GA based predicted system and serial hybrid optimization and prediction

5.2.1.2.2. Comparisons of occupants comfort index results

Figure 5.15 shows the results of user comfort index in case of proposed hybrid optimization based prediction with preprocessing/post-processing model and GA based prediction system.

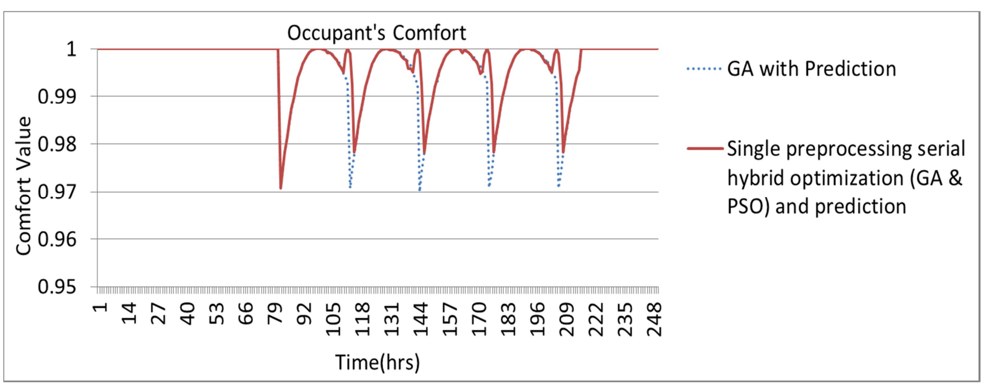

Figure 5.15. Comparison of comfort value/index with GA based predicted system and serial hybrid optimization and prediction

From the occupants comfort index it is clear that serial hybrid optimization based prediction and preprocessing/post-processing model provides better and improved comfort index as compared to GA based prediction model [3]. Although in serial hybrid optimization, prediction and preprocessing/post-processing model, less power is consumed as compare to that of GA based prediction system, but still proposed model achieved improved and better comfort index as compared to GA and based predicted system.

5.2.1.3. Optimization algorithm based on PSO and MIGA serial

5.2.1.3.1. Comparisons of power consumption prediction results

Figure 5.16, 5.17, 5.18 and 5.19 shows the comparisons of power consumption. X-axis shows the time in hours while Y-axis shows the predicted power consumption in kilowatts, and comfort index between 0.0 and 1.0 is the minimum and maximum comfort index respectively. From the results of Figure 5.16 it can be observed that in case of power consumption for temperature, proposed serial hybrid optimization and prediction based on single preprocessing model consumed less power as compared to the GA based system with no hybrid optimization and preprocessing. When environmental intermission occur, serial hybrid optimization, hybrid prediction and preprocessing model consumed less power as compared to GA based predicted model where no hybrid optimization and preprocessing involved. Less power consumption is ensured by controllers using optimized parameters. For illumination as shown in Figure 5.17, serial hybrid optimization and hybrid prediction with preprocessing model consumed minimum power as compared to GA based predicted model.

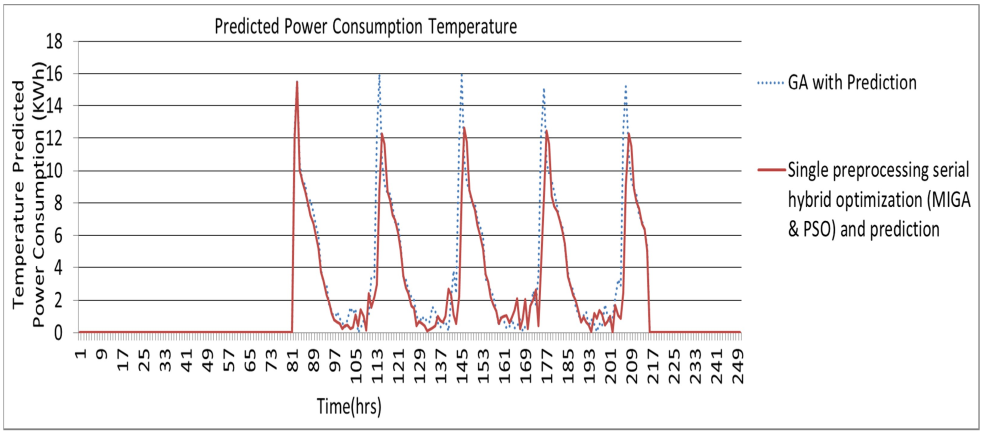

Figure 5.16. Comparison of predicted power consumption for temperature with MIGA based predicted system and serial hybrid optimization and prediction

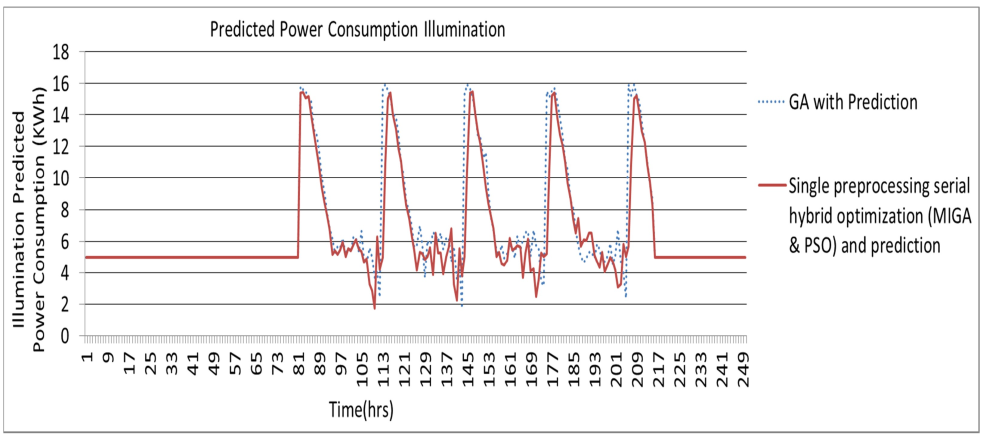

Figure 5.17. Comparison of predicted power consumption for illumination with MIGA based predicted system and serial hybrid optimization and prediction

Figure 5.18 shows the results for the air-quality control. Here we can see that serial hybrid optimization and hybrid prediction model consumed little power as compared to its equivalent GA based predicted system. Figure 5.19 shows the total predicted power consumption in case of proposed serial hybrid optimization model and GA based predicted model with no hybrid optimization, prediction and preprocessing involved. The total predicted power consumption of serial hybrid optimization and hybrid prediction model with preprocessing consumed less power than its counterpart GA based prediction system with no hybrid prediction and preprocessing.

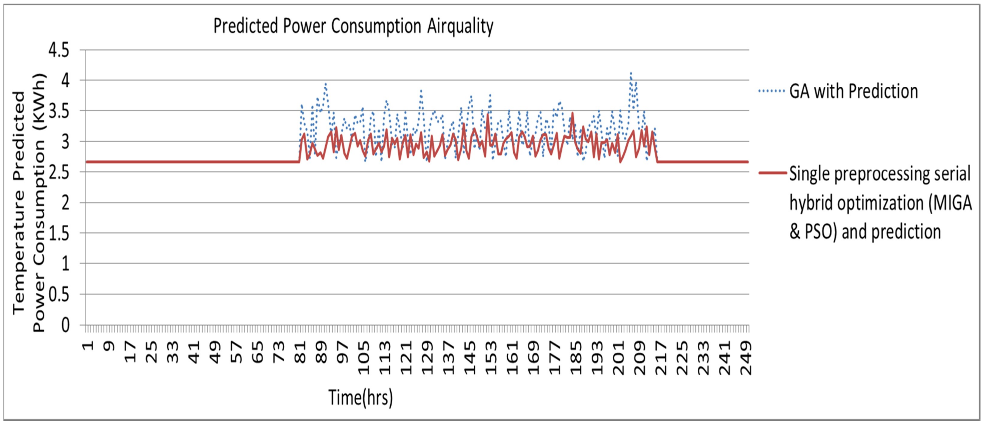

Figure 5.18. Comparison of predicted power consumption for air-quality with MIGA based predicted system and serial hybrid optimization and prediction

First time power disturbance occurs at time 82hrs. At this time comfort level of proposed hybrid optimization based system with hybrid prediction and preprocessing goes down to 0.970 same as to GA based predicted system with no hybrid prediction and preprocessing. When second time power disturbance occurs, the GA based predicted system immediately goes down as compared to proposed hybrid optimization based prediction and preprocessing model. When second time power disturbance arises proposed serial hybrid optimization model degraded to 0.978 as compared to 0.970 of GA based prediction model with no preprocessing. Similarly in all cases of comfort degradation, the proposed hybrid optimization based predicted with preprocessing system provides improved comfort index as compared to GA based predicted system where no preprocessing applied. So whenever there is an environmental disturbance, hybrid optimization based prediction and smoothing system provides better comfort index as compared to its counterpart GA based predicted system.

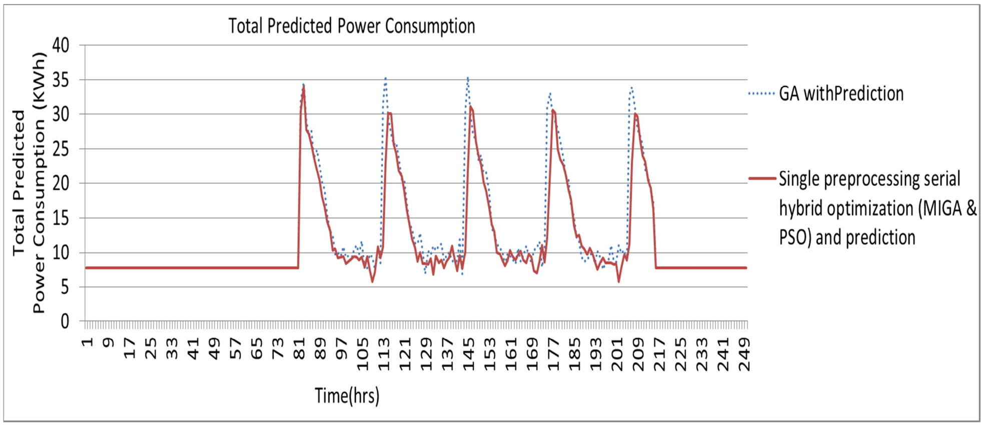

Figure 5.19. Comparison of total predicted power consumption with MIGA based predicted syste m and parallel hybrid optimization and prediction

5.2.1.3.2. Comparisons of occupants comfort index results

Figure 5.20 shows the results of user comfort index in case of proposed hybrid optimization based prediction with preprocessing model and GA based p rediction system.

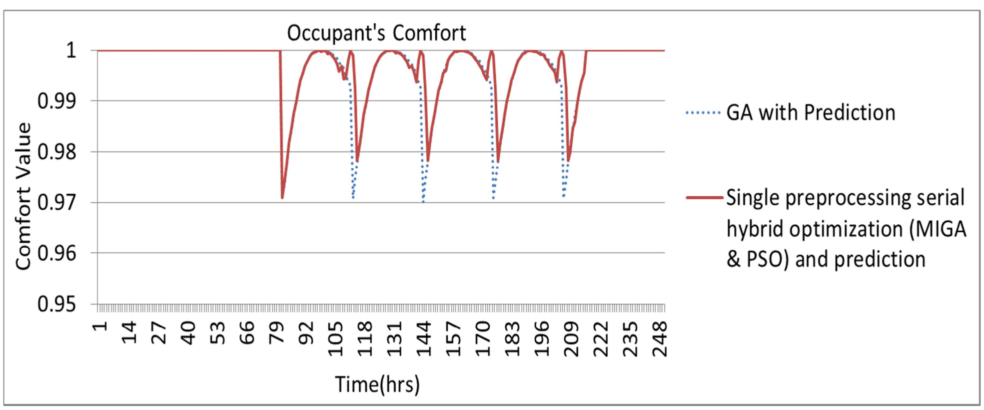

Figure 5.20. Comparison of comfort value/index with MIGA based predicted system and serial hybrid optimization and prediction

From the comfort index it is clear that serial hybrid optimization based prediction and preprocessing model provides better and improved comfort index as compared to GA based prediction model [3]. Although in serial hybrid optimization, prediction and preprocessing model, less power is consumed as compare to that of GA based prediction system, but still proposed model achieved improved and better comfort index as compared to GA and based predicted system.

5.2.2. Multi-preprocessing hybrid optimization model based on prediction

5.2.2.1. Optimization algorithm based on PSO and GA parallel

5.2.2.1.1. Comparisons of power consumption prediction results

Figure 5.21, 5.22, 5.23 and 5.24 shows the comparisons of power consumption. X-axis shows the time in hours while Y-axis shows the predicted power consumption in kilowatts, and comfort index between 0.0 and 1.0 is the minimum and maximum comfort index respectively. From the results of Figure 5.21 it can be observed that in case of power consumption for temperature, proposed parallel hybrid optimization and prediction based on Kalman filter and multi-preprocessing model consumed less power as compared to the GA based system with no hybrid optimization and multi-preprocessing. When environmental disturbance occur, parallel hybrid optimization, prediction and multi-preprocessing model consumed less power as compared to GA based predicted model where no hybrid optimization and preprocessing involved. Minimum power consumption is guaranteed by controllers using optimized parameters and multi-preprocessing. For illumination as shown in Figure 5.22, parallel hybrid optimization and prediction with multi-preprocessing model consumed minimum power as compared to GA based predicted model. Figure 5.2 3 shows the results for the air-quality control.

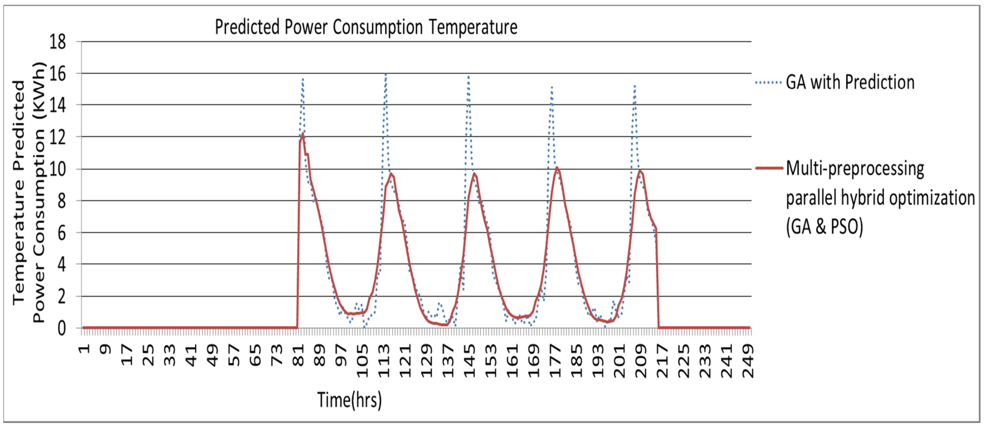

Figure 5.21. Comparison of predicted power consumption for temperature with GA based predicted system and parallel hybrid optimization and prediction (with multi-preprocessing)

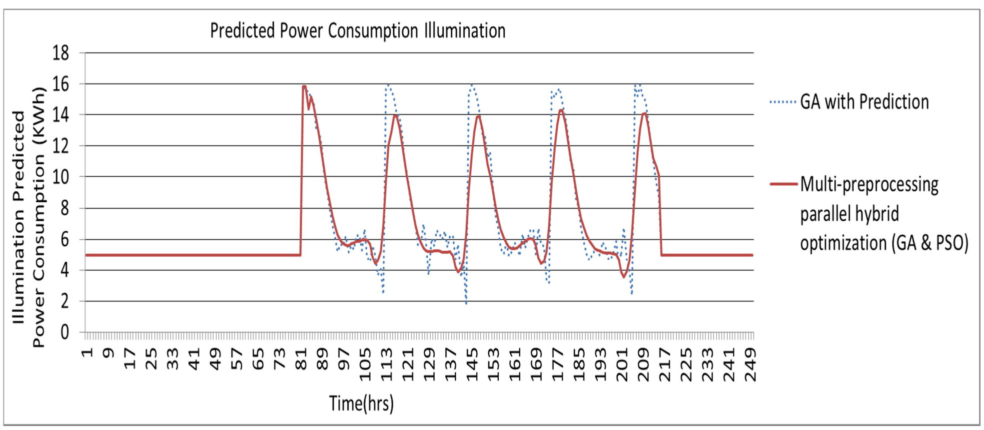

Figure 5.22. Comparison of predicted power consumption for illumination with GA based predicted system and parallel hybrid optimization and prediction (with multi-preprocessing)

Here we can see that parallel hybrid optimization and prediction with multi-preprocessing model consumed a little bit more power as compared to its equivalent GA based predicted system. Figure 5.24 shows the total predicted power consumption in case of proposed parallel hybrid optimization with multi-preprocessing model and GA based predicted model with no hybrid prediction and preprocessing involved. The total predicted power consumption of parallel hybrid optimization and prediction model with multi-preprocessing consumed less power than its counterpart GA based prediction system with no hybrid prediction and preprocessing.

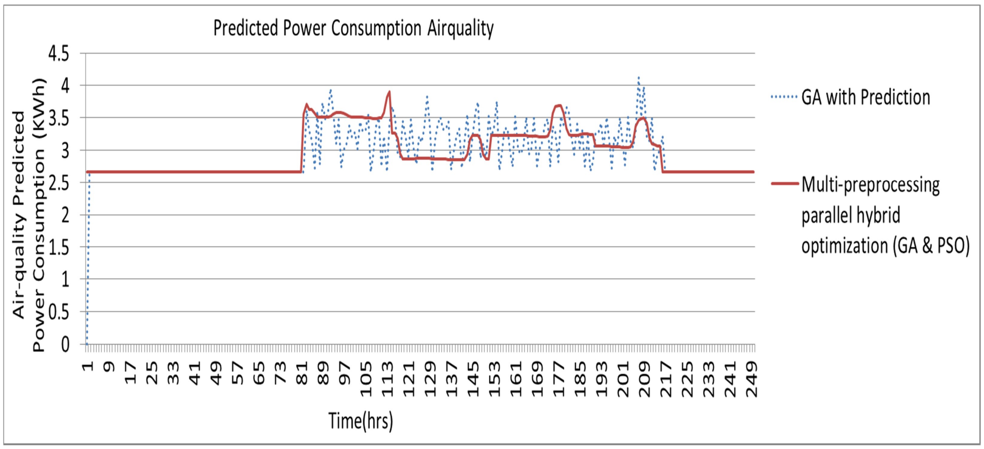

Figure 5.23. Comparison of predicted power consumption for air-quality with GA based predicted system and parallel hybrid optimization and prediction (with multi-preprocessing)

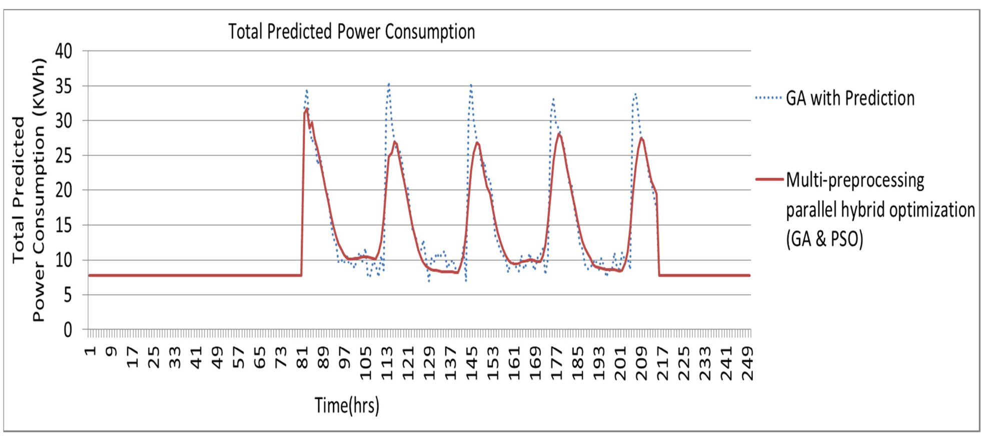

Figure 5.24. Comparison of total predicted power consumption with GA based predicted system and parallel hybrid optimization and prediction (with multi-preprocessing)

First time the power disturbance arises at time 82hrs. At this time comfort level of hybrid optimization based proposed system with prediction and multi-preprocessing goes down to 0.970 same as to GA based predicted system with no hybrid prediction and preprocessing. When second time power disturbance occurs, the comfort index of GA based predicted system immediately goes down as compared to proposed hybrid optimization based prediction with multi-preprocessing model. When second time power disturbance arises proposed parallel hybrid optimization with multi-preprocessing model degraded to 0.996 as compared to 0.970 of GA based prediction model with no. Similarly in all cases of degradation the proposed hybrid optimization based predicted with multi-preprocessing system provides improved comfort index as compared to GA based predicted system where no preprocessing applied. So whenever there is an environmental disturbance, hybrid optimization based prediction and multi-preprocessing system provides better comfort index as compared to its counterpart GA based predicted system.

Figure 5.25, 5.26, 5.27 and 5.28 shows the comparisons of power consumption for parallel hybrid optimization prediction with single and multi-preprocessing. From the results of Figure 5.25 it can be observed that in case of power consumption for temperature, parallel hybrid optimization and prediction based on Kalman filter with multi-preprocessing model consumed more power as compared to the single preprocessing based system. For illumination as shown in Figure 5.26, parallel hybrid optimization and prediction with single preprocessing model consumed more power as compared to multi-preprocessing based predicted model. Figure 5.27 shows the results for the air-quality control.

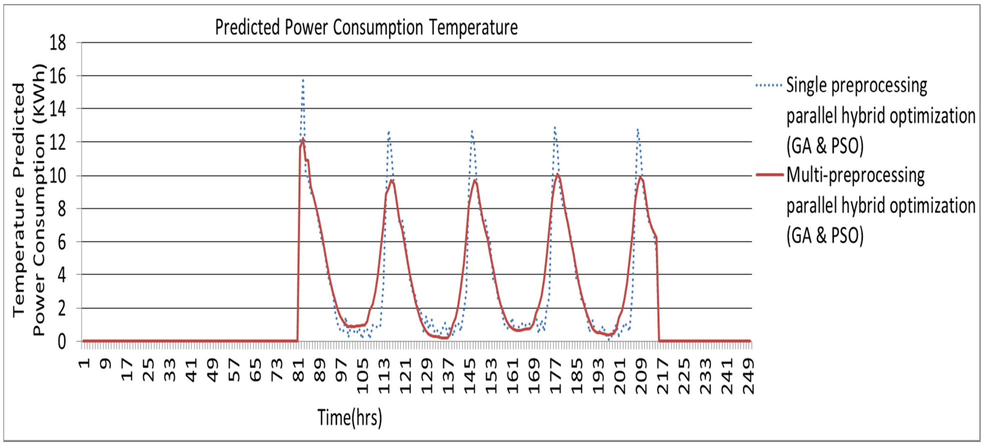

Figure 5.25. Comparison of predicted power consumption for temperature (single and multi-preprocessing based predicted systems)

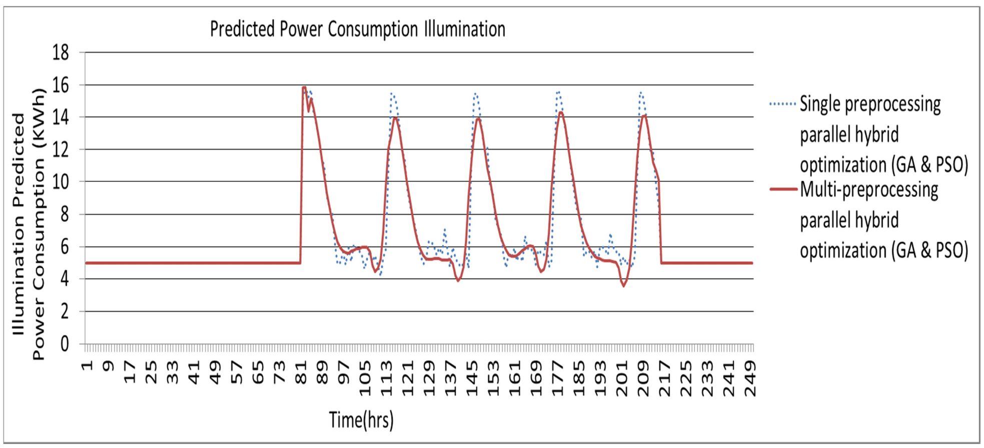

Figure 5.26. Comparison of predicted power consumption for illumination (single and multi-preprocessing based predicted systems)

Here we can see that parallel hybrid optimization and prediction model with multi-preprocessing consumed a little bit more power as compared to its equivalent single preprocessing based predicted system. Figure 5.28 shows the total predicted power consumption in case of single and multi-preprocessing based hybrid optimization. The total predicted power consumption of single preprocessing based on optimization and prediction model consumed less power than its counterpart multi-preprocessing based prediction system.

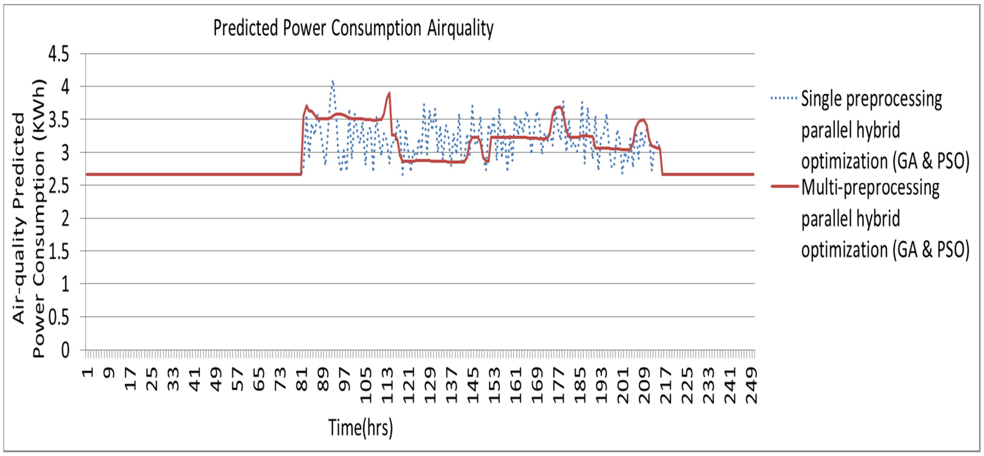

Figure 5.27. Comparison of predicted power consumption for air-quality (single and multi-preprocessing based predicted systems)

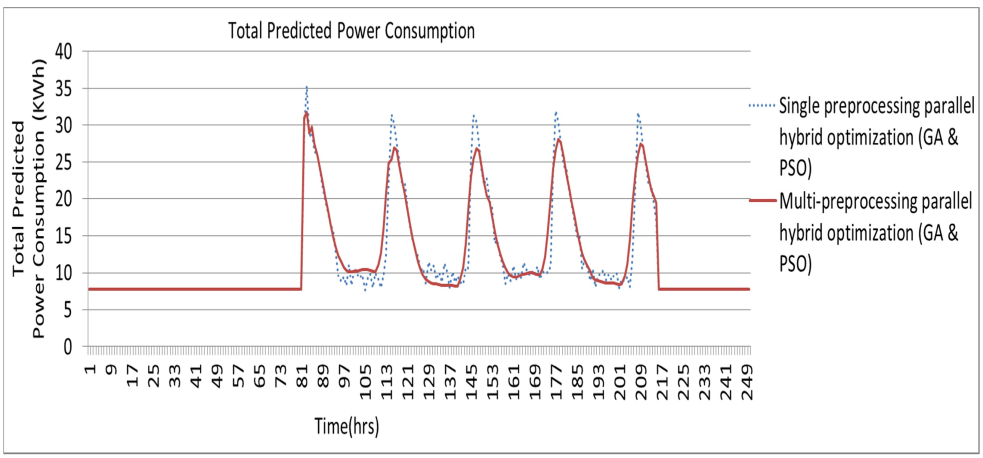

Figure 5.28. Comparison of total predicted power consumption (single and multi-preprocessing based predicted systems)

5.2.2.1.2. Comparisons of occupants comfort index results

Figure 5.29 shows the results of user comfort index in case of proposed hybrid optimization based prediction with preprocessing model and GA based prediction system. In Figure 5.29, it is clear that parallel hybrid optimization based prediction and multi-preprocessing model provides better and improved comfort index as compared to GA based prediction model [3]. Though in parallel hybrid optimization, prediction and multi-preprocessing model, minimum power is consumed as compare to that of GA based prediction system, but still proposed model achieved improved and better comfort index as compared to GA and based predicted system.

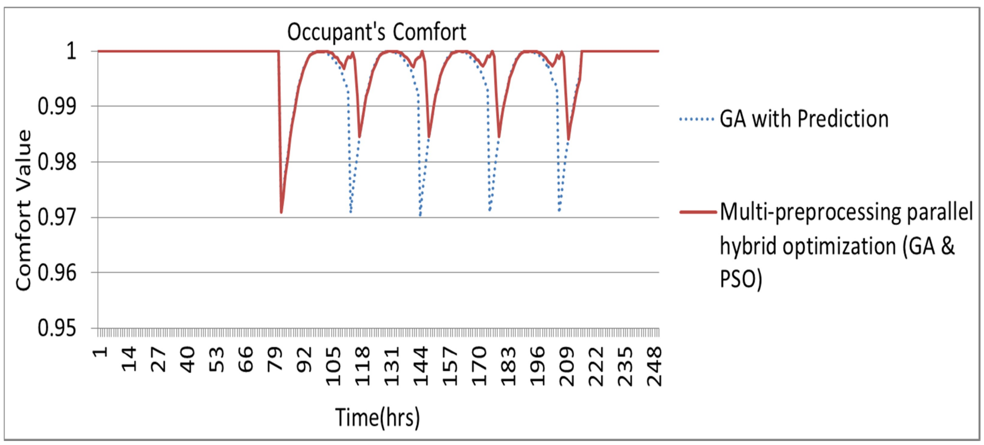

Figure 5.29. Comparison of comfort value/index with GA based predicted system and parallel hybrid optimization and prediction (with multi-preprocessing)

Figure 5.30 shows the results of user comfort index in case of proposed hybrid optimization based prediction with multi-preprocessing model and single preprocessing based prediction system. In Figure 5.30, it is clear that parallel hybrid optimization based prediction and multi-preprocessing model provides better and improved comfort index as compared to single preprocessing based prediction model. Although parallel hybrid optimization, prediction and multi-preprocessing model consumed more power than its counterpart single preprocessing based optimization and prediction model, but the comfort index it provided is much better than single preprocessing based optimization and prediction model.

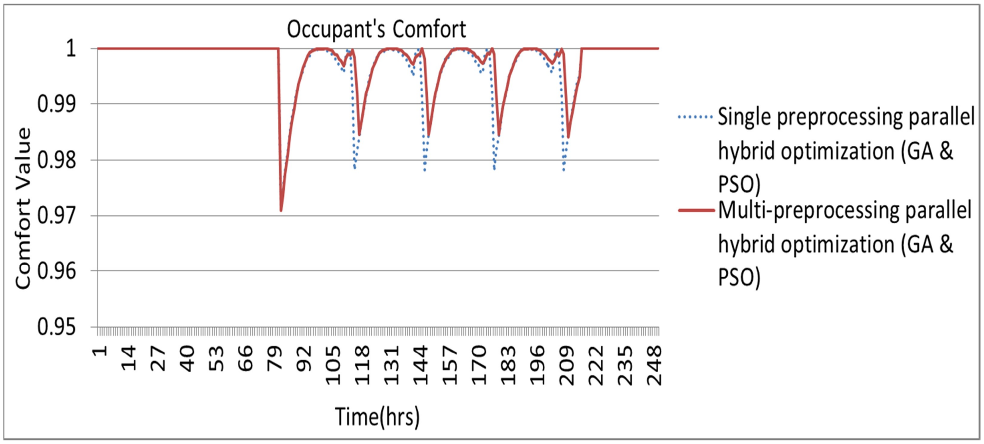

Figure 5.30. Comparison of comfort value/index (GA and PSO based parallel hybrid energy optimization with single and multi-preprocessing systems)

5.2.2.2. Optimization algorithm based on PSO and GA serial

5.2.2.2.1. Comparisons of power consumption prediction results

Figure 5.31, 5.32, 5.33 and 5.34 shows the comparisons of power consumption. X-axis shows the time in hours while Y-axis shows the predicted power consumption in kilowatts, and comfort index between 0.0 and 1.0 is the minimum and maximum comfort index respectively. From the results of Figure 5.31 it can be observed that in case of power consumption for temperature, proposed serial hybrid optimization and prediction based on Kalman filter and multi-preprocessing model consumed more power as compared to the GA based system with no hybrid optimization and multi-preprocessing. When environmental intermission occur, serial hybrid optimization, prediction and multi-preprocessing model consumed more power as compared to GA based predicted model where no hybrid optimization and preprocessing involved. For illumination as shown in Figure 5.32, serial hybrid optimization and prediction with multi-preprocessing model consumed minimum power as compared to GA based predicted model. Less power consumption is ensured by controllers using optimized parameters.

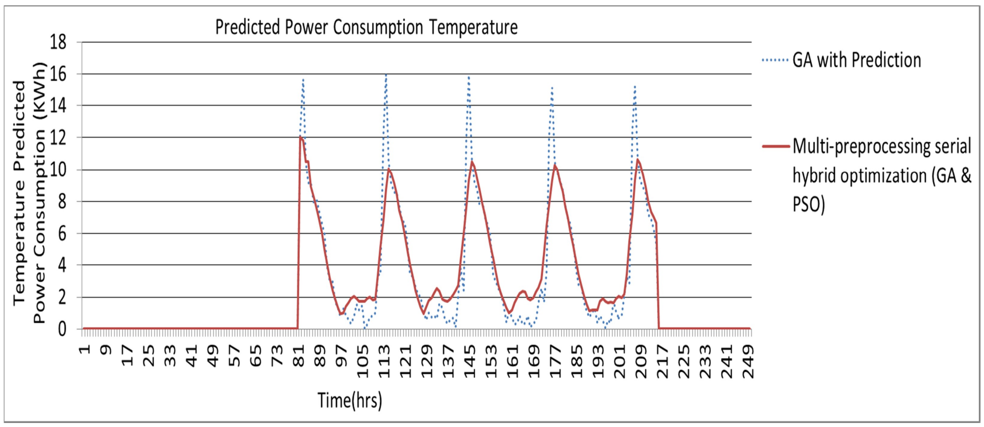

Figure 5.31. Comparison of predicted power consumption for temperature with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

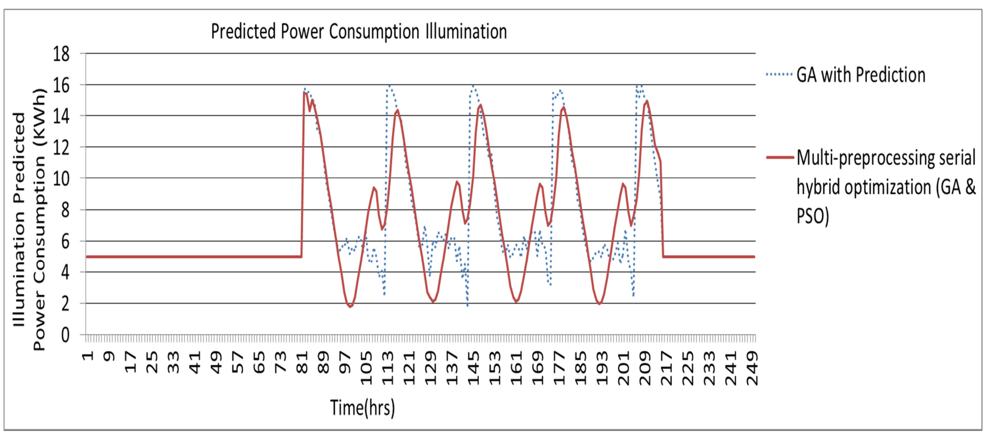

Figure 5.32. Comparison of predicted power consumption for illumination with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

Figure 5.33 shows the results for the air-quality control. Here we can see that serial hybrid optimization and prediction model consumed a little bit less power as compared to its equivalent GA based predicted system. Figure 5.34 shows the total predicted power consumption in case of proposed serial hybrid optimization model and GA based predicted model with no hybrid prediction and preprocessing involved. The total predicted power consumption of serial hybrid optimization and prediction model with multi-preprocessing consumed a little bit more but almost same power as compared to its counterpart GA based prediction system with no hybrid prediction and preprocessing.

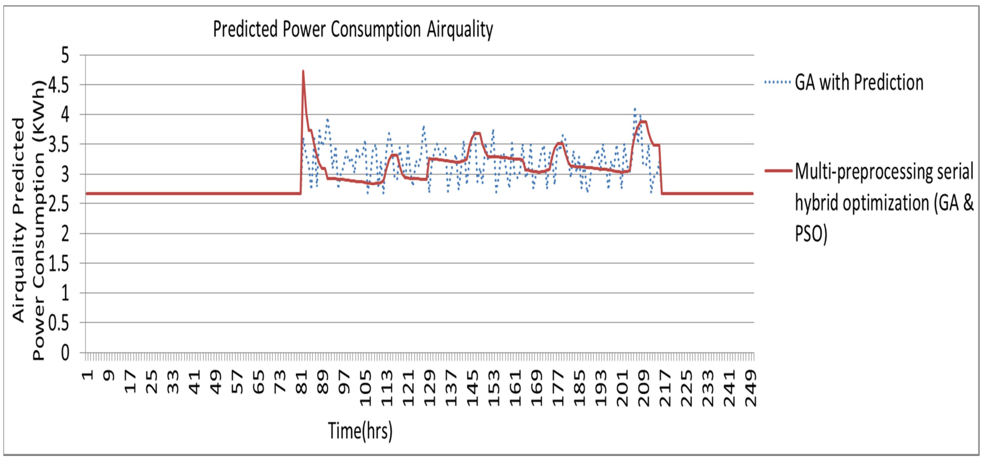

Figure 5.33. Comparison of predicted power consumption for air-quality with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

The power disturbance at first time arises at 82hrs. At this time comfort level of hybrid optimization based proposed system with prediction and multi-preprocessing goes down to0.970 same as to GA based predicted system with no hybrid prediction and preprocessing. When second time power disturbance occurs, the comfort index of GA based predicted system immediately goes down as compared to proposed hybrid optimization based prediction and multi-preprocessing model. When second time power disturbance arises proposed serial hybrid optimization model degraded to 0.984 as compared to 0.970 of GA based prediction model with no preprocessing. Similarly in all cases of degradation the proposed hybrid optimization based predicted with multi-preprocessing system provides improved comfort index as compared to GA based predicted system where no multi-preprocessing applied. So whenever there is an environmental disturbance, hybrid optimization based prediction and multi-preprocessing system provides better comfort index as compared to its counterpart GA based predicted system.

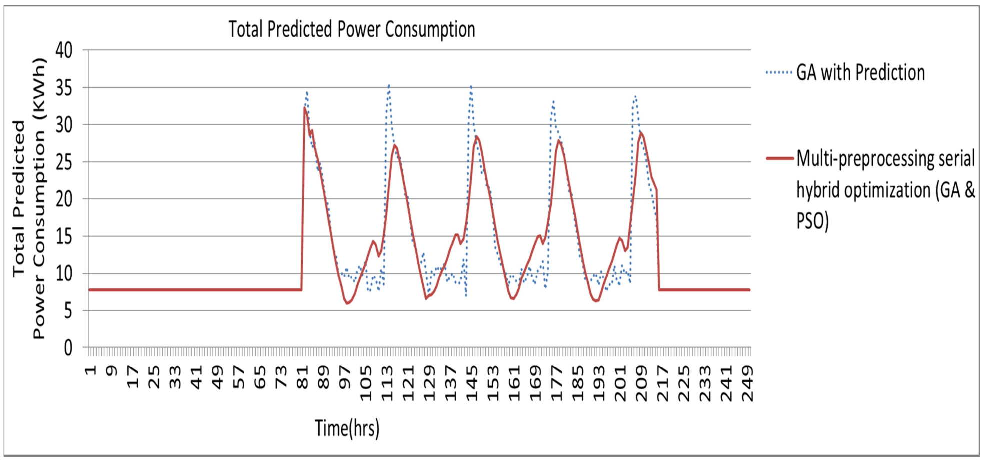

Figure 5.34. Comparison of total predicted power consumption with GA based predicted system and parallel hybrid optimization and prediction (with multi-preprocessing)

Figure 5.35, 5.36, 5.37 and 5.38 shows the comparisons of power consumption for serial hybrid optimization prediction with single and multi-preprocessing. From the results of Figure 5.35 it can be observed that in case of power consumption for temperature, serial hybrid optimization and prediction with multi-preprocessing model consumed more power as compared to the single preprocessing based system. For illumination as shown in Figure 5.36, serial hybrid optimization and prediction with single preprocessing model consumed less power as compared to multi-preprocessing based predicted model. Figure 5.37 shows the results for the air-quality control. Here we can see that serial hybrid optimization and prediction model with multi-preprocessing consumed almost similar power as compared to its equivalent single preprocessing based predicted system. Figure 5.38 shows the total predicted power consumption in case of single and multi-preprocessing based hybrid optimization. The total predicted power consumption of single preprocessing based on optimization and prediction model consumed less power than its counterpart multi-preprocessing based prediction system.

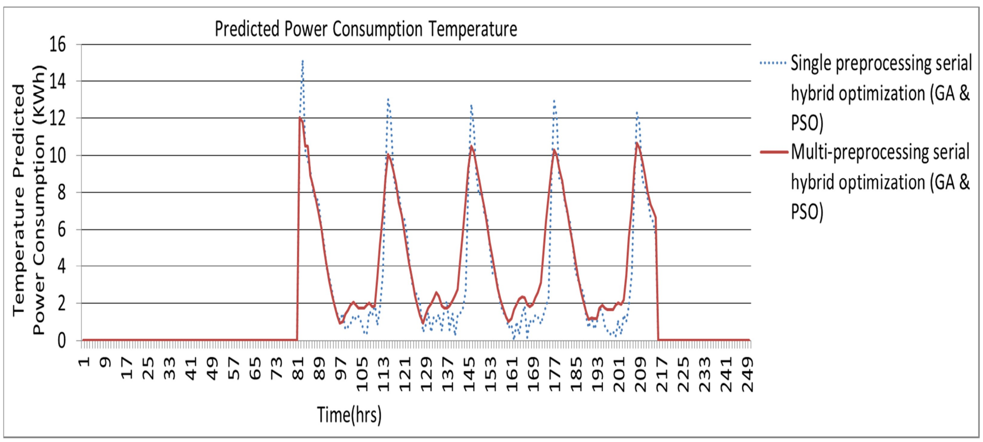

Figure 5.35. Comparison of predicted power consumption for temperature with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

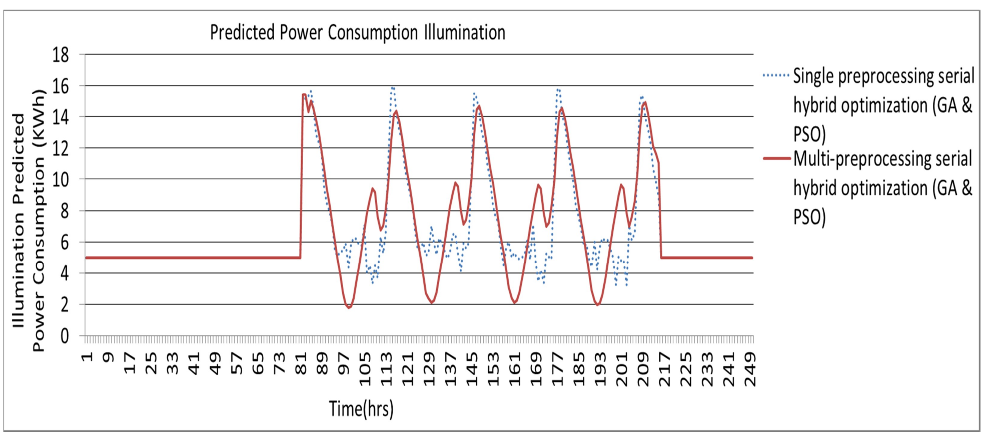

Figure 5.36. Comparison of predicted power consumption for illumination with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

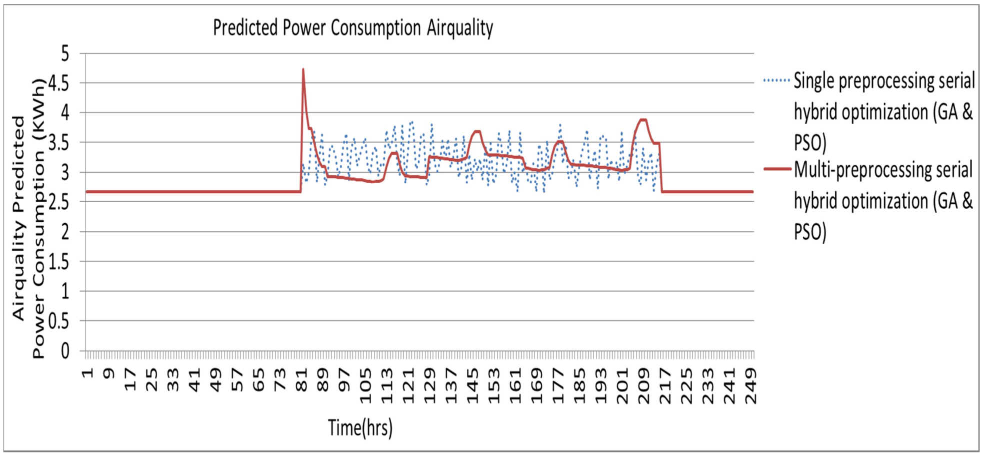

Figure 5.37. Comparison of predicted power consumption for air-quality with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

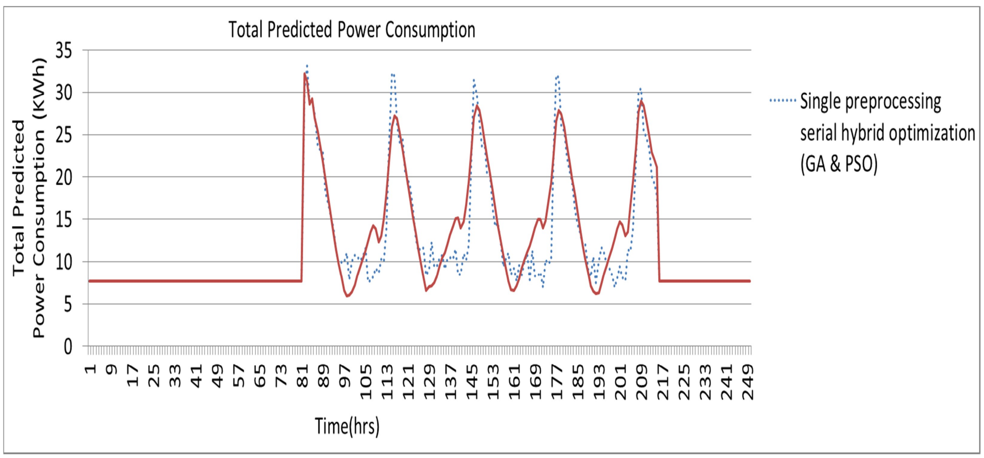

Figure 5.38. Comparison of total predicted power consumption with GA based predicted system and parallel hybrid optimization and prediction (with multi-preprocessing)

5.2.2.2.2. Comparisons of occupants comfort index results

Figure 5.39 shows the results of user comfort index in case of proposed hybrid optimization based prediction with multi-preprocessing model and GA based prediction system. In Figure 5.39, it is clear that parallel hybrid optimization based prediction and multi-preprocessing model provides better and improved comfort index as compared to GA based prediction model [3]. Though in parallel hybrid optimization, prediction and multi-preprocessing model same power is consumed as compare to that of GA based prediction system, but still proposed model achieved improved and better comfort index as compared to GA and based predicted system. So the drastic factor here is that proposed hybrid optimization and prediction with multi-preprocessing system provides better comfort index with consumption almost same power as that of GA based prediction system.

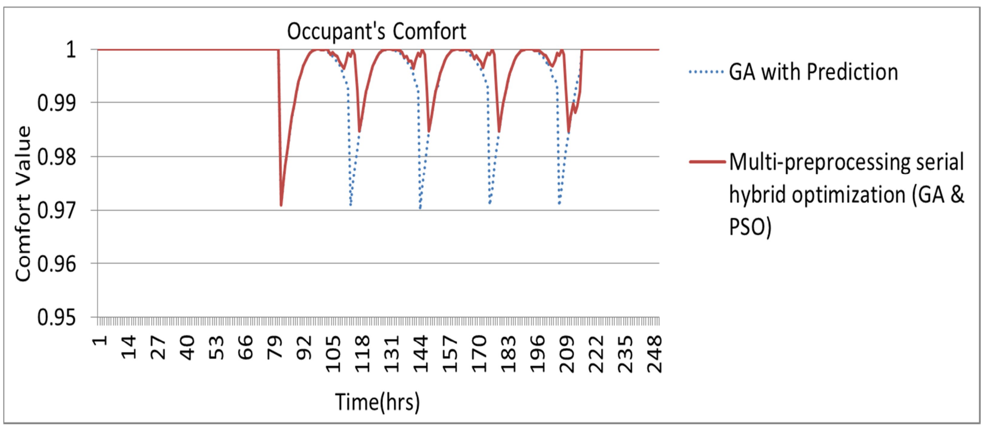

Figure 5.39. Comparison of comfort value/index with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

Figure 5.40 shows the results of user comfort index in case of proposed hybrid serial optimization based prediction with multi-preprocessing model and single preprocessing based prediction system. In Figure 5.40, it is clear that serial hybrid optimization based prediction and multi-preprocessing model provides better and improved comfort index as compared to single preprocessing based prediction model. Although serial hybrid optimization, prediction and multi-preprocessing model consumed more power than its counterpart single preprocessing based optimization and prediction model, but the comfort index it provided is much better than single preprocessing based optimization and prediction model.

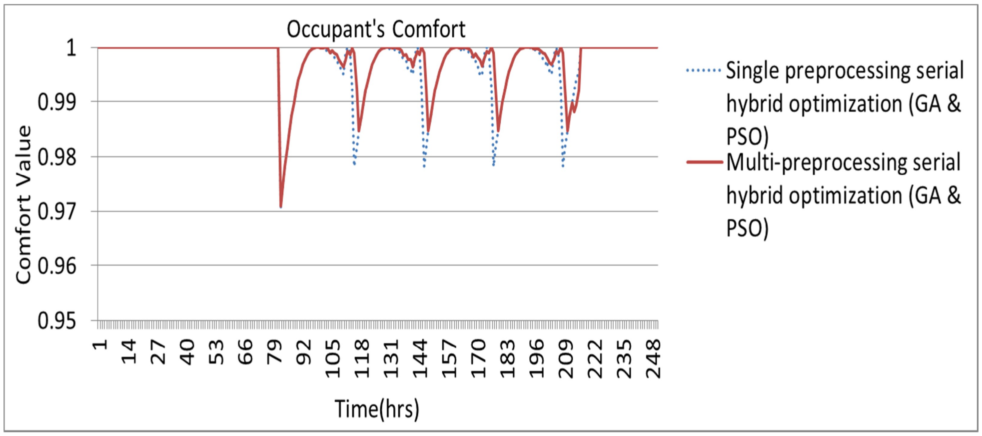

Figure 5.40. Comparison of comfort value/index (GA and PSO based serial hybrid energy optimization with single and multi-preprocessing systems)

5.2.2.3. Optimization algorithm based on PSO and MIGA serial

5.2.2.3.1. Comparisons of power consumption prediction results

Figure 5.41, 5.42, 5.43 and 5.44 shows the comparisons of power consumption. X-axis shows the time in hours while Y-axis shows the predicted power consumption in kilowatts, and comfort index between 0.0 and 1.0 is the minimum and maximum comfort index respectively. From the results of Figure 5.41 it can be observed that in case of power consumption for temperature, proposed serial hybrid optimization and hybrid prediction with multi-preprocessing model consumed less power as compared to the GA based system with no hybrid optimization and multi-preprocessing. When environmental intermission occur, serial hybrid optimization, hybrid prediction and multi-preprocessing model consumed less power as compared to GA based predicted model where no hybrid optimization and preprocessing involved. Less power consumption is ensured by controllers using optimized parameters. For illumination as shown in Figure 5.42, serial hybrid optimization and prediction with multi-preprocessing/ model consumed minimum power as compared to GA based predicted model.

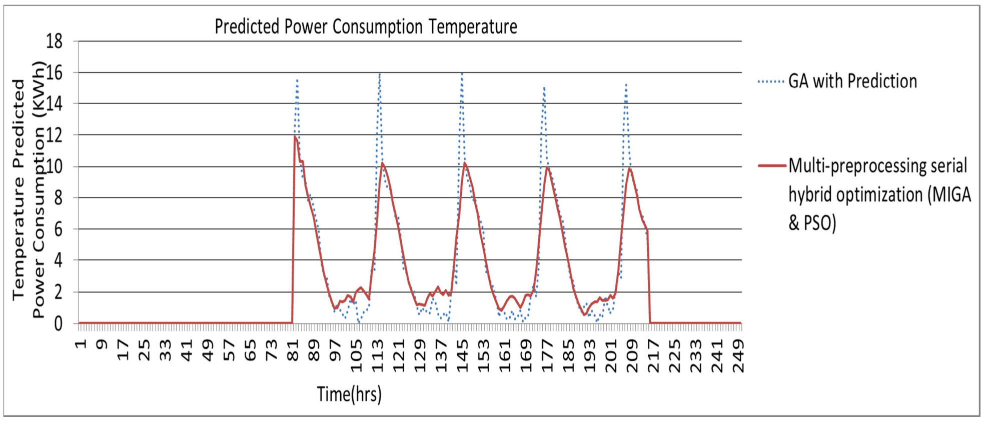

Figure 5.41. Comparison of predicted power consumption for temperature with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

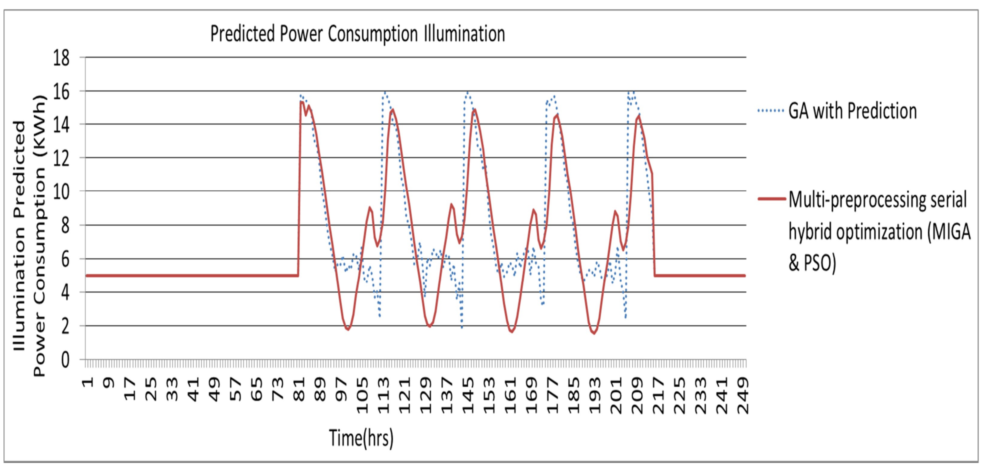

Figure 5.42. Comparison of predicted power consumption for illumination with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

Figure 5.43 shows the results for the air-quality control. Here we can see that serial hybrid optimization and hybrid prediction model consumed little power as compared to its equivalent GA based predicted system. Figure 5.44 shows the total predicted power consumption in case of proposed serial hybrid optimization model and GA based predicted model with no hybrid prediction and multi-preprocessing involved. The total predicted power consumption of serial hybrid optimization and prediction model with multi-preprocessing consumed less power than its counterpart GA based prediction system with no hybrid prediction and preprocessing.

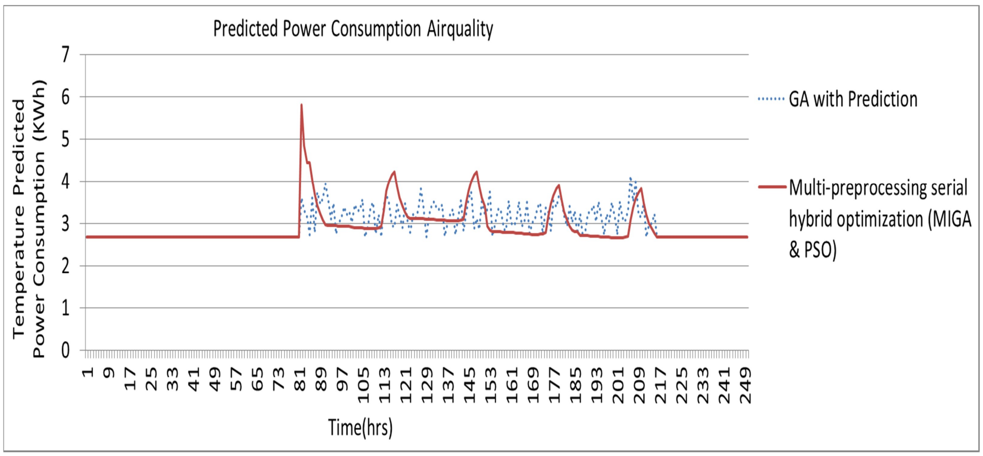

Figure 5.43. Comparison of predicted power consumption for air-quality with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

The power disturbance at first time arises at 82hrs. At this time comfort level of hybrid optimization based proposed system with prediction and preprocessing/post-processing goes down to 0.9870 same as to GA based predicted system with no hybrid prediction and multi-preprocessing. When second time power disturbance occurs, the comfort index of GA based predicted system immediately goes down as compared to proposed hybrid optimization based prediction and multi-preprocessing model. When second time power disturbance occurs proposed serial hybrid optimization model degraded to 0.984 as compared to 0.970 of GA based prediction model with no multi-preprocessing. Similarly in all cases of degradation the proposed hybrid optimization based predicted with multi-preprocessing system provides improved comfort index as compared to GA based predicted system where no preprocessing applied. So whenever there is an environmental disturbance, hybrid optimization based prediction and multi-preprocessing system provides better comfort index as compared to its counterpart GA based predicted system.

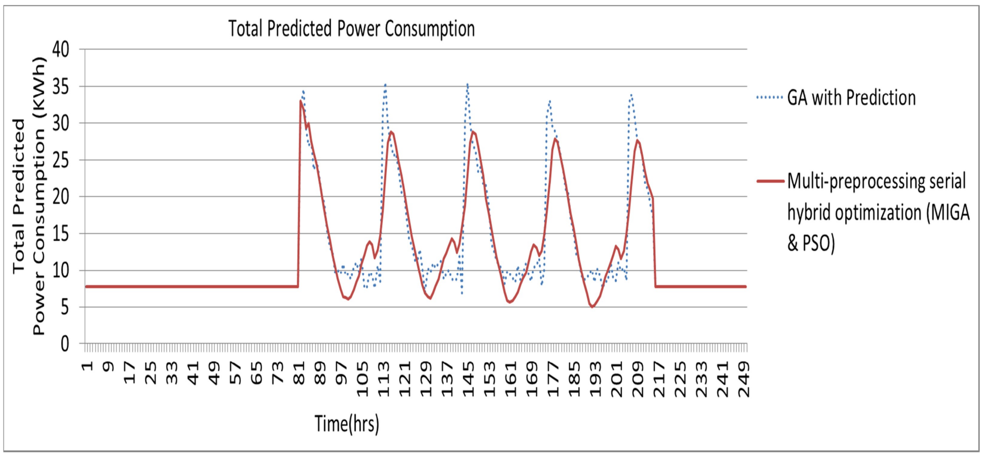

Figure 5.44. Comparison of total predicted power consumption with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

Figure 5.45, 5.46, 5.47 and 5.48 shows the comparisons of power consumption for serial hybrid optimization based on MIGA and PSO and prediction with single and multi-preprocessing. From the results of Figure 5.45 it can be observed that in case of power consumption for temperature, serial hybrid optimization and prediction with multi-preprocessing model consumed more power as compared to the single preprocessing based system. For illumination as shown in Figure 5.46, serial hybrid optimization and prediction with single preprocessing model consumed less power as compared to multi-preprocessing based predicted model.

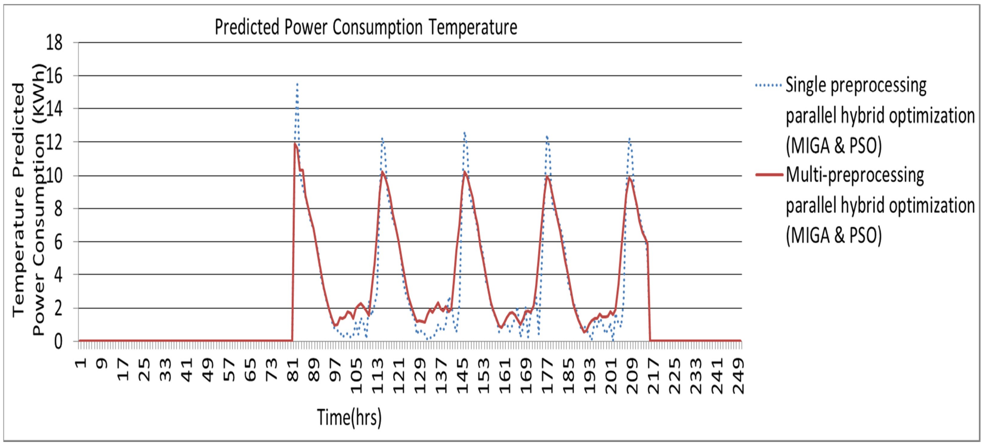

Figure 5.45. Comparison of predicted power consumption for temperature with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

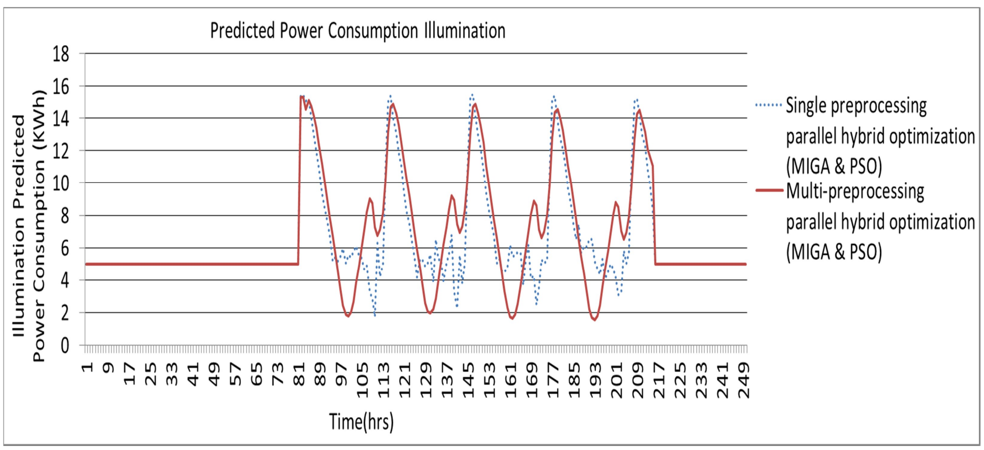

Figure 5.46. Comparison of predicted power consumption for illumination with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

Figure 5.47 shows the results for the air-quality control. Here we can see that serial hybrid optimization and prediction model with multi-preprocessing consumed more power as compared to its equivalent single preprocessing based predicted system. Figure 5.48 shows the total predicted power consumption in case of single and multi-preprocessing based hybrid optimization. The total predicted power consumption of single preprocessing based on optimization and prediction model consumed less power than its counterpart multi-preprocessing based prediction system.

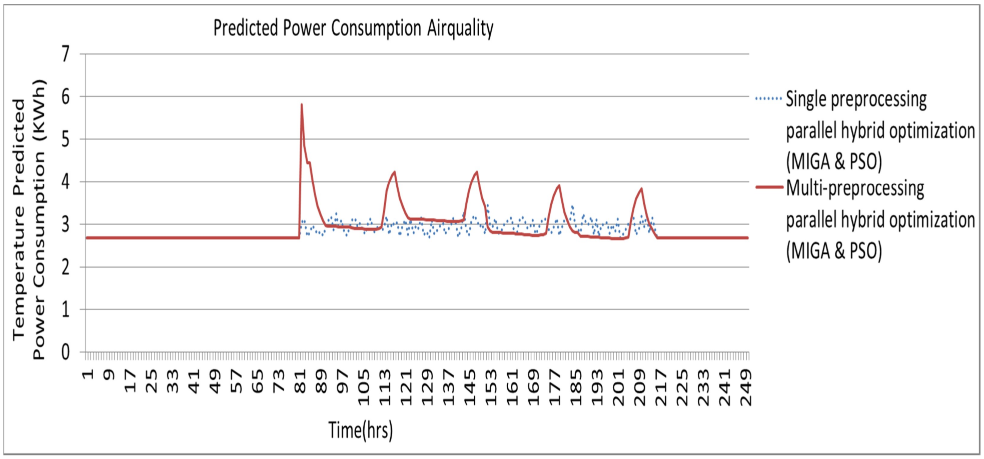

Figure 5.47. Comparison of predicted power consumption for air-quality with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

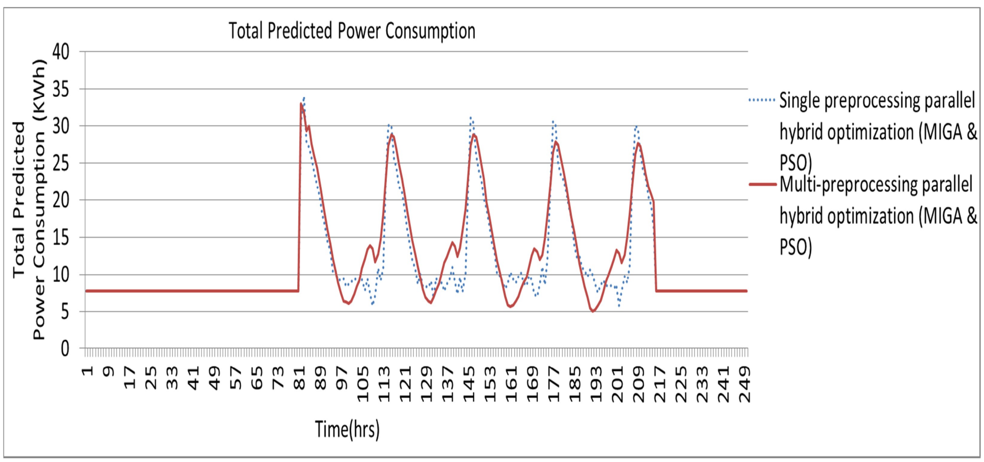

Figure 5.48. Comparison of total predicted power consumption with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

5.2.2.3.2. Comparisons of occupants comfort index results

Figure 5.49 shows the results of user comfort index in case of proposed hybrid optimization based prediction with multi-preprocessing model and GA based prediction system. In Figure 5.49, it is clear that serial hybrid optimization based prediction and multi-preprocessing model provides better and improved comfort index as compared to GA based prediction model [3]. Although in serial hybrid optimization, hybrid prediction and multi-preprocessing model, less power is consumed as compare to that of GA based prediction system, but still proposed model achieved improved and better comfort index as compared to GA and based predicted system.

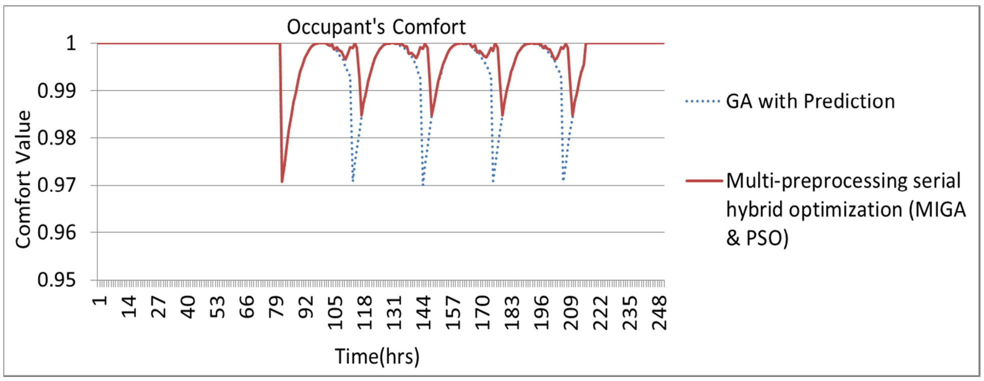

Figure 5.49. Comparison of comfort value/index with GA based predicted system and serial hybrid optimization and prediction (with multi-preprocessing)

Figure 5.50 shows the results of user comfort index in case of proposed hybrid serial optimization based on prediction with multi-preprocessing model and single preprocessing based prediction system. In Figure 5.50, it is clear that serial hybrid optimization based prediction and multi-preprocessing model provides better and improved comfort index as compared to single preprocessing based prediction model. Although serial hybrid optimization, prediction and multi-preprocessing model consumed more power than its counterpart single preprocessing based optimization and prediction model, but the comfort index it provided is much better than single preprocessing based optimization and prediction model.

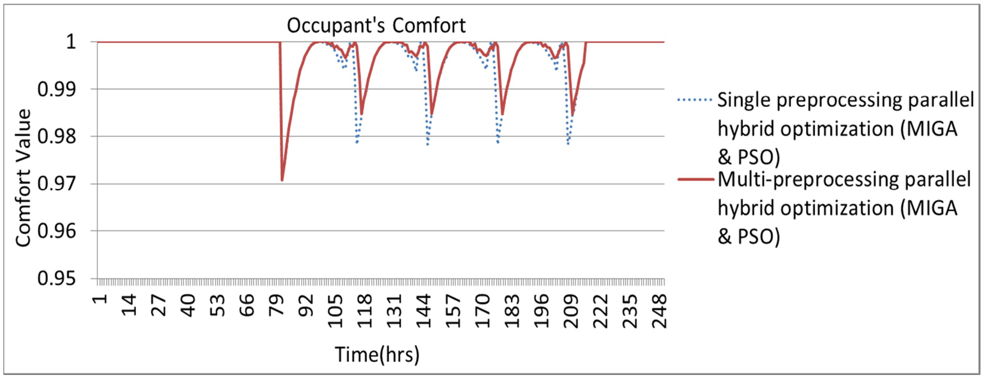

Figure 5.50. Comparison of comfort value/index (MIGA and PSO based serial hybrid energy optimization with single and multi-preprocessing systems)

Figure 5.51 shows the overall comparisons of power consumption and comfort index using basic model (GA based prediction and PSO based prediction models), model 1 (Single pre-processing hybrid optimization and prediction models) and model 2 (Multi-preprocessing hybrid optimization and prediction models). Step by step comparison is described below.

1. GA based prediction model consumed less power as compared to PSO based prediction model.
2. GA based prediction model provides better comfort index as compared to PSO based prediction model.
3. Single preprocessing hybrid optimization and prediction models consumed less power as compared GA based prediction model and PSO based prediction model.
4. Single preprocessing hybrid optimization provides better comfort index as compared to GA based prediction model and PSO based prediction model.
5. Multi-preprocessing hybrid optimization and prediction models consumed less

power as compared to GA based prediction model and PSO based prediction.

6. Multi-preprocessing hybrid optimization and prediction models provides better comfort index as compared to GA based and PSO based prediction models.

7. Although multi-preprocessing hybrid optimization and prediction models consumed more power as compared to single preprocessing hybrid optimization and prediction models, but it provides better comfort index than single preprocessing hybrid optimization and prediction models.

			Predicted Power Consumption							
Model	Scenario	Algorithms	Temperature	Illumination	Air-quality	Total				
Basic Model	Basic Model PSO	PSO & K	601.0802	1707.274675	738.7475591	3047.102434	Power consumption reduction		Comfort Index Improvement	
							Compared to Basic Model PSO	Compared to Basic Model GA	Compared to Basic Model PSO	Compared to Basic Model GA
	Basic Model GA	GA & K	581.5458	1704.905275	739.7908591	3026.241934				
MODEL 1	Model 1 Scenario 1 Parallal	GA in PSO and K	518.5121	1665.396575	738.3986591	2922.307334	Yes	Yes	Yes	Yes
	Model 1 Scenario 2 Serial	PSO & GA and K	532.4037	1641.953175	739.8774591	2914.234334	Yes	Yes	Yes	Yes
	Model 1 Scenario 3 Serial	PSO & MIGA and ARIMA & K	507.9625	1599.290075	705.5110591	2812.763634	Yes	Yes	Yes	Yes
MODEL 2	Model 2 Scenario 1 Parallal	GA in PSO and K	551.4128	1659.428575	742.5160591	2953.357434	Yes	Yes	Yes	Yes
	Model 2 Scenario 2 Serial	PSO & GA and K	610.2795	1679.486675	738.3256591	3028.091834	Yes	Almost same power consumption	Yes	Yes
	Model 2 Scenario 3 Serial	PSO & MIGA and ARIMA & K	572.0822	1667.389775	729.4107591	2968.882734	Yes	Yes	Yes	Yes

Figure 5.51. Overall comparison of power consumption and comfort index

6. Conclusions

In this work, we propose hybrid energy optimization methodologies for users comfort index and energy saving in building environment. Our proposed techniques address both energy savings and occupants comfort index simultaneously. Proposed hybrid techniques integrates in its fitness function the indoor occupants' comfort index and the corresponding energy consumption. Hybrid energy optimization techniques targets to satisfy the occupant's requirements along with minimal energy consumption. A range of user set parameters (temperature, illumination, air-quality) which constitute occupants' comfort index in building are selected and then optimized using proposed hybrid energy optimization algorithms according to the user's comfort index.

The error difference of optimal parameters and real environmental parameters is input to the fuzzy controller. The output of the fuzzy controller is the minimum required power according to the user's comfort index. Coordinator agent takes required power (fuzzy controller output) and optimal parameters from the hybrid optimization algorithms as input. The coordinator agent adjusts the input power of the building on the basis of available power, required power and user comfort index. The adjusted power is compare with the required power to get the actual consume power. The consumed power is input to the Kalman filter and ARIMA prediction algorithms to predict consume power. The predicted consume power is used by the actuators.

Our proposed single and multi-preprocessing based optimization and prediction algorithms consumed less power as compared to basic models. Multi-preprocessing based optimization and prediction models provides much better comfort index as compared to single preprocessing models, but consumed more power than single preprocessing models. Our proposed hybrid energy optimization based on prediction models are simple, user friendly and maintains better user's comfort index and minimized the power consumption without compromising the comfort index as compare to previous works [1-3, 23-32].

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