Non–Intrusive Appliance Load Disaggregation in Smart Homes Using Hybrid Constrained Particle Swarm Optimization and Factorial Hidden Markov Model

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Nowadays, the prediction of the load performances in the smart systems is necessary to generate the minimum energy. In a smart home, there are various appliances that each of them has different behavior. These differences defined as appliance states. In this paper, an effective hybrid method is proposed for load disaggregation of appliances. Factorial hidden Markov model (FHMM) with high accuracy is used for appliances states modeling. In this model, the present state of each appliance is available, and then the defined allowable states for the next instant are provided. For optimal estimation of states, the particle swarm optimization (PSO) algorithm is employed. Furthermore, three constraints are applied in PSO to modify the states matrix; first, every appliance must have one state at any instant; second, considering of the appliances that always is active; and last, using of FHMM for load models production. In the last constraint, by using FHMM, counts of the estimated databases as well as the calculation time are remarkably reduced. In order to show the effectiveness of the proposed method, speed, and accuracy of the responses for practical data of six smart homes are compared with other methods.

keywords: *Non–Intrusive Appliance Load Disaggregation; Smart Home; Swarm Particle Optimization; Factorial Hidden Markov Model*

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NOMENCLATURE

Symbols

i Index of appliance

j, k Index of state

r_i State matrix for ith appliance

L_i Number of states of ith appliance

m Number of all states for each smart home

a_i State value of ith appliance

P_i Power consumption of ith appliance

P_j Nominal rating power of ith state

$s_t^{(i)}$ Total estimated power consumption of ith appliance at instant t

S_t Total estimated power consumption of smart home

S_t Total estimated power consumption of smart home

$\bar{S_t}^{(i)}$ Total actual power consumption of smart home

$AC_{App^{(i)}}$ Mean value of power consumption of ith appliance

AC_{Home} Accuracy of ith appliance

MAE Accuracy of the smart home

$RMSE$ Mean absolute error

MGS Root mean square error

R^2 Relative square error

1. INTRODUCTION

The energy demand reduction instead of increasing the production capacity is necessary to alleviate the costs [1]. The efficiency augment is the main goal for each smart power system. The most of consumers have a smart meter in smart systems. All smart homes (SH) depending on its number of the household have various appliances with different transient and steady behaviors. These behaviors are due to the predefined performance for that appliance. Generally, the two appliances may have the same steady-state performance, but other features can make a significant difference in their transient performance [2]. As the number of appliance transient states increase, the number of operational states will be increased. Non–Intrusive appliance load monitoring (NIALM) is an important service that can help in planning the demand respond of utilities [3]. The task of NIALM is the total energy signal disaggregation of SHs, and reporting of the loads' operation only by measuring the indicated total power consumption on the smart meter [4]. In other words, the purpose of the load disaggregation is the determination consumption patterns of the appliances as well as the demand prediction without using additional sensors. Then, load balancing will be obtained [5]. In Intrusive Appliance load monitoring (IALM), the connected sensors to the appliance are used, which is not cost effective [6]. In contrast, NIALM is an advanced method that can analyze the load data through different and low-cost solutions [7]. Recently, the attractiveness of the load disaggregation using various methods in researches has also brought its practical experiences [8–10]. In [11], an experimental method for estimation of the lighting systems in commercial buildings based on the received signal intensity of the lights is proposed to optimize the energy consumption. In [12], the proposed method accuracy for load disaggregation by using measured data is benchmarked. For identifying the appliances signals based on the analysis and recognition of the active and reactive powers as well as the measured power factor in the steady–state is a novel method which was proposed in [13]. Using the same method in [13], the loads grouping of SH are achieved with accuracy up to 80 % in [14]. The modified linear integer programming (LIP) algorithm is a successful method in the load disaggregation and prediction of the states of the appliances [5], [15], which the final responses are an integer. Consequently, the difference between the predicted and actual powers of the appliances reduces the accuracy, since the appliances don't work in their nominal rating usually. In [16], an algorithm has been used for load disaggregation of electrical vehicle (EV) charging. The use of the fuzzy logic system makes it possible to be an interpretable description of appliances operation and their consumption [17]. In [18], a learning model on the SH data and verified energy efficiency and various sources of the practical errors have been discussed. For estimating the state of appliances, there are various intelligent methods are documented in the literature. The Viterbi algorithm [19] and its modified model [20] has been used to the loads disaggregate of appliances. In [21], authors have converted the load disaggregation into a knapsack problem and solved it with its proposed method. Other heuristic and meta–heuristic algorithms have been used for load disaggregation, which include: feedback algorithm (FA) [22], segmented integer quadratic constraint programming (SIQCP) [?], dynamic fixed share (DFS) [?], graph signal processing (GSP) [?] random forest optimized by particle swarm optimization (RFPSO) [?], Tabu search (TS) [?], two–layer feed–forward artificial neural network (FFANN) [?] and so on. The common drawback of these algorithms is disregarding of the constraints and limiting conditions of a final response, completely. The state of an appliance is a real value between zero and one, which are related to "OFF" and working at the maximum rating defined for the desired state, respectively. If an appliance has more than one operating mode, different power levels and states can be generated at transient instants. One of the accurate methods for modeling the operating modes of the loads is the hidden Markov model (HMM). The HMM is a machine learning algorithm for modeling a set of states at a particular time [?]. Due to its suited structure for modeling appliances consumption, it has a wide application for load disaggregation [?]. In this modeling, appliances with one state can only disaggregate. If the number of appliances states is more than one, the factorial HMM (FHMM) has been utilized for that [?]. Recent researches have shown that the effective method of FHMM can be used to solve the load disaggregation problem [?, ?]. In addition, since most SH appliances change their state independently; the FHMM model is much more suitable for NIALM [20]. Due to the high ability of FHMM, all of the NIALM methods can use this model [?, ?] and its extension [?, ?] for modeling the energy consumption of appliances. In this paper, FHMM is used for loads modeling and the constrained PSO (CPSO) algorithm for their states' disaggregation. In this algorithm, three constraints of the problem have been applied. First, all responses are provided as the initial guess. After applying the proposed constraints, it is optimized to satisfy problem conditions. In the first constraint, each appliance can only be in one defined state for that appliance at any instant. In the second constraint, some appliance is always in "ON" state and it should be considered at all of the instants. In the last, the next allowable states of the appliance are provided by FHMM, so the appliances will be in these states. This constraint not only increases the results accuracy, but it also leads to raise the response speed of the proposed algorithm. Actually, these constraints act as filters to optimize the final answer. The main contributions of the paper can summarize as follows:

- Apply FHMM to define the next allowable state of the appliance. By this model, every appliance can be modeled in a specific tree diagram.
- Apply three constraints for increasing the accuracy of the load disaggregation. These constraints optimize the response and update it for the next steps.
- Mounting three constraints in PSO algorithm and making a hybrid method for optimal load disaggregation.

The paper is organized as follows. In section 2, the problem of optimization of the disaggregation is formulated. In section 3, applied constraints of the problem and the CPSO algorithm are described. Section 4 represents the result of the computer simulations of practical data. Finally, conclusions are presented in Section 5.

2. LOAD DISAGGREGATION OPTIMIZATION PROBLEM

Let assume that a SH has a smart power meter which can record and show the power consumption of any appliances at any instants. If it is considered the total number of appliances at SH is n, and the number of states of appliance i is Li, the state matrix for all appliances is as follows:

$$R = [r_1 \, ; \, r_2 \, ; \, ... \, ; r_i \, ; \, ... \, ; \, r_n]_{m\times 1} \quad , \quad m = \sum_{i=1}^{n} L_i \qquad \textbf{(1)}$$

where,r_i is the state matrix of the appliance i and its size is $L_i \times 1$. The members of the matrix R, generally, are considered as a fraction of the nominal rating for the intended state and can be defined as:

$$
\begin{aligned}
&\qquad\qquad if\\
&a_j \in R\ \forall j \in \{1,2,...,m\}\ \ , \sum_{t=1}^{i-1} L_t\ <\ j\ \le\ \sum_{s=1}^{i} L_s\\
&\Rightarrow \begin{cases} 0 \le a_j \le 1 \Rightarrow \begin{cases} P_i\ >\ P_j\ \rightarrow\ a_j\ =\ 0\\ P_i = P_j\ \rightarrow\ a_j\ =\ 1\\ P_i < P_j\ \rightarrow\ 0 < a_j < 1 \end{cases}\\ if:\ P_j\ <\ P_i \le\ P_{j+1} \Rightarrow \begin{cases} a_j\ =\ 0\\ a_{j+1}\ =\ \frac{P_i}{P_{j+1}} \end{cases} \end{cases}
\end{aligned} \tag{2}
$$

where, P_i is the power consumption of the appliance i, P_j and P_{j+1} are the nominal rating of states j and $j+1$, respectively, and a_j and a_{j+1} are the value of states j and $j+1$, respectively. If a_j is equal to 0, it means that considered state is inactive. If it is equal to 1, it means that the appliance works at a nominal rating of desired state [5]. Finally, if a_j is between 0 and 1, it works on the less than the nominal rating. Also, with regard to 2 it is clear that if the obtained rating for an appliance is greater than the nominal rating of state j and less than the nominal rating of state j+1, the state j value will be zero in the state matrix, and state j+1 value will be the ratio of power consumption (P_j) to its nominal rating (P_{j+1}). In this case, the state matrix at any instant will be has only one non–zero element. At instant t, the smart meter shows the total consumption power of SH as S_t, which is the sum of the power drawn from all appliances at this instant [?]. The total power consumption of appliance i at instant t with the number of L_i states can calculate as:

$$
s_t^{(i)}\ =\ \sum_{j=1}^{L_i} r_{ij}^t\, s_{r_{ij}}\ =\ r_{i1}^t\, s_{r_{i1}}\ +\ r_{i2}^t\, s_{r_{i2}}\ +\ \cdots\ +\ r_{iL_i}^t\, s_{r_{iL_i}} \tag{3}
$$

where in 3, r_{ij}^t is the j–th member of the state matrix at instant t, and S_{rij} is the j–th member of the nominal rating matrix of appliance i; Thus, by using the same method for all appliances, the total estimated power for the SH will be obtained. The final object function for optimization is the minimization of error value between actual power, which is recorded by smart meters, and estimated power ($\underset{t}{\widetilde{S}}$) obtained by the proposed method is as follows [21]:

$$
\min\ \ e_t\ =\ \left|S_t - \tilde{S}_t\right|\ =\ \left|S_t\ -\ \sum_{i=1}^{n}\sum_{j=1}^{L_i} r_{ij}^t\, s_{r_{ij}}\right| \tag{4}
$$

It should be noted that each appliance used at SH has one or more operating states that are specific to it. Some of the working appliances have only two “ON” and “OFF” states [6]. Other ones may have several operating states.

3. LOAD DISAGGREGATION CONSTRAINTS IN CPSO ALGORITHM

A. The Description of constraints

All SHs have different appliances with different states, but some of the conditions are common between all appliances. For example, an appliance cannot be in two operation modes at the same time; or some of them are normally operating 24 hours. In order to simulate the actual situation, these conditions are modeled as constraints. In the following, some basic conditions of the problem are described.

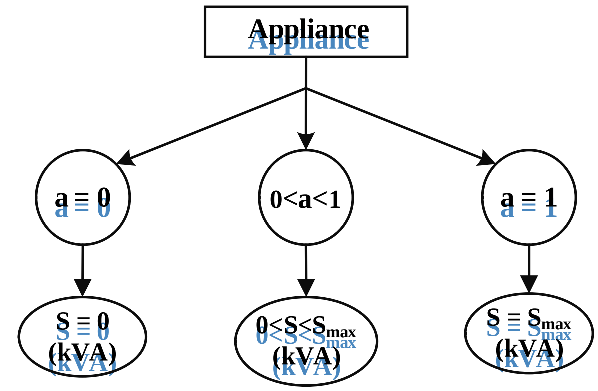

Fig. 1. The tree diagram of power consumption in the appliances with one operational state

Every appliance in one state at any instant

This constraint applies in all appliances in terms of all instants. According to this constraint, at any instant, every appliance can operate in a single state [9]. So, the transient measurements between two sequential instants can be assumed constant, although the instant measurements cannot be equal. In other words, if at $t = t_x$ and $t = t_{x+1}$ the power consumptions are equal to P_x and P_{x+1}, respectively, the following assumption can be applied:

$$
P = \begin{cases} P_x & t_x \le t < t_{x+1}\\ P_{x+1} & t_{x+1} \le t < t_{x+2} \end{cases} \tag{5}
$$

Generally, the connected circuit of the appliance to the home power system can be stated in two types:

a) The appliance has only one state which the three sub-states are defined as: it can operate in “OFF”, sub-nominal power, and in the nominal power;

b) The appliance has more than one (L_i) states, in which case, sub-states ($2L_i + 1$) can be defined for it.

The tree diagram of the sub–states of an appliance with one and more than one state are illustrated in 8 and 2, respectively. In 8,$a = 0$ shows that the appliance is “Offline” or “plug–outed”; so the power consumption will be $S = 0$. Also in this figure, $a = 1$ shows that the appliance operates at its maximum power rating; then $S = S_{\max}$ and appliance is “Online”. Finally, in 8, $0 < a < 1$ shows the “Online” where works at sub–nominal power; in other words, the power consumption of appliance in this mode will be $0 < S < S_{\max}$.

In 2, all appliances work with multiple states ($L_i > 1$). In this Fig., a1 = 0 shows two different conditions:

1) If other states are also in “OFF” mode, it means that the desired appliance is “Offline”.

2) If one of the other states is in “ON” mode ($a_j \neq 0$ and j > 1), the appliance will be “Online”.

Furthermore, in 2, when $a_k = 1$, it means that the $a_{k+1} = 0$. Consequently, the total sub–states for an appliance with L_i state

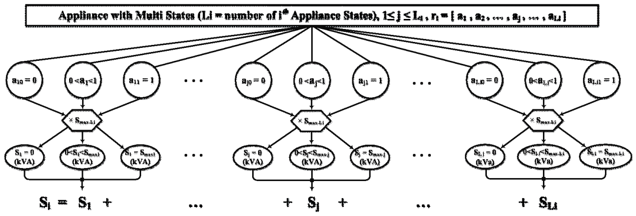

Fig. 2. The tree diagram power of consumption for appliances with more than one operational state

Table 1. The pseudo code for the first constraint

Pseudo Code 1: All appliances must be in only one state at each instant
Inputs: Solution, AppStates, n
Output: NewSolution
for i=1:n
if AppStates(i) >1
Z = Find the State–Number of the Solution Where is Maximum;
for j = 1:Li
if Solution (j) Solution (z)
Solution (j) = 0;(De–Active the Other States)
end
end
end
end
NewSolution = Solution;
Return NewSolution

can be calculated as $2L_i + 1$. The summary explanation for 2 is given in 6 as:

$$S_i = \begin{cases} 0 & if\ :\ a_j\ =\ 0\ \ \forall j \in \{1,2,3,...,L_i\} \\ S_1 & if\ :\ 0 < a_1 < 1\ \ a_j\ =\ 0\ \forall j \in \{2,3,...,L_i\} \\ S_{\max 1} & if\ :\ a_1\ =\ 1\ ,\ a_j\ =\ 0\ \forall j \in \{2,3,...,L_i\} \\ S_j & if\ :\ a_1\ =\ 0\ ,\ 0 < a_j < 1\ \forall j \in \{2,3,...,L_i\} \\ S_{\max -j} & if\ :\ a_1 = 0\ ,\ a_j\ =\ 1\ \forall j \in \{2,3,...,L_i\} \end{cases} \tag{6}$$

where, S_1 is the power consumption of the first state in "Online" mode which is less than maximum power rating, S_{max1}. Also, S_j and $S_{\max -j}$ are the sub-nominal power and nominal rating of state j respectively. S_i is the total power consumption of appliance i which is the sum of all states power consumptions. The pseudo code of the proposed algorithm for this constraint is given in Table 1. In this Table, Solution is the estimated state matrix, AppStates is the defined intrinsic states matrix for appliances, and NewSolution is the updated matrix of Solution after applying the first constraint.

Appliances that always is "Online"

Some appliances in the homes work for 24 hours, although they consume low power. These appliances may only consume the power at their nominal rating during certain hours and in the rest of the day may be in standby mode which has a low power consumption but no non-zero [5]. In the obtained state matrix for these appliances, at least one state must be foreseen to be "ON" state in order to satisfy the intended constraint. The pseudo code of the proposed algorithm for this constraint is shown in Table 2. In this Table, Online$_{A}ppisthematrixofthenumberoftheappliancewhichalwaysis_{1}Online_{in}$

The FHMM to create state transition diagrams

In this paper, FHMM is used to create the next allowable states matrix. The tree diagrams of the HMM [?] and FHMM [?, ?], models are shown in Fig. 3. In HMM, the appliances can have one non–zero state. In this case, only one row is used to model its instantaneous states, which their columns define different instants. Therefore, at each instant of examination, the power consumption of the appliance can be different, which is a fractional of its nominal rating. In FHMM, each appliance has more than one non–zero operation states. This structure is drawn in Fig. 3(a). In this figure, n is the number of states for appliance i. The total time examined in this figure is equal to T, and the output power at any instant is equal to the total power consumption of all states at that instant. According to the first constraint, every appliance can only have a state at any instant. In an HMM, information about the past is conveyed through a single discrete variable—the hidden state. We have used a generalization of HMMs in which this state is factored into multiple state variables and is therefore represented in a distributed manner. Also, in FHMM, There are several independent hidden state chains evolving in parallel and the observation is a joint function of these chains [?]. When an appliance has multi-states, its value of the power consumption is depended to the instant state of the appliance. In the HMM, every appliance works with one state, which cannot change to other. So, it needs a model that describes several chains. Also in the load disaggregation results, it can be seen that embedding interaction characteristics to FHMM decreases errors [?]. FHMM, on the other hand, is well suited to model the interaction of several processes such as appliances contributing independently to the aggregated power measurements [?].

By using the FHMM, the state transition diagrams (STD) can be obtained. Noted that most appliances work as finite state machines, the next possible state can be determined using the STD [5]. Due to having more than one state for most of the examined appliances, it is used the FHMM to get the next permitted state of the appliances. An example of STD is illustrated in Fig. 4. In this figure, which is illustrated for an appliance with 3 operating states, the next allowable states can be derived from this diagram. For example, the allowable states of the appliance after state 2 are states as 1, 2, and 3; while the next allowable states for state 3 are states as 1 and 3. After obtaining the STD, allowable states matrix, A, is formed. It is assumed that the current state is j and the next desired state is k. If the state k belongs to allowable states after the state j, element a_k of matrix A is equal to 1 and if it is not allowable states, it is equal to zero:

Table 2. The pseudo code for the second constraint

Pseudo Code 2: Consider the “Online” appliances in all times
Inputs: Solution, Online_App, n
Output: New Solution
for i=1:n
if i = member of Online_App
Z = Find the Solution for i–th App
if Sum of Solution (i–th App) = 0
Create new random solution for i–th App
end
end
end
NewSolution = Solution;
Return NewSolution

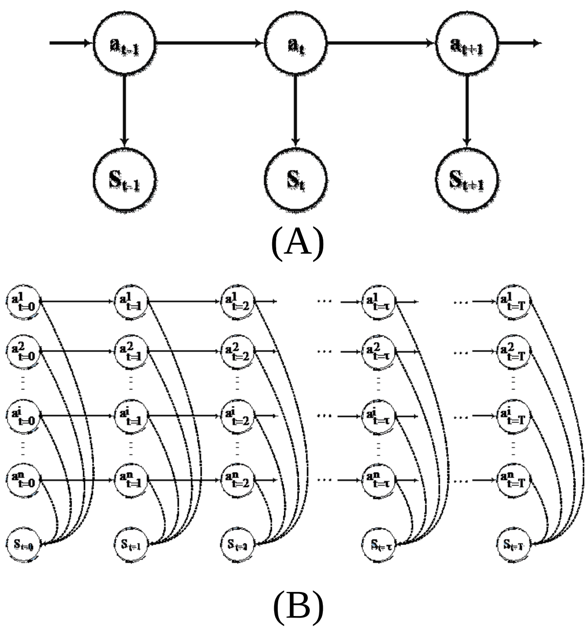

Fig. 3. The tree diagrams: (a) HMM, (b) FHMM

$$\mathbf{A} = \begin{array}{c} \\ s_1 \\ s_2 \\ \vdots \\ s_{L_i} \end{array} \begin{array}{c} \begin{array}{cccc} s_1 & s_2 & \dots & s_{l_i} \end{array} \\ \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1L_i} \\ a_{21} & a_{22} & \dots & a_{2L_i} \\ \vdots & \vdots & a_{jk} & a_{jL_i} \\ a_{L_i1} & a_{L_i2} & \dots & a_{L_iL_i} \end{pmatrix} \end{array} \tag{7}$$
$$\Rightarrow \begin{cases} \forall\, i \in \{1, 2, \ldots, n\} \\ \forall\, j, k \in \{1, 2, \ldots, l_i\} \end{cases}$$
$$\Rightarrow a_{jk} = \begin{cases} 1 & k = j \;\; or \;\; k \in M_j \\ 0 & k \notin M_j \end{cases}$$

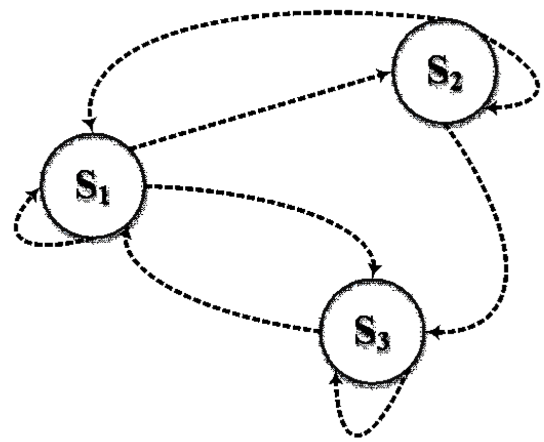

Fig. 4. The STD of an example appliance

where, M_j is the next allowable state matrix for state j of appliance i. It will be calculated for all appliances by the mentioned method. For the appliance which its state diagram is shown in Fig. 4, the allowable states matrix will be as follows:

$$\mathbf{A} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 0 & 1 \end{bmatrix} \tag{8}$$

It can realize from 6 that all elements of the main diagonal of A will equal to 1. This is because of a reasonable assumption that any working appliance in any state can operate in the same state at the next instant. The pseudo code of the proposed algorithm for modeling the allowable matrices to modify the state matrix is presented in Table 3. In this Table, $Old_Solution$ is the old estimated state matrix before this constraint, $Allowable_States$ is the matrix of allowable states for each appliance which is created by FHMM, and $Allow_Solution$ is the updated of $Old_Solution$ after the third constraint.

B. The constrained PSO (CPSO) algorithm

The optimization method used in this paper is the PSO algorithm. In order to compare the speed and accuracy of the results, conditional constraints are also applied to the whale optimization algorithm (WOA) which is a novel meta-heuristic method [?]. In order to achieve the intended response with the conditions stated in section 3.1, the intended constraints were applied separately to the final response. The flowchart of the proposed algorithm is drawn in Fig. 5. In the proposed method, at first, an initial response is generated randomly by the algorithm. The initial error is assumed to be infinite $e_{t0} = \infty$. In the first step, the constraints are applied to update the responses to adapt to problem condition. In the following, an evaluation of the final value is done to find the optimal response. Then, in the second step, the PSO update the velocity and positions of each state as follows:

Table 3. The pseudo code for the last constraint

Pseudo Code 3: Find the STD for All Appliances
Inputs: Old_Solution, n, m
Output: Allow_Solution
Create the Allowable_States Matrix After
Old_Solution by FHMM Algorithm
Allow_Solution = $[1]_{m\times 1}$;
for i=1:n
if App(i).States >1
Find the Indices in Allowable_States Where is zero;
Allow_Solution (Indices) = 0 (Update the Allow_Solution)
end
end
Return
Allow_Solution

$$Velocity\,(:,i) = w\,.\,Velocity\,(:,i) + c_1 \times \eta \times (BestPositions\,(:,i)$$
$$-Positions\,(:,i)) + c_2 \times \eta \times (GlobalPositions\,(:,i)$$
$$-Positions\,(:,i) \tag{9}$$

$$Solution\,(j,i) = Positions\,(:,i) + Velocity\,(:,i) \tag{10}$$

where, Position is the estimated matrix of all appliances states, Velocity is the instant velocity of all appliances, BestPosition and GlobalPosition, are the matrices of the best response obtained at each step and all simulation steps in one instant of measurement for all appliances, respectively. In 9 w, c_1 *and* c_2 are constant coefficients, and η is a random matrix with m members, and its value is between zero and one. In 10, Solution is the new matrix of the estimated states after optimization by the CPSO algorithm.

Then, three constraints are applied to the optimized responses again. As seen in Fig. 5, the proposed method has three main steps; the first production of response, second apply the desired constraints to response in order to optimize it, and last, optimize by PSO and proposed constraints. After re-evaluating the final responses, the best one is defined again. After completing all of the optimization iterations to find the final answer in the first moment, the next step time will be started. If all the instants are optimized completely, the problem is solved. The parameters used in the proposed algorithm are presented in Table 4. The results obtained to determine the accuracy of each appliance and, ultimately, the accuracy of the whole SH can be calculated using the relationships presented in the next section.

After re-evaluating the final responses, the best answer is defined. With completing all of the optimization iterations to

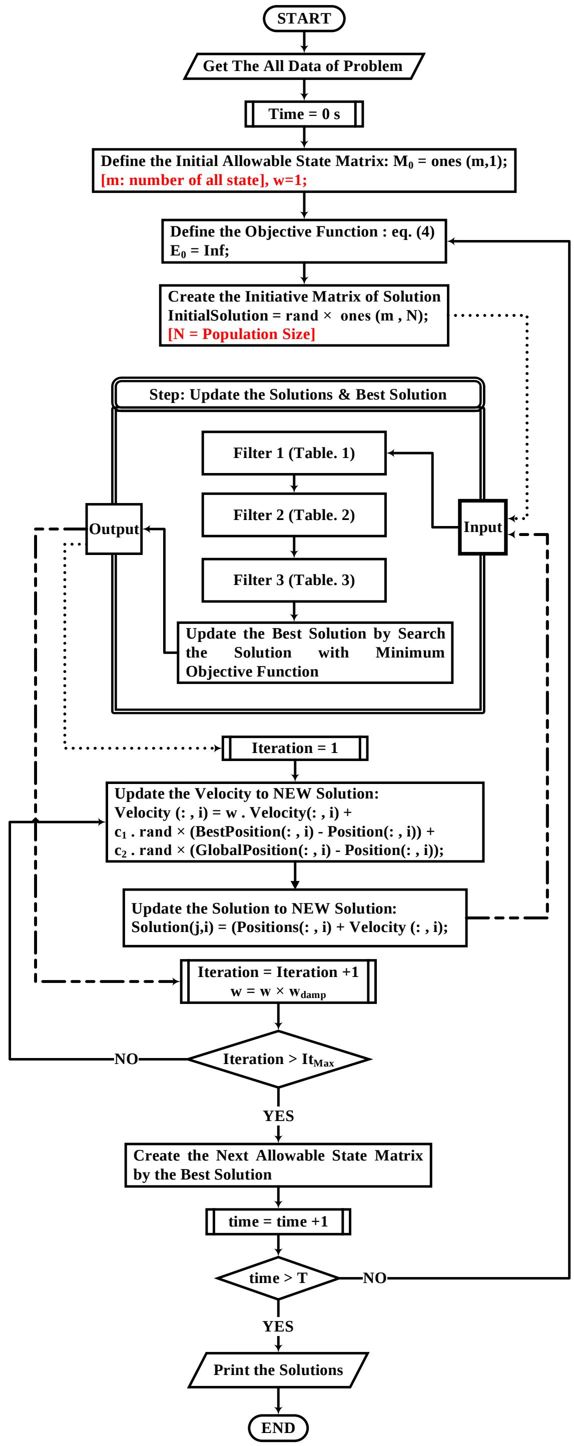

Fig. 5. Flowchart of the proposed algorithm

find the final answer at first instance, the next instant will be began. If all of the instants are optimized, the problem is solved. The obtained results to determine the precision of each appliance and finally, the accuracy of the entire SH can be calculated by using the equations presented in the next section.

Table 4. PSO parameters value

Parameters	Value
Acceleration constants(c_1, c_2)	1.4455, 1.4455
Inertia Weight Damping Ratio (W_{damp})	0.95
Population size (N)	200
Maximum iteration Number (It_{Max})	30

4. SIMULATION RESULTS

After providing the proposed algorithm within the software MATLAB 2016b, different tests have been conducted for proving its optimality. All simulations have been implemented in computer with an Intel(R) Core(TM) i7–6500 CPU@2.50 GHz processor and 12.0 GB RAM. And also, the prediction of obtaining the result is measured by various methods examined in this part as two forms. This accuracy of the result has been divided into the accuracy of the smart appliances and accuracy of the SH that are as follows [1], [9]:

$$AC_{App^{(i)}} = 1 - \frac{\sum_{t=1}^{T} \left| S_t^{(i)} - \tilde{S}_t^{(i)} \right|}{2 \sum_{t=1}^{T} \left| S_t^{(i)} \right|} \tag{11}$$

$$AC_{Home} = 1 - \frac{\sum_{t=1}^{T} \sum_{i=1}^{n} \left| S_t^{(i)} - \tilde{S}_t^{(i)} \right|}{2 \sum_{t=1}^{T} \sum_{i=1}^{n} \left| S_t^{(i)} \right|} \tag{12}$$

where, T is the last instant of the measurement, n is the total number of appliances, $\tilde{S}_t^{(i)}$ is the estimated rating of appliance i at instant t, $S_t^{(i)}$ is real power of appliance i recorded by smart meter at instant t, $AC_{App^{(i)}}$ is the accuracy of the appliance i and AC_{Home} is the accuracy of the consumed load related to the smart house. Data and information of all experiment are taken from [9]. Also, three factors to interpret the estimations error are considered as follows:

$$MAE_{App^{(i)}} = \frac{1}{T} \sum_{t=1}^{T} |S_t^{(i)} - \tilde{S}_t^{(i)}| \tag{13}$$

$$RMSE_{App^{(i)}} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \left[S_t^{(i)} - \tilde{S}_t^{(i)} \right]^2} \tag{14}$$

$$R^2_{App^{(i)}} = 1 - \frac{\sum_{t=1}^{T} \left[S_t^{(i)} - \tilde{S}_t^{(i)} \right]^2}{\sum_{t=1}^{T} \left[\overline{S}^{(i)} - S_t^{(i)} \right]^2} \tag{15}$$

where, $MAE_{App^{(i)}}$ is the mean absolute error of appliance i, $RMSE_{App^{(i)}}$ is the root mean square error of appliance is the root mean square error of appliance i, $R^2_{App^{(i)}}$ is the relative square error of appliance i (or the coefficient of determination), and $\bar{S}^{(i)}$ is the mean value of the appliance i power consumption that can be calculated as:

$$\overline{S}^{(i)} = \frac{1}{T} \sum_{t=1}^{T} S_t^{(i)} \tag{16}$$

RMSE presents a sample to sample comparison between the estimated and true signal [?]. The MAE can get the error of average in a period about the direction which could give a good idea of the performed error in the load disaggregation. We suppose the RMSE to get the average error considering error direction. Also, the RMSE gives the idea concerning the average error between the predicted and actual signal which neglects the error direction. [?, ?, ?]. It is important that in this paper "non-intrusive" loads are addressed. Therefore, the number and rate of the appliances are assumed to be determined. Although for a condition that an appliance is plugged in, the proposed method treats as the flowchart which is shown in Fig.6. In this benchmarking of the proposed method, six SHs have been considered. The values of power consumption of each appliance in the SHs are measured throw the smart meters. Some appliances are commonly used, while others used separately for each home. Also, the other difference between SHs is in the number of appliances which is always is "ON" state. In addition, different sampling times for power consumption of SH appliances are considered to confirm the validity of the proposed method.

A. Experiment NO. 1

In experiment 1, the SH has $n = 7$ appliances with $m = 13$ states. The information for these appliances is summarized in Appendix A. According to this information, during the study time, only appliance 4 always is "Online". Total measurement time is considered as 2 weeks. For this, the data are downsampled by factor 20 for sampling at the 1 minute. In this respect, the number of samples will be 201600. The simulation results with the proposed algorithm, LIP [15], ALIP [5] and CWOA algorithms for (11)–(15) are tabulated in Table 5. As shown in this table, the results obtained for the proposed algorithm are better than other methods. But due to the existence of the long loops in evolutionary algorithms (EA), the time of the calculation for these algorithms is relatively high. The average execution time (AET) per sample for CPSO is 450 ms, while this time for the IP is 14 ms, because of its simplicity of operation. On the contrary, the results obtained for all the appliances show the high accuracy of the proposed algorithm. In the case of appliances 1, 3, 4, 5, and 6, the accuracy of CPSO and CWOA are same. Also, the overall accuracy of SH for CPSO is better than others. In a SH there are a different condition of plug in/out for every appliance. For instance, consider an appliance with 3 states and its defined nominal rating; if it plugs in at instant $t = t_k > 0$, data estimation for that appliance should carry out after tk. Stove is considered for studying this condition. Also, $t_k = 1000$. The new results after adding this appliance are written in Table 6. It shows the best result for the proposed method.

B. Experiment NO. 2

In this experiment, SH 2 has $n = 6$ appliances with $m = 17$ states. The information of these appliances is summarized in Appendix A. The total measurement time is 10 days. So, the data are downsampled by factor 5 for sampling at 15 seconds. Therefore, the number of all data will be 57600 samples. The simulation results of load disaggregation by implementing of aforementioned algorithms are tabulated in Table 7. As seen in this Table, the AET per sample of the proposed algorithm is 462 ms which is lower than CWOA, and more than LIP and ALIP. The accuracy of the appliance 4, i.e. Microwave, for CWOA is higher than others and is 0.99. About the appliance 6, i.e. Dishwasher, the ALIP algorithm has as same accuracy as CPSO, 0.89. The load disaggregation accuracy of appliances 1, 3, 5 for

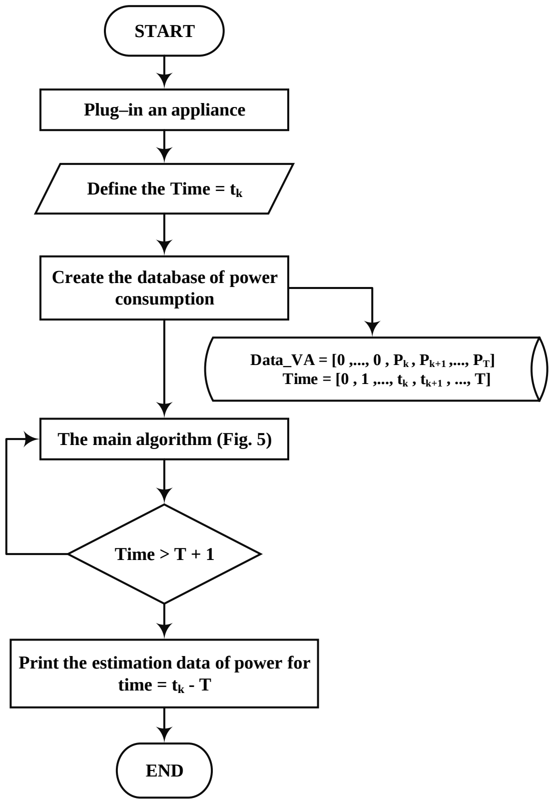

Fig. 6. Flowchart of the proposed method for appliances which plug in after evaluating

CPSO and CWOA is equal. Finally, the overall accuracy of SH 2 has the least value for the LIP algorithm and the highest value for the CPSO algorithm. Also, the other results of the proposed method are better than others. The truth and estimated data by four method for all 2 are drawn in Fig. 7.

C. Experiment NO. 3

We considered SH 3 with $n = 7$ appliances $m = 20$ states. The total measuring time is 13 days. So, factor 10 is applied to down-sample the data for sampling at the 30 seconds. In this case, the total number of data will equal to 37440. In Table 8, the simulation results of load disaggregation for desired SH appliances have been written. According to this table, in appliance 3, i.e. Clothes–Dryers, the accuracy is given by ALIP, CWOA and CPSO are the same. Also, the obtained accuracy by CWOA is equal to CPSO for appliance 2, 4, and 5. In other cases, the proposed method is more accurate; so that the accuracy of the most appliances is approximately is near to 1. Likewise, it has been taken lower AET than CWOA for every load disaggregation. Furthermore, the R^2 results for CPSO are so better than the other three algorithms. For example, the value for SMK is obtained 0.45 by CPSO, while for CWOA it is –0.79; worse still, its value for ALIP and LIP is –4.08 and –36.36 which it means divergent results.

D. Experiment NO. 4

In experiment 4 for SH 4, $n = 8$ appliances with $m = 20$ states are considered. The total measuring time is taken to 2 weeks. The data are sampled by factor 10 for sampling at 30 seconds. Thus, the total number of data will equal to 40320. The simulated results for SH 4 brought in Table 9. For appliance 2, i.e. kitchen Outlets, the accuracy is obtained 0.8 for tow ALIP and CWOA methods, while the proposed algorithm shows the better, 0.98. Also, the appliances 4 and 7 have the same accuracy, 0.99, for both CWOA and CPSO. Furthermore, CWOA has better performance than others in appliance 6, i.e. Smoke Detector. As seen in Table 9, the load disaggregation of appliance 5, i.e. Air Conditioner, is unsuccessful for all of the methods, while the maximum accuracy is related to the CPSO algorithm, 0.84. For the other appliances, the proposed algorithm has high accuracy in the loads' disaggregation for the considered SH. As well as, the calculated overall accuracy of SH 4 by the proposed algorithm is more than the other algorithms.

E. Experiment NO. 5

In experiment for SH 5, we considered $n = 6$ appliances that have $m = 24$ states. The data are sampled by factor 10 for sampling at the 30 second, which the number of all data will be 5760 sample. The load disaggregation accuracy values for all appliances and desired SH are tabulated in Table 10. In the appliances 2, 3, and 6 the accuracies of the proposed method are less than the CWOA algorithm. Also, it is equal for these methods for appliance 4, i.e. Sub–Panel. About other appliances and SH, the load disaggregation for CPSO is more successful than other algorithms.

F. Experiment NO. 6

In this experiment, SH 6 was assumed with $n = 7$ appliances and $m = 20$ states. The total measuring time is taken to 2 days. For this, the data are sampled by factor 10 for sampling at the 30-second intervals. In this case, the total number of data will equal to 17280. In Table 11, the simulated results are shown for the SH 6 in terms of all algorithms. The accuracy of the appliance 2, i.e. Bathroom GFI, calculated from CPSO and CWOA is the same, 0.99. According to Table 11, the obtained accuracy is the same each other for three ALIP, CWOA and CPSO in appliance 6, i.e. Air Conditioner. In the other appliances as well as overall accuracy, the proposed algorithm has better performance. Generally, the results of the proposed algorithm, including the appliance accuracy and overall accuracy, are better than other algorithms. In all experiments 1 to 5, the LIP algorithm has the least AET, while it is so much for both EA–based algorithms. It should be mentioned that the AET for CPSO is less than CWOA. According to the enhancement of the overall accuracy of SH with CPSO algorithm, aside from AET, it can be stated that the proposed method outperforms than others. The overall accuracy of all SHs for all discussed methods is illustrated in Fig. **??**. It should be noted that in all cases, the LIP method has the least accuracy and CPSO method has the highest one.

G. Conclusion

In this paper, a method for the loads' disaggregation of appliances of the SHs equipped with the smart meter is proposed. In this study, the PSO optimization algorithm is used to increase the accuracy of the load disaggregation result. Given the being constrained of the principle of the load disaggregation problem, three constraints added to this algorithm to find a more exact response. This method increased the success of the proposed method with regard to a vast application in these problems. The indicated results also prove this subject. This means that, on

Table 5. Simulation results for SH 1

APP.	LIP				ALIP				CWOA				CPSO			
	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2
OVN	0.65	39.02	393.2	–1.99	0.63	11.88	207.0	0.16	0.99	0.80	3.53	0.99	0.99	0.11	0.79	1.00
FRG	0.78	31.24	87.51	0.03	0.85	21.90	72.1	0.34	0.69	32.36	80.0	0.19	0.97	1.47	18.90	0.95
DSH	0.88	40.95	145.0	0.06	0.92	7.386	58.5	0.84	0.99	1.36	6.39	0.99	0.99	0.37	3.43	0.99
MIC	0.74	27.66	188.9	–0.27	0.83	19.69	152.9	0.16	0.99	0.37	1.78	0.99	0.99	0.17	1.38	0.99
DRY	0.64	34.81	266.6	0.24	0.78	22.96	204.0	0.55	0.98	2.29	24.9	0.99	0.98	1.24	24.89	0.99
BTH	0.62	22.62	185.6	–2.56	0.70	13.21	139.1	–1.00	0.99	1.37	3.54	0.99	0.99	0.15	1.15	0.99
DIF	0.61	50.67	322.0	0.13	0.95	26.74	175.4	0.74	0.97	16.36	62.0	0.96	0.99	4.44	15.51	0.99
AC_{Home}	0.51				0.76				0.89				0.98			
AET (ms)	14.133				19.098				509.251				450.321			

Table 6. Simulation results for SH 1, after plugging new appliance

APP.	LIP				ALIP				CWOA				CPSO			
	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2
STV **	0.82	6.21	75.11	0.18	0.83	4.22	65.65	0.61	0.89	0.09	0.88	0.97	0.93	0.07	1.44	0.97
AC_{Home}	0.58				0.79				0.89				0.96			
AET (ms)	14.111				19.101				509.258				450.325			

Table 7. Simulation results for SH 1, after plugging new appliance

APP.	LIP				ALIP				CWOA				CPSO			
	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2
KTC	0.89	11.82	68.08	0.59	0.94	5.62	52.80	0.75	0.99	0.32	1.50	0.99	0.99	0.39	4.54	0.99
LTE	0.92	8.29	17.57	0.85	0.92	4.94	20.85	0.80	0.93	3.37	12.87	0.92	0.94	2.04	9.39	0.95
STV	0.75	7.61	77.63	0.27	0.71	8.28	75.17	0.31	0.99	0.12	1.42	0.99	0.99	0.07	1.54	0.99
MIC	0.81	7.07	57.95	0.64	0.87	4.18	46.58	0.76	0.99	0.21	3.11	0.99	0.98	0.31	4.63	0.99
DRY	0.97	2.27	26.44	–0.78	0.84	2.19	25.83	–0.70	0.99	0.03	0.37	0.99	0.99	0.01	0.34	0.99
DSH	0.83	0.61	1.15	–1.26	0.89	0.38	0.79	–0.05	0.86	0.46	0.94	–0.50	0.89	0.31	0.72	0.11
AC_{Home}	0.72				0.81				0.97				0.98			
AET (ms)	14.352				17.018				574.091				462.112			

average, the appliances examined for each of the six SHs have an accuracy of above 0.98. Also, the average overall accuracy for all homes is equal to 0.99, which indicate the high focus of the proposed method. In comparison with other methods, LIP and ALIP, the accuracy of the proposed method is adequately great. Moreover, the speed of the proposed method is so higher than CWOA. While the speed of both considered smart algorithms is less than the IP algorithms. Its cause is a high volume of search space that these algorithms create in work starting. In fact, by integrating three methods based on possibility, constraining, and FHMM an optimum method is yielded with suitable accuracy.

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Table 8. Simulation results for SH 3

APP.	LIP				ALIP				CWOA				CPSO			
	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2
FRG	0.90	7.62	40.56	0.45	0.89	4.36	28.10	0.73	0.89	6.79	25.68	0.77	0.98	0.30	8.21	[illegible]
DSH	0.83	10.04	75.46	–1.01	0.90	8.91	59.97	–0.27	0.99	0.25	5.04	0.99	0.99	0.28	0.71	[illegible]
DRY	0.85	21.21	253.68	0.71	0.99	4.93	42.83	0.99	0.99	0.32	6.75	0.99	0.99	0.60	13.10	[illegible]
MIC	0.61	12.75	124.41	–1.20	0.87	2.45	60.07	0.48	0.99	0.26	2.43	0.99	0.99	0.21	0.57	[illegible]
BTH	0.68	14.45	130.87	–0.30	0.90	3.74	64.21	0.68	0.99	0.45	2.31	0.99	0.99	0.09	2.58	[illegible]
FRN	0.62	10.48	79.77	–0.51	0.75	4.66	54.87	0.28	0.98	0.42	4.41	0.99	0.99	0.19	3.43	[illegible]
SMK	0.13	1.64	3.32	–36.36	0.63	0.49	1.22	–4.08	0.80	0.21	0.72	–0.79	0.85	0.16	0.40	[illegible]
AC_{Home}	0.66				0.87				0.96				0.99			
AET (ms)	12.112				19.569				534.281				489.648			

Table 9. Simulation results for SH 4

APP.	LIP				ALIP				CWOA				CPSO		
	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE
LTE	0.75	23.5	55.02	–0.51	0.73	8.56	34.48	0.40	0.89	2.55	15.45	0.88	0.98	0.25	3.25
KTC	0.64	33.41	76.72	–0.20	0.80	15.16	57.22	0.33	0.80	21.58	52.78	0.43	0.98	0.98	11.79
DRY	0.67	9.43	64.13	–1.11	0.64	6.34	51.01	–0.33	0.98	0.22	4.45	0.98	0.99	0.12	2.03
STV	0.64	7.06	60.43	0.006	0.67	3.56	54.47	0.19	0.99	0.49	4.07	0.99	0.99	0.79	2.11
ARC	0.57	10.11	20.09	–110.48	0.52	0.71	5.48	–7.30	0.67	0.59	2.25	–0.40	0.84	0.21	1.06
SMK	0.32	1.69	3.12	–396.07	0.77	0.12	0.38	–4.91	0.91	0.34	0.61	–14.51	0.74	0.22	0.47
DSH	0.70	4.90	77.78	0.28	0.88	2.58	54.25	0.65	0.99	0.17	1.07	0.99	0.99	0.13	1.01
BTH	0.82	2.54	47.08	–2586.34	0.89	0.89	17.92	–374.02	0.83	0.32	0.64	0.50	0.96	0.10	0.22
AC_{Home}	0.41				0.76				0.83				0.98		
AET (ms)	14.721				24.789				683.341				540.790		

Table 10. Simulation results for SH 5

APP.	LIP				ALIP				CWOA				CPSO		
	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE
MIC	0.25	3.67	26.90	–17.94	0.58	0.86	7.85	–0.61	0.77	0.35	4.44	0.48	0.97	0.09	[illegible]
LTE	0.77	7.84	40.54	0.34	0.86	3.5	29.27	0.66	0.99	0.20	2.42	0.99	0.98	0.16	[illegible]
UKN	0.59	3.89	20.48	–3.75	0.67	1.49	11.90	–0.60	0.95	0.08	1.92	0.95	0.94	0.10	[illegible]
SBP	0.58	5.08	43.85	–0.41	0.69	3.49	37.71	–0.04	0.98	0.21	3.20	0.99	0.98	0.06	[illegible]
HEA	0.50	0.52	28.69	–9.06 × 104	0.50	0.19	17.72	–3.46 × 104	0.91	0.01	0.16	–2.16	0.98	0.008	[illegible]
DIF	0.64	2.97	23.69	–0.25	0.69	1.94	21.35	–0.02	0.98	0.34	3.72	0.96	0.97	0.53	[illegible]
AC_{Home}	0.55				0.78				0.97				0.98		
AET (ms)	15.679				16.605				673.711				550.412		

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Table 11. Simulation results for SH 6

APP.	LIP				ALIP				CWOA				CPSO			
	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2	AC	MAE	RMSE	R^2
ELE	0.72	10.02	78.08	–4.63	0.70	3.75	44.42	–0.82	0.98	0.08	2.77	0.99	0.99	0.04	1.73	0.99
BTH	0.53	6.31	73.45	–33.77	0.55	0.33	12.47	–0.004	0.99	0.47	1.06	0.99	0.99	0.26	0.65	0.99
FRG	0.65	22.54	66.40	–1.38	0.78	12.22	44.53	–0.07	0.96	1.08	8.85	0.95	0.98	0.18	7.84	0.96
UKN	0.65	37.17	80.65	–2.25	0.74	9.76	41.11	0.15	0.88	3.79	18.26	0.83	0.98	0.21	4.33	0.99
LTE	0.61	26.71	89.93	–19.94	0.90	6.45	25.23	–0.64	0.93	3.96	13.75	0.51	0.99	0.32	5.66	0.91
ARC	0.68	29.94	235.18	0.39	0.98	4.117	31.22	0.98	0.98	1.54	13.50	0.99	0.98	1.47	15.59	0.99
DIF	0.48	24.21	68.91	–3.99	0.69	11.89	46.10	–1.23	0.93	2.82	11.46	0.86	0.98	0.49	5.99	0.96
AC_{Home}	0.43				0.83				0.95				0.98			
AET (ms)	16.029				23.54				738.390				567.284			

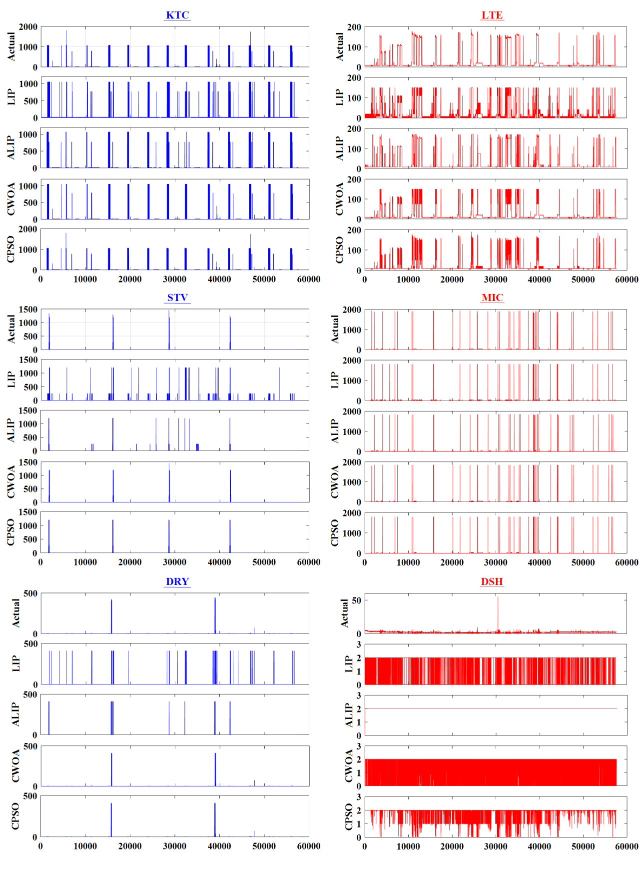

Fig. 7. The truth and estimated data by four methods for all appliance of SH 2

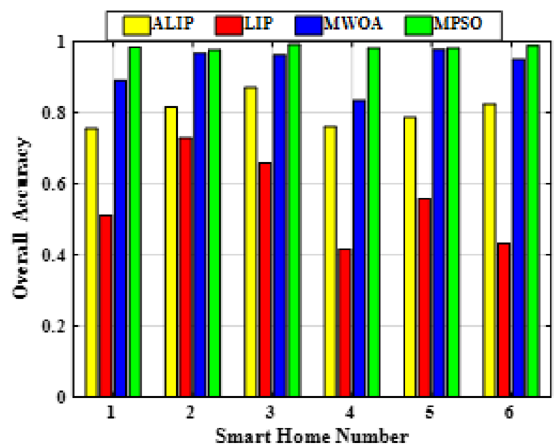

Fig. 8. The overall accuracy of all methods

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