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Baseline Demand Responsiveness Framework for the Conventional Grid through Appliance Scheduling by Evolutionary Metaheuristics

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ABSTRACT

Baseline Demand Responsiveness Framework for the Conventional Grid through Appliance Scheduling by Evolutionary Metaheuristics

A major problem of many energy environments nowadays, is an obsolete and highly inefficient electricity supply system, the Conventional Grid (CG), characterized by a high peak to average ratio, out of an uncontrollable demand, worsened by a native lack of communications infrastructures and resources for performing a proper automated demand side management, which has resulted in blackouts, harsh user discomfort, high electricity cost, huge economic losses and a high carbon footprint.

Designed to tackle this problem is the emerging Smart Grid (SG). Most research works are devoted to providing automation and efficiency to the SG (or the intermediate SG-like) environments. There is a scarcity of research devoted to providing automated demand responsiveness to the information layer deprived CG environments, although as evident, an Automated Demand Response (ADR) is badly required, since there is still a long way until we get to the SG, all the more when developing world is concerned.

Such context, set our focus towards the CG. So, this research work, developed a framework for providing a "blind" baseline Demand Responsiveness (bbDR) for CG environments, wherein, a pseudo real time electricity pricing function, built from a country load profile, is used as a guiding function for the autonomous scheduling of controllable appliances, which seeks to improve electricity consumption patterns, while also preserving user satisfaction by complying to their preferences. For performance evaluation, the optimized energy consumption patterns (peak load, peak to average ratio, load and cost profiles and mean energy rate) of the controlled use of appliances, are compared to those ones produced by their uncontrolled use. The controlled usage schedules are produced by an evolutionary metaheuristics, whilst the uncontrolled usage is stochastically generated from appliances' rate-of-use probabilities sourced from the literature. The results proved that, such framework is capable of, without DR communications, delivering meaningful, ADR-like, performances to a communications deprived CG environment.

As part of the work for simulating the above bbDR framework, we developed and demonstrated a Real Parameter Blackbox Optimization Approach to Appliance Scheduling (RPBBOAS) model, which describes the household, and provides the logical interface with the optimization algorithms. This real parameter model, vis-a-vis its discrete parameter counterpart, tackles combinatorial explosion by, in a novel way, reducing the problem dimension that is traded with the external blackbox optimization algorithms, in such a way that boosts performance and widens the window of applicable algorithms.

While developing the above RPBBOAS model, readily available state-of-the-art metaheuristics showed a lackluster performance, which propelled us to design a novel hybrid evolutionary metaheuristics (HyPERGDx) that was eventually used in the bbDR simulations. It showed a better all-around performance and robustness vs the state-of-the-art, when benchmarked on a wide range of non-linear problems.

Overall, such deliveries, demonstrated the potential of the proposed bbDR framework for improving demand patterns and quality of service figures, in a communication free way, which with an appropriate follow-up development, makes it suitable for application in severely affected, communications deprived (or communications limited), energy networks such as South Africa or worse energy ecosystems.

Keywords: Appliance, Appliance Scheduling, Household Energy Management, Demand Side Management, Demand Response, Conventional Grid, Smart Grid, Smart Load, Smart Appliance, Grid Friendly Appliance, Swarm Intelligence, Evolutionary Computation, Heuristic optimization, Blackbox Optimization, Metaheuristics, Hybrid Algorithms

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I lastly, but endlessly, thank God!, for His protection and all what He has been giving!

Contents

List of Figures

List of Acronyms

ADR Automated Demand Response. iii, x, 9

AIS Artificial Immune System. 39

AMI Advanced Metering Infrastructure. 9, 19

AMO analytical/mathematical optimization. 42

bbDR "blind" baseline Demand Responsiveness. iii, x, 5, 7

BBOA Blackbox Optimization Algorithm. 73

BEMS Building Energy Management System. 22

BPSO Binary Particle Swarm Optimization. 38

CG Conventional Grid. iii, 3, 9

CHP Combined Heat and Power. 20

CMA-ES Covariance Matrix Adaptation Evolution Strategy. xxiv, 156, 157

CoD "curse of dimensionality". 6, 59

CPP Critical Peak Pricing. 28

CSA Cuckoo Search Algorithm. xvii, 158

CvxP Convex Programming. 42

DAP Day Ahead Pricing. 28

DE Differential Evolution. ix, 160, 161, 160

DER Distributed Energy Resources. 11, 17, 20

DESto Distributed Energy Storage. 20

DEvec3 Storn&Price's Standard Differential Evolution. 83

DG Distributed Generation. 20

DLC direct load control. 2, 27

DLP Daily Load Profile. vii, 7, 9, 24, 32, 45

DP Dynamic Programming. 42

DR Demand Response. vii, x, 1, 8, 22, 28

DSM Demand Side Management. 2, 9, 21

DSO Distribution System Operator. 12

dUPW cycle duration UPW. 66

EBO Effective Butterfly Optimizer. ix

EBOwithCMAR Effective Butterfly Optimizer with CMA Retreat Phase. 82

EC Energy Consumption. viii, 1, 8, 46

ED-CPP Extreme Day CPP. 28

EDP Extreme Day Pricing. 28

EMS Energy Management System. 11, 40

ERT Expected Running Time. 83, 89, 90

ES Evolution Strategies. 44, 156

ESto Energy Storage. 38

EV Electric Vehicle. 17, 19

FIT Feed-In Tariff. 30

FLP Flat-Price. 30

FPGA Field-Programmable Gate Array. 26

GA Genetic Algorithm. 59

GFA Grid-Friendly Appliance. 17

GHGs greenhouse gases. 9

HAN Home-Area-Network. 9, 17

HEMS Home Energy Management System. vii, 4, 8, 35

HyPERGDx Hybrid, Particle swarm, Evolution strategies, Random walks, Genetic, Differential and miscellaneous Ant-Inspired Cooperative Xplorers. viii, 48

IBR Inclining Block Rates. 30

IR instant reserve. 27

JADE Adaptive Differential Evolution. 160

L-SHADE Linear (Population Reduction), Success History (based) Adaptive DE. 160

LDWPSO Linearly Decreasing Inertia Weight Particle Swarm Optimization. 81

LIWPSO Linearly Increasing Inertia Weight Particle Swarm Optimization. 81

LP Linear Programming. 42

LR-CMA-ES Local Restart Covariance Matrix Adaptation Evolution Strategy. 83

Mat.GA Matlab's ga. 83

Mat.PSO Matlab's particleswarm. 83

MILP Mixed Integer Linear Programming. 42

MINLP Mixed Integer Non-Linear Programming. 42

NFL "No-Free-Lunch". 43, 90

NIST National Institute of Standards and Technology. 15

PAR Peak-to-Average Ratio. vii, 2, 9, 23, 24, 121, 132

PBM population based metaheuristic. xvii, 43, 155

PNNL Pacific Northwest National Laboratory. 25

PSO Particle Swarm Optimization. xxii

PV Photo-Voltaic. 13

QP Quadratic Programming. 42

QPSO Quantum Particle Swarm Optimization. 83

RBFNN Radial Base Function Neural Network. 39

REMS Residential Energy Management System. 35

RoPs Rate of Problems Solved. 82, 83, 92, 93

RoU Rate of Use. 110

RPBBOAS Real Parameter Blackbox Optimization Approach to Appliance Scheduling. vii, 6, 7, 48, 73

RTP Real Time Pricing. 5, 45

SG Smart Grid. iii, 3, 9, 14

SPSO2011 Standard PSO 2011. 83

SR spinning reserve. 27

SSM Supply Side Management. 14

ToUP Time of Use Probability. x, 110

ToUT Time of Use Tariff. 28, 45

TSO Transmission System Operator. 12

tUPW cycle placement UPW. 66

UAS uncertainty-aware system. 25

UEC Unit Energy Consumption in KWh/Year. 112

UPW User preferred appliance working window. x

WPSO Inertia Weight Particle Swarm Optimization. 81

Glossary of Symbols

Symbol	Description
$DLPh$	Daily (24h) load profile for some household.
$DLPc$	Country daily (24h) load profile.
τ	Simulation/control horizon unit time step.
ρ	The hourly relative resolution; it equates to the number of τ time steps comprised in 1h; i.e., $\rho = 3600/\tau$.
T	Continuous time simulation/control horizon.
D, d	Used frequently as the dimension of the given candidate solution, the problem size, the dimension of the problem space.
X, x	X or x, is frequently used to represent the design space parameter of some dimension D. X or x is also called solution, candidate solution, particle in population based metaheuristic (PBM) parlance. Note that X has also been used with other meaning in (Eq.22), where it is a homogeneous Poisson point process random variable, representing the number of arrival events in a given time interval.
X_L	The lower bound of the problem space, a scalar or a vector of the problem size.
X_U	The upper bound of the problem space, a scalar or a vector of the problem size.
N_t	Number of discrete time steps comprised in the simulation/control horizon.
Td	Discrete time representation of the simulation/control horizon T.
t	most frequently used as time index, for pointing to discrete time steps of the simulation/control horizon T or T_d. Then for all such cases, it also equates to discrete time. t is also used as: continuous time: as in (Eq.22); as iteration counter (implicitly continuous time) in (Eqs.25) through (Eqs.27).

Symbol	Description
N_a	Number of appliances for some household.
α	Household's user centricity coefficient; a greater α prioritizes user comfort over energy cost reduction.
β	Household's energy centricity coefficient ($\beta = 1-\alpha$), a greater β prioritizes energy cost reduction over user comfort. β is also used as the Lévy distribution index, used in the generation of Lévy random walks (Lévy flights) in the Cuckoo Search Algorithm (CSA).
ς	Household's user preference window start-up time (or active timeslot) misplacement penalty coefficient; the greater is ς vs δ, the greater the share of cycle placement vs cycle duration in the user preference window penalty function $\Pi_{upwd}(.)$.
δ	Household's user preference window duration mismatch penalty coefficient; the greater is δ vs ς, the grater the share of cycle duration vs cycle placement in the user preference window penalty function $\Pi_{upwd}(.)$.
P_{Bi}	Household's controlled appliances instant power budget (in KW): the total maximum allowed instant power demand for schedulable appliances.
E_{Bd}	Household's 24h total energy consumption budget (KWh) for schedulable appliances: the maximum allowed total per 24h energy consumption for schedulable appliances.
H_{def}	Household's settings vector. It holds the current values of $\alpha, \varsigma, \delta, \tau, T, P_{Bi}$ and E_{Bd}.
i	Used as a generic index with different meanings in different contexts.
j	Used frequently (but not exclusively) to reference the generic appliance, eg. "appliance j", i.e., the j-th of the household's appliances.
k	Used most frequently to index the generic cycle of certain appliance j; it frequently comes along with j as indexes for some cycle C, eg.: C_{jk} denotes the cycle k of appliance j. However, k is not used exclusively with the above meaning; eg.: in (Eq.22), k is a number of random events.
m	m is used frequently (but not exclusively) for the total number of household's appliances. m is also used to represent the mean of an evolution strategy metaheuristics.

Symbol	Description
K_j	The total number of cycles for some appliance j in the household.
K	Used frequently (but not exclusively) for the collective total number of appliances' cycles, ie, for all appliances. K is also used in the CSA algorithm, to represent the component-wise portion of the nest that will effectively mutate as a result of applying the mutation operation according to pa.
c	Used frequently (but not exclusively) as a linear cycle index, a pointer to some cycle in $\{C_i\}$ the vector of linear indexes for the union set of all appliances' duty cycles.
C_{jk}	Represents the working cycle number k of the j-th appliance, a vector of length 2, comprised by a start-up time and an end time.
C_{Ojk}	Represents the extended working cycle number k of the j-th appliance, a vector of length 2, comprised by a start-up time and a end time, wherein the end time is extended to include an inter-cycle time.
C_{Ovr}	Represents the union set of all extended working cycles that a given C_{Ojk} cycle should not be overlapped with, i.e. no contemporaneity is admitted between C_{Ovr} and C_{Ojk}.
$\{C_{jk}\}$	The vector containing linear indexes for the union set of all appliances' working cycles in the household's appliance database.
S_t, s_c	Represents starting time pertaining to some appliance cycle.
D_t, d_c	Represents duration time pertaining to some appliance cycle.
N_{Cdef}	A vector holding the total number of preferred ducty cycles for each one of the hosehold's schedulable appliances.
Pn_j	Nominal power of the j-th appliance.
Psb_j	Standby power of the appliance j.
Ton_j	The vector of active (powered on) time steps of the appliance j, out of the simulation/control horizon.
Tsb_j	The vector of standby (= inactive) time steps of the appliance j, out of the simulation/control horizon.

Symbol	**Description**
A_{T_j}	Power control type of the appliance j; a boolean variable, determines whether the appliance is or not controllable. A value $A_{T_j} = 1$, determines that the appliance is controllable.
W_{zj}	Set of predefined "no-go" zones for appliance j: design space windows not allowed, for schedules placement for the schedulable appliance j.
W_{pj}	Set of run time adaptive "precedent" zones for appliance j: schedules placement not allowed before the end of latest W_{pj} window (which may vary at run time), for the schedulable appliance j.
A_{def}	User preferred appliance settings tuple. It holds the current values of Pn_j, Psb_j, A_{T_j}, W_{zj}, W_{pj} for each one of the m household appliances.
W_{Tdef}	A tuple containing definitions of user preferences or baseline values for appliances' cycles start times and their boundary constraints.
π^T_{jk}	Start-up (or generally: active time slot) misplacement penalty type for appliance j cycle k.
T^L_{jk}	The absolute lower bound start-up time for cycle k of the j-th appliance.
T^U_{jk}	The absolute upper bound active time for cycle k of the j-th appliance.
T^{OL}_{jk}	User preferred cycle placement window lower bound start-up time for cycle k of the j-th appliance.
T^{OU}_{jk}	User preferred cycle placement window upper bound active time for cycle k of the j-th appliance.
T^O_{jk}	User preferred optimal start-up time for cycle k of the j-th appliance.
W_{Ddef}	A tuple containing definitions of user preferences or baseline values for appliances' cycles duration times and their boundary constraints.
W^T_{jk}	User preferred window interval for cycle k of the j-th appliance, bounded by the worst case preferred active time placements .
W^{TO}_{jk}	User preferred optimal sub-window (within W^T_{jk}); the user preferred optimal placement for working cycle k of the j-th appliance.
W_{oEt}	The end time of the user preferred optimal sub-window (W^{TO}_{jk}).

Symbol	**Description**
W_{jk}^{DO}	User preferred optimal duration sub-window; the user preferred optimal duration for working cycle k of the j-th appliance.
π_{jk}^{D}	Duration mismatch penalty type for appliance j cycle k.
D_{jk}^{L}	The absolute lower bound duration for cycle k of the j-th appliance.
D_{jk}^{U}	The absolute upper bound duration for cycle k of the j-th appliance.
D_{jk}^{OL}	User preferred lower bound cycle duration for cycle k of the j-th appliance.
D_{jk}^{OU}	User preferred upper bound cycle duration for cycle k of the j-th appliance.
D_{jk}^{O}	User preferred optimal duration for cycle k of the j-th appliance.
D_{jk}^{Ocnt}	User defined range of the preferred optimal duration for cycle k of the j-th appliance.
I_{ct}, I_{jk}^{CT}	The minimum inter-cycle time as per user preference or per operational/technical imperative; I_{jk}^{CT} is the inter-cycle time for appliance j cycle k: a minimum delay before staring next cycle, $k+1$, if any.
$Q_j(t)$	Boolean active state of the j-th household appliance at time step t. A value of $Q_j(t) = 1$ corresponds to "ON" state, whereas the value of $Q_j(t) = 0$, corresponds to inactive state: "OFF" (or standby for some appliances, and then, consuming a standby power).
$q_j(t)$	The complementary boolean state of $Q_j(t)$: i.e., $q_j(t) = 1 - Q_j(t)$.
N_{Cj}	The total number of cycles of appliance j, computed at simulation/run time.
t_j	A vector of length N_{Cj} holding the starting times of the simulation time computed cycles of appliance j.
t_j^e	A vector of length N_{Cj} holding the end times of the simulation time computed cycles of appliance j.
d_j	A vector of length N_{Cj} holding the durations of the simulation time computed cycles of appliance j.
X_τ	in (Eqs.4h), represents the linear conversion of some odd dimensional component of X in number of τ time slots.

Symbol	Description
$P_i(t)$	A vector of size N_t, that serves to hold the instantaneous (per each t) power demand for all appliances.
E_d	A scalar for holding the 24h total power consumption for all appliances.
E_{Cj}	Total energy consumption of appliance j.
U_{Dj}	User discomfort for appliance j departure from its user preferred optimal working times and durations.
U_{Dh}	Total user discomfort for all schedulable appliances' departures from their user preferred optimal working times and durations.
P_s	Start-up/active time misplacement penalty, a vector of per time slot misplacement penalties representing the user discomfort for some cycle jk (per each time slot) departure from its user preferred working time window and optimal sub-window.
P_d	Duration time misplacement penalty, a scalar duration misplacement penalty representing the user discomfort for some cycle jk duration departure from its user preferred working time window and optimal sub-window.
$U_{pwd}(t)$	The penalty for either cycle misplacement or cycle mislength, given the time t; standing for either the start-up/active time or the duration.
Π_{upwd}	Agreggate cycle misplacement/mislength penalty.
β_p	Represents the exponential penalty value at the boundaries of the user preferred cycle placement window. β_p is approximately equal to 1, at these locations with just an error ε.
ε	in (Eq.14) Represents the distance (should be small) of the exponential penalty β_p to the full penalty (=1) at the boundaries of the user preferred cycle placement window.
$R(t)$	A vector of length N_t containing the energy rate per each τ time step of the simulation/control horizon T.
$Pr_j(t)$	A vector for holding the active power rating (either Pn_j or Psb_j) according to the active state of appliance j at time step t, where $t \in \{1, 2, ..., Nt\}$.

Symbol	Description
S_j	The α (and ς, δ) regulated soft penalty for appliance j departure from its user preferred optimal working times and durations (user preferences were modelled as soft constraints).
H_j	Hard penalty for appliance j violation of these "hard" constraints: some (either instant or daily) power budget; or some cycles overlapping (which could happen in the model of (Eqs.4)).
B_j	The hard penalty for those working cycle placements of appliance j, that in some way violate the following feasible problem space ("hard") constraints: box constraints, "no-go" zones and cycle precedence zones.
E_{PCh}	Total penalized energy consumption for the household.
r	The number of optimization runs.
r_s	The number of successful optimization runs, out of r.
S_r	Success rate: the ratio of the successful runs to the total number of optimization runs, $S_r = \frac{r_s}{r}$.
ERT	Expected Running Time [80].
ERT_r	Expected Running Time for the mean run in number of function evaluations (Eq.19f). It is the mean number of function evaluations wherein the failed runs are awarded the budget number of function evaluations per run (Sec.3.5.2).
FE_{max}	The advertised budget number of function evaluations (FEs) per run. The budget FEs that is given to the metaheuristics as one of the stopping criteria per a single optimization run.
$FE_{max2\lambda}$	The actual budget number of function evaluations per run. The budget $FE_{max2\lambda}$ that is awarded to failed runs and used in other calculations where the maximum number of function evaluations metric is required, such as, in the calculation of the ERT_r. See (Sec.3.5.2).
$FE_{succAvg}$	The average number of function evaluations pertaining to the successful optimization runs.
B_V	The best ever function value out of all optimization runs for a given metaheuristics.

Symbol	Description
μ_V	The mean of the best function values out of all optimization runs.
M_{edV}	The median of the best function values out of all optimization runs.
O_{Fs}	Objective function score. The score given to a metaheuristics at a particular objective function (Eq.19a).
O_{Frk}	Objective function rank. It is the weak order rank for a certain metaheuristics among the contending metaheuristics, out of their O_{Fs}.
$B_{V reward}$	A reward, the lower the better, that is given to the metaheuristics with tied values of ERT_r, based on their values of B_V in conjunction with the values of M_{edV} and μ_V, where necessary.
R_{oPs}	Rate of problems solved. Represents the proportion of solved (where solved equates to any non null success rate) by a metaheuristics, out of the total of testbed problems.
N_{pb}	Number of problems composing a certain testbed of benchmarking problems.
$N_{non100s}$	Number of non perfectly solved (where a perfectly solved is the one solved with a 100% success rate), out of the total number of problems, N_{pb}, comprised in a testbed.
F_{Ss}	Function set score. It is the aggregate testbed score awarded to a certain metaheuristics, obtained by a weighed sum derivation from its: mean of objective function ranks, proportion of problems solved, mean success rate and the proportion of non-100% success rates.
W_{mOF}	Mean objective function rank weight. A weight that determine the contribution of the mean of objective function ranks in the aggregate testbed (the function set) score, F_{Ss}, awarded to a certain metaheuristics.
W_{RoPs}	The weight for the proportion of problems solved. A weight that determine the contribution of the rate of problems solved in the aggregate testbed score awarded to a certain metaheuristics.

Symbol	**Description**
W_{mSr}	The weight for the mean of success rates of a given metaheuristics, out of all testbed problems. A weight that determine the contribution of the mean success rate in the aggregate testbed score awarded to the metaheuristics.
W_{n100s}	The weight for the proportion of non perfect (non 100%) success rates. A weight that determine the amount of the penalty over the proportion of non 100% success rates in the aggregate testbed score awarded to a certain metaheuristics.
λ, *PS*	λ or *PS*, are used to represent the population size in population based metaheuristics. λ has been used with another meaning in (Eq.22), where it represents the constant rate of a homogeneous Poisson point process.
μ	Represents the mean of a homogeneous Poisson point process, in (Eq.22).
$X_j(t)$	Represents the number of Poisson process events at time t for the appliance j.
$\lambda_j(t)$	Represents the variable rate of a non-homogeneous Poisson point process.
$ToUPs_j(t)$	The time of use probability of the appliance j at time slot t were $t \in \{1, 2, ..., Nt\}$.
minCPD	The minimum number of cycles per day for certain appliance.
meanCPD	The mean number of cycles per day for certain appliance.
maxCPD	The maximum number of cycles per day for certain appliance.
minCT	The minimum cycle duration for a given cycle of certain appliance.
meanCT	The mean cycle duration for a given cycle of certain appliance.
maxCT	The maximum cycle duration for a given cycle of certain appliance.
$V_i(t)$	The velocity of the i-th particle at iteration t in the Particle Swarm Optimization (PSO) metaheuristics.
$X_i(t)$	The location in the problem space, of the i-th particle at iteration t in the PSO metaheuristics.
C_1	Cognitive component acceleration, a scalar constant, of the particle velocity, in the PSO metaheuristics.
C_2	Social component acceleration, a scalar constant, of the particle velocity, in the PSO metaheuristics.

Symbol	**Description**
R_1	Uniformly distributed random vector of the size of $X_i(t)$, pertaining to the cognitive component of the particle velocity in the PSO metaheuristics.
R_1	Uniformly distributed random vector of the size of $X_i(t)$, respective to the social component of the particle velocity in the PSO metaheuristics.
$w, w(t)$	The constant, or the time (t) dependent inertia weight, of the momentum component of the particle velocity in the PSO metaheuristics. Otherwise, w, as a vector, is used to represent the recombination weights of the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) optimization metaheuristics.
X_{PB_i}	The particle's (personal) best, the fittest, location ever visited, in the PSO metaheuristics.
X_{GB_i}	The population's (global) best, the fittest, location ever visited by any particle (equates to the best of the individual X_{PB_i} locations), in the PSO metaheuristics.
C	The covariance matrix of the particle population of the evolution strategy optimization metaheuristics.
σ	The step size of the evolution strategy optimization metaheuristics.
ρ_{ud}, ρ_{nd}	Uniformly and normaly distributed random numbers in the CSA metaheuristics.
S_{szG}, S_{szL}	Global explorarion and local exploitation random walks step sizes in the CSA metaheuristics.
α_1, α_2	Global explorarion and local exploitation random walks scaling factors in the CSA metaheuristics.
x_{best}	Global best position ever achieved by any nest/particle in the CSA metaheuristics; the same as the X_{GB_i}.
p_a	Alien eggs discovery rate, a crossover probability determining the amount of change on the nests that will undergo mutation, component-wise, into new nests, in the CSA metaheuristics.

Chapter 1

Introduction and Background

1.1 Motivations

The most critical concerns of energy supply and management in any electrical grid, are (i) keeping the Energy Consumption (EC) and energy losses as low as possible, while (ii) meeting the energy needs of the end-use consumers (households, industry, etc.)(see further discussion on energy goals and stakeholders under 2.1.1 and 2.1.2). Finding an agreement of these objectives has been a difficult task in the management/control point of view, since energy production and distribution is performed and managed in one extreme (the utility side or the **"supply side"**), whereas EC is normally controlled by the consumer (at the other extreme, the "consumer side" or **"demand side"**). To make things worse, it turns out also that in the general case, consumers are apparently insensitive and unresponsive to the power saving and Demand Response (DR) practices (on DR, see 2.1.7), as pointed out in various research works. Just to cite some, according to Beaudin and Zareipour [1], "residential consumers do not want to spend time to analyse consumption decisions and micro-manage household devices to save money"; Adika and Wang [2], state that "manual participation by customers in demand response will not be possible" being "one of the impediments to consumer involvement in DR". Multiple works cited herein are unanimous on that issue, which underlines the importance of an automated DR, a goal pursued by HEMSs and other types of management and control automata, of the energy ecosystem.

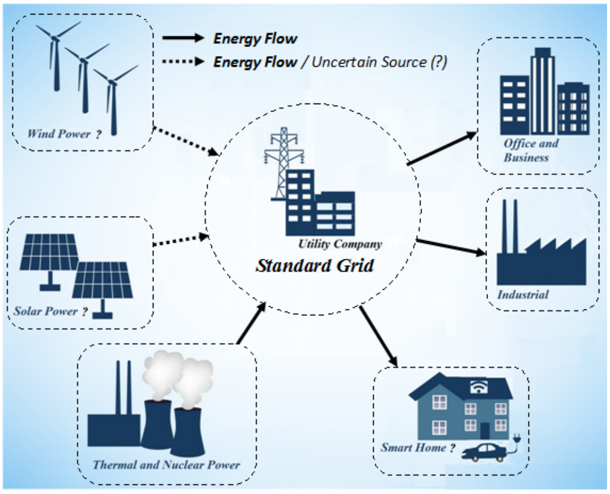
So, providing an automated functionality to energy efficiency, user satisfaction and demand response are the first motivations for this research. While demand response is a gridwise feature, energy efficiency and user satisfaction are universal concerns which apply to off-grid scenarios as well.

The above problem, allied to other contributors, has been an important driving factor to the uncontrollability, unpredictability and persistent increasing of the energy demand in CG based electricity, characterized with high Peak-to-Average Ratios (PARs), making it very difficult for the utility company to maintain a balance between energy supply and demand, leading to power blackouts (be they unpredicted, or scheduled load-shedding events) and brown-outs (under-voltages and other kinds of network electricity signal instabilities), and a big list of other negative issues. All that, end in driving up the costs for the generation and distribution of electricity, and thence, high electricity price for the end-use consumer, etc.

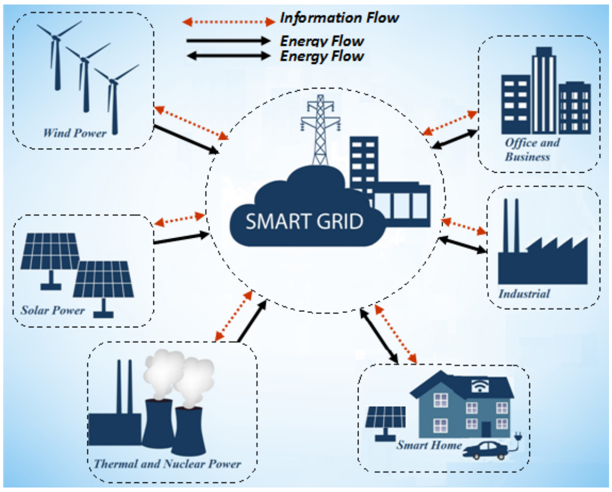
All these problems are underlying the CG outdated overall working philosophy, which we discuss further in section 2. One of the motivations for the present work is helping to address such problems in the general perspective, and with the end-user at household level as the focus.

The advent of the SG, and other smaller scale initiatives in the same direction, is an intent to collectively address those shortcomings. It is among the many SG's goals, tackling said load profile unpredictability, bringing about an automated Demand Side Management (DSM) by performing a better control of the consumer's loads, either by direct load control (DLC) (similar to that addressed by Neglia *et al.* [3]) or through autonomous controllers located at customers' premises, as the proposed by Adika and Wang [2] and many other works that we discuss in next sections.

The following problem persists: the referenced works and the majority of research in the area of energy management, as further investigated in later sections, are flocking around providing automated DSM and ADR **for SG environments**, which simply put, are systems based on **"must have"** seamless information exchange and coordination between the consumer and the utility company over advanced distribution and metering infrastructures, as depicted in Figure 2, which represents a smart home under a smart grid paradigm. In turn, the illustrations in Figure 1(a) and Figure 1(b) are simplified representations of a standard and a smart grid re-



(a) Generic Conventional Grid (CG).



(b) Generic Smart Grid (SG).

Figure 1 (a) CG and (b) SG representations. Adapted from [4].

spectively. We elaborate further on those concepts in the next sections, however, at this stage, it should be underlined that aside from new and more advanced power sources of energy and newer and more advanced distribution and metering infrastructures of the SG, the most important difference between the CG and the SG representations as far as automated DSM and automated DR are concerned, is the existence in the SG of permanent and multi-directional data and information pathflows, otherwise absent in the conventional grid. Without said information exchange, automated DSM and ADR are rather impractical under the conventional grid paradigm, which are one of the base motivations of our work.

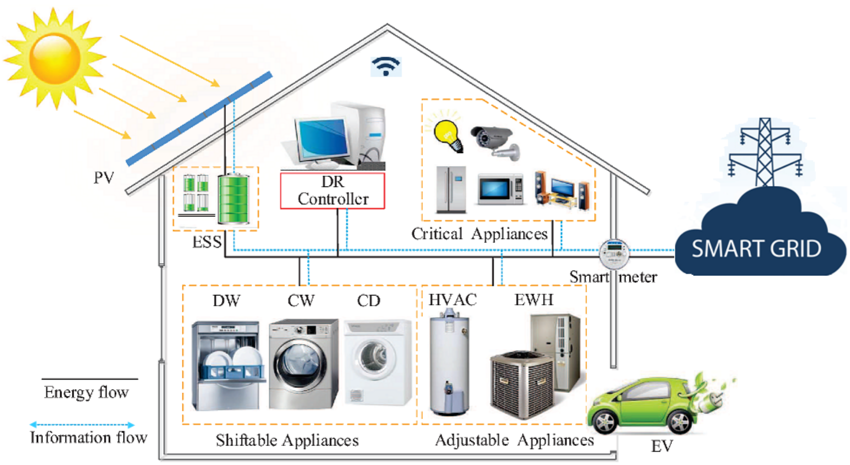


Figure 2 Smart Home in SG environment. Adapted from [5].

Our concern and the main rationale for the present work is that, for most countries like South Africa and the majority of the developing world, there is still some time before they build their SGs, and nonetheless, demand responsiveness is badly required in the CG environment; So, in the mean time, some measures are needed to bridge the gap, and one such measures lies in designing systems with optimization techniques and control approaches that can tackle the above problems, without relying on the smart features of the SG and provide proactive demand response and energy efficiency as well as some degree of fail-safeness; such control approaches that can still work under the upcoming SG paradigm.

So in summary the motivations of this research are:

(i) **the lack of energy efficiency and demand responsiveness in households under the CG based energy landscape** in many countries, especially the developing ones, and also

(ii) **the difficulty of trying to provide such energy efficiency and demand responsiveness under the CG**, due to lack of proper infrastructures, and

(iii) **the fact that such energy efficiency and demand responsiveness are still badly required under CG until getting into the SG**, and therefore,

(iv) **solutions are required, the ones that try to tackle the limitations of the CG** aiming at providing energy efficiency and a degree of demand responsiveness with fair user satisfaction, even under the CG until getting into the SG.

1.2 Objectives

With these motivations and with the discussed perspectives, the general objectives of this research work are:

a) To make a contribution in the creation of smart Home Energy Management Systems (HEMSs) and appliances by designing and simulating optimization and control technologies that leverage their energy saving and efficiency in compromise with consumer's satisfaction. In tandem with that, it is also a general objective,

b) to make such HEMSs to contribute in a broader level to energy demand response, by making them help to reshape the demand profile, and to reduce the total demand and thereby attaining other goals, such as: the reduction of electricity production cost and selling price, the reduction of the consumer's bill, the improvement of power quality, and, at another and general level, the contribution in fighting climate change.

Complementing this, in light of the motivations, a third general objective is

c) to provide said HEMSs demand response functionality, with a robust fail-safe approach, wherein the complete absence or temporary failure or uncertainty of smart communication and coordination features with the supply grid, will not cause the energy efficiency and demand responsiveness functions of such HEMSs to completely collapse. It is assumed that in conventional grid paradigm, which is our main target, smart DR information handshake is absent; but it is available (albeit sometimes with some kind of information uncertainty) in SG environment. So, said fail-safe approach aims at making the proposed HEMS demand responsive under the conventional grid, and still be readily applicable to SG environments (without or with little modification), thus helping to bridge the gap between the two paradigms.

The Specific objectives consist of simulating, for a CG environment, the scheduling function of a household energy management system, against its uncontrolled workflow, such that:

(i) it performs an autonomous appliance scheduling, *i.e.* create a schedule, for programmable appliances, based on a **simulated** energy Real Time Pricing (RTP) information under a conventional grid paradigm. Such a **simulated** pricing information aims at tackling the absence of automated, gridwise DR in the CG paradigm (this is, as stated, our main target), and nonetheless look ahead for its use under SG environment. The scheduling aims at placing the appliance working cycles at optimal times, where such optimality means a good trade-off, a compromise between user utility (comfort) and energy saving.

(ii) it performs a centralized control of the complete household with all kinds of appliances (programmable or not), using the above schedule of the controllable appliances plus a probabilistically generated schedule for the user operated (uncontrollable) appliances.

1.3 Contributions

1. We propose and demonstrate by simulations, a framework for providing a "blind" baseline Demand Responsiveness (bbDR) for the communications deprived CG environments, based on a pseudo real time pricing (pseudo-RTP) function learned from a country or region daily load profile, wherein such pseudo-RTP serve as a guiding function for the autonomous scheduling of controllable appliances.

2. We propose and demonstrate a Real Parameter Blackbox Optimization Approach to Appliance Scheduling (RPBBOAS) model, which tackles combinatorial explosion, and provides the above bbDR with an heuristic based appliance scheduling meta model, which describes the household and provides the logical interface with external optimization algorithms.

3. We design and demonstrate a new hybrid metaheuristics (HyPERGDx) that shows a better or competitive performance against some of the top state of the art population based metaheuristics, and shows consistently a better performance in the above appliance scheduling model, and thus showing the best all-around performance. This metaheuristics provides the referenced bbDR scheme with a real parameter blackbox capable global optimization algorithm to perform the appliance scheduling, guided by the above pseudo-RTP function and mediated by the referenced RPBBOAS model.

1.4 Outline of the dissertation

The rest of dissertation is organized as follows:

(i) In chapter 2 a background on household energy management and demand response is presented. After seeking to understand the concepts building around that of HEMSs, a special focus is placed on modelling approaches and optimization concepts, and methods that are most commonly used in the area of HEMSs, to help us elicit the best method for our own problem case: The prospective investigation at the beginning of this work, led us to the strong belief that an heuristic based optimization approach to the household appliance scheduling, is the best way to tackle model complexity, non-linearity, and combinatorial explosion / "curse of dimensionality" (CoD) issues.

(ii) In chapter 3, we discuss a "blind" baseline Demand Responsiveness (bbDR) framework aimed at providing a degree of demand responsiveness for unconnected CG environments. As part of such a framework, we also address appliance scheduling, where we propose a Real Parameter Blackbox Optimization Approach to Appliance Scheduling (RPBBOAS) household model, which is successfully implemented and tested into a function the *ApplianceSchedule1(.)* function. While trying to optimize appliance schedules via such RPBBOAS model, readily available general purpose state-of-the-art metaheuristics, showed a lackluster performance. To tackle such issue, in the course of this Chapter, we designed and successfully tested a hybrid metaheuristics (HyPERGDx) that showed a more robust and better all around performance, vs the state of the art. The pair HyPERGDx and the *ApplianceSchedule1(.)* function, was eventually used to perform the bbDR simulations of Chapter 4.

(ii) In chapter 4 a number of simulation experiments, featuring both the uncontrolled and the controlled energy consumption workflows, were performed. The experiments were designed to demonstrate, and it was eventually proved, that based on a country or region Daily Load Profile (DLP) generated pseudo-RTP function it is possible to perform appliance scheduling that deliver DR-like performances to such unconnected scenarios.

(iv) Chapter 5 closes the report starting by looking back at the contributions and finally placing closing remarks.

Chapter 2

Background on Household Energy Management and Energy Demand Response

Our research work was developed around energy management in the broader perspective, and centred at the management of household electricity consumption in its particular focus.

So it is straightforward that we perform, as starting point, a review of Home Energy Management Systems (HEMSs), beginning by addressing the most relevant energy concepts around HEMSs, in the wider landscape of energy production, distribution, consumption and management, and the challenges faced in that process, as well as the measures and techniques placed to address such challenges.

In the later part, a particular focus is given to HEMSs related matters, especially on: the structural environment where the specific HEMS is applied, the goals pursued, methods and approaches for how the HEMS is modelled to perform for achieving such goals, in connection with the higher level, gridwise Demand Response (DR).

Despite choosing to firstly address the energy matters, it is worth noting that a central feature of a HEMS functionality is the Energy Consumption (EC) optimization process, which to be precise is the ultimate focus and contribution of this work. So, in our discussions of HEMSs and DR matters, frequent references to methods and function optimization approaches will be made.

2.1 Home Energy Management Systems and the Energy Environment

It is pertinent to perform a closer review of a number of critical energy concepts that relate to that of HEMSs, albeit with bias to the ones that are the most relevant to discuss our problem case (HEMSs), without a particular order, namely: "energy supply goals", "energy stakeholders", "consumer and consumer satisfaction", Conventional Grid (CG), Smart Grid (SG), "meter/smart meter and Advanced Metering Infrastructure (AMI)", Demand Side Management (DSM), DR, Automated Demand Response (ADR), Daily Load Profile (DLP), Peak-to-Average Ratio (PAR), "smart appliance", "smart home, Home-Area-Networks (HANs) and HEMS". In the discussion of these matters, other terms of interest to our universe of discourse, not explicitly listed are covered.

2.1.1 The Main Goals of the Energy Production and Use

The management of electric loads (household appliances included) has been a matter of huge investigation and action, aiming at satisfying the ***main energy goals (eGoals)*** of the many energy stakeholders, being chiefly (for conciseness, and seeking to summarize what is found in the literature):

eGoal1: **reduction of the energy costs for the end-use consumer to the best extent**, which should also trade-off with

eGoal2: **keeping a *fair* level of user comfort**;

eGoal3: **to the best extent: reduction of the EC, as well as the peak load and the peak-to-average ratio**, which enforces *eGoal1* but should trade-off with *eGoal2*;

eGoal4: **to the best extent: reduction of energy production and distribution costs**; and

eGoal5: **reduction of greenhouse gasess (GHGss) emissions and whatever environmental evils arising from the energy supply chain**; and *eGoal6:* **maximizing profitability and sustainability (for the utility company)**, in tandem with *eGoals 1 through 4* and subject to

eGoal7: **keeping the *necessary* level of supply quality, and insuring its protection, safety and stability, meeting regulatory compliance**.

The above list can obviously be represented in many other ways, and should unfold to much more items as matters are looked at in a closer perspective in each specific field. However, we are certain that these ***eGoals*** encompass generically the goals that are frequently listed in works studying demand side matters (such as HEMSs and alike, DSM/DR) and supply side matters (such as, energy production supply chain operations, optimal power flow / economic dispatch, ancillary services, etc.).

2.1.2 Main Energy Stakeholders, Their Roles and Limitations

The energy landscape (the production and use of energy, the infrastructures and devices, the problems arising, and the seeking of solutions and new horizons), involves many stakeholders and they hold complex relationships to symbiotically explore and evolve the energy ecosystem, a matter of special interest for energy policy makers. It falls out of our scope performing an in-depth discussions of such complex matters. However, it is important to leave some remarks on two particular stakeholders, namely: (1) The end-use consumer (the primary stakeholder) and (2) the utility company. Other stakeholders are the energy industry, government, technical and regulatory institutions and society as a whole.

The end-use consumer, also frequently referred to as: "the user", "the end-user", "the customer" (in utility company's perspective), "the end-use consumer" or lately "the prosumer" §2.1.5.3); represents the **demand side** of the said energy landscape, whilst the utility company represents the supply side of the matters. Concerning the end-use consumer and the demand side management, it is worth remarking that:

(1) Although the consumer is the main benefiter and main focus of the energy supply, which is directly related to achieving the above *eGoals*, nevertheless, as discussed in section 1.1, one cannot rely on the consumer for performing real-time / on-line monitoring and

control activities aimed ad achieving any such *eGoals* and therefore,

(2) DR and customer premises energy management, time and mission critical activities, should be performed automatically without the critical human involvement, aside from the choice of parameters, configuration and supervisory.

(3) in trying to achieve any *eGoals* by implementing any policy, strategy or automated program such as the ones in (2), whatever is performed should anyway deserve consumer's support. For instance an Energy Management System (EMS) or the utility company, cannot automatically setup an action to control, whatever the way, a user appliance without their consent, and that upon this consent is given, it is under the assumption that the expected performance is delivered.

The above remarks are the rationale for seeking for and implementing automated household (and generally demand side) energy management including achieving a good demand responsiveness, concepts that further discussed in next sections.

Concerning the utility company the other major stakeholder, it is worth remarking that,

(i) Its business position as the supplier of the "energy commodity" and related services, holds it accountable for dispatching an energy of good quality which also means insuring the safety, protection and stability of the whole supply system at any instant. The said accountability includes meeting regulatory compliance on the energy supply matters, set forth by relevant regulatory bodies (one of the other stakeholders).

(ii) The obligation by the utility company to comply with these roles has been a major challenge for it to adopt new technologies that are installed at the demand side, since by being hard to control them (especially under the CG paradigm), the utility cannot rely on them to perform its roles up to the performance requirements.

Adding to technical and economic constraints at geopolitical level in any specific country, the limitations and challenges discussed above, are especially severe under the conventional grid, one of the reasons for the introduction of a smart grid, which, with its ADR and Distributed Energy Resources (DER) capabilities together with the smart home/building and other smart features, can bring more controllability and predictability to the demand side EC and thus tackle the lack of confidence on the demand side in pursuing the seamless achievement of the above ***eGoals***. However it is also very important seeking to bring some demand responsiveness to the conventional grid as it is likely to prevail for some time until the smart grid eventually takes over.

2.1.3 Consumer satisfaction

The ***consumer satisfaction*** is translated by many aspects, such as a low electricity bill, comfort of different types, or in general, well being. We would say that "user comfort" stands for some kind of benefit the consumer expects from the use of an appliance. Aside from, "well-being", other terms have been used for describing the said user comfort [6], such as "utility", "quality of service", etc., or by their antonyms (depending on modelling perspective), such as "frustration" [7], "discomfort", "desutility".

The concepts that are encompassed in "consumer satisfaction" are some times conflicting, such as for instance: "room temperature comfort" and "low electricity bill". Both concepts express consumer satisfaction, however keeping a high level of temperature comfort may translate to a high electricity bill. So the achieving of user satisfaction in such a situation, should be a trade-off of the two concepts (objectives). The "fair" term in *eGoal2* above, stands for such trade-off; whereas the terms "subject to" and "necessary" express constraints or performance requirements (this will be addressed later as it is one of the concerns of the modelling and optimization in HEMSs).

On the other hand, to avoid confusion concerning "utility", throughout this report, unless especially noted, we will seek to reserve the term "utility" or "utility company" to refer to the producer and distributor of electricity. As referenced above, by "utility" we also mean collectively any operator, for instance an Transmission System Operator (TSO) or a Distribution System Operator (DSO), that, franchising some utility company's roles, is in charge of distribution and management of electricity in an specific area, which includes performing DSM.

2.1.4 The Conventional Grid

The CG which is also know by other names, such as: "legacy grid", "standard grid", "traditional grid" or just "the grid"; is the current solution, the *status quo* of energy supply grids in most countries.

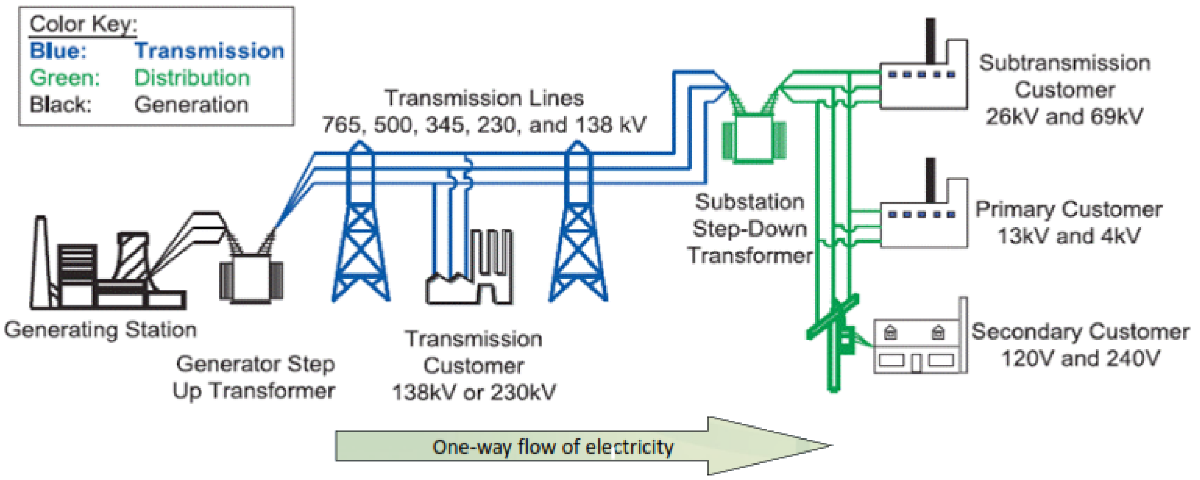


Figure 3 NIST's Conventional Grid Representation [8]

The illustration in Figure 1(a) is a generalized depiction of a CG. Figure 3 is another view of the CG. Aside from other structural aspects, the illustrations underline the one way energy flow from the production to the end-user, and a lack of a proper information handshake between the supply grid and the end-user.

The CG, starting from being a true solution, turns otherwise, at some stage, as the demand increases, the root of new problems: its overall working philosophy turns out to be plagued by serious existential shortcomings, which are driving the change to smart grids. As discussed by Arnold in [8], the CG is characterized by (our remarks enclosed and unquoted) :

a) "Centralized, bulk generation, mainly coal and natural gas" (fossil fuels that drive climate change and are supposed to exhaust within the next 100 years: According to Shafiee and Topal [9] the reserves of oil, coal and gas will be completely depleted in approximately 35, 107 and 37 years. The greater the overall EC, the greater the amount of greenhouse gases are emitted to environment. Otherwise the reduction of fossil fuel based energy by reducing consumption along with an incremented use of clean sources - Photo-Voltaic

(PV), Solar-thermal, Wind - contributes to curb climate change);

b) "Responsible for 40% of human-caused CO_2 production" (this means it is one of the main drivers of global warming and overall climate change);

c) "Controllable generation and predictable loads" (these are rather requirements for fair CG functionality. Unfortunately for many grids, **the loads**, or in other words **the demand**, have proven to be more and more unpredictable, driven by demographic and economic growth);

d) "Sized for infrequent peak demand - operates at 50% capacity" (It is a 50% reserve seeking to tackle supply-to-demand imbalances among other disturbance fighting Supply Side Management (SSM) operations. 50% means inefficient; and nonetheless unable to tackle sudden, abnormally high demand changes, especially if reserve capacity falls much below the said 50%. This huge reserve capacity requirement, drives high generation costs and high retail electricity prices);

e) "Lots of customized proprietary systems" (that means non-open systems, which are difficult to maintain and to evolve. Furthermore, many of the CG infrastructures and technologies rapidly become obsolete);

f) "Limited automation and situational awareness" (which also translates to limited or no data collected thereof: cannot properly act pro-actively nor actively react to tackle sudden higher then expected demand changes. Context-driven and AI/machine-learning capabilities cannot be exploited with lack of stored and contextual data);

g) "Lack of customer-side data to manage and reduce energy use" (The absence of a bidirectional data flow and underlying computer resources and databases is the reason behind this shortcoming; the shortcomings in f) and g) lead to the impossibility to perform ADR under the CG environment. This is one of the problems our research is trying to address).

It is important to underline that aside from other infrastructural and logical shortcomings, the absence of a permanent bidirectional information flow between the utility and the consumer is the main drawback of a CG, as far as automated demand response is concerned.

2.1.5 The Smart Grid and the transition from conventional grid

The Smart Grid (SG) is an emerging and evolving paradigm, a complex system, designed to address the CG problems, see [8] and [10]), for which it tries to encompass and streamline the above referenced and other concepts. SG is defined as "an electric system that uses information, two-way, cyber-secure communication technologies, and computational intelligence in an integrated fashion across electricity generation, transmission, substations, distribution and consumption to achieve a system that is clean, safe, secure, reliable, resilient, efficient, and sustainable" [6].

Figure 1(b) is a generic representation of a smart grid, whose most important characteristic, as far as automated DSM and ADR are concerned, is a permanent bidirectional, multipath and multilateral information flow between the "utility" grid and the consumer, which ultimately implies that all the required subsystems should be prepared to produce and handle such information and work together as a system.

In turn, Figure 4 and Figure 5 show a formal representations of the SG as per its release 3 specification by National Institute of Standards and Technology (NIST) [10]. These two diagrams and other found in [10] are a conceptual guidance to the actual implementations, and underline the complexity of the SG. A number of standards and technical organizations from different corners of the world (including the IEEE, ISO/IEC[1]) have been working together in evolving the conceptual framework as well as in going from the conceptual framework to the actual standards, and thereby helping to carry out the actual smart grid implementations.

[1]IEEE (Institute of Electric and Electronic Engineers); ISO (International Standards Organization); IEC (International Electrotechnical Commission)

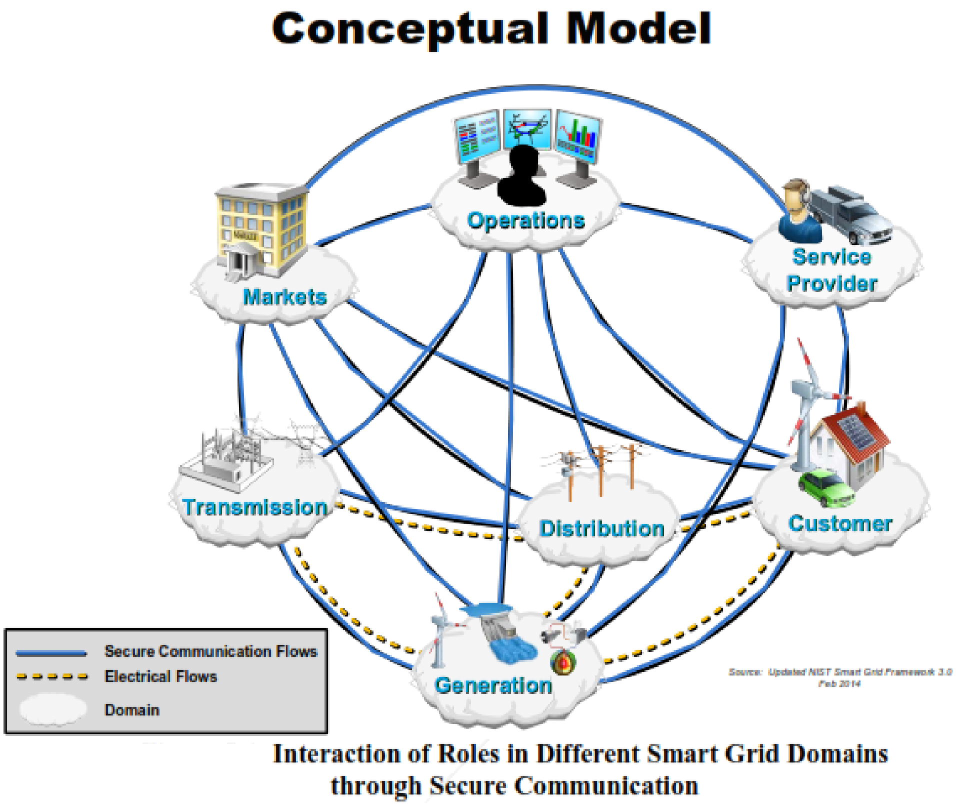


Figure 4 NIST's Smart Grid Conceptual Model [10]

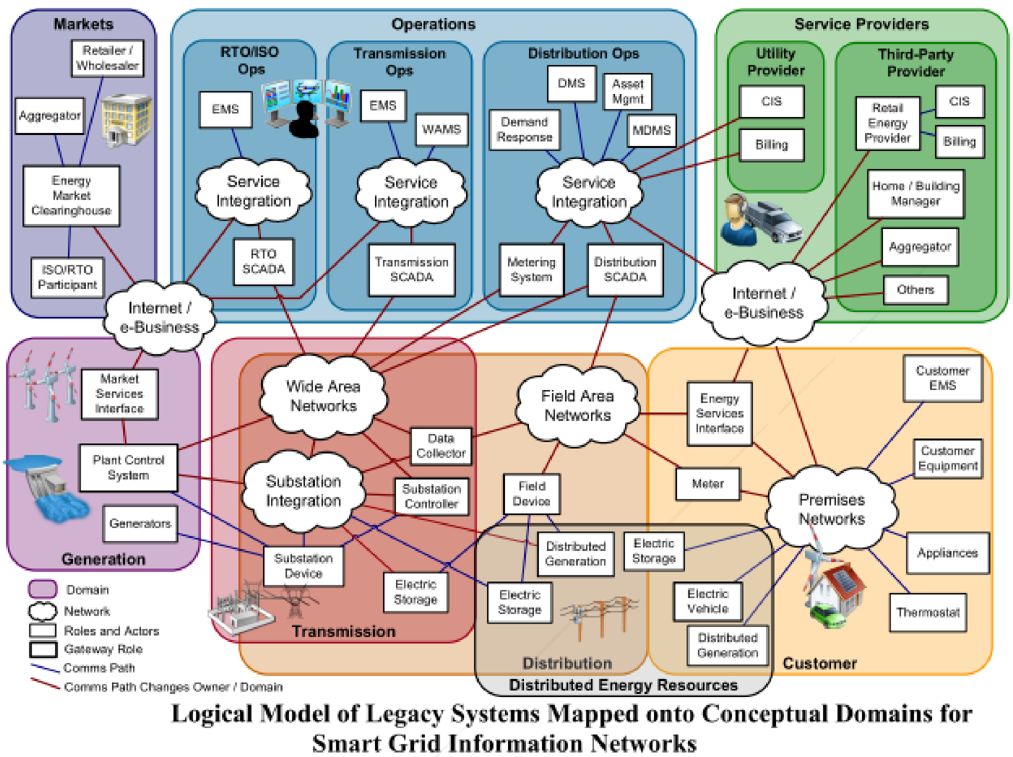


Figure 5 NIST's Smart Grid Information Networks Conceptual Reference Model [10]

2.1.5.1 Selected Consumer and Grid Devices and Infrastructures

The energy grid (CG or SG) is a whole world of devices and systems. It falls out of the scope of this work describing all such infrastructures. However there are some that hold special interest for our treatment of HEMSs and related DSM/DR functionalities, namely:

- **Appliance / Load / Smart Appliance / Smart Load**:

  A device that consumes electric energy is called a "load", a physical system perspective, a general term which disregards any further specificity. An electrical appliance (treated here as just an "appliance") is a "load" in the sense that it consumes electricity, and we will use the term "load" to reference an appliance from that electricity consumption perspective. On the other hand, there are obviously many categories of appliances which in the HEMSs perspective are further discussed in section 4.1. Another term, electrical ***device***, is used [6] to reference and encompass any type of electricity-consuming or producing component in the household. In such a way a TV set, a PV-panel, an Electric Vehicle (EV) are all treated as simply devices. The energy producing or energy storing devices (including the EV) are inclusive in the smart grid concept of Distributed Energy Resources (DER) further discussed in section 2.1.5.3.

  Smart load / ***smart appliance*** / ***smart device***: refers to a device that has embedded capabilities to recognize environmental context (which may include detecting some characteristics of the electricity supply signal) or whatever an external information (sent intentionally or not), beyond the basic switch on/off and dimming-level commands. The smart device, will then use such acquired context information , to (pro)actively modify its electricity prosumption pattern, aimed at bringing about some advantage pertaining to the ultimate goals (the above referenced *eGoals*). The Grid-Friendly Appliances (GFAs) (see 2.1.10), with the discussed smart features, are smart appliances.

- **Home / Smart Home / Home-Area-Network (HAN)**:

  A home, or ***household*** or ***dwelling***: describe a single residential unit comprising electrical devices and occupants (frequently a family but not necessarily) which with their appliance-using activities drive EC. A **smart home** is the one that possesses a communications layer linking together the appliances, driven by occupant activities in a collaborative way as a system, such that, as with a single smart appliance, they can bring about some advantage pertaining the eGoals referenced above. Such collaborative interaction may be (frequently is) coordinated by a central controller (a standalone HEMS, a smart meter hosted HEMS, a remote utility side application running through a communications gateway) or may be solely or inclusively based on the embedded capabilities of any existing smart devices.

A HAN is a networking communications framework, including a physical network infrastructure (wired or wireless) and logical standardized protocol stacks, which collectively provide the smart home with connectivity among all devices, as well as connectivity with the grid, through either the smart meter linked AMI or other communication paths likely in the Internet domain. In this sense, the term HAN has oftentimes been used as a reference to a ***smart home***. There are a choice of different standardized HAN frameworks, based on either wired protocols (Ethernet, powerline-communications, etc.) or wireless ones (Zigbee, WiFi, Bluetooth, Z-Wave, etc.). In the smart grid communication, upward the HAN, there are other wider level network infrastructures, that can be seen in Figure 6.

Smart Homes may exist in any grid paradigm (CG, SG). However it is under the SG paradigm where the smart capabilities can be fully explored by the existence of smart meters and the appropriate communications layers, which are used to perform DSM/ADR in connection with the SG.

Al Sumaiti *et al.* [11] and Chan *et al.* [12], performed reviews on smart homes, and aside from presenting their definitions of the smart homes, describe and discuss the home infrastructure (devices, networks and logical communication layers and types of network protocol standards), as well as how such smart activities are performed and supervised.

In Figure 2, a smart home is depicted, which features the main of the above devices and infrastructures.

- **The Smart Meter**:

  While any standard meter is the central feature of the energy billing functionality in any grid paradigm (CG or SG), a smart meter with its layer of bidirectional communication with the utility company is a central feature of a baseline DR in a smart grid environment, by providing pricing information and demand states to the consumer's HEMS controller, and sending back to the utility the EC data and the estimates for next hour or next day consumer's demand needs among other information, such as estimated prosumer's DER surplus contribution, when such DER are present (2.1.5.3). Aside from the baseline billing functions, and the described baseline DR communication, a smart meter may also host control functions, taking the role of a HEMS controller itself (as suggested in [2]), among other features.

- **Advanced Metering Infrastructure (AMI)**:

  For communication of the smart meter with the utility side, there is normally an underlying AMI, a physical infrastructure and a logical bidirectional communication layer between the smart meter and other actors. Other actors may be other smart meters or data aggregating devices, in a protocol designed to easy-up and fail-safe the exchange of the above referenced information between the consumer/prosumer and the utility which in turn runs other computational resources as the system backbone.

  It is worth noting however that the SG features many communication layers and infrastructures other then the AMI; so, the DR functionalities may be provided through multiple, secure and fail-safe pathways in the SG paradigm (see for instance OpenADR under section 2.1.7). Figure 6 helps to represent and explain the concepts of smart home, HAN and other same level or upward communication network frameworks of the SG.

2.1.5.2 SG transition from the conventional grid

The **transition** from a CG to SG is supposed to be gradual, so it is natural to find at some point a certain conventional grid already incorporating part of the infrastructures and computational resources characteristics of a smart grid (we assume, that is the current landscape in many grids, especially in the developed world, or even in some developing countries in a small scale, such as in South Africa). That is partly represented in Figure 1(a) where some newer sources of

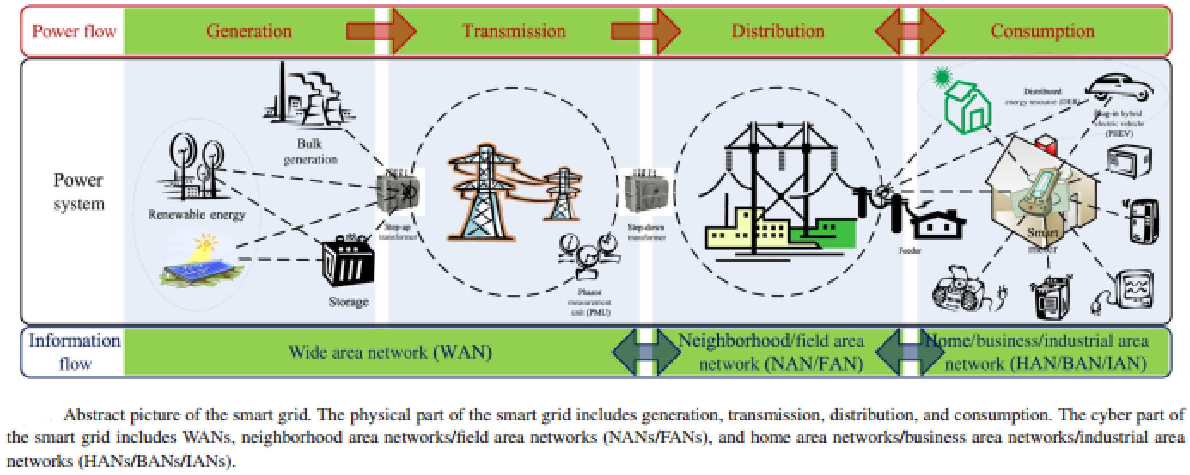


Figure 6 Alternative SG representation, highlighting energy and communication sub-domains (from [13])

electricity (photo-voltaic, and wind, etc.) are featured, albeit not guaranteed in this type of grid. A smart home incorporating smart devices like an Electric Vehicle (EV) may also likely exist under a CG, although without benefiting from the full features they could get when operating under a smart grid. We underline that it is precisely this transitional period and beyond, the focus and target of our work on HEMS.

2.1.5.3 Distributed Energy Resources and Prosumers

One of the cornerstones of the SG paradigm is the distributed nature of the energy resources, know as Distributed Energy Resources (DER) or also as Distributed Generation (DG) or 'energy mix', wherein the production of electricity is not just located centrally at the traditional supply side (the utility), but rather distributed either side along the energy ecosystem, a feature that together with DR enforces the resiliency and stability of the supply system against disturbances of different types, such as the supply-demand imbalances discussed herein.

Inline with the DER concept, the power flow between the utility grid and the consumers is not always unidirectional and the concept of producers and consumers of electricity is no longer crisp, as in the traditional perspective, since some consumers at home, business, industry and community (microgrid) levels, become distributed producers of electricity through their local generation (called also micro-generation [14]) and local energy storage, chiefly PV, wind, Combined Heat and Power (CHP) among others, including very importantly local energy storage: Distributed Energy Storage (DESto). These facts lead to such new type of consumers being re-branded prosumers (producers-consumers).

Although such locally produced electricity is primarily intended for prosumers' use, they are able to feed in their surplus production to the grid (see more about this in section 2.1.12.1). So, the energy pathflow from the grid to the prosumers will actually flip or flop its direction according to the current state of the energy-to-demand differential at prosumer's side along with other criteria. That of course is subject to the local EMS, in charge of scheduling and control of EC, for which it uses DR pricing schemes along with some contextual information (time of day, temperature, irradiation/cloud cover, state-of-charge of local energy storage, etc.) which are evaluated in its optimization/control strategy to perform the right decisions and take control actions. The bidirectional power flow arrows next to the consumer domain in the SG representations, stand for such flip/flopping electricity flow behaviour which belongs to the above described DER concept.

Otherwise, concerning the said **resiliency** and **stability** promoted by DER, for instance, for fighting an under-frequency (§"Fighting and under-frequency") or other system disturbances, when DER is available and to the extent allowed by currently energy resources, a household can be selectively or completely interrupted or a microgrid (covering a community of consumers) can be islanded from the grid, without severely affecting the quality of service to the consumers.

2.1.6 Demand Side Management

Demand Side Management (DSM) consists of all the dispositions and actions collectively aimed at managing the consumer loads by different means, which includes: first, placing a good set of regulations and educative actions, and then establishing and implementing good DR strategies according to the specific market, which should take into account the level of the installed production facilities and distribution network and metering infrastructures. DSM is an old concept of the conventional energy grid itself, which is evolving to automated DSM under the SG. According to Costanzo [15], "DSM, is the planning, implementation, and monitoring of those utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utilities load shape".

The concept of demand side management suggests the referencing of the SSM, which encompasses all management activities performed at the utility side of the grid, in all the chain of logistics for production, transmission and distribution, collectively aimed at achieving the *eGoals* referenced above, from the utility's perspective, especially the ones of insuring the safety and stability of the supply grid from the short to the long term.

2.1.7 Demand Response

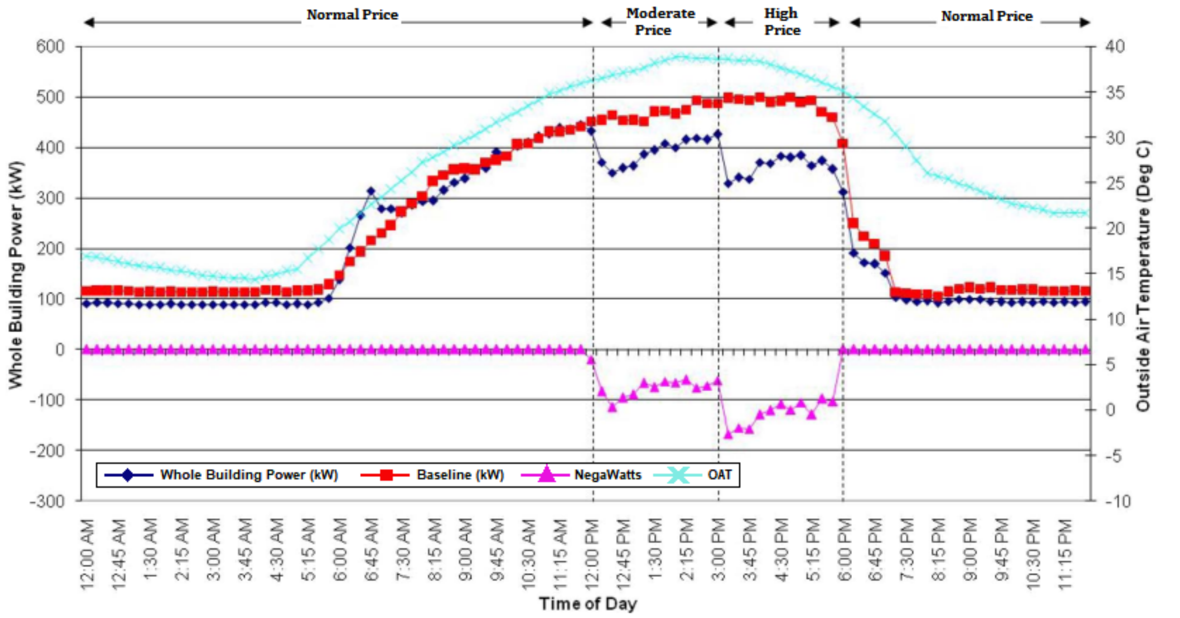
Demand Response (DR) is an essential part of DSM. As addressed in various literature ([6,16–18]), DR is the change in consumption patterns from the consumer, in response to utility request signals or in reaction to perceived changes in the current demand, which collectively seek to positively influence the demand profile (see 2.1.13) and other metrics in pursuing the above mentioned ***eGoals***. According to Albadi *et al.* [16], DR, is "defined as the changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time. Further, DR can be also defined as the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized", including "all intentional modifications to consumption patterns of electricity of end-use customers that are intended to alter the timing, level of instantaneous demand, or the total electricity consumption."

While the concept of DR applies to any grid paradigm, ADR is supposed to properly work under a SG or SG-like paradigm, wherein both the infrastructures and logical/control subsystems are present and work together as a system to perform an automated DR.

OpenADR (Open Automated Demand Response) [19] is a computational and communication framework, and an open programming interface specification, a part of SG specifications. It defines computational resources and DR-signaling and guides ADR implementations. More insights and discussion of ADR and OpenADR matters may be found in [20], [21].

Figure 7 shows the energy performance of a ADR driven Building Energy Management System (BEMS) as discussed by Samad *et al.* [21]. Our discussions of the DR matters and as illustrated in the figure are to underline the potential contributions of a demand responsive

HEMS to energy saving and efficiency, for the profit of the user; a contribution that, at a higher level, extends to the utility grid.



ADR example for a commercial building in California (from June 2006). The top light-blue curve is the outside air temperature (OAT), the next, red curve is a calculated estimated baseline consumption (based on ambient temperature and other factors), the dark-blue curve is the actual consumption, and the bottom purple curve shows the reduction in use with ADR ("negawatts" during the DR event). In this case, two DR signals were sent, at around noon ("moderate price") and at around 3 P.M. ("high price").

Figure 7 ADR example (Adapted from [21], [22])

2.1.8 Demand response role in reducing the Peak-to-Average Ratio (PAR)

Demand response is designed to perform these three main actions [13], which collectively in the end reduce the Peak-to-Average Ratio (PAR):

1. **Peak shaving**: Reduces peak energy consumption. It is performed, at and around peak load times, by load shedding actions and/or by load shifting activities (see below). Load shedding can be done as the following:

   (i) by selectively shedding load via DLC, an action that is agreed upon beforehand with the customer as part of incentive based DR programs (see section 2.1.11); instant power capping via some customer side controller, which frequently happens at peak load times, has also a contribution to peak shaving.

(ii) when the above schemes are likely to be overwhelmed, load shedding is then done by cutting the supply to entire blocks, neighbourhoods or districts; a harsh and compulsory action aimed at curbing an increasing demand that could otherwise be higher than the network capacity. This type of load shedding is undesirable since it causes extreme user discomfort and severely harms the economy.

2. **Load shifting**: It is the action of displacing shiftable appliances (see appliance classification, section 4.1.1) from peak load times to off-peak times, which is performed by automatic appliance scheduling and control via customer side controllers (HEMSs, BEMSs or generally EMSs).

3. **Valley filling**: It happens when the described peak shaving is done by load shifting: then, peaks are shaved while, synergistically, valleys are filled. It is a practice encouraging the displacement of energy consumption activities from high pick to off-peak times, thus filling the load profile valleys that are characteristic of such times. In the other hand, insofar the likelihood of another peak being formed at such off-peak times is kept very low, these actions translate into reducing the PAR. If time based pricing is in charge, and since off-peak times are cheaper than the mid/on-peak ones, then, energy cost reduction is achieved as well.

The **Peak-to-Average Ratio (PAR)** is the ratio of the maximum (peak) load, to the average load during the time horizon of 1 day (other horizons are possible). The PAR tells how high is the peak load compared to the average load. The lower (the closer to the average) the better, since a high PAR increases the likelihood of supply-to-demand imbalance and the negative issues such disturbance carries together.

Such peak and average loads are found or calculated from the utility grid's aggregated daily Daily Load Profile (DLP) (a concept described in subsection 2.1.13), which also applies to a *PAR* for a household's DLP (see (Eq.2)).
When the load axis of a DLP is expressed as **"per unit"** (***pu***), then, the corresponding PAR is the maximum (peak) value of such ***pu*** profile. See equations: 1a through 2, and DLPs: Figure 10, Figure 12, where these concepts are illustrated. We point out however that, since the

aggregate daily load profile is a mean profile over a number of days, the actual instant PARs may generally be higher than what can be learned from the mean DLP. In turn, the reduction of the PAR contributes: (i) in general, to improve network stability, (ii) to reduce or eliminate the likelihood for under-frequency load-shedding events, (iii) to reduce energy generation costs, (iv) to improve other power quality indicators, (v) to reduce consumer's electricity bill; or collectively to synergistically improve the *eGoals*.

2.1.9 Demand response and uncertainty

The concept of DR as a reaction to control signals (sent intentionally from the utility) is also extended to include proactive DR according to self-learned (from statistical records or in some way forecasted or simulated) demand changes, or electricity pricing information, etc., when for some reason, the utility borne signals are not available or are in some way inaccurate. All those instances collectively translate to a capacity from a demand side control system to tackle uncertainty, in other words, an uncertainty-aware system (UAS). The target system of the present research is a kind of an UAS.

2.1.10 Demand response and smart devices: grid-friendly appliances

Alternatively or complementarily, self-perceived events (over/under-frequency, over/under-voltage, phase-imbalance, etc.) in the electricity supply signal (regardless of the presence of utility borne information), may also be added to the drivers of automated DR reaction from the consumer devices. There is a growing tendency of many smart appliances coming with embedded capabilities of self-detecting demand response needs: GFAs. In GFAs, frequently, the primary network frequency monitoring is used to detect a potential overload condition (an under-frequency is due to a load-to-generation imbalance, more load then generation), in which case the GFA will automatically adapt its electricity usage by curtailing (*e.g.* dimming) or even standby or completely shut-down. This is a consumer side reaction performed by the consumer.

A work by Kintner-Meyer *et al.* [23] (followed-up by [24], [25]) in a project under the Pacific Northwest National Laboratory (PNNL), prototypes a frequency based GFA controller, and most importantly, discusses the motivations, the goals, and the approaches for the proposed device).

The work by Bao and Li [26] also discusses GFAs and their role in DR and proposes a frequency based GFA controller over a Field-Programmable Gate Array (FPGA) hardware platform.

Another work by Fuller *et al.* [27] also under the PNNL, addresses a more advanced GFA, with capabilities to handle DR signals in addition to the basic under-frequency (load-to-generation imbalance) detection functionality. Otherwise, smart-plugs (as addressed in [28], [29], are DR-friendly devices designed to control "old/dumb" (although can control any) appliances, conferring them GFA-like capabilities.

It is worth underlining that the utility borne DR management signals, are meant to inform changes in the current demand profile or pricing (like the ones in [27]) and thereby requesting the underlying DR actions (according to the current user's choice of the pre-defined DR strategies), which collectively cause the load to be (i) just curtailed, or (2) shifted (from critical or high peak, to off-peak or mid-peak zones), resulting, at the end of the day, in either the reduction of the overall EC or/and the reduction of the PAR.

The GFA features referenced above, are of special interest for HEMSs under the CG paradigm, since such features can provide a minimal demand responsiveness based on the auto-detection of an on-going or potentially ensuing supply system condition, considering the absence of utility-consumer ADR signalling under the CG, which also applies for HEMSs under the SG on communication faulty conditions.

However, the role and effectiveness of GFAs as grid system protection and stability helpers, can only be achieved as many GFAs are deployed on the energy landscape to serve as the first line of action, aimed at preventing the on-set of a system imbalance, because as soon as the imbalance has crossed a determined threshold (meaning that the demand side preventive capabilities have been overwhelmed), supply side management remedial actions will have to be triggered:

2.1.10.1 Fighting an under-frequency

In fact, taking for instance that, a worsening under-frequency (a supply-to-demand imbalance) has crossed its critical threshold, then the utility company (taking its due role) will/should automatically trigger its ancillary services (spinning and non-spinning reserve, etc.) to deal with it (see [24]) so as to insure safety, protection and stability of the supply system, comply with regulations and fulfil its obligations as the energy supplier stakeholder. The utility will act in automatic fashion through the appropriate devices, approximately the following way:

(i) **activating, *i.e.*, shedding, DLC connected consumer loads**, selected, if any, to acting as instant reserve (IR); or

(ii) **activating spinning reserve (SR)**, another kind of IR, consisting of generators that are kept on-line, "spinning", ready for any such events; or *in extremis*, when the use of the former two combined is not enough to curb the system imbalance condition,

(iii) **performing load-shedding events to entire districts**, a situation that sometimes became frequent and severe in South Africa mostly in 2008 and 2015 [30], causing huge economic losses. Such losses are too high in comparison to setting up reserve capacity and DSM operations, sized to avoid such extreme load-shedding events [31].

To get to the last stage above, may be due to either (a) not enough instant reserve capacity has been purchased/established due to economic reasons, or (b) SR generation units suddenly became severely unavailable for some reason, such as a higher then expected number of breakdowns, or improperly planed or improperly executed maintenance operations.

2.1.11 Demand Response Approaches

There are two main demand response strategies [16], [17], [18]: (i) incentive based and (ii) price (penalty) based strategies, as depicted in Figure 8 [18]. Other works address DR functionality from multiple other perspectives, such as in [32] or the above discussed GFAs.

In the incentive based DR strategies, among other options, the utility encourages the user to let it perform a direct load control (DLC) of their appliances so as to remotely and selectively shut them down under the right circumstances, in exchange for rewards in the form of pre-payments or price rebates [16]. Neglia *et al.* [3] worked on a smart-plug for providing DLC functionality.

There is a number of other incentive based offers, as discussed in the above referenced [16], [17], [18]. Although the incentive approach is meant to bring about reciprocal (utility-consumer) rewards, the user's failure to meet the terms and conditions may lead to penalties, which is one of the challenges to the adoption of the these DR schemes by the end-consumer, and a reason that supports the use of automated DR-friendly HEMS to reduce error-prone human involvement in the supervisor control DR activities.

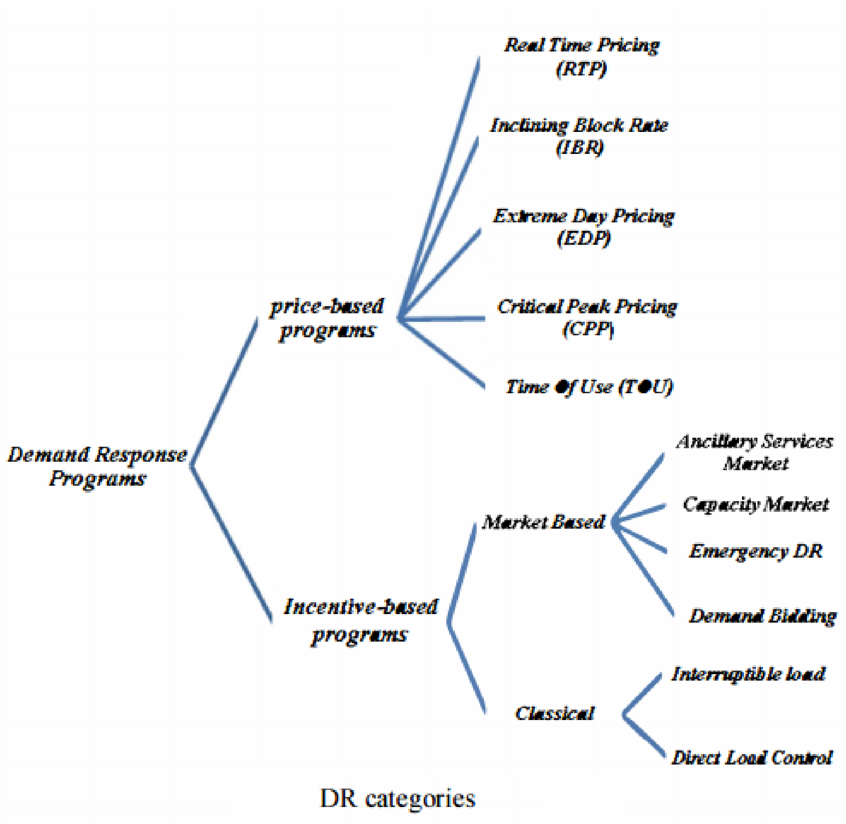
An evolving and important segment of the energy market that may leverage DSM/ADR adherence and effectiveness, are the above referenced franchising operators, service providers, working as middlemen between the utility company and the end-use consumer: If equipped with the appropriate management tools and strategies, supported by an in-depth research (such as the ones presented by Herath and Venayagamoorthy in [33], [34] and [35]) can, among other benefits, ease and improve DR operations, enhance the degree of trust of the utility company towards the end-user/demand-side, and boost the satisfaction of all the parties involved.

2.1.12 Price Schemes

In the price based DR strategies, different price schemes are practiced, most frequently: Time of Use Tariff (ToUT), Critical Peak Pricing (CPP), Extreme Day Pricing (EDP), Extreme Day CPP (ED-CPP) and RTP. All these schemes are demand-sensitive, holding some capability of penalizing the consumers (demand-wise, through cost) for the use of electricity at the points of higher demand, and thus coerce them to adapt and thus, respond to the demand reduction/shifting needs.

The ToUT, seeks to divide the 24h period in frequently 2 or 3-tier pricing zones (established by the utility according to the DLP and other underlying variables or econometrics), and it is currently the most used ([36]) of all above mentioned schemes. Otherwise, CPP, EDP, and ED-CPP only apply for special (critical load) circumstances.

In turn the RTP, seeks to reflect the real price at the considered time slot of the 24h horizon (a



(a) DR strategies [18]

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Table 1. Comparison of DR Techniques based on Selected Quality Criteria

Technique	Objectives	Scheduler	Pricing Scheme	Optimization	Assumptions	Renewable Energy
1	Minimize energy bill, appliance waiting time and PAR.	Manual	RTP combined IBR	LP	Future pricing parameters are known for the users ahead of time	PHEV as a BES used
2	Minimize energy bill and user discomfort	Automatic	RTP	Converted-Linear	Temperature band is uniform, Mean error of 10% is assumed in forecasted price	Not used
3	Minimize energy bill by consumer reward	Automatic	TOU	NLP	Power consumption profile in each house is assumed to be the same	Not used
4	Minimize energy bill and PAR	Manual	RTP combined with IBR	Non-linear	Nine kinds of AOAs and 16 operation per day for them	Not used
5	Minimize energy bill and user discomfort	Automatic	RTP,FIT and Net Sale/Purchase	Linear	Convex cost function, PV generation is able to meet 50% of its load requirement	PV
6	Minimize energy bill and user discomfort	Manual	RTP	Linear stochastic	Solar power is cheaper than grid	PV and BES

(b) A sample Comparison of DR strategies [17]

Figure 8 Sample Demand Response (DR) Strategies

time slot of desired granularity or resolution: hourly, 30-minutely, 10-minutely, minutely, etc.) [37]. The hourly fashion is the most accounted in the literature, while the higher granularities are scarce. In tandem with the selected granularity, RTP data is sent in advance, 1 hourly (the most frequent), or up to 1 day ahead. In some literature, this 1-day in advance fashion is branded Day Ahead Pricing (DAP), a pricing scheme by itself, independent of RTP.

There is obviously a challenge on the granularity of the time slot: the greater the granularity, the more intensive the communications overhead and computational burden to process the whole scheme by the in-premises controller. Otherwise a low granularity and also, too much time advance of the RTP data, sways the data from the real-time/actual price patterns. Real-time control applications, will require fine granularities in the seconds or better scale [6] pp.114.

It is worth noting however that a desired and reasonable time horizon in advance of the RTP data, is important for allowing pre-scheduling to cover that intended time horizon. A day ahead RTP data allows for a 1 day pre-schedule. In the unavailability of such advance time horizon, data built from a forecast or from any other means, will have to be used for the pre-schedule to cover the intended time horizon.

Concerning said pricing information unavailability, it is worth remarking that one of the focus of our research work is seeking to preserve cost effectiveness in balance with comfort for the user and a degree of demand responsiveness, in such instances when RTP (or whatever the elected pricing scheme) advance information is unavailable (including all such instances when pricing or DR management signals are either temporarily or completely unavailable); so an approach is proposed for the replacement of that utility-borne pricing information.

On the other hand, since ToUT, CPP, EDP, and ED-CPP prices are not likely to change frequently, just one to four times a year [38], RTP offers by far the best option for the real time control of user appliances and a better approach for DR, since it seeks to reliably influence the demand patterns in a matched proportion of the real-time on-going imbalance. In fact, as discussed by Albadi and El-Saadany [16], RTP is believed to be the most direct and efficient of the DR programs and thus worth endorsing its focus to energy policy makers. It is also worth noting that, as instanced in [38], RTP has also been used in hybrid synergy with other pricing schemes for some DSM/DR related comparative advantage.

2.1.12.1 Other Price Schemes

Aside from the price schemes referenced above, there are many other found in the literature, like Flat-Price (FLP), Feed-In Tariff (FIT), Inclining Block Rates (IBR), etc., which may be important for (and not limited to) the exercise of DR. Otherwise the existence and format of any of the price schemes, mentioned or not, may vary with the utility company or distributor and market area.

FLP or flat rate, it is normally a default, fixed pricing scheme which is applied when no other demand sensitive pricing scheme is chosen, and not requiring any kind of special electricity meter or infrastructure.

FIT It is a price scheme in the incentive based group of DR strategies, designed to accommodate the rising adoption of renewable energy (chiefly PV) sources at residential level, which aside from providing an alternative and cheaper source of energy for the end-consumer, it can feed in an excess energy to the grid, and thus contribute to relieve the demand in critical situations in a bi-faceted way, as discussed in section 2.1.5.3. This FIT pricing scheme is featured in various research works as in Adika and Wang [2], Wang *et al.* [39], Qayyum *et al.* [40], and as discussed in [17]; just to cite some.

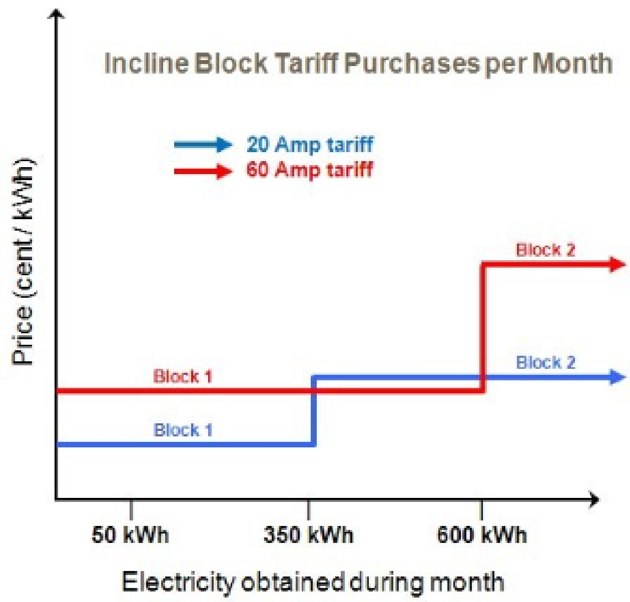

Figure 9 A sample representation IBR pricing scheme, from [41]

IBR divides the user's monthly power consumption in frequently 2 or 3 stair-cased pricing zones (a sample in Figure 9 from Eskom [41]). Since it is based in a monthly metric (supposedly based on the FLP), compared to the other above referenced demand based pricing schemes, IBR is less attractive in terms of causing a direct impact on DR. However, considering that one of the DR measures is imposing (either instant or cumulative/monthly) power consumption limits per consumer or household, we find that IBR plays its role in DR by penalizing the huge power consumers who climb the IBR stairs (=limits). There are also possibilities that have been practised to make IBR more DR-friendly by (i) using a 24h metric (or less) for the definition and evaluation of the stair-case levels, and/or (ii) by synergistically combining it with other demand sensitive, time based, pricing schemes, like for instance combined RTP-IBR used by [42] and [38] (as referenced in [17]); or the combined ToUP-IBR (found in [43]).

2.1.13 Daily Load Profile (DLP)

Within a certain geographically limited utility grid, during a 24h time horizon period, the summation of the power consumptions of all users per a specific time slot of desired granularity (hourly, 30-minutely, 10-minutely, minutely, etc.), produces a daily demand load profile. Statistics are performed out of several days records, and normally two (Summer and Winter) or three (Summer, Winter and shoulder) load profiles are established. "Load profiles" are referenced by other names, such as "load curves", "consumption profiles", just to cite some.

To illustrate a DLP with a simplistic view: let the j-th household with N_a appliances, be a simplistic representative of anyone of the country's M consumers: The expression in equation 1a defines a household's DLP, for a resolution of τ, *i.e.* $DLPh(\tau)$. The country daily load profile $DLPc(\tau)$ is the summation of all the households' DLPs per each time slot τ, as shown in Equations 1a and 1b.

$$DLPh(\tau) = \sum_{i=1}^{N_a} P_i(\tau) \tag{1a}$$

$$DLPc(\tau) = \sum_{j=1}^{M} DLPh_j(\tau) \tag{1b}$$

$$DLP(\tau)_{pu} = \frac{DLP(\tau)}{\frac{1}{N_t}\sum_{\tau=1}^{N_t} DLP(\tau)} \tag{1c}$$

$$PAR = \frac{\max_\tau(DLP(\tau))}{\frac{1}{N_t}\sum_{\tau=1}^{N_t} DLP(\tau)} \tag{2}$$

where:

$N_a \in A = \{N_1, N_2, ..., N_j, ..., N_M\}$; N_j is the number of appliances for the j-th household (consumer), whereas A is a set with M elements, listing the number of appliances for each one of the M households (consumers);

$\tau = 1, ..., N_t$; τ is the time slot resolution, which translates to how many samples are taken per day: if τ is 1h than it spans from 1 to N_t=24; if τ is 10 minutes, then it spans from 1 to N_t=144, and so on; The sampling horizon can be made to be any other value if the desired load profile is other than 1 day long. N_t is of course, the number of τs per the sampling horizon of 1 day. Let τ be 1 hour. Then,

$P_i(\tau)$ is the power consumption of the i-th of the N_a household appliances at the time slot τ, *i.e.* at hour τ.

$DLPh(\tau)$ is the household's daily load profile for a hourly resolution (since τ=1h), and

$DLPc(\tau)$ the country daily load profile, which is as well for a hourly resolution.

$DLP(\tau)_{pu}$ stands for either *DLPh* or *DLPc*, with the load expressed ***"per unit"***.

PAR is the peak-to-average ratio, a scalar, which may be calculated for either *DLPh* or *DLPc*. Then,

DLP in the *PAR* expression, stands for either *DLPh* or *DLPc* when the respective *PAR* is sought.

$DLPh(\tau)$, $DLPc(\tau)$ and $DLP(\tau)_{pu}$ are vectors of length N_t, whereas the *PAR* is a scalar.

We should point out that at utility's (or country) level, especially under the CG, the per appliance DLP information is not available and only the aggregated household (consumer) load information is sent to the utility, which is the billing information it uses to charge the consumers for their use of electricity. The DLP is learned from the utility own energy metering infrastructure. However, in the SG or in SG-like (transitional) ecosystems, where there are smart meters under an AMI, it is possible to gather a "per appliance" consumption, or derive it from the aggregate load through non intrusive load monitoring (NILM) algorithms, which are being amply researched [44] [45].

The determination of the DLP (as in [46]) is of huge importance since it is the basis for the determination of various other metrics and dispositions for DSM, DR, and other functionalities. For instance, the DLP is divided into demand categories: Off-peak, Mid-Peak and On-Peak zones, at the core of DR pricing signals. For extreme demand days, which happen only a few days (1 to 4) during the year, there is a fourth tier, the Critical-Peak zone. These zones along with other utility econometrics, determine pricing schemes thresholds and are the basis of many of DR functionalities.

The works by Jenkins *et al.* [47], Macedo *et al.* [46], are instances of load profile determination.

It is worth underlining that although 24 has been the most used time horizon, load profiles must not span just 24h. The horizon for data sampling or the one for simulation or real time control purposes may be less or greater than 24h.

Figure 10 show South Africa's 2014 aggregate DLPs, from [48], and the ***per unit*** profiles in Figure 11 were built from the DLP in Figure 10. In turn, Figure 12, shows the 2001 DLPs for some European countries (see [49], [50]).

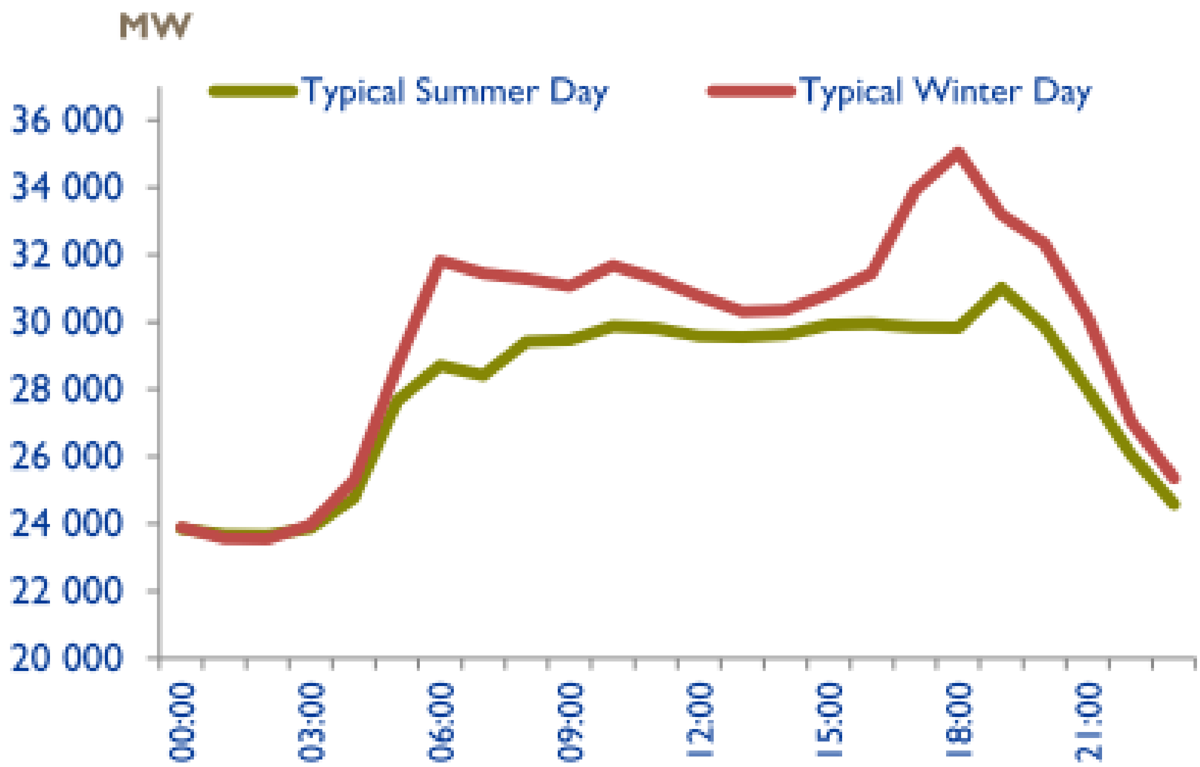

Figure 10 South Africa's 2014 Aggregate Daily Load Profiles [48]

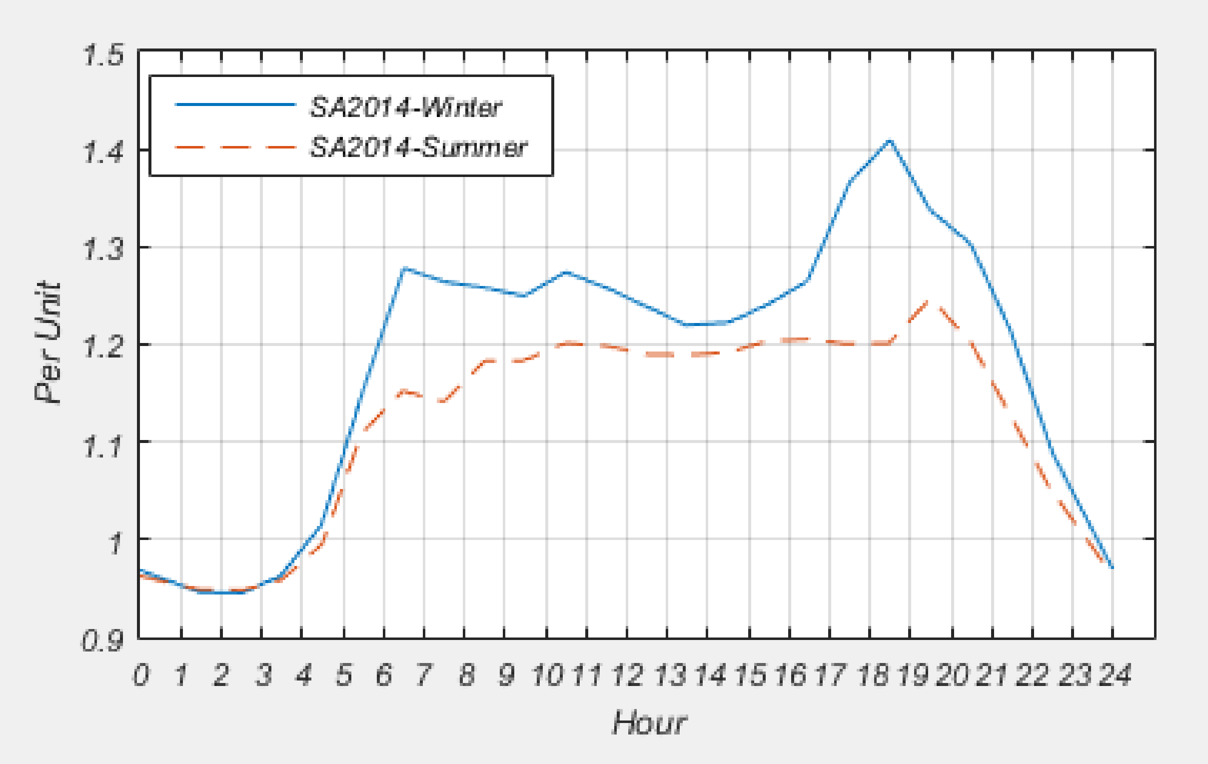

Figure 11 South Africa 2014 Aggregate Daily Load Profiles (per unit)

At household level there is also an interest in determining the DLP for each appliance, in which case, the statistics along a relevant number of days translate to the appliance's time of use probability per the considered time slot during the time horizon of 24h. The aggregate household DLP is the statistical mean of the appliances total DLP per the given time slot resolution.

The great importance of the household load profiles either at appliance or at the entire household level, is witnessed by many studies, that try to model the residential load profile, such as: Capasso *et al.* [51], Paatero *et al.* [52], Richardson *et al.* [14], Chuan and Ukil [53], Marszal-Pomianowska *et al.* [54]; where the appliances' and households' load profiles are not just determined experimentally (by measurements followed by statistical analysis) but also determined from models created from such statistics.

These load profiles along with a chosen DR strategy, are harnessed together to perform the modelling, simulation and implementation of residential energy management systems with DR capabilities.

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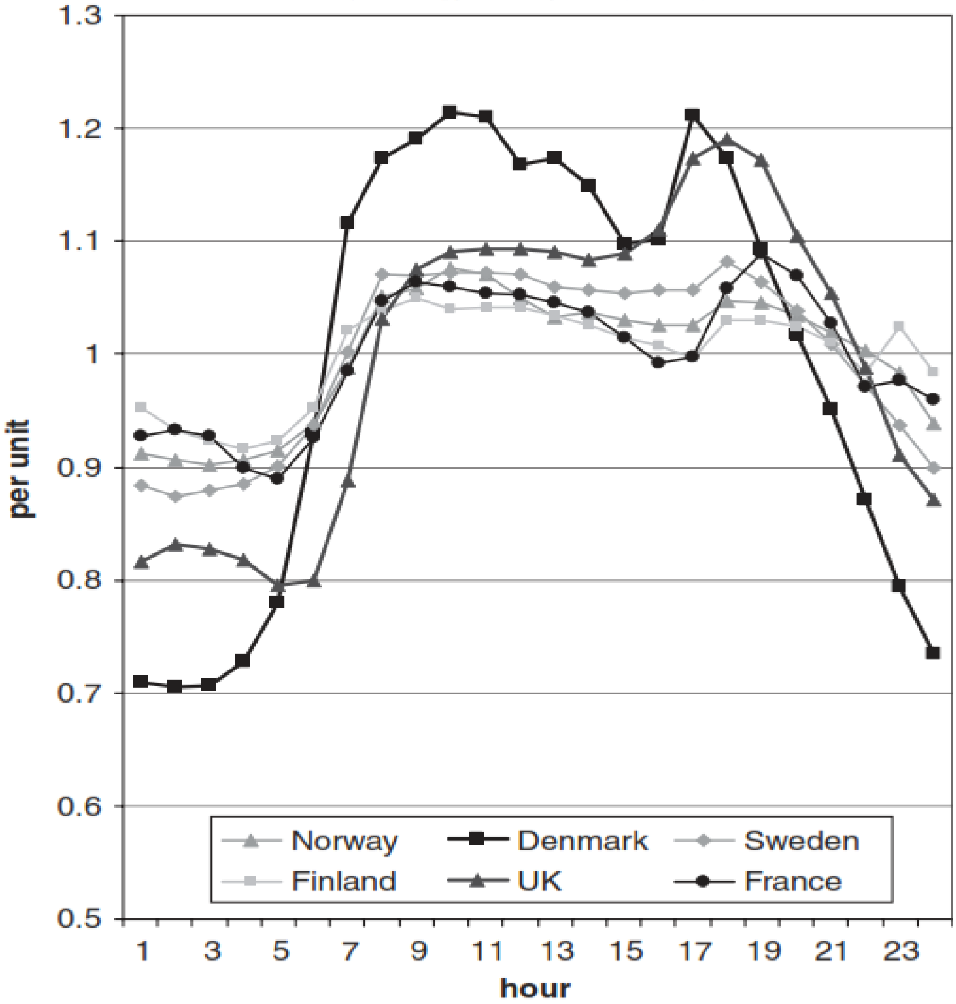


Daily load curves in the Nordic countries, the UK, and France (peak winter days, 2001). Source: EFFLOCOM (2003).

Figure 12 DLPs of some European countries [50]

2.1.14 Review of Literature on Appliance Scheduling and Household Energy Management

As introduced above, the control of user appliances, or in other terms: Home Energy Management Systems (HEMSs), is central to the pursuit of energy efficiency, energy saving and the resultant reduction in costs while keeping comfort. Otherwise, it is (along with DLC) at the core of the whole concepts of DSM and DR as discussed above. By HEMS we are also referencing any type of Residential Energy Management System (REMS) at single household level, and furthermore, we are sure that the discussions and learnings from a HEMS can be in some way extrapolated to any EMS pertaining to consumers of other levels such as for instance a BEMS which refers to an entire building (business, institutional) etc.

Our research work is performed around the scheduling and control of user appliances, and it was important to examine the huge body of research work that has been carried out in the area.

Many of these works were already cited in other instances of the discussion. Although all works are built around almost the same goals (generally speaking: some of the above referenced ***eGoals***), each work used different methods and placed a different focus on that multifaceted concepts of HEMS, and directly or indirectly covered DR functionalities in their specific coverage of the said *eGoals*.

We should point out that, a central feature of a HEMS functionality is the optimization process which starts from problem formulation to its solution, that is eventually encoded into the controller in some format. So, along with and beyond the review of HEMSs matters, we performed a review of concepts and practices in the field of function optimization (which put simply is: problem modelling into functions, followed by finding the optimal values that satisfy such functions).

In our review of the concepts around HEMSs in the researched works, beyond the general understanding, we sought to investigate and get insights regarding mainly the following aspects:

The EMS target environment (household and grid: CG or SG); the household appliance types (how the work classify then), the motivations and/or goals of the EMS, the demand response approaches, the model and optimization approaches, including how the method copes with problem complexity and uncertainty. Our remarks are also added throughout or at the end.

So, with those remarks considered, in the following, we present some of the revised works, which we do without any assumption or special preference about any perspective of merit, and without a particular order:

(1) Rastegar *et al.* [36]:

In this work, Rastegar *et al.* propose a HEMS for a household under a SG **paradigm** aiming at minimizing EC, while seeking to keep a fair level of user comfort, as well as providing a price based DR functionality. The availability of SG type infrastructures and communication are implied from the HEMS description.

The home appliances are classified into two categories: (i) Uncontrollable (user operated), and (ii) Controllable appliances. The last group is in turn further subdivided into (iia) On/Off controlled (their power consumption is fixed; they can just be switched on or off), and (iib) regulating appliances (their power consumption can be regulated within certain range).

In this way, a ToUT or a (24h) IBR pricing are used for said DR functionality, with an appliance scheduling that seeks to incorporate user specified appliance's operational priorities. The scheduling method also used the penalty approach (through VOLL-value of lost load) to incorporate user comfort constraints into the optimization cost function, wherein the VOLL translates to a proportional penalty for not operating an appliance at the time of user's preference.

(2) Adika and Wang [2]:

propose an *"Autonomous Appliance Scheduling for household energy Management"*, under a ***SG paradigm***, for a **smart home**, equipped with a **smart meter** and featuring a PV type DER for local generation of electricity without storage (although an electrical vehicle can be regarded as a type of part-time Energy Storage (ESto)), along with the main utility grid supply.

Their design objectives are reducing prosumer's bill and participate in DR. They use a simulated RTP and FIT as trading-off pricing schemes to accomplish ADR functionality. Whit those trading schemes along with appliances' ToUPs and user preferred working times for schedulable appliances, they perform appliance scheduling, using a heuristic/stochastic approach, aimed at placing the schedulable appliances at optimal times slots of the day, according to the referenced design optimization goals. User comfort is also handled through the use of penalties: a frustration coefficient which decreases fitness in the aggregate single objective function.

(3) Pedrasa *et al.* [55]:

Pedrasa *et al.* [55] propose an EMS, designed to perform DLC of interruptible appliances supposedly placed in multiple households (so, this is not a HEMS problem, in the proper sense; but it is alike, and is built around the similar or interrelated motivations and goals).

The goals of the scheduling are "to achieve a system requirement of total hourly curtailments while satisfying the operational constraints of the available interruptible loads, minimizing the total payment to them and minimizing the frequency of interruptions imposed upon them". They used the Binary Particle Swarm Optimization (BPSO) algorithm to perform the schedule, over a single aggregate objective function, wherein the constraints were expressed as hard and soft penalties. They assert that the Binary Particle Swarm Optimization (BPSO) algorithm proved capable of achieving near-optimal solutions in manageable computational time-frames for such a relatively complex, non-linear and non-continuous problem.

(4) Zhao el al. [38] propose a HEMS built over a HAN network infrastructure, with a genetic-algorithm based scheduling of the automatically operated appliances; and, taking advantage of the availability of an AMI and SG infrastructure and communications, they use a combined RTP-IBR pricing scheme as the basis to provide DR functionality, aiming with this combination, at stabilizing possible fluctuations of the PAR, since, they argue, there is a risk that as everyone shift their loads to cheaper times, new PAR spikings may arise.

(5) Likewise, Herath and Venayagamoorthy (2017) [34] propose a multi-objective PSO based electricity consumption scheduling for a smart neighbourhood. One interesting feature in this study, is the use of multi-objective optimization in a multi-household setting: multiple customers' objectives and utility's load profile flatness objective are optimized together, wherein aside from seeking the best compromise between cost and comfort for the individual households, it is also sought to produce such household schedules that will not harm the collective demand profile, i.e., the ones that better satisfy the utility's load profile flatness objective function. The scheme is aimed at providing an automated and efficient management tool for service providers franchising utility roles as discussed earlier.

As it would be difficult to keep simplicity and conciseness, and it would otherwise be excessive, to walk through a very long list of works, we defer the reader to see a further list of related works, that we reviewed, which are similar in the general picture (the HEMS environment, the motivations, the goals) and just differ in specifics (such as for instance, the optimization methods used): [6, 37, 56–62]. It is worth remarking that these works, for instance the one by Si et al. [60], using a Radial Base Function Neural Network (RBFNN) for office lighting control; or the one by Navarro-Caceres et al. [62], using an Artificial Immune System (AIS) for household energy optimization, etc.; underline the fact that while some methods may, at some stage, be the more prevalent (such as genetic algorithms or particle swarms), emerging methods or the innovative application of know methods, have their potential for delivering competitive solutions.

Aside from the above discussed literature, and to help build the big picture and outline important and common features and practices of the state of the art, we also examined a number of survey papers on HEMS and energy DR related matters, whose insights are worth discussing ([1, 7, 13, 16, 17]). These works, have different degrees of merit on the breadth, depth, accuracy, focus or perspective of their coverage of HEMSs and DR related matters. It became evident that, of the cited works, the one by Beaudin and Zareipour [1] stands aside in terms of breadth, depth and focus on the HEMS area, whereas the work by Deng et al [13] also digs deep in the HEMSs matters from the DR perspective, as compared to the remaining.

2.1.14.1 Summary Take-outs from the Review on Household Energy Management

From the reviewed literature (both the ordinary papers and the surveys), some important insights and take-outs are as follows:

(i) **On The HEMS environment, motivations and goals:**

The target environment of the proposed Energy Management Systems (EMSs) is mostly the single household, frequently a smart home, under the SG paradigm. Some works target also multiple households. Some other [55] address DLC based DR on multiple customers (households included) so the proposed control system is not quite a HEMS, however it shares many similarities with the other works, which is not strange since we also observed that for all the works, the motivations and goals are generally the same, instances of the ***eGoals*** (2.1.1), which are basically around: lowering energy bill and keeping comfort for the end-user, and providing demand response functionality, which brings the benefits we already discussed (2.1.7).

(ii) **On the model approaches and mathematical formulation:**

In many works, the problem was multi-objective by nature: two or more conflicting objectives were to be traded-off for an acceptable solution, as well as complying with a number of constraints. We found that, the most popular method of formulation, especially for the heuristic based approaches, is the conversion of the multiple objectives into an aggregate single objective by applying the **weighted-sum method**. In these "aggregate objective approach" works, also we found that, to further lessen the complexity of the problem formulation, it had been a popular practice to include the constraints into the aggregate objective function through the penalty approach, wherein the constraints are translated to a component of the aggregate single objective function.

(iii) **On tackling uncertainty and the CG:**

Some of the works are designed to tolerate uncertainty (UAS), by incorporating the capability of (re)building missing information, that may be just unavailable or be inaccurate at time of performing scheduling optimization, such as: pricing information, estimate of the available renewable energy resources, estimate of next-day household EC, etc. So, such information is (re)built by forecasting or "learning" from some available statistical data, and/or using some model previously built from some kind of data.

However, albeit we tried, we were unfortunate to not find works targeted to providing energy efficiency or demand responsiveness for the CG or for the transitional state from the CG to the SG. In those scenarios, such kind of works would require the capability to tackle DR information uncertainty, scarcity or bare unavailability. This was, as discussed in the introduction, a motivation and perspective in the present research work.

(iv) **On the types of optimization approaches commonly used:**

We observed that the most frequent optimization methods is the heuristic class, including the PSO, in particular BPSO for appliance scheduling optimization. This is corroborated by Beaudin and Zareipour [1] review: the approximate stakes of the most accounted optimization methods are:

(a) (Meta)heuristic approaches (PSO, GAs, TS, SA, etc.): 39.7%;

(b) Mixed Integer Linear Programming (MILP): 27.4%;

(c) Linear Programming (LP): 16.4%;

(d) Quadratic Programming (QP): 8.2%;

(e) Convex Programming (CvxP): 2.7%;

(f) Dynamic Programming (DP): 4.1%;

(g) Mixed Integer Non-Linear Programming (MINLP): 1.4%;

The methods in (b)-(e) are in the camp of so called "analytical/mathematical optimization (AMO)" methods: LP and MILP require linear (or affine) models, whereas CvxP and QP will require convex and convex-quadratic models. That lends them substantial model inflexibility pertaining the whole optimization process, in instances when the real life problem will need to change parameters or function definition, for some reason, such as in real time optimization applications scenarios, wherein some model parameters would change on-the-fly. Otherwise, many appliances schedules operation, translate to non-linear formulations among other model complexity features.

We can conclude that, in the surveyed [1] works, vis-a-vis analytical/mathematical optimization (AMO) methods, heuristic based approaches are the ones with the most substantive stake (near 40%), all the more so as we consider that the other methods, especially MILP, may probably feature some heuristic/computational intelligence based helper method as part of their algorithmic framework.

2.1.14.2 Choice of an Optimization Approach

From the above review and discussion, it is apparent that, from the general problem solution perspective, there is no absolute winner as best method for HEMS (and for any area) as also discussed in [1]. The choice will depend on further specificities and complexity of objective function(s) and constraints of the real life problem under analysis.

However, it is a common consensus (as for instance argued by [1, 13, 63–65]) that heuristic based approaches, are better choices as compared to conventional analytical/mathematical optimization (AMO) methods, when it comes to tackling non-linear, non-convex or non-continuous mathematical models, and providing near-optimal solutions with less computational effort, not being greatly affected with the "CoD" issue, which is the exponential increase in the volume of the search space with the problem size undermining computational performance.

Also, in a feature that helps the above capability, meta-heuristic methods, especially the ones in the camp of the population based metaheuristics (PBMs) (GAs, ESs, DE, PSO, etc.), generally take few or no assumptions about the problem mathematical model, regarding it as a blackbox function under the usual assumption that such function will timely return a "landscape" metric, a scalar, translating to relative fitness for each candidate position it submits to such blackbox ([1,66,67]).

Meeting the blackbox functionality, gives an optimization method, the capability of handling the instances when there is not a clear mathematical model for the problem, including unknown or uncertain parameters, that characterizes many real life problems, including in the area of household energy management, where, for instance informations like these will change unpredictably: (i) ordinary users will define system parameters in the form of their preferences for appliances' operational settings, (ii) next-day energy pricing information, (iii) next-day solar energy availability, etc. These changes will need to be reflected in the problem mathematical model, which would require a change in the optimization method if a conventional deterministic AMO method is used.

Otherwise, regarding the population based metaheuristic approaches among themselves (GAs, DE, ES, PSO, etc.), a number of research works comparing optimization approaches, found that the PSO algorithm, outperform other heuristic approaches (among GAs, DE, TS, SA), in both accuracy and computational effort. The PSO algorithm is also praised regarding the relative simplicity of its algorithmic framework and less assumptions towards meeting the blackbox functionality. However, there are many other research works that give superiority to some of the other parties using different sets of functions and/or algorithmic parameters and variants. Actually for many years, algorithm versions of evolution strategies (ES/CMAES) and differential evolution (SHADE family) among other families, have established themselves as the current state of the art.

Thence, most likely, no single heuristic based method (or indeed no method) will be the absolute winner for all kinds of problems (as addressed by the "No-Free-Lunch" (NFL) by Wolpert and Macready [68], and widely discussed in various literature, as in [67, 69–72]). So, the use of multiple optimization methods or a single hybrid method, may be better suited to address blackbox and model changing, real life problems, at least of a particular class, with determined limits.

In conclusion, the above discussion, deepened our understanding of the common methods used not just in the area of HEMSs and energy management, but in engineering and science in general. In this way, the discussion strengthened our prospective choice of using population based heuristic optimization methods (such as PSO, Evolution Strategies (ES)), as the best approach for our work in appliance scheduling, on the basis of their versatility in tackling complexity, uncertainty, non-linearity, which, in a real time control scenario, include unpredictable changes of objective functions and constraints parameters, driven by changes in the pricing functions, and changes in user's choice of operating parameters, such as appliance preferred time and duration of operation, etc. Those changes would likely require profound model changes if an analytical mathematical optimization method was the choice.

Chapter 3

Pseudo-RTP Guided Appliance Scheduling for Demand Responsiveness in Unconnected CG Environments

3.1 A Framework for a bbDR for Communications Deprived CG environments

Most works that we researched are flocking around providing automated DSM and ADR **for SG environments**, which imply default communications capabilities and supposedly an actual real time exercise and effectiveness of DSM and ADR protocols from all the parties. But the current energy landscape, characterized by the high prevalence of CG supply networks, all the more when Developing world is concerned, suggest that something should be done for providing a baseline automatic demand responsiveness for the CG environment, to tackle an increasingly uncontrollable high energy demand, which results in frequent blackouts, among other evils. So, to start with, we are outlining this research as a framework or vision for providing bbDR for the communication deprived networks (although other results of wider application are also envisaged). Such framework is depicted in Figure 13, where the main features are:

1. A pseudo-Real Time Pricing (RTP), is created from a country or region Daily Load Profile (DLP) as shown in next section. Such pseudo-RTP gives a rough approximation of the

daily demand evolution and thereby a valid guiding signal for the autonomous scheduling of a controllable appliance with lack of energy rate data. Such pseudo-RTP can be replaced by other types of pricing realizations deemed appropriate, including existing alternative pricing functions (such as Time of Use Tariff (ToUT)), or could be one specially crafted by the utility company for this special purpose. The energy rate function can then be placed as a built-in default inside the HEMS, with possible future update: for this, the HEMS is supposed to be ready for (a) offline update and/or for (b) a basic online update, when a communication channel and some DR functionality become available.

2. An appliance scheduling program as part of the HEMS will be guided by such pseudo-RTP, along with appliance scheduling data and user preferences, to produce optimized schedules, whereby user Energy Consumption (EC) patterns will be improved to some meaningful extent.
3. Incentive: the effectiveness of a DR measure, such as proposed bbDR, may need some kind of incentive from the utility in harmony with other stakeholders (*e.g.*: the government; see section 2.1.2) to boost the adherence by the end-use consumer to such scheme.

3.1.0.0.1 Sample Generation of a Pseudo-RTP Function We have used the following procedure for generating the pseudo-rtp (which does not exclude other possible ways, when other type of data are available): (1) digitization of the country load profile; see Figures 11-10; (2) normalization into "per unit" metrics; (3) fitting to a desired granularity (p/hour, p/10 minutes, p/minute, etc.) and (4) multiplying the "per units" by an average price, for instance 70c/KWh (cents of Rands/KWh; could be another currency or another average price).

in Figure 13, the picture in (b), shows the digitized RSA 2014 Winter profile vs. the pseudo-rtp-hourly graph generated using the above procedure, whilst the picture in (c), depicts the same SA2014 Winter load profile along with the resulting minutely pseudo-real-time price, also derived using the above procedure. Any of the simulated RTPs is time-step piecewise constant. The time step is also a unit time. The realization and demonstrations of using such DLP information to produce a pseudo-rtp and test it as a guiding signal for a bbDR approach, can be found in next sections/chapters.

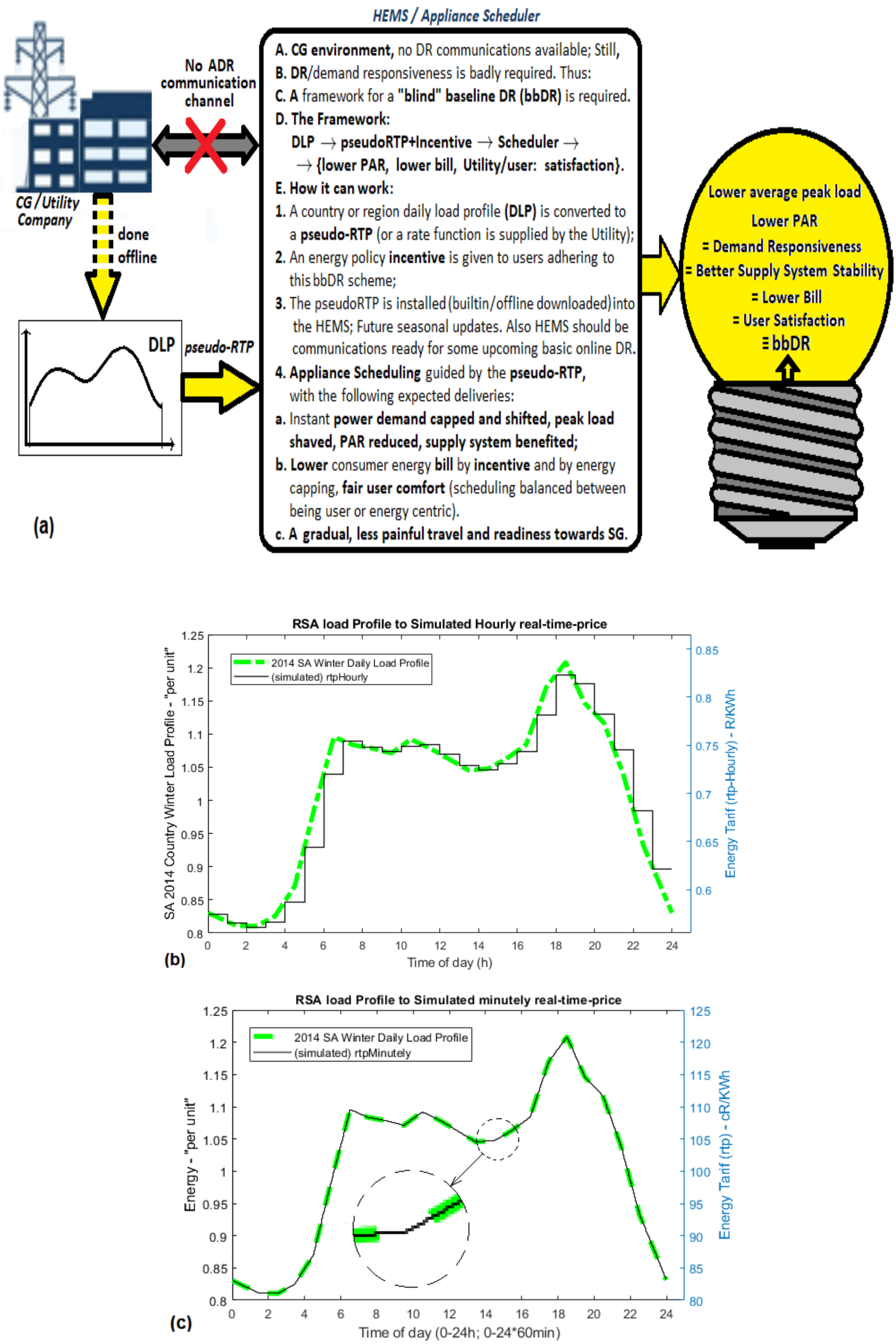


Figure 13 (a) Proposed bbDR Framework; (b-c) SA2014 Winter DLP along with: (b) pseudo-RTPhourly; (c) pseudo-RTPminutely

3.2 Pseudo-RTP and Heuristic Based Appliance Scheduling

To tackle appliance scheduling optimization, a process themed Real Parameter Blackbox Optimization Approach to Appliance Scheduling (RPBBOAS) model was developed. Also, a companion algorithm, named "Hybrid, Particle swarm, Evolution strategies, Random walks, Genetic, Differential and miscellaneous Ant-Inspired Cooperative Xplorers (HyPERGDx)", was developed to address shortcomings that we faced when trying to use readily available state-of-the-art algorithms to perform appliance scheduling on the *ApplianceSchedule1(.)* function, the Matlab implementation of said Real Parameter Blackbox Optimization Approach to Appliance Scheduling (RPBBOAS) model. Both the proposed works (the RPBBOAS model and the HyPERGDx algorithm), which we present and thoroughly discuss below, were also presented and discussed as a journal paper, undergoing a publication process.

3.2.1 Blackbox Optimization Approach

As addressed in section 2.1.14.2, blackbox capable algorithms, such as most metaheuristic methods, especially the ones in the camp of the PBM (GAs, ESs, DE, PSO, ES, etc.), generally don't require any specific knowledge of the problem mathematical model, aside from its dimensionality (problem size) and the boundaries of the problem space (box constraints); no further assumption is taken aside from expecting that such function will timely return a "landscape" metric, a scalar, translating to the relative fitness of the candidate position submitted ([1, 66, 67]). Figure 14 tries to describe the blackbox optimization concepts, which we are seeking to reproduce in our RPBBOAS model.

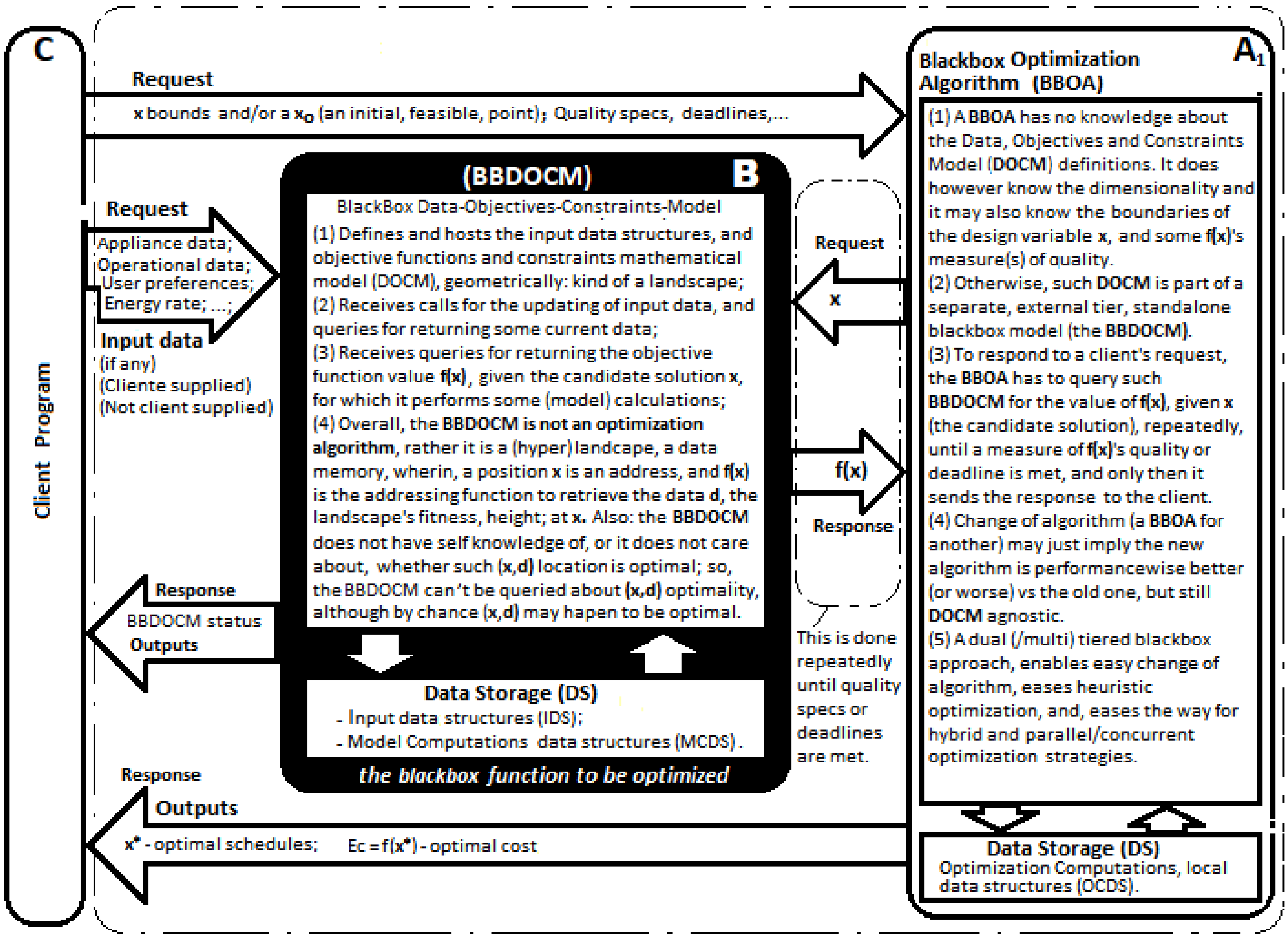


Figure 14 Blackbox Optimization Framework

3.3 Real Parameter Blackbox Optimization Approach to Appliance Scheduling

3.3.1 RPBBOAS Modelling Goals

Starting from the grounds of the above discussion, this work is an attempt to approach the appliance scheduling problem trying to address the above concerns, specifically aiming at the following:

1. The use of a real parameter, unconstrained or box constrained blackbox appliance scheduling optimization model, to allow for the use of any blackbox capable global optimization algorithm; along with such an approach we are also seeking to reduce the effect of the CoD/combinatorial explosion issue which is more serious if the problem space is modelled and optimized as pure combinatorial one, wherein each discrete time step (hour, minute, second,...etc., down to the adopted resolution) is a dimensional component of the problem space, *i.e.,* the variable that is optimized, from the optimization algorithm perspective, as with BPSO and alike.

2. The use of a simulated (pseudo) real time pricing, rebuilt from a country load profile, which is a fair representation of a one day evolution of demand in a specific country and thereby can be used as a rough replacement to the otherwise unavailable RTP information in a CG environment. Other pricing functions should however remain as interchangeable options to such simulated real time pricing function;

3. Providing a multi-appliance and multiple working cycles per appliance per day scheduling, and insure non overlapping working cycles for the same appliance; or non overlapping between cycles of different appliances where required, and specified by input parameters; should also insure some appliance A_1 working time precedence over another appliance A_2 where specified;

4. Providing instant power budget aiming at the reduction of global PAR and a shorter electricity bill by promoting power saving or power shifting to cheaper time slots.

5. Allowing for user defined, preferred appliance working time windows and optimal times, which paired with a user centricity parameter, regulate the amount of user satisfaction/frustration for the degree of displacement of the appliance's candidate schedules relative to such user specified optimal working times. In tandem with and to streamline the realization of such feature, establish penalty functions of different types to reflect different appliance based evolutions of the amount of user frustration vs the amount of schedule misplacement.

3.3.1.0.1 Appliance properties

A partial sample of house appliances, just appropriate for the discussion of the RPBBOAS model, is presented in Table 2.

Table 2 Appliance Properties and basic operational characteristics

Abrev.	Appliance Name/Group	Appliance Type	Nominal Power (W)	Standby Power (W)
WH	Water Heater	Shiftable, Schedulable	4500	100
CW	Clothes Washer	Shiftable, Schedulable	610	0
CD	Clothes Drier	Shiftable, Schedulable	5000	0
CF	Ceiling Fan	User operated, Non-schedulable	500	0
FG	Fridge	User operated, Non-schedulable	500	100
ST	Stove	User operated, Non-schedulable	2100	0
TV	Television	User operated, Non-schedulable	200	0
IL	Lighting	User operated, Non-schedulable	120	0

3.3.2 Basic, Combinatorial, Appliance Scheduling Model

Starting from the above grounds, the following equations (Eqs.3), are an introductory combinatorial appliance scheduling mathematical model, intended to serve as the basis, to support the motivations and discussion our proposed target RPBBOAS model in (Eqs.4):

Appliance Schedule Model 1: (Eqs.3)

$$H_{def} = \{\alpha,\ \varsigma,\ \delta,\ P_{Bi},\ E_{Bd},\ T,\ \tau\} \tag{3a}$$

$$A_{def} = \Big\{\{Pn_1, Psb_1, A_{T1}, W_{z1}, W_{p1}\}, \{Pn_2, Psb_2, A_{T2}, W_{z2}, W_{p2}\}, \ldots, \{Pn_m, Psb_m, A_{T_m}, W_{zm}, W_{pm}\}\Big\} \tag{3b}$$

$$N_{Cdef} = \{K_1, K_2, \ldots, K_j, \ldots, K_m\};\ K = \sum_{j=1}^{m} K_j \tag{3c}$$

$$W_{Tdef} = \Big\{\{\pi^T_{j1}, [T^L_{j1}, T^U_{j1}], [T^{OL}_{j1}, T^{OU}_{j1}], T^O_{j1}\}, \ldots, \{\pi^T_{jk}, [T^L_{jk}, T^U_{jk}], [T^{OL}_{jk}, T^{OU}_{jk}], T^O_{jk}\},\ \ldots\Big\};\ \forall j = 1,\ldots,m;\ \forall k = 1,\ldots K_j;\ K_j \in N_{Cdef} \tag{3d}$$

$$W_{Ddef} = \Big\{\{\pi^D_{j1}, [D^L_{j1}, D^U_{j1}], [D^{OL}_{j1}, D^{OU}_{j1}], D^O_{j1}, D^{Ocnt}_{j1}, I^{CT}_{j1}\}, \ldots, \{\pi^D_{jk}, [D^L_{jk}, D^U_{jk}], [D^{OL}_{jk}, D^{OU}_{jk}], D^O_{jk}, D^{Ocnt}_{jk}, I^{CT}_{jk}\},\ \ldots\Big\};$$

$$\forall j = 1,\ldots,m;\ \forall k = 1,\ldots K_j;\ K_j \in N_{Cdef} \tag{3e}$$

$$Q_j(t) = \begin{cases} 1, & \text{if appliance } j \text{ is swithched ON at time step number } t; \\ 0, & \text{otherwise;} \end{cases} ; \tag{3f}$$

$$q_j(t) = \overline{Q_j(t)} = 1 - Q_j(t). \tag{3g}$$

$$N_{Cj} = Q_j(1) + \sum_{t=1}^{N_t - 1} q_j(t) \cdot Q_j(t+1);\ \ j = 1,\ldots,m \tag{3h}$$

$$t_j = \{Q_j(1) \mid Q_j(1) = 1\} \cup \{t \mid (q_j(t-1)).(Q_j(t)) = 1\}; t = 2,\ldots,N_t \quad j = 1,\ldots,m \tag{3i}$$

$$t^e_j = \{t+1 \mid (Q_j(t)).(q_j(t+1)) = 1\} \cup \{Q_j(N_t) \mid Q_j(N_t) = 1\};\quad t = 1,\ldots,N_t - 1;\quad j = 1,\ldots,m \tag{3j}$$

$$d_j = \{d_{jk} \mid d_{jk} = e_{jk} - t_{jk};\quad t_{jk} \in t_j;\quad t^e_{jk} \in t^e_j;\quad \forall k = 1,\ldots,N_{Cj};\quad j = 1,\ldots,m \tag{3k}$$

$$\{P_i(t),\ t = 1,\ldots,N_t\} = \{\sum_{j=1}^{m} Pr_j(t);\ t = 1,\ldots,N_t\};\ Pr_j(t) = \begin{cases} Pn_j, & Q_j(t) = 1; \\ Psb_j, & \text{otherwise;} \end{cases} \tag{3l}$$

$$E_d = \frac{1}{\rho} \sum_{t=1}^{N_t} P_i(t);\ \rho = 3600/\tau; \tag{3m}$$

$$E_{Cj} = Pn_j \left(\sum_{t=1}^{N_t} R(t) \cdot \boldsymbol{Q_j}(t)\right) + Psb_j \left(\sum_{t=1}^{N_t} R(t) \cdot \Big(1 - \boldsymbol{Q_j}(t)\Big)\right) \tag{3n}$$

$$E_{Ch} = \sum_{j=1}^{m} E_{Cj} = \sum_{j=1}^{m} \left\{ Pn_j \left(\sum_{t=1}^{N_t} R(t) \cdot \boldsymbol{Q_j}(t)\right) + Psb_j \left(\sum_{t=1}^{N_t} R(t) \cdot \Big(1 - \boldsymbol{Q_j}(t)\Big)\right) \right\} \tag{3o}$$

$$U_{Dj} = \sum_{k=1}^{N_{Cj}} U_{pwd}(t_{jk},\ d_{jk},\ W_{Tdef}(j,k),\ W_{Ddef}(j,k)) \tag{3p}$$

$$U_{Dh} = \sum_{j=1}^{m} U_{Dj} = \sum_{j=1}^{m} \left\{ \sum_{k=1}^{N_{Cj}} U_{pwd}(t_{jk},\ d_{jk},\ W_{Tdef}(j,k),\ W_{Ddef}(j,k)) \right\} \tag{3q}$$

$$P_i(t) \le P_{Bi};\quad \forall t \in \{1,\ldots,N_t\} \tag{3r}$$

$$E_d \le E_{Bd} \tag{3s}$$

$$T^L_{jk} \le t_{jk} \wedge t_{jk} \le T^U_{jk};\quad k = 1,\ldots,N_{Cj};\quad j = 1,\ldots,m;\quad t_{jk} \in t_j \tag{3t}$$

$$D^L_{jk} \le d_{jk} \wedge d_{jk} \le D^U_{jk};\quad k = 1,\ldots,N_{Cj};\quad j = 1,\ldots,m;\quad d_{jk} \in d_j \tag{3u}$$

$$N_{Cj} = K_j;\ \ j = 1,\ldots,m;\ K_j \in N_{Cdef};\ \sum_{j=1}^{m} K_j = K \tag{3v}$$

$$S_j(t) = \begin{cases} 0, & Q_j(t) = 0; \\ \bigcup_{k=1}^{N_{Cj}} \Big(\Pi_{upwd}(t_{jk}, d_{jk}, W_{Tdef}(j,k), W_{Ddef}(j,k), \alpha, \varsigma, \delta)\Big), & \text{otherwise;;} \end{cases} ;\ \forall t \in \{1,\ldots,N_t\};\ t_{jk} \in t_j;\ d_{jk} \in d_j; \tag{3w}$$

$$H_j(t) = \begin{cases} 10^{100}\ \forall j \in \{1,\ldots,m\}, & \text{if: (Eq.3r) or (Eq.3s) do not hold; or for some } j \text{ there is a cycle overlaping violation;;} \\ 0, & \text{otherwise} \end{cases} \tag{3x}$$

$$B_j = \begin{cases} \infty, & \text{for some cycle } k \text{ of appliance } j\text{, any of (Eq.4t - Eq.4v) do not hold;} \\ 0, & \text{otherwise.} \end{cases} \tag{3y}$$

$$\min_{Q(t)} \boldsymbol{E}_{PCh} = \sum_{j=1}^{\boldsymbol{m}} \left\{ \boldsymbol{Pn_j} \left(\sum_{t=1}^{N_t} R(t) \cdot \boldsymbol{Q_j}(t) \cdot \Big(\boldsymbol{1} + \boldsymbol{\alpha} \cdot \boldsymbol{S_j(t)}\Big)\right) + \boldsymbol{Psb_j} \left(\sum_{t=1}^{N_t} R(t) \cdot \Big(1 - \boldsymbol{Q_j}(t)\Big)\right) + \boldsymbol{H_j} + \boldsymbol{B_j} \right\} \tag{3z}$$

where:

(A) Settings in (Eqs.3a-3e), represent the appliances' data definitions, namely:

1. H_{def} in (Eq.3a), holds:

   (a) the system wide *user centricity* coefficient (α) which determines the balance of user satisfaction to energy cost in the schedule optimization penalized cost function E_{Ch} in (Eq.3z). It goes along with;

   (b) ς and δ, whose values represent the relative share of cycle start-time misplacement vs the cycle duration mismatch, in the user preference window penalty function. ς regulates the contribution of the start-up penalty, whereas δ regulates the contribution of the duration mismatch in the aggregate user preference window penalty as calculated and returned by $\Pi_{upwd}(.)$ penalty function in (Eq.3w).

   (c) P_{Bi} and E_{Bd}: respectively the instant power demand budget (in KW) and the daily power consumption budget (in KWh) for schedulable appliances.

   (d) T is the simulation/control horizon, in seconds (We used a $T = 86400s$).

   (e) τ is the resolution or time granularity relative to T, *i.e.*, the duration of a discrete time step in seconds (We used a $\tau = 60s$). Whereas N_t is the number of τ's comprised in T, such that $T = \tau N_t$ (We herein assume that for convenience, *i.e.* no roundings, τ and T are chosen such T/τ produce an integer N_t). In turn ρ, in (Eq.3m), is the hourly relative resolution; it equates to the number of time steps comprised in 1h for the intended resolution τ; i.e., $\rho = 3600/\tau$; for instance, $\rho = 1,4,6,60,...$, correspond to 3600s (1h), 900s (15min), 600s (10min), and 60s (1min) τ resolutions. The coefficient ρ offers a means for adjustment of entities that are expressed in terms of the currently adopted resolution, vs some entities expressed relative to 1h, such as energy rate; for instance: calculating the daily energy consumption from the logged instant power demands (one instant means the discrete time slot τ).

The power budget settings are the energy limits the user defines and is eager to be subject to, in exchange for a lower energy price (based on maximum instantaneous household power demand) and a lower energy bill as a result of capping de daily energy consumption and shifting the consumption of schedulable appliances to lower priced time slots (to the best extent, as much as allowed by α, the user-centricity coefficient).

From the supply side perspective, the instant power cap (a demand side measure) results in power shifting from higher load to lower load profile time slots (as guided by the energy pricing function), leading to peak shaving and hence a lower PAR.

2. A_{def} in (Eq.3b), holds appliance power ratings (nominal: Pn_j and standby: Psb_j), as well as A_{Tj} the power control type (the appliance type in Table 17) and definitions for W_{zj} the "No-Go" and W_{pj} "precedent" zones for the appliance j; the terminal index $j = m$ is the number of appliances; The "No-Go" zones are predefined sections of the time horizon unallowed for operation for appliance j whereas the "precedent" zones are cycle precedence definitions (*e.g.* cycle Y should be placed after cycle K), in this case the actual compliant placement is done at scheduling time, whilst the "No-Go" zones are explicitly pre-defined.

3. N_{Cdef} in (Eq.3c), holds the definition (user preferences or baseline) for the number of cycles per appliance, wherein K_j is the number of cycles for the appliance $\boldsymbol{j}$, and $\boldsymbol{K}$ the overall total number of cycles, pertaining to all schedulable appliances.

4. W_{Tdef} in (Eq.3d), holds the definition (user preferences or baseline) appliance working windows (the subsets, enclosed in '{ }'), comprising:

   (a) π^T_{j1}, start-up (or generally: active time slot) misplacement penalty type for appliance j cycle 1;

   (b) T^L_{j1} is the absolute lower bound start-up time, whereas T^U_{j1} is the absolute upper bound active time ; for appliance j cycle 1; and,

   (c) T^{OL}_{j1} and T^{OU}_{j1}: are respectively the user preference cycle placement window worst case lower and upper bound active time for appliance j cycle 1; and,

(d) T^{O}_{j1} the user preference window optimal cycle start-up time, for appliance j cycle 1. T^{O}_{j1}, together with D^{O}_{j1} from (Eq.3e), form the optimal sub-window for cycle 1, as: $W^{TO}_{j1} = [T^{O}_{j1},\ T^{O}_{j1} + D^{O}_{j1} - 1]$ (the strict user preference window).

The above descriptions, which cited appliance j and cycle 1, apply to any other combination of appliance m and cycle k.

5. W_{Ddef} in (Eq.3e), holds the definition (user preferences or baseline) for the appliance cycles durations, wherein each subset (enclosed in '{ }') pertains to a particular appliance cycle:

(a) π^{D}_{j1}, duration mismatch penalty type for appliance j cycle 1;

(b) D^{L}_{j1} and D^{U}_{j1}: respectively the absolute lower and upper bound duration (times) for appliance j cycle 1; and,

(c) D^{OL}_{j1} and D^{OU}_{j1}: respectively the user preference duration window worst case lower and upper bound duration (times) for appliance j cycle 1; and,

(d) D^{O}_{j1} the (minimal of equally) optimal duration(s) as per user preference, for appliance j cycle 1.

(e) D^{Ocnt}_{j1} the count of adjacent equally optimal durations as per user preference, for appliance j cycle 1.

(f) I^{CT}_{j1} the minimum inter-cycle time as per user preference, for appliance j cycle 1: a minimum delay before staring next cycle.

The above descriptions, which cited appliance j and cycle 1, apply to any other combination of appliance m and cycle k.

(B) $Q_j(t)$ in (Eq.3f) is the switching state, either ON (1) or OFF (0), of the appliance j at the time step number t; whereas $q_j(t)$ in (Eq.3g) is $Q_j(t)$'s complement to 1 at the time step t.

(C) N_{Cj} in (Eq.3h) is the run time number of cycles for the appliance $\boldsymbol{j}$, calculated from the current candidate switching states $Q_j(t)$; N_{Cj} goes in tandem with t_j, t^{e}_{j} and d_j (their vector lengths should be equal to N_{Cj}):

(D) t_j in (Eq.3i) the set of the respective cycles starting times;

(E) t_j^e in (Eq.3j) the corresponding end times, and

(F) d_j in (Eq.3k) the respective durations;

(G) $P_i(t)$ (a vector of size N_t) and E_d (a scalar) are respectively the instantaneous (per each t) power demand and daily power consumption for the current candidate solution. These entities are checked for compliance with the constraints established by (Eq.3r) and (Eq.3s) respectively; *i.e.,* if a candidate schedule violates anyone of these budgets, then it is awarded a hard penalty via the H_j component in (Eq.3z) and (Eq.3x), so as to render it very unattractive a candidate solution for the fitness based optimization processes, which will be querying the model function for their fitness.

(H) E_{Cj} in (Eq.3n), represents the energy cost pertaining to the appliance $\boldsymbol{j}$, wherein Pn_j and Psb_j are as described in (Eq.3b), the nominal and the standby powers for appliance $\boldsymbol{j}$, respectively; t represents, in discrete time, the time step number, which, as discussed, is of fixed duration τ.

(I) $R(t)$ is the electricity price per unit time at time step t: $R(t)$ is time varying, but it is piecewise (time step-wise) constant;

(J) E_{Ch} in (Eq.3o), is the total household's cost of energy consumption per the control horizon T, whereas m remains the number of appliances, and index $j = 1,2,...,m$, the appliance number; E_{Ch} is (would be) one of the objectives to minimize, along with the one in (Eq.3q), both subject to (Eqs.3r - 3v);

(K) U_{Dj} in (Eq.3p) is a measure that tries to translate the user discomfort for appliance j cycles misplacement/mislength; whereas,

(L) U_{Dh} in (Eq.3q) is the total per the household (all schedulable appliances), for such measure of user discomfort, in (Eq.3p). U_{pwd} under both discomfort equations, is the function that calculates such measure of discomfort (further addressed in section 3.3.4);

Otherwise, U_{Dh} and E_{Ch} are the two conflicting objectives for optimization, which however is eventually done in (Eq.3z) using a penalized unconstrained approach. For specifics on the mathematical model U_{Dh} and the penalties, see section 3.3.4;

(M) Equations (3r - 3v) are collectively the constraints to comply with for the would be minimization of conflicting (Eq.3o) and (Eq.3q), as discussed above. Otherwise, for the minimization of the eventual objective in (Eq.3z), these constraints are enforced via the penalty components: $\alpha \cdot S_j$, H_j and B_j. Such constraints are namely:

1. (Eqs3r-3s) determine compliance to user specified instant and daily power caps, enforced via the H_j component of (Eq.3z);
2. (Eqs.3t-3u) define the box constraints, for whose violation a candidate solution is awarded infinity fitness (infeasible objective value);
3. (Eq.3v), defines that N_{Cj}, the optimization time (evaluated from the current candidate solution) number of cycles for any appliance j, be equal to its predefined K_j number of duty cycles per day.

(N) S_j in (Eq.3w) and H_j in (Eq.3x) are respectively the user-centric soft penalty and the operational hard penalty for the appliance j. The first represents quantitatively the penalty awarded for the user frustration in proportion to the amount of appliance cycles misplacement and duration mismatch relative to their predefined preference (it is a soft penalty that does not make a candidate solution roughly an infeasible one); and the hard penalty (H_j) is placed where an unacceptable violation occurs such as: (i) power budgets violations, (ii) cycle overlapping for appliances that are predefined not to overlap in determined cycles, (iii) cycle placement on prohibited ("no-go") zone. For any single occurrence of these cases, a very high penalty H_j is applied on every time slot for the whole offending candidate schedule. For specifics on the mathematical model and sample depictions of S_j and H_j penalties, see section 3.3.4. In turn,

(U) B_j in (Eq.3y) is concerned with the extreme violations, namely box constraints violation, wherein, candidate solutions place themselves outside the predefined feasible design space bounds, in which case they are awarded an infinity (∞, the hardest) penalty, which likely equates to assigning an infeasible objective value to (Eq.3z), to meet the infeasible input. This hardest penalty, ∞, may be replaced by the platform's largest number, which may be more convenient for feasibility of number comparisons somewhere in the external optimization process. This hardest (or generally any very high) penalty, is otherwise branded as the death penalty [74], underlining what it is meant for over the offending candidate solution.

(V) E_{PCh} in (Eq.3z), is the objective function of the model. It represents the total penalized cost of schedulable appliances, a function summing up the conflicting components (E_{Cj} and S_j) and constraints penalties (H_j and B_j), in a penalized unconstrained fashion, wherein, the presence of S_j, H_j and B_j components in (Eq.3z) insures that the minimization is already subject to the constraints handled by such components, turning it an unconstrained objective. The E_{PCh} function, is a result of merging together multiple conflicting objectives along with problem constraints into a single aggregate objective function, so as to help lessen the complexity of both the definition and the ensuing optimization process, a usual technique that we have discussed earlier. For such aggregation, specifically, the second objective (user discomfort) was treated as a soft constraint (an ε-constraint type approach [70] [73]) and then converted to a penalty which is aggregated to the main objective (E_{Ch}) using a multiplicative penalty approach [74] [75] in (Eq.3z). In turn, hard constraints (H_j and B_j) were aggregated into (Eq.3z) using an additive penalty approach [74] [75]. In any case, were the penalties are null (*i.e*, there is no violation whatsoever), then the pure energy cost prevails. Also, null penalty means full compliance to the entities represented by such penalties, being in particular, user satisfaction to the extent regulated by α (the *user-centricity* coefficient, in (Eq.3a)). Here α acts as the ε-constraint which helps the decision maker (the user, the designer) to *a priori* articulate their preference, *i.e.* to choose, their suitable optimal solution which satisfies both the energy cost objective and the user satisfaction objective; a solution that in any case is located over the Pareto front of all possible satisfying solutions for different values of α (the ε-constraint). Other variables in (Eq.3z), are already defined above.

Aside from what already discussed, it is assumed that for the feasibility of the optimization in (Eq.3z), the feasible solutions space is contiguous enough and its granularity τ referenced in (Eq.3a) should be as fine as enough to allow the optimal placement of all required, predefined schedules as per the settings in (Eqs.3a-3e). Also, as discussed earlier, the finer the granularity defined by ρ the better the placements and thereby the eventual optimal solution. Furthermore, for the feasibility of the optimization in (Eq.3z), it is also assumed that other definitions and user preferences are not conflicting or in whatever the manner ill defined.

3.3.2.1 Considerations about the Appliance Scheduling Basic Combinatorial model

From the above model (Eqs.3) it follows that: The appliance scheduling problem optimization turns out to be: the determination of the optimal combination of the binary $Q_j(t)$ states that yields the lowest possible penalized cost E_{PCh} in (Eq.3z).
In other words, and **very importantly**: $\{Q = Q_j(t); \quad j = 1,...,m, t = 1,...,N_t\}$ is the design space variable, sampled for determining its optimal bit pattern, the one that yields the lowest penalized cost, or the best compromise between cost and user comfort, according to the preferences and parameters thereof, set forth for the calculation of E_{PCh}, including most importantly the *user centricity* (α) parameter. So, for easy interpretation, $Q_j(t)$ (or its complement $q_j(t)$) should be regarded as the current candidate sample bit pattern, a candidate solution, a particle (in PBM jargon).

The first intuitive and straightforward approach to optimize the model in (Eqs.3) is to go combinatorial, using those $Q_j(t)$'s straight away as the design space variables, and performing a binary combinatorial optimization of some kind, such as using BPSO, Genetic Algorithms (GAs). However, a combinatorial optimization, is bound to be affected by the combinatorial explosion/"curse of dimensionality" (CoD) issue: the number of $Q_j(t)$ binary variables and thereby the volume of the design space increases exponentially with the number of appliances and their duty cycles, and mostly, with the desired granularity (whether $Q_j(t)$ represents hours or minutes or seconds, etc., time slots). This is the reason behind departing from the introductory model in (Eqs.3) to the RPBBOAS discussed in next section.

3.3.3 Proposed Reduced Dimensionality Real Parameter Scheduling Model

The main attempt, of the following model representation in (Eqs.4) is allowing for a reduced number of design space variables mainly from the optimization algorithm perspective, and also, allowing that such external variables, or candidate solutions, be real parameters in lieu of the discrete parameters, discrete $Q_j(t)$'s, of the above introductory model. At same time, the new model should, to the best extent, reduce the internal problem representation and computational complexity and encapsulate and "hide" it from the outside blackbox optimization algorithms querying for fitnesses of candidate solutions. Figure 14 is a reference model.

With such considerations in place, the below mathematical model, in (Eqs.4a-4z), collectively (Eqs.4), of which we underline the last one (Eq.4z); makes a modified representation of the previous model in (Eqs.3). Aside from some new variables, most equations from previous model (Eqs.3) make part of the new model (Eqs.4), some of them without change (Eqs.4a-4e), other with the same logical meaning and changes in their mathematical representation. Except for (Eqs.4f-4k) and (Eq.4v), every other variables naming and their meaning are the same of the previous model (and also, they keep the same alphabetical equation sub-index). In any case we will add due comments for the sake of emphasis or completeness. The following is the meaning of the variables and equations of the proposed model:

1. Settings in (Eqs.4a-4e), represent the household and appliances' data definitions, as in previous model, and, remain unchanged.

2. $\{C_{jk}\}$ in (Eq.4f): Is a vector comprising the linear sequence of all cycles from all appliances, orderly placed from cycle 1 to last cycle K_1 (of appliance 1) and then from cycle 1 to last cycle K_2 (for appliance 2), ..., until last cycle of appliance m (cycle K_m); then,

3. $\{C_i\} = \boldsymbol{I}(\{\boldsymbol{C}_{jk}\})$ in (Eq.4g) is its index set, a linear index, mapping the i-th element of such vector $\{C_{jk}\}$ to i; $\quad i \in C_i$; $\quad C_i \subset \mathbb{N}$; Also, very importantly: $O_{wnerJ}(C_i) = j$ and $O_{wnerJK}(C_i) = \{j,k\}$ give back the reverse appliance indexes j and $\{j,k\}$ of the cycle C_{jk} whose linear index is C_i.

   The linear index is used to map bijectively the vector of cycles $\{C_{jk}\}$ to the vector of components X_d; $d = 1, \ldots, D$, where, X_d is a component of the continuous time external design variable X, and, D is the dimension of X; also, D should comply with (Eq.4v) which include $D \leq 2K$; K keeps being the collective total number of appliances' cycles, and the length of vector $\{C_{jk}\}$. We underline the index function $\boldsymbol{I}(\{\boldsymbol{C}_{jk}\})$ that we use as the formal representation of such mapping, as well as $\boldsymbol{O}_{wnerJ}(\boldsymbol{C_i})$ as well as $\boldsymbol{O}_{wnerJK}(\boldsymbol{C_i})$, which represent the reverse mapping from the linear index C_i to the owning j or jk (where j is the owning appliance number and k the appliance cycle number).

4. s_c in (Eq.4h), is the starting time of cycle c; $c \in \{C_i\}$; s_c is the discretization of the $(2c-1)$-th dimensional component, of the external variable X; a discretization done up to the desired resolution or granularity specified by τ. *i.e.*, the odd index $2c-1$ under X in (Eq.4h), maps the starting time of the c-th cycle, to the design variable component X_d, where $d = 2c-1$. In turn, d_c in (Eq.4i), is the duration of cycle $c; c \in \{C_i\}$; similar to the above case, d_c is the discretization of the $(2c)$-th dimensional component, of the external variable X: *i.e.*, the even index $2c$ under X in (Eq.4i), maps the duration of the c-th cycle, to the design variable component X_d; where now $d = 2c$.
   Just to underline, it follows that, s_c is mapped to some odd indexed X_d, and the corresponding duration d_c is mapped to the next (even indexed) X_{d+1}, dimensional component of the external variable X;

5. Ton_j in (Eq.4j) is the collection of time slots where appliance j current state is "**ON**", *i.e.*, Ton_j is appliance j active time during the simulation horizon $T_d = \{1, ..., N_t\}$; whereas,

6. Tsb_j in (Eq.4k), is the standby time, the complement of Ton_j relative to the simulation horizon $T_d = \{1, ..., N_t\}$; $Ton_j \cup Tsb_j = T_d$, the discrete time counterpart of the continuous T horizon;

Reduced Dimensionality Real Parameter Appliance Scheduling Model (Eqs.4)

$$H_{def} = \{\alpha,\ \varsigma,\ \delta,\ P_{Bi},\ E_{Bd},\ T,\ \tau\} \tag{4a}$$

$$A_{def} = \Big\{\{Pn_1, Psb_1, A_{T1}, W_{z1}, W_{p1}\}, \{Pn_2, Psb_2, A_{T2}, W_{z2}, W_{p2}\}, \ldots, \{Pn_m, Psb_m, A_{T_m}, W_{zm}, W_{pm}\}\Big\} \tag{4b}$$

$$N_{Cdef} = \{K_1, K_2, \ldots, K_j, \ldots, K_m\};\ K = \sum_{j=1}^{m} K_j \tag{4c}$$

$$W_{Tdef} = \Big\{\{\pi^T_{j1}, [T^L_{j1}, T^U_{j1}], [T^{OL}_{j1}, T^{OU}_{j1}], T^O_{j1}\}, \ldots, \{\pi^T_{jk}, [T^L_{jk}, T^U_{jk}], [T^{OL}_{jk}, T^{OU}_{jk}], T^O_{jk}\},\ \ldots\Big\};\ \forall j = 1,...,m;\ \forall k = 1,...K_j;\ K_j \in N_{Cdef} \tag{4d}$$

$$W_{Ddef} = \Big\{\{\pi^D_{j1}, [D^L_{j1}, D^U_{j1}], [D^{OL}_{j1}, D^{OU}_{j1}], D^O_{j1}, D^{Ocnt}_{j1}, I^{CT}_{j1}\}, \ldots, \{\pi^D_{jk}, [D^L_{jk}, D^U_{jk}], [D^{OL}_{jk}, D^{OU}_{jk}], D^O_{jk}, D^{Ocnt}_{jk}, I^{CT}_{jk}\},\ \ldots\Big\};$$
$$\forall j = 1,...,m;\ \forall k = 1,...K_j;\ K_j \in N_{Cdef} \tag{4e}$$

$$\{C_{jk}\} = \{C_{1.1},\ C_{1.2},\ ...,\ C_{1.K_1},\ C_{2.1},\ C_{2.2},\ ...,\ C_{2.K_2},\ ...,\ C_{j.1},\ C_{j.2},\ ...,\ C_{j.K_j},\ ...,\ C_{m.1},\ C_{m.2},\ ...,\ C_{m.K_m}\} \tag{4f}$$

$$\{C_{jk}\} \leftrightarrow \{C_i\};\ \{C_i\} = I(\{C_{jk}\}) = \{1, \ldots, i, \ldots,\ K\};\ i = I(C_{jk});\ i = 1,\ ...,\ K;\ O_{wnerJ}(C_i) = j;\ O_{wnerJK}(C_i) = jk;\ j = 1,\ ...,\ m \tag{4g}$$

$$s_c = Q_{uantX}(X_\tau) = \lceil X_\tau \rceil + 1_{if};\ X_\tau = \frac{X_{2c-1}}{\tau};\ 1_{if} = \begin{cases} 1, \text{ if } X_\tau = \lceil X_\tau \rceil; \\ 0, \text{ otherwise} \end{cases};\ c \in \{C_i\};\quad 2c-1 \in \{1,\ 3,\ ...,\ D-1\};\ s.t.\ (4v); \tag{4h}$$

$$d_c = \left\lfloor \frac{X_{2c}}{\tau} \right\rceil = Round(X_{2c}/\tau);\ c \in \{C_i\};\quad 2c \in \{2,\ 4,\ ...,\ D\};\ s.t.\ (4v) \tag{4i}$$

$$Ton_j\ =\ \bigcup_{c \in \{C_j\}} [s_c,\ s_c + d_c - 1];\ \{C_j = C_i \mid O_{wnerJ}(C_i) = j\} \tag{4j}$$

$$Tsb_j = \Big\{t \in \{1, \ldots, N_t\} \ \Big|\ t \notin Ton_j\Big\};\ \{C_j = C_i \mid O_{wnerJ}(C_i) = j\} \tag{4k}$$

$$\big\{P_i(t),\ t = 1,...,N_t\big\} = \big\{\sum_{j=1}^{m} Pr_j(t);\ \forall t \in \{1, \ldots, N_t\}\big\};\ Pr_j(t) = \begin{cases} Pn_j,\ t \in Ton_j; \\ Psb_j,\ \text{ otherwise; } ie,\ t \in Tsb_j \end{cases} \tag{4l}$$

$$E_d = \frac{1}{\rho} \sum_{t=1}^{N_t} P_i(t);\ \rho = 3600/\tau; \tag{4m}$$

$$E_{Cj}\ =\ Pn_j \sum_{c \in \{C_j\}} \sum_{t=s_c}^{s_c+d_c-1} R(t)\ +\ Psb_j \sum_{t \in Tsb_j} R(t);\ \{C_j = C_i \mid O_{wnerJ}(C_i) = j\} \tag{4n}$$

$$E_{Ch}\ =\ \sum_{j=1}^{m} E_{Cj}\ =\ \sum_{j=1}^{m} \left\{ Pn_j \sum_{c \in \{C_j\}} \sum_{t=s_c}^{s_c+d_c-1} R(t)\ +\ Psb_j \sum_{t \in Tsb_j} R(t) \right\};\ \{C_j = C_i \mid O_{wnerJ}(C_i) = j\} \tag{4o}$$

$$U_{Dj}\ =\ \sum_{c \in \{C_j\}} \sum_{t=s_c}^{s_c+d_c-1} U_{pwd}(s_c,\ d_c,\ W_{Tdef}(j,k),\ W_{Ddef}(j,k));\ \{C_j = C_i \mid O_{wnerJ}(C_i) = j\}; jk = O_{wnerJK}(c) \tag{4p}$$

$$U_{Dh}\ =\ \sum_{j=1}^{m} U_{Dj}\ =\ \sum_{j=1}^{m} \left\{ \sum_{c \in \{C_j\}} \sum_{t=s_c}^{s_c+d_c-1} U_{pwd}(s_c,\ d_c,\ W_{Tdef}(j,k),\ W_{Ddef}(j,k)) \right\};\ \{C_j = C_i \mid O_{wnerJ}(C_i) = j\}; jk = O_{wnerJK}(c) \tag{4q}$$

$$P_i(t) \le P_{Bi};\quad \forall t = 1, \ldots, N_t \tag{4r}$$

$$E_d \le E_{Bd} \tag{4s}$$

$$T^L_{jk} \le s_c\ \wedge\ s_c \le T^U_{jk};\quad \forall c \in \big\{1, ..., K\big\}; jk = O_{wnerJK}(c);\ k = 1, ..., K_j;\ K_j \in N_{Cdef};\ K = \sum_{j=1}^{m} K_j;\quad j = 1, ..., m; \tag{4t}$$

$$D^L_{jk} \le d_c\ \wedge d_c \le D^U_{jk};\quad \forall c \in \big\{1, ..., K\big\}; jk = O_{wnerJK}(c);\ k = 1, ..., K_j;\ K_j \in N_{Cdef};\ K = \sum_{j=1}^{m} K_j;\quad j = 1, ..., m; \tag{4u}$$

$$\{n_k = D/2 \Leftrightarrow n_k = \lfloor D/2 \rfloor\} \wedge n_k \le K;\ K = \sum_{j=1}^{m} K_j; \tag{4v}$$

$$S_j(t) = \begin{cases} 0,\ t \in Tsb_j;\ \forall t \in \{1, \ldots, N_t\}; \\ \bigcup_{c \in C_j} \Big(\varPi_{upwd}(s_c, d_c, W_{Tdef}(j,k), W_{Ddef}(j,k), \alpha, \varsigma, \delta)\Big),\ \text{otherwise;} \end{cases} ;c \in \{C_j = C_i | O_{wnerJ}(C_i) = j\};\ jk = O_{wnerJK}(c) \tag{4w}$$

$$H_j(t) = \begin{cases} 10^{100}\ \forall j \in \{1, ..., m\}, \text{ if: (Eq.4r) or (Eq.4s) do not hold; or for some } j \text{ there is a cycle overlaping violation;;} \\ 0,\ \text{ otherwise} \end{cases} \tag{4x}$$

$$B_j(t) = \begin{cases} \infty, \text{for some cycle } k \text{ of appliance } j, \text{ any of (Eq.4t - Eq.4v) do not hold;} \\ 0,\ \text{ otherwise.} \end{cases} ;\ \forall t \in \{1, \ldots, N_t\} \tag{4y}$$

$$\min_X \boldsymbol{E}_{PCh}\ =\ \sum_{j=1}^{\boldsymbol{m}} \left\{ \boldsymbol{Pn_j} \left(\sum_{c \in \{C_j\}} \sum_{t=s_c}^{s_c+d_c-1} R(t) \Big(\boldsymbol{1 + \alpha S_j(t)}\Big) \right)\ +\ \left(\boldsymbol{Psb_j} \sum_{t \in Tsb_j} \boldsymbol{R(t)} \right)\ +\ \boldsymbol{H_j + B_j} \right\} \tag{4z}$$

7. $P_i(t)$ (a vector of size N_t) in (Eq.4r) and E_d (a scalar) in (Eq.4s), are respectively the run-time instantaneous power demand and daily power consumption as discussed earlier; albeit $P_i(t)$ is now expressed in terms of cycle start times and durations as derived from (Eqs.4g-4k);

8. E_{Cj} in (Eq.4n), represents the energy cost pertaining to the appliance j, wherein Pn_j, Psb_j, $R(t)$, Psb_j, keep their definitions from model (Eqs.3).
   However, E_{Cj} time is not expressed in a per time slot $Q_j(t)$ design space binary variable, but rather expressed in cycle start times and durations (s_c and d_c respectively), themselves derived from a real, *i.e.* continuous time parameter X, a derivation made via its discretization, following a mapping between the appliance cycles (start times and durations) and X. The mapping was already discussed above in (Eqs.4f - 4i).

9. E_{Ch} in (Eq.4o) represents the daily (*i.e.* a per the simulation horizon T_d) household's energy cost, as in (Eq.3o); however, as with E_{Cj} it is now expressed in terms of the new s_c and d_c derived from the externally submitted candidate solution X;

10. U_{Dj} in (Eq.4p), and U_{Dh} in (Eq.4q), keep their meanings of the previous model, as per the descriptions for (Eq.3p) and (Eq.3q) respectively. However, they are now expressed in terms of cycle start times and durations (s_c and d_c respectively) of a new type as derived from (Eqs.4g-4k) above. For specifics on the mathematical model U_{Dh} and the penalties, see section 3.3.4;

    It is worthless repeating that U_{Dh} and E_{Ch} are the two conflicting objectives for optimization, which however is eventually done in (Eq.4z) using a penalized unconstrained approach;

11. Equations (4r - 4v) are collectively the constraints to comply with for the optimization in (Eq.4z): (Eqs.4r-4s) determine compliance to user specified instant power demand and daily power consumption caps, constraints that are enforced via the H_j component of (Eq.4z), and discussed above; (Eqs.4t-4u) define the box constraints, which are enforced via the $B_j$component of (Eq.4z); whilst (Eq.4v) determine that the dimension D of the real valued candidate solution X submitted by external parties querying for its fitness, be

compliant with expected model properties and relationships as follows: (i) D should be even (or for generality: D should be multiple of v where for now $v = 2$, for start time and duration), and number of cycles thereof, should be $n_k = D/v = D/2$. If the input D is not compliant with such properties and relationships, than the offending candidate solution is awarded the hardest penalty via the said B_j component of (Eq.4z) as further described below.

12. $S = S(g_j)$ in (Eq.4w) and $H = H(h_j)$ in (Eq.4x) are respectively, the user centric, soft penalty (which translates compliance to user comfort, to the extent regulated by α) and the hard penalty for the appliance j. Their definitions and meaning remain the same as in previous model, except for the function signatures that now use the new s_c and d_c from X as described above. Also, for specifics on the mathematical model of S_j and H_j penalties, as well as some sample depictions, see section 3.3.4;

13. B_j in (Eq.4y), is aimed at enforcing compliance to box constraints, whose violation is an extreme offence, meeting such violations with the hardest penalty. B_j keeps its meaning and descriptions of the previous model, albeit worth underlining a small difference: (Eq.3v) of the previous B_j in (Eq.3y), is replaced by (Eq.4v) in the current B_j in (Eq.4y). However, (Eq.3v) and (Eq.4v) have been duly described in their respective sections.

14. E_{PCh} in (Eq.4z), is the objective function of the model. It represents the total penalized cost of schedulable appliances, as discussed in previous model. However, it is worth noting that, as with some of its components, it is now formulated and optimized by a real valued parameter X of a reduced dimensionality. We should underline however, that E_{PCh} in (Eq.4z) keeps the same multi-objective to single-objective transformation and representation approaches, as well as the constrained to unconstrained optimization approach, bringing together the multiplicative (for soft constrains) and additive (for hard constrains) into the eventual E_{PCh} (Eq.4z) penalized single-objective function. See previous description for E_{PCh} in (Eq.3z) for completeness. However and obviously, the E_{PCh} in (Eq.4z) and the model in (Eqs.4) are the ones implemented in the subsequent experimental investigation steps.

3.3.4 User Discomfort, Constraints and Penalties

This section describes the mathematical model for handling user discomfort (one of the two conflicting objectives to minimize) and constraints, by way of a penalty approach. We should point out that, although the approach addresses both the above appliance scheduling mathematical models (Eqs.3 and Eqs. 4), we will focus the explanation and eventual examples on the later model, but we will place remarks where there could be any differences deserving mention.

As we discussed in the previous sections, we addressed the multi-objective optimization by:

- (i) setting the energy cost (E_{Ch}) as the main objective; and
- (ii) considering the user discomfort (U_{Dh}) as a constraint; and then,
- (iii) we modelled U_{Dh} as the α-regulated soft constraint S_j in (Eq.4z) (which can be regarded as an ε-constraint type approach [70] [73], an *a priori* choice of a Pareto optimal point, from a Pareto optimal set, whose points are found by setting different values of the ε-constraint, in this case α, the user-centricity coefficient);
  With the user discomfort regarded as a constraint, we then represent it as a penalty in the interval [0,1]. On the other hand, two types of user discomfort were considered: (a) the discomfort for any arbitrary active time slot (itself part of an appliance C_{jk} cycle) being placed outside the boundaries of the user preferred optimal C_{jk} placement; and (b) the discomfort for the C_{jk} duration mismatch relative the user preferred optimal duration. In this way, these two discomfort objectives, are scaled and added to the eventual S_j penalty using a weighed sum approach as further addressed below in (Eq.10).

Since user discomfort (of the two types) is addressed as a penalty as discussed, we are going to henceforth mostly just talk about penalties. Now, looking back at both (Eq.3z) or (Eq.4z), we recall that we have three penalty components, namely: (1) S_j, for soft constraints penalties, modelling user discomfort and described in either (Eq.3w) or (Eq.4w); (2) H_j, for hard constraints penalty, described in either (Eq.3x) or (Eq.4x); and (iii) B_j, for the extreme hard constraints and penalties. From that grounds, the penalty handling is modelled as the following:

1. **Soft constraints penalties (over user discomfort)**: Any penalty of this category is calculated given the appliance cycle C_{jk} to be evaluated, and the respective pair of UPWs. The cycle C_{jk} is comprised by a number of adjacent time slots the first of which is the cycle start-up time S_t; and a cycle duration D_t which is precisely the number of such time slots. The indexes j and k represent respectively de appliance number and the cycle number; The cycle is thus the interval of discrete time slots given as:

$$C_{jk} = [S_t,\ \ S_t + D_t - 1] \tag{5}$$

Importantly: S_t and D_t are assumed to be within their respective absolute box constraints ($[T^L_{jk}, T^U_{jk}]$ and $[D^L_{jk}, D^U_{jk}]$) defined for C_{jk} in either (Eq.3d) or (Eq.4d); otherwise, a B_j penalty will be applicable. The pair of preference windows and companion settings for penalty evaluation are:

   (a) For cycle time slot misplacement penalty (P_s): a cycle placement UPW (tUPW) comprising: (i) $W^T_{jk} = [T^{OL}_{jk}, T^{OU}_{jk}]$, preference window bounds, worst case preference window placements for C_{jk}, (ii) T^O_{jk}, the optimal start-up time (as per user preference) of the optimal sub-window itself inside such W^T_{jk}; (iii) the time slot soft penalty type (π^T_{jk}); and (iv) D^O_{jk}, the optimal duration (as per user preference) of the optimal sub-window. The first 3, are drawn from either (Eq.3d) or (Eq.4d), and the last one drawn from either (Eq.3e) or (Eq.4e); As suggested, T^O_{jk} and D^O_{jk}, determine an optimal sub-window:

$$W^{TO}_{jk} = [T^O_{jk},\ \ T^O_{jk} + D^O_{jk} - 1] \tag{6}$$

   where it is assumed any such optimal sub-window is a subset of the preference window W^T_{jk}, *i.e.*:

$$[T^O_{jk},\ \ T^O_{jk} + D^O_{jk} - 1] \subseteq [T^{OL}_{jk}, T^{OU}_{jk}] \tag{7}$$

   And, letting the optimal sub-window end time be denoted as $W_{oEt} = T^O_{jk} + D^O_{jk}$ then (Eq. 7) is rewritten as:

$$[T^O_{jk},\ \ W_{oEt} - 1] \subseteq [T^{OL}_{jk}, T^{OU}_{jk}] \tag{8}$$

(b) For cycle duration mismatch penalty (P_d): a cycle duration UPW (dUPW) comprising: (i) $W_{jk}^{D} = [D_{jk}^{OL}, D_{jk}^{OU}]$, preference window bounds, worst case preference duration window for C_{jk}; (ii) D_{jk}^{O}, the optimal duration (as per user preference) of cycle C_{jk}; and (iii) the cycle C_{jk}'s duration soft penalty type (π_{jk}^{D}); all of them drawn from either (Eq.3e) or (Eq.4e). In turn, duration optimal sub-window is given by D_{jk}^{O} and D_{jk}^{Ocnt}, as:

$$W_{jk}^{DO} = [D_{jk}^{O},\ D_{jk}^{O} + D_{jk}^{Ocnt} - 1] \tag{9}$$

As said, numerically, any of these soft penalties ($P_s = U_{pwd}(.)$ or $P_d = U_{pwd}(.)$) is a number in the interval [0,1], wherein 0 means no penalty and 1 full (100%) penalty. Cycle time slot penalties P_s are calculated per each time slot of the cycle C_{jk}, whereas duration penalty P_d is a scalar, a single penalty for the cycle C_{jk} duration mismatch.

For P_s penalties, if a time slot of cycle C_{jk} is outside the tUPW, than it is awarded the full penalty; if the time slot is within the optimal portion of the tUPW, (*i.e.*, within W_{jk}^{TO}), then it is awarded a null penalty. Otherwise, when such time slot is within the UPW but outside the optimal sub-window W_{jk}^{TO}, then, a penalty is awarded proportional to its distance to the nearest edge of W_{jk}^{TO}, a proportionality given by the penalty function specified by π_{jk}^{T}. In any of the cases, P_s is calculated by the user discomfort penalty function as $P_s = U_{pwd}(C_{jk}, W_{jk}^{T}, W_{jk}^{TO}, \pi_{jk}^{T})$.

For P_d penalties, if the cycle C_{jk} duration, *i.e*, D_t, is outside the dUPW, than it is awarded the full penalty; if the duration D_t is within W_{jk}^{DO} (itself within dUPW), then it is awarded a null penalty. Otherwise, when the cycle duration D_t is within the dUPW but outside W_{jk}^{DO}, then, a penalty is awarded proportional to its distance to the nearest edge of the W_{jk}^{DO} optimal duration sub-window, a proportionality given by the penalty function specified by π_{jk}^{D}. In any of the cases, P_d is calculated by the user discomfort penalty function as $P_d = U_{pwd}(D_t, W_{Djk}, D_{jk}^{O}, \pi_{jk}^{D})$.

Eventually, these soft penalties (P_s and P_d), actually representing the two measures of user discomfort as discussed earlier, are scaled by ς and δ respectively and added together (*i.e.* in a weighted sum approach), converting them into the eventual aggregate penalty, as the following:

$$\Pi_{upwd} = \varsigma \cdot P_s + \delta \cdot \mathbb{1}(D_t) \cdot P_d \tag{10}$$

where $\mathbb{1}(Dt)$ is the all-ones vector of length D_t; ς and δ are definitions drawn from either (Eq.3a) or (Eq.4a); ς and δ determine the relative importance of the P_s and P_d penalties in the aggregate penalty function $\Pi_{upwd}(.)$, which in turn, is repeatedly calculated/returned into S_j in either (Eq.3w) or (Eq.4w).

We wrote the following penalty types associated with either π^T_{jk} or π^D_{jk} (represented by $\boldsymbol{n}$ below), therefore applying to both the P_s and P_d penalties on free choice:

(i) **Type $\boldsymbol{n = 0}$: A null-inbounds and full-outbounds penalty**: null penalty inside whole preference window UPW bounds, and full penalty otherwise (as suggested by and used in [36]):

$$U_{pwd}(t) = \begin{cases} 0, \ \ t \in [T^{OL}_{jk}, T^{OU}_{jk}); & \text{left bound in, right bound out;} \\ 1, \ \ \text{otherwise} \end{cases} \tag{11}$$

(ii) **Type $\boldsymbol{n = 1}$: linear penalty**: full outside preference window bounds, null inside optimal sub-window bounds, and linear (affine) varying from null at the optimal sub-window bound to full (=1) at the respective preference window bound:

$$U_{pwd}(t) = \begin{cases} 0, \ \ t \in [T^{O}_{jk}, \ \ T^{O}_{jk} + D^{O}_{jk}); \\ 1, \ \ t \notin [T^{OL}_{jk}, T^{OU}_{jk}); \\ \frac{T^{O}_{jk} - t}{T^{O}_{jk} - T^{OL}_{jk} + 1}, \ \ t \in [T^{OL}_{jk}, T^{O}_{jk}); \\ \frac{t - (T^{O}_{jk} + D^{O}_{jk} - 1)}{T^{OU}_{jk} - (T^{O}_{jk} + D^{O}_{jk} - 1)}, \ t \in [T^{O}_{jk} + D^{O}_{jk}, T^{OU}_{jk}); \end{cases} \tag{12}$$

A linear type penalty is a power law penalty of exponent 1 (type $n = 1$).

(iii) **Type $\boldsymbol{n = 1, 2, \ldots, Pmax}$: power law penalty**: full outside preference window bounds, null inside optimal sub-window bounds, and power law varying with exponent n (where n is a positive integer penalty type), from null at the optimal sub-window bound to full (=1) at the respective preference window bound. It is assumed

$[T^O_{jk},\ T^O_{jk}+D^O_{jk}] \subseteq [T^{OL}_{jk}, T^{OU}_{jk}]$:

$$U_{pwd}(t) = \begin{cases} 0,\ t \in [T^O_{jk},\ T^O_{jk}+D^O_{jk}); \\ 1,\ t \notin [T^{OL}_{jk}, T^{OU}_{jk}); \\ \left(\frac{T^O_{jk}-t}{T^O_{jk}-T^{OL}_{jk}+1}\right)^n,\ t \in [T^{OL}_{jk}, T^O_{jk}); \\ \left(\frac{t-(T^O_{jk}+D^O_{jk}-1)}{T^{OU}_{jk}-(T^O_{jk}+D^O_{jk}-1)}\right)^n,\ t \in [T^O_{jk}+D^O_{jk}, T^{OU}_{jk}); \end{cases} \tag{13}$$

when $\boldsymbol{n}$ increases towards infinity the penalty turns less harsh and tends to the $n=0$, bounded null-in full-out penalty type, above described. That said, there is not an established *Pmax* but given the discussed tendency, a $Pmax < 10$ is reasonable, otherwise type $n=0$ could be used instead, since it is less computationally expensive.

(iv) **Type $\boldsymbol{n = -1, -2, \ldots, -Emax}$: exponential penalty**: full outside preference window bounds, null inside optimal sub-window bounds, and exponential law varying with an exponent derived from n (n is the negative integer penalty type, as above specified), from null at the optimal sub-window bound to near full ($\beta_p = 1-\varepsilon$) at the respective preference window bound, where it is assumed $[T^O_{jk},\ T^O_{jk}+D^O_{jk}] \subseteq [T^{OL}_{jk}, T^{OU}_{jk}]$; Let the optimal sub-window end time be denoted as $W_{oEt} = T^O_{jk}+D^O_{jk}$; Also let $\varepsilon = 5^n$ (these settings can be adjusted to designer's convenience), then:

$$U_{pwd}(t) = \begin{cases} 0,\ t \in [T^O_{jk},\ T^O_{jk}+D^O_{jk}); \\ 1,\ t \notin [T^{OL}_{jk}, T^{OU}_{jk}); \\ 1-\varepsilon e^{\left\{-log(\varepsilon)\frac{t-T^{OL}_{jk}}{T^O_{jk}-T^{OL}_{jk}+1}\right\}},\ t \in [T^{OL}_{jk}, T^O_{jk}); \\ 1-e^{\left\{log(\varepsilon)\frac{t-W_{oEt}+1}{T^{OU}_{jk}-W_{oEt}+1}\right\}},\ t \in [W_{oEt},\ T^{OU}_{jk}); \end{cases} \tag{14}$$

It is worth remarking that the above penalties are as seen, calculated just at the given discrete time steps and (the penalties) are thus piecewise (time slot-wise) constant.

Looking at the above soft penalty types, it can be seen that some are less harsh, more lenient penalty types (type 0, or power law the higher the exponent), and there are harsher (type 1: linear) and the harshest ones (the exponential, the higher the exponent modulus). That goes in tandem with the real-life household, where some appliances could be more (or less) flexible then other, concerning their working cycle misplacement, vis-a-vis user satisfaction.

Figures 15 (for cycle placement) and 16 (for duration); depict the main penalty evaluation entities described above, including a *type 0, null-inside UPW bounds* penalty, applied do cycle C_{jk} or to duration D_t respectively, whereas Figure 17 depicts the run-time demo of the penalty types vs candidate cycle placements of the *HyperPopulation Best* particle, at 3 stages of the optimization process by the HyPERGDx, the newly proposed hybrid metaheuristic. On Figure 17, it is also worth pointing out and witnessing that an optimal placements of a cycle C_{jk} is the position of best compromise between its UPWs optimal sub-windows and the lowest costed interval of the energy pricing function (the black dotted line labelled as ***p-rtpZA2014W***), whereby the particle best position is a summation of such cycle best compromises, which can be found in looking at the 1st and final placement stages on the figure. It goes without saying that the final optimal position depend on both the pricing function and the preference settings (UPW and penalty types) which can be adjusted to user's (or generally, decision maker's) better convenience.

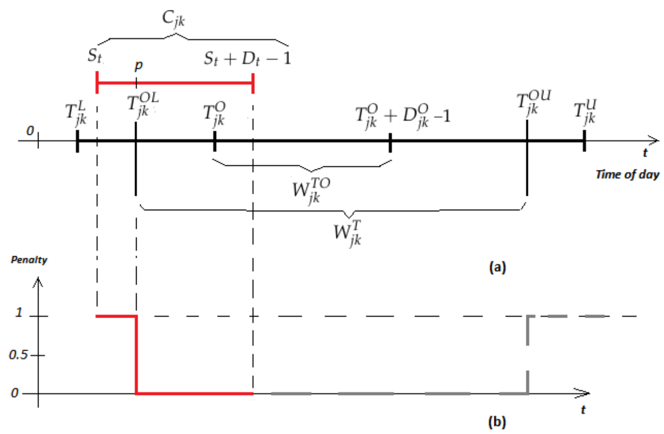


Figure 15 (**a**) Time slot penalty evaluation structures. (**b**) *Type 0* penalty.

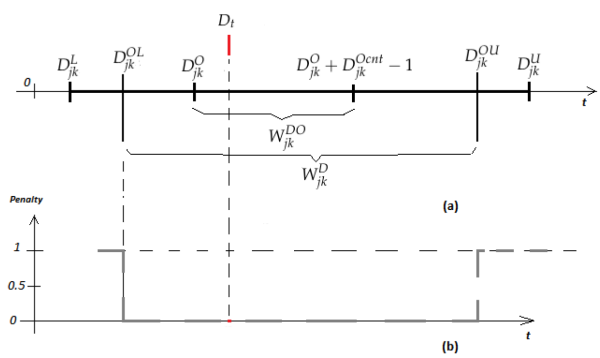


Figure 16 (**a**) Duration penalty evaluation structures. (**b**) *Type 0* penalty.

2. **Hard constraints:**

   As discussed earlier, the following set of circumstances trigger a hard penalty: (i) a power budget - instant: P_{Bi} in either (Eq.3l) or (Eq.4l), or daily: E_{Bd} in either (Eq.3m) or (Eq.4m) - is violated; (ii) a candidate schedule has overlapped a prohibited ('No-Go') zone (which is a per appliance zone that is defined through W_{zj} in either (Eq.3b) or (Eq.4b)); (iii) an overlap occurs between two cycles, say, C_{22} and C_{31}, where they are pre-defined to not overlap. Such is (a) the case when the cycles belong to the same appliance, which could happen in model 2 (Eqs. 4) but not in model 1; or (b) the case when a precedence of, for instance, cycle C_{22} over C_{31} has been set, wherein these cycles should not overlap (let alone their order of execution: C_{22} first and then C_{31}). Cycle precedence is set through W_{pj} in either (Eq.3b) or (Eq.4b).

   For the evaluation of cycle overlapping, the contending cycles have to be specified: C_{Ojk} and C_{Ovr} (this one can also be a set of cycles instead), and fed to the overlapping/contemporaneity check function as:

   $$L_{value} = A_{nyContemporary}(C_{Ojk}, C_{Ovr})$$

   where j and v denote appliance number, whereas k and r denote appliance cycle number. Also, in particular, so far as overlapping is concerned, it is worth noting that, C_{Ojk} or (any of the) C_{Ovr} have an inter-cycle time I_{jk}^{CT} as defined in either (Eq.3e) or (Eq.4e) which is added to the duration Dt and has thereby an influence on the outcome of (Eq.16). Inter-cycle time is an inactive (appliance *Off*) period which may be needed for any technical/physical or scheduling reason. So for overlapping check, C_{Ojk} (or any of the C_{Ovr} contender cycles), *vis-a-vis* C_{jk} in 5; thus, we call C_{Ojk} an extended cycle, and expressed as:

   $$C_{Ojk} = [S_t,\ \ S_t + D_t + I_{ct} - 1] \tag{15}$$

   Given the above *modus operandi*, mathematically $A_{nyContemporary}(.)$ is computed as:

   $$L_{value} = A_{nyContemporary}(C_{Ojk}, C_{Ovr}) = \begin{cases} 0, \{C_{Ojk} \cap C_{Ovr}\} = \emptyset \\ 1,\ \ \text{otherwise} \end{cases} \tag{16}$$

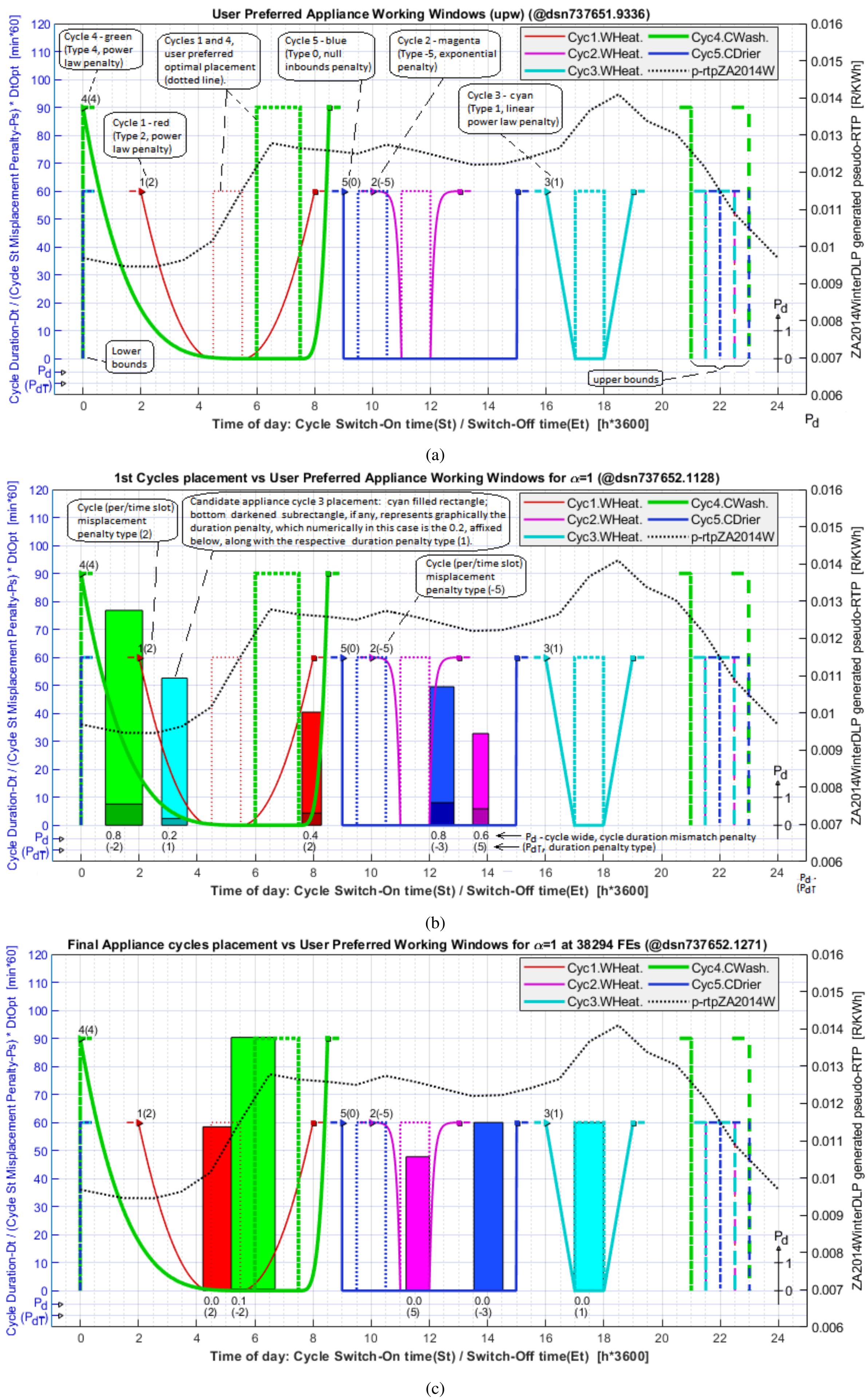


Figure 17 Run-time depiction of user preferred working windows and penalties vs candidate schedules: (**a**) at the initial stage (prior to placements), (**b**) initial stage with candidate placements; (**c**) Final stage.

where C_{Ovr} should be interpreted as the union set of all cycles that C_{Ojk} should not be overlapped with. Given the above, the definition of H_j turns out more specifically to be (Eq.17), which is equivalent to (Eq.18):

$$H_j = \begin{cases} 10^{100}, \left\{\exists t \in \{1,\ 2,\ \ldots, N_t\} \mid P_i(t) > P_{Bi}\right\} \vee \{E_d > E_{Bd}\} \vee A_{nyContemporary}(C_{Ojk}, C_{Ovr}); \\ 0,\ \text{otherwise} \end{cases} \tag{17}$$

$$H_j = \begin{cases} 10^{100}, \left\{\exists t \in \{1,\ 2,\ \ldots, N_t\} \mid P_i(t) > P_{Bi}\right\} \vee \{E_d > E_{Bd}\} \vee \{C_{Ojk} \cap C_{Ovr} \neq \emptyset\}; \\ 0,\ \text{otherwise} \end{cases} \tag{18}$$

In both (Eq.17) and (Eq.18) above, C_{Ovr} should as in (Eq.16), be regarded as the union set of all cycles that C_{Ojk} should not be overlapped with.

No additional mathematical description is required for the B_j "death" penalty component, beyond either (Eq. 3y) or (Eq. 4y).

In Figure 18, pictures (a) and (b) depict pseudo RTP, energy rate functions simulated from a country load profile; the one in (b) along with other parameters (α, ς, δ, UPWs, etc.) was used to generate the graphs in (c-h) by appropriately calling the *ApplianceSchedule1(.)* function described by Algorithm 1. Pictures (c) and (d) show the 3D surface graphs of the *ApplianceSchedule1(.)* function, for user-centricity coefficient $\alpha = 0.5$ and $\alpha = 0$ respectively, rendered for just the first 2 dimensions (*i.e.*, just cycle 1, belonging to the water heater, ***WH***, in Table 17). In turn, the last two rows of pictures, in (e-h), show the 2D contour plot of the function in (c), where additionally, in (f-h) 3 stages of an optimization process by the HyPERGDx metaheuristics are depicted, wherein the coloured circles represent a sub-population of "ants" *i.e.* the 5 metaheuristics comprising the HyPERGDx. The naive population in (f) is the one before specialization into these 5 casts, according to Algorithm 2.

3.3.5 Appliance Scheduling Function Algorithmic Framework

Algorithm 1 below is a pseudo-code describing in simplified terms the algorithmic framework of the implementation of model in (Eqs.4), where it also seeks to implement the discussed Real Parameter Blackbox Optimization Approach to Appliance Scheduling (RPBBOAS).

```
// ApplianceSchedule1(.), implements model in (Eqs.4) as well as the BBDOCM and framework assumptions of Figure 14
Function {E_PCh, E_Ch, P_iHpp, x_L, x_U, f_bko, x_bko, α} = ApplianceSchedule1 (x, Apx, τ, β, D, f_OptTg)
    // x-candidate sol., Apx-Appliance data, τ-resolution, α-user centricity, D-x Dim, f_OptTg-target optim;
    // E_Ch-Energy cost; E_PCh-penalized E_Ch; P_iHpp-instant pwr, [x_L,x_U]-x bounds, x_bko-best known x*, f_bko=f(x_bko);
    static ApplianceDatabase = { H_def, A_def, N_Cdef, W_Tdef, W_Ddef }; // Reference sample appliance data, (Eqs.4a-4e);
    // BestKnownOptimum {f_bko, x_bko} is function of:D,τ,α; and also assuming other ApplianceDatabase vars fixed;
    BestKnownOptim = { {D_=2, τ_=1, {α_=0, f*_x0, x*_0}; {α_=0.25, f*_x0.25, x*_0.25}; {α_=0.5,}; {α_=0.75,...}; ...}; {{D_=2, τ_=60,...}...}; {{D_=10...}} };
    if β ≠ ∅ then α = 1 − β; // α-user centricity coefficient; β-energy centricity coef.
    if Apx ≠ ∅ then // Assumed:x passed alone (from Blackbox Optimization Algorithm (BBOA)), upon client passes any
      of Apx, τ, β, D, f_OptTg (Figure 14)
        ApplianceDatabase = UpdateApplianceDatabase(ApplianceDatabase, Apx, τ, α)
    end
    {m_s, K, C_i} = GetApplianceInfo(ApplianceDatabase, D); // m_s-selctd.appl.; K-cycles; C_i-Lin.indexes, Eqs.4f-4g;
    E_PCh = ∞; E_Ch = ∞; P_iHpp = ∞; // infinity by default, for output energy cost and instant power variables;
    if D = ∅ then D = 2K;
    {x_L, x_U} = GetXBounds(ApplianceDatabase, D);
    f_bko = f_OptTg; x_bko = 0; // set f_OptTg to assymptotic optimum: force the BBOAs (Figure 14), into optima discovery;
    if f_OptTg = ∅ then {f_bko, x_bko} = GetBestKnownOptimum(BestKnownOptim, α, τ, D) ;
    if {x = ∅} then return; // with current status of: {E_PCh, E_Ch, P_iHpp, x_L, x_U, f_bko, x_bko, α}
    {N_p, D} = size(x); // N_p-Number of rows; D-number of columns; N_p-population size; D-dimension of x;
    {x_L, x_U} = GetXBounds(ApplianceDatabase, D); // Update x bounds: D may have changed;
    {T, τ, α ς, δ} = GetTimeAndComfortParameters(ApplianceDatabase, D); // T is herein assumed to be 24h;
    N_t = T/τ; // N_t, is the number of time slots comprised in the continuous time, control horizon T ;
    ρ = 3600/τ; // ρ, is the hourly relative time resolution;
    T_d = {1, 2, ..., N_t}; // T_d, is the discrete time control horizon: T = τ∑(T_d);
    R(T_d) = GetEnergyRate(τ); // e.g.: for τ = 60 (1 min resolution) it returns R(T_d) from RtpMinutely(T_d);
    if {D > 2K} ⋁ {Modulus(D,2) > 0} then // n_k = D/2; if not complying with (Eq.4v), then return
        return // with E_PCh = E_Ch = P_iHpp = ∞; i.e., B_j = ∞; j = 1, ..., m; m−number of appliances;
    end
    for j=1 to m_s do // Account for each appliance power ratings;   m_s-curent nr of D selected appliances
        {Pn(j), Psb} = GetApplxPowerRatings(ApplianceDatabase, j);
        P_i0(j, Td) = Psb; // set standby power as default to every time slot in T_d, of every appliance j;
    end
    for p=1 to N_p do // For each particle nr p of the population of size N_p, do:
        x_p = x(p, 1:D); // extract the particle nr p from x;
        if CyclesInbounds(x_p, x_L, x_U) then
            P_i = P_i0; P_Cjt = P_i0; P_PCjt = P_i0; // default all time slot powers to Psb;
            j_Prv = 0; C_Ovr = ∅; C_Ojk = ∅; // initialize cycle overlap check vars to null;
            for c=1 to D/2 do // where c ∈ C_i, is a linear index
                i = 2c-1; // i is the odd dim component of x, encoding for τ's;
                C_Ovr = C_Ovr ∪ C_Ojk; // put previous cycle C_Ojk into union C_Ovr that next C_Ojk should not overlap;
                S_t = Q_quantX(x_p(i)/τ); // cycle start time; according to (Eq.4h);
                D_t = round(x_p(i+1)/τ); // cycle duration;
                I_ct = round(GetInterCycleTime(ApplianceDatabase, c)/τ); // cycle to next cycle delay time;
                {j, k} = O_wnerJK(ApplianceDatabase, C_i, c); // get the indexes of appl.cycle owning linear cycle c;
                C_Ojk = {S_t, D_t, I_ct}; // C_Ojk-current extended cycle, for overlap check;
                Zp = GetPrecedentZone(ApplianceDatabase, j); // Get the "precedent" zone for appliance j;
                Zn = GetNoGoZone(ApplianceDatabase, j); // Get the "no-go" zone for appliance j;
                if j ≠ j_Prv then C_Ovr = ∅;
                j_Prv = j;
                C_Ovr = C_Ovr ∪ Zp ∪ Zn; // C_Ovr is the union of cycles that C_Ojk should not overlap;
                H_asOverlap = AnyContemporary(C_Ojk, C_Ovr);// Check whether there is some overlap;
                if H_asOverlap then
                    E_PCh(p) = 1e+100; // there is cycle overlapping: Apply hard penaly to particle;
                    break; // out of the current For loop, performancewise;
                end
                C_jk = [S_t : S_t + D_t − 1]; // interval of timeslots comprising cycle C_jk;
                {W^T_jk, W^TO_jk, π^T_jk} = GetTimeslotUserPreferenceWindowSettings(ApplianceDatabase, c);
                {W^D_jk, W^DO_jk, π^D_jk} = GetDurationUserPreferenceWindowSettings(ApplianceDatabase, c);
                P_s = Upwd(C_jk, W^T_jk, W^TO_jk, π^T_jk); // P_s = User discomfort due to cycle misplacement;
                P_d = Upwd(D_t, W^D_jk, W^DO_jk, π^D_jk); // P_d = User discomfort due to cycle mislength;
                P_i(j, C_jk) = Pn(j);
                P_Cjt(j, C_jk) = Pn(j) // appliance j's energy cost;
                P_PCjt(j, C_jk) = Pn(j) ⊙ {1 + α·[ς·P_s + δ·𝟙(D_t)·P_d]}; // appl.j's penalized P_Cjt; ⊙-elementwise;
            end
            if H_asOverlap == false then
                P_iHp = ∑_{j=1}^{m} P_i(j) // calculate households' instant power demand for current p;
                P_iHpp(p, T_d) = P_iHp; // Replace the initial defaut ∞ by the actual P_iHp;
                E_d = ∑_{t=1}^{N_t} P_iHp(t)/ρ; // Calculate E_d = daily power consumption;
                if {∃t ∈ T_d | P_iHp(t) > P_Bi} ⋁ {E_d > E_Bd} then
                    E_PCh(p) = 1e+100; // Some power budget violated: Apply hard penaly H_j;
                else
                    P_Ct = ∑_{j=1}^{m} P_Cjt; // Sum the power consump. j-wise, leave the t dim. alone, and then ...;
                    E_Ch(p) = ∑_{t=1}^{N_t} (P_Ct ⊙ R(t)); // ... calculate total energy cost. R(t)-energy rate;
                    P_PCt = ∑_{j=1}^{m} P_PCjt; // Sum penalized pwr consump. j-wise, and then ... ;
                    E_PCh(p) = ∑_{t=1}^{N_t} (P_PCt ⊙ R(t)); // ... calculate total penalized energy cost;
                end
            end
        end
    end
end
```

Algorithm 1: Appliance Scheduling Framework for Real Parameter Blackbox Optimization

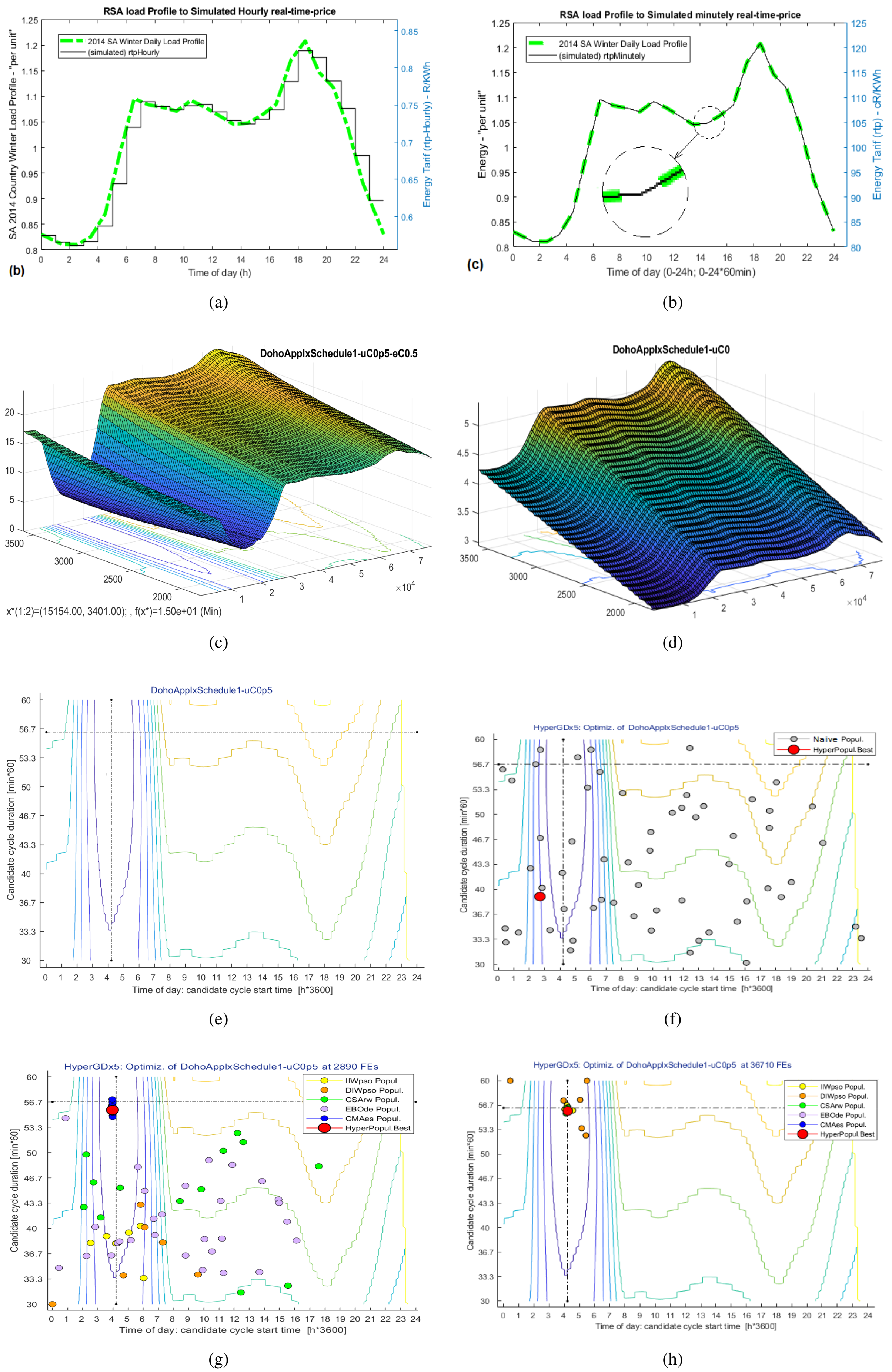


Figure 18 Pricing and Appliance Scheduling Functions and Optimization Stages

3.3.6 RPBBOAS Model Discussion

3.3.6.0.1 On the Experimental evaluation of the RPBBOAS

The above RPBBOAS model in (Eqs.3.3.3) and Algorithm 1, was written into a Matlab code equivalent blackbox function called *ApplianceSchedule1(.)*. Experiments were conducted to find its best known optima for 5 values of the user-centricity parameter α (along with an appliance database and user preferred appliance working settings), which are listed in Table 5 along with other parameters. Also experiments were conducted to jointly evaluate the performance of both *ApplianceSchedule1(.)* and the proposed HyPERGDx (section 3.4). We refer the reader to sections 3.5 and 3.5.3 to see the experimental setup and the results.

3.3.6.0.2 Discussion

In the above new RPBBOAS model in (Eqs.4) we can find that there are substantive changes to the mathematical structure and underlying optimization approach vs the basic combinatorial model in (Eqs.3), with implications to the range of eligible optimization algorithms and their performance, as follows:

1. From the outside (blackbox) optimization algorithm perspective, the $\boldsymbol{Q_j(t)}$ binary design variable whose design space volume grew exponentially with the granularity of the time axis in conjunction with the number of appliances, was replaced by X whose dimension is $D = v * K; v = 2$, where K is the total number of appliances' cycles. This implies that the problem space (X) now grows polynomially, and regardless of the internal granularity chosen for the time horizon. In other words, the complexity of the original design space, from the optimization program perspective (from outside the blackbox), which would be based on 4320 $Q_j(t)$ discrete state variables in 1 minute granularity (a figure that gets worse for finer granularities), is now one X real variable of D=10, *i.e.*, we go from a combinatorial volume of $V = 2^{4320}$ (exponential growth with the number of $Q_j(t)$ variables) to a real state space volume of $V = X^{10}$ (polynomial growth with number of variables); Furthermore,

2. the fact that X is a real parameter, allows for a broader range of optimization algorithms

to be eligible for use, with their unmodified original code versions (except for some parameter passing compliance minor adaptation);

3. The internal complexity of the model is not visible to the optimization algorithms since the model function approach is a black box, just trading X with its dimension D and box constraints (the boundaries of the design space). Also,

4. The internal representation of the design space and treatment does not need to directly deal with a single bit by itself, as per the new cost function structure, but rather, by groups of bits in intervals (vectors, matrices), representing the appliance cycles and durations. Such groups are evaluated in a vectorial fashion, which contributes to lessen the computational burden. Also by encoding the appliance cycle properties into the external design variables X, exempts the runtime calculation of appliance cycles from the $Q(t)$ state bits as well as the associated cycle compliance verification . Such lessened internal computing requirements bring performance advantages at the internal side of the model, adding to the reduced dimensionality and real parameter that is traded with the outside blackbox optimization algorithms.

With the described structure and working, we can argue that the proposed model tackles the concerns laid out in the introductory section 3.3.1, and accomplishes the goals set forth, namely: Modelling and implementing a continuous parameter blackbox, box constrained global optimization approach to appliance scheduling, which also successfully addresses the curse of dimensionality/combinatorial explosion issues, which also brings together another advantage: the wider area of eligible optimization algorithms that are made possible by a real parameter approach; and the intrinsic high granularity of time horizon supported internally by the metamodel, not greatly affecting the size of the traded design space variable X. Such high resolution enables finer, more optimalistic, schedule placements.

3.4 HyPERGDx Global Optimization Hybrid Metaheuristics

3.4.1 Design Motivations

The development of a companion general purpose, blackbox compliant, global optimization hybrid metaheuristics was spurred by a lackluster performance of a number of readily available general purpose state-of-the-art algorithms, when we were trying to optimize our *ApplianceSchedule1(.)* function, notwithstanding they were fast and/or reliable on general testbed problems. That brought the idea of a hybrid approach in an intent to build a more robust algorithm.

3.4.2 Hybrid Optimization Approaches

Notwithstanding the merits in tackling non-linearity, non-continuity and blackbox problems, a metaheuristics, will fail at some problems, where performance dependence on the parametrization, and the parametrization dependence on the type of problem, are some of the most challenging issues affecting their robustness. Aimed at tackling such drawbacks, other classes of methods have emerged: **Hybrid metaheuristics**, **hyperheuristics** [76] [77] and also **memetic algorithms** [78]. They all bring the idea of associating different pieces of heuristics in an adaptive and convenient way that leverage their collective performance relative to the one of the individual pieces, which will not prevent them from failing at some kind of problem as discussed, but will likely improve the universe and the rate of problems solved.

Figure 19 depicts an example hybrid or hyperheuristic framework (themed after the appliance scheduling, for convenience. See [76] [77] for generic representations and discussions). Note that, the block **B** of Figure 19, represents a blackbox problem, such as the *ApplianceSchedule1(.)*, whilst the block $\boldsymbol{A_2}$ in Figure 19, represents the framework of hybrid metaheuristic sought herein.

3.4.3 The HyPERGDx Algorithmic Framework

The HyPERGDx, which stands for: **Hy**brid, **P**article swarm, **E**volution strategies, **R**andom Lévy walks, **G**enetic, **D**ifferential evolution, and (**x**)Miscellaneous, ant-inspired cooperative strategies; is a hybrid heuristics framework which embeds, coordinates and optimizes the in-

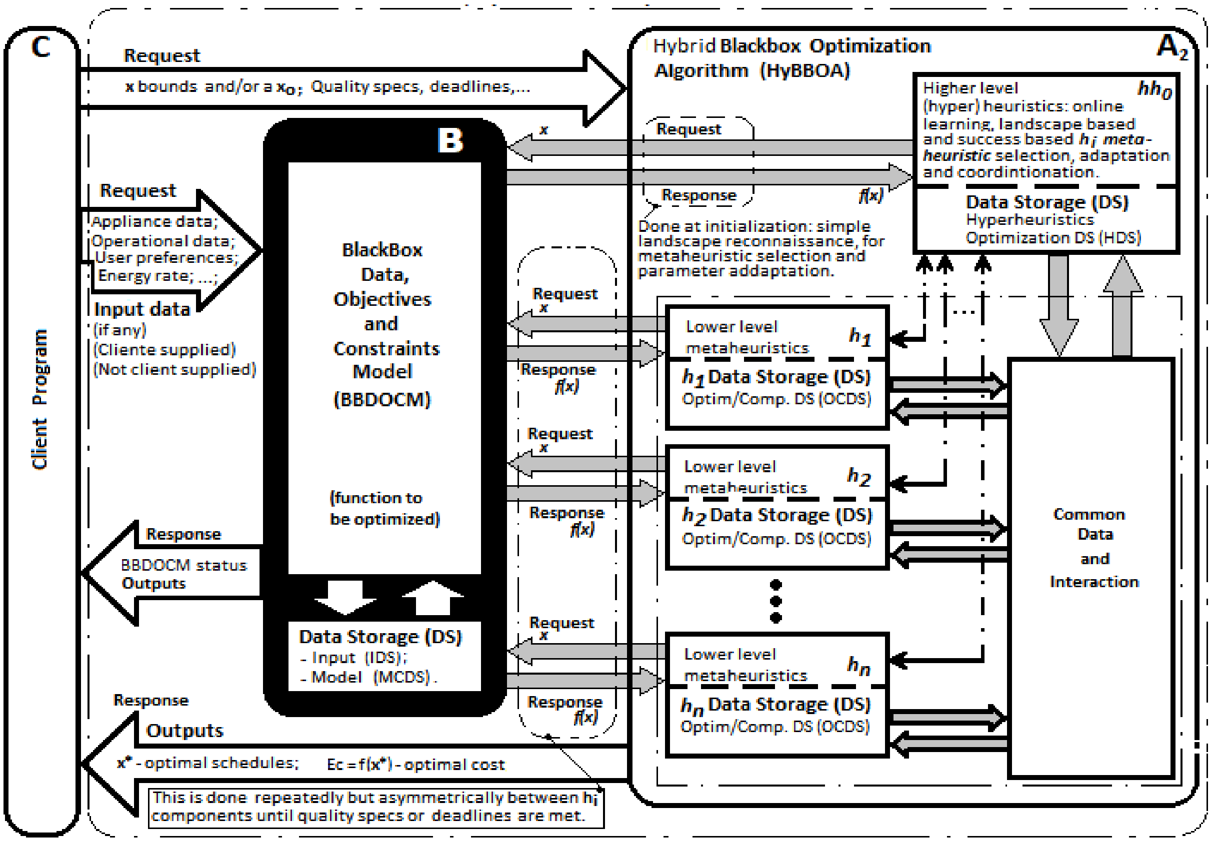


Figure 19 Hybrid or Hyperheuristic Optimization Framework

dividual and overall working behaviour of a number of lower level metaheuristics, themselves modified versions of state-of-the-art algorithms as discussed next section. However, the basic frameworks of such state-of-the-art 'mother' metaheuristics are briefly discussed in the Appendix B. The HyPERGDx is thus an intent to write a hybrid algorithm that to the best extent, takes the strengths and reduces the weaknesses of the "mother" algorithms and thereby have a better all-around performance. The ideal is: to be (a) faster or as fast as the fastest algorithm; (b) more or as reliable as the most reliable algorithm (where speed is the inverse of the mean function evaluations needed to solve the problem up to an acceptable tolerance, and high reliability translates to: high mean success rate and high rate of problems solved). Our realistic expectation is: it can show a good compromise between speed and reliability and have a higher all around performance as compared to any of the "mother" metaheuristics. The proposed hybrid metaheuristic, based on the reference model of Figure 19, block A_2, is outlined in Algorithm 2 below.

Some details on the structure and working of the above algorithm framework:

Function $\{xBest, fBbest, ...\}$ = *HyPERGDx* $(PopStruc,\ g_m ax,\ x_L,\ x_U,\ f(.),\ f_{x^*},\ f_\varepsilon, Xparams, ...)$

  Initialization:

  Perform naive hyper-population uniformly random initialization, across x-bounds;

  Do simple landscape reconnaissance: is it strong global structure(I_{sQcvx})?; meanwhile get closer to prospective $\boldsymbol{x}^*$ and its basin;

  Perform further parametrization in accordance to landscape reconnaissance presumptions;

  Distribute initial population into metaheuristics sub-populations;

  while *stopping criterion not met, and with success and context based probability, adaptatively* **do**

    With ES pop. and prob pES: do exploitation: if I_{sQcvx}, use longer local loop and smaller σ; else, use shorter local loop and larger σ;

    With EBO/DE pop. and prob. pDE: do exploration/exploitation;

    With PSO pop(s) and prob pWP: : do exploration as regulated by varying inertia; do inter-pop mutation when right conditions arise;

    With CSA/RW pop and prob. pCS: do exploration with exponential decreasing α scal.factor; do inter-pop mutation, at right conditions;

    With GA pop. and prob. pGA: do exploration;

  end

end

Algorithm 2: HyPERGDx Summary Algorithmic Framework

1. **The hybrid heuristics loop, metaheuristics selection and switching:**

   The individual metaheuristics are nested sequentially, but executed adaptively (asymmetrically), within the hybrid heuristic loop. Each metaheuristic runs one or more generations local loop of its own, while other remain idle, in a way that resemble a crowded ants working field (also, a metaheuristics population may be just prevented from working by setting their population size to null). Prior to such loop, a (not deterministic) landscape reconnaissance (and prospective approximation to x^* and its basin) is done, which determines that the landscape (i) is likely unimodal with a strong global structure; (ii) is not unimodal (for sure) but has likely an underlying unimodal global structure; (iii) is not unimodal (for sure) and has not been found to have a strong underlying global structure and it likely has a rugged surface. Such probabilistic perceptions/presumptions, determine the choice of values for control parameters and thereby influence metaheuristics performance and the share of execution time given to the metaheuristics. Otherwise, later, based on the effective success of the metaheuristics inside the hyperheuristics loop, and in tandem with their main roles (general explorers or local searchers), such share is adapted along the optimization process. Such effective success probability is approximately: the ratio of the number of successful loops (the ones in which the particular metaheuristics improved the global fitness value) over the number of loops executed so far by the metaheuristic; and, accordingly the share of the execution time granted is increased or reduced. Further contextual corrections are applied, aimed at keeping adaptability to a wide range of problems which are black-box and non-linear. This way, the hyperheuristics framework adaptively selects (or grants more time to) the more successful metaheuristics.

2. **Inter-population social networking and learning**:
   The individual metaheuristics, in their local frameworks within the loop, have embedded heuristics for multi-population social learning, competition and collaboration consisting of (a) the sharing of the hyper-population global optimum and (b) an inter-population replacement mutation, wherein the worst performing members/particles of a given metaheuristics **M** are replaced by the best performing or criss-cross selected particles of the metaheuristics **H**, an operation that is regulated by a mutation rate coefficient, and only happening when improvement/solution has not been achieved after a percentage number of the budget function evaluations have been spent, and also, performed as often as allowed by a linearly evaporating pheromone, a measure to promote inter-population competition and to reduce the likelihood of them dragging one-another into local minima.

3. **A few specific details on the individual metaheuristics comprising the HyPERGDx**:

   (i) Two particle swarm components are used, Linearly Increasing Inertia Weight Particle Swarm Optimization (LIWPSO) and Linearly Decreasing Inertia Weight Particle Swarm Optimization (LDWPSO) algorithms, written from the basic Inertia Weight Particle Swarm Optimization (WPSO) laws in (Eqs.25), wherein the inertia weight parameter ***w(t)*** in (Eq.25a) varies linearly (between 0.4 and 0.9, a choice).

Also, as above referenced, after certain points of the function evaluations time line are reached before successful convergence, a fitness based replacement mutation regulated by a specified rate and as often as allowed by a pheromone counter, is performed with either the DE or CSA components, whichever has the best sub-population fitness.

(ii) An abridged, modified and adapted CMA-ES from Hansen's CMAES version 3.62.beta is used for the ES component. CMA-ES is used essentially as a local searcher/exploiter and it is the first strategy taken, although such is done with initial control parameters dependent on the type of landscape identified (presumed) from the early reconnaissance optimization stage: for instance, if a unimodal landscape, or a multimodal one with strong convex/quasiconvex global structure, was presumed, then, a shorter sigma and a longer local loop are chosen (among other features), all such modification aimed at adaptively accelerating convergence, according to context; and/or for opting out of the algorithm, when it fails to reach/improve solution within the budget loops granted;

(iii) a modified CSA from [70], wherein the scaling factor α_1 from (Eq.27b) is made exponentially decreasing from 0.5 to 0.0075. Also, similar to the particle swarm sub-population, a fitness based replacement mutation, is performed with either the DE or PSO components, whichever has the best sub-population fitness. That step is taken if solution is not found after a percentage number of function evaluations are spent; and it is regulated by a specified mutation rate, and performed as often as allowed by the respective pheromone counter.

(iv) Effective Butterfly Optimizer with CMA Retreat Phase (EBOwithCMAR) (actually just the main EBO procedure, without the CMAR) is called as the secondary explorer/exploiter. Also alternatively, for some difficult functions, and as a certain point of the function evaluations time line is reached, near the end, meaning EBO has so far apparently failed to help deliver a solution, the standard DE component is used, albeit with mixed results (it boosts the Rate of Problems Solved (RoPs) performance but seems to harm the mean success rate). Such standard DE component is an abridged and modified DEvec3 version from [79]), where only the DE/rand/1 and DE/best/1 strategies are used, in an adaptive fashion.

(v) A GA component, was initially included but eventually set aside in this version of HyPERGDx.

3.5 RPBBOAS and HyPERGDx Experimental Evaluation

To evaluate the RPBBOAS working as well as the performance of HyPERGDx versus the state-of-the-art, we selected the list comprising: the HyPERGDx itself, and its "mother" metaheuristics: Matlab's particleswarm (Mat.PSO), Local Restart Covariance Matrix Adaptation Evolution Strategy (LR-CMA-ES), CSA, EBOwithCMAR. We actually also tested HyPERGDx against a longer list of testbeds and algorithms (including: WPSO, Quantum Particle Swarm Optimization (QPSO), Standard PSO 2011 (SPSO2011), Storn&Price's Standard Differential Evolution (DEvec3), Matlab's ga (Mat.GA), etc. that performed worse), which we do not include here for conciseness.

3.5.1 Test beds and experimental setups

3.5.1.0.1 Experiments:

(i) Experiment 1: To investigate the Expected Running Time (ERT), the success rate and the Rate of Problems Solved (RoPs) and the rank thereof of the 5 contending algorithms, when benchmarked on testbed ***DG***, under different parameter configurations as defined and explained further below (see section 3.5.2 for the performance evaluation model). Results found in Tables 7-12

(ii) Experiment 2: To investigate the ERT, the success rate and the RoPs and the rank thereof of the 5 contending algorithms, when benchmarked on testbed ***DAu***, under different parameter configurations as defined and explained further below. Results found in Tables 13 and 14.

(ii) Experiment 3: To investigate the ERT, the success rate and the RoPs and the objective function rank thereof (see section) of the 5 contending algorithms, when benchmarked on testbed ***DAk***, under different parameter configurations as defined and explained further below. Results found in Tables 15 and 16.

(iv) Experiment 4: To investigate the mean convergence performance of the 5 contending algorithms, when benchmarked over selected functions of mixed testbeds, of which we present 4 namely: (a) On testbed ***DG***: f_{DG_1}, f_{DG_6}, $f_{DG_{13}}$, $f_{DG_{24}}$; and on testbed ***DAu***, the f_{DAu_1} setup of ***ApplianceScheduling1(.)*** function. The resulting convergence graphs are depicted on Figure 20.

The following experimental parameters and procedures were used across the above experiments:

(i) The **problem sizes** (dimensions): In testbed DG, benchmarks were done for dimensions $D = \{2, 10, 30, 50\}$ whereas for the remaining testbeds (appliance scheduling) benchmarks were done for dimension $D = 10$;

(ii) The **number of runs** per dimension per function were: $r = 50$ for $D = 2$; or $r = 30$ otherwise;

(iii) **Tolerance** (f_{Tol}): In testbeds DG, a tolerance of 10^{-8} was used in all benchmarks, whereas for the remaining testbeds (appliance scheduling) a tolerance of 10^{-5} was used; For the Experiment 5 however, tolerance was not used as an early termination criterion.

(iv) **Maximum number of function evaluations** ($maxFEs$) per run: The value was set proportional to the problem size, the dimension D as: $maxFEs = 10000 * D$;

(v) The base **population sizes** were: $PS = \{50, 60, 80, 100\}$ for $D = \{2, 10, 30, 50\}$ respectively.

(vi) **Stopping criteria:**

For experiments 1-3, when benchmarking a function in a certain dimension, the stopping criteria were:

(a) The fitness is not worse than the target value f_{Target}; where $f_{Target} \leq f_{Optim} + f_{Tol}$; and f_{Optim} is the global optimum value at the solution x* (or one of them if multiple) of the benchmarking function;

(b) The maximum number of function evaluations (*maxFEs*) per run has been reached;

(c) a budget computing execution (clock) time per run has been spent; or,

(d) Other, algorithm specific, non mandatory stopping criteria, including *stagnation* (of various types), are met.

For experiment 4, aimed at the mean global fitness convergence behaviour, the stopping criteria were: the budget number of function evaluations (*maxFEs*) per run has been spent; or, the budget computing execution (clock) time per run has been spent.

3.5.1.0.2 Testbeds: Two test beds were used, with the last one split into 2 subcategories:

1. **Generic testbed (*DG*)**, as described in Table 3, composed by a mix of different types of the most common benchmark functions found in the literature, with shifted optimizer values to generally avoid the $x^* = 0$. In most cases where the optimizer is normally not zero, then it was not further shifted. It is described by Table 3.

2. ***ApplianceSchedule1(.)* function (Algorithm 1) testbed**, with two categories of test setups (*DAu* and *DAk*):

   (a) *ApplianceSchedule1(.)* function, with optimum function values set to unknown (asymptotic value of f_{Optim} = 0) (*DAu*). This function is the Matlab code equivalent implementation of the RPBBOAS pseudo-code in Algorithm 1.

   This testbed is a setup for the discovery of (if any) new optimal values, better than the currently best known optima for the current set of appliance parameters. It is also intended to evaluate the convergence performance of the contender algorithms to the best possible function values in cases when the optimal values are unknown, which is the general case of the real life scenario for which the optimal values will change at every change of the appliance cycle data, input from the user. For the above reasons, the value of $f_{Optim} = 0$ is actually not attainable, arising from the fact that for the current setup a non-null (at every time step) electricity pricing function is used, and also that the structure of the appliance cycle data is not ill defined and there will not be a case of null consumption or null cost. Otherwise, if in some scenario a null consumption or null cost is feasible, then another not attainable value could be a negative one, including $-\infty$. However, the use of $-\infty$ is not recommended since that hampers the evaluation and comparison of contenders' convergence performance to such target optimum ($-\infty$). Table 4, describes this test setup.

(b) *ApplianceSchedule1(.)* function, with Best Known Optima Setup (*DAk*):

Featuring different user comfort levels, regulated by a parameter that we call user centricity (denoted α in (Eq.4a)) index: 1, 0.75, 0.5, 0.25 and 0 (which respectively translate to maximum comfort to bare minimum appliance utility levels). In turn, when user centricity decreases, another complementary parameter, energy centricity (denoted β) increases: $\beta = 1 - \alpha$. These comfort level parameters, determine different function optima (different optimal schedule placements). For these values of user centricity ($\alpha = \{1, 0.75, 0.5, 0.25, 0\}$), and applicable only for the given sample appliance database and set of parameters and pricing function, thorough initial runs have been performed which determined the current best known function optima, thereafter used for the benchmarks. Table 5, describes this test setup.

Table 3 Generic Shifted X* (*DG*) Testbed

f_n	Name	Math.Expression	f_{opt}	x_{opt}	x bounds
f_{DG_1}	Sphere	$\sum_{i=1}^{D}(x_i-x_o)^2$	0	x_o^D	$[-100,100]^D$
f_{DG_2}	Rosenbrock	$\sum_{i=1}^{D-1}\left(\{1-(x_i-x_{oT})\}^2+100*\{(x_{i+1}-x_{oT})-(x_i-x_{oT})^2\}^2\right);$	0	$(1+x_{oT})^D$	$[-30,30]^D$
f_{DG_3}	Ackley	$-20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D}(x_i-x_{oA})^2}\right)-\exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi(x_i-x_{oA}))\right)+20+e$	0	x_{oA}^D	$[-30,30]^D$
f_{DG_4}	Schwefel 2.26	$418.9828872724339D-\sum_{i=1}^{D}\left(x_i\, sin\left(\sqrt{\lvert x\rvert}\right)\right)$	0	420.9687460745404^D	$[-500,500]^D$
f_{DG_5}	Elliptic	$\sum_{i=1}^{D}\left\{(x_i-x_o)^2\left(10^{6(i-1)/(D-1)}\right)\right\}$	0	x_o^D	$[-100,100]^D$
f_{DG_6}	Rastrigin	$\sum_{i=1}^{D}\left((x_i-X_{o5})^2-10\cos(2\pi(x_i-X_{o5}))+10\right)$	0	X_{o5}^D	$[-6,6]^D$
f_{DG_7}	Schaffer F7	$\frac{1}{D-1}\sum_{i=1}^{D}\left(\sqrt{s_i}\left(1+sin^2(50s_i^{0.2})\right)\right);\quad$ where: $s_i=\sqrt{(x_i-x_o)^2+(x_{i+1}-x_o)^2}$	0	x_o^D	$[-100,100]^D$
f_{DG_8}	Griewank	$\frac{1}{4000}\sum_{i=1}^{D}(x_i-x_{oG})^2-\prod_{i=1}^{D}cos\left(\frac{x_i-x_{oG}}{\sqrt{i}}\right)+1$	0	x_{oG}^D	$[-600,600]^D$
f_{DG_9}	Bent Cigar	$(x_1-x_o)^2+10^6\sum_{i=1}^{D}(x_i-x_o)^2$	0	x_o^D	$[-100,100]^D$
$f_{DG_{10}}$	Alpine	$\sum_{i=1}^{D}\left\lvert(x_i-x_{oT})sin(x_i-x_{oT})+0.1(x_i-x_o)\right\rvert$	0	x_{oT}^D	$[-10,10]^D$
$f_{DG_{11}}$	Step Ellipsoid	$\sum_{i=1}^{D}\lfloor x_i-x_o\rfloor^2$	0	$x=x_{oS}$	$[-100,100]^D$
$f_{DG_{12}}$	Hyper Ellipsoid	$\sum_{i=1}^{D}\left(i(x_i-x_{o3})^2\right)$	0	x_{o3}^D	$[-5,5]^D$
$f_{DG_{14}}$	Schwefel 2.22	$\sum_{i=1}^{D}\lvert x_i-x_{oT}\rvert+\prod_{i=1}^{D}\lvert x_i-x_{oT}\rvert$	0	x_{oT}^D	$[-10,10]^D$
$f_{DG_{15}}$	Weierstrass	$\sum_{i=1}^{D}\sum_{k=1}^{m}0.5^k cos\left(2\pi 3^k(x_i+0.5)\right)-D\sum_{k=1}^{m}0.5^k cos\left(2\pi 3^k\right);\ \ m=11$	0	$x=x_{oW}$	$[-2.5,2.5]^D$
$f_{DG_{16}}$	Discus	$10^6(x_1-x_o)^2+\sum_{i=1}^{D}(x_i-x_o)^2$	0	x_o^D	$[-100,100]^D$
$f_{DG_{17}}$	Wavy F7	$1-\frac{1}{D}\sum_{i=1}^{D}\left\{\exp\left(-0.5(x_i-x_{oH})^2\right)cos\left(k(x_i-x_{oH})\right)\right\};\quad k=10$	0	x_{oH}^D	$[-\pi,\pi]^D$
$f_{DG_{18}}$	Trigonometric2	$\sum_{i=1}^{D}\left\{8sin\left(7(x_i-x_{oG})^2\right)^2+6sin\left(14(x_i-x_{oG})^2\right)^2+(x_i-x_{oG})^2\right\}$	1	x_{oG}^D	$[-500,500]^D$
$f_{DG_{19}}$	Zakharov	$\sum_{i=1}^{D}i(x_i-x_{oT})^2+\left(0.5\sum_{i=1}^{D}i(x_i-x_{oT})\right)^2+\left(0.5\sum_{i=1}^{D}i(x_i-x_{oT})\right)^4$	0	x_{oT}^D	$[-10,10]^D$
$f_{DG_{20}}$	Trid	$\sum_{i=1}^{D}(x_i-1)^2-\sum_{i=2}^{D}x_i x_{i-1}$	f_{opTrid}	x_{opTrid}	$[-D^2,D^2]^D$
$f_{DG_{21}}$	Schwefel 2.21	$max\left(\{\lvert x_i-x_{oT}\rvert,\forall i=1,\ldots,D\}\right)$	0	x_{oT}^D	$[-10,10]^D$
$f_{DG_{22}}$	Bohachevsky	$\sum_{i=1}^{D}\left((x_i-x_{oT})^2+2(x_{i+1}-x_{oT})^2-0.3cos(3\pi(x_i-x_{oT}))-0.4cos(4\pi(x_i-x_{oT}))+0.7\right)$	0	x_{oT}^D	$[-15,15]^D$
$f_{DG_{24}}$	Schwefel 1.2	$\sum_{i=1}^{D}\left(\sum_{j=1}^{i}(x_j-x_{oT})\right)^2$	0	x_{oT}^D	$[-10,10]^D$
$f_{DG_{24}}$	Katsuuras	$\frac{10}{D^2}\left\{\prod_{i=1}^{D}\left(1+i\sum_{j=1}^{m}\frac{\lvert 2^j x_i-\lfloor 2^j x_i\rceil\rvert}{2^j}\right)^{\frac{10}{D^{1.2}}}-1\right\};\quad m=32$	0	$x=\{0.5k:k\in\mathbb{Z}\}:\#x=D$	$[-5,5]^D$

Where: D-problem size; $\#x$-cardinality (element count) of x; $f_{opTrid}=-D(D+4)(D-1)/6$; $x_{opTrid_i}=i(D+1-i)$; $i=1,2,...,D$;
$x_o=round(now()/10000,4)$; $now()$ a Matlab current date/time to date serial number; x_o changes slightly at each day, *i.e.*, at an increment of 1e-4 per day;
$x_{oA}=round(x_o/3-3,1)$; $x_{o5}=0.1x_o-5$; $x_{o3}=0.1x_o-3$; $x_{oG}=3x_o$; $x_{oT}=0.1x_o$ $x_{oH}=0.01x_o$; $x_{oS}=\{x_i\in(x_o-1,x_o+1),\ i=1,...,D\}$;
$x_{oW}=\{x_i\in\mathbb{Z},\ i=1,...,D\}$;

Table 4 ApplianceSchedule1(.) Function, Unknown (asymptotic) Optimum (= 0) Test Setup (*DAu*)

				WH-Water Heater						CW-Clothes Washer		CD-Clothes Drier	
f_{nn}	in-Testbed Descriptive Name	α	$f_{Optimum}$	x_{L_1},x_{U_1}	x_{L_2},x_{U_2}	x_{L_3},x_{U_3}	x_{L_4},x_{U_4}	x_{L_5},x_{U_5}	x_{L_6},x_{U_6}	x_{L_7},x_{U_7}	x_{L_8},x_{U_8}	x_{L_9},x_{U_9}	$x_{L_{10}},x_{U_{10}}$
f_{DAu1}	ApplianceSchedule1-uO0	1											
f_{DAu2}	ApplianceSchedule1-uO0.25	0.75											
f_{DAu3}	ApplianceSchedule1-uO0.5	0.5	f_{asyOpt}	1,86400	1800,3600	1,86400	1800,3600	1,86400	1800,3600	1,86400	3600,7200	1,86400	1800,3600
f_{DAu4}	ApplianceSchedule1-uO0.75	0.25											
f_{DAu5}	ApplianceSchedule1-uO1	0											

$f_{asyOpt} = 0$, for all function instances;

Table 5 ApplianceSchedule1(.) Function, Best Known Optima Test Setup (*DAk*)

				WH-Water Heater						CW-Clothes Washer		CD-Clothes Drier	
f_{nn}	in-Testbed Descriptive Name	α	f_{bko}	x_{L_1},x_{U_1}	x_{L_2},x_{U_2}	x_{L_3},x_{U_3}	x_{L_4},x_{U_4}	x_{L_5},x_{U_5}	x_{L_6},x_{U_6}	x_{L_7},x_{U_7}	x_{L_8},x_{U_8}	x_{L_9},x_{U_9}	$x_{L_{10}},x_{U_{10}}$
f_{DAk1}	ApplianceSchedule1-uO0	1	15.143524581										
f_{DAk2}	ApplianceSchedule1-uO0.25	0.75	15.074466564										
f_{DAk3}	ApplianceSchedule1-uO0.5	0.5	14.936721774	1,86400	1800,3600	1,86400	1800,3600	1,86400	1800,3600	1,86400	3600,7200	1,86400	1800,3600
f_{DAk4}	ApplianceSchedule1-uO0.75	0.25	14.630067130										
f_{DAk5}	ApplianceSchedule1-uO1	0	7.303659824										

- f_{bko} - best known optimal penalized cost for the given user-centricity coefficient α.
- For both the above tables: x_{L_n}, x_{U_n} are respectively the absolute lower and upper problem space bounds in discrete seconds time slots, wherein the indices denote the dimensional component. Further: odd indices (example: 3) are bounds for appliance cycle start times; and, the immediate even indices (4) are the respective cycle duration bounds.

3.5.2 Performance Evaluation and Comparison Model

For assessing how the HyPERGDx gauges against the state-of-the-art, we have used two main performance metrics, the one for comparing performance at the single objective function level, and the second for comparing the aggregate performance at testbed (multiple functions) level, as follows:

(A) **Performance evaluation at a single objective function level**: Objective Function score ($\boldsymbol{O}_{Fs}$) and the companion objective function rank ($\boldsymbol{O}_{Frk}$), are computed from 5 main measures of performance, namely: the best function value (B_V), the mean function value (μ_V), median function value (M_{edV}), the success rate (S_r), the number of function evaluations (FEs) and its close relative the Expected Running Time (ERT). Equations (19) describe how these 5 measures and additional function level metrics are blended together into $\boldsymbol{O}_{Fs}$ and $\boldsymbol{O}_{Frk}$, where:

(1) ERT_r (further discussed below) is the Expected Running Time (ERT) for the mean run; FE_{max} the budget number of function evaluations (also the running time of any failed run). Further, in (Eqs.19f-19g), r_s is the number of successful runs; $FE_{succTot}$ the sum of the run lengths (in number of function evaluations) of such r_s runs; $FE_{succAvg}$ the average successful run length.

(2) $B_{Vreward}(i)$, in (Eq.19e), is, for the i-th contending algorithm, an additional, tie-breaking measure, over the main measure ERT_r, representing its comparative convergence quality. $B_{Vreward}(i)$ is null for $S_r(i) > 0$ as long as $ERT_r(i)$ is not tied with another $ERT_r(j)$, as per the value $isTied$ from $\{woRank, tbReason, isTied\} = W_{oRankMTB}(ERT_r)$ function, wherein the (ERT_r) argument is the vector of metaheuristics' ERT_r's to be checked for ties; B_{Vrk} is the weak order rank (produced by $W_{oRankMTB}(V,\{Y,Z,...\})$) of the objective function best fitness values ever achieved by any of the N_m metaheuristics in all runs; in $W_{oRankMTB}(V,\{Y,Z,...\})$, ranking ordinals may be duplicated (because same values are given the same rank) but with no gaps thereof (*i.e*, there are no suppressed ranking ordinals arising from the duplicates. Example weak order rank: "11233345..."). Also, additionally, a total order (or, at least, a better ranking arrangement) is attempted by tie-breaking: the $W_{oRankMTB}(V,\{Y,Z,...\})$ performs a weak order rank on V vector and; on tie, it then performs a tie-breaking based upon the companion vector list $\{Y,Z,...\}$, if any; Y

vector is tried first and then Z vector, ...; and, same rank is awarded if eventually the tie persists. In (Eq.19d): rank is given based on $B_{Vreward}$ vector; for any ties on $B_{Vreward}$, a tie breaking is attempted on the vector of median values M_{edV} first, and then on the vector of mean values μ_V; same rank is awarded on tie persistence. N_m is the number of contending algorithms.

Single objective function performance evaluation (19)

$$O_{Fs} = \frac{ERT_r}{FE_{max2\lambda}}; \tag{19a}$$

$$FE_{max2\lambda} = FE_{max} + 2\lambda \tag{19b}$$

$$O_{Frk} = W_{oRankMTB}(O_{Fs}, B_{Vrk}); \tag{19c}$$

$$B_{Vrk}(i) = W_{oRankMTB}(B_{Vreward}(i), \{M_{edV}, \mu_V\} \odot B_{Vreward}); \tag{19d}$$

$$B_{Vreward(i)} = \begin{cases} 0, \ S_r(i) > 0 \vee \{\nexists j \mid ERT_r(i) = ERT_r(j); i \neq j; \forall i, j \in \{1, \ \dots, \ N_m\}\} \\ \frac{B_V(i)}{FE_{max2\lambda}}, \ S_r(i) > 0 \vee \{\exists j \mid ERT_r(i) = ERT_r(j); i \neq j; \forall i, j \in \{1, \ \dots, \ N_m\}\} \\ B_V(i), \ \text{otherwise}; \quad i \in \{1, \ \dots, \ N_m\} \end{cases} \tag{19e}$$

$$ERT_r = (1 - S_r)FE_{max2\lambda} + S_r \cdot FE_{succAvg}; \tag{19f}$$

$$FE_{succAvg} = \frac{FE_{sucTot}}{r_s} \tag{19g}$$

The ERT_r metric, is a derivation we made from the common Expected Running Time (ERT), in its ***SP2*** version, from [80], and shown in (Eq.20a) below; It is worth noting that oftentimes ERT (as in [81]) refers to just the successful parcel of *SP2*, which we denoted as $ERT_{(s)}$ in (Eq.20b).

$$ERT = SP2 = \left(\frac{1 - S_r}{S_r}\right) FE_{max} + \underbrace{FE_{succAvg}}_{ERT_{(s)}}; \tag{20a}$$

$$ERT_{(s)} = FE_{succAvg} = \frac{FE_{sucTot}}{r_s} \tag{20b}$$

Our derivation of ERT_r from the one in (Eqs.20), arises from the need for a better handling of the null S_r and null r_s issues in (Eqs.20a, 19g=20b), and in respect to other issues as follows:

(a) On the one hand, one cannot guarantee a non null success rate by any of the metaheuristics: actually a few null success rates are common, and bound to happen at some point for some reason, as also guaranteed by the "No-Free-Lunch" (NFL) theorem [68]. But a null S_r in (Eq.20a) yield a non existent metric value (i.e., an infinity ERT). However null S_r's shouldn't render the ERT useless, but accounted for instead, which is done by the modified ERT_r in (Eq.19f). Also, because there is still different measures of convergence quality even in a failed run, the accounting for the null S_r's in ERT_r gives way for the accounting for the quality of such failed runs, which is done by the B_{Vrk} metric;

(b) On the other hand, since we cannot control the internal handling of stopping criteria, restarts, etc., of the arbitrary metaheuristics; then, to insure uniformity, we have adopted setting the budget function evaluations FE_{max} per a single run. That way, exactly r independent runs of FE_{max} limit each, are performed per each contending metaheuristics, and data is registered. Any failed run is awarded FE_{max} score. Further, there are cases when a successful run will exceed the FE_{max} budget: the effective stopping number of function evaluations (FE_{max_i}) of an arbitrary run i, may happen to be higher than FE_{max} by some additional counts e, *i.e.*, $FE_{max_i} = FE_{max} + e$, where, albeit infrequent, FE_{max_i} could be a successful run. The miss-alignment is frequently due to performance reasons, including parallel function evaluation, wherein stopping criterion cannot not be enforced at each single function evaluation, and, it has been a practice granting some fair amount of leniency to this kind of budget violation. That is the rationale behind the adjustment of FE_{max} to $FE_{max2\lambda}$ in (Eq.19b): trying to prevent the ERT of a failed run to ever be better or tied with the ERT of a successful one. The λ in (Eq.19b), is the population size. The adjustment of 2 λ's (which can be raised or lowered) means that we are not granting further leniency to the algorithms that will exceed such scale of violation.

The ERT_r in (Eq.19f) is thus a more convenient ERT performance measure, insofar it yields a non infinity metric for the null S_r's and also in the way, along with the B_{Vrk} metric, allows the accounting for other measures of quality, namely $B_{Vreward}$, M_{edV} and μ_V, where all runs are included, failed or not, which either ERT's in (Eqs.20a) are not supporting. It is worth pointing out that other derivations of the ***SP2*** in

(Eq.20a) aimed at a better handling of null S_r's are possible, such as, for instance, replacing the null S_r (which is also the probability of success estimator) by a very small number (=very small probability), say $\frac{1}{10r}$ where r is the total number of optimization runs per algorithm. Such a derivation (with additional transformations thereof), along with the use of the B_{Vrk} metric, would anyway yield the same O_{Frk} ranks.

(3) O_{Frk} in (Eq.19c), is the weak order ranking (performed by the $W_{oRankMTB}(.)$ function) of the O_{Fs} objective function scores of the contenders, where the B_{Vrk} rank is a O_{Fs} tie-breaking measure.

(B) **Performance evaluation at the aggregate testbed level**:

The above O_{Frk} ranking evaluation is performed and logged for each one of the N_{pb} problems of a given benchmarking testbed. These logs are used thereafter for calculating the aggregate level performance, as follows:

Four (4) measures of performance, derived from the single objective logged data are considered for the aggregate performance model: (1) the mean of O_{Frk}'s from (Eq.19c); (2) the Rate of Problems Solved (RoPs), which is the ratio: number of successfully solved problems (i.e., the ones with non null S_r), to the total of problems N_{pb}; (3) the mean success rate; and, (4) the ratio of non 100% S_r's. Further, there are times when the relative importance of these individual metrics (essentially from the "reliability vs speed" perspective) in the aggregate performance outcome, would differ according to the sole criterion of the user or decision maker. Arising from such considerations, F_{Ss} in (Eqs.21) below, is a weighed sum approach, giving the decision maker the right to '*a priori*' define their preferences on the relative importance of these 4 measures in the aggregate performance outcome.

Additionally in Table 6 we define sample schedules of performance weights for 5 choice levels of speed-reliability relative importance.

Aggregate, testbed performance evaluation:

(Eqs.21)

$$F_{Ss} = W_{mOF} \cdot \overline{O_{Frk}} + W_{RoPs} \cdot (1 - R_{oPs}) + W_{mSr} \cdot (1 - \overline{S_r}) + W_{n100s} \cdot N_{on100s}/N_{pb} \quad (21a)$$

$$F_{Srk} = W_{oRankMTB}(F_{Ss}) \quad (21b)$$

where F_{Ss} is the testbed ('function set') score . W_{mOF}, W_{RoPs}, W_{mSr}, W_{n100s}, are the weights that determine the relative contributions to F_{Ss} for respectively: the mean O_{Frk} rank, the Rate of Problems Solved (RoPs), the mean S_r, and, the ratio of non-100% S_r's. The weights should be non negative and summing up to 1. In turn, F_{Srk} is the weak order rank of F_{Ss} score and defines which is(are) the winning algorithm(s) for a given schedule of weights, and that is given for just one problem size $\boldsymbol{D}$.

Table 6 Performance Evaluation Choice Weights

# Performance Class	$\overline{O_{Frk}}$	R_{oPs}	$\overline{S_r}$	$\%N_{on100s}$
1 Speed Scoring weights	1	0	0	0
2 Moderate Speed Scoring weights	0.75	0.15	0.7	0.03
3 Balanced Speed-Reliability Scoring weights	0.35	0.35	0.25	0.05
4 Moderate Reliability Scoring weights	0.25	0.5	0.17	0.08
5 Reliability Scoring weights	0	0.6	0.3	0.1

3.5.3 Results

The following tables and graphs present the results of the 4 experiment groups, which is followed by their discussion. For the "Generic Shifted X* Testbed" we have 6 tables (7-12), the first 5 showing the "Per Function Benchmark Results (4 to 5 functions per table), and the last one being the summary table (12), the most important one, summing up the performances of all the "per function" tables. Concerning the Appliance schedule testbeds, there are just 2 tables per testbed sub-category: the first one with the "per function" results, and the second one being the summary performance table. In any of the testbeds the evaluation is based on the model discussed in section 3.5.2, where the characterization of performance variables is done. However some legend aids are placed on the tables footnotes, aimed at easing interpretation.

Table 7 Generic Shifted X* Testbed - Per Function Benchmark Results (pg.1/6)

Func. Info	Perf. Measure	HyPERGDx				CSA				Mat.PSO				EBOwithCMAR				CMAES			
		D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50
	Best(B_{Vrk})	2.03e-10(4)	2.78e-09(3)	6.25e-09(3)	7.17e-09(3)	2.33e-10(5)	5.15e-09(4)	9.14e-08(5)	1.1e-05(5)	2.99e-13(1)	2.28e-09(2)	5.67e-09(2)	6.37e-09(2)	3.36e-11(2)	5.16e-09(5)	7.41e-09(4)	8.29e-09(4)	8.16e-11(3)	1.36e-10(1)	6.46e-10(1)	6.97e-10(1)
	Mean	4.756e-09	7.14e-09	8.725e-09	9.213e-09	4.716e-09	8.568e-09	2.714e-07	2.307e-05	2.577e-09	5.759e-09	22.96	8.735e-09	4.853e-09	8.101e-09	9.096e-09	9.386e-09	2.124e-09	1.199e-09	1.225e-09	1.253e-09
f_{DG1}	Median	4.79e-09	7.644e-09	8.874e-09	9.477e-09	4.83e-09	8.753e-09	2.582e-07	2.23e-05	2.023e-09	5.888e-09	8.113e-09	8.975e-09	5.102e-09	8.009e-09	9.248e-09	9.449e-09	9.73e-10	1.154e-09	1.148e-09	1.285e-09
fOpt= 0;	Std	3e-09	2.2e-09	1.1e-09	6.9e-10	2.9e-09	1.2e-09	9.4e-08	7e-06	2.4e-09	1.7e-09	1.3e+02	9.4e-10	3e-09	1.4e-09	7.2e-10	5.1e-10	2.5e-09	7.3e-10	3.8e-10	2.4e-10
fTol= 1e-08	Succ.Rate	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%	0.00%	100.00%	100.00%	96.67%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT$_r$	664	3.19e+03	1.23e+04	2.33e+04	1.51e+04	8.65e+04	3e+05	5e+05	1.79e+03	8.6e+03	4.06e+04	6.27e+04	2.35e+03	7.6e+03	2.09e+04	3.72e+04	1.06e+03	6.63e+03	1.82e+04	3.02e+04
	O$_{Fs}$(O$_{Frk}$)	**0.03319(1)**	**0.03193(1)**	**0.04106(1)**	**0.04654(1)**	0.7565(5)	0.8646(5)	1(5)	1(5)	0.08925(3)	0.08604(4)	0.1353(4)	0.1254(4)	0.1176(4)	0.076(3)	0.06964(3)	0.07439(3)	*0.05275(2)*	*0.06626(2)*	*0.06058(2)*	*0.06034(2)*
	Best(B_{Vrk})	1.03e-10(2)	6.4e-09(3)	6.66e-09(2)	7.5e-09(2)	8.22e-06(5)	0.312(5)	17.1(5)	43.7(5)	3.02e-10(3)	0.00578(4)	0.000338(4)	0.00209(4)	4.74e-10(4)	3.93e-09(2)	8.38e-09(3)	9.2e-09(3)	3.98e-11(1)	3.3e-10(1)	7.36e-10(1)	9.02e-10(1)
	Mean	4.015e-09	0.5446	8.93e-09	9.021e-09	0.002619	2.111	23.29	45.13	7.349e-05	1.592	4.941	32.3	5.024e-09	8.236e-09	0.6644	1.196	2.296e-09	1.587e-09	1.284e-09	1.38e-09
f_{DG2}	Median	3.144e-09	0.00493	9.079e-09	9.14e-09	0.0008581	1.631	23.57	45.25	6.763e-09	0.167	4.224	19.39	5.147e-09	8.582e-09	9.893e-09	9.963e-09	1.844e-09	1.377e-09	1.226e-09	1.34e-09
fOpt= 0;	Std	3e-09	0.91	7.4e-10	5.4e-10	0.0047	1.4	1.6	0.56	0.0004	2.2	4.9	32	2.6e-09	1.7e-09	1.5	1.9	2.1e-09	1.2e-09	3.3e-10	3.5e-10
fTol= 1e-08	Succ.Rate	100.00%	36.67%	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	66.00%	0.00%	0.00%	0.00%	100.00%	100.00%	83.33%	70.00%	100.00%	100.00%	100.00%	100.00%
	ERT$_r$	2.64e+03	7.01e+04	8.17e+04	2.17e+05	2e+04	1e+05	3e+05	5e+05	1.12e+04	1e+05	3e+05	5e+05	6.38e+03	3.27e+04	2.06e+05	4.1e+05	2.01e+03	1.63e+04	9.95e+04	2.65e+05
	O$_{Fs}$(O$_{Frk}$)	*0.132(2)*	0.701(3)	**0.2725(1)**	**0.4333(1)**	1(5)	1(5)	1(5)	1(5)	0.5606(4)	1(4)	1(4)	1(4)	0.319(3)	*0.3269(2)*	0.6854(3)	0.8198(3)	**0.1007(1)**	**0.1634(1)**	*0.3316(2)*	*0.5302(2)*
	Best(B_{Vrk})	6.21e-10(2)	6.48e-09(3)	7.88e-09(2)	8.87e-09(2)	6.02e-06(5)	0.0341(5)	4.46(5)	20.5(5)	1.36e-09(4)	5.44e-09(2)	8.39e-09(3)	1.27(4)	1.35e-09(3)	6.67e-09(4)	8.96e-09(4)	9.27e-09(3)	2.15e-10(1)	1.87e-09(1)	2.69e-09(1)	3.03e-09(1)
	Mean	6.051e-09	8.46e-09	9.292e-09	9.543e-09	0.000128	0.2769	17.02	20.66	4.773e-09	7.932e-09	1.428	5.38	6.935e-09	8.706e-09	9.696e-09	9.751e-09	4.276e-09	3.776e-09	0.1911	3.503
f_{DG3}	Median	6.463e-09	8.479e-09	9.442e-09	9.576e-09	9.644e-05	0.1361	20.24	20.65	4.689e-09	7.973e-09	0.4657	2.344	7.885e-09	8.936e-09	9.766e-09	9.8e-09	4.051e-09	3.723e-09	3.646e-09	5.193
fOpt= 0;	Std	2.5e-09	1e-09	4.9e-10	3e-10	0.00011	0.36	5.8	0.08	2.3e-09	1.1e-09	3.6	6.7	2.4e-09	8.5e-10	2.7e-10	2.2e-10	2e-09	8.9e-10	0.58	3
fTol= 1e-08	Succ.Rate	100.00%	100.00%	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	50.00%	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	80.00%	40.00%
	ERT$_r$	1.34e+03	7.63e+03	2.98e+04	5.51e+04	2e+04	1e+05	3e+05	5e+05	3.02e+03	1.33e+04	1.74e+05	5e+05	4e+03	1.18e+04	3.75e+04	7.2e+04	1.83e+03	1.1e+04	8.91e+04	3.2e+05
	O$_{Fs}$(O$_{Frk}$)	**0.06691(1)**	**0.0763(1)**	**0.09919(1)**	**0.1102(1)**	1(5)	1(5)	1(5)	1(5)	0.1509(3)	0.133(4)	0.5805(4)	1(4)	0.1999(4)	0.118(3)	*0.1251(2)*	*0.1441(2)*	*0.0913(2)*	*0.11(2)*	0.2971(3)	0.6395(3)
	Best(B_{Vrk})	1.53e-10(2)	4.32e-09(2)	8.15e-09(2)	9.09e-09(2)	6.46e-08(5)	311(4)	2.92e+03(3)	6.24e+03(4)	1.73e-11(1)	118(3)	2.96e+03(4)	4.77e+03(3)	1.53e-10(3)	1.81e-10(1)	1.27e-11(1)	5.42e-10(1)	7.15e-10(4)	475(5)	3.79e+03(5)	6.96e+03(5)
	Mean	5.388e-09	75.46	467.3	1058	0.000483	544.9	3426	6900	11.84	868.8	4162	6798	4.187e-09	7.896	55.27	11.84	150.9	1381	5323	9559
f_{DG4}	Median	5.592e-09	59.22	118.4	118.4	3.693e-05	540.6	3388	6877	2.41e-09	832.1	4168	6917	3.981e-09	7.526e-09	9.748e-09	7.789e-09	140.9	1390	5340	9720
fOpt= 0;	Std	2.9e-09	91	1.1e+03	2.5e+03	0.0018	1.2e+02	2.6e+02	3.8e+02	36	3.1e+02	8e+02	1e+03	2.8e-09	30	60	36	72	3e+02	7.4e+02	1e+03
fTol= 1e-08	Succ.Rate	100.00%	50.00%	36.67%	13.33%	0.00%	0.00%	0.00%	0.00%	90.00%	0.00%	0.00%	0.00%	100.00%	93.33%	53.33%	90.00%	6.00%	0.00%	0.00%	0.00%
	ERT$_r$	4.98e+03	8.4e+04	2.83e+05	4.9e+05	2e+04	1e+05	3e+05	5e+05	4.38e+03	1e+05	3e+05	5e+05	4.2e+03	3.39e+04	2.18e+05	2.86e+05	1.89e+04	1e+05	3e+05	5e+05
	O$_{Fs}$(O$_{Frk}$)	0.2489(3)	*0.8404(2)*	*0.9436(2)*	*0.9798(2)*	1(5)	1(4)	1(3)	1(4)	*0.219(2)*	1(3)	1(4)	1(3)	**0.21(1)**	**0.3385(1)**	**0.7266(1)**	**0.5729(1)**	0.9472(4)	1(5)	1(5)	1(5)
	Best(B_{Vrk})	1.91e-11(3)	3.88e-09(4)	5.6e-09(2)	7.11e-09(3)	3.33e-09(5)	4.07e-07(5)	0.000588(5)	0.209(5)	1.88e-11(2)	2.37e-09(2)	6.22e-09(3)	6.58e-09(2)	3.06e-10(4)	3.35e-09(3)	8.07e-09(4)	8.23e-09(4)	6.26e-12(1)	2.6e-10(1)	5.96e-10(1)	7.79e-10(1)
	Mean	3.433e-09	0.001734	8.603e-09	9.137e-09	1.612e-06	3.027e-06	0.001701	0.8131	2.851e-09	6.255e-09	7.939e-09	8.196e+04	4.636e-09	7.942e-09	9.195e-09	9.41e-09	2.992e-09	1.342e-09	1.29e-09	1.333e-09
f_{DG5}	Median	2.305e-09	8.063e-09	8.771e-09	9.283e-09	5.32e-07	2.169e-06	0.00171	0.7471	2.628e-09	5.695e-09	7.792e-09	8.621e-09	4.296e-09	8.492e-09	9.331e-09	9.484e-09	1.746e-09	1.338e-09	1.287e-09	1.262e-09
fOpt= 0;	Std	3.1e-09	0.0066	1.1e-09	6.9e-10	4.7e-06	2.2e-06	0.00069	0.38	2.2e-09	2.1e-09	1e-09	4.5e+05	2.7e-09	1.8e-09	5.4e-10	4.5e-10	2.7e-09	6e-10	2.9e-10	3.6e-10
fTol= 1e-08	Succ.Rate	100.00%	90.00%	100.00%	100.00%	4.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	96.67%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT$_r$	1.31e+03	2.21e+04	4.9e+04	1.32e+05	1.99e+04	1e+05	3e+05	5e+05	2.41e+03	1.17e+04	4.14e+04	9.75e+04	3.16e+03	9.98e+03	3.46e+04	6.66e+04	1.39e+03	1.14e+04	6.07e+04	1.61e+05
	O$_{Fs}$(O$_{Frk}$)	**0.0654(1)**	0.2215(4)	0.1633(3)	0.2639(3)	0.9966(5)	1(5)	1(5)	1(5)	0.1206(3)	0.1167(3)	*0.1381(2)*	*0.1951(2)*	0.1581(4)	**0.09981(1)**	**0.1153(1)**	**0.1333(1)**	*0.0695(2)*	*0.1144(2)*	0.2023(4)	0.321(4)

Note: See summary table (12) footnotes for additional legend aids or remarks, as well as section 3.5.2 for the performance evaluation and comparison model.

Table 8 Generic Shifted X* Testbed - Per Function Benchmark Results (pg.2/6)

Func. Info	Perf. Measure	HyPERGDx				CSA				Mat.PSO				EBOwithCMAR				CMAES			
		D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50
f_{DG6} fOpt= 0; fTol= 1e-08	Best(B_{Vrk})	3.44e-11(3)	2.79e-09(2)	6.91e-09(2)	8.56e-09(2)	3.56e-09(5)	4.19(5)	71.7(5)	159(5)	3.48e-12(1)	2.98(4)	40.8(4)	95.5(4)	2.89e-10(4)	4.53e-09(3)	4.41e-09(1)	4.52e-09(1)	1.43e-11(2)	2.17e-09(1)	4.97(3)	11.9(3)
	Mean	4.382e-09	8.151e-09	2.8	41.62	4.561e-06	7.988	89.57	202.1	3.749e-09	7.993	62.89	152.3	4.748e-09	8.412e-09	8.322e-09	8.186e-09	0.02618	2.985	10.28	38.71
	Median	4.039e-09	8.961e-09	9.624e-09	9.928e-09	1.201e-06	8.142	88.74	202.6	3.477e-09	7.96	59.2	146.8	4.913e-09	8.955e-09	9.117e-09	8.598e-09	2.479e-09	2.985	9.95	18.41
	Std	3e-09	1.9e-09	15	94	9.6e-06	2.1	11	18	2.7e-09	3.1	17	42	2.7e-09	1.3e-09	1.7e-09	1.4e-09	0.14	1.4	3.7	79
	Succ.Rate	100.00%	100.00%	90.00%	66.67%	2.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%	94.00%	3.33%	0.00%	0.00%
	ERT_r	1.11e+04	6.42e+04	2.38e+05	4.81e+05	2e+04	1e+05	3e+05	5e+05	2.4e+03	1e+05	3e+05	5e+05	3.37e+03	2.53e+04	1.01e+05	2.08e+05	2.69e+03	9.7e+04	3e+05	5e+05
	$O_{Fs}(O_{Frk})$	0.5535(4)	*0.6425(2)*	*0.7936(2)*	*0.9623(2)*	0.9987(5)	1(5)	1(5)	1(5)	**0.1198(1)**	1(4)	1(4)	1(4)	0.1683(3)	**0.2531(1)**	**0.3364(1)**	**0.4169(1)**	*0.1343(2)*	0.9697(3)	1(3)	1(3)
f_{DG7} fOpt= 0; fTol= 1e-08	Best(B_{Vrk})	0(2)	0(2)	0.000149(3)	0.0114(3)	0.0316(3)	2.04(5)	6.37(5)	7.61(5)	0(1)	0(3)	0.754(4)	1.49(4)	0(1)	0(1)	5.85e-09(1)	8.52e-09(1)	0(1)	1.27e-07(4)	2.39e-07(2)	2.34e-07(2)
	Mean	1.588e-05	4.619e-05	0.063	0.4267	0.07408	2.935	7.273	8.616	0	0.09596	1.681	2.682	0	3.974e-05	0.02617	0.04242	0	0.0001194	0.0003408	0.002612
	Median	8.538e-07	9.417e-09	0.01747	0.2431	0.07561	2.995	7.227	8.69	0	0.01153	1.548	2.542	0	9.417e-09	0.007117	0.0167	0	1.707e-07	2.874e-07	0.0002284
	Std	0.0001	0.00022	0.17	0.67	0.028	0.52	0.45	0.4	1e-308	0.29	0.8	0.65	1e-308	0.00022	0.053	0.071	1e-308	0.00033	0.00047	0.012
	Succ.Rate	8.00%	86.67%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	20.00%	0.00%	0.00%	100.00%	96.67%	6.67%	6.67%	100.00%	0.00%	0.00%	0.00%
	ERT_r	1.98e+04	8.2e+04	3e+05	5e+05	2e+04	1e+05	3e+05	5e+05	5.31e+03	8.48e+04	3e+05	5e+05	8.84e+03	3.14e+04	2.99e+05	4.97e+05	3.38e+03	1e+05	3e+05	5e+05
	$O_{Fs}(O_{Frk})$	0.9918(4)	*0.8197(2)*	1(3)	1(3)	1(5)	1(5)	1(5)	1(5)	*0.2656(2)*	0.8476(3)	1(4)	1(4)	0.4418(3)	**0.3137(1)**	**0.9958(1)**	**0.9945(1)**	**0.1692(1)**	1(4)	*1(2)*	*1(2)*
f_{DG8} fOpt= 0; fTol= 1e-08	Best(B_{Vrk})	1.06e-11(1)	2.7e-09(3)	6.23e-09(3)	7.79e-09(3)	1.4e-10(5)	1.61e-08(5)	6.99e-09(4)	7.73e-08(5)	1.41e-11(2)	1.47e-09(2)	5.72e-09(2)	7.5e-09(2)	3.49e-11(3)	4.07e-09(4)	7.66e-09(5)	8.66e-09(4)	4.24e-11(4)	3.23e-10(1)	7.12e-10(1)	7.21e-10(1)
	Mean	2.656e-07	7.742e-09	8.404e-09	9.243e-09	2.118e-07	8.785e-08	9.21e-09	2.629e-07	3.137e-07	7.058e-09	7.82e-09	8.809e-09	4.498e-09	7.639e-09	9.3e-09	9.429e-09	4.089e-05	1.308e-09	1.302e-09	1.183e-09
	Median	4.156e-09	8.29e-09	8.612e-09	9.491e-09	1.241e-07	8.223e-08	9.27e-09	2.186e-07	4.373e-09	7.295e-09	7.928e-09	8.829e-09	3.93e-09	8.168e-09	9.415e-09	9.475e-09	1.492e-09	1.137e-09	1.205e-09	1.182e-09
	Std	1.8e-06	1.7e-09	9.8e-10	6.8e-10	2.6e-07	4.8e-08	8.6e-10	1.1e-07	2.2e-06	1.7e-09	9.9e-10	6.2e-10	2.8e-09	1.8e-09	5.1e-10	4.3e-10	0.00022	6.7e-10	3.4e-10	2.4e-10
	Succ.Rate	94.00%	100.00%	100.00%	100.00%	10.00%	0.00%	96.67%	0.00%	98.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	96.00%	100.00%	100.00%	100.00%
	ERT_r	7.43e+03	3.17e+03	1.07e+04	1.96e+04	1.99e+04	1e+05	2.94e+05	5e+05	4.01e+03	9.84e+03	2.6e+04	5.09e+04	3.14e+03	8.22e+03	1.78e+04	3.12e+04	2.36e+03	6.07e+03	1.57e+04	2.59e+04
	$O_{Fs}(O_{Frk})$	0.3714(4)	**0.03165(1)**	**0.03578(1)**	**0.03923(1)**	0.9936(5)	1(5)	0.979(5)	1(5)	0.2005(3)	0.09844(4)	0.08678(4)	0.1018(4)	*0.1571(2)*	0.08225(3)	0.05928(3)	0.06233(3)	**0.1178(1)**	*0.06068(2)*	*0.05222(2)*	*0.05186(2)*
f_{DG9} fOpt= 0; fTol= 1e-08	Best(B_{Vrk})	7.02e-11(3)	0.182(4)	5.91e-09(3)	7.28e-09(3)	1.81e-09(5)	3.66e+04(5)	1e+10(5)	1e+10(5)	5.42e-12(1)	3.33e-09(2)	5.87e-09(2)	6.66e-09(2)	2.7e-10(4)	4.09e-09(3)	7.31e-09(4)	8.61e-09(4)	3.89e-11(2)	4.11e-10(1)	5.86e-10(1)	8.6e-10(1)
	Mean	3.807e-09	2309	8.494e-09	9.056e-09	7.926e-07	1.063e+09	1e+10	1e+10	2.997e-09	6.332e-09	2.296e+07	2.296e+07	4.098e-09	7.454e-09	8.986e-09	9.477e-09	2.179e-09	1.685e-09	1.203e-09	1.217e-09
	Median	3.066e-09	780.1	8.919e-09	9.285e-09	2.319e-07	6.888e+06	1e+10	1e+10	1.971e-09	6.638e-09	8.068e-09	8.975e-09	3.824e-09	7.662e-09	8.875e-09	9.532e-09	1.213e-09	1.377e-09	1.162e-09	1.195e-09
	Std	2.9e-09	3.4e+03	1.1e-09	6.8e-10	1.5e-06	3e+09	1e-308	1e-308	2.5e-09	1.6e-09	1.3e+08	1.3e+08	2.9e-09	1.6e-09	7.6e-10	3.5e-10	2.5e-09	1.3e-09	3.8e-10	2.4e-10
	Succ.Rate	100.00%	0.00%	100.00%	100.00%	2.00%	0.00%	0.00%	0.00%	100.00%	100.00%	96.67%	96.67%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT_r	1.3e+03	1e+05	5.19e+04	1.26e+05	2e+04	1e+05	3e+05	5e+05	2.51e+03	1.28e+04	5.3e+04	1.06e+05	3.19e+03	1.11e+04	3.64e+04	6.36e+04	1.53e+03	1.23e+04	4.04e+04	7.01e+04
	$O_{Fs}(O_{Frk})$	**0.0652(1)**	1(4)	0.1731(3)	0.2528(4)	0.9999(5)	1(5)	1(5)	1(5)	0.1253(3)	0.1284(3)	0.1767(4)	0.2121(3)	0.1594(4)	**0.1114(1)**	**0.1215(1)**	**0.1272(1)**	*0.0764(2)*	*0.1226(2)*	*0.1346(2)*	*0.1401(2)*
f_{DG10} fOpt= 0; fTol= 1e-08	Best(B_{Vrk})	9.97e-10(4)	5.85e-09(3)	8e-09(3)	8.91e-09(2)	1.8e-07(5)	0.129(5)	6.42(5)	23(5)	2.52e-10(1)	5.17e-09(2)	7.89e-09(2)	9.26e-09(3)	8.89e-10(3)	7.25e-09(4)	8.93e-09(4)	9.31e-09(4)	5.9e-10(2)	2.25e-09(1)	3.09e-09(1)	3.1e-09(1)
	Mean	5.738e-09	8.538e-09	9.575e-09	7.065e-07	5.784e-06	0.3953	9.783	28.75	4.425e-09	0.052	2.184	5.252	6.38e-09	8.947e-09	9.624e-09	9.815e-09	3.638e-09	3.824e-09	3.888e-09	0.104
	Median	5.807e-09	8.648e-09	9.731e-09	9.882e-09	2.852e-06	0.3204	9.326	28.52	4.224e-09	7.733e-09	1.56	4.68	7.004e-09	9.327e-09	9.692e-09	9.877e-09	3.041e-09	3.753e-09	3.867e-09	3.63e-09
	Std	2.5e-09	1.1e-09	5.1e-10	3.8e-06	9.7e-06	0.19	2	3.6	2.5e-09	0.28	2.3	4.4	2.5e-09	9e-10	2.9e-10	1.8e-10	2e-09	1.1e-09	4.9e-10	0.4
	Succ.Rate	100.00%	100.00%	100.00%	86.67%	0.00%	0.00%	0.00%	0.00%	100.00%	96.67%	43.33%	10.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	93.33%
	ERT_r	1.86e+03	2.65e+04	1.4e+05	3.39e+05	2e+04	1e+05	3e+05	5e+05	2.8e+03	1.38e+04	1.86e+05	4.59e+05	6.87e+03	3.59e+04	3.62e+04	6.2e+04	2.01e+03	1.13e+04	3.07e+04	8.07e+04
	$O_{Fs}(O_{Frk})$	**0.09284(1)**	0.2654(3)	0.4678(3)	0.6782(3)	1(5)	1(5)	1(5)	1(5)	0.14(3)	*0.1381(2)*	0.6215(4)	0.9181(4)	0.3436(4)	0.3592(4)	*0.1208(2)*	**0.124(1)**	*0.1005(2)*	**0.1132(1)**	**0.1025(1)**	*0.1613(2)*

Note: See summary table (9) footnotes for additional legend aids or remarks, as well as section 3.5.2 for the performance evaluation and comparison model.

Table 9 Generic Shifted X* Testbed - Per Function Benchmark Results (pg.3/6)

Func. Info	Perf. Measure	HyPERGDx D=2	HyPERGDx D=10	HyPERGDx D=30	HyPERGDx D=50	CSA D=2	CSA D=10	CSA D=30	CSA D=50	Mat.PSO D=2	Mat.PSO D=10	Mat.PSO D=30	Mat.PSO D=50	EBOwithCMAR D=2	EBOwithCMAR D=10	EBOwithCMAR D=30	EBOwithCMAR D=50	CMAES D=2	CMAES D=10	CMAES D=30	CMAES D=50
f_{DG11}	Best(B_{Vrk})	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(2)	1(2)	1(2)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)
fOpt= 0;	Mean	0	0	0	0	0	0	0	0	0	0.06667	70.2	386.3	0	0	0	0	0	0	0	0
fTol=	Median	0	0	0	0	0	0	0	0	0	0	3	68.5	0	0	0	0	0	0	0	0
1e-08	Std	1e-308	1e-308	1e-308	1e-308	1e-308	1e-308	1e-308	1e-308	1e-308	0.25	2.7e+02	5.2e+02	1e-308	1e-308	1e-308	1e-308	1e-308	1e-308	1e-308	1e-308
	Succ.Rate	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	93.33%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT_r	214	1.41e+03	5.54e+03	9.41e+03	2.66e+03	3.38e+04	1.6e+05	3.61e+05	712	9.63e+03	3e+05	5e+05	649	3.1e+03	1.68e+04	4.54e+04	460	2.7e+03	7.44e+03	1.25e+04
	$O_{Fs}(O_{Frk})$	**0.0107(1)**	**0.01406(1)**	**0.01846(1)**	**0.01881(1)**	0.1329(5)	0.3381(5)	0.5337(4)	0.7216(4)	0.0356(4)	0.09627(4)	1(5)	1(5)	0.03244(3)	0.03101(3)	0.05611(3)	0.09077(3)	*0.023(2)*	*0.02696(2)*	*0.02481(2)*	*0.02498(2)*
f_{DG12}	Best(B_{Vrk})	2.98e-11(4)	6.66e-09(4)	9.21e-09(4)	6.58e-09(2)	1.94e-11(3)	1e+10(5)	1e+10(5)	1e+10(5)	9.01e-13(1)	7.78e-10(1)	4.76e-09(2)	6.27e-09(1)	9.2e-12(2)	3.9e-09(3)	6.64e-09(3)	7.84e-09(4)	2.89e-10(5)	1.49e-09(2)	4.48e-09(1)	6.71e-09(3)
fOpt= 0;	Mean	3.534e-09	9.267e-09	9.8e-09	9.171e-09	3.353e-09	1e+10	1e+10	1e+10	2.335e-09	5.091e-09	7.416e-09	8.356e-09	3.531e-09	6.989e-09	8.896e-09	9.293e-09	2.959e-09	5.325e-09	8.255e-09	8.698e-09
fTol=	Median	2.887e-09	9.501e-09	9.842e-09	9.543e-09	2.415e-09	1e+10	1e+10	1e+10	8.111e-10	5.643e-09	7.457e-09	8.49e-09	2.284e-09	6.984e-09	8.982e-09	9.315e-09	2.199e-09	4.987e-09	8.584e-09	8.854e-09
1e-08	Std	2.9e-09	7.7e-10	1.9e-10	7.7e-10	3e-09	1e-308	1e-308	1e-308	2.7e-09	2.7e-09	1.3e-09	8.6e-10	3.2e-09	2e-09	9.6e-10	5.1e-10	2.7e-09	2.4e-09	1.1e-09	6.2e-10
	Succ.Rate	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT_r	680	8.6e+03	4.16e+04	1.16e+05	1.22e+04	1e+05	3e+05	5e+05	1.51e+03	7.09e+03	3.15e+04	7.25e+04	1.9e+03	6.75e+03	3.05e+04	5.84e+04	931	9.7e+03	5.55e+04	1.29e+05
	$O_{Fs}(O_{Frk})$	**0.034(1)**	0.08599(3)	0.1387(3)	0.2324(3)	0.6087(5)	1(5)	1(5)	1(5)	0.07545(3)	*0.0709(2)*	*0.1051(2)*	*0.145(2)*	0.09521(4)	**0.06753(1)**	**0.1018(1)**	**0.1168(1)**	*0.04655(2)*	0.09698(4)	0.185(4)	0.2574(4)
f_{DG13}	Best(B_{Vrk})	6.6e-11(4)	2.95e-09(5)	6.32e-09(4)	7.89e-09(4)	3.52e-11(3)	2.33e-09(2)	4.54e-09(2)	6.09e-07(5)	1.53e-11(2)	2.84e-09(4)	5.76e-09(3)	7.62e-09(3)	7.36e-11(5)	2.51e-09(3)	7.98e-09(5)	7.12e-09(2)	8.94e-12(1)	5.49e-10(1)	7.12e-10(1)	8.76e-10(1)
fOpt= 0;	Mean	3.586e-09	7.072e-09	8.613e-09	9.263e-09	4.4e-09	8.426e-09	9.075e-09	1.082e-06	2.672e-09	0.09236	7.884e-09	8.666e-09	4.509e-09	7.511e-09	9.299e-09	9.352e-09	1.997e-09	1.692e-09	1.287e-09	1.333e-09
fTol=	Median	3.184e-09	7.33e-09	8.794e-09	9.332e-09	3.888e-09	8.809e-09	9.088e-09	1.013e-06	2.454e-09	5.201e-09	7.702e-09	8.615e-09	4.266e-09	8.06e-09	9.364e-09	9.651e-09	1.196e-09	1.441e-09	1.235e-09	1.291e-09
1e-08	Std	2.7e-09	1.9e-09	1e-09	4.7e-10	2.9e-09	1.5e-09	1.4e-09	3.7e-07	2.4e-09	0.51	1.1e-09	6.4e-10	2.8e-09	2e-09	4.9e-10	6.9e-10	2.3e-09	1.1e-09	4e-10	3.1e-10
	Succ.Rate	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	96.67%	0.00%	100.00%	96.67%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT_r	539	3.14e+03	1.38e+04	2.85e+04	1.01e+04	7.13e+04	2.94e+05	5e+05	1.39e+03	1.03e+04	2.91e+04	6.27e+04	1.82e+03	6.56e+03	1.86e+04	3.43e+04	876	5.83e+03	1.83e+04	3.54e+04
	$O_{Fs}(O_{Frk})$	**0.02695(1)**	**0.03136(1)**	**0.04605(1)**	**0.05693(1)**	0.5074(5)	0.7126(5)	0.9792(5)	1(5)	0.0693(3)	0.1032(4)	0.09701(4)	0.1254(4)	0.0912(4)	0.06555(3)	0.06211(3)	*0.06853(2)*	*0.0438(2)*	*0.0583(2)*	*0.06095(2)*	0.07078(3)
f_{DG14}	Best(B_{Vrk})	3.11e-10(2)	7.17e-09(4)	8.05e-09(3)	8.18e-09(3)	1.08e-07(5)	7.75e-05(5)	12.4(5)	1e+10(5)	1.01e-09(4)	5.06e-09(2)	6.67e-09(2)	7.94e-09(2)	7.55e-10(3)	5.41e-09(3)	8.75e-09(4)	8.4e-09(4)	8.78e-11(1)	2.93e-09(1)	2.79e-09(1)	2.77e-09(1)
fOpt= 0;	Mean	5.875e-09	8.952e-09	9.261e-09	9.44e-09	1.21e-06	0.0001685	2.439e+09	1e+10	5.09e-09	7.745e-09	9.151e-09	5.556e-08	6.526e-09	8.46e-09	9.543e-09	9.727e-09	3.572e-09	4.485e-09	3.801e-09	3.67e-09
fTol=	Median	5.536e-09	8.982e-09	9.378e-09	9.494e-09	1.068e-06	0.0001738	574	1e+10	4.771e-09	7.784e-09	9.221e-09	9.277e-09	6.899e-09	8.555e-09	9.56e-09	9.846e-09	3.008e-09	4.484e-09	3.738e-09	3.683e-09
1e-08	Std	2.5e-09	7.3e-10	5.9e-10	4.1e-10	9.1e-07	5e-05	4.1e+09	1e-308	2.4e-09	1.3e-09	8.8e-10	1.7e-07	2.5e-09	1.4e-09	3.6e-10	3.3e-10	2.6e-09	1.1e-09	6.2e-10	3.8e-10
	Succ.Rate	100.00%	100.00%	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	96.67%	86.67%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT_r	1.06e+03	7.8e+03	4.06e+04	5.79e+04	2e+04	1e+05	3e+05	5e+05	2.8e+03	1.22e+04	4.94e+04	1.46e+05	3.65e+03	1.25e+04	3.5e+04	6.85e+04	1.63e+03	1.12e+04	3.33e+04	5.83e+04
	$O_{Fs}(O_{Frk})$	**0.05298(1)**	**0.07803(1)**	0.1352(3)	**0.1157(1)**	1(5)	1(5)	1(5)	1(5)	0.1398(3)	0.122(3)	0.1647(4)	0.2917(4)	0.1826(4)	0.1247(4)	*0.1167(2)*	0.137(3)	*0.08155(2)*	*0.1119(2)*	**0.1111(1)**	*0.1166(2)*
f_{DG15}	Best(B_{Vrk})	2.81e-11(1)	2.72e-09(3)	6.22e-09(3)	7.02e-09(2)	0.00191(5)	1.17(5)	12.1(5)	29.7(5)	6.27e-11(2)	2.8e-09(4)	0.154(4)	6.51(4)	1.72e-10(4)	2.15e-09(2)	4.51e-09(2)	7.08e-09(3)	7.65e-11(3)	4.63e-10(1)	6.77e-10(1)	7.32e-10(1)
fOpt= 0;	Mean	4.817e-09	7.622e-09	0.07256	0.09365	0.005853	1.459	14.34	33.59	0.008123	0.1284	4.936	15.71	4.31e-09	7.162e-09	8.458e-09	8.973e-09	3.019e-09	0.3714	2.851	7.678
fTol=	Median	4.727e-09	8.419e-09	9.69e-09	9.647e-09	0.005878	1.468	14.23	32.75	1.998e-09	7.385e-09	4.748	15.94	3.469e-09	7.572e-09	8.789e-09	9.207e-09	1.692e-09	1.408e-09	1.331e-09	1.264e-09
1e-08	Std	2.9e-09	2.1e-09	0.29	0.31	0.0025	0.2	1.6	3.4	0.057	0.38	3.5	4.9	3e-09	1.9e-09	1.5e-09	8.2e-10	3.1e-09	2	11	23
	Succ.Rate	100.00%	100.00%	66.67%	73.33%	0.00%	0.00%	0.00%	0.00%	98.00%	76.67%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	96.67%	93.33%	90.00%
	ERT_r	4.45e+03	1.85e+04	1.56e+05	2.01e+05	2e+04	1e+05	3e+05	5e+05	3.54e+03	3.27e+04	3e+05	5e+05	9.16e+03	4.9e+04	1.87e+05	3.66e+05	2.46e+03	1.72e+04	5.74e+04	1.07e+05
	$O_{Fs}(O_{Frk})$	0.2226(3)	*0.1847(2)*	*0.5204(2)*	*0.4022(2)*	1(5)	1(5)	1(5)	1(5)	*0.1769(2)*	0.3272(3)	1(4)	1(4)	0.458(4)	0.4899(4)	0.6227(3)	0.7314(3)	**0.1229(1)**	**0.1724(1)**	**0.1914(1)**	**0.2132(1)**

Note: See summary table (10) footnotes for additional legend aids or remarks, as well as section 3.5.2 for the performance evaluation and comparison model.

Table 10 Generic Shifted X* Testbed - Per Function Benchmark Results (pg.4/6)

Func. Info	Perf. Measure	HyPERGDx				CSA				Mat.PSO				EBOwithCMAR				CMAES			
		D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50
	Best(B_{Vrk})	1.27e-10(3)	4.15e-09(4)	6.21e-09(2)	8.91e+03(5)	3.58e-08(5)	9.42e-09(5)	2.65e-07(5)	1.41e-05(4)	7.9e-13(1)	2.54e-09(2)	6.71e-09(3)	7.38e-09(2)	1.91e-10(4)	3.79e-09(3)	7.9e-09(4)	8.52e-09(3)	7.6e-11(2)	3.58e-10(1)	6.4e-10(1)	9e-10(1)
$\mathbf{f_{DG16}}$	Mean	4.174e-09	7.886e-09	8.843e-09	1.233e+04	1.519e-06	2.673e-08	7.993e-07	3.139e-05	3.11e-09	6.646e-09	7.916e-09	8.573e-09	4.306e-09	7.426e-09	9.255e-09	9.432e-09	2.647e-09	1.134e-09	1.144e-09	1.355e-09
fOpt= 0;	Median	3.84e-09	8.191e-09	8.915e-09	1.209e+04	6.852e-07	2.176e-08	7.578e-07	2.927e-05	2.011e-09	6.336e-09	7.735e-09	8.596e-09	4.033e-09	7.532e-09	9.474e-09	9.476e-09	1.479e-09	1.086e-09	1.125e-09	1.414e-09
fTol=	Std	2.9e-09	1.7e-09	9e-10	2e+03	2.5e-06	1.9e-08	3.6e-07	1.1e-05	2.6e-09	2.2e-09	8e-10	7.3e-10	2.9e-09	1.5e-09	5.4e-10	4.1e-10	2.6e-09	5.6e-10	2.6e-10	2.1e-10
1e-08	Succ.Rate	100.00%	100.00%	100.00%	0.00%	0.00%	13.33%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT_r	1.46e+03	8.83e+03	4.74e+04	5e+05	2e+04	9.97e+04	3e+05	5e+05	2.47e+03	9.59e+03	3.09e+04	6.54e+04	3.2e+03	8.57e+03	2.31e+04	4.07e+04	1.57e+03	1.05e+04	4.02e+04	8.31e+04
	$O_{Fs}(O_{Frk})$	**0.07279(1)**	*0.08827(2)*	0.1579(4)	1(5)	1(5)	0.9974(5)	1(5)	1(4)	0.1236(3)	0.09594(3)	*0.1029(2)*	*0.1307(2)*	0.1599(4)	**0.08574(1)**	**0.07685(1)**	**0.08133(1)**	*0.07825(2)*	0.1047(4)	0.134(3)	0.1661(3)
	Best(B_{Vrk})	2.56e-11(1)	2.56e-09(1)	8.53e-09(2)	8.19e-09(2)	7.93e-11(3)	0.125(5)	0.309(4)	0.395(4)	3.53e-11(2)	0.0178(3)	0.292(3)	0.304(3)	1.07e-10(4)	4.46e-09(2)	3.31e-09(1)	4.23e-09(1)	1.64e-10(5)	0.071(4)	0.343(5)	0.416(5)
$\mathbf{f_{DG17}}$	Mean	4.36e-09	7.638e-09	0.002196	3.41e-05	1.447e-07	0.1669	0.3674	0.4337	2.805e-09	0.1931	0.5018	0.5494	4.58e-09	7.438e-09	8.423e-09	8.558e-09	0.007424	0.2982	0.6075	0.7035
fOpt= 0;	Median	3.636e-09	8.262e-09	9.649e-09	9.678e-09	2.555e-08	0.1634	0.3652	0.4271	2.496e-09	0.1531	0.4602	0.4887	4.118e-09	7.547e-09	8.897e-09	8.816e-09	1.643e-09	0.2952	0.6759	0.7516
fTol=	Std	2.9e-09	2.1e-09	0.0088	0.00019	2.7e-07	0.027	0.026	0.025	2.3e-09	0.13	0.16	0.17	2.8e-09	1.7e-09	1.7e-09	1.4e-09	0.024	0.12	0.13	0.11
1e-08	Succ.Rate	100.00%	100.00%	90.00%	93.33%	30.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%	90.00%	0.00%	0.00%	0.00%
	ERT_r	3.88e+03	3.88e+04	1.82e+05	3.61e+05	1.95e+04	1e+05	3e+05	5e+05	1.99e+03	1e+05	3e+05	5e+05	3.1e+03	2.25e+04	8.82e+04	1.83e+05	3.44e+03	1e+05	3e+05	5e+05
	$O_{Fs}(O_{Frk})$	0.1939(4)	*0.3882(2)*	*0.6073(2)*	*0.7217(2)*	0.977(5)	1(5)	1(4)	1(4)	**0.0994(1)**	1(3)	1(3)	1(3)	*0.1548(2)*	**0.2249(1)**	**0.294(1)**	**0.3653(1)**	0.172(3)	1(4)	1(5)	1(5)
	Best(B_{Vrk})	1(3)	1(2)	1(3)	1(3)	1(5)	4.44(5)	72.6(5)	191(5)	1(2)	1(4)	22.1(4)	44.1(4)	1(4)	1(3)	1(1)	1(2)	1(1)	1(1)	1(2)	1(1)
$\mathbf{f_{DG18}}$	Mean	1	1.345	1.419	2.301	1	8.365	86.55	224.5	1	3.346	52.04	166.1	1	1	1.015	1.015	1	1.03	1.12	1.179
fOpt= 1;	Median	1	1	1	2.122	1	8.386	82.9	224.5	1	1.449	46.33	143.5	1	1	1	1	1	1	1	1
fTol=	Std	2.5e-09	0.53	0.56	1.3	1.5e-06	2.2	13	16	2.6e-09	4.7	27	86	2.9e-09	1.5e-09	0.082	0.082	2.7e-09	0.11	0.26	0.28
1e-08	Succ.Rate	100.00%	53.33%	53.33%	20.00%	2.00%	0.00%	0.00%	0.00%	100.00%	43.33%	0.00%	0.00%	100.00%	100.00%	96.67%	96.67%	100.00%	93.33%	80.00%	66.67%
	ERT_r	817	5.1e+04	1.78e+05	4.06e+05	1.99e+04	1e+05	3e+05	5e+05	2.13e+03	6.2e+04	3e+05	5e+05	3.82e+03	1.87e+04	7.87e+04	1.65e+05	1.33e+03	1.45e+04	7.85e+04	1.92e+05
	$O_{Fs}(O_{Frk})$	**0.04086(1)**	0.5099(3)	0.5927(3)	0.8126(3)	0.9964(5)	1(5)	1(5)	1(5)	0.1065(3)	0.6203(4)	1(4)	1(4)	0.1908(4)	*0.1868(2)*	*0.2622(2)*	**0.33(1)**	*0.06655(2)*	**0.1451(1)**	**0.2616(1)**	*0.3846(2)*
	Best(B_{Vrk})	6.46e-11(2)	2.9e-09(2)	5.34e-09(2)	7.88e-09(2)	1.69e-10(5)	4.8e-09(5)	0.43(5)	1e+10(5)	7.99e-11(3)	2.91e-09(3)	6.39e-09(3)	8.53e-09(3)	1.65e-10(4)	4.79e-09(4)	7.94e-09(4)	8.81e-09(4)	1.48e-11(1)	2.82e-10(1)	1.01e-09(1)	7.93e-10(1)
$\mathbf{f_{DG19}}$	Mean	4.189e-09	7.709e-09	8.805e-09	9.137e-09	5.163e-09	8.517e-09	3e+09	1e+10	3.13e-09	6.789e-09	0.6932	469.4	4.745e-09	7.585e-09	9.396e-09	9.716e-09	1.832e-09	1.376e-09	1.433e-09	1.358e-09
fOpt= 0;	Median	3.296e-09	8.463e-09	8.914e-09	9.188e-09	5.433e-09	8.634e-09	11.46	1e+10	2.13e-09	6.79e-09	9.125e-09	9.742e-09	4.864e-09	7.808e-09	9.485e-09	9.773e-09	6.903e-10	1.266e-09	1.387e-09	1.304e-09
fTol=	Std	2.9e-09	2e-09	9.4e-10	5.7e-10	2.9e-09	1.2e-09	4.7e+09	1e-308	2.9e-09	1.6e-09	3.8	1.3e+03	2.6e-09	1.6e-09	4.8e-10	2.6e-10	2.3e-09	8.7e-10	3.3e-10	3.2e-10
1e-08	Succ.Rate	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%	0.00%	100.00%	100.00%	96.67%	66.67%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT_r	536	3.98e+03	2.58e+04	1.05e+05	1.15e+04	9.52e+04	3e+05	5e+05	1.52e+03	1.01e+04	7.28e+04	2.83e+05	2.02e+03	8.16e+03	3.5e+04	8.81e+04	969	6.54e+03	2.67e+04	6.02e+04
	$O_{Fs}(O_{Frk})$	**0.02682(1)**	**0.03982(1)**	**0.08597(1)**	0.2094(3)	0.5738(5)	0.9516(5)	1(5)	1(5)	0.0759(3)	0.1011(4)	0.2427(4)	0.5651(4)	0.1008(4)	0.08165(3)	0.1167(3)	*0.1762(2)*	*0.04845(2)*	*0.0654(2)*	*0.08914(2)*	**0.1205(1)**
$\mathbf{f_{DG20}}$	Best(B_{Vrk})	-2(3)	-210(3)	-4.93e+03(2)	-2.2e+04(2)	-2(5)	-210(4)	-4.89e+03(5)	-1.75e+04(5)	-2(1)	-210(5)	-4.93e+03(4)	-2.17e+04(4)	-2(4)	-210(2)	-4.93e+03(3)	-2.2e+04(3)	-2(2)	-210(1)	-4.93e+03(1)	-2.21e+04(1)
fOpt(D)= -2, -210,	Mean	-2	-210	-4930	-2.205e+04	-2	-210	-4859	-1.416e+04	-2	-210	-4846	-1.529e+04	-2	-210	-4930	-2.205e+04	-2	-210	-4930	-2.205e+04
-4930, -22050;	Median	-2	-210	-4930	-2.205e+04	-2	-210	-4870	-1.401e+04	-2	-210	-4860	-1.76e+04	-2	-210	-4930	-2.205e+04	-2	-210	-4930	-2.205e+04
fTol=1e-08	Std	2.8e-09	1.5e-09	9.7e-10	2.3e-09	2.9e-09	5.3e-08	44	1.9e+03	2.7e-09	1.6e-07	84	7.7e+03	2.8e-09	1.7e-09	9.2e-10	8.3e-07	2.2e-09	6.6e-10	4.1e-10	3.3e-09
	Succ.Rate	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	26.67%	100.00%	100.00%	100.00%	100.00%
	ERT_r	484	3.11e+03	1.64e+04	4.22e+04	9.79e+03	1e+05	3e+05	5e+05	1.45e+03	1e+05	3e+05	5e+05	1.85e+03	1.03e+04	1.33e+05	4.68e+05	817	6.78e+03	2.85e+04	6.67e+04
	$O_{Fs}(O_{Frk})$	**0.02419(1)**	**0.03106(1)**	**0.05458(1)**	**0.08443(1)**	0.4893(5)	1(4)	1(5)	1(5)	0.0724(3)	1(5)	1(4)	1(4)	0.09249(4)	0.1026(3)	0.4439(3)	0.9363(3)	*0.04085(2)*	*0.06784(2)*	*0.09508(2)*	*0.1333(2)*

Note: See summary table (11) footnotes for additional legend aids or remarks, as well as section 3.5.2 for the performance evaluation and comparison model.

Table 11 Generic Shifted X* Testbed - Per Function Benchmark Results (pg.5/6)

Func. Info	Perf. Measure	HyPERGDx				CSA				Mat.PSO				EBOwithCMAR				CMAES			
		D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50
f_{DG21} fOpt= 0; fTol= 1e-08	Best(B_{Vrk})	9.15e-10(4)	6.24e-09(3)	7.08e-09(2)	8.04e-09(2)	1.97e-07(5)	0.000468(5)	0.0347(5)	0.15(4)	1.98e-10(1)	5.51e-09(2)	0.000149(4)	0.261(5)	7.15e-10(3)	6.54e-09(4)	9.57e-09(3)	9.54e-09(3)	7.08e-10(2)	3.01e-09(1)	3.37e-09(1)	4.09e-09(1)
	Mean	5.785e-09	8.916e-09	9.286e-09	9.405e-09	1.944e-06	0.0008356	0.04867	0.2466	4.978e-09	0.08748	0.09034	0.724	6.212e-09	8.938e-09	9.879e-09	1.887e-06	4.39e-09	4.751e-09	5.033e-09	5.113e-09
	Median	5.32e-09	9.144e-09	9.478e-09	9.589e-09	1.674e-06	0.0007984	0.0477	0.2348	4.026e-09	8.362e-09	0.001015	0.7268	7.131e-09	9.282e-09	9.922e-09	1.36e-08	3.985e-09	4.497e-09	4.926e-09	4.967e-09
	Std	2.1e-09	8.4e-10	6.9e-10	5.2e-10	1.3e-06	0.00021	0.0089	0.051	2.6e-09	0.48	0.48	0.25	2.9e-09	9.5e-10	1.3e-10	4.4e-06	2.2e-09	1.5e-09	7.3e-10	6.3e-10
	Succ.Rate	100.00%	100.00%	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	100.00%	96.67%	0.00%	0.00%	100.00%	100.00%	100.00%	43.33%	100.00%	100.00%	100.00%	100.00%
	ERT_r	1.04e+03	5.31e+03	2.3e+04	5.39e+04	2e+04	1e+05	3e+05	5e+05	2.77e+03	2.22e+04	3e+05	5e+05	3.78e+03	1.42e+04	1.41e+05	4.89e+05	1.57e+03	1.08e+04	3.47e+04	6.35e+04
	$O_{Fs}(O_{Frk})$	**0.0522(1)**	**0.05313(1)**	**0.07672(1)**	**0.1078(1)**	1(5)	1(5)	1(5)	1(4)	0.1387(3)	0.2224(4)	1(4)	1(5)	0.1892(4)	0.1421(3)	0.4716(3)	0.9772(3)	*0.0783(2)*	*0.1077(2)*	*0.1158(2)*	*0.127(2)*
f_{DG22} fOpt= 0; fTol= 1e-08	Best(B_{Vrk})	1.81e-10(4)	4.31e-09(4)	6.38e-09(3)	7.28e-09(3)	1.83e-11(2)	5.81e-07(5)	0.562(4)	3.83(4)	5.9e-11(3)	3.46e-09(2)	1.05(5)	4.61(5)	1.86e-10(5)	3.78e-09(3)	3.31e-09(2)	3.79e-10(1)	1.59e-11(1)	3.08e-10(1)	3.97e-10(1)	8.68e-10(2)
	Mean	4.133e-09	0.01376	8.658e-09	0.2438	5.103e-09	3.674e-05	1.611	7.029	2.91e-09	0.1187	4.434	10.02	4.798e-09	8.131e-09	0.1388	0.8037	2.482e-09	0.01376	0.04129	0.02753
	Median	3.453e-09	8.558e-09	8.938e-09	9.423e-09	4.879e-09	1.766e-05	1.502	7.031	2.481e-09	5.991e-09	4.406	9.448	3.958e-09	8.738e-09	9.225e-09	0.7314	1.612e-09	1.061e-09	1.313e-09	1.225e-09
	Std	2.9e-09	0.075	1.1e-09	0.43	3.1e-09	6.1e-05	0.74	1.6	2.2e-09	0.32	1.7	3.5	2.9e-09	1.7e-09	0.34	0.95	2.5e-09	0.075	0.13	0.1
	Succ.Rate	100.00%	96.67%	100.00%	70.00%	100.00%	0.00%	0.00%	0.00%	100.00%	86.67%	0.00%	0.00%	100.00%	100.00%	80.00%	46.67%	100.00%	96.67%	90.00%	93.33%
	ERT_r	658	9.45e+03	3.76e+04	1.67e+05	1.57e+04	1e+05	3e+05	5e+05	1.84e+03	2.07e+04	3e+05	5e+05	2.58e+03	8.16e+03	1e+05	3.31e+05	1.02e+03	9.98e+03	4.72e+04	6.24e+04
	$O_{Fs}(O_{Frk})$	**0.03291(1)**	*0.09453(2)*	**0.1252(1)**	*0.3334(2)*	0.784(5)	1(5)	1(4)	1(4)	0.09175(3)	0.2073(4)	1(5)	1(5)	0.1292(4)	**0.08159(1)**	0.3337(3)	0.6618(3)	*0.05085(2)*	0.09977(3)	*0.1572(2)*	**0.1249(1)**
f_{DG23} fOpt= 0; fTol= 1e-08	Best(B_{Vrk})	3.45e-12(1)	2.99e-09(3)	6.69e-09(2)	51.9(5)	4.68e-10(5)	9.41e-08(5)	0.0862(5)	2.43(4)	4.06e-11(4)	3.25e-09(4)	9.39e-09(4)	4.33e-07(3)	3.98e-11(3)	2.74e-09(2)	9.25e-09(3)	9.2e-09(2)	2.01e-11(2)	5.08e-10(1)	5.54e-10(1)	9.57e-10(1)
	Mean	3.185e-09	7.667e-09	8.869e-09	85.92	4.829e-09	3.72e-07	0.1435	3.388	3.22e-09	1.337e-05	0.574	3.029	4.727e-09	7.717e-09	9.808e-09	9.876e-09	2.152e-09	1.321e-09	1.443e-09	1.595e-09
	Median	2.466e-09	8.083e-09	9.035e-09	85.55	4.688e-09	3.087e-07	0.1388	3.529	2.725e-09	8.226e-09	2.087e-08	3.444	4.67e-09	7.958e-09	9.87e-09	9.926e-09	1.081e-09	1.185e-09	1.38e-09	1.473e-09
	Std	2.7e-09	1.8e-09	9.3e-10	15	2.8e-09	2.6e-07	0.027	0.49	2.6e-09	7.3e-05	1.3	3.6	2.7e-09	1.9e-09	1.9e-10	1.6e-10	2.2e-09	5.7e-10	4.1e-10	4.1e-10
	Succ.Rate	100.00%	100.00%	100.00%	0.00%	100.00%	0.00%	0.00%	0.00%	100.00%	96.67%	30.00%	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	ERT_r	573	4.84e+03	5.53e+04	5e+05	1.22e+04	1e+05	3e+05	5e+05	1.57e+03	2.02e+04	2.7e+05	5e+05	2.09e+03	9.15e+03	9.23e+04	2.89e+05	921	6.23e+03	2.36e+04	5.33e+04
	$O_{Fs}(O_{Frk})$	**0.02864(1)**	**0.04837(1)**	*0.1844(2)*	1(5)	0.6112(5)	1(5)	1(5)	1(4)	0.0786(3)	0.2023(4)	0.8984(4)	1(3)	0.1046(4)	0.0915(3)	0.3078(3)	*0.5777(2)*	*0.04605(2)*	*0.06234(2)*	**0.07856(1)**	**0.1066(1)**
f_{DG24} fOpt= 0; fTol= 1e-08	Best(B_{Vrk})	2.46e-09(4)	6.7e-09(4)	8e-09(1)	2.48e-05(1)	0.00109(5)	0.0866(5)	0.323(5)	0.728(5)	1.46e-09(3)	6.23e-09(3)	0.00344(4)	0.000814(3)	5.14e-10(2)	5.38e-09(2)	8.55e-09(2)	0.00453(4)	3.48e-10(1)	4.46e-09(1)	0.00132(3)	0.000663(2)
	Mean	7.004e-09	1.163e-06	0.0004508	0.000483	0.01277	0.1322	0.5402	1.101	0.06121	0.3764	1.151	0.9656	6.872e-09	8.663e-09	1.04e-08	0.006424	0.01435	1.18	3.09	4.066
	Median	7.005e-09	9.669e-09	0.0003021	0.0003329	0.01156	0.1276	0.5387	1.106	6.767e-09	0.0156	0.02937	0.008716	7.552e-09	9.034e-09	9.838e-09	0.006199	3.995e-09	1.544	3.337	4.259
	Std	2.8e-09	3e-06	0.00066	0.00048	0.0069	0.029	0.095	0.18	0.13	0.58	1.6	1.8	2.4e-09	1.3e-09	1.3e-09	0.0011	0.1	0.79	0.96	0.91
	Succ.Rate	98.00%	53.33%	13.33%	0.00%	0.00%	0.00%	0.00%	0.00%	68.00%	40.00%	0.00%	0.00%	100.00%	100.00%	63.33%	0.00%	98.00%	3.33%	0.00%	0.00%
	ERT_r	9.44e+03	7.22e+04	2.77e+05	5e+05	2e+04	1e+05	3e+05	5e+05	1.11e+04	6.66e+04	3e+05	5e+05	1.26e+04	5.52e+04	2.3e+05	5e+05	4.89e+03	9.74e+04	3e+05	5e+05
	$O_{Fs}(O_{Frk})$	*0.4721(2)*	0.722(3)	*0.9238(2)*	**1(1)**	1(5)	1(5)	1(5)	1(5)	0.5538(3)	*0.6655(2)*	1(4)	1(3)	0.6308(4)	**0.5523(1)**	**0.7661(1)**	1(4)	**0.2446(1)**	0.9737(4)	1(3)	*1(2)*

Note: See summary table (12) footnotes for additional legend aids or remarks, as well as section 3.5.2 for the performance evaluation and comparison model.

Table 12 Generic Shifted X* Testbed - Summary Benchmark Performance Results (pg.6/6)

		Perf. Measure	HyPERGDx				CSA				Mat.PSO				EBOwithCMAR				CMAES			
			D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50	D=2	D=10	D=30	D=50
	1	Ratio of Problems Solved (RoPs):	1	0.96	0.96	0.83	0.58	0.21	0.13	0.042	1	0.79	0.5	0.42	1	1	1	0.96	1	0.88	0.79	0.79
	2	(#solved / totalOfProblems):	(24 / 24)	(23 / 24)	(23 / 24)	(20 / 24)	(14 / 24)	(5 / 24)	(3 / 24)	(1 / 24)	(24 / 24)	(19 / 24)	(12 / 24)	(10 / 24)	(24 / 24)	(24 / 24)	(24 / 24)	(23 / 24)	(24 / 24)	(21 / 24)	(19 / 24)	(19 / 24)
	3	RoPs Testbed Rank:	1	2	2	2	2	5	5	5	1	4	4	4	1	1	1	1	1	3	3	3
	4	Mean Success Rate (mSR):	95.83%	86.11%	85.42%	71.81%	35.42%	17.22%	12.22%	4.17%	96.67%	68.61%	42.08%	35.69%	100.00%	99.58%	90.97%	82.50%	95.17%	78.89%	76.81%	74.31%
	5	mSR Testbed rank:	3	2	2	3	5	5	5	5	2	4	4	4	1	1	1	1	4	3	3	2
	6	Ratio of Non-100% SRs (non100s)	0.13	0.33	0.29	0.46	0.67	0.83	0.96	0.96	0.21	0.63	0.79	0.79	0.00	0.08	0.25	0.33	0.21	0.33	0.38	0.42
	7	non100s Testbed rank:	2	2	2	3	4	4	5	5	3	3	4	4	1	1	1	1	3	2	3	2
Testbed,	8	Mean O_{Frk}:	1.75	1.95833	1.95833	2.16667	5	4.91667	4.79167	4.70833	2.79167	3.45833	3.79167	3.66667	3.54167	2.20833	2.08333	2.04167	1.91667	2.45833	2.375	2.41667
Aggregate	9	(Nr of $O_{Frk} = 1$ / Nr of $O_{Frk} = 2$):	(16 / 2)	(10 / 7)	(10 / 6)	(10 / 5)	(0 / 0)	(0 / 0)	(0 / 0)	(0 / 0)	(2 / 3)	(0 / 3)	(0 / 3)	(0 / 3)	(1 / 2)	(10 / 2)	(9 / 4)	(10 / 4)	(5 / 17)	(4 / 12)	(5 / 11)	(4 / 12)
Performance	10	Max.Speed Testbed rank:	**1**	**1**	**1**	*2*	5	5	5	5	3	4	4	4	4	*2*	*2*	**1**	*2*	3	3	3
	11	Reliability Score (@weights: 0, 60, 30, 10):	*2.50*	*10.00*	*9.79*	*23.04*	51.04	80.67	88.42	95.83	3.08	28.17	55.29	62.21	**0.00**	**0.96**	**5.21**	**11.08**	3.53	17.17	23.21	24.38
	12	Max.Reliability.Testbed rank:	*2*	*2*	*2*	*2*	5	5	5	5	3	4	4	4	**1**	**1**	**1**	**1**	4	3	3	3
	13	Reliability (Moderate) Score (@weights: 25, 50, 17, 8):	**10.46**	*16.90*	*16.69*	*27.63*	62.15	84.91	90.30	95.42	16.19	38.04	60.14	64.77	17.71	**11.78**	**13.95**	**17.93**	*12.07*	24.80	29.23	30.20
	14	Moderate.Reliability.Testbed rank:	**1**	*2*	*2*	*2*	5	5	5	5	3	4	4	4	4	**1**	**1**	**1**	*2*	3	3	3
	15	Balanced Speed-Reliability Score (@weights: 50, 30, 15, 5):	**18.75**	*24.58*	*24.48*	*33.19*	75.52	89.50	92.13	95.00	29.46	48.67	65.56	67.77	35.42	**22.56**	**23.44**	**25.96**	*20.93*	33.17	35.35	36.35
	16	Balanced.Speed/Reliability.Testbed rank:	**1**	*2*	*2*	*2*	5	5	5	5	3	4	4	4	4	**1**	**1**	**1**	*2*	3	3	3
	17	Speed (Moderate) Score (@weights: 75,15,7,3):	**26.92**	**31.97**	**31.90**	*38.35*	87.77	93.92	94.02	94.58	42.73	59.07	70.80	70.63	53.13	*33.40*	*32.63*	**33.48**	*29.71*	41.23	41.50	42.42
	18	Moderate.Speed.Testbed rank:	**1**	**1**	**1**	*2*	5	5	5	5	3	4	4	4	4	*2*	*2*	**1**	*2*	3	3	3

Notes:

- ✓ Except for lines 1, 2, 4 and 9 (respectively ***RoPs***, ***"#solved..."***, ***mSR***, and ***"#OFrank1s/#OFrank2s"***), the greater a measure of performance, the worse it is.
- ✓ In particular, the greater a ***score*** or a ***rank***, the worse it is.
- ✓ Where every single contender algorithm totally failed, *i.e.*, got the worse value of some measure of performance, all algorithms were awarded the worst rank.

See section 3.5.2 for the performance evaluation and comparison model.

Table 13 *ApplianceSchedule1(.)* Unknown Optima Test Setup - Per Function Benchmark Results (pg.1/2)

Func. Info	Perf. Measure	D = 10				
		HyPERGDx	CSA	Mat.PSO	EBOwithCMAR	CMAES
f_{DAu1} **(uC=1)** fOpt= 0; fTol= 1e-05	Best(B_{Vrk})	15.1435(1)	15.1555(5)	15.1435(2)	15.1435(3)	15.1435(4)
	Mean	15.9771	15.2162	20.0014	18.8724	38.5885
	Median	15.1435	15.1994	18.8563✗	19.5025✗	37.8607✗
	Std	2.2	0.062	5.6	3.7	22
	Succ.Rate	0.00%	0.00%	0.00%	0.00%	0.00%
	ERT_r	1.1e+05	1.1e+05	1.1e+05	1.1e+05	1.1e+05
	$O_{Fs}(O_{Frk})$	**0.909091(1)**	0.909092(5)	*0.909091(2)*	0.909091(3)	0.909092(4)
f_{DAu2} **(uC=0.75)** fOpt= 0; fTol= 1e-05	Best(B_{Vrk})	15.0745(1)	15.0885(5)	15.0745(3)	15.0745(2)	15.0745(4)
	Mean	15.4096	15.1159	19.552	18.2059	31.6528
	Median	15.0745	15.1032	18.2059✗	16.1143✗	28.6098✗
	Std	1.3	0.041	5.4	4.1	17
	Succ.Rate	0.00%	0.00%	0.00%	0.00%	0.00%
	ERT_r	1.1e+05	1.1e+05	1.1e+05	1.1e+05	1.1e+05
	$O_{Fs}(O_{Frk})$	**0.909091(1)**	0.909092(5)	0.909091(3)	*0.909091(2)*	0.909092(4)
f_{DAu3} **(uC=0.5)** fOpt= 0; fTol= 1e-05	Best(B_{Vrk})	14.9367(1)	14.9511(5)	14.9367(2)	14.9367(3)	14.9367(4)
	Mean	15.699	14.9991	16.5627	16.9983	26.1471
	Median	14.9367	14.9789	16.5243✗	17.6381✗	24.9026✗
	Std	1.2	0.055	1.9	1.5	11
	Succ.Rate	0.00%	0.00%	0.00%	0.00%	0.00%
	ERT_r	1.1e+05	1.1e+05	1.1e+05	1.1e+05	1.1e+05
	$O_{Fs}(O_{Frk})$	**0.909091(1)**	0.909092(5)	*0.909091(2)*	0.909091(3)	0.909092(4)
f_{DAu4} **(uC=0.25)** fOpt= 0; fTol= 1e-05	Best(B_{Vrk})	14.6301(1)	14.6388(3)	14.6398(4)	14.6301(2)	14.9998(5)
	Mean	14.8879	14.7073	15.7545	15.3526	18.7947
	Median	14.9229	14.6934	15.4042	15.4344✗	18.1226
	Std	0.26	0.059	1.3	0.23	5.2
	Succ.Rate	0.00%	0.00%	0.00%	0.00%	0.00%
	ERT_r	1.1e+05	1.1e+05	1.1e+05	1.1e+05	1.1e+05
	$O_{Fs}(O_{Frk})$	**0.909091(1)**	0.909091(3)	0.909092(4)	*0.909091(2)*	0.909092(5)
f_{DAu5} **(uC=0)** fOpt= 0; fTol= 1e-05	Best(B_{Vrk})	7.30366(1)	7.31134(3)	7.31185(4)	7.30541(2)	7.64336(5)
	Mean	7.40164	7.34057	7.4699	7.42488	8.10856
	Median	7.41442	7.33335	7.42558	7.41817	8.05242
	Std	0.076	0.029	0.14	0.12	0.78
	Succ.Rate	0.00%	0.00%	0.00%	0.00%	0.00%
	ERT_r	1.1e+05	1.1e+05	1.1e+05	1.1e+05	1.1e+05
	$O_{Fs}(O_{Frk})$	**0.909091(1)**	0.909091(3)	0.909092(4)	*0.909091(2)*	0.909092(5)

Notes:

- ✓ A pair of type '***V(r)***' is a performance measure's value '***V***' with its resulting rank '***(r)***'; wherein a boldface '***V(1)***' is a rank 1 performance, noting that the affixed rank is '**(1)**'. In turn, a slanted/italics '*V(2)*', means rank 2 performance, noting in this case the affixed rank '*(2)*'.
- ✓ On the ***Best (rank)*** pair: an equal rank (B_{Vrk}) is awarded to all algorithms that have the same ***Best*** function values, but only after a tie-breaking has been done over their ***Median*** function values, and then, on tie persistence, over their ***Mean*** function values; In cases such tie was broken, the winning algorithm keeps their current ranking, while the other is relegated (newrank = rank+1) and then along with the ***Best(newrank)*** of such relegated contender, a cross (✗) is placed aside the underlying tie-breaking measure (either the Median or the Mean). If a tie persisted through the Median and beyond the Mean checks, then the tied algorithms keep their current rank and no "✗" is affixed. No "✗" for no ties as well.
- ✓ The ***Best(rank)*** performance measures, are specially useful for telling apart the ***OFrank*** performances of those algorithms with a null success rate or in general: with tied ***ERTs***. Otherwise the ***OFrank*** is determined by the ***ERTs*** in first place.
- ✓ See summary table (14) footnotes for additional legend aids or remarks, as well as section 3.5.2 for the performance evaluation and comparison model.

Table 14 *ApplianceSchedule1(.)* Unknown Optima Test Setup - Summary Benchmark Performance Results (pg.2/2)

		Perf. Measure	D = 10				
			HyPERGDx	CSA	Mat.PSO	EBOwithCMAR	CMAES
Testbed, Aggregate Performance	1	Ratio of Problems Solved (RoPs):	0	0	0	0	0
	2	(#solved / totalOfProblems):	(0 / 5)	(0 / 5)	(0 / 5)	(0 / 5)	(0 / 5)
	3	RoPs Testbed Rank:	5	5	5	5	5
	4	Mean Success Rate (mSR):	0.00%	0.00%	0.00%	0.00%	0.00%
	5	mSR Testbed rank:	5	5	5	5	5
	6	Ratio of Non-100% SRs (non100s)	1.00	1.00	1.00	1.00	1.00
	7	non100s Testbed rank:	5	5	5	5	5
	8	Mean O_{Frk}:	1	4.2	3	2.4	4.4
	9	(Nr of $O_{Frk} = 1$ / Nr of $O_{Frk} = 2$):	(5 / 0)	(0 / 0)	(0 / 2)	(0 / 3)	(0 / 0)
	10	Max.Speed Testbed rank:	**1**	4	3	*2*	5
	11	Reliability Score (@weights: 0, 60, 30, 10):	100.00	100.00	100.00	100.00	100.00
	12	Max.Reliability.Testbed rank:	5	5	5	5	5
	13	Reliability (Moderate) Score (@weights: 25, 50, 17, 8):	**80.00**	96.00	90.00	*87.00*	97.00
	14	Moderate.Reliability.Testbed rank:	**1**	4	3	*2*	5
	15	Balanced Speed-Reliability Score (@weights: 50, 30, 15, 5):	**72.00**	94.40	86.00	*81.80*	95.80
	16	Balanced.Speed/Reliability.Testbed rank:	**1**	4	3	*2*	5
	17	Speed (Moderate) Score (@weights: 75,15,7,3):	**40.00**	88.00	70.00	*61.00*	91.00
	18	Moderate.Speed.Testbed rank:	**1**	4	3	*2*	5

Notes:

- ✓ Except for lines 1, 2, 4 and 9 (respectively ***RoPs***, ***"#solved..."***, ***mSR***, and ***"#OFrank1s/#OFrank2s"***), the greater a measure of performance, the worse it is.
- ✓ In particular, the greater a ***score*** or a ***rank***, the worse it is.
- ✓ Where every single contender algorithm totally failed, *i.e.*, got the worse value of some measure of performance, all algorithms were awarded the worst rank.

See section 3.5.2 for the performance evaluation and comparison model.

Table 15 *ApplianceSchedule1(.)* Function Test Setup - Per Function Benchmark Results (pg.1/2)

Func. Info	Perf. Measure	D = 10				
		HyPERGDx	CSA	Mat.PSO	EBOwithCMAR	CMAES
	Best(B_{Vrk})	15.1435(1)	15.1677(4)	15.1436(2)	15.1437(3)	22.3783(5)
f_{DAk1}	Mean	16.3544	15.2166	24.0405	19.4058	32.0137
(uC=1)	Median	15.1443	15.2153	22.4021	22.3783	23.1434
fOpt=	Std	2.7	0.037	8	3.7	12
15.143;	Succ.Rate	73.33%	0.00%	6.67%	26.67%	0.00%
fTol= 1e-05	ERT$_r$	5.93e+04	1.1e+05	1.03e+05	8.44e+04	1.1e+05
	O$_{Fs}$(O$_{Frk}$)	**0.514701(1)**	0.909092(4)	0.85203(3)	*0.700247(2)*	0.909092(5)
	Best(B_{Vrk})	15.0745(1)	15.0799(3)	15.0879(4)	15.0746(2)	15.0879(5)
f_{DAk2}	Mean	15.8582	15.1393	20.9123	17.19	27.0289
(uC=0.75)	Median	15.0752	15.1284	20.056	15.0879	21.2098✗
fOpt=	Std	2.4	0.041	5.7	3	8.5
15.074;	Succ.Rate	63.33%	0.00%	0.00%	33.33%	0.00%
fTol= 1e-05	ERT$_r$	6.64e+04	1.1e+05	1.1e+05	7.78e+04	1.1e+05
	O$_{Fs}$(O$_{Frk}$)	**0.570358(1)**	0.909091(3)	0.909092(4)	*0.646322(2)*	0.909092(5)
	Best(B_{Vrk})	14.9367(1)	14.9541(4)	14.9367(2)	14.937(3)	17.6381(5)
f_{DAk3}	Mean	15.5788	14.9989	18.0762	16.4029	22.6733
(uC=0.5)	Median	14.9376	14.9826	17.5034	14.956	19.3247
fOpt=	Std	1.1	0.056	2.7	1.7	6
14.937;	Succ.Rate	70.00%	0.00%	13.33%	40.00%	0.00%
fTol= 1e-05	ERT$_r$	6.29e+04	1.1e+05	9.61e+04	7.18e+04	1.1e+05
	O$_{Fs}$(O$_{Frk}$)	**0.54498(1)**	0.909092(4)	0.794915(3)	*0.597842(2)*	0.909092(5)
	Best(B_{Vrk})	14.6301(1)	14.6527(3)	14.6802(4)	14.6306(2)	15.0647(5)
f_{DAk4}	Mean	15.0108	14.7447	15.6009	15.2243	17.7646
(uC=0.25)	Median	15.0647	14.7124	15.2806	15.0898	15.7533
fOpt=	Std	0.28	0.1	1.2	0.24	2.9
14.630;	Succ.Rate	26.67%	0.00%	0.00%	3.33%	0.00%
fTol= 1e-05	ERT$_r$	9.38e+04	1.1e+05	1.1e+05	1.07e+05	1.1e+05
	O$_{Fs}$(O$_{Frk}$)	**0.786098(1)**	0.909091(3)	0.909092(4)	*0.882006(2)*	0.909092(5)
	Best(B_{Vrk})	7.30366(1)	7.31378(4)	7.30491(2)	7.30541(3)	7.51884(5)
f_{DAk5}	Mean	7.38279	7.34064	7.46687	7.40388	7.93624
(uC=0)	Median	7.41442	7.33232	7.42375	7.41817	8.05259
fOpt=	Std	0.064	0.025	0.14	0.091	0.18
7.304;	Succ.Rate	10.00%	0.00%	0.00%	0.00%	0.00%
fTol= 1e-05	ERT$_r$	1.04e+05	1.1e+05	1.1e+05	1.1e+05	1.1e+05
	O$_{Fs}$(O$_{Frk}$)	**0.86737(1)**	0.909092(4)	*0.909091(2)*	0.909091(3)	0.909092(5)

Notes:

- ✓ See tables 14 and 16, footnotes for some legend aids or remarks, as well as section 3.5.2 for the performance evaluation and comparison model.

Table 16 *ApplianceSchedule1(.)* Function Test Setup - Summary Benchmark Performance Results (pg.2/2)

		Perf. Measure	D = 10				
			HyPERGDx	CSA	Mat.PSO	EBOwithCMAR	CMAES
Testbed, Aggregate Performance	1	Ratio of Problems Solved (RoPs):	1	0	0.4	0.8	0
	2	(#solved / totalOfProblems):	(5 / 5)	(0 / 5)	(2 / 5)	(4 / 5)	(0 / 5)
	3	RoPs Testbed Rank:	1	4	3	2	4
	4	Mean Success Rate (mSR):	48.67%	0.00%	4.00%	20.67%	0.00%
	5	mSR Testbed rank:	1	4	3	2	4
	6	Ratio of Non-100% SRs (non100s)	1.00	1.00	1.00	1.00	1.00
	7	non100s Testbed rank:	5	5	5	5	5
	8	Mean O_{Frk}:	1	3.6	3.2	2.2	5
	9	(Nr of $O_{Frk} = 1$ / Nr of $O_{Frk} = 2$):	(5 / 0)	(0 / 0)	(0 / 1)	(0 / 4)	(0 / 0)
	10	Max.Speed Testbed rank:	**1**	4	3	*2*	5
	11	Reliability Score (@weights: 0, 60, 30, 10):	**25.40**	100.00	74.80	*45.80*	100.00
	12	Max.Reliability.Testbed rank:	**1**	4	3	*2*	4
	13	Reliability (Moderate) Score (@weights: 25, 50, 17, 8):	**21.73**	93.00	70.32	*42.49*	100.00
	14	Moderate.Reliability.Testbed rank:	**1**	4	3	*2*	5
	15	Balanced Speed-Reliability Score (@weights: 35, 35, 25, 5):	**24.83**	90.20	72.40	*47.23*	100.00
	16	Balanced.Speed/Reliability.Testbed rank:	**1**	4	3	*2*	5
	17	Speed (Moderate) Score (@weights: 75,15,7,3):	**21.59**	79.00	66.72	*44.55*	100.00
	18	Moderate.Speed.Testbed rank:	**1**	4	3	*2*	5

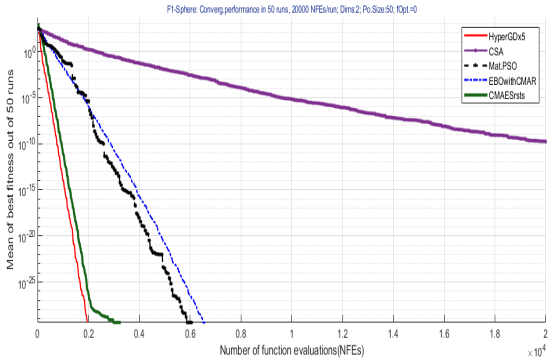
Notes:

✓ Except for lines 1, 2, 4 and 9 (respectively ***RoPs***, ***"#solved..."***, ***mSR***, and ***"#OFrank1s/#OFrank2s"***), the greater a measure of performance, the worse it is.

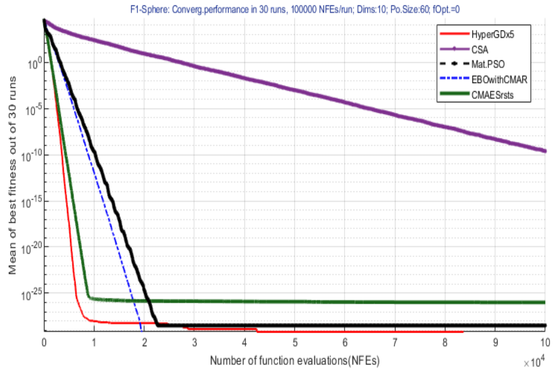
✓ In particular, the greater a ***score*** or a ***rank***, the worse it is.

✓ Where every single contender algorithm totally failed, *i.e.*, got the worse value of some measure of performance, all algorithms were awarded the worst rank.

See section 3.5.2 for the performance evaluation and comparison model.



$(f_{DG_1} - Sphere, D = 2)$



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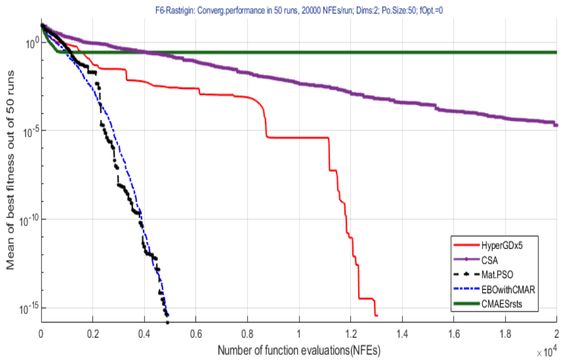
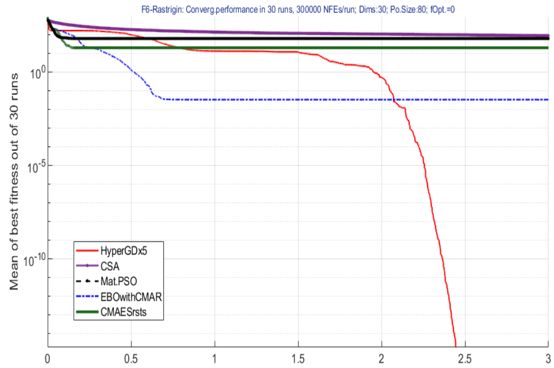
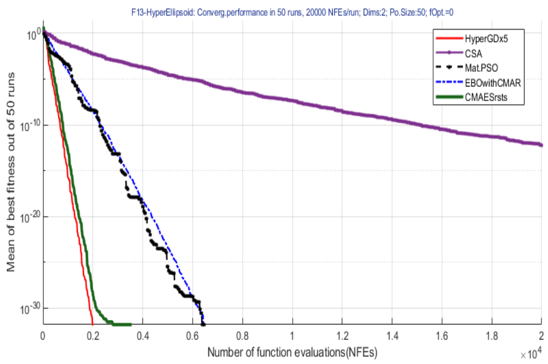


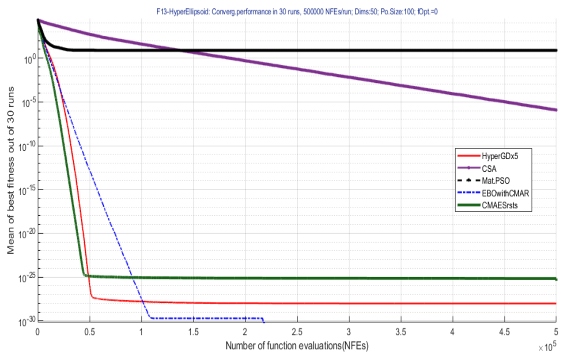
$(f_{DG_6} - Rastrigin, D = 2)$



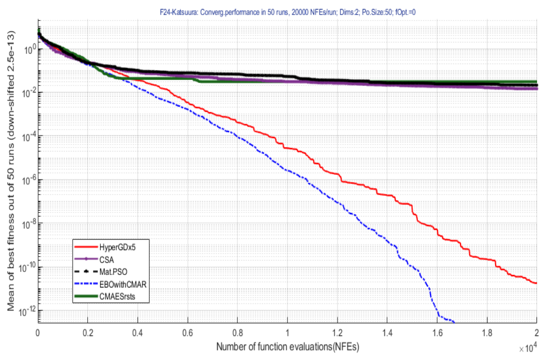
$(f_{DG_6} - Rastrigin, D = 30)$



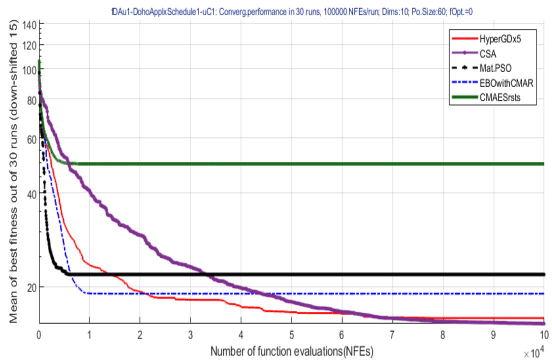
$(f_{DG_{13}} - HyperEllipsoid, D = 2)$



$((f_{DG_{13}} - HyperEllipsoid, D = 50)$



$((f_{DG_{24}} - Katsuura, D = 2)$



$((f_{DAu_1} - ApplianceSchedule1, D = 10,\ \alpha = 1)$

Figure 20 Samples of mean convergence performance of selected functions from 2 testbeds

Figure 20, shows the average global best fitness convergence (in log10 scale), calculated over all the r (50 for D=2 or 30 otherwise) runs; where the graph touches the $NFEs$ axis before $maxFEs$, means the respective algorithm has reached the f_{Target}.

3.6 Discussion of Metaheuristics Benchmarking Results

Looking at the results tables from 7 to 16, especially the summary performance Tables 12, 14 and 16; and, having in mind the performance evaluation model discussed in section 3.5.2, as well as the definitions of the testbeds and benchmarking setups, we come up with these findings:

(1) Concerning the generic shifted X^* testbed benchmarking results, Table 12 shows that HyPERGDx has a competitive performance relative to EBOwithCMAR: HyPERGDx is better in speed (rows nr 10 and 18) but EBOwithCMAR is better in reliability (rows nr 12, 14 and 16). Overall, on the second half of the Table (from row 8 to 18, where different weighed levels of aggregate performance, are presented), HyPERGDx has 8 first places and 12 second place ranks, vs 12 first places and 4 second places of EBOwithCMAR. Otherwise HyPERGDx and EBOwithCMAR are better than any other of the remaining state-of-the-art metaheuristics, namely: CMAES, Matlab's PSO and CSA, ranked that same order.

(2) Concerning the *ApplianceScheduling1* function, "unknown optima" test setup, benchmarking results: Table 14 shows that HyPERGDx has the best performance relative to the remaining metaheuristics (5 first place wins vs nil of any other in any category of either speed or reliability). Overall, HyPERGDx is the clear winner of this testbed, showing that it is likely to fare better than the other metaheuristics for unknown new optimal values, that would be spurred by change of parameters or part of, or the whole, appliance database.

    On the other hand, the presence of null success rates, in this case for all metaheuristics (which is not unexpected, since we used an unattainable, asymptotic optimum of zero), would hamper the use of the traditional ERT measure in either (Eq.20a) or (Eq.20b). Arising from the null S_r's, the RoPs is null as well, for all algorithms, so it is not useful either. In this way the performance evaluation defined in section 3.5.2, proves to be useful for telling apart the performances of the algorithms even as some success rates are null, by accounting for the quality of the relative level of their mean convergence towards the target optimum.

(3) Concerning the *ApplianceScheduling1* function, with "currently best known optima" test setup, benchmarking results: Table 16 shows that HyPERGDx has again the best performance relative to the remaining metaheuristics (5 first place wins vs nil of any other in any category of either speed or reliability). Aside from the Rank 1 performance at the all testbed ranks, another aspect standing out is the 100% RoPs and high mean success rate as compared to the rest. Otherwise, relatively to the rest of the field, EBOwithCMAR ranks better than the remaining 3. Overall, HyPERGDx is the clear winner of this other testbed.

Conclusions:

(i) The facts that the HyPERGDx algorithm has shown a competitive performance including that, in the generic testbed of 24 functions, it keeps being comparatively as fast as the best of its "mother" state-of-the-art metaheuristics and fairly competitive concerning reliability, it shows it has a balanced performance between speed and reliability. Also,

(ii) The fact that in both the appliance scheduling testbed HyPERGDx is the clear winner; is of especial importance, all the more if we consider that our motivation for the design of a new hybrid heuristics was spurred by the lack of consistent performance of the other metaheuristics when it came to the appliance scheduling problem.

(iii) From the above grounds, we can conclude that HyPERGDx showed the best all around performance, meaning it has a wider range of successfully solved classes of problems while being fairly fast as compared to CMA-ES (the fastest of the group, but with higher failure rate as compared to HyPERGDx and EBOwithCMAR) and in the overall stand point showed a competitive of better performance also in terms of reliability and robustness. As a caveat, HyPERGDx apparently has sometimes a higher execution time than the other contenders, mostly when the problem is not successfully solved by the first sub-population loop. This is partly due to hybrid heuristics logical overhead, consuming some extra time, something that cannot be completely avoided, but can for sure be addressed, which remains to be done. However, as evident, the discussed robustness shown by the algorithm, out-waits such caveat to a great extent.

(iv) Another good result of importance is the fact that any of the real parameter global optimization metaheuristics were used almost without modification of their original code to perform a household's appliance scheduling using a RPBBOAS model *ApplianceSchedule1(.)* function as the medium. Thus, in the one side this successfully evaluated the HyPERGDx performance vs its state-of-the-art "mother" metaheuristics, and in the other side it offered an experimental demonstration of the RPBBOAS model effectiveness, and thereby, we can argue that we have successfully addressed the motivations and accomplished the goals laid out in the introductions to these components of the research work and, from these grounds we henceforth assume that both models (the blackbox function and the algorithm) are right tools to be used in our next chapter, next step of trying to build and demonstrate a bbDR framework for DR-unconnected CG environments.

Both the HyPERGDx hybrid metaheuristics and the RPBBOAS model, along with its effective code implementation, the *ApplianceSchedule1(.)* function, are modest individual contributions of this research work.

Chapter 4

Household Appliances and Uncontrolled vs Controlled Energy Consumption Workflows

4.1 Household Devices and Appliances

In section 2.1.5.1 we made an introductory reference to household devices and appliances, as regarded in a wider, grid perspective. The appliances structure of a household (how many appliances of which type) depend on various factors related to its energy environment, such as: the country/geographic region, the status of grid development (SG/CG), the social and economical stratification and composition of the household occupants, etc. These factors determine appliance saturation (the ratio of the number of households that have the considered appliance to the total number of households in a chosen region), appliance's UEC (unit EC, in average number of KWh/year), the level of appliance controllability or smartness (as discussed in said section 2.1.5.1), among other characteristics. It is important to remark that while there are different types of appliances, and generally, electric devices, we will refer all them by appliances, except where needed.

4.1.1 Appliances Classification and Controllability Limitations

Appliances can be classified in different ways. However from the controllability or schedulability perspective we can divide the appliances in roughly 2 categories: (1) the controllable appliances and (2) the non-controllable ones. The controllable appliances are the ones that can be scheduled and controlled by the home energy management system, whereas the last category is composed by those that (to certain extent) cannot or should not be automatically controlled and the user is in charge of switching it on or off as needed. Otherwise, some special appliances may be placed in the group of the non-controllable appliances, once a dedicated control is in charge once deemed appropriate to achieve required performance and gains, such as a thermostat for a fridge.

Aside from alternate namings of identical meaning, beyond the controllable/uncontrollable classification there are further sub-classifications, namely for the controllable branch: (a) Shiftable appliances (working time can be shifted to arbitrary times: actually any schedulable appliance should be shiftable to some extent), (b) on/off controllable vs regulating or dimmable or curtailable appliances (the first subcategory can only be controlled by switching either on or off, and for the second subcategory, aside from switching on or off, the power consumption level can be adjusted within determined boundaries); (c) Pausable or deferrable appliances vs uninterruptible appliances (the pausables can be interrupted midway without harming their operational duty, aside from user frustration for the amount of delay or duty cycle displacement; whereas the uninterruptible, although schedulable, once switched on, cannot be paused to resume later without harming its normal operational workflow). Other sub-classifications or alternate classifications or namings exist.

A partial sample of house appliances, deemed appropriate for the experiments conducted herein is presented in Table 17. The sample data in the table is intended for just the demonstration of the uncontrolled/controlled workflow models following up next sections. The data come from different sources, with some limitations in consistency thereof, but still considered appropriate for the intended demonstration purposes herein.

4.1.1.0.1 Special Devices

As technology advances, new or enhanced types of electrical devices are born: (1) smart or intelligent appliances with embedded automatic controllers and with capability of sensing environment variables of its interests, aside from smart networking communications capabilities with a HEMS/HAN, a Smart meter/AMI, SG; (2) composite or multifunction devices, for instance, a device taking roles of both an energy consumer and energy storage, allowing it to facilitate load shifting and other DR operations, as described in section 2.1.8. That is the case of a water heater or an electric vehicle.

4.1.1.0.2 On the possibility of contextual controllability of user operated appliances

For severely affected energy ecosystems regarding energy demand, it is justifiable to rethink the concept of uncontrollable appliances, and consider a contextual controllability for some appliances where appropriate, to allow home energy management systems to control such "uncontrollable" appliances under given extreme conditions, when without such measure a severe outcome is likely to occur, such as a blackout.

4.2 The Uncontrolled EC Workflow via ToUPs

4.2.1 Time-of-Use Probability

The uncontrolled EC simulation that we perform here, seeks to mimic the load profiles of an uncontrolled use of household appliances. For that we rely on appliance switched-on status statistics performed by previous works in the literature, such as in [52], [53]. In such works (or in their references), appliance usage (switched-on or switched-off states and power consumption) was recorded for each single time slot of a determined resolution (eg. hourly time slots), and at the end of a time horizon period of data collection (eg. 365 days), statistics were performed to evaluate, among other variables of interest, what is the probability that appliance j is switched-on at each one of the recorded data points of interest. Such statistics is called the Time of Use Probability (ToUP), known also by Rate of Use (RoU) of the appliance j. Table 18 shows the sample ToUPs that we used, which We have built from tables 19 and 21 in the Appendix **??**.

The pictures of Figure 21 show the ToUPs graphically for 4 of the appliances in tables 17 and 18. The time-of-use probability (or rate of use) of the appliance j at each data point (time slot number) is calculated as the ratio of the number of times that the appliance j is found to be switched-on at that specific time slot, to the total of recorded days, the more days the better (see Figure 22). For instance, suppose that the number of time slots (data points) per day is 1440 (1 minute time slots): if at data point 1080 (*i.e*, at time slot, minute, number 1080) the appliance j is found to be switched-on 263 times in a 365 days statistics, then, its time-of-use probability at the minute number 1080 is: $263/365 \approxeq 0.72$. This quantity can be further divided by the total number of activations per day so that the daily distribution is a probability mass function and than the daily cumulative time of use probabilities amount to 1.

Figure 22 depicts 2 samples of the generated events (dots connected for line chart). The effect of the number of simulation days is shown: The model assume that, and the statistics hold when, the number of observations is high. The higher the number of simulations, the closer the the simulated graph to the input reference data graph. See the results section 4.5 for the complete set of ToUPs simulations.

In this work, we used the above described ToUPs to generate appliance cycle placements that try to mimic their uncontrolled (non automated) usage by household occupants. It is worth remarking that, these statistically generated time-of-use probabilities, just as above described, do not say how to predict or how to determine the ToUPs from other possibly recorded variables, such as household occupancy, which drive appliance activities. We assume that our model is agnostic of the occupancy and other systems parameters that can be difficult to measure, since we are seeking a simple baseline demand responsive behaviour, with reduced information requirement, characteristic of underdeveloped CG environments.

Table 17 Appliance Properties and basic operational characteristics

Abrev.	Appliance Name/Group	Appliance Type	Nom.Power (W)	Stby.Power (W)	UEC (KWh/Year)	minCPD	meanCPD	maxCPD	minCT (min)	meanCT (min)	maxCT (min)
WH	Water Heater	Shiftable, Schedulable	4500	100	3169	3	3	3	30	60	60
CW	Clothes Washer	Shiftable, Schedulable	610	0	121	1	1	1	60	90	120
CD	Clothes Drier	Shiftable, Schedulable	5000	0	719	1	1	1	30	60	60
CF	Ceiling Fan	User operated, Non-schedulable	500	0	96	7	7	*7*	60	60	*1440*
FG	Fridge	User operated, Non-schedulable	500	50	827	1	40.5	*42*	12	18	*24*
ST	Stove	User operated, Non-schedulable	2100	0	310	1	1.46	*8*	6	12	*1440*
TV	Television	User operated, Non-schedulable	200	8	738	1	1.95	*2*	60	60	*1440*
LG	Indoor Lighting (group)	User operated, Non-schedulable	120	0	388	18	18	*20*	30	30	*1440*

Where:

UEC: Unit Energy Consumption in KWh/Year (UEC) $minCPD$, $meanCPD$, and $maxCPD$ are respectively the minimum, the mean and the maximum operating cycles per day;

while $minCT$, $meanCT$, and $maxCT$ are respectively the minimum, the mean and the maximum appliance duty cycle time.

Table 18 Adopted time-of-use probabilities *(ToUPs)* for the appliances in Table 17

Appl.	d↓ $h\rightarrow$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
WH	wd	2.32	1.67	1.39	0.93	0.74	0.65	0.56	1.11	1.86	2.23	3.53	3.81	4.64	5.39	6.04	7.24	8.36	9.29	9.10	8.36	6.50	6.13	4.64	3.53
	we	2.32	1.67	1.39	0.93	0.74	0.65	0.56	1.11	1.86	2.23	3.53	3.81	4.64	5.39	6.04	7.24	8.36	9.29	9.10	8.36	6.50	6.13	4.64	3.53
CW	wd	0.5	0	0	0	0	0	0	0.7	2	4.61	7.02	7.23	7.23	7.34	7.34	7.34	7.43	7.43	7.74	7.74	7.43	6.12	3.91	0.9
	we	1.73	0.96	0.40	0.40	0.40	0.96	1.73	2.93	3.75	4.58	4.68	4.68	4.68	4.68	4.68	6.11	6.83	7.16	7.80	8.60	8.16	7.01	5.05	2.03
CD	wd	0.5	0	0	0	0	0	0	0.7	2	4.61	7.02	7.23	7.23	7.34	7.34	7.34	7.43	7.43	7.74	7.74	7.43	6.12	3.91	0.9
	we	1.73	0.96	0.40	0.40	0.40	0.96	1.73	2.93	3.75	4.58	4.68	4.68	4.68	4.68	4.68	6.11	6.83	7.16	7.80	8.60	8.16	7.01	5.05	2.03
CF	wd	2.17	2.53	2.90	2.90	2.90	4.20	7.24	6.52	7.24	6.52	6.52	4.49	4.34	3.62	2.90	2.90	3.62	4.34	3.62	3.19	5.07	5.07	3.04	2.17
	we	2.17	2.53	2.90	2.90	2.90	4.20	7.24	6.52	7.24	6.52	6.52	4.49	4.34	3.62	2.90	2.90	3.62	4.34	3.62	3.19	5.07	5.07	3.04	2.17
FG	wd	2.17	2.53	2.90	2.90	2.90	4.20	7.24	6.52	7.24	6.52	6.52	4.49	4.34	3.62	2.90	2.90	3.62	4.34	3.62	3.19	5.07	5.07	3.04	2.17
	we	2.17	2.53	2.90	2.90	2.90	4.20	7.24	6.52	7.24	6.52	6.52	4.49	4.34	3.62	2.90	2.90	3.62	4.34	3.62	3.19	5.07	5.07	3.04	2.17
ST	wd	0.37	0.05	0	0	0	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.30	1.02
	we	0.20	0.20	0.40	0.40	1.78	2.59	3.19	3.83	3.70	4.13	4.29	4.15	3.89	4.46	5.79	8.76	10.00	10.30	9.24	8.15	5.82	2.79	1.51	0.36
TV	wd	3.40	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.40	3.88	4.85	4.85	5.93	6.13	6.80	6.80	6.80	7.77	8.25	6.80	5.34	4.85	3.88
	we	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
LG	wd	2.55	1.33	1.23	1.23	1.33	1.53	2.13	4.05	5.07	4.99	4.27	3.82	3.57	4.27	4.97	5.50	6.02	6.69	7.34	7.56	6.64	6.17	4.49	3.22
	we	1.03	0.33	0.33	0.83	1.78	2.64	3.56	3.74	3.44	3.04	3.04	3.24	3.94	4.14	4.55	4.96	5.79	6.70	8.21	9.11	9.81	8.50	4.32	2.96

Where: ***wd*** indicates a row of weekday time-of-use probabilities; whereas, ***we*** indicates a row of weekend time-of-use probabilities.

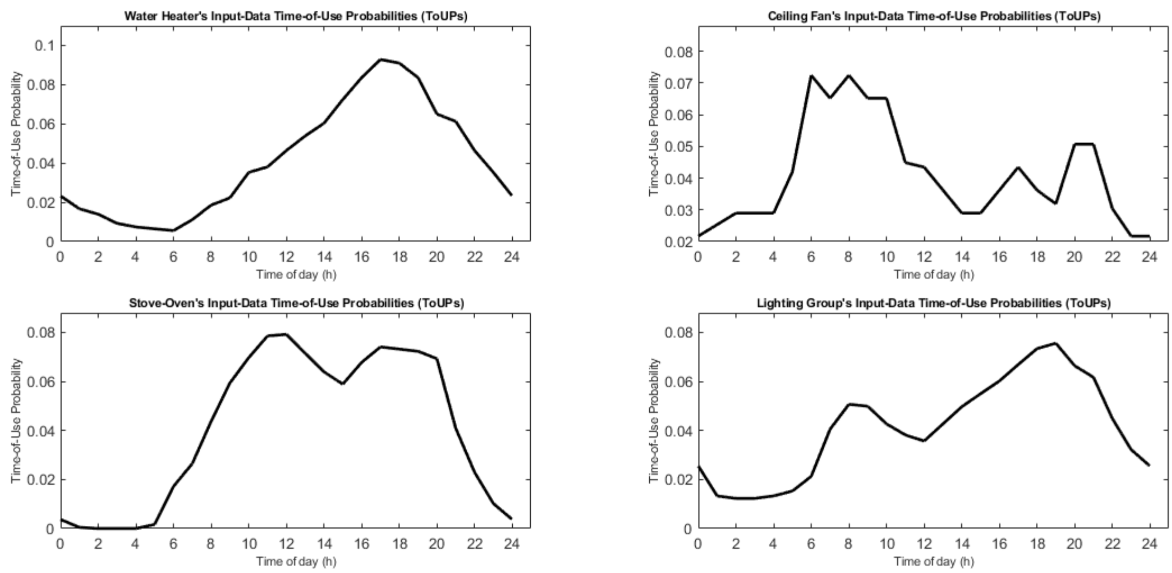


Figure 21 Weekday ToUPs for a water heater, a cooling fan, a stove/oven, and indoor lighting group

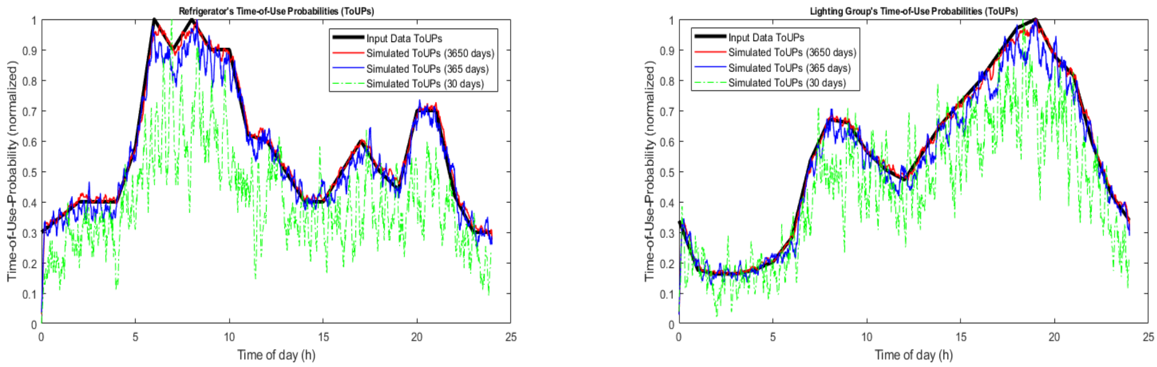


Figure 22 Sample uncontrolled appliance ToUPs generation by Algorithm 3 logically equivalent code

4.2.2 The Uncontrolled EC Workflow

We modelled the on-statuses for an uncontrolled usage of the household appliance $\boldsymbol{j}$ as a non-homogeneous Poisson point process, starting from the grounds of a homogeneous one. Given a homogeneous Poisson point process [82] [83] with parameter or mean μ and rate $\lambda : \mu = \lambda t$, in the time interval $[0,t]$; then X is a Poisson random variable, $X \sim Pois(\mu)$, representing the number of arrival events $\{0, 1, 2, ...\}$ during the interval $[0,t]$ if for any $\lambda > 0$ it holds:

$$X \sim Pois(\mu) \Rightarrow Pr(X = k) = \frac{\mu^k}{k!} e^{-\mu} = \frac{(\lambda t)^k}{k!} e^{-(\lambda t)} \tag{22}$$

where it is assumed: there is no arrival at time t=0, *i.e.*, X(0) = 0; as well as for non overlapping intervals the events are independent and have identical Poisson distribution with constant rate λ (the process is stationary).

When a non-homogeneous Poisson point process is concerned the rate or intensity λ is not constant, *i.e.*, it turns a time dependent $\lambda(t)$. A time varying arrival rate of the events, is a feature that resembles many real life arrival processes, which is the case of the rate of the appliance usage in a household.

That is the rationale for why we modelled the start-up/on-statuses events for an uncontrolled usage of the household appliance $\boldsymbol{j}$ as a non-homogeneous Poisson point process, whose rate or intensity $\lambda(t)$ is equal to the appliance's ToUP, as described by (23). Such statistical model assumes that, the expected number of events for the considered horizon time of observation is very high. This is the case of statistically observing the on-statuses of appliances of the same type, say washing machines, that are present in large number in an equally large community, during a single day or more days. It is, as well, the case of statistically observing the on-status of one appliance of a single household, say again a washing machine, during a large number of days.

$$X_j(t) \sim Pois(t\lambda_j(t)); \quad \lambda_j(t) = ToUPs_j(t) \quad \forall t \in [0,T]; \tag{23}$$

where $X_j(t)$ are the arrival times, which may be appliance $\boldsymbol{j}$ start-up times or its switched-on status (if already started before time slot t), $\boldsymbol{j} \in \{1,2,...,8\}$ denotes the appliance number, and T is the time horizon under consideration.

With those assumptions, we wrote a simulation procedure based on the ideas and examples from [82] and [83] pp.72-77, which is presented in the Algorithm 3, a Matlab biased pseudo-code. The pseudo-code logic seeks to describe in general terms the procedure to generate non-homogeneous Poisson process arrivals; whose main difference relative to a homogeneous process, lies in that its intensity $\lambda(t)$ varies with time. As a consequence, there is an admission control for a generated event to be accepted, as set in line number: 21 of said Algorithm 3: A candidate event $X(t_1)$ *i.e* occurring at time t_1 is only accepted with a probability pt (not worse than the normalized arrival rate at that point, *i.e.*):

$$\{X_j(t_1) = t_1 \mid rand() < pt;\}; \quad pt = \frac{\lambda_j(t_1)}{max(\lambda_j(t))} \tag{24}$$

where $X_j(t)$ are the appliance j arrival times (switch-on times / on-states), and $\lambda_j(t_1)$ equates to the appliance's ToUP at time t_1, *i.e.,* $\lambda_j(t_1) = ToUPs_j(t_1)$, this given in discrete time slots $t = 1, 2, ..., N_t$; $N_t = 1440$, $T = N_t \cdot \tau$; $\tau = 60s$ corresponding to 1 day in 1 minute time slots. Also, the ToUP is constant within a given timeslot. Note that the 1 minute resolution is obtained by linear interpolation from the 1h resolution input data of Table 18.

Aside from the above basic non-homogeneous events admission control based on the appliance's $ToUPs_j(t)$, we placed additional restrictions aimed at making the Poisson simulation results comply with and to the best extent mimic the real life uncontrolled EC scenario, as described by the referenced Tables 17 and 18. The exercise of adapting a pure Poisson probabilistic model to suit the real life problem is common and likely a hardly avoidable measure. Many real life stochastic processes follow the Poisson model, as with the area of energy management [3, 84–86].

The following additional restrictions to the above events admission control were performed:

(a) Events at time t_1 that were already registered in $X_j(t_1)$ were rejected (repetitions could happen due to the use of discrete time). Also, the discrete time is being used as unit time, so, contiguous events, for instance $X_j(t)$ and $X_j(t+1)$, belong to the same appliance working cycle; Furthermore,

(b) While the starting (switching-on) times of the appliances are generated as Poisson point process events, the duty cycles (the switched-on durations) are not modelled by such events, since generally the inter-event times do not match the duration times (as with the arrival vs the service times of many Poisson process models). Since the switched-off events/probabilities of the appliances are also a non homogeneous Poisson point process, the durations can be thought as being another Poisson process of varying rate $\lambda_d(t)$; And, in the absence of a suitable varying rate model, we have modelled the appliance cycle durations as homogeneous Poisson processes of some parameter (mean) μ_d whose estimator is the mean cycle duration drawn from Table 17), which is as well the expected mean appliance cycle duration that the simulation process should produce. In this way, a parallel point process produces the durations from such expected mean; and, as a consequence for each accepted event, additional non-overlapping contiguous events are placed a posteriori of the current event until the generated cycle duration is reached, or until just before an overlapping occurs;

(c) Following the above steps, at the end of events $X_j(t)$ generation, contiguous events are grouped into appliance cycles and paired with the corresponding duration times, in number of discrete time slots; This resulting candidate sequence of cycles start times paired along with their cycle durations, is only accepted if the number of cycles are within bounds, namely, lower/upper bounds: a minimum/maximum number of appliance cycles per day, and each cycle with a minimum/maximum duration, as per the data drawn or generated from Table 17.

The Algorithm 3 below is the base pseudo-code that we have written into a Matlab coded function, which was further optimized, and is called repeatedly to perform the uncontrolled usage simulation for a single appliance, featuring the behaviours that we outlined above. In the algorithm pseudo-code: T is the simulation horizon; $lambdaT$ is the time varying Poisson process rate (equating to the $ToUP(t)$); *minCPD*, *meanCPD* and *maxCPD* are respectively the minimum, the mean and the maximum cycles-per-day constraints, while $minCT$,$meanCT$ and $maxCT$ are respectively the minimum, the mean and the maximum appliance duty cycle time constraints. The *meanCPD* and *meanCT* parameters are drawn from Table 17, and *minCPD* and *maxCPD*; as well as *minCT* and *maxCT* are derived from *meanCPD* and *meanCT* as their 99% confidence interval bounds using the $paramci(.)$ and $fitdist(.)$ built-in Matlab functions, as for instance: $ci = paramci(fitdist(meanCT, 'poisson'), 'Alpha', 0.01)$ which produces a 2 element vector comprising the 99% confidence interval.

Figure 23 depicts 2 samples of the generated appliance cycles for a single day by using Algorithm 3.

```
// Non-Homogeneous Poisson Process of parameter Tλ
Function [X,ST,DT] = NonHomoPoiss(T, lambdaT, minCPD, meanCPD, maxCPD, minCT, meanCT,
  maxCT)
    Result: X, ST, DT
    // X-event times; ST,DT-cycle start times, durations
    maxLambda = max(lambdaT);
    meanEvs ∼ Poiss(maxLambda*T); // Matlab's poissrnd(.)
    CycT = 1; // event time is pontual, unit, discrete time by default;
    if meanEvs > 0 then
        repeat// unitil we got a valid sequence:
            X = [ ];    ST = [ ];    DT = [ ];
            pointCount = 0;    exitCond = False;
            for i = 1 to meanEvs do
                t1 = T * rand; // draw a random event;
                if t > 0 then // exclude arrival at t = 0
                    tz = ceil(t1); // discretize the event time;
                    if meanCT > 0 then
                        CycT ∼ Poiss(meanCT); // draw a random CycTime from meanCT;
                    end
                    pT = lambdaT(tz) / maxLambda; // the probabilty for event tz
                    // accept event tz with probabilty pT; reject duplicates:
                    r ∼ U(0,1);
                    if r < pT AND tz ∉ X then
                        for c=1 to CycT do
                            Y = X;
                            if tz + c ∉ X then
                                pointCount = pointCount + 1;
                                X(pointCount) = tz + c;
                                X = sort(X);
                            end
                        end
                    end
                end
            end
            if pointCount > 0 then // Convert X pontual events to cycle ST's and DT's;
                X = sort(X);
                sti = X(1);    prevST = sti;
                j=1;    dtx=1;
                for i = 2:pointCount do
                    if X(i) > prevST+1 then
                        ST(j)=sti;
                        DT(j)=dtx;
                        sti = X(i);
                        dtx = 1;
                        j=j+1;
                    else
                        dtx = dtx+1;
                    end
                    prevST = X(i);
                end
                ST(j)=sti;
                DT(j)=dtx;
            end
        until pointCount=numEvs AND {length(ST) ∈ [minCPD,maxCPD] AND All(DT_j ∈
          [minCT,maxCT])};
    end
end
```

Algorithm 3: Non-Homogeneous Poisson Process of rate $lambdaT = ToUPs_j(t)$

4.3 The Controlled EC Workflow

4.3.1 Scenarios of Controlled EC

At household level and beyond, as opposed to the uncontrolled case, controlled EC comprises a number of possible workflows according to the range of controlled appliances and the type of real time control actions exerted over the controlled appliances. In general, we could consider the following (not exhaustive) list of controlled EC scenarios:

(i) Just control the schedulable appliances by performing their switching ON/OFF as per their optimized-schedules, without real time modification of the schedule, with disregard to any real-time event that could violate system model assumptions and constraints.

(ii) Control of the optimized-schedule controllable appliances with real time update of the schedule to account for unpredictable real-time events, aiming at keeping compliance to system model assumptions/requirements and constraints. For instance: A pausable appliance could be stopped (to resume later) for complying with instant power budget (one including the uncontrollable appliances). Other real time events to try to cope with, could be among others: DR signals (for DR connected systems), power signal stability issues (under/over-voltage, power factor, under-frequency: eminent blackout).

(iii) Other Control options: stand alone control, distributed control, mixed control types.

We have used the first option, which is the simplest one, since our focus has been placed on

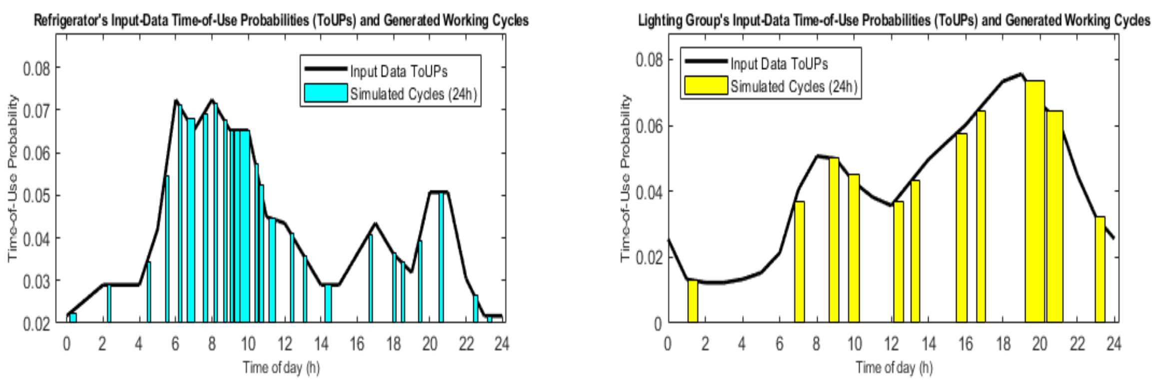


Figure 23 Sample uncontrolled appliance cycle placements generated by Algorithm 3 logically code equivalent

creating new approaches to appliance scheduling as performed under Chapter 3, and their use within a bbDR framework. However, the second option or whatever in the third group of options, may be a subject of follow-up works.

4.4 Household appliances' EC simulations setups

Starting from the above discussions, we performed the following experimental investigations, aimed at (1) mimicking the household's uncontrolled use of appliances, and (2) evaluating how far a heuristic based appliance scheduling, guided by a pseudo-RTP energy rate function, can lower pick load, lower the PAR and cut the electricity bill while keeping a fair level of comfort, in a framework designed to assess the probable feasibility of a bbDR for communications deprived CG environments:

4.4.1 Uncontrolled EC simulation setup

1. **Exp.U1 - Single day simulation**:
   Aimed at reproducing samples of uncontrolled appliance activities for the duration of one day. For this simulation the Matlab logic equivalent of Algorithm 3 was called 1 time (i.e. a simulation for 1 day horizon) for each appliance j ($j = 1,...,8$) of Table 17 with the following parameters:

   (a) $T = 1440$, total time (corresponding to 1 day, discrete time, in 1 minute granularity);

   (b) $ToUPs_j(t); t = 1,...,T$, appliance j time-of-use probabilities (generated from Table 17), which, as discussed, serve as the intensity function for a non-homogeneous Poisson arrival process simulation of the appliance switch-on/on-state events: Events are accepted with the time-of-use probability as set by (24), and with compliance to additional restrictions as per the parameters in 1.(c)-(d).

   (c) *minCPD*, and *meanCPD*, and *maxCPD* set from Table 17. Further to the event acceptance condition in (b) these parameters place additional acceptance constraints to insure that the type and number of events to be returned by the Algorithm 3 are compliant with the statistical observations interpreted by Tables 18 and 17; and according to the parameters description of the Algorithm 3, above.

(d) *minCT*, *meanCT* and *meanCT*; according to the parameters description of the Algorithm 3, above. These parameters in (c) and (d), are used along with others to place additional admission control measures: accepting/rejecting candidate events or candidate appliance cycle sequences, to insure compliance with the reference statistics from appliance tables 18 and 17.

The recorded simulation data for each appliance are: a number n of cycles per the single day; each cycle being a start time (switch-on time) paired with a duration, all them compliant with the acceptance/rejection splitting constraints as discussed in (b)-(d). For each appliance, a chart is then drawn pairing the simulated cycle events with the reference input data $ToUPs_j$ for analysis.

2. **Exp.U2 - 3650 days simulation, 1 day at a time**:

   Aimed at investigating whether our event simulation model and the algorithmic code interpreting it, can reproduce the statistically observed appliance behaviour represented by its ToUPs; For this simulation the Matlab code logical equivalent of Algorithm 3 was called 3650 times for each appliance j ($j = 1,...,8$) of Table 17 with the same parameters defined in Exp.U1.(a)-(d) with *meanCT* set to 0 equating to unit time cycle durations.

   The recorded simulation data for each appliance are: a number n of cycles per each single day; each cycle being a start time (switch-on time) paired with a duration, all them compliant with the acceptance/rejection conditions as discussed. From the simulated data, for each appliance, a chart is drawn pairing the simulated cycle events (30 or 365 days) with the input data $ToUPs_j$ for analysis.

3. **Exp.U3 group**: Single, and multi-day Simulations, 1 day at a time, namely:

   (i) **U3i**: 1 day;
   (ii) **U3ii**: 30 days; and
   (iii) **U3iii** 365 days.

Aimed at calculating for analysis and registering for later comparison, the average daily EC profiles and the average daily energy costs, and the following energy and cost metrics/statistics: Total energy vs total energy cost; uncontrolled appliances subtotal energy vs uncontrolled appliances subtotal energy cost; mean Peak-to-Average Ratio (PAR); average energy price; and, average monthly bill (this applicable only for 30 and 365 days simulations).

For cost calculations, we used a simulated price, the RTPminutely() version pseudo real time price (pseudo-rtp), described in section 3.1 and depicted in Figure 13(c).

For these 3 simulations (U3i, U3ii and U3iii) the Matlab code logical equivalent of Algorithm 3 was called 1 time, 30 and 365 times respectively for each appliance j ($j = 1, ..., 8$) of Table 17 with the same parameters defined in Exp.U1.(a)-(d).

The recorded simulation data for each appliance are: a number n of cycles per each single day; each cycle consisting of a start time (switch-on time) along with duration, all them compliant with the acceptance/rejection splitting constraints as discussed.

4.4.2 Controlled (Optimized-Schedules) EC Simulation Setup:

Exp.C1 group: Single day, and multi-day simulations, 1 day at a time, namely:

(i) **Exp.C1i**: 1 day;

(ii) **Exp.C1ii**: 30 days; and

(iii) **Exp.C1iii**: 365 days.

(iv) **Exp.C1iii-b**: 365 days.

These setups are pear simulations relative to the above uncontrolled Exp.U3i (1 day), Exp.U3ii (30 days) and Exp.U3iii (365 days) respectively, where, alongside each simulation performed in the Exp.U3 group, its controlled EC version in the Exp.C1 group is performed. Exp.C1 group is performed just for the controllable appliances ($j = \{1, 2, 3\}$), wherein their events are produced by metaheuristics based appliance schedule optimization. Such schedule optimization, was performed using the HyPERGDx algorithm over the *ApplianceSchedule1(.)* as the function to optimize, itself an implementation of the RPBBOAS model, all discussed under Chapter 3.2).

The full characterization of the experiment parameters used herein is found in such RPBBOAS model. On the other hand, an additional **Exp.C1iii-b** to pair with **Exp.C1iii**, is done aimed at assessing the influence of the choice of parameters in the outcome of the controlled EC profiles.

The following main parameters are used in calling the pair HyPERGDx algorithm / *ApliianceSchedule1(.)*:

(i) User centricity coefficient α: is randomly varied, by normally distributing it around 0.5 with a standard deviation of 0.2. The seldom values falling out of [0,1] are defaulted to nearest bound of that interval; This procedure gives 0.5 as the mean and median for α which means a balanced stance towards either user or energy centricity. This choice of α influences the optimal schedules placements. That is assessed in **Exp.C1iii-b** by setting $\alpha = 0.251$ and, the tUPWs penalty type to zero (the most lenient) and the dUPWs penalty type to 5 (also very lenient), for cycle misplacement and duration mismatch respectively.

(ii) Stopping criteria: 100000 function evaluations spent or target optimum found within a tolerance of 10^{-3}.

(iii) time slot resolution and energy rate: $\tau = 60s$, the default value, which corresponds to energy rate of: *pseudoRTPminutely(.)* (see Figure 13c for a depiction).

4.5 Results and Discussion

4.5.1 Results for experiments Exp.U1 and Exp.U2

In Figures 24 and 25, we have drawn in chart format the results for experiments ***Exp.U1*** and ***Exp.U2***. For better clarity and interpretation, charts for experiment ***Exp.U2*** were placed on the left column, whereas charts for experiment ***Exp.U1*** were placed on right column of either Figures 24 and 25.

4.5.2 Discussion over Exp.U1 and Exp.U2 Results

Findings: *The simulated events time of use statistics for a given appliance j mimic the respective time-of-use reference data ($ToUPs_j$):*

Results for experiment *Exp.U2* **Results for experiment *Exp.U1***

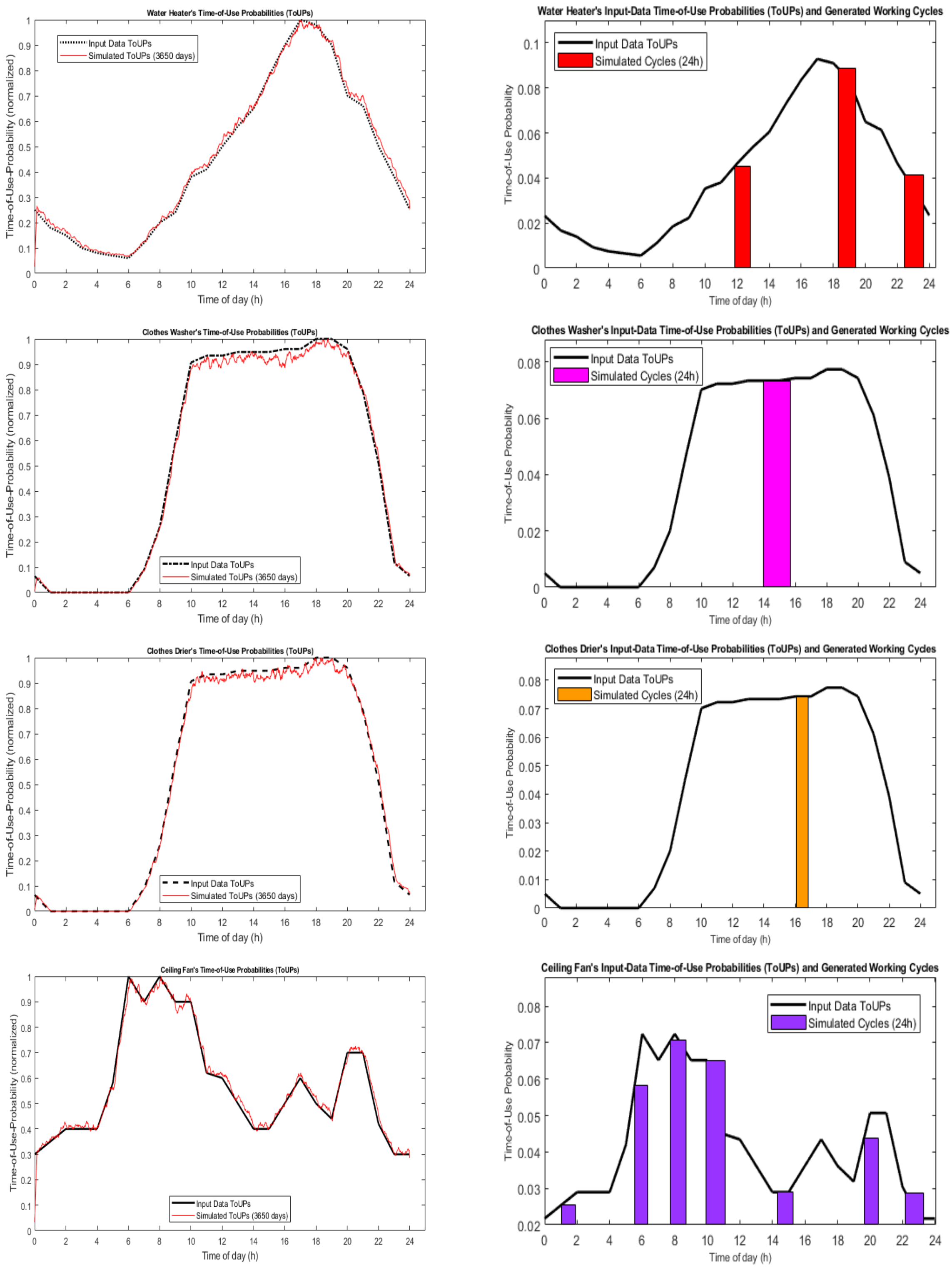


Figure 24 Results of Exp.U1 (simulated ToUPs) and Exp.U2 (appliance cycle generation) for water heater, clothes washer, clothes drier and cooling fan.

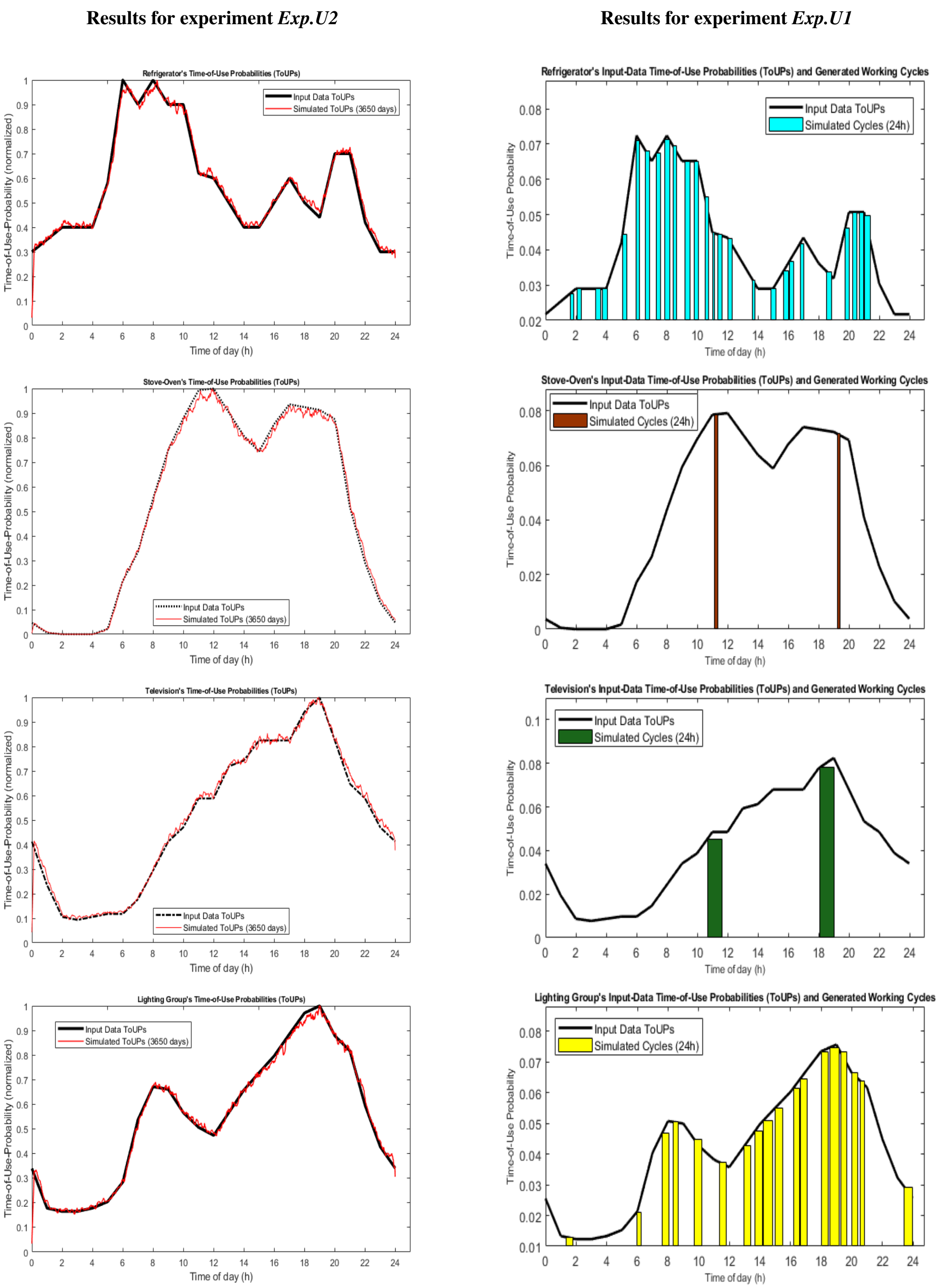


Figure 25 Results of Exp.U1 (simulated ToUPs) and Exp.U2 (appliance cycle generation) for refrigerator, stove/oven, TV and an indoor lighting group.

In the charts of left column or both Figures 24 and 25, the results of the simulation, that seeks to reproduce the uncontrolled use of a household appliance, given its reference behaviour represented by its ToUPs, a simulation that used a non-homogeneous Poisson point process, we can see that the simulated events of a given appliance j mimic the respective time-of-use reference input data ($ToUPs_j$) that served as intensity function for the Poisson point process.

4.5.2.0.1 Caveats or Limitations:

(1) As discussed earlier a pure Poisson mathematical process may differ in many aspects with a real world problem. Aside from the aspects that were already addressed in the discussion leading to the experiments, a slight difference is noticeable near 0h at the time axis: all the simulated graphs tend to zero (both at Exp.U2 and Exp.U3). That can be attributed to the geometric nature of the Poisson process, wherein there is an increasing probability of failure when approaching the null time. In other words: there is a number of failed attempts before the first successful event, when departing the null time, and the probability of success only increases with time (or whatever the state space), so when time tends to 0h (the start of point process) the probability of failure increases and that of success decreases (null time events were rejected). But in the actual real world statistics the appliance's rate-of-use probabilities at or towards 0h, are not null or tending to null in all cases, it depends on the appliance type and underlying occupants behaviour.

(2) At the right side there is also a tendency to zero, more pronounced than the reference ToUP, when approaching 24h, also not unexpected: candidate cycles placed close to 24h, the right bound of time axis, are only accepted if they can fit inbounds as per their *minCT* specification; So, a number of cycles must be being rejected, the closer their placement to 24h; but in real life usage, appliances are allowed to traverse into the next day.

(3) On the other hand, where the additional cycle count and cycle duration restrictions were enforced, aimed at closer compliance with the tabled appliance characteristics (table 17), imply that the resulting Poisson process variable rate, will be different from the pure $ToUPs_j$. However, it is evident that the limitations are not substantive, since the graph of the simulated data show a great statistical resemblance with the one of the reference data,

the higher the number of observations. There must be however, ways for addressing the limitations where dimmed imperative.

4.5.2.0.2 Exp.U1 and Exp.U2 Conclusions and Implications:

(1) Based on the close resemblance between the statistics of the simulated chart and the reference input chart in the left columns (Exp.U2) of both the Figures 25 and 24, we are confident that the simulated EC and cost thereof presented within the ensuing uncontrolled EC simulations in Figures 26-28, should as well fairly describe the actual uncontrolled EC scenario of identical *ToUPs*. Also, from these grounds, we henceforth assume that,

(2) It is appropriate to use the results of the uncontrolled EC simulations in Exp.U3 group as due references to compare with those of Exp.C1 group, in the final evaluation of the performance of the controlled EC workflow against its uncontrolled counterpart, given the same appliances settings (power ratings and *ToUPs*).

4.5.3 Results for experiments *Exp.U3* and *Exp.C1*

Description and interpretation aids: Note that, it is from the grounds of previous experiments conclusions and assumptions, that we perform the interpretation and discussion of experiments Exp.U3 vs Exp.C1 results:

(1) Figures 26 through 28 show the summary results drawn from the simulation of either the uncontrolled or the controlled (optimized) household appliance usage scenarios, a joint, pair to pair, results presentation, for the convenience of comparison.

(2) Figure 26 presents results for 1 and 30 days simulations , whereas

(3) Figure 27 presents results for the 365 days version.

(4) Except for Figure 27(e,f), on both Figures 26 and 27, charts at left column depict the average daily load profile; whereas the ones at the right column depict the corresponding energy cost profiles, whereas in Figure 27, the left column presents 30 days, while the right column depicts 365 days statistics. Also, additionally, to ease analysis, the *pseudo-RTPminutely()* energy rate function has been placed on all "Costs" (right column) charts and on any controlled EC simulation charts. In turn, and as closing statistics,

(5) Figure 28(a-d) presents comparison results for 30 and 365 days of peak load evolution; 30 and 365 days PAR evolution; and; 30 and 365 days mean price evolution.

Results for experiments *Exp.U3i,ii* and *Exp.C1i,ii* - Load **Results for experiments *Exp.U3i,ii* and *Exp.C1i,ii* - Costs**

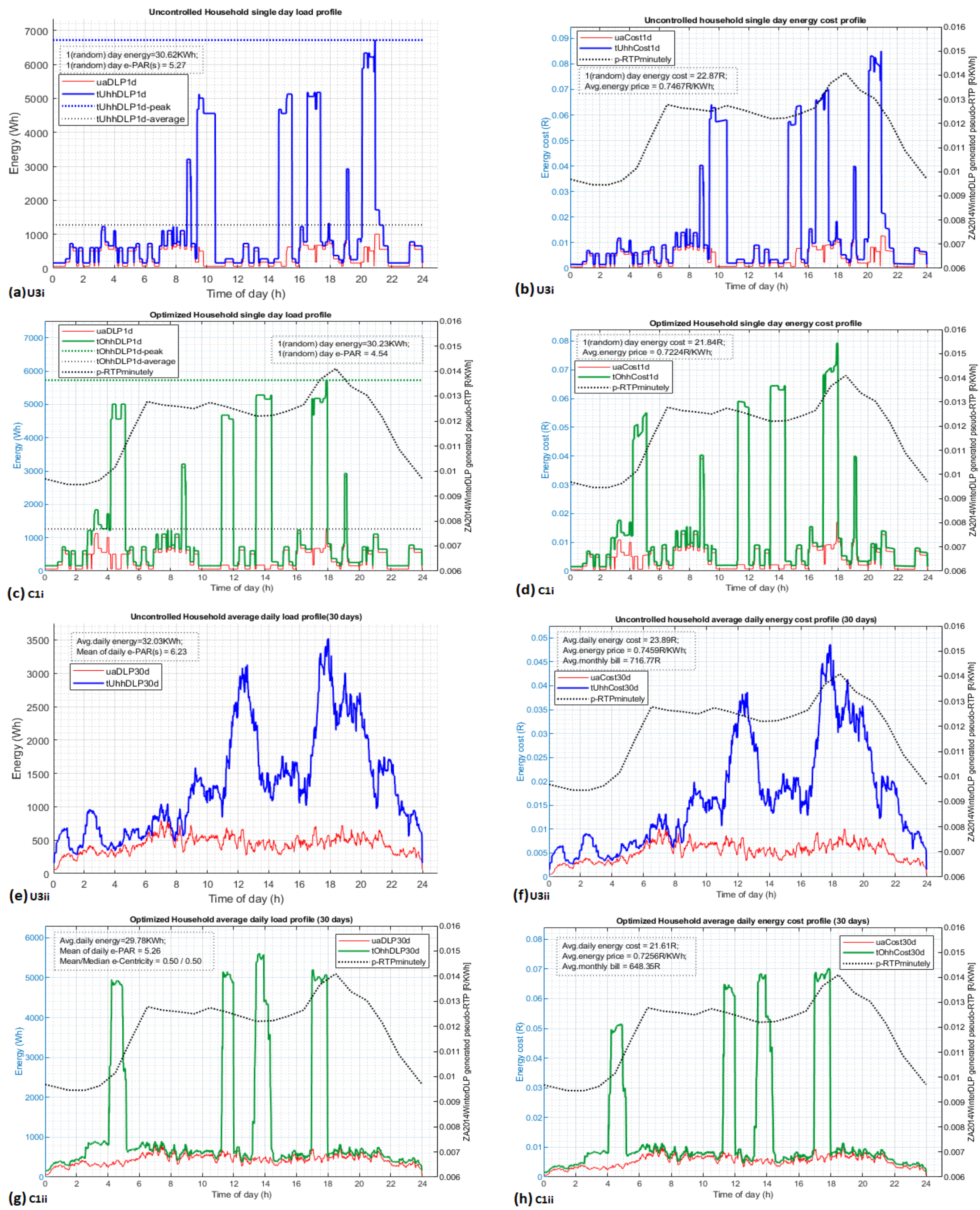


Figure 26 1 and 30 days uncontrolled vs optimized daily load and cost profiles.

The following are additional legend aids for the charts in Figure 26:

1. On Figure 26(a):

uaDLP1d: Single random day uncontrolled load profile, for just the uncontrollable appliances;
tUhhDLP1d: Single day uncontrolled load profile, for all household appliances;
tUhhDLP1d-peak: Single day uncontrolled peak-load for all household appliances;
tUhhDLP1d-average: Single day uncontrolled average-load for all household appliances;

2. On Figure 26(b):

 uaCost1d: Single day uncontrolled energy cost profile, for just the uncontrollable appliances;
 tUhhCost1d: Single day uncontrolled energy cost profile, for all household appliances;

3. On Figure 26(c):

 uaDLP1d: Single day uncontrolled load profile, for just the uncontrollable appliances; same in (a);
 tOhhDLP1d: Single day optimized load profile, for all household appliances;
 tOhhDLP1d-peak: Single day optimized peak-load for all household appliances;
 tOhhDLP1d-average: Single day optimized average-load for all household appliances;

4. On Figure 26(d):

 uaCost1d: Single day uncontrolled energy cost profile, for just the uncontrollable appliances; same in (b);
 tOhhCost1d: Single day optimized energy cost profile, for all household appliances;
 Statistical info.box:: Single day, household's total optimized energy cost and its average price.

5. On Figure 26(e):

 uaDLP30d: 30 days average daily uncontrolled load profile, for just the uncontrollable appliances;
 tUhhDLP30d:30 days average daily uncontrolled load profile, for all household appliances;

6. On Figure 26(f):

 uaCost30d: 30 days average daily uncontrolled energy cost profile, for just the uncontrollable appliances;
 tUhhCost30d:30 days average daily uncontrolled energy cost profile, for all household appliances;

7. On Figure 26(g):

 uaDLP30d: 30 days average daily uncontrolled load, for just the uncontrollable appliances; same in (e);
 tOhhDLP30d: 30 days average daily optimized load profile, for all household appliances;

8. On Figure 26(h):

 uaCost30d: 30 days average uncontrolled energy cost profile, for just the uncontrollable appliances; same in (f);
 tOhhCost30d: 30 days average daily optimized energy cost profile, for all household appliances;

The following, are additional legend aids for the charts in Figure 27:

1. On Figure 27(a):

 uaDLP365d: 365 days average daily uncontrolled load profile, for just the uncontrollable appliances;
 tUhhDLP365d:365 days average daily uncontrolled load profile, for all household appliances;

2. On Figure 27(b):

 uaCost365d: 365 days average uncontrolled energy cost profile, for just the uncontrollable appliances;
 tUhhCost365d:365 days average daily uncontrolled energy cost profile, for all household appliances;

3. On Figure 27(c,e):

 uaDLP365d: 365 days average uncontrolled load profile, for just the uncontrollable appliances; as in (a);
 tOhhDLP365d: 365 days average daily optimized load profile, for all household appliances;

4. On Figure 27(d,f):

 uaCost365d: 365 days average uncontrolled energy cost profile, for just the uncontrollable appliances; the same in (b);
 tOhhCost365d: 365 days average daily optimized energy cost profile, for all household appliances;

Results for experiments *Exp.U3iii* and *Exp.C1iii* - Load **Results for experiments *Exp.U3iii* and *Exp.C1iii* - Costs**

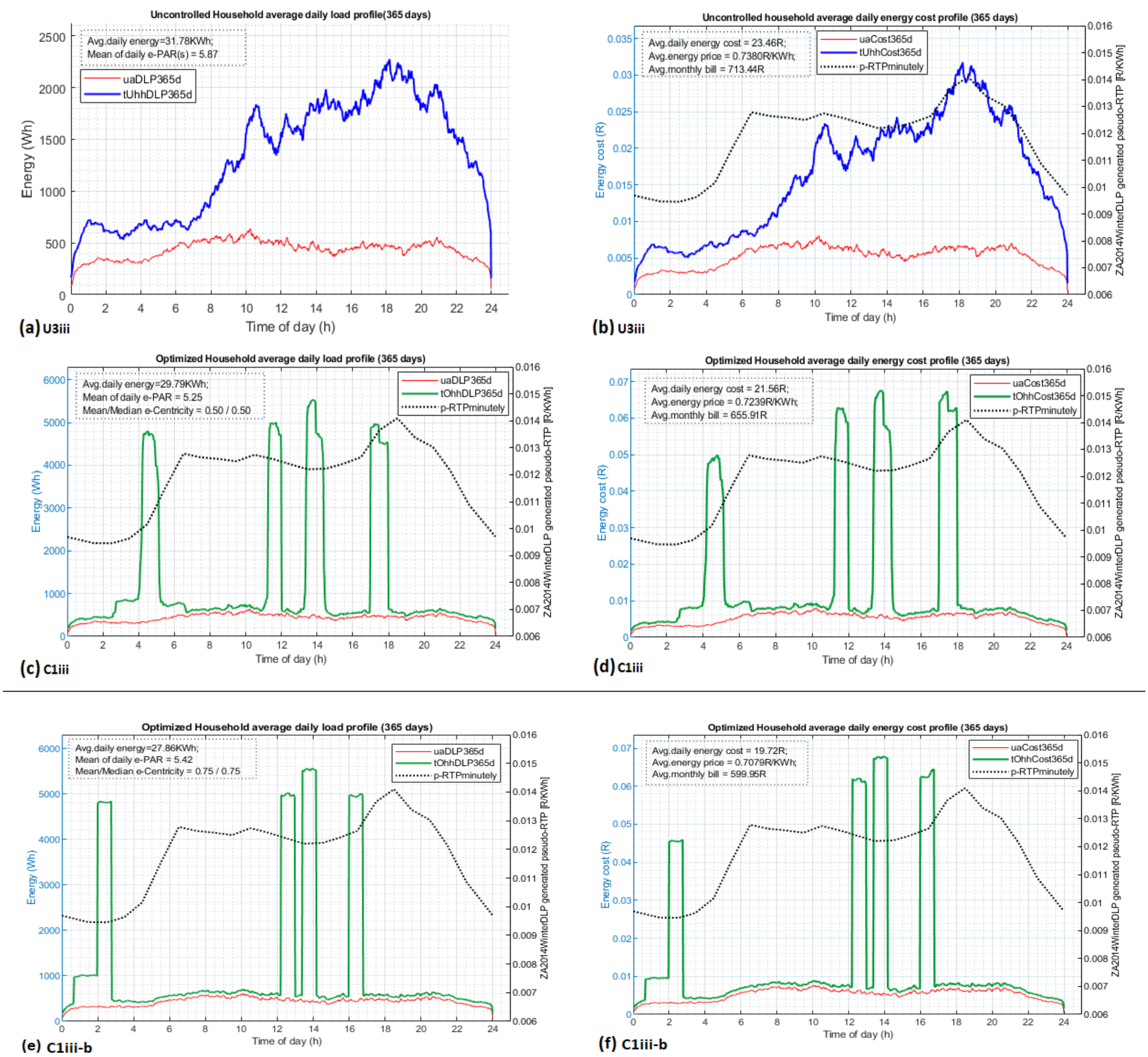


Figure 27 (a-d): 365 days uncontrolled vs optimized load and cost profiles

4.5.4 Discussion of Exp.U3 vs Exp.C1 Results

There are two types of charts: (1) The "per experiment type" charts and (2) the "evolution statistics" charts:

(1) **Discussion on the "Per experiment type" charts, Figures 26 and 27:**

Summary findings: *Peak load and PAR are substantially better in the controlled EC simulation vs the uncontrolled one, and mean energy rate improvement is modest, however consistent.*

Results for experiments *Exp.U3ii,iii* and *Exp.C1iii* - Peak Load/Mean Price Evolution

Results for experiments *Exp.U3iii* and *Exp.C1ii,iii* - Peak Load/Mean Price Evolution

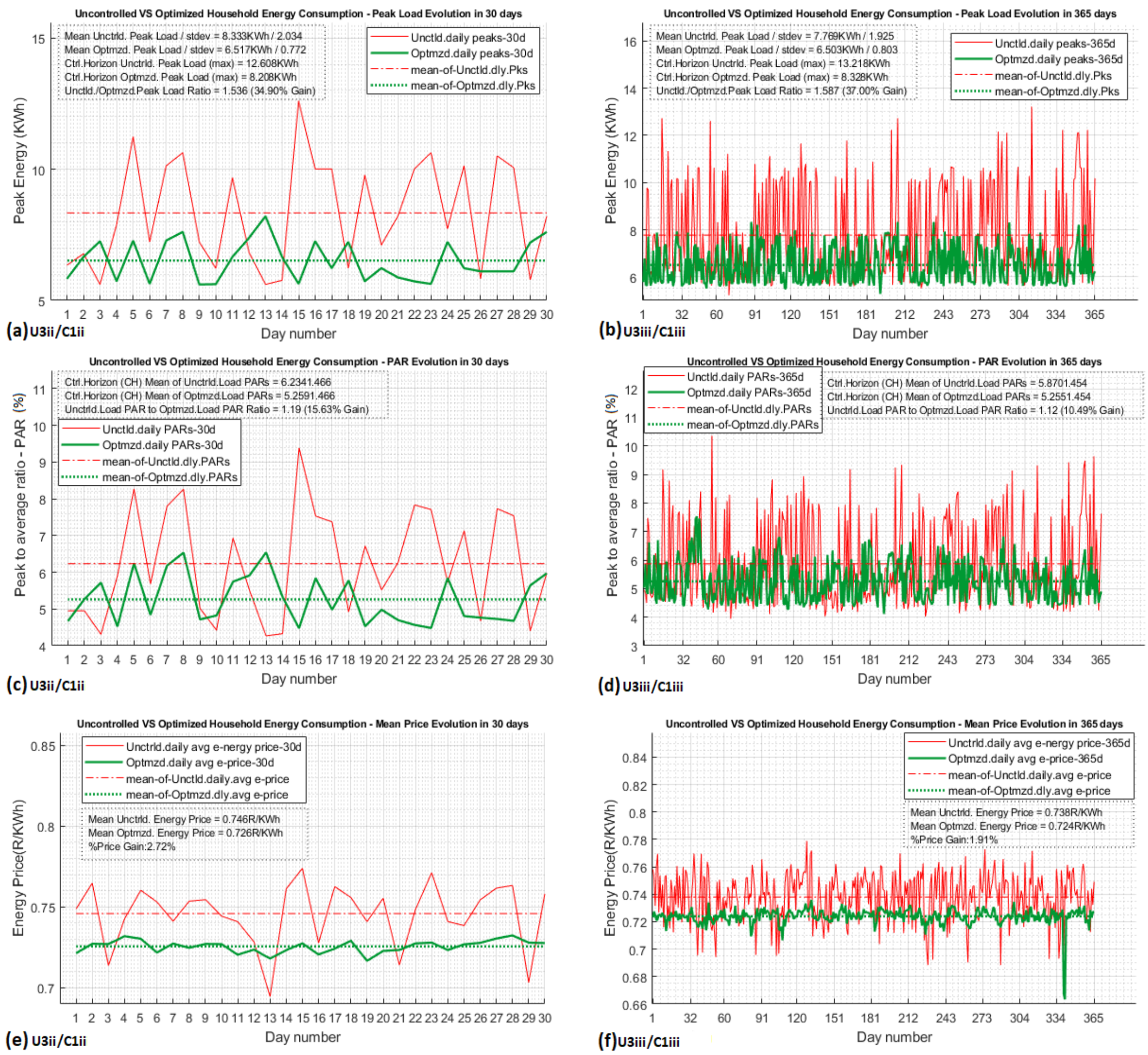


Figure 28 30 and 365 days evolution of uncontrolled vs optimized daily peak load, PAR, and mean energy rate.

Details:

(i) Comparing the chart pairs: Figure 26(a) vs 26(c) we find that: Both the peak load and the PAR of the optimized simulation (c) are better than their uncontrolled counterparts. That also, correlates to lower mean energy rates and costs, when looking at Figure 26(b) charts. The improved figures may not happen every single day but they are supposed to prevail frequently, when a multi-day statistics is performed.

(ii) Comparing the multi-day charts of Figure 26(e) vs 26(g) as well as Figure 27(a) vs

27(c), wherein most load is placed after 7AM in the uncontrolled EC, we see that a huge chunk of load has been moved to the interval [0,7h] in the optimized EC. This load shift is behind the improvement in the mean energy price and eventually the energy bill, which can observed in the paired "Costs" charts at the right.

(2) **Discussion on the "evolution statistics" charts, Figure 28:**

Summary findings: *The evolution statistics for (i) peak load and (ii) PAR show a substantial and consistent improvement of the controlled EC workflow over the uncontrolled one, and the evolution statistics for (iii) mean energy rate shows a modest but consistent improvement of the controlled over the uncontrolled workflow*.

Details:

(i) Peak-load: the mean peak-load of the optimized EC simulation is substantially better, around 37% lower, than the uncontrolled EC workflow, as visible in charts (a) vs (b) of Figure 28.

(ii) PAR: the mean Peak-to-Average Ratio (PAR), along 30 and 365 days, is also better, about 10% to 16% lower, than the uncontrolled EC workflow, as visible in charts (c) and (d) of Figure 28.

(iii) Mean Energy rate: a modest improvement of around 2% is observed. A modest improvement of the energy bill is also observed.

(3) **DR activities identified**:

Looking at the observations in (1) and (2) above, despite there is no actual RTP signal, guiding the scheduling process (we are trying to proof that the one we used, the pseudo-RTP does work), the following main traditional demand response activities can be identified as behind the improvements:

(i) Load shifting/valley filling: looking at the *p-RTPminutely* signal present in the relevant charts of either Figures 26 and 27 we notice a valley in the interval [0h, 6h] which is the cheapest interval of the day. However coincidentally, [0h, 6h] is also a valley for all uncontrolled load profiles in both Figure 26(a,e) and Figure 27(a).

In turn, for all optimized load profiles, in both Figure 26(c,g) and Figure 27(c) load has been shifted from elsewhere and now it substantially fills the interval [0h, 6h], previously a valley. This activity is behind the modest but consistent improvement of the average energy price and monthly bill thereof; And, it is also behind the peak load and PAR reduction because peak shaving is done in concertation with load shifting/valley filling actions;

(ii) Peak shaving: All charts in Figure 28, show a substantial and persistent reduction of per day peak load and PAR which means peak shaving. That is due to the capping of instant power demand, while forcing/allowing the load to be placed elsewhere. It is worth noting however that peak reduction may not imply a PAR reduction in the same figures, since and oftentimes a peak load reduction may be accompanied by a reduction on the average load on some proportion.

(iii) Energy saving: there is a lower energy consumption as a result of minimizing energy, via the daily power budget or via the inherent energy minimization in (Eq.4z) underlying the whole *ApplianceSchedule1(.)* function, to the extent allowed by parameters, namely, the user-centricity α, the UPWs settings along with time horizon parameters.

(4) **Caveats or Limitations**:

In performing the above controlled EC action, using the described tools and procedures, there are some caveats or limitations, and precautions thereof to take into account, which influence the controlled EC results in particular, and the goal of demand responsiveness in general:

(i) The choice of parameters (mainly: α, user preferred appliance working windows, and, the granularity, contiguity and length of the time horizon), as well as the shape of the pseudo-RTP function, collectively influence the optimality of the placements, in whatever the perspective. In this case, which is the energy centric perspective, the choice of parameters influence those demand response like improvements. In effect, looking at the Figure 27(e,f) vis-a-vis (c,d) we notice that in (e,f) the load peaks have been moved further into the centre of the *p-RTPminutely* valleys which is allowed by a more energy centric $\alpha = 0.251$ and more lenient user preference windows as described in the experiment *C1iii-b*. Such load shifting to the valleys as per those parameters, resulted in a much lower monthly bill. This of course may affect other dimensions of the user comfort concept.

(ii) Up to a substantial extent, per the limitations noted in (i) above, there will be a consistent peak load shaving, a degree of PAR, mean energy rate, and monthly bill improvements, as supported by the statistics of Figure 28. However, as a repeated placement is performed on to a valley or whatever the optimal location determined by the optimization algorithm, new average peaks are formed, at such locations, **not in the same day / same schedule / single household perspective**, but in the multi-household point of view, or the equivalent to the average monthly or yearly load profiles in Figures 26(g,h) and 27(c to f). This issue, is something that other researchers have noticed and successfully addressed as focus of their works, using actual DR signals under DR-ready connected environments, namely Zhao [38], Mohsenian-Rad [42], as well as Herath and Venayagamoorthy [34]. However, that is not just yet our stage and environment and focus: at this point we are trying to show that the pseudo-RTP based DR under the proposed bbDR framework is theoretically possible and proofed by those simulations results.

(iii) Since the energy pricing function is not an actual one, the above figures of energy prices and costs thereof are not actual as well.

(iv) For the sake of a bbDR functionality, notwithstanding the openly positive figures for peak load and PAR, if the reduction of the electricity bill is not that substantial (*e.g.*, for mid to high values of the user-centricity α in conjunction with harsh comfort penalties), and, the pseudo-RTP generated from country/region DLP has no added incentive, then, that is a situation when effective direct user satisfaction may not be guaranteed. So, as suggested in the motivations and introductory discussion of the bbDR, an incentive from, and involvement of the relevant stakeholders may be a need, for a successful implementation of such a framework.

(5) Conclusion:

The above substantial improvements in all these figures (of peak load, PAR, energy rate, user bill) of an optimized over the uncontrolled household's energy consumption, are the eventual outcome of performing appliance scheduling optimization by *ApplianceSchedule1(.)* function a RPBBOAS model, which performs optimal placements that better satisfy conflicting objectives and comply with constraints of various types.

With the above positive performance of the controlled EC simulation, using a pseudo-rtp signal, we can argue that:

(i) A RPBBOAS mediated household's EC optimization via a companion blackbox compliant metaheuristic (HyPERGDx) developed during this research work, have shown their effectiveness for delivering a DR-like performance to an unconnected household using a pseudo-RTP function generated from a country DLP under the also proposed bbDR framework aimed at providing demand responsiveness for DR-unconnected CG environments.

(ii) As supported by the above simulations, and taking the precautions and limitations that were discussed along the way, the proposed bbDR framework, is theoretically feasible and thus, if taken seriously by the relevant players, it holds the potential of, to some extent, alleviate the high demand that has been causing blackouts in SA and elsewhere with similar or worse energy environments.

Chapter 5

Conclusions

This work has addressed the lack of demand responsiveness in DR signalling deprived, unconnected CG environments. The above expositions have presented and discussed what has been achieved and the limitations.

Before we draw the final conclusion, it is essential to outline the main results which are at the same time the modest contributions of this research work, namely:

1. We have proposed and demonstrated by simulations, the functionality of a framework for providing a baseline demand responsiveness for the communications deprived networks, based on a pseudo real time pricing function learned from a country or region daily load profile, wherein such pseudo-RTP, served as a guiding function for the autonomous scheduling of controllable appliances. With the simulations performed in Chapter 4, we have demonstrated and proved that, based on such pseudo-RTP function it is possible to perform appliance scheduling that deliver DR-like performances to the unconnected CG environments.

2. We have proposed and demonstrated a real parameter blackbox optimization appliance scheduling model (the RPBBOAS model implemented as the *ApplianceSchedule1(.)* function), which tackles the course of dimensionality/combinatorial explosion issues, and provides the above bbDR with an heuristic based appliance scheduling meta model, which describes the household and provides the logical interface with optimization algorithms.

3. We have designed and tested a new hybrid metaheuristics (HyPERGDx) that shows a

better or competitive performance against some of the top state of the art population based metaheuristics, and shows consistently a better performance in the appliance scheduling function, and thus showing the best all-around performance. This metaheuristics provides the discussed bbDR scheme with a real parameter blackbox capable global optimization algorithm to perform the appliance scheduling guided by the pseudo-RTP function and mediated by the discussed RPBBOAS model.

5.1 Conclusions and outlook of future work

Taking always into account the motivations, and given the results and the contributions that we discussed above, and taking due note of the limitations that were discussed along with, we can positively argue that the objectives we outlined for the present research work were achieved.

As an outlook, we see that there are ample avenues for improvement of the work, including, but not limiting to:

(1) Proposing multi-household optimization approaches aimed at taking further and deeper view of the bbDR framework and addressing the limitations (as discussed in the contributions section and elsewhere in results discussion sections), is one of the possible ways forward from the grounds of the results of the present research.

(2) seeking a possible real life implementation of a bbDR framework based energy management system for the CG environments and thereby define and plan branches of activities towards such goal is also a way forward.

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Appendix A

Source Data of Sample Household Appliances' Properties and Time-of-Use Probabilities

Table 19 Sample household appliances' time-of-use probabilities, from [52]

Hourly probability factors applied in the load model for appliances and groups.

Appliances		Hours 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Stove and oven	we	0.20	0.20	0.40	0.40	1.78	2.59	3.19	3.83	3.70	4.13	4.29	4.15	3.89	4.46	5.79	8.76	10.0	10.3	9.24	8.15	5.82	2.79	1.51	0.36
	wd	0.37	0.05	0.00	0.00	0.00	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.30	1.02
Microwave oven and coffee maker	we	0.20	0.20	0.40	0.40	1.78	2.59	3.19	3.83	3.70	4.13	4.29	4.15	3.89	4.46	5.79	8.76	10.0	10.3	9.24	8.15	5.82	2.79	1.51	0.36
	wd	0.37	0.05	0.00	0.00	0.00	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.30	1.02
Refrigerator and freezers	we	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
	wd	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Dishwasher	we	1.73	0.96	0.40	0.40	0.40	0.96	1.73	2.93	3.75	4.58	4.68	4.68	4.68	4.68	4.68	6.11	6.83	7.16	7.80	8.60	8.16	7.01	5.05	2.03
	wd	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.70	2.00	4.61	7.02	7.23	7.23	7.34	7.34	7.34	7.43	7.43	7.74	7.74	7.43	6.12	3.91	0.90
Clothes-washer and tumble dryer	we	1.73	0.96	0.40	0.40	0.40	0.96	1.73	2.93	3.75	4.58	4.68	4.68	4.68	4.68	4.68	6.11	6.83	7.16	7.80	8.60	8.16	7.01	5.05	2.03
	wd	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.70	2.00	4.61	7.02	7.23	7.23	7.34	7.34	7.34	7.43	7.43	7.74	7.74	7.43	6.12	3.91	0.90
Televisions and video recorder	we	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
	wd	3.40	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.40	3.88	4.85	4.85	5.93	6.13	6.80	6.80	6.80	7.77	8.25	6.80	5.34	4.85	3.88
Radio/player	we	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
	wd	3.40	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.40	3.88	4.85	4.85	5.93	6.13	6.80	6.80	6.80	7.77	8.25	6.80	5.34	4.85	3.88
Personal computer and printer	we	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
	wd	3.40	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.40	3.88	4.85	4.85	5.93	6.13	6.80	6.80	6.80	7.77	8.25	6.80	5.34	4.85	3.88
Lighting	we	1.03	0.33	0.33	0.83	1.78	2.64	3.56	3.74	3.44	3.04	3.04	3.24	3.94	4.14	4.55	4.96	5.79	6.70	8.21	9.11	9.81	8.50	4.32	2.96
	wd	2.55	1.33	1.23	1.23	1.33	1.53	2.13	4.05	5.07	4.99	4.27	3.82	3.57	4.27	4.97	5.50	6.02	6.69	7.34	7.56	6.64	6.17	4.49	3.22
Other occasional loads	we	1.03	0.83	0.83	0.83	1.03	2.04	3.06	3.24	3.44	3.54	3.64	3.74	3.94	4.14	4.55	4.96	5.79	6.70	7.71	8.51	9.01	8.10	5.67	3.66
	wd	2.55	1.33	1.23	1.23	1.33	1.73	2.13	3.55	4.07	3.99	3.77	3.97	4.07	4.47	4.97	6.00	6.32	6.84	7.34	7.56	6.79	6.67	4.84	3.22

we = weekend day; wd = weekday.

Table 20 Sample household appliances' data, from [52]

Daily starting frequencies, standby loads and consumption cycle information applied in the load model for appliances and groups.

	Power (W) and time (min) cycles									Daily frequency		
Appliances and groups	P1	T1	P2	T2	P3	T3	P4	T4	Stand-by (W)	Weekday	Weekend	Other
Stove and oven	1050	12	525	18	220	12			0	0.56	0.61	C,G
	1100	12	550	6						0.70	0.76	C,G
	2100	24	700	6	1400	6	0	6		0.20	0.21	
Microwave oven	800	6							3	0.98	1.06	
Coffee maker	640	6	105	18						0.98	1.06	
Refrigerator	110	12	0	24						40.5	41.3	
Freezer	155	12	0	12						40.5	41.3	
Second freezer	190	12	0	12						40.5	41.3	
Dishwasher	1800	18	220	18	1800	6	220	12		1.16	1.26	
Clothes-washer	2150	12	210	24	450	6				0.31	0.33	
	2150	18	210	24	450	6				0.11	0.12	
Tumble dryer	2500	72								0.28	0.30	
Television	105	60							8	1.95	2.12	
Second television	75	60							4	0.28	0.30	
Video recorder	—	—							9	—	—	
Radio/player	30	60							5	4.18	4.54	
Personal computer	125	60							3	0.70	0.76	
Printer	30	60							4	0.14	0.15	
Lighting	120	30								18.0	19.5	C,G
Other occasional loads	1000	30							3	0.14	0.15	G

P# = power in Watts for cycle #; T# = time in minutes for cycle #; C = cumulative use allowed; G = represents a group of appliances.

Table 21 Sample Household Appliances' Time-of-Use Probabilities, built from [87]

Space Heating	TUS1	TUS2	TUS3	TUS4	TUS5	TUS6	TUS7	TUS8	TUS9	TUS10	TUS11	TUS12	TUS13	TUS14	TUS15	TUS16	TUS17	TUS18	TUS19	TUS20	TUS21	TUS22	TUS23	TUS24
Heat Pump Heating	0.3	0.35	0.4	0.4	0.4	0.58	1	0.9	1	0.9	0.9	0.62	0.6	0.5	0.4	0.4	0.5	0.6	0.5	0.44	0.7	0.7	0.42	0.3
Portable Heater	0.3	0.35	0.4	0.4	0.4	0.58	1	0.9	1	0.9	0.9	0.62	0.6	0.5	0.4	0.4	0.5	0.6	0.5	0.44	0.7	0.7	0.42	0.3
Fan (Attic)	0.3	0.35	0.4	0.4	0.4	0.58	1	0.9	1	0.9	0.9	0.62	0.6	0.5	0.4	0.4	0.5	0.6	0.5	0.44	0.7	0.7	0.42	0.3
Furnace Fan	0.61	0.56	0.56	0.55	0.52	0.56	0.68	0.73	0.61	0.52	0.55	0.55	0.52	0.55	0.58	0.61	0.73	0.87	0.94	0.97	1.00	0.97	0.84	0.74
Central AC	0.3	0.35	0.4	0.4	0.4	0.58	1	0.9	1	0.9	0.9	0.62	0.6	0.5	0.4	0.4	0.5	0.6	0.5	0.44	0.7	0.7	0.42	0.3
Room AC	0.25	0.18	0.15	0.1	0.08	0.07	0.06	0.12	0.2	0.24	0.38	0.41	0.5	0.58	0.65	0.78	0.9	1	0.98	0.9	0.7	0.66	0.5	0.38
Evap Cooling	0.25	0.18	0.15	0.1	0.08	0.07	0.06	0.12	0.2	0.24	0.38	0.41	0.5	0.58	0.65	0.78	0.9	1	0.98	0.9	0.7	0.66	0.5	0.38
Water Heating	0.25	0.18	0.15	0.1	0.08	0.07	0.06	0.12	0.2	0.24	0.38	0.41	0.5	0.58	0.65	0.78	0.9	1	0.98	0.9	0.7	0.66	0.5	0.38
Clothes Dryer	0.2	0.18	0.17	0.17	0.18	0.3	0.61	1	0.9	0.75	0.65	0.55	0.5	0.45	0.4	0.4	0.42	0.58	0.65	0.65	.62.	0.6	0.5	0.35
Clothes Washer	0.13	0.08	0.06	0.04	0.06	0.08	0.20	0.38	0.63	0.85	0.98	1.00	0.94	0.85	0.75	0.73	0.69	0.69	0.66	0.65	0.65	0.69	0.55	0.31
Dishwasher	0.12	0.09	0.06	0.06	0.09	0.13	0.25	0.59	0.82	1.00	0.98	0.88	0.80	0.71	0.61	0.58	0.59	0.58	0.58	0.58	0.56	0.54	0.35	0.18
First Refrigerator	0.16	0.14	0.04	0.03	0.03	0.15	0.18	0.27	0.53	0.56	0.52	0.45	0.37	0.40	0.35	0.34	0.35	0.45	0.77	1.00	0.77	0.64	0.38	0.29
Second Fridge	0.8	0.76	0.74	0.72	0.7	0.7	0.74	0.8	0.82	0.84	0.8	0.8	0.84	0.84	0.82	0.84	0.9	0.96	1	0.96	0.94	0.92	0.9	0.84
Freezer	0.8	0.76	0.74	0.72	0.7	0.7	0.74	0.8	0.82	0.84	0.8	0.8	0.84	0.84	0.82	0.84	0.9	0.96	1	0.96	0.94	0.92	0.9	0.84
Indoor Lighting	0.8	0.76	0.74	0.72	0.7	0.7	0.74	0.8	0.82	0.84	0.8	0.8	0.84	0.84	0.82	0.84	0.9	0.96	1	0.96	0.94	0.92	0.9	0.84
Oven	0.07	0.07	0.07	0.07	0.16	0.36	0.39	0.36	0.16	0.13	0.13	0.13	0.13	0.13	0.13	0.18	0.39	0.54	0.75	0.87	0.89	0.64	0.36	0.14
Range Burner	0.05	0.05	0.03	0.03	0.05	0.07	0.17	0.28	0.30	0.33	0.28	0.33	0.39	0.33	0.29	0.39	0.60	1.00	0.80	0.40	0.27	0.17	0.12	0.08
TV	0.05	0.05	0.03	0.03	0.05	0.07	0.17	0.28	0.30	0.33	0.28	0.33	0.39	0.33	0.29	0.39	0.60	1.00	0.80	0.40	0.27	0.17	0.12	0.08
Microwave	0.61	0.56	0.56	0.55	0.52	0.56	0.68	0.73	0.61	0.52	0.55	0.55	0.52	0.55	0.58	0.61	0.73	0.87	0.94	0.97	1.00	0.97	0.84	0.74
PC	0.61	0.56	0.56	0.55	0.52	0.56	0.68	0.73	0.61	0.52	0.55	0.55	0.52	0.55	0.58	0.61	0.73	0.87	0.94	0.97	1.00	0.97	0.84	0.74
Well Pump	0.61	0.56	0.56	0.55	0.52	0.56	0.68	0.73	0.61	0.52	0.55	0.55	0.52	0.55	0.58	0.61	0.73	0.87	0.94	0.97	1.00	0.97	0.84	0.74
Misc	0.61	0.56	0.56	0.55	0.52	0.56	0.68	0.73	0.61	0.52	0.55	0.55	0.52	0.55	0.58	0.61	0.73	0.87	0.94	0.97	1.00	0.97	0.84	0.74

Source: Building America Research Definition Benchmark http://www.nrel.gov/docs/fy10osti/47246.pdf
Source: Northwest Power and Conservation Council
http://www.nwcouncil.org/energy/powerplan/6/final/SixthPowerPlan_Appendix_E.pdf

Table 22 Sample Household Appliances' Properties, from [87]

	UEC (kWh/yr)	Sat (%)	Power Active (kW)	Power Standby (kW)	Cycle Length (hour)	Cycle Max (daily)	Max kWh/day	Ave kWh/day	Controllable	Max Delay (hours)
Space Heating	1171	0	1.00	0.07	1	3	4.68	3.21	1	2
Heat Pump Heating	994	0	0.11	0	1	8	0.84	2.72	1	2
Portable Heater	382	0	1.00	0	1	3	3.00	1.05	0	0
Fan (Attic)	96	0.2	0.5	0	1	7	3.50	0.26	0	0
Furnace Fan	216	0.73	0.38	0	1	8	3.00	0.59	1	2
Central AC	894	0.56	2.80	0	1	7	19.62	2.45	1	2
Room AC	293	0.13	0.90	0	1	7	6.32	0.80	1	1
Evap Cooling	650	0.06	0.40	0	1	12	4.80	1.78	0	0
Water Heating	3169	0.05	4.50	0.1	1	3	15.90	8.68	1	1
Clothes Dryer	719	0.33	5.00	0	1	1	5.00	1.97	1	1
Clothes Washer	121	0.96	0.51	0	1	1	0.51	0.33	1	1
Dishwasher	83	0.74	1.20	0	1	1	1.20	0.23	1	2
First Refrigerator	827	1.00	0.50	0.1	1	10	7.40	2.27	1	1
Second Fridge	1286	0.33	0.50	0.1	1	10	7.40	3.52	1	1
Freezer	968	0.23	0.29	0.1	1	10	5.28	2.65	1	1
Indoor Lighting	388	1.00	0.36	0	1	4	1.44	1.06	0	0
Oven	310	0.42	2.10	0	1	1	2.10	0.85	0	0
Range Burner	310	0.42	0.40	0	1	1	0.40	0.85	0	0
TV	738	1.00	0.20	0	1	6	1.27	2.02	0	0
Microwave	133	0.94	0.25	0	1	1	0.32	0.36	0	0
PC	673	0.88	0.35	0	1	1	0.45	1.84	0	0
Well Pump	562	0.1	0.9	0	1	12	10.80	1.54	0	0
Misc	2177.00	1	0.31	0	24	1	7.39	5.96	0	0

Source: 2009 California RASS http://www.energy.ca.gov/2010publications/CEC-200-2010-004/CEC-200-2010-004-ES.PDF

Source: National Grid "Cost of Operating Appliances" http://www.nationalgridus.com/niagaramohawk/non_html/eff_costappliance.pdf

Source: LBNL Standby Power http://standby.lbl.gov/summary-table.html

Appendix B

Summary Introduction of the state-of-the-art Algorithms taking part in the HyPERGDx Algorithm

B.1 Particle Swarm Optimization

The PSO is a population based metaheuristic (PBM) algorithm introduced by Kennedy and Eberhart [88] [89] in 1995, and followed by many variants. As with the other PBM metaheuristics addressed below, the PSO is a heuristic based stochastic process where a population of particles, each one a candidate solution, search, compete and cooperate for the best position, *i.e.* the (best possible) solution, inside a hyperspace of dimension d. This search process is likened to the competition and collaboration of ants (and other swarms) foraging for food. Mathematically the standard (inertia weight) PSO is described by:

The Inertia Weight PSO, a standard for the PSO algorithm: (Eqs.25)

$$V_i(t+1) = \underbrace{w \cdot V_i(t)}_{\substack{momentum\\component}} + \underbrace{C_1 \cdot R_1 \odot \left(X_{PB_i} - X_i(t)\right)}_{\substack{cognitive\\component}} + \underbrace{C_2 \cdot R_2 \odot \left(X_{GB} - X_i(t)\right)}_{\substack{social\\component}} \tag{25a}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{25b}$$

where: $\boldsymbol{i}$ is the particle index; $i = \{1, \ldots, p_{sz}\}$; p_{sz} the population size; $\boldsymbol{t}$ is the iteration counter; d is the dimensionality of the search space. The $\odot$ denotes element-wise matrix multiplication, and the following variables, X_i, V_i, R_1, R_2, X_{PBi}, X_{GB}; are $\boldsymbol{d}$-dimensional vectors.

$\boldsymbol{C_1}$ and $\boldsymbol{C_2}$ are scalars, positive constants, both usually set to 2 in the WPSO. C_1 is the cognitive acceleration coefficient and C_2 is the social acceleration coefficient. The two affect the balance of how the particle accepts social contribution over is own (cognitive) experience for its next velocity (Eq.25a); In turn, $\boldsymbol{R_1} \sim \mathscr{U}(0,1)$ and $\boldsymbol{R_2} \sim \mathscr{U}(0,1)$, are uniformly and independently distributed random numbers in [0,1].

$\boldsymbol{V_i(t)}$ and $\boldsymbol{V_i(t+1)}$ are the current and next velocity of the i-th particle at the iteration t; while $\boldsymbol{w}$ (or a varying $\boldsymbol{w(t)}$ [90]) is the inertia weight, and $\boldsymbol{w}v(t)$ is the momentum component, the influence of the current velocity, over the next particle movement; whereas $\boldsymbol{X_i(t)}$ and $\boldsymbol{X_i(t+1)}$ are the current and next particle's position. A linearly increasing or decreasing $\boldsymbol{w(t)}$ in (Eq.25a) gives place to the LIWPSO and LDWPSO variants respectively.

$\boldsymbol{X_{PBi}}$ is the particle's personal best experience ever, whilst $\boldsymbol{X_{GB}}$ is the population's position of best experience ever.

Algorithm 4 shows an outline of the PSO search process (with global neighbourhood and synchronous updates).

```
// Generalized PSO heuristic process
// find x* the optimizer of f(x); x a position within the feasible problem space
begin
   //swarm initialization loop
   for each particle i of the population (with population size=n):
       assign it a random position and a random velocity, within allowed bounds;
       assign that position to the memory of particle's best experience (X_PBi).
   end for
   find the fittest X_PBi position among all particles, and
   set such X_PBi position as the population's best so far (X_GB).
   //main optimization loop
   repeat:
      for each particle i of the population:
          calculate, clamp and update particle velocity, using (Eq.25a)
          calculate, clamp and update particle position, using (Eq.25b)
          if the particle i current position is fitter than its X_PBi, then
              set that position as the new X_PBi for this particle.
          end if
      end for
      find the fittest X_PBi position among all particles, and
      set such X_PBi position as the population's best so far (X_GB).
   until termination criterion is met
   // X_GB is the best approximation to x* up to the termination criterion
   assign X_GB to x*;
   return x* and f(x*)
end
```

Algorithm 4: PSO algorithmic framework

B.2 Covariance Matrix Adaptation Evolution Strategy

Evolution Strategies (ES), are a class of evolutionary algorithms, formerly developed by Rechenberg, Schwefel and Fogel [70] [91] [92], wherein the successive stochastic candidate solutions are sampled from a multivariate normal distribution, along with performing mutation and selection operations. The Covariance Matrix Adaptation Evolution Strategy (CMA-ES), as represented by one of its versions, the $(\mu/\mu_w,\ \lambda)$-CMA-ES, outlined in the Algorithm 5, was developed by Hansen and Ostermeier [93]. CMA-ES optimizes (a function by) a population (of candidate solutions, particles, offsprings); described by its: offsprings (with: position, dimensionality, fitness, rank, weight, ...) $x_{i:\lambda}$, of $\boldsymbol{d}$ (problem) size, population size $\boldsymbol{\lambda}$, and the elite fraction of the population (parent population) $\boldsymbol{\mu}$, *mean* $\boldsymbol{m}$, covariance matrix $\boldsymbol{C}$, step size $\boldsymbol{\sigma}$, etc.; Along with these descriptors, there are also a number of learning and control parameters. All of them, can to some extent, be fine-tuned to circumstance (see (Eqs.26), Algorithm 5, as well as [94] [95] for detailed explanations and options), aimed at adapting either $\boldsymbol{C}$ or $\boldsymbol{\sigma}$ and thereby guide the iterative optimization process, outlined by Algorithm 5.

The $(\mu/\mu_w,\ \lambda)$-CMA-ES main mathematical representation (details/explanations in: [94] [95]) is:

The Covariance Matrix Adaptation Evolution Strategy (CMA-ES) (Eqs.26)

$$\boldsymbol{y}_i^{(t+1)} \sim \mathcal{N}(0,\boldsymbol{C}^{(t)}),\ \ \forall i = 1...\lambda;\ \ t = 0,1,...;\ \text{is the iteration number; any } y_i = \{y_{i1}, y_{i2}, \dots, y_{id}\}; \tag{26a}$$

$$\boldsymbol{x}_i^{(t+1)} \sim m^{(t)} + \sigma^{(t)} \underbrace{\mathcal{N}\left(0,\boldsymbol{C}^{(t)}\right)}_{\boldsymbol{y}_i^{(t+1)}};\ \ \forall i = 1...\lambda;\ \text{any } x_i = \{x_{i1}, x_{i2}, \dots, x_{id}\}; \tag{26b}$$

$$\left(\boldsymbol{m}^{(t+1)} = \sum_{i=1}^{\mu} w_i \boldsymbol{x}_{i:\lambda}^{(t+1)}\right) \equiv \left(\boldsymbol{m}^{(t+1)} = m^{(t)} + \sigma^{(t)} \boldsymbol{y}_w^{(t+1)}\right);\quad \text{since: } \boldsymbol{y}_w^{(t+1)} = \sum_{i=1}^{\mu} w_i \boldsymbol{y}_{i:\lambda}^{(t+1)};\ \sum_{i=1}^{\mu} w_i = 1; \tag{26c}$$

$$p_c^{(t+1)} = (1-c_c)p_c^{(t)} + h_\sigma^{(t+1)} \sqrt{c_c(2-c_c)\mu_w}\ \boldsymbol{y}_w^{(t+1)}; \tag{26d}$$

$$p_\sigma^{(t+1)} = (1-c_\sigma)p_\sigma^{(t)} + \sqrt{c_\sigma(2-c_\sigma)\mu_w}\ \boldsymbol{y}_w^{(t+1)} \left(\sqrt{\boldsymbol{C}^{(t)}}\right)^{-1}; \tag{26e}$$

$$\boldsymbol{C}^{(t+1)} = (1-c_1-c_\mu)\boldsymbol{C}^{(t)} + c_1 p_c^{(t+1)} \left(p_c^{(t+1)}\right)^T + c_\mu \sum_{i=1}^{\mu} w_i \boldsymbol{y}_{i:\lambda}^{(t+1)} \left(\boldsymbol{y}_{i:\lambda}^{(t+1)}\right)^T; \tag{26f}$$

$$\boldsymbol{\sigma}^{(t+1)} = \sigma^{(t)} \exp\left(\frac{c_\sigma}{d_\sigma}\left(\frac{\|p_\sigma^{(t)}\|}{\mathbf{E}\|\mathcal{N}(\mathbf{0},\mathbf{I})\|} - 1\right)\right); \tag{26g}$$

$$\text{where:}\quad \mathbf{E}\|\mathcal{N}(\mathbf{0},\mathbf{I})\| \approx \sqrt{d}\left(1 - \frac{1}{4d} + \frac{1}{21d^2}\right);\quad \text{and:}\quad h_\sigma^{(t+1)} = \begin{cases} 1, & \frac{\|p_\sigma^{(t)}\|}{\sqrt{1-(1-c_\sigma)^{2(t+1)}}\ \mathbf{E}\|\mathcal{N}(\mathbf{0},\mathbf{I})\|} < 1.4 + \frac{2}{d+1} \\ 0, & \text{otherwise}; \end{cases} \tag{26h}$$

Function $\{f_B, x_B, ...\}$ = `CMAES` $(m \in \mathbb{R}^d, \sigma \in \mathbb{R}_+,\ \lambda \geq 2,\ x_L,\ x_U,\ f,\ f_{x^*},\ f_\varepsilon, ...)$

  //$\boldsymbol{m}$-mean; $\boldsymbol{\sigma}$-step size; $\boldsymbol{\lambda}$-popul.size; $\boldsymbol{x_L}, \boldsymbol{x_U}$ bounds; $\boldsymbol{f}_{x^*}$ optimal $\boldsymbol{f}$; $\boldsymbol{f}_\varepsilon$ tolerance, whereby: $f_{Target} = \boldsymbol{f}_{x^*} + \boldsymbol{f}_\varepsilon$.

  Initialize: **C = I**; $p_c = 0$; $p_\sigma = 0$; // $\boldsymbol{C}, \boldsymbol{I}$-Covariance, identity matrices; $p_c,\ p_\sigma$ control parameters for C and σ;

  Set: $c_c \approx 4/d$; $c_\sigma \approx 4/d$; $c_1 \approx 2/d^2$; $c_\mu \approx \mu_w/d^2$; $c_1 + c_\mu \leq 1$; $d_\sigma \approx 1 + \sqrt{\mu_w/d}$; $w_i, i = 1...\lambda$; such that ...

  the variance effective selection mass: $\mu_w = \frac{1}{\sum_{i=1}^{\mu} w_i^2} \approx 0.3\lambda$; Also: $\sum_{i=1}^{\mu} w_i = 1$; and $w_1 \geq w_2 \geq \cdots \geq w_\mu > 0$;

  while *a stopping criterion not met, and applying the elected boundary handling, restarts and other strategies* **do**

    Sample λ offsprings from a multivariate normal distribution of 0 mean and covariance matrix C:

    $\boldsymbol{x}_i = m + \sigma \boldsymbol{y}_i$; where: $\boldsymbol{y}_i \sim \mathcal{N}(0, \boldsymbol{C})$; $\forall i = 1...\lambda$;

    Evaluate $\boldsymbol{f}(\boldsymbol{x}_i)$, $\forall i = 1, ..., \lambda$; and sort $\boldsymbol{x}_i$ ascending, on $f(\boldsymbol{x}_i)$, yielding ranked $\boldsymbol{x}_{i:\lambda}$ and thereof ranked $\boldsymbol{y}_{i:\lambda}$:

    $x_{i:\lambda} \leftarrow arg(SortAscending(f(\boldsymbol{x}_i)))$, $i = 1, ..., \lambda$; *i.e.*, such that: $f(\boldsymbol{x}_{1:\lambda}) \leq f(\boldsymbol{x}_{2:\lambda}) \leq \cdots \leq f(\boldsymbol{x}_{\lambda:\lambda})$;

    Update the *mean*, by μ truncation selection, and weighed recombination of the μ parent $x_{i:\lambda}$ $(i = 1...\mu)$ offsprings: $\left(m \leftarrow \sum_{i=1}^{\mu} w_i \boldsymbol{x}_{i:\lambda}\right) \equiv \left(m \leftarrow m + \sigma \boldsymbol{y}_w\right)$; where: $\boldsymbol{y}_w = \sum_{i=1}^{\mu} w_i \boldsymbol{y}_{i:\lambda}$

    Determine the current best solution:

    Set $\{x_B, f_B = f(x_B)\}$ as the fitter between $\{m, f(m)\}$ and $\{x_1, f(x_1)\}$;

    Cumulation for $\boldsymbol{C}$ adaptation:

    $p_c \leftarrow (1 - c_c) p_c + h_\sigma \sqrt{c_c(2 - c_c)\mu_w}\ \boldsymbol{y}_w$; where, h_σ, is given in (Eqs.26h);

    Cumulation for $\boldsymbol{\sigma}$ adaptation:

    $p_\sigma \leftarrow (1 - c_\sigma) p_\sigma + \sqrt{c_\sigma(2 - c_\sigma)\mu_w}\ \boldsymbol{y}_w \boldsymbol{C}^{-\frac{1}{2}}$;

    Update/adapt the covariance matrix: $\boldsymbol{C} \leftarrow (1 - c_1 - c_\mu)\boldsymbol{C} + c_1 p_c p_c^T + c_\mu \sum_{i=1}^{\mu} w_i \boldsymbol{y}_{i:\lambda} \boldsymbol{y}_{i:\lambda}^T$;

    Update/adapt the step size: $\boldsymbol{\sigma} \leftarrow \sigma \exp\left(\frac{c_\sigma}{d_\sigma}\left(\frac{\|p_\sigma\|}{\mathbf{E}\|\mathcal{N}(\mathbf{0}, \mathbf{I})\|} - 1\right)\right)$; where, $\mathbf{E}\|\mathcal{N}(\mathbf{0}, \mathbf{I})\|$ is given in (Eqs.26h);

    Evaluate whether some stopping criteria are met:

    Usually: f_B (fitness) meets f_{Target} (*i.e.*: $f_B \leq f_{Target}$); a deadline met (*e.g.*: some of these budgets is spent: funtion evaluations, iterations, clock time, ...), some type of stagnation occur, etc.

  end

end

Algorithm 5: The $(\mu/\mu_w,\ \lambda)$-CMA-ES algorithm; compiled and adapted from [94] [95]

B.3 Cuckoo Search Algorithm (CSA)

The CSA is a derivative free PBM, developed 2009 by Yang and Deb [96], based on Lévy flight random walks, inspired by cuckoo's brood parasitism as well as by the Lévy random walking foraging behaviour of bacteria, insects, and higher animals (including humans, birds, flies, etc.) [96] [70]. The standard CSA metaheuristics workings (based mainly on [70]) are represented in the Algorithm 6 and (Eqs.27) as follows:

The standard Cuckoo Search Algorithm (CSA) (Eqs.27)

$$\text{new nests random initialization:}\quad \boldsymbol{x}_i^{(t=0)} = \rho_{ud} \odot (x_U - x_L) + x_L;\ \ \forall i = 1,\dots,\lambda;\quad \rho_{ud} \sim \mathscr{U}(0,1);\quad x_i = \{x_{i1}, x_{i2}, \dots, x_{id}\}^T; \tag{27a}$$

$$\text{global exploration random walk:}\ \boldsymbol{x}_i^{(t+1)} = \boldsymbol{x}_i^{(t)} + S_{szG}^{(t)} \odot \rho_{nd} = \boldsymbol{x}_i^{(t)} + \underbrace{\alpha_1 (x_i^{(t)} - x_{best}^{(t)}) \odot s}_{S_{szG}=step\ size} \odot \rho_{nd};\ \rho_{nd} \sim \mathscr{N}(0,1);\ s \sim \mathscr{L}evy(\beta); \tag{27b}$$

$$\text{from [97]:}\ \boldsymbol{s} = \frac{u}{|v|^{1/\beta}};\ \ u \sim \mathscr{N}(0, \sigma_u^2);\ \ \sigma_u = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma\big((1+\beta)/2\big) \cdot \beta\, 2^{(\beta-1)/2}} \right\}^{(1/\beta)};\ \ 0.3 \le \beta \le 1.99;\ \ v \sim \mathscr{N}(0, \sigma_v^2);\ \ \sigma_v = 1; \tag{27c}$$

$$\text{local exploitation random walk:}\ \boldsymbol{x}_i^{(t+1)} = \boldsymbol{x}_i^{(t)} + S_{szL}^{(t)} \odot K = \boldsymbol{x}_i^{(t)} + \underbrace{\alpha_2 \rho_n (x_j^{(t)} - x_k^{(t)})}_{S_{szL}=step\ size} \odot \underbrace{H(p_a - \varepsilon)}_{K};\ \ i,j,k \in \{1,\dots,\lambda\}; \tag{27d}$$

$$\rho_n \sim \mathscr{N}(0,1);\quad x_j^{(t)} \sim \mathscr{R}_p(x^{(t)});\ \ x_k^{(t)} \sim \mathscr{R}_p(x^{(t)});\quad K = H(p_a - \varepsilon) = \begin{cases} 1, & \text{if } p_a - \varepsilon \ge 0 \\ 0, & \text{otherwise} \end{cases};\ \ \varepsilon \sim \mathscr{U}(0,1); \tag{27e}$$

where: x_i is a d-dimensional candidate solution vector (one of the cuckoo nests); λ is population size; and x_U, x_L are the x_i bounds, scalars or d-sized vectors; t is the iteration counter (wherein $t = 0$ denotes the initialization stage);

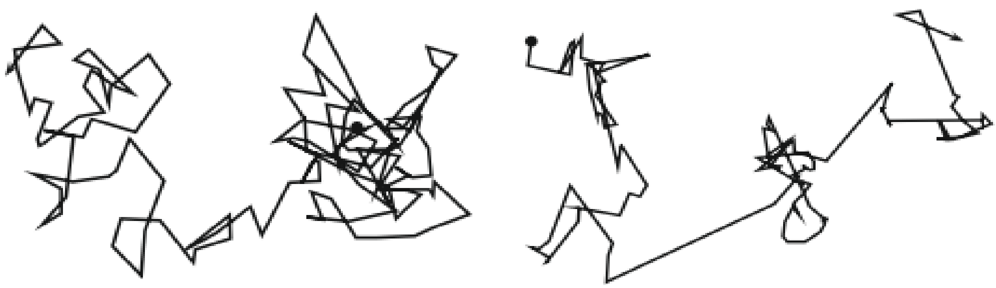
In turn, $\boldsymbol{s}$ is the random walk step drawn from Lévy distribution via Mantegna's algorithm [97], and, α_1 is a scaling factor constant tuned to characteristic scale of the problem under consideration (*e.g.*, $\alpha_1 = 0.01$); S_{szG} is the resulting step size which has a contribution of the iteration-wise difference of $(x_i^{(t)} - x_{best}^{(t)})$ wherein $x_{best}^{(t)}$ is the fittest nest so far.

K, an outcome of $H(.)$ a Heaviside function, represents the component-wise fraction (the eggs) of the old nests that will mutate, into new nests, with probability p_a , the alien egg discovery rate (or else, a crossover probability, similar to the DE's ***Cr*** parameter). S_{szL} is the step size for this mutation, which has a uniformly randomized contribution of α_2 and the difference $(x_j^{(t)} - x_k^{(t)})$ wherein $x_j^{(t)} \sim \mathscr{R}_p(x^{(t)})$ and $x_k^{(t)} \sim \mathscr{R}_p(x^{(t)})$ are different ($j \neq k$) random permutations of the solutions pool $x^{(t)}$.

The $\odot$ denotes element-wise matrix multiplication wherein $x_i, x_k, x_j, u, v, s, \rho_{ud}, \rho_{nd}, \varepsilon, S_{szG}, S_{szL}, K$ are d-dimensional vectors.

Function $\{bestNest, bestFitness, ...\}$ = `CSA` $(\lambda, p_a, \alpha_1, \alpha_2, \beta,\ x_L,\ x_U,\ f,\ f_{x^*},\ f_\varepsilon, ...)$
  //λ pop.size; p_a alien egg discovery rate; α_1, α_2-step size scaling factors; β LÃl'vy distribution index;
  //x_L, x_U x-bounds; f fitness function; f_{x^*} optimal f; f_ε tolerance to f_{x^*};
  Initialization: generate initial nests/solutions/particles:
   $\boldsymbol{Xnests} = \boldsymbol{XnewNests}$ = (λ uniformly distributed random d-sized vectors, within x-bounds); //using (Eq.27a);
  Evaluate $\boldsymbol{XnewNests}$ fitnesses, find and keep the fittest nest:
   $\{bestNest, bestFitness, bestNests, bestFitnesses\} = GetBestNest(Xnests, XnewNests, Xfitness, f)$
  while *stopping criterion not met* **do**
    Generate new nests ($\boldsymbol{XnewNests}$) by performing a LÃl'vy flight, using (Eq.27b), as also (Eq.27c);
    Evaluate $\boldsymbol{XnewNests}$ fitnesses; find and keep the fittest nest
    Mutate 'doomed' (alien egg) nests with probability p_a, thus generating $\boldsymbol{XnewNests}$, using (Eq.27d);
    Evaluate $\boldsymbol{XnewNests}$ fitnesses, find and keep the fittest nest:
  end
end

Algorithm 6: CSA Algorithmic Framework



(a) (b)

Figure 29 Random Walks in 50 consecutive steps (origin marked •): (a) Brownian; (b) Lévy (in: [70])

B.4 EBO and Differential Evolution (DE)

Differential Evolution (DE) is a derivative free PBM, developed 1995 by Storn and Price [79] [98]. It evolves a population of candidate solutions by iteratively performing: (i) differential mutation (mutant vectors are produced), (ii) crossover with rate Cr (which produces trial vectors); and then (iii) fitness based selection, which produces evolved (hopefully) target vectors/candidate solutions). The process is outlined in the Algorithm 7.

EBO/EBOwithCMAR is a derivative free PBM, developed 2017 by Kumar et.al [99], inspired by the mate-locating behaviour of male butterflies. It evolves 2 populations of candidate solutions, while also optimizing the control parameter space and featuring new diversity and exploitation strategies under such butterfly memetics perspective. That said, EBO and EBOwith-CMAR are a DE cast of algorithms: they generate target, mutant and trial vectors through an iterative evolution process comprising differential based mutation, crossover and selection,

Function $\{xBest, fBbest, ...\}$ = `DE` $(p, F, Cr,\ x_L,\ x_U,\ f(.),\ f_{x^*},\ f_\varepsilon, ...)$

  //p pop.size; F scaling factor; Cr crossover rate; x_L, x_U x-bounds; $f(.)$ fitn. func; f_{x^*} optim. f; f_ε gap to f_{x^*};

  Initialization: generate initial population (target vectors) by drawing uniform random vectors over x-hyperspace:

  $\boldsymbol{x}_{ij}^{(t=0)} \sim \mathscr{U}(0,1) \cdot (x_U - x_L) + x_L$; t - iteration counter;

  while *stopping criterion not met, for each target vector* x_i **do**

    Generate mutant vector: F-scaled difference of random target vectors (other mutant strategies available):

    $v_i^{(t+1)} = \boldsymbol{x}_i^{(t)} + F \cdot (x_{r_1}^{(t)} - x_{r_2}^{(t)})$; $i \neq r_1 \neq r_2$; r_1 and r_2 are random indexes of the target population;

    Generate trial vector $u_i^{(t+1)}$ by (exponential or binomial) crossover with probability Cr:

    $u_i^{(t+1)} = DoCrossover\left(x_i^{(t+1)},\ v_i^{(t+1)},\ Cr,\ crossoverType,\ \{OtherCrossOverParameters\}\right)$;

    Evaluate $u_i^{(t+1)}$ fitnesses, and, perform fitness based selection:

    $x_i^{(t+1)} = u_i^{(t+1)}$; iif: $f\left(u_i^{(t+1)}\right) \leq f\left(x_i^{(t)}\right)$; or else $x_i^{(t+1)} = x_i^{(t)}$: *i.e.*, in this case, x_i remains unchanged;

  end

end

Algorithm 7: Differential Evolution (DE) Algorithmic Framework

and using the same DE's main control parameters of crossover probability (***Cr***) and differential scaling factor (***F***); wherein most of such parameters and procedures are consistent with the basic workings of the DE metaheuristics (as seen in [99]). EBOwithCMAR however come with significant new or modified features over the basic DE paradigm, while also inheriting a number of features from the Adaptive Differential Evolution (JADE)/Linear (Population Reduction), Success History (based) Adaptive DE (L-SHADE) [100] lineage of DE variants/hybrids. EBO/EBOwithCMAR although not as fast as CMA-ES, has shown a high reliability in optimizing a wide range of global optimization test problems, which is supported by it (EBOwithCMAR) being the winner of the CEC'2017 competition [101], and corroborated by our own experiments/results in section (3.5.3).