COMPARISON OF LINEAR PROGRAMMING AND SIMULATED ANNEALING METHODS FOR OPTIMAL LOAD CONTROL AND ENERGY SCHEDULING IN SMART HOME

Master of Science Thesis

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Eskişehir, 2019

COMPARISON OF LINEAR PROGRAMMING AND SIMULATED ANNEALING METHODS FOR OPTIMAL LOAD CONTROL AND ENERGY SCHEDULING IN SMART HOME

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MASTER OF SCIENCE THESIS

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Eskişehir
Eskişehir Technical University
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August 2019

FINAL APPROVAL FOR THESIS

This thesis titled **"Comparison of Linear Programming and Simulated Annealing Methods for Optimal Load Control and Energy Scheduling in Smart Home"** has been prepared and submitted by **Emre GÜLER** in partial fullfilment of the requirements in "Eskişehir Technical University Directive on Graduate Education and Examination" for the Degree of Master of Science in Electrical and Electronics Engineering Department has been examined and approved in 22/08/2019.

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ABSTRACT

COMPARISON OF LINEAR PROGRAMMING AND SIMULATED ANNEALING METHODS FOR OPTIMAL LOAD CONTROL AND ENERGY SCHEDULING IN SMART HOME

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Many tariffs are used for electricity pricing. Electricity bills can be minimized by choosing the optimal working hours of appliances and for appropriate tariffs in smart homes. For this reason, Linear Programming (LP) and Simulated Annealing (SA) optimization methods are used. One of the aims of the thesis is to compare the results of these methods. The multi-time tariffs which have different energy unit prices at different times of the day are used in the thesis. Energy Management System (EMS) shifts time slots of some appliances to cheap energy unit prices. There may be overload in system because of shifting of working hours of appliances. Optimal load control is applied to prevent high peak demand as the second aim of the thesis. Mathematical model of the problem is created and GAMS application is used in the solution. The cost table consisting of the energy unit prices of each time slot is used as input. Also, SA technique which is one of the metaheuristic solution methods is used and the solution has been reached using C# program. Optimum electricity cost, working hours of the appliances and peak to average ratio are achieved by two different solutions and the results are compared. The results of the LP are better than SA.

Keywords: Linear programming, Simulated annealing, Smart home, Energy management system, Load control

ÖZET

AKILLI EVLERDE OPTİMUM YÜK KONTROLÜ VE ENERJİ PLANLAMASI İÇİN DOĞRUSAL PROGRAMLAMA VE TAVLAMA BENZETİMİ METOTLARININ KARŞILAŞTIRILMASI

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Eskişehir Teknik Üniversitesi, Lisansüstü Eğitim Enstitüsü, Ağustos, 2019
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Elektrik fiyatlandırılması için birçok tarife kullanılmaktadır. Akıllı evlerde cihazlar için optimum çalışma saatleri ve uygun tarife seçilerek elektrik faturaları minimize edilebilir. Bunun için tezde, optimizasyon metotlarından Doğrusal Programlama ve Tavlama Benzetimi kullanılmıştır. Tezin amaçlarından biri bu metotların sonuçlarını karşılaştırmaktır. Tezde kullanılan çok zamanlı tarifelerde günün farklı saatlerinde farklı enerji birim fiyatları bulunur. Enerji yönetim sistemi, bazı cihazları ucuz enerji birim fiyatları olan zaman aralıklarına kaydırır. Cihazların çalışma saatlerini kaydırmaktan dolayı sistemde aşırı yük oluşabilir. Tezin ikinci amacı olarak aşırı yük oluşmasını engellemek için optimum yük kontrolü uygulanmıştır. Problemin matematiksel modeli oluşturulmuş ve GAMS uygulaması çözümde kullanılmıştır. Girdi olarak her saat aralığının enerji birim fiyatından oluşan maliyet tablosu kullanılmıştır. Ayrıca metasezgisel çözüm yöntemlerinden Tavlama Benzetimi teknikleri kullanılmış ve C# programı ile çözüme ulaşılmıştır. İki farklı çözüm yolu ile optimum elektrik maliyeti, cihazların çalışma saatleri ve pik-ortalama güç oranına ulaşılmış ve sonuçlar kıyaslanmıştır. Doğrusal Programlamanın daha iyi çözümler verdiği görülmüştür.

Anahtar Kelimeler: Doğrusal programlama, Tavlama benzetimi, Akıllı ev, Enerji yönetim sistemi, Yük kontrolü

ACKNOWLEDGEMENT

I would like to thank my advisor, Assoc. Prof. Dr. Ümmühan Başaran Filik for all her patience, support, and guidance.

I would also like to thank to my thesis committee Prof. Dr. Doğan Erol and Assist. Prof. Dr. Şener Ağalar for their guidance and advices.

I am thankful to my family for moral support and patience. I would also thank my friends for their supportive behaviors.

22/08/2019

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with "scientific plagiarism detection program" used by Eskişehir Technical University, and that "it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

…………………..

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NOMENCLATURE

T	: Temperature (K)
k	: Boltzmann's constant (J/K)
δ	: Amplitude (m)
$C(S)$	: Initial solution
$C(S')$	: Neighboring solution
L	: Electrical load (V)
h	: Hour (hr)
L_{peak}	: Load at peak demand (V)
L_h	: Load at h hour (V)
L_{avg}	: Average load (V)
i	: Time Slots
j	: Appliances
C	: Cost (TL)
x	: Working status of appliances
P_j	: Power of j^{th} appliance (kW)
t	: Working hours of appliances (hr)
E_j	: Energy consumption of j^{th} appliance consumes at a single time slot (kWh)
a_i	: Hourly cost at i^{th} time slot (kr/kWh)
C_{ij}	: The cost of j^{th} appliance consumes at i^{th} time slot (TL)
T_0	: Initial temperature (K)
T_l	: Temperature Length
P_r	: Cooling ratio
E	: Energy (kWh)

ABBREVIATIONS

ABC: Artificial Bee Colony

ACO: Ant Colony Optimization

AMI: Advanced Metering Infrastructure

BA: Bat Algorithm

BFO: Bacterial Foraging Optimization

BPSO: Binary Particle Swarm Optimization

CAP: Capacity Market Program

CPP: Critical Peak Pricing

CSO: Cuckoo Search Optimization

DER: Distributed Energy Resources

DLC: Direct Load Control

DP: Dynamic Programming

DR: Demand Response

DSB: Demand Side Bidding

DSM: Demand Side Management

EDRP: Emergency Demand Response Program

EMS: Energy Management System

GA: Genetic Algorithm

HEMS: Home Energy Management System

HGPO: Hybrid Genetic Algorithm- Particle Swarm Optimization

IDA*: Iterative Deeping A*

ILP: Interruptible Load Program

LAN: Local Area Network

LP: Linear Programming

MDMS: Meter Data Management System

MILP: Mixed Integer Linear Programming

MINLP: Mixed Integer non-linear Programming

NLP: Non-linear Programming

PAR: Peak to Average Ratio

PSO: Particle Swarm Optimization

RTP: Real Time Pricing

SA: Simulated Annealing

TOU: Time of Use

WDO: Wind Driven Optimization

1. INTRODUCTION

Literature about home energy management system (HEMS), optimal load control, and optimization techniques for energy scheduling in smart home; is given in Section 1.1. In Section 1.2, aims of thesis are explained. Section 1.3 explains the organization of subjects.

1.1. Literature Review

Electricity consumption changes on hourly for a day in residential [1]. There are different tariffs for pricing electricity costs. The price of energy for each time slot may be different. Electricity costs can be reduced by shifting usage time of appliances in smart homes. However, shifting high load of appliances to night time tariff causes peak to average ratio (PAR) increasing. Optimization techniques are used to schedule household appliances in residential. Mathematical based and heuristic methods are usable for optimizing electricity cost.

The Advanced Metering Infrastructure (AMI) devices enable to communicate between power utilities and smart home users by accepting instruction information and sending data information [2-3]. Thus, HEMS schedules working times of household appliances. Recently, diverse decision support tools have been notified to optimize and implement scheduling appliances for residential consumers in smart homes [4-12]. Demand response (DR) strategies of power market are mainly named as price based DR or incentive based DR. Emergency demand response program (EDRP), direct load control (DLC), capacity/ancillary service program, interruptible load program (ILP), and demand side bidding (DSB) are classed in incentive based DR. Time of use pricing (TOU), critical peak pricing (CPP), and real time pricing (RTP) are categorized in price based DR. Price of electricity varies during 24 hours in TOU pricing model while electricity prices fluctuates hourly, picturing change of wholesale price of electricity in RTP. In RTP tariff, automatic energy consumption scheduling strategies was proposed in [8,9] to minimize electricity payment and these strategies have price predictors. Electricity prices are specified beforehand at peak hours of critical day in CPP strategy. Interruptible load strategy may be defined as interrupting or reducing the system's contribution to the load in emergencies. In DLC, operator remotely closes or deactivates electrical equipment in unreliable and emergency conditions. In DSB, customers offer reduction offers based on wholesale electricity market prices. EDRP handles system reliability accident due to blackouts, network operation risk, and power outages. Transmission line fault and generator fault are dealt with capacity/ancillary service program. The program is about demand side resource reserve, voltage control, and regulation of frequency [13].

DR is a significant form of demand side management (DSM) [14,15]. The traditional solution used to compensate growing and unsteady electricity demand is to create new generation capacity on the power generation side [16]. Industrial and commercial sector has the potential to provide less DR than the residential sector [17]. A residential load control strategy in a RTP tariff combined with inclining block rates in [8]. Achieving a trade-off between minimizing the waiting time and electricity cost for processing of appliances are aimed. The results show that the proposed optimal energy consumption strategy is particularly beneficial for consumers. The main objective of optimal DR scheme of HEMS is to minimize PAR and control the power consumption of household appliances in order to reduce the energy cost of consumers [13]. Optimal load scheduling provides stability of power system and improves energy efficiency [18,19]. Electricity consumption behaviors are affected by management tools. By this way, optimization of load shapes and achieving the adjustment are provided [20]. Stochastic and robust optimization techniques are compared in [21] and it is seen that these optimization techniques enable reducing energy cost. Derakshan, Shayanfar and Kazemi presented a model which is about optimal scheduling for residential. The model includes different electricity price, including TOU price, RTP, CPP, and no tariff for pricing. The results show that model helps to reduce cost [22].

Smart homes have system which controls working hours of appliances by user. There are various tariffs in each country. Single time tariffs and multi-time tariffs are used in some countries. Single time tariff allows same energy price for each time slot in a day. Multi-time tariff allows different energy prices for different time slot periods. As an advantage of multi-time tariff, high power appliances can be shifted to cheaper time slots. The load shifting may reduce electricity cost but peak load demand increases at cheaper time slots when most of high power appliances are shifted. Different optimization methods are used to reduce electricity bills and manage PAR. Game theory is as significant subject of mathematical optimization. Optimal decision making problem is solved by game theory [23]. By using conventional mathematical optimizations, the optimal DR solution was determined in [24]. A non-linear programming (NLP) approach is used to solve DR problem. Nikzad, Mozafari, Bashirvand, Solaymani, Ranjbar proposed a model using TOU rates as a two stage stochastic Mixed Integer Linear Programming (MILP) [25]. Nizami and Hossain presented that MILP can make significant saving to electricity costs [26]. MILP is a mathematical model to solve optimization problems. Besides, Amini, Frye, Ilic, and Karabasoglu made similar study to solve smart residential energy scheduling by using MILP [1]. In [27-29] MILP is used for optimal scheduling and performs significantly.

Heuristic algorithms are inspired by animal behavior and natural experience. Ahmad, Khan, Javaid, Hussain, Abdul, Almogren, Alamri, Niaz made comparison for HEMS with using metaheuristic algorithms like genetic algorithm (GA), binary particle swarm optimization (BPSO), wind driven optimization (WDO), bacterial foraging optimization (BFO), hybrid GA-PSO (HGPO) [30]. They found less electricity cost and PAR using HGPO. Vilar and Alfonso put forward Simulated Annealing (SA) is useful for residential energy management system [31]. Some thesis about LP and SA are examined. It is seen that LP and SA methods are helpful for many problems. The optimization methods are used for either energy scheduling or optimal load control in most of the examined thesis. In this thesis, LP and SA methods are used both energy scheduling and optimal load control problems. Emre Güler and Ümmühan Başaran Filik presented the advantages and disadvantages of MILP and SA methods for energy scheduling [32].

1.2.Aim and Objectives of Thesis

The main purposes of this study can be divided into three parts. Firstly, reduction of energy cost is planned in smart home. HEMS helps to schedule appliances and working on time slots with less unit prices for appliances is aimed. The optimum working hours of appliances are determined by optimization methods. Mathematical based and metaheuristic optimization methods are used for scheduling. LP and SA methods are used for this study.

The shifting high power household appliances to cheaper time slots may increase peak load demand at these hours so it causes PAR increasing as well. For this reason, developing an optimal load control is the second purpose of this study. Optimal load control avoids high PAR values by controlling the load on certain limit. Finally, comparison of LP and SA methods is one of the objectives of this study. The results of

LP and SA methods compared. Also, the results which optimal load control is applied the system and is not applied the system are compared. The best results of electricity cost and PAR values for all scenarios are discussed.

1.3. Organization of Thesis

In Chapter 2, infrastructure HEMS, classification and properties of optimization methods, mathematical formulations of optimal load control and pricing strategies are clarified. Mathematical expressions of problem, algorithms and results are stated in Chapter 3. Conclusion is given in Chapter 4.

2. OPTIMIZATION OF SYSTEM

In this part, HEMS structure, optimization methods, optimal load control principles, and pricing strategies are explained.

2.1. HEMS Structure

HEMS mainly aims to minimize the electricity cost and reduce load demand in peak time slots. Control center, billing center, smart meter, and communication are used in HEMS infrastructure. Billing center serves to prepare electricity bills for different tariff choices and conditions. Control center takes information from smart meters and could shift the load from high peak. Smart meter measures voltages, frequencies, consuming energy. It transmits measured data to control center [33].

Communication between power utility and home consumers is realized with AMI devices that send data information and accept instruction information. Advanced metering systems are contained of digital hardware and software which combine interval data measurement with continuously available remote communications. AMI measures time-based, detailed information and frequent collection and transmittal of such information to various parties [34]. Local area network (LAN) communication, head end data collectors, smart meters, and meter data management system (MDMS) are some subsystems of AMI system. There are shiftable loads like dishwasher, washing machine and non-shiftable loads like television. HEMS advices user to change manually working hours of non-shiftable loads in this proposed study.

2.2. Optimization Methods

Classical optimization methods are mainly divided into two parts as exact and approximate methods which are shown in Figure 2.1. Branch and bound, branch and cut, branch and price, constraint programming (CP), dynamic programming (DP), A^*, iterative deeping A^* (IDA^*) are the parts of exact methods. Heuristic and approximation algorithms are subject of approximate methods. Also, heuristic algorithms are divided into metaheuristics and problem-specific heuristics [35].

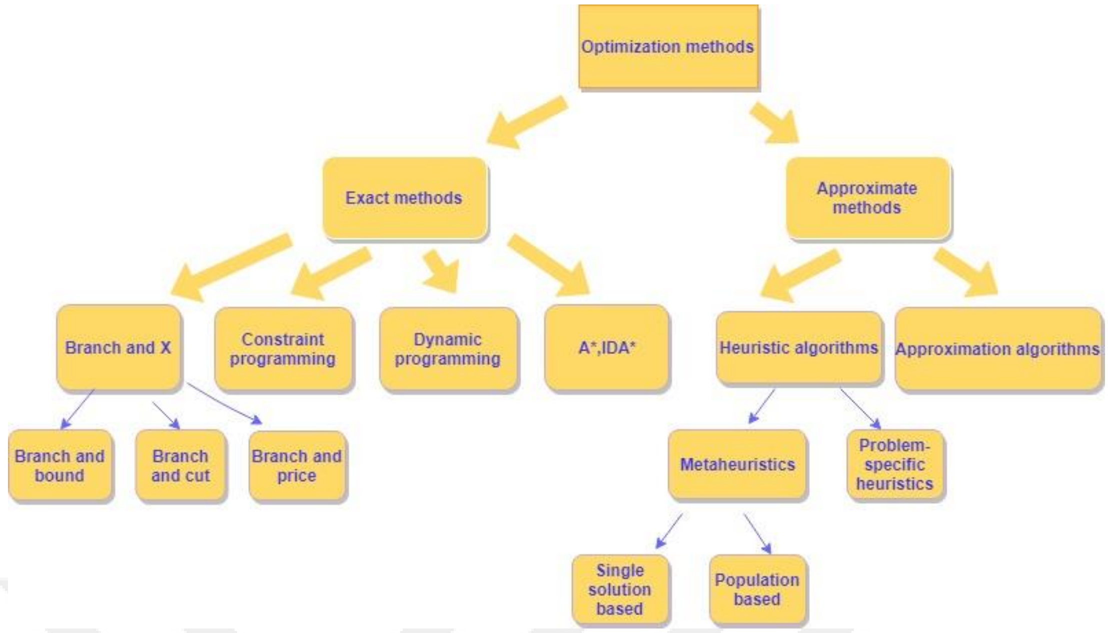

Figure 2.1. Classical Optimization Methods [35]

2.2.1. Exact methods

DP is attributed on recursive division of a question into simpler subparts of question. A^* and branch - bound algorithm are attributed on exact counting of all solutions of problem. CP problems are modeled by a set of variables linked by a set of constraints. Small instances of difficult problems may be applied by exact methods [35].

2.2.1.1. Dynamic programming (DP)

DP is a special planning method that achieves multiple operations sequentially. DP solves the problem in stages and tries to find the most appropriate solution at each stage. Calculations at different stages are obtained by associating them with repetitive calculations in which an optimal solution is ultimately obtained [36]. Many mathematical programming methods are used to achieve the best solution. DP uses iteration method. Since there is no sequential relationship, the stages are not a solution alone, but contain the information to reach the optimum solution [37]. There are two types of DP problem models, deterministic and stochastic. In a multi-stage decision-making process, the process is deterministic if all factors affecting the decision are fully known. Stochastic structured DP is mentioned if there is randomness in the transition function related to the process [38].

2.2.2. Approximate methods

Approximate methods do not guarantee optimality of solutions while exact methods mostly do. Nevertheless, approximate methods create good quality solutions. Heuristics obtain good performance in a wide range of problems. Approximation algorithms guarantee the bound of obtained solution from global optimum [39].

2.3. Mathematical Optimizations

Mathematical optimization is the selection of the best element in terms of some existing criteria. These optimization studies can be mainly divided into two parts as LP and NLP. Mixed integer nonlinear programming (MINLP) and MILP are some examples of conventional mathematical optimizations. The advantage of mathematical optimization models is their fast computational solutions. The application time is realized in milliseconds for results of LP while in seconds for results of SA for this thesis. Also, optimal solutions of mathematical optimization models can mostly be guaranteed. However, they are not good at dealing with non-convex cost functions. They do not give the best results in solving larger scale combinatorial optimization problem [40].

2.3.1. Linear programming (LP)

Under certain constraints the mathematical model created for a specific purpose in the form of profit maximization or cost minimization by making the most efficient use of scarce resources, is called LP. Some assumptions need to be provided to minimize the loss of information in mathematical expression of a real system. The assumption of linearity shows that the contribution of each decision variable to the objective function is proportional to the value of that decision variable unlike the values of other decision variables. The assumption of certainty is that each parameter and coefficient is known in the LP model. The assumption of summability is a natural consequence of the assumption of linearity while expressing the sum of the contributions formed according to the value of the decision variables. The assumption of severability is the ability of decision variables to take continuous values [38, 41]. In a mathematical expression of a typical LP model, there are three basic elements: objective function, restrictive functions and positivity constraint [42].

Objective Function: A LP model includes the objective function, which is a linear function of decision variables ($x1$, $x2$,…, xn). Objective function shows the functional relationship between decision variables and the purpose of the decision maker. This purpose function can be maximized or minimized.

$$Z_{max/min} = \sum_{j=1}^{n} c_j x_j = c_1 x_1 + c_2 x_n + \ldots + c_n x_n \tag{2.1}$$

Restrictive Functions: Restrictive functions explain decision variables and the relationship between these variables and parameters as mathematical equations. The values of the restrictive functions used to express not only the limits of resources but also the requirements and management decisions are predetermined and used to define the model. Each constraint set exists in the form of linear equation or inequality.

$$\sum_{j=1}^{n} a_{ij} x_j \{\geq, =, \leq\} b_i, \mathrm{i} = (1, 2, \ldots, \mathrm{m})$$

$$a_{11} x_1 + a_{12} x_2 + \ldots + a_{1n} x_n \{\geq, =, \leq\} b1$$

$$a_{21} x_1 + a_{22} x_2 + \ldots + a_{2n} x_n \{\geq, =, \leq\} b2$$

$$\ldots$$

$$\ldots$$

$$a_{m1} x_1 + a_{m2} x_2 + \ldots + a_{mn} x_n \{\geq, =, \leq\} \mathrm{m}\ 2 \tag{2.2}$$

Non-Negative Constraint: Decision variables under the control of the decision maker are unknown for the model and their values are determined by the analysis of the model. These variables, also called control variables, do not take negative values because they are under the control of the decision maker [43].

$$x_j \geq 0, (j = 1, 2, \ldots, n) \tag{2.3}$$

$$x_1, x_2, \ldots, x_n \geq 0 \tag{2.4}$$

The parameters in formulations; z is objective function, x_j is decision variable, c_j is objective function coefficient of decision variables, a_j is input coefficient of decision variables, b_i is restricted amount of resources, m is number of constraints and n is number of variable [44].

2.3.1.1. Mixed integer linear programming (MILP)

Some decision variables should definitely take integer values when constructing a model of LP problems. On the other hand, they may be allowed to take fractional values with the idea that the fractional part of the decision variable which can take large values to suit the DP, can be ignored. In such cases, problems are called integer programs and the solution of such programs is called integer programming. MILP guarantees the globally optimal solution within the limits of tolerance [45]. Branch-bound algorithm is mostly used in MILP problems [45-48]. Branch-bound algorithm is based on the solution of the problems obtained by loosening the integer variables to any real number between the smallest and largest values in the set of integers. Each branch in branch-bound algorithm terminates in the following cases:

- All of the variables that need to take integer value in completely or partially loosened problem and this solution is called integer solution and updated if the best objective function value is required,
- The objective function value in a node is worse than the current best objective function value.
- Solving the problem in a node does not provide some of the constraints.

A branch-bound tree is created for the problem by following these criteria, and the best solution is reached after all branches are terminated [49].

2.3.2. Non-Linear programming (NLP)

General cases where objective function or constraints are not linear are examined by NLP models. In NLP, operation is performed according to whether the function is convex or concave. It is not always possible to solve systems with LP models. The fact that the conditions of the problems or the objective function or both are nonlinear, makes the situation more difficult and complex [34]. NLP problems can be examined under three titles. These are unconstrained univariate optimization methods, unconstrained multivariate optimization methods, and constrained multivariate optimization methods. The aim of the univariate NLP problem is to find the optimal point of the univariate objective function without any restrictions [50].

2.4. Metaheuristics

Metaheuristics handle wide range problems by satisfying solutions in acceptable time. They do not guarantee optimal solutions. Aerodynamics, structural optimization in electronics, fluid dynamics, engineering design, planning in routing problems, scheduling and production problem, supply chain management, logistics and transportation are some of the applications of metaheuristics [35].

When designing metaheuristic system, encouraging regions are defined by good solutions. Encouraging regions are detected more to find better solutions. One of the reasons to need metaheuristics is the optimization problem may have a structure in which the process of finding the exact solution cannot be defined. Other reason is that heuristic algorithms in terms of intelligibility can be much simpler for decision maker. Also, heuristic algorithms can be used for learning purposes and as part of finding the exact solution [51].

There are numerous type of metaheuristic algorithms like local search, GA, BFO, WDO, ant colony optimization (ACO), artificial bee colony (ABC), particle swarm optimization (PSO), simulated annealing (SA), cuckoo search optimization (CSO), bat search algorithm or bat algorithm (BA) and so on [35]. The advantages of metaheuristic optimization methods have handling high dimensional optimization problems. They could be used in parallel operations. Computational times of metaheuristics usually take long time. The other disadvantage of metaheuristics is they need to define numerous relevant parameters [40].

2.4.1. Simulated annealing (SA)

S. Kirkpatrick et al. and V. Cerny derived this algorithm and it applies to optimization problems. VLSI and graph partitioning are the first applied subjects with SA. It is based on statistical mechanical principles in which the annealing process requires heating and then slowly cooling a material to obtain a strong crystalline structure. The SA algorithm simulates energy changes in a system exposed to the cooling state until it approaches equilibrium state [35].

The probability of increase at T of δE amplitude in energy is shown as below where k is Boltzman constant:

$$p(\delta E) = \exp(-\delta E / kT) \tag{2.5}$$

General options define elements of cooling strategy. A cooling schedule should answer some questions. Determination of a suitable initial value for temperature parameter T, definition of cooling rate and temperature change rule, determination of the number of iterations to be performed at each temperature, determination of the criterion for stopping the investigation are mentioned questions. Basic steps of algorithm of SA are specified as:

- **Step 1:** Generate heuristic or random initial solution S

- **Step 2:** Generate a neighboring solution S ' and calculate the difference between the objective values of solution S with this solution. $\Delta = C(S') - C(S)$

- **Step 3:** Replace the solution S with the S 'solution If $\Delta < 0$ or $\Delta > 0$ but if the randomness process $e^{-\Delta/T} > 0$ defined by the current temperature T is accepted.

- **Step 4:** T temperature varies according to some conditions,

  - according to the used cooling schedule,
  - whether there is an improvement in the solutions produced in the Step 3,
  - whether the neighborhood of the S solution has been fully searched.

- **Step 5:** Stop search if stop criterion is met, otherwise go to step 2.

2.4.2. Genetic algorithm (GA)

GA is developed by J. Holland in 1975 [36]. GA is a kind of directed random research algorithms. In GA, the structure of the problem is coded as chromosome. Then, a population of these chromosomes is generated. New chromosomes are obtained by some chromosomes are selected from the population with crossing and mutation. Those who have better conformity than their new chromosomes are transferred to the next generations. This process is performed recursively until the stop criterion [53]. Steps of genetic algorithm can be shown as [51]:

Step 1: Create a startup population that corresponds to the solutions.

Step 2: Calculate the conformity value of each solution in the population.

Step 3: Stop the search if the stop criterion is provided.

If not, perform the following steps.

Step 3.1: Apply natural selection (solutions with higher suitability are more represented in the new population).

Step 3.2: Apply crossover (Two new solutions are generated from the two existing solutions).

Step 3.3: Apply mutation (Random changes in solutions are generated). Create new population.

Step 4: Go to Step 2.

2.4.3. Particle swarm optimization (PSO)

PSO is an evolutionary calculation technique inspired by the behavior of bird flocks [54]. The first was the optimization of non-linear functions and was introduced by Kennedy and Eberhart on 1995 [55].

Each particle has its own speed which accelerates the thread to the best result with the information it receives from other parts. In each generation, this speed is recalculated using previous best results. In this way, the individuals in the population are getting better positions. The steps of the algorithm are as follows [56].

Step 1: Formation of population; The particles are generated together with randomly generated starting positions and speeds.

Step 2: Calculation of conformity values; conformity values of all individuals in the population are calculated.

Step 3: Finding the best member; In each generation, all individuals are compared with the best (pbest) in the previous generation. The place is replaced if there are better individuals.

Step 4: Globally the best; is replaced if the best value in the generation is better than the global best value.

Step 5: Update of position and speed;

Step 6: Repeat steps 2 to 5 until the maximum number of cycles is reached.

2.4.4. Artificial bee colony (ABC) algorithm

The first application of bee behavior in the field of optimization was made by Sato and Hagiwara. Sato and Hagiwara were inspired by the behavior of real bees and developed an intuitive so-called “Bee System” [57]. Finally, Derviş Karaboğa developed the ABC algorithm by modeling the foraging behavior of bees [68]. In nature, bees follow the steps below when searching for food [51]:

- At the beginning of the foraging process, explorer bees start searching for food by random searching around
- Once food sources have been discovered, explorer bees become workers bees and carry nectar to the hive. After the bees discharge the nectar to the hive, they either return to the food source or transmit the information about the source to the bees waiting in the hive.
- Scout bees watch dances that point to rich sources and prefer the food source depending on the frequency of the dance, proportional to the quality of the food.

The basic steps of the ABC algorithm are as follows:

Step 1: Production of initial food supply zones

Step 2: Sending bees to food supply areas

Step 3: Calculation of probability values to be used in probability selection according to the information coming from the tasked bees

Step 4: Choosing food source region according to probability values of bees

Step 5: Release of resources to be left and explorer bee production

Step 6: Repeat Steps 2 through 5 until the maximum number of cycles is reached.

2.4.5. Ant colony optimization (ACO)

Ant colony optimization is a heuristic inspired by the behavior of real ants to find the shortest path between food and nest [54]. Ants leave a certain amount of pheromone substance on the way they are moving. Ants are more likely to prefer aspects in which the pheromone substance is denser. The amount of ant in the preferred route increases due to the density of the pheromone substance [51]. The steps of algorithm of ACO are as below [59]:

Step 1: Initial pheromone values are determined.

Step 2: Ants are randomly placed on each node.

Step 3: Each ant selects the next city based on the possibility of local search and completes its round.

Step 4: The length of the roads traveled by each ant is calculated and local pheromone update is performed.

Step 5: The best solution is calculated and used for global pheromone update.

Step 6: Go to Step 2 until the maximum number of iterations or stop criterion is met.

2.5. Optimal Load Control

Most of appliances are supposed to work at cheaper tariff to minimize electricity cost when multi-time tariff is used in optimization model. This may be cause increasing peak to average ratio (PAR). Optimal load control aims to reduce PAR. Power system is more reliable with low PAR values because high load demand is not good for power capacity of system. Let assume L load at hour of $h \in H = \{1, \dots, H\}$ where H=24. The daily peak load and average load is respectively [5],

$$L_{peak} = \max_{h \in H} L_h \tag{2.6.a}$$

$$L_{avg} = \frac{1}{H} \sum_{h \in H} L_h \tag{2.6.b}$$

Also, PAR is calculated as in Equation 2.7,

$$PAR = \frac{L_{peak}}{L_{avg}} = \frac{H \max_{h \in H} L_h}{\sum_{h \in H} L_h} \tag{2.7}$$

2.6. Pricing Strategies

Electricity pricing can be made in several ways. Many pricing strategies are developed. DR provides reducing high load power consumption and shifting electricity usage in peak periods. DR can be categorized into price based DR and incentive based DR. Figure 2.2 shows the role of DR programs in power system planning and operations. Price based DR includes TOU pricing, CPP, and RTP. DLC, ILP, EDRP, DSB, and capacity/ancillary service program can be classified in incentive based DR.

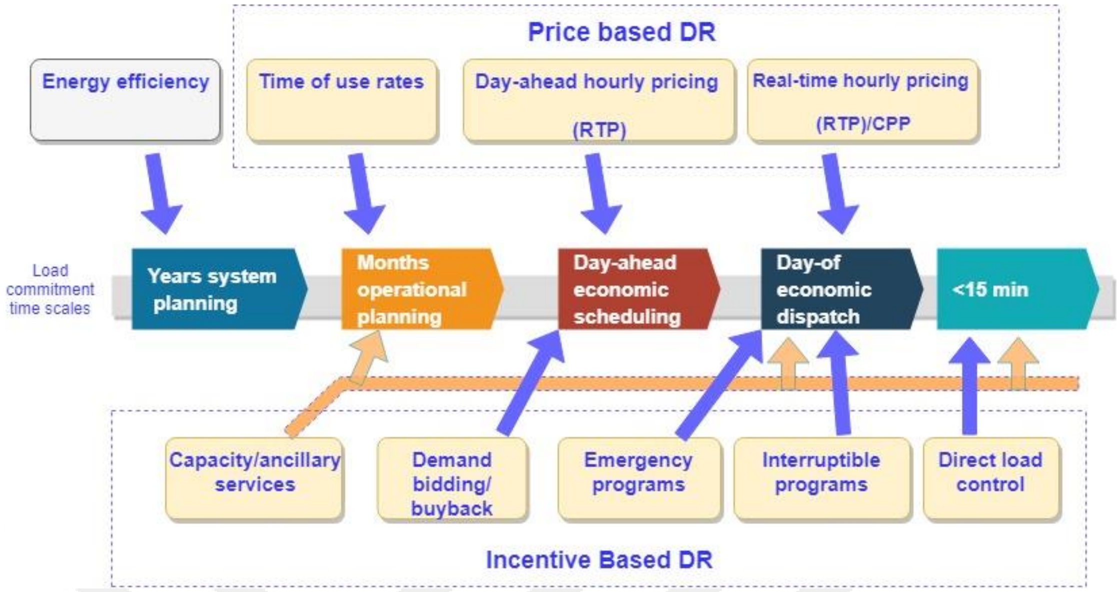

Figure 2.2. Role of DR programs in power system planning and operations [24]

2.6.1. Price based DR

TOU pricing gives information about long term electricity power system cost. There is monthly operational planning. TOU provides different unit prices for 24 hour period. Peak, off-peak and mid-peak are common periods of TOU pricing. Off peak has the lowest price of all while peak has the highest price. An optimized TOU program could make better load curve characteristics. Also, it reduces energy costs [60, 61]. The load characteristics are affected by many situations. Energy prices, periods of the off peak, on peak and mid peak, elasticity values are examples of these situations.

Electricity prices can change hourly in RTP and this shows RTP is a dynamic price. RTP reflects supply and demand balance. RTP helps electricity bills to reduce because it has lower prices in some time slots. Time slots are generally divided as one hour. RTP provides reducing peak load values so system gets more reliable. Day ahead prices and hourly ahead prices are two kinds of RTP rates. Prices are determined a day before in day ahead prices and they are different for each hour in next day while prices are determined previous hour in hourly ahead prices [62]. CPP is used in specific time periods and emergency situations. The price of electricity is raised reasonably. It can be named as real time hourly pricing.

2.6.2. Incentive based DR

The incentive based programs are regulated by utility for customers. DLC program is a control system which can turn on or off power system remotely. ILP is a tariff which gives chance of discount to customers if they reduce load. However, if customers do not reduce, they pay huge sum of fine. DSB is a mechanism that big customers can bid in wholesale market and it aims to reduce load. EDRP provides incentive payments to customers if they succeed to reduce load. Capacity market program (CAP) is offered to customers to reduce load when reliability of the system is not appropriate [62].

3. APPLICATION AND RESULTS

Mathematical based approaches and heuristic methods can be used to solve minimization electricity bills and reduction of high load demand problem. LP and SA methods are compared for this study. This part of study consists three parts. The first part explains objective function of the problem, constraints, assumptions and mathematical expression of optimal load control. The second part contains algorithm of SA. Results for both solutions are given in the third section.

3.1. Mathematical Definition of the Problem

This section consists from objective function, assumptions, constraints and mathematical expression of optimal load control.

3.1.1. Objective function of the problem

The appliance can work during 24 hours within some constraints, j represents the appliances and i represents the time slots. Minimum cost function is shown as:

$$\min \sum_{i \in I}^{i} \sum_{j \in J}^{j} C(\mathrm{i}, \mathrm{j}) \cdot x(\mathrm{i}, \mathrm{j}) \tag{3.1}$$

3.1.2. Assumptions of the problem

Let us assume binary variable x indicate turning “On”

$x_{ij} = 1$; j^{th} appliance is used at i^{th} time slot

$= 0$; else

P_j= power of j^{th} appliance

t= working hours of appliances

E_j is the energy consumption of j^{th} appliance consumes at a single time slot (kWh)

$$E_j = P_j . t \tag{3.2}$$

and a_i is the price of i^{th} time slot (kr/kWh).

C_{ij}= the cost (kr) of j^{th} appliance consumes at i^{th} time slot

$$C_{ij} = E_j \cdot a_i \tag{3.3}$$

Multi-time tariff prices without taxes in Turkey since 1/1/2019 are shown in Table 3.1. All prices will be shown without taxes through paper.

Table 3.1. Residential multi time tariff prices [63]

Tariffs	Time Slots	Price(kr/kWh)
Daytime	06-17	43.8686
Peak	17-22	63.8935
Nighttime	22-06	27.8547

3.1.3. Constraints of working status of appliances

Appliances are represented by j and appliances are washing machine, dishwasher, air conditioner, television, iron, oven, refrigerator respectively. Power values of appliances and how long will they work are shown in Table 3.2.

Table 3.2. Power information of household appliances

Appliances	j	Power(kW)	Hours of work
Washing Machine	1	0.8	3
Dishwasher	2	1.8	2
Air Conditioner	3	2	3
TV	4	0.2	2
Iron	5	2.5	1
Oven	6	2	2
Refrigerator	7	0.9	24

Equation 3.4 means every appliance has to work at least one time in a day. In this model, working hours of some appliances can be any hour, others' potential working hours are determined by user. In example, washing machine, dishwasher, refrigerator can be work anytime in a day. Air conditioner has to work 3 hours between 12:00 - 18:00. TV works 2 hours between 20:00 - 24:00. Iron works one hour between 09:00 - 24:00 while oven works 2 hours between 09:00 - 21:00 according to equation 3.9 and 3.10. Equation 3.11 means refrigerator works 24 hours.

$$\sum_{i=1}^{24} x(i,\ j) \geq 1, \forall j \tag{3.4}$$

$$\sum_{i=1}^{24} x(i,\ j) = 3, \forall j = 1 \tag{3.5}$$

$$\sum_{i=1}^{24} x(\mathrm{i},\ \mathrm{j}) = 2, \forall j = 2 \tag{3.6}$$

$$\sum_{i=12}^{17} x(i,\ j) = 3, \forall j = 3 \tag{3.7}$$

$$\sum_{i=20}^{23} x(i,\ j) = 2, \forall j = 4 \tag{3.8}$$

$$\sum_{i=9}^{23} x(\mathrm{i},\ \mathrm{j}) = 1, \forall j = 5 \tag{3.9}$$

$$\sum_{i=9}^{20} x(i,\ j) = 2, \forall j = 6 \tag{3.10}$$

$$\sum_{i=1}^{24} x(i,\ j) = 24, \forall j = 7 \tag{3.11}$$

3.1.4. Mathematical expression of optimal load control

Optimal load control is applied to system and is not applied the system scenarios are compared for both methods. In our design, if hourly cost is greater than 0.9 TL, up to two appliances will work to reduce PAR. Let us assume a_i is hourly cost value, this operation is shown in Equation 3.12:

$$(if\ (a_i) > 0.9), \tag{3.12}$$

$$\text{then} \sum_{j=1}^{j} x_{ij} \leq 2, \forall i \tag{3.13}$$

3.2. Algorithm of SA

The objective of algorithm is to shifting load of household appliances from high priced time slots to low priced time slots. Making an analogy between the optimization problem and the physical annealing process: X corresponds solutions, C corresponds the cost of energy, T represents temperature and it simulates cooling process. Algorithm compares time slots. If compared one is smaller, it is considered a new solution. If it is bigger and the possibility of acceptance is realized, then it is considered as new solution. Initial temperature is considered as $T_0 = 30$, cooling ratio $P_r = 0.85$, temperature length $T_l = 24$ and algorithm is as follows [31] :

Select an initial state X_i and temperature T_0;

Repeat

for i = 1 to T_L do

Generate a new state Xn by applying a small randomly generated perturbation;

Calculate the change in energy cost $\Delta C = C(X_n) - C(X_i)$;

$if \nabla C \leq 0$ then

The new state is accepted as the starting point for the next move: X = Xn;

else if ΔC > 0 then

The new state is accepted with probability $Pr = \exp(-\Delta C / T)$

end if

end for

Decrease the temperature monotonically (T = Pr * T);

until stopping criterion is reached

3.3. Comparison of the Results

The results of the LP and SA methods are compared in this part. Electricity cost and PAR values are the important criterion for comparison. Applied optimization technique and load control situation are categorized as scenario numbers which are shown in Table 3.3.

Table 3.3. Applied modes with scenario numbers

Scenario Number	Applied Mode
Scenario 0	Single time tariff
Scenario 1	LP optimized and optimal load control is not applied
Scenario 2	LP optimized and optimal load control is applied
Scenario 3	SA optimized and optimal load control is not applied
Scenario 4	SA optimized and optimal load control is applied

3.3.1. Results with using LP

Single time tariff price is 43.3187 kr/kWh and energy consumption is 40.5 kWh for the proposed system. Therefore, electricity cost for single time tariff is obtained as 17.544 TL for one day. LP optimizes the system as electricity cost is 15.838 TL for optimal load control is not applied scenario for one day. The energy cost of appliances is shown in Table 3.4 for LP optimization when optimal load control is not applied the system and (Scenario 1).

Table 3.4. Used tariffs and energy costs of appliances for Scenario 1

Appliance	Used Tariff	Energy Cost(kr/kWh)
Washing machine	Night time	66.852
Dishwasher	Night time	100.276
Air Conditioner	Day time	263.211
Television	Night time	18.350
Iron	Night time	69.637
Oven	Day time	175.474
Refrigerator	Day time-Peak-Night time	897.305

Multi-time tariff with LP optimized and optimal load control is not applied the system provides 9.72% saving than single time tariff .Table 3.5 shows LP optimization when optimal load control is applied to system (Scenario 2). LP optimizes the system as electricity cost is 15.911 TL for optimal load control is applied scenario for one day.

Table 3.5. Used tariffs and energy costs of appliances for Scenario 2

Appliance	Used Tariff	Energy Cost(kr/kWh)
Washing machine	Night time	66.852
Dishwasher	Night time	100.276
Air Conditioner	Day time	263.211
Television	Peak-Night time	11.142
Iron	Night time	69.637
Oven	Day time	175.474
Refrigerator	Day time-Peak-Night time	897.305

Use of household appliances during day is shown in Figure 3.1 and 3.2 for Scenario 1 and Scenario 2. Multi-time tariff with LP optimization when optimal load control is applied to system (Scenario 2) provides 9.3 % saving than single time tariff.

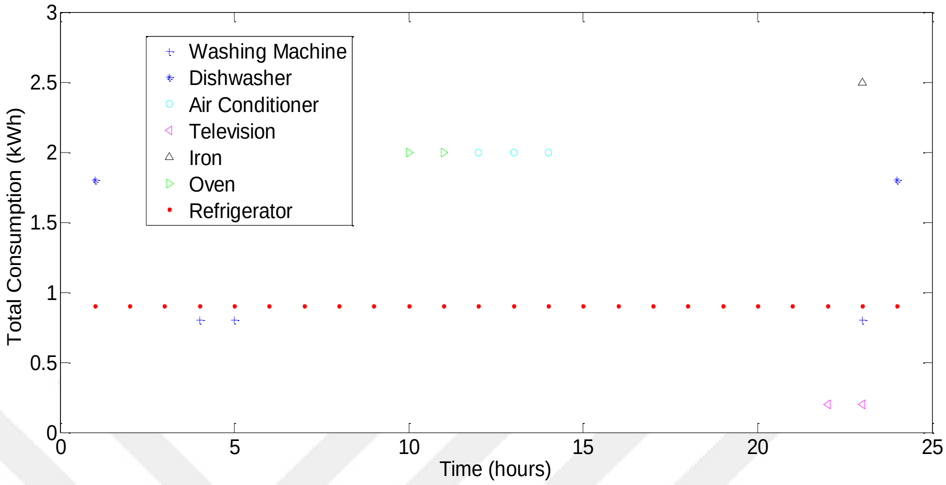

Figure 3.1. Use of household appliances during the day (Scenario 1)

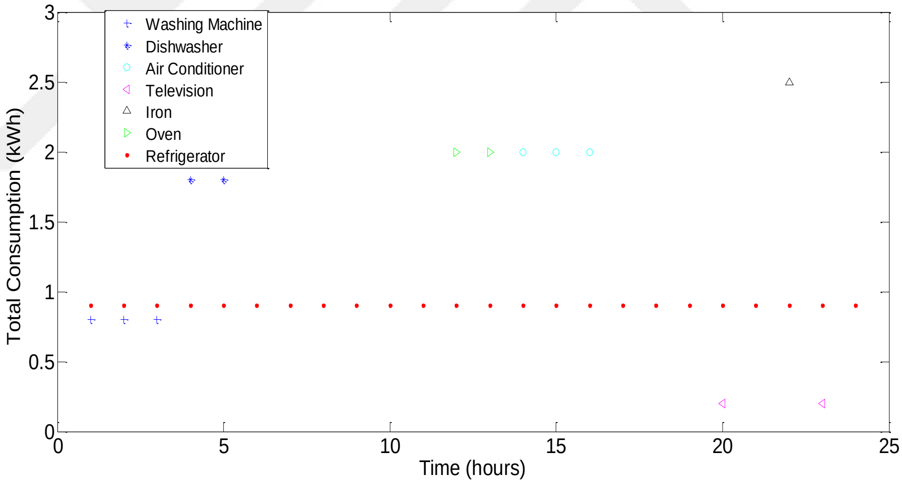

Figure 3.2. Use of household appliances during the day (Scenario 2)

Peak load for load control is not applied scenario is obtained as 4.4 kW while for load control is applied as 3.4 kW which is shown in Figure 3.3. The load control system reduces PAR in Scenario 2 as 22.7 % than Scenario 1 for LP optimization. Therefore, PAR for Scenario 1 and Scenario 2 are respectively,

$$PAR = \frac{L_{peak}}{L_{avg}} = \frac{4.4}{1.687} = 2.607 \tag{3.14}$$

$$PAR = \frac{L_{peak}}{L_{avg}} = \frac{3.4}{1.687} = 2.015 \tag{3.15}$$

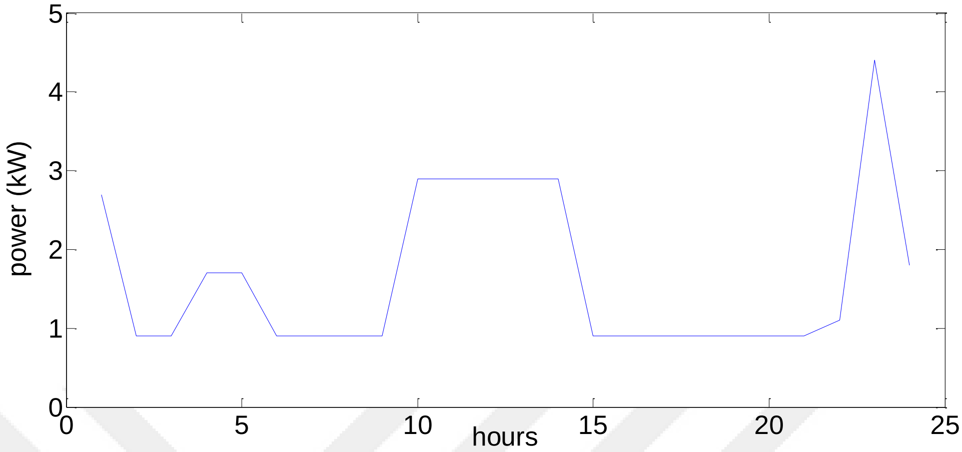

Figure 3.3. Hourly load values for Scenario 1

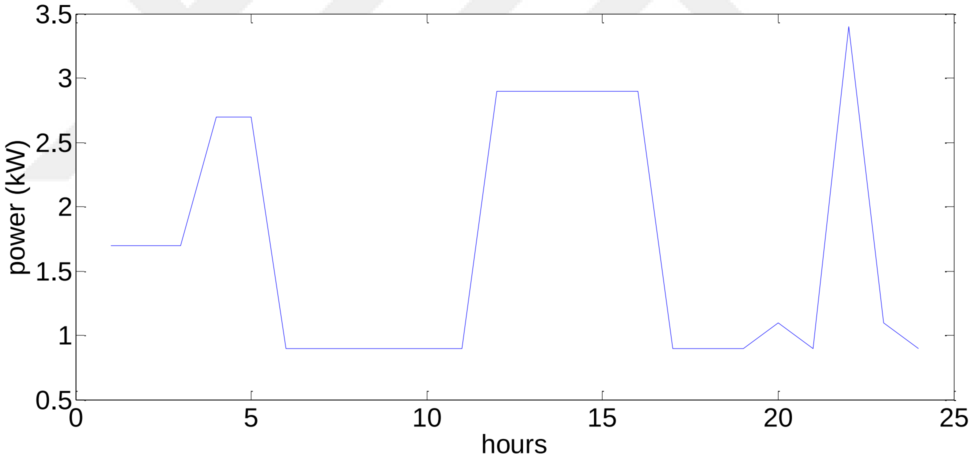

Figure 3.4. Hourly load values for Scenario 2

3.3.2. Results with using SA

The system which is optimized by SA algorithm and optimal load control is not applied (Scenario 3) shows same performance as LP optimized and optimal load control is not applied to system (Scenario 1). Used tariffs and energy cost for SA when optimal load control is not applied (Scenario 3) and SA when optimal load control is applied (Scenario 4) are shown in Table 3.6 and 3.7. Use of household appliances during day is shown in Figure 3.5 and 3.6 for Scenario 3 and Scenario 4.

Table 3.6. Used tariffs and energy costs of appliances for Scenario 3

Appliance	Used Tariff	Energy Cost(kr/kWh)
Washing machine	Night time	66.852
Dishwasher	Night time	100.276
Air Conditioner	Day time	263.211
Television	Night time	11.142
Iron	Night time	69.637
Oven	Day time	175.474
Refrigerator	Day time-Peak-Night time	897.305

Table 3.7. Used tariffs and energy costs of appliances for Scenario 4

Appliance	Used Tariff	Energy Cost(kr/kWh)
Washing machine	Night time	66.852
Dishwasher	Night time	100.276
Air Conditioner	Day time	263.211
Television	Peak-Night time	18.350
Iron	Day time	109.671
Oven	Day time	175.474
Refrigerator	Day time-Peak-Night time	897.305

SA optimization performs as 9.72% saving than single time tariff. On the other hand, SA optimized and optimal load control is applied to the system costs higher than LP optimized and load control is applied to the system. Energy cost for SA when load control is applied to the system is 16.31 TL for one day. Even so, it saves 7.03% than single time tariff.

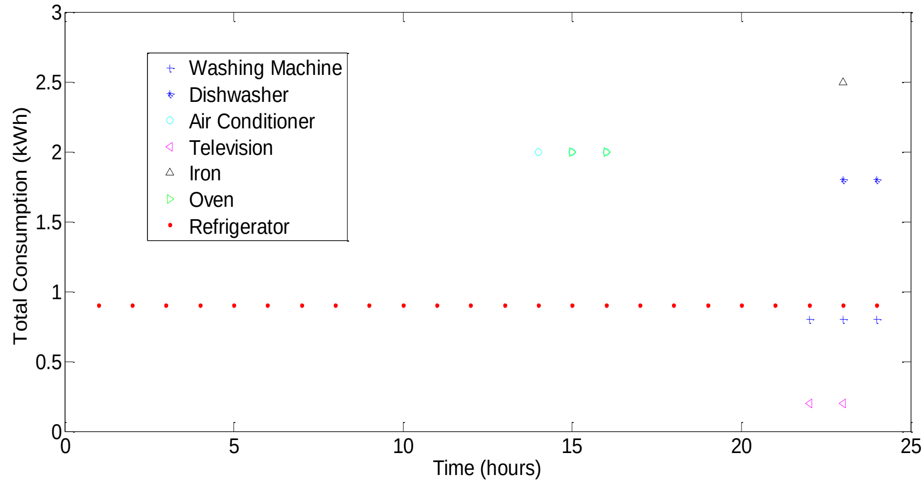

Figure 3.5. Use of household appliances during the day (Scenario 3)

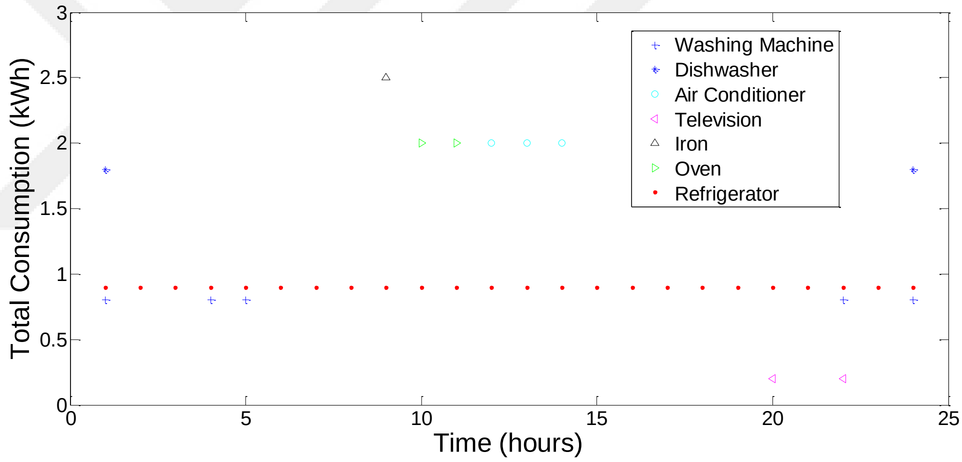

Figure 3.6. Use of household appliances during the day (Scenario 4)

Peak load for load control is not applied scenario is obtained as 6.2 kW and for load control is applied scenario is obtained as 3.5 kW which is shown in Figure 3.7 and Figure 3.8. The load control system reduces PAR in Scenario 4 as 43.5 % than Scenario 3 for SA optimization. Therefore, PAR for Scenario 3 and Scenario 4 are respectively,

$$PAR = \frac{L_{peak}}{L_{avg}} = \frac{6.2}{1.687} = 3.675, \tag{3.16}$$

$$PAR = \frac{L_{peak}}{L_{avg}} = \frac{3.5}{1.687} = 2.074 \tag{3.17}$$

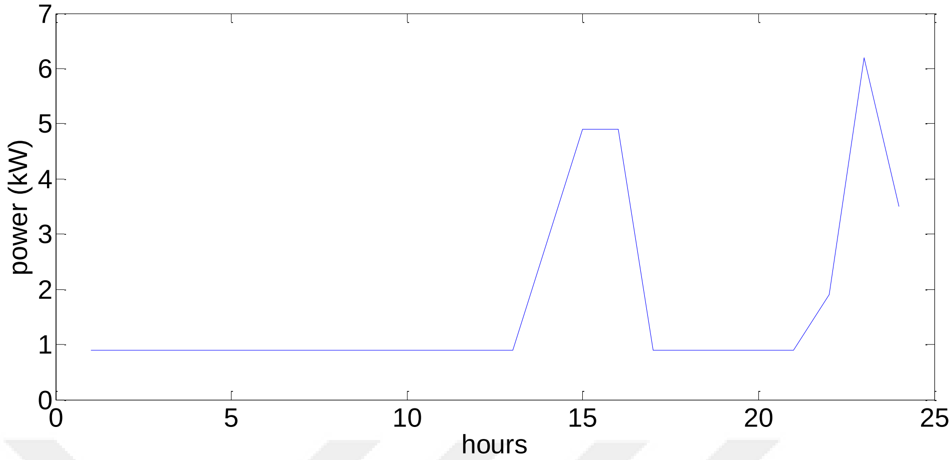

Figure 3.7. Hourly load values for Scenario 3

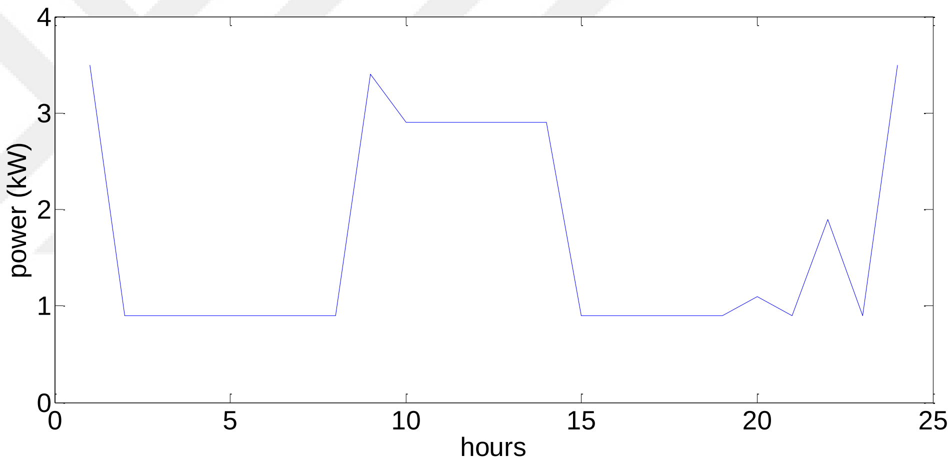

Figure 3.8. Hourly load values for Scenario 4

3.3.3. Comparison of PAR and cost

Multiple scenarios are examined considering optimal load control, tariff sorts and optimization techniques. PAR values are nearly same for both optimization methods but SA optimized system has a bit more PAR than LP when both systems use optimal load control. However, when the systems do not use optimal load control, SA has higher PAR values 1.41 times than LP. Graphically comparison of PAR is shown in Figure 3.9. Electricity costs are same in LP and SA if the scenario which the systems do not use optimal load control is realized. On the other hand, Figure 3.10 shows electricity costs are significantly higher in SA algorithm than LP when the systems use optimal load control. Electricity cost for all scenarios which are applied by LP model and SA algorithm are less than the cost when user uses electricity with single time tariff.

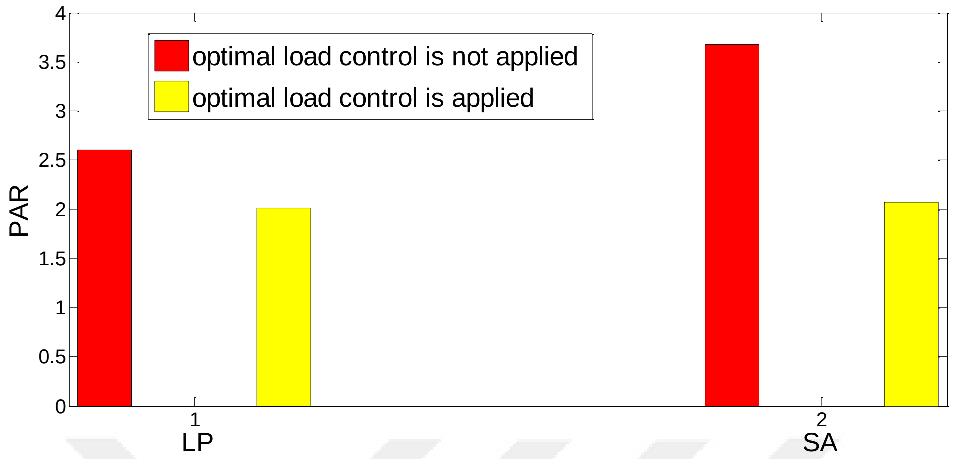

Figure 3.9. Comparison of VAR between LP and SA methods

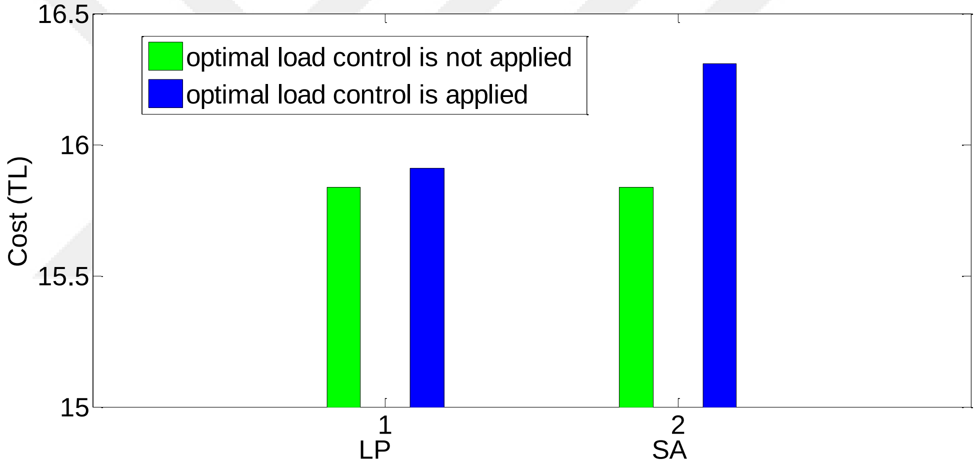

Figure 3.10. Comparison of electricity costs between LP and SA methods

Scenario 2 gives the best PAR values and Scenario 1 and 3 gives optimum electricity cost as it is seen in Table 3.8. Load of appliances for all scenarios is shown in Figure 3.11.

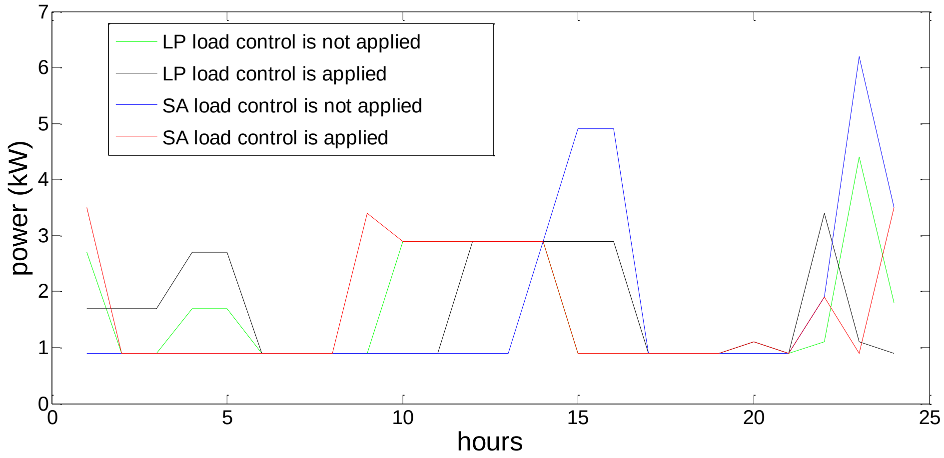

Figure 3.11. Comparison of hourly load during day for all scenarios

Table 3.8. Comparison electricity cost and PAR for all scenarios

Scenario Number	Applied Mode	Electricity Cost (TL)	PAR
Scenario 0	Single time tariff	17.544	-
Scenario 1	LP optimized and optimal load control is not applied	15.838	2.607
Scenario 2	LP optimized and optimal load control is applied	15.911	2.015
Scenario 3	SA optimized and optimal load control is not applied	15.838	3.672
Scenario 4	SA optimized and optimal load control is applied	16.310	2.704

4. CONCLUSIONS

Minimizing electricity costs in smart homes requires some optimization techniques to use in HEMS. Mathematical based and heuristic methods can be used to solve this kind of problems. There are various types of tariff. TOU, CPP, RTP are time based tariffs. Single time and multi-time tariffs are choices to develop optimized HEMS. When system uses multi-time tariffs, appliances are shifted from expensive time slots. This may cause a high load demand in cheap time slots. Optimal load control is improved the system to avoid high load demand and high PAR values.

This thesis has three objectives. The main objective of this thesis is to reduce electricity cost by using optimization methods. For this reason, LP method which is one of the mathematical solutions is used. There are priorities while deciding optimization method to solve problem. It is desired to find the exact value of optimum solution. Some assumptions need to be provided to reach a real system in mathematical expression. Certainty, summability, severability, linearity are assumptions that have to be in an expression to solve with LP. Certainty specifies coefficients of every decision variable are certain. In this study, the variable which is working status of appliances carries these conditions.

Since the parameters used in the LP method are limited, the problem can be solved with GAMS application. However, if the data set or parameters or decision variables are increased, the probability of finding the exact solution of the problem will be reduced. In such a case, the mathematical model may not give exact result so the problem is solved by SA method.

The optimization methods are applied to the system to shift the load of the devices from high cost time slots to low cost time slots. This can cause overload during low cost time slots. In order to avoid overloading, optimal load control is applied to the system which is the second objective of the thesis. Optimal load control is applied to both solutions in scenario 2 and 4. In the case of load control is applied (Scenario 2 and 4), the electricity cost of LP is significantly lower than that of SA. PAR values of them are nearly same.

The electricity costs are same in scenario 1 and 3 when optimal load control is not performed. On the other hand, PAR value is considerably higher in scenario 3 than scenario 1. All optimized scenarios (using multi-time tariff) gives better result than Scenario 0 (using single time tariff). Scenario 2 gives the best result if low PAR value is determined as the most important criterion and Scenario 1 when low electricity cost is the most important criterion. In any case, the results of LP are better than SA.

In scheduling and load control problem, LP method might have more parameters and variables. In this case, mathematical based methods could not be enough. For this reason, a metaheuristic algorithm is used the problem of this study. For the future work, more complicated parameters, variables, and decision variables can be used.

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Date of access: 29/03/2019

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