# SMART GRID'S BIG DATA WIRELESS COMPUTING

by

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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Baraa Adil Mahmood Mahmood

# DEDICATION

First, I would like to thank Allah Almighty for the power of mind, health, strength, guidance, knowledge and skills to complete this study.

This thesis is wholeheartedly dedicated to my parents. There are no words to describe what you mean to me, there is nothing that I can repay for what you have done to me. I will continue to do my best to achieve your expectations.

And lastly, I dedicated this to the family, relatives and friends who have been encouraging me during this study.

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# ABSTRACT

## SMART GRID’S BIG DATA WIRELESS COMPUTING

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The main reason for seeking a better improvements in the smart grid development which increases data volume and complexity is economics, reliability and efficiency of the grid. This type of data requires a powerful technology to analyze and process big data. In this report, we propose an intelligent grid analysis architecture for the analysis of data transmission, storage and resources based on four fields of communication. We are proposing a data-enabled large-scale storage plan for big data wireless computing, that makes wireless communication big data awareness for smart grids. Genetic Algorithm (GA) for storage planning and internal optimization to plan daily energy was adopted as an optimization approach. This will reduce the long - term costs of consumers.

**Keywords**: Artificial neural network, Backpropagation, Partial swarm optimization, Mean square error, optimization, classification.

## ÖZET

## AKILLI AĞININ BÜYÜR VERİ KABLOSUZ HİSAPLAMA

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Veri hacmini ve karmaşıklığını artıran akıllı şebeke gelişiminde daha iyi bir gelişme arayışının temel nedeni; şebekenin ekonomisi, güvenilirliği ve verimliliğidir. Bu veri türü, büyük verileri analiz etmek ve işlemek için güçlü bir teknoloji gerektirir. Bu raporda, dört iletişim alanına dayanan veri iletimi, depolama ve kaynakların analizi için akıllı bir şebeke analizi mimarisi öneriyoruz. Kablosuz iletişimi akıllı şebekeler için büyük veri farkındalığı yapan, büyük veri kablosuz bilgi işlem için veri etkin büyük ölçekli bir depolama planı öneriyoruz. Kablosuz iletişimi akıllı şebekeler için büyük veri farkındalığı yapan, büyük veri kablosuz bilgi işlem için veri etkin büyük ölçekli bir depolama planı öneriyoruz. Depolama planlaması için Genetik Algoritma (GA) ve günlük enerjiyi planlamak için iç optimizasyon, bir optimizasyon yaklaşımı olarak kabul edildi. Bu, tüketicilerin uzun vadeli maliyetlerini azaltacaktır.

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# 1. INTRODUCTION

Frameworks are described as an ' interdisciplinary methodology ' through INCOSE Systems Engineering Handbook and are intended to enhance the recognition of fruitful frameworks (INCOSE, 2004). The objective of accomplishing effective frameworks is cultivated when those frameworks offer some benefit to the general public and are socially satisfactory. As the populace develops, new difficulties should be tended to on areas, for example, wellbeing, vitality, and transportation. In addition, the size and multifaceted nature of frameworks increment after some time and the test of very much structured building frameworks is to create practical frameworks that are progressively solid, have shorter life cycles, increase their utility and be available at a lower cost at all times. The Systems Engineering Vision 2025 of INCOSE (INCOSE, 2014), the control will be progressively applicable in extensive scale venture frameworks, for example, the vitality division by 2025. To achieve this objective it is important to expand the utilization of innovation driven frameworks designing apparatuses, for example, cloud-based processing, huge information systematic strategies, and information representation. With the expansion of information accumulation, chiefs have more data to reach the most ideal inference. Vitality Management frameworks have risen in the ongoing years as a PC helped apparatus utilized by the power lattice to improve, screen, and control the execution of the age, transmission, and appropriation of vitality.

Lately, the persistent utilization of cutting edge metering foundation (AMI) has created exceptionally granular information on client utilization from keen meters. Furthermore, this progression has permitted bi-directional correspondence among buyers and electric utilities. So as to appropriately utilize the immense measure of data gathered by brilliant meters, it is important to create frameworks that are versatile, secure, strong, and versatile as a component of the major routine with regards to frameworks building (INCOSE, 2014). The worldwide brilliant meter market is forecast to grow by 2020 from $4 billion in 2011 to $20 billion. In addition, in 2009 the U.S. Government stated that a brilliant progress of $four billion is to be achieved under the American Recovery and Reinvestment Act (USA Global Trade Commission, 2014).

Their usual usage concepts in light of changes in power costs after a certain time or to motivating force installments intended to prompt lower power use now and again of high discount showcase costs or when framework dependability is risked" (U.S. Branch of Energy, 2006). The biggest undiscovered DR potential is in the private division as indicated by the FERC. With the utilization of savvy network innovations, approximately half the decline in pinnacle capacity is due to a full interest of private customers in DR programs in the United States (Albadi and El-Saadany 2007). Photovoltaic (PV)-based microgrids are increasingly becoming an essential source of vitality for private vitality customers speaking to real energy buyers (Guo, Pan and Fang, 2012). The creation of vitality by sun oriented PV frameworks displays a promising vitality hotspot for private clients. With home vitality the board expected to contribute fundamentally to the strength of the power framework, the interest side administration (DSM) framework verifies vitality investment funds because of a superior utilization of private power assets (Palensky and Dietrich, 2011). Hence, DR program architects ought to incorporate clients with sun oriented PV frameworks since they assume an imperative job popular side vitality the executives (Zhang, Gatsis, and Giannakis, 2013).

## 1.1 PURPOSE AND IMPORTANCE OF THESIS

In order to avoid the collective device demand from the exceptional level to that of a fixed household, this analysis suggests an intelligent loading system that monitors victimization of the social energy consumption by the smart meters. The intelligent meters learn the energy consumption patterns of the representative customer clusters automatically, and load management thus depends on well-known load profiles. The purpose of this analysis is to apply the time-based DR as the ToU evaluation to optimize energy resources management at the level of social units. Associate degrees formulate an optimisation bottom to reduce the electricity pricing performance that is solved victimization LBFGS-B algorithmic optimization rule. It ensures that the best amounts of energy for automatic appliance management are allocated at entirely different times of the day through DR victimization ToU and the L - BFGS - B algorithmic optimization rule.

This work cooperates with people in DR programs, which requires users to take manual actions in response to a DR event. Customers enjoy this arrangement jointly by saving cash on electricity prices, as long as their devices are run by a lower demand every now and then. The customer's own AMI infrastructure does not require monitoring time and rates off-season. During this analysis, the methodology projected mechanically handle equipment reactions to cost changes and various grid energy management signals.

This analysis analyzes the results of 247 house prosumers with star photovoltaic systems which supported electric charging information within 15 minutes. The Info-Analytics provides details on the consumption of energy in a social unit and concentrates on optimizing household energy consumption. A memory algorithm that allows continuous interaction with the service company to optimize the use of energy is applied for certain stressful problems called L - BFGS - B. In comparison to conventional Newtonian strategies, this optimization method provides increased machine power and robust convergence. The gradient is designated and thus the second by-product jackboot matrix can best respond to the use of muckles of resources, for example time and machine price. The solution provided during the thesis may modify the utilities to optimize the utilization of the residential energy industry by (a) providing incentives to customers in order to reduce their electricity prices through a ToU evaluation system; Various benefits are provided to residential customers: 1) increase the use of power by optimizing hundreds of energy uses and reducing energy bills; 2) increasing the use of the Star phenomenon system by shifting fixed operation - to provide information and communication for customized users through daily, weekly and monthly data concerning their periodic energy consumption patterns, as well as making recommendations, in order to enable buyers to receive information on the day, weekly and monthly basis of their own electricity consumption. The planned system will also benefit from the individual planning process and support its respective energy demand and freight profile as an opposed scheme that gives the best response to the entire system. In addition, the smart loading system is provided with ToU information in real time by the Utility Company. In addition, the proposed optimization model was analyzed for the efficiency of the projected model before and once every cluster and class were applied in ToU assessments. Once many authors have examined the methodology projected with the model proposed in subsequent chapters, the methodology described in this analysis provides for a less advanced structure for managing social planning load planning.

# 2. LITERATURE REVIEW

## 2.1 THE ART STATE

The programming of equipment needs the right attention when it comes to energy management systems, including renewable resources such as star and winds as DGs (Ziadi et al, 2014). In recent decades the use of psychographic information to promote planning for the response of demand programs in the domestic and industrial sectors has been increasing in the use of renwable energy (Kwac, Flora, & Rajagopal, 2014). This seems to encourage and optimize households ' use of energy. Recent analyzes have provided numerous mathematical models for automated energy management systems. Some of these publications plan automatic machinery to victimize dominant systems in order to plan equipment to ensure that nursing staff gets the best price for electricity. Different analytical work uses computing mechanisms to manage automatic device systems. Sanjari et al. (2017), for example, suggested an on-line programming strategy with ToU performance in energy and gas utilization calculation, based on best cell (FC), chamber and power storage tool. However, the authors have shown that their systems are efficient, through violence, real electricity knowledge in electricity and heating and an uncontested for grid connection. The best online scheduling system controls the smart domestic energy system working hours. A mechanism to calculate the best world resolution to function the FC has been provided by the Sanjari et al. authors in 2017. The cell system was best planned if no consideration was given to all the amount of electrical or thermal masses. Shrewd can lead to customer discontent in a global resolution, because the energy allotment is not customized per device but as complete energy consumption in an extraordinarily large unit. This analytical study takes a different approach to the approach given in Sanjari et al. (2017) that takes account of individual electrical equipment optimisation and programming. Customer satisfaction will grow once the appliances are individually programmed because households use each appliance at completely different times of the day. For each appliance, the electricity programming optimization is performed individually during this analysis since the charging profile differs from one another.

Sanjari et al. (2016) also offers a programming system for managing the energy used by a unit at predefined times. They projected the use of the HAA system and the daily forward programming system (DAS) in nursing hour. The combination of the two models is intended to search for best value for money from a smart home energy system created by electric battery and a membrane (PEMFC) nucleon exchange cell. Optimization of hyper-sphere screening (HSS) has calculated the results of a day forward system, and can be corrected by a shrewd load forecast. Furthermore, when the forecasting errors are sharp, the system can deal with uncertainties. In order to make changes to the day-to-day scheme the author planned to use the trained Artificial Neural Network (ANN). In order to create a further complicated and attractive price system, the authors of Sanjari et al. (2016) designed an optimization and forecasting mix of models. If the methodology envisaged by Sanjari et al. (2016) is examined in accordance with the model envisaged in the following chapters, the methodology described in the treatise offers a less difficult structure once the load programming has been managed. The authors of Hu and Li (2013) have provided a hardware style of an energy management system on the demand side that schetles energy use of appliances at an extremely local level due to a scale of residential electricity prices during peak periods. To achieve this objective, Hu Associate in Nursingd Li planned the best resolution of a mixture of 2 maschine learning algorithms. In Hu and Li (2013), continuous customer interaction is necessary and load planning will not take place until customers choose their preferences. This disadvantage has been explained. While a far-away management system can be accessed via a screen and a web page to customers, the appliance is not scheduled unless the customer takes any measures. Loloish et al. (2013) are planning another localized or distributed programming system. In the case of opportunistic real-time victimization (RTP) programming, the authors have created a basis for nursing optimization to determine the best time available for activating the devices to maximize the profits and minimize costs. The measures in their model are the initial times of the operation of household appliances. The calculated programming system shall be calculated by reducing the Associate price for infant programming. The Loloish et al. (2013) methodology is based on the projection of the price decline as a alleged problem, which results in entirely different outputs with the same revenues and quality for implementation of the system. Two further major disadvantages for your model are (1) that waiting time is simply too long for the best programming of your device. 2) throughout the month of Gregorian calendar, the results of its programming system have been shown to have negative costs that are unlikely.

One of the widely used algorithms in appliance programming systems, the genetic algorithm program clarifies the best power unit downside. Arun and Selvan, for instance (2017), provided an intelligent load system based on prosumer. The analysis of the GA was done to calculate the best programming of household mass. Thus, a case study containing battery storage, solar systems and masses was used to validate the system at an extraordinarily housing facility.

The study conducted in Zhao et al. (2013) also included the use of GA for energy use optimization. Two entirely different rating models were used: the IBR and the price for the period of time. To improve the low - level device formatting during the day, GA algorithms are adopted. As victims of electric knowledge of a single house with device optimization have been performed the results of the Zhao et al. (2013) methodology are not reliable. When a dataset with many households is taken as completed in the analysis work provided during this treatise, the effectiveness of the methodology may be different. The authors have planned a hybrid system, which blends associated in the nursing power storage with renewable energy generation, in Arabali et al. (2013). An additional analysis has supported the use of GA optimisation. Air conditioning, ventilation and heating masses only were provided by the programming system. The projected C-Means cluster for GA optimization in Arabali et al. (2013) aims to lower electricity prices and increase power. One of the drawbacks of this approach is that it deals solely with a range of the HVAC - like rulers.

It is projected that other approaches claim to handle many different devices. For instance, Logenthiran, Srinivasan, and Shun (2012) delineate a requirement-based approach to victimization load management with an organic process-algorithm program based on the heuristic process. Their model was designed to follow the target loading curve so that the final loading curve is some sort of the lens image. Once GA Optimization is implemented to solve problems of load programming, fitness performance should be tuned to completely different parameters, mainly supported by the experiment and mistakes. The optimization model results are inconsistent and do not create an accurate judgment if one of the parameters is erroneously entered into the system. GA Algorithms This adds quality to each electricity company's methodology and inconvenience, which must enter right values when programming is used in the excessive unit, and the World Health Organization shoppers have to wait long times until their appliances are adequately conceited. The lack of a guided search leading to long periods of time to respond to GA optimization is another disadvantage.

The game idea models are a further technique for optimizing the load smoothing downside that was used in the past. The authors, for instance, reformulated a game model in Li et al's work (2017), to optimize energy utilization and to delineate a distributed load shifting strategy.

Newton was developed to reduce the inconvenience of households and to coordinate energy allocation in demand management manners in an extremely centralized manner. The drawback of the classical Newton technique is the fact that the gradient must be calculated and the boot matrix for the second spin to achieve the best resolution. As stated later during this treatise, the gradient and boot matrix calculation is high computationally, and it enables the demand management system to improve its quality.

In the analysis project, the L-BFGS-B optimization technique uses the convergence times of the projected optimization downside. This guided search is carried out. For certain issues affected, L-BFGS-B may be a limited memory algorithm. In comparison with the classical Newton modes used in the Li et al. optimization downside, it provides higher procedure power and strong convergence.

## 2.2 TECHNOLOGY OF SMART GRID

In previous years, advanced measuring infrastructure (AMI) has generated a great deal of knowledge in many formats and intervals about the demand for electricity from the customers. Smart meters that are electrical devices introduced by users ' homes and typical utilities for the promotion of communication with their customers regarding electricity requirements and energy distribution have captured this Brobdingnagian quantity of knowledge. The Smart Grid provides communication of energy and knowledge through a communications network, automation, control and new technologies in two directions between customers and power plants. The intelligent grid makes the grid economic, safe, dependable and green. It makes it much cheaper as it makes it easily deploys energy efficiency optimisation systems, prevents energy use during peak times, and significantly reduces customers ' electricity billing by working together on DR-specific programs (Aghaei & Alizadeh, 2013).

The smart grid is reliable as long-term electrical failures are avoided. As an example the smart grid will re-run the electricity flow once the impact is broken so that customers will immediately have access to electricity even though they do not notice that the impact is out of hand. As it uses new wireless technologies which prevent the use of additional cables to transfer knowledge from one location to another, it is environmentally friendly. The web operation Protocol (IP), which facilitates the exchange of knowledge with customers, is being enforced (Pipattanasomporn, Feroze & Rahman, 2009). In order to guarantee network safety, the regulation of regime in situ cyber - security controls should adapt to the needs and vulnerabilities of power utilities, as explained in Yan et al. (2012), and ensure that quality of service (QoS) is provided for all mobile and fiber networks.

As electricity employment changes for all social units and communities throughout the day, utility companies should change the quantity of plants that need to supply the electricity they are looking for over various periods of the day. The Smart Grid may be a tool for collecting information from users and jointly using the Smart Grid to see how many active power plants are required to meet demand, operation of fewer or more power plants during off - peak and on - peak times.

### 2.2.1 Smart Grid

The infrastructure and new technologies in sensitive grids are illustrated by Figure 1. Smart grids are using the new technology to change the information flow and connections between all parties involved. In addition to transmission and distribution systems, the actors comprise generation entities in an extremely massive and miniature scale, like star or wind energy generation on the customer side. When using electricity statements, distribution systems and their individual intelligence play a key role. The electricity load profile which ends with lower production prices can be modest and swished by distribution intelligence as well. If electricity costs are reduced, customers can benefit greatly and benefit from lower prices.

In period of use accessible communications networks, the data exchange between entities within the intelligent grid is carried out for the sending or receipt of international and native data. The grid thus detects nearly instantaneous problems and resolves issues promptly when the top user does not move over long periods with the power supply suspension (Amin and Wollenberg, 2005). As shown in Figure 1, the smart grid supports renewable energy use by connecting it to the grid when it is generated on an extravagantly large scale, such as alternative power plants. In addition, the smart grid allows for consumers with energy generated systems to inject energy into the grid only if the energy generated is greater than the electricity consumption and the customer also does not have energy Storage Systems (Brange, Englund & Lauenburg, 2016).

A bunch of houses in the electricity consumption section is shown as intelligent homes. The figure shows these intelligent homes can talk to the grid on an ongoing basis and exchange information and provide customers with valuable information on their use of electricity. Intelligent homes are often found in the home space networks (HAN) as are intelligent appliances, intelligent thermostats and an intelligently-oriented meter for gathering knowledge about electricity consumption.

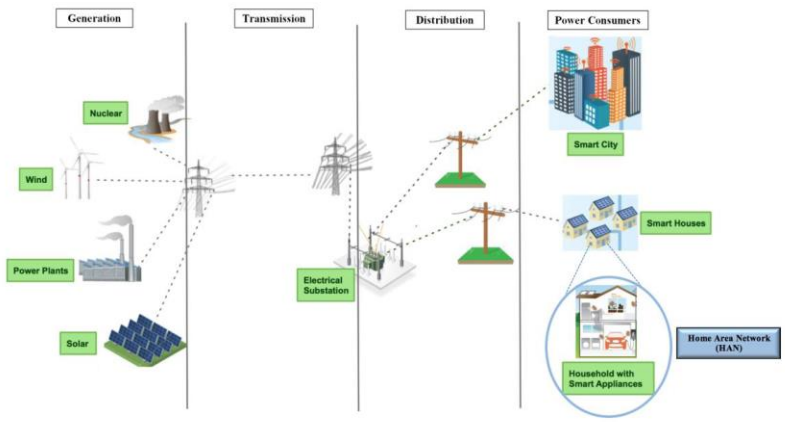


**Figure 2.1:** Smart grid Infrastructure.

### 2.2.2 Smart meter

By 2016, 71 million smart meters were installed by the US Electrical utilities (EIA, 2017), which accounts for 47 percent of the US 150 million power customers. Nearly half of all U.S. power users have intelligent meters. Smart meters enable information to be collected and shared in real time on households and users ' consumption of electricity. Its main function is to exchange and monitor information about the smart grid between various entities in real time for electricity consumption.

These automatic devices facilitate information exchange within the smart grid, allow the integration of new and more advanced price models and make it easier to use household energy use optimizing technology.

The following six features and capabilities for smart meters automatically define Asghar et al. (2017):

a. Reading household, business and industrial electricity consumption.

b. Data capture for electricity consumption in different time intervals. Some smart metres, in 1 minute, 15 minutes or 30 minutes or 1 hour of data collection, are programmable.

c. The reporting by a data management system meter (MDMS) of any activity or energy.

d. Receive in real time any price changes. Therefore, electricity costs are immediately adjusted and consumers always pay the right amount. e. Exchange of data between appliances on energy consumption.

f. Allow the application of new technology to significantly improve energy use and to enable any household to participate in DR schemes regardless of their availability during the day to react to changed energy prices. Their inclusion of embedded optimisation models is possible in the system.

The 2012 Working Group Report on the BioInitiative on the other hand states that the use of wireless devices such as smart meters, cellular telephones and cell phones may result in health risks caused by electromagnetic radiation. Some of the health topics included memory, sleep disturbances, neurological diseases such as Alzheimer's. The survey concludes that safety requirements for wireless exposure protection and electromagnatic fields are necessary to achieve public confidence and to prevent health risks.

### 2.2.3 Home Area Network

HAN is a smart and automated household - base electricity distribution system based on the priority every appliance has to modulate electricity consumption and minimize energy costs at any time and also develops in - house energy distribution models. Furthermore, as described in Fan et al. (2013), the HAN can distinguish between controllable and non-controlled loads.

The collection of rich and timely data makes it easier for all power system players to make better choices, thus improving energy reliance, distributing the energy used optimally, and reducing energy costs both for themselves and for the system. Utilizing AMI to efficiently address high demand at certain times per day by applying various pricing promotions, such as the use of DR programs and the price of ToU, to ultimately minimize running costs for utilities or any entity producing and supplying end users with energy. Thus, the use of AMI makes it possible to implement programs and technology at peak times, rather than build additional energy plants at this critical moment (Siano, 2014). This reduces energy consumption in peak times, allowing electrical appliances and equipment to work at other times of the day to ensure a uniform distribution of electricity during the day.

### 2.2.4 Smart Grid Communications Cyber Security

As the new type of electrical grid, Smart Grid has the capability of transforming proprietary and outdated technology into a new kind of power grid using advanced technologies of communication. A safe, smart communication infrastructure must be available to upgrade the existing electricity network into a smart grid. The optimization of this intelligent energy system relies upon the communication in real time of various grid elements (e.g. load, distribution, transfer and generation), as demonstrated in Figure 1. Optimization of energy consumption. Due to the highly dynamic smart grid technology and environment, privacy strategies are important to build public confidence. Smart grid privacy technologies are well matured using established authentication and approval systems. The Advanced Encryption Standards (FIPS) as described in (NIST, 2001), and the 3DES standard for three data encryptions as (NIST, 1999) were approved for the use, for example, of high-performance and high security for all grid companies, such as customers, utilities and government. The Federal Information Processing Standards (FIPS) were also approved for this purpose.

The Electric Power Research Institute (EPRI) states that, because the grid interconnects, cyber security for the systems is deploying a reliable intelligent network (NIST, 2016). In order to address and prevent any kind of cyber-attack, cyber security preparedness in the energy sector is crucial. Organizations like the National Service Protection Plan (NIPP)(Dumont, 2010) and the International Smart Grid Safety Plan (IEEE 1402) (IEEE 2000) are working on developing Smart Grid Security (Guerrero etal. 2011). The NERC Critical Investment Protection Corporation (NERC - CIP), the IEEE 1402 (IEEE) and the NSSSP.

In order to coordinate security needs coherence across smart Grid components and domain systems, several Smart Grid Cyber Security programs were implemented at the NIST (NIST), including the CSCTG (Zhang et al. 2010).

In order to develop the need to scalable and safe Smart Grid (Rohjans etal., 2010), domain expert working groups (DEWG), for instance: Home - to - Grid (H2 G), Industry to - Grid (I2 G), Built to - Grid (B12 G), Business and Policies (B&P), T&D (T&D) have been set up the DoE GWAC and NIST.

## 2.3 SMART GRID BENIFET

The long - term strategy of smart grid, not only the utilization of new technology, but also energy infrastructure can play an important role, with a view to optimizing and improving energy use on household, commercial and industrial levels. Hamilton and Summy (2011) said that this investment represents $100 billion in gross domestic product growth for every $1 billion invested in the smart grid, respectively. Furthermore, the same study suggests that with the addition of data on electricity available, higher energy consumption controls are possible, which could increase GDP annually by $15-20 billion by 2020. Their research shows that investments in smart grid infrastructure have been good over years and may well go beyond traditional energy investments because the smart grid can serve all power system firms with a high degree of granular data shared and analyzed. For instance, the report shows that investment in intelligent grids can lead to some 16.7 jobs per 1 million dollars of spending. If traditional fossil fuels are invested in the same amount, estimated US $1 million in spending can be generated by 5.3 jobs.

The intelligent grid offers not only financial benefits but environmental benefits. A recent report from the US Energy shows that the integration of smart grid infrastructures in the USA will be driven by a 100 per cent reduction in carbon dioxide emissions by 2030 (EPRI 2011). The same research shows that 42 coal-fired power stations -equivalent to 53 million Greenhouse cars -can be moved with the current grid at just 5% higher efficiency.

The smart grid's other advantages include:

a. In real - time distribution networks can be managed.

b. It is also possible to restore the electricity grid quickly and reduce the time required to respond to failures, making the system more reliable and allowing end users to gain more power consumption.

d. The utility companies can focus instead of spending their own resources on the construction of additional power plants on optimizing current energy generation.

c. In response to these price changes and the choice of energy consumption at peak- and mid - peak - time rather than peak - hour, the pricing of real - time electricity can change the behavior of the customers.

## 2.4 DEMAND RESPONSE

In the context of changes in electricity price over time or incentives to lead to a lower energy use at a time of threatening high wholesale prices and system reliability, DR is defined by the Federal Energy Regulatory Committee as a "change in electricity use by end - users '" (DR 2006). The US data is based on an annual Energy Sales, Revenue and Environmental Efficiency Survey (EIA, 2016) of around 9.3 million U.S. customers participated in DR programs in 2014. The residential sector accounted for 93 percent of these clients. According to the FERC, the residential sector provides the largest DR potential in every consumer sector. If 100% of domestic customers take the demand response system (Albadi & el -Saadany 2007), smart grid technologies will represent a possible 50% lower peak in the US. The use of PVMs among such users is growing popular and becomes an important energy source (Guo, Pan & Fang, 2012). The energy supply chain is also increasing, with a large volume of energy. The whole electricity grid can benefit as well if households not only consume but generate energy. Photovoltaic solar energy generation is becoming a promising source of energy for residential users.

The use of DSM systems, which can lead to significant energy saves and a reduction in electricity prices, is a better use of domestic resource energy. Intelligent home energy management systems are resources expected to contribute to grid stabilization and QOS growth. Intelligent home energy systems are a resource. The optimal layout, is an important factor for the efficient application of the smart grid. DR programmes, based on various schemes and characteristics, may be categorized and studied extensively in literature. For instance, Vardakas, Zorba, and Verikoukis (2015) considered that the three following categories constituted the best methods of classifying DR programs: DR programs based on motivations, control mechanisms and decisions variables offered. This classification covers different viewpoints and perspectives of DR programs and allows end users to understand the various options.

The type and subdivisions of the DR methods. The characteristics and classification of all three types of DR methods are described in this section.

### 2.4.1 DR Controlling Mechanism Methods

The classification is based on where decision making takes place in DR programmes. The DR methodologies are classified. It can be centrally located or centrally located. In the case of decision-making from various locations, a decentralized or distributed system is referred to (Motegi et al., 2007).

a. Schemes central. Schemes centralized. All actions and operations are conducted from a central location in a central controller. In a default time interval the central controller collects customer data on the electricity consumption and decides on DR devices. Moreover, the central controls enable microgrids or other type of distributed generation units to be incorporated into the electrical grid. Electric balances must be kept independently of the grid and must be coordinated and allocated in due course to achieve this objective (Kostková, 2013). Electronic power planning programs.

b. Distributed schemes. These systems allow consumers to access their electricity data directly and collect it without the involvement of other equipment. Users can react almost immediately, in high or critical times, to incentives from public utilities and use price reductions and reduce their electricity bills and support utilities in avoiding the activation of additional power stations during critical times. The price information received by the customers is supplied by services and computed according to added charges. These data enable customers to instantly adjust their use of electricity (Motegi et al., 2007).

### 2.4.2 DR Methods based on the motives offered

This type of DR program reduces or changes customers ' energy consumption at certain times of the day. These can be divided into two categories: time - boosted DR and time - boosted DR.

#### 2.4.2.1 Time-Based DR

At different times of the day electricity prices vary. It is used as an incentive to reduce and change demand when prices are high. This data is provided to families. Although electricity prices don't affect customers, they play a vital role in the functioning of such programs. Energy providers sometimes send motivating signals, allowing users to react in real time to these times, by reducing electricity consumption. As described in the following paragraphs, six types of DR programming based on time are available:

a) Price for flat. This is the sort of price system that has been in use for years. Consumers know that they can reduce their electricity bill only through less energy during the day. The prices of electricity can vary from season to season, allowing energy suppliers to adjust their price. There are no frequent changes to electricity prices; they can happen every 3 to 4 months (Doostizadeh & Ghasemi, 2012).

b) Pricing for timing of use (TOU). Each period is divided into three types of maximum times: on top, mid-peakand off-peak. The day is assigned to each one. A price is determined for every peak time according to the aggregate energy consumed by network users. Default periods may vary from day to week to hour of the day according to the price of the ToU (Aghaei & Alizadeh, 2013). Consequently, customers pay for their consumption or more particularly for their peak time consumption, the amount of energy they consume. Customer A, for example, usesx energy at peak times and consumes less than 1000 kWh per month. As Customer A, Customer B consumes samex energy, but its energy consumption overall exceeds 2500 kWh. Customer B ends up paying higher energy prices, as Customer B belongs to a category that is slightly higher in terms of energy prices. For example, Austin, TX customers pay a pre-determined rate at various times of the day based on peak time consumed during peaks, off-peak, or intermediate peaks (Austin City Council, 2017). Electricity prices are between $0.0218/kWh and $0.1219 during peak periods for users consuming 1,000 kWh to 1,500 kWh.

c) Critical peak pricing (CPP). This kind of DR program is like the ToU price system, since flat rates apply for predefined periods. The change in CPP is that in only one period or just when the electrical system is under stress, the cost of electricity can change regularly. The CPP only takes account of two types of peaks, on and off peak, is another difference from ToU rates. Generally, energy providers choose to send consumer notifications, and they usually send the notification one day in advance.

The state of California for example uses a fixed-term CPP program (CPP-F) in which the highest wholesale price is selected for the single critical peak price (Faruqui, Sergisi & Rugul, 2010.). Using CPP-F, utilities maximize profits and provide customers with an energy reduction mechanism when generation of power is usually high. On the other hand, the modified version of the high price variable (VPP) method, varied from highest to high, is used by Oklahoma Gas and Electric Company. In off - peak hours, customers pay $ 0.045 per kWh and off - peak hours are divided into standard peak, high peak and critical peak rates. Users of each sub - clash shall be paid $ 0.113 $ /kWh or $ 0.23/kWh for standard — high - and critical - peak rates, or $ 0.45 /kWh, different from the other.

d) Pricing for peak loads (PLPs). The day is divided into different time periods and the energy price of each period is predefined. The price of electricity is usually announced one day in advance for every time period. Engineering providers maximize their profits, using the overall power load and calculating the mean consumption for each period to calculate the prices by interval. A study found that customers have changed or changed their power consumption with Auckland based on high - time power prices, New Zealand (Ragnarsson, 2012) using the implemented PLP method. The more expensive the price is at peak times, the better customer participation in master program.

e) Peak Day Discounts (PDR). Utilities set an estimated base load threshold for this type of program. All customers who decide to participate in such a DR program during critical events will be given a discount bonus. In order to achieve the benefits, energy consumption must be below the fixed load limit. If customers do not decide to participate, they pay a standard fee, which does not exceed their normal costs (Newsham & Bowker, 2010). For each critical event and each customer, the estimated basic load threshold is calculated; thus additional resources are required to determine precise national prices.

f) Pricing for real time (RTP). Under this scheme, energy suppliers fix prices and announce them beforehand for predefined periods, for example 15 minutes in advance. Customers are informed of the change in energy prices and then they decide whether they want their energy consumption to be reduced or shifted at specific times. In order to ensure the smart grid implements efficiently and successfully, a two-way communications system must be established between the household and the utility company. In each house EMC can be installed, e.g. to increase response time, decision making and speed of two-way communication between consumers and energy suppliers. RTP is a common business-industry mechanism (Cappers, Goldman and Kathan, 2010). Unfortunately, such a DR program is not popular in the residential sector as households have a low return on investment (ROI) for the introduction of the RTP system. Moreover, the price customers have to pay in order to make this type of system possible, compared to the cost savings resulting from participation in the RTP programme. One of the difficulties preventing this type of programme's growth is the need for manual customer participation and actions. The customer can not participate in the RTP program unless the client is available at home at the time of the critical event. Effective time communication between entities is required on a daily basis. The Day-Ahead Real Time Program (DA-RTP) is an improved version of RTP. The DA - RTP system predict and inform customers about electricity prices for the following day. Electricity - using customers are charged on the day before that day for this RTP based on the predicted price values.

#### 2.4.2.2 Incentive-Based DR

The incentives provided to consumers are a type of program. Incentives may be established or may vary over time, and the aim is to reduce energy consumption during certain stressful periods (Mohagheghi et al., 2010). Registration is voluntary; in case of critical situations, however, the client may be penalised if he or she does not respond quickly and has to pay higher prices at the time of the on-screen notification.

Incentive DR programs are divided into market and traditional programs. In addition, both wholesale and retail markets are available (Parvania & Fotuhi - Firuzabad, 2010). They are available.

Bonuses are generally given to customers who choose to be a part of traditional incentive-based DR programs. Traditional DR-based incentive programs are not subject to new technologies and energy systems were used to encourage consumers to decrease their daily consumption of electricity. On the other hand, the participants in the market - based program are encouraged by paying them money to respond properly to their energy demand programs. The amount of money or income each customer receives is based in critical times on a total reduction in power consumption. The less electricity in these times of critical importance, the more money or rewards customers receive. A two - way communication system between the utilities and consumers could be necessary for such programs to be implemented.

a. Management of direct loads (DLC). It is a widely used energy program that allows energy suppliers to control electric equipment from all customers from a remote location. Depending on the need for electric resources, equipment can be activated and switched off (Palensky & Dietrich 2011). DLC-controlled loads generally include water heaters and home air conditioners. DLC programs controlled remotely. The utilities measure the balance between power generation and power consumption to determine whether an appliance needs to be shipped directly. Smart switches must be installed by the involved energy consumers, so that energy can be controlled remotely by the power station. The switches also allow the exchange of energy data between customers and services. In certain cases, power providers don't directly or from a distance control the system, but instead send customer control signals to react for incentives alone. In industrial sector, DLC is seldom used because it can affect customer operations and lead to loss and not incentives. The particular characteristics of industrial loads prevent an industrial load adjustment by the controllable system (Samadi et al. 2010). DLC is primarily used in the residential and small business sectors, which control electricity without having an enormous effect on any type of operations. DLC is generally implemented relatively quickly to prevent customers from receiving a remote control report much in advance (Samadi et al. 2010). Nevertheless, customers who choose to take part in this type of program are paid in advance and are expecting to lower energy consumption by default. DLC is currently used in the United States as a common and straightforward solution. One benefit of this type of DR program is that customers don't need smart equipment. The installation, as described in the Samad-Kiliccote works (2012), of remote control switching systems to manage control loads for air conditioners, rather than smart power control devices.

b. Emergency DR (EDRP) programmes. These programs are market-based programs in which clients can opt out and thus ignore incentives from energy companies. Generally specified these encouragement measures in advance, so that customers know how much they can earn in case of a future emergency. EDRP is currently offered by a New York ISO that operates the New York City grid (Lee et al., 2012). (DRC). (DERP). Participants in New York ISO EDRP must register before using all their incentives. Once the registration has been established, EDRP members receive payments when responding to calls and reducing energy consumption during emergencies. This kind of program rewards participants in emergencies but offers no capacity incentives (Aalami, Moghaddam, & Yousefi, 2010). In other words, customers will receive the same amount, regardless of the amount of electricity used in emergencies, and only if the consumption falls below the predetermined threshold.

c. Request for bidding (DB). This scheme is another DR - based scheme that is generally available to industrial consumers. The DB programmes, in fact - Aalami, Moghaddam & Yousefi, 2010 - offer cuts for consumers on the wholesale energy market. Usually, when an offere is approved, the customers need to act and cut their electricity loads by the amount of the quote when the offer price is less than the wholesale rate. In the absence of any measures, customers are entitled to sanctions and eventually pay higher electricity prices (Kostková et al. 2013). The study by Alizadeh and other researchers (2012) states that the Federal Energy

Regulatory Commission (federal energy regulatory committee-FERC) assumes that demand bidding will' be cheaper than a program in which the end user receives payments that are greater than the market-clearing price to reduce his demand.' The research believes that during the market design, problems may arise. The Texas Electric Reliability Board (ERCOT) is one of the utilities using this DR technology. They implement a customer upload offset scheme in which customers can only submit formal bids on requests. Customers are not enough to encourage them to participate, to make formal offerings by providing incentives, such as capacity payments, because participation in these market-based DR programs is small. The program is also being slightly changed via the DR - supported DB in conjunction with an DR solution that allows energy suppliers to demand a lower energy use at key times so that loads and peak demands are reduced.

#### 2.4.2.3 DR Methods on the basis of variable decision

A decision variable is another way of subclassifying DR methods. DR Methods of Task Planning and DR Energy Methods are mainly two major groups in this context. DR Methods of Task Planning refer to programs that decide when to load a request. Energy management methods DR Methods, however, determine how much energy should be allotted at any given time for certain equipment or electricity loads (Albadi & El-Saadany, 2008).

a. DR methods of task planning. The main function of these types of DR programs is the activation time of devices and electrical loads. Two groups can divide the loads: obligatory loads and programmable loads. Loads must be operated, which are known as unplanted loads as lighting, refrigerators and television stations, and do not tolerate any delay in activation. Schedulable charges are a type of loads in which air conditioning, PHEVs and water heaters can be adjusted, stopped or transferred to different timescales; and the planning charges are exemplary (Rastegar et al. 2012). The quantity of energy available, load operating times and deadlines set in advance are parameters considered in the work schedule for DR programs (Rastegar et al., 2012). The DR program aims to transform households ' energy consumption from low to low hours. During peak demand periods the target power limit is not reached.

b. DR Methods based on energy management. This kind of DR program aims at reducing controllable loads energy consumption at the highest demand time to reduce household energy consumption (Dong et al, 2012). This goal is achieved by planning for the use of power supplies when electricity prices are lower and energy consumed in peak times when energy prices are higher. Air conditioners, for example, can be operated during the summer at 25 ° C instead of 22 ° C and during a certain period the customer can still feel comfortable with less power. Strengthen the customers ' participation of Energy37 Management-based DR Methods using different strategies. Some strategies may include bonuses, electrical loans and reductions in bills. For the research work presented in this thesis, this type of DR Program, which has a DR-based energy management method. This kind of DR program was selected because it takes decisions automatically. It also automatically determines whether a certain amount of controllable loads and electricity can be set on, thus avoiding the manual intervention of the customer.

The results show that the DR program is effective in the field of energy management and can substantially increase the intelligent Grid as a whole.

### 2.5 ENERGY CONSUMPTION OPTIMIZATION

Systems engineering encourages decision makers to use optimization tools to gather new insights into data and to draw confidential conclusions. In the process of identifying system alternative solutions and using optimization tools in line with Systems Engineering Vision 2025, System Engineers will use cost-effective cloud computing resources for optimization (INCOSE, 2014). The document also says that decision support systems must support quick data analysis; multiple variables and uncertainty must be managed through optimization of complex systems.

This section explores various types of DR programs and systems of optimization. Models for optimization are defined as mechanisms to identify the system's conditions to provide it with minimal costs or maximum profit. The use of optimization techniques is examined in newly published papers to design the best DR system possible and to ensure good results. Some of these publications minimize energy costs and social protection programs and increase consumer satisfaction. Mathematically determining the problem of optimization is a set of variables that maximize (or minimize) a set of functions. The main feature is the objective feature (Borwein & Lewis 2006), and there are certain limitations for every single vector or design vector. The design vector forms variables which are part of a particular DR problem. For example, the design vectors of the DR program can be calculated by calculate the demand time in the household, the type of load (e.g. the type of appliance in the household) or the load time and the degree of urgency or priority for the electrical appliance. In an energy management system, charging type plays a major role as it can help define variables. The amount of power that should be decreased and the length of time the load is reduced may specify this type of energy management system. Objective characteristics, e.g. costs of electricity, overall energy consumption, social benefits or a mix are generally defined. Finally, for each individual constraint, the conditions of the DR program under consideration are used.

Limitations are normally parameters or features specific to the system operation (e.g. the power required in certain times of the day for operating air conditioners), such as the energy stored in the system, operating constraints, and energy capacity for operating certain instruments. Optimization models can be classified based on nature and the limitations used in the problem and objective function of the variables or design vectors. A mathematical model will solve a problem of optimization on the basis of this information once it is formulated. For example, if there is a nonlinear function between constraints and objective functions, and all variables of the vector design can be considered integrals, then an integer, non - linear programming problem can be formulated.

Instead, a non - linear mixed integer programming problem (Rao 2009) can be formulated, if there are some (not everyone) variables considered integer, the limitation and objective function of the problem is the same. Furthermore, problems of optimization can, depending upon the nature of the problem, be classified as problem detergent or stochastic. Stochastic issues, interrelationships between them, uncertainties and the stochastic nature of renewable energy generation and energy consumption can define these problems. There are different techniques to solve optimization problems, but each problem is unique and a certain mathematical technique is the only way to solve that problem. Therefore, a correct technique that can lead to a viable solution must be chosen. For instance, a linear integer program can be used for solving a problem because the results are optimal.

Applying optimisation to a formulation is not inevitably an optimal solution. It should be noted. A solution, which is the case with NP-hard problems, cannot be found for several optimization issues. The computer time to find a solution is too high for other optimization problems. In these cases, classic methods of optimisation are avoided as computing costs are unworthy for reaching the solution; the system needs to wait a long time for a solution to be found. This applies to linear programming for major and linear problems and also for quadratic programming which is not suitable for computational problems. Instead of using a heuristic approach when the complexity of a problem is too great, it provides optimal solutions to optimization problems in a short period of time (Maringer, 2005). In this section, DR optimization strategies are classified by optimization objective. Vardakas, Zorba, and Verikoukis categories are divided (2015): (a) minimizing electricity costs; (b) maximizing social welfare; (c) reducing energy; (d) reducing overall power consumption combined; and reducing electricity.

### 2.5.1 Energy Management Optimization Methods

This section discusses several optimization issues that can be identified in the design of DR programs and possible optimization solutions. With the application of optimization methods, a problem with its function, constraints and object variables can be found in an optimal way. Optimization approaches for DR programs in Vardakas, Zorba and Verikoukis (2015) are divided into the following cities:

a) Reduce electricity costs; b) maximize social welfare; c) minimize aggregate energy consumption; d) minimize energy costs; and e) maximize social welfare and minimize aggregate power consumption. literature reviews are provided information to resolve the problems.

### 2.5.2 Minimization of Electricity Cost

In order to minimize electricity costs, the main aim of optimization techniques is to find a final curve that is close to the objective function and represents the objective cargo curve. The DR strategy's goal is achieved when the optimization technique can find an optimal solution. Other aims of the DR strategy may involve minimizing electricity costs to maximize the consumption of renewables, minimizing energy production costs, maximizing the supplier's economic benefits, or minimizing the use of power during peak periods. A procedure for the load scheduling must be developed through defining an objective function in order to effectively formulate a cost minimisation problem (Cui et al. 2012). In finding a solution to this problem, the mathematical formulation of this objective function will be critical. It can be formulated using suitable pricing schemes. The development of a precise load scheduling scheme, taking account of each load type as part of the electrical system, is one of the challenges to formulate optimisation problems, and the particular consumer needs as discussed in Hu et al. 2016. For example, users can define the temperature limits in order to reflect the comfort of their customers in the course of the day for air conditioners or any thermo controlled apparatus. The comfort of customers can be defined as the design vector for reducing electricity costs in order to optimize the problem.

In addition, the nature of the problem of optimization is determined by certain limitations of these features. When mathematically formulating the problem, the complexity of the problem must be determined. In order to determine the problem difficulty, it is necessary to understand the characteristics of the design vector and its objective function and the number of clients involved. This work creates a problem of optimisation when the solution is intended to reduce electricity costs for electrical systems. A mathematical formulation of the optimization model is presented in this chapter. The optimization issue was formulated by the ToU price scheme and by using the optimization L - BFGS - B algorithm, the optimization problem was solved with Newton's methodology to prevent computer costs.

### 2.5.3 Social Welfare Maximization

Difference between energy suppliers ' profit and the total costs of power and transmission networks can be defined in the objective function of formulating the maximization of social protection optimisation issues. The design vector represents the unique features of power charges for this kind of problem optimization, and the line capacity of the system's generation and transmitting parts. Where multiple generators (e.g. using renewable resources) are part of the system, additional constraints can be taken into account in optimization problems (Li, Chen & Low, 2011). To solve this type of optimisation problem, distributed algorithms are recommended as optimal solutions can be found. Some of the information to be taken into account in the wording of the issue include: 1) the addition to the problem of all restrictions that are part of the system, and 2) the inclusion of price schemes in an optimization model. This information can be used to propose different solutions or optimization techniques to solve the social welfare problem's maximization.

The optimization of social protection has been formulated as a convex problem by several research approaches. The Cao et al (2012) model, for instance, assumes that all customers must pass on information on energy consumption to the utilities via smart meters, but that customers who are unable to share information on electricities may be subject to specific payment provisions. The Cao et al (2012) convex optimization model addressed problems using smart meters ' electricity data. The solution to this optimization issue provides every customer with optimal energy resources and maximizes social well-being by the same solution. One of the disadvantages of this solution is that it is computer - intensive and limited to small housing networks.

### 2.5.4 Reduced Energy Consumption Minimization

The best schedule is based on the incentive the utility company receives to encourage clients in certain times of the day to reduce energy consumption. The best planning solution is to find the consumer who can use electricity at peak and medium times, and the consumption of electricity at peak time can be avoided in order to reduce the total energy consumed by households during day.

The stimuli the utility company offers its customers to reduce the electricity consumption at key times are needed to determine the optimal scheduling. The design vector needs to be carefully defined in order to formulate such power-consumption minimization problems. In the event that several types of appliances are involved in the optimization problem with different power requirements and requirements, this should be included in the initial energy consumption reduction system. In addition, all user preferences have to be considered in the load scheduling decision mechanism, to enable customers to engage with the DR method easily (Tan & Ibrahim, 2003). The planning decision also has to take account of the requirements for running and planning loads in the system and the limitations and conditions for the various loads. Moreover, minimizing aggregate energy consumption can be done through encouraging customers to change their own power habits and recompensing them when significant advances have been made.

### 2.5.5 Electricity Cost And Energy Consumption Minimization

This type of problem of optimization is not only aimed at minimizing electricity costs, but also reducing energy consumption. Goldberg (1989) recommends that the following algorithms be used to optimize the problems necessary in order to minimize several types of objective functions: optimization methods based on Pareto and decomposing algorithms. In Pareto methods, the creation of relationships between solutions via a Pareto-dominance concept is an optimal solution and a series of optimal solutions is found after calculating these relationships.

The power system is unconnected to subsystems that cause a series of less complex problems when decomposing algorithms to solve such an optimization problem. Using methods that are compatible with system optimisation, each subsystem is optimised individually. The aim of breaking down the algorithm is to create a less complex set of computer complexity problems. A third solution to minimize electricity and energy consumption is the use of combined weight functions. The weight of the original objective function is set to indicate the importance (Battaïa & Dolgui, 2013). Two or more objectives are combined in a single function in this case.

### 2.5.6 Improve Social Welfare and Reduce Aggregate Energy Consumption

To solve the combined problem of optimizing one of the social welfare objectives and achieving combined energy consumption through multiple optimisation approaches, the other function can be minimized. A cooperative multiresidential programming approach explained in Samadi et al, 2010) must be used to solve this optimization problem if every customer is assumed to have a set of two types of adjustable loads. These loads must be less than a defined amount of energy, however, during different periods this consumption can be adjusted. The cargoes of the second class have to be adjustable, but the total energy requirement will be lacking. The price to be paid with such flexibility is that if the loads operate at a lower power level, they can lead to customer discomfort.

With a distributed sub-gradient algorithm, the final problem of convex optimisation is resolved (Samadi et al, 2010). Some of them are pointed out in Kallitsis et al. (2012) that the solution of the problem of social welfare optimization and the allocation of optimum power can lead to external communications networks. The incertitudes of message reporting due to constraints of the transmission network are one of the communication network problems.

The proposed methodology therefore considers data network components in the intelligent grid to reduce likelihoods for communications network uncertainties like delays. For the optimal scheduling of resources, a distributed algorithm can be used to consider that other customers ' actions can affect individual customers.

# 3. METHODOLOGY

The methodology used during this study including the mathematical formulation is presented in this chapter. Firstly, it defines the classification of prosumers and then describes the proposed Smart Controllable Load (SCL) model. In order to explain the mathematical formulation of the proposed DR methodology, the distinction between different load types considered in the research is also described. The Genetic Algorithm Optimizer is used to reduce the electricity costs by using time - base DR, ToU - price systems and DR optimization techniques.

## 3.1 PROSUMER CLUSTERING

This research utilizes real electrical load data to evaluate the information gathered from the recorded data using a 24-hour clustering technique for groups of customers. A group of customers with similar energy consumption behaviour, such as those in Chicco, Napali, and Piglione (2006), utilizes clustering techniques that segment customers based on similar consumption behaviour.

Clustering is important in the proposed methodology, as the results provide information in the analyzed data set on the most typical kinds of power, and reveal significant data on the customer lifestyle of electrical domestic appliances. With thousands of thousands of data, each cluster has a curve of power load. Each form describes households for various electricity load profiles in their respective clusters.

Four variables are used for the proposed clustering model: data-id, application, gene, Grid. The data ID is the unique home ID of each residential unit, as previously stated. Differents use, gene and grid are the three types of energy in the data set, respectively, which represent the energy used, generated and generated by the grid. The aim of this problem sub-set is to define clusters in order to minimize the total variation intra-cluster for the With-In-Sum-Of-Squares (WSS) parameter.

## 3.2 PROPOSED SCL MODEL

This section offers an optimal approach to the planning of electricity use in a clever house under the ToU price scheme. When power demand goes up or down in ToU prices, the cost of generating electricity goes up or down. (1) it is a voluntary program that enables people to achieve the energy cuts objectives; (2) informs electricity customers during various times of the day, allowing households to turn off their energy consumption when the price is lower; and 3) Effective - time communication between customers and energy suppliers reflects the ToU system – any changes in electricity expenses for any period of time.

Smart meter can be used to control residential appliances or devices. Through communication of the smart meter and the equipment, the operation of each piece can therefore be regulated and used to perform one-on - one control. In the context of energy consumption regulation and electrical appliance choices, the wireless communication level is a promising alternative to better communications between appliances and the Smart Meter.

### 3.2.1 Formulation of SCL model

In order to optimize the energy usage of residents using solar PV systems, the presented energy management system uses household energy patterns. In accordance with ToU electrical prices and usage patterns the proposed optimization model makes decisions on the DR.

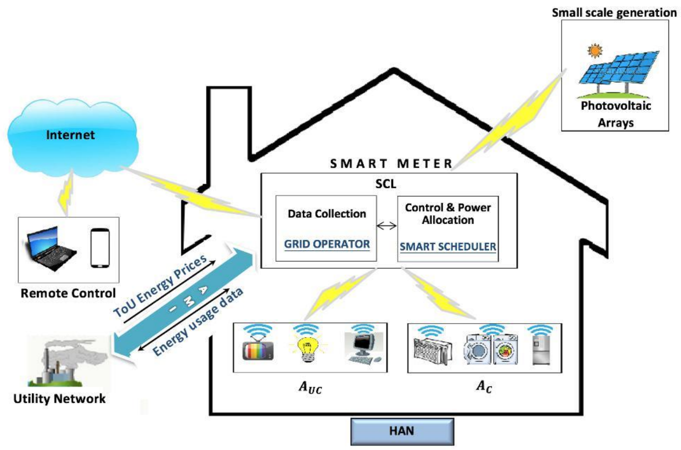


**Figure 3.1:** Architecture of proposed SHEMS.

In particular in the area of cabling, a wireless communications network requires minimum support. Setup for this network type is not necessary because electronic devices can be easily added or removed. Behr (2010) claims that customers are not generally aware of electricity rates or benefit from the absence of electrical devices. Figure 2 shows the energy management system architecture in an intelligent home. It consisted principally of an AMI, an intelligent meter with a grid operator and an intelligent scheduler and intelligent home equipment. The AMI enables double-way communication between the intelligent meter and the utility network. AMI is responsible for collecting and transmitting the collected data to the utility company for electricity consumption from distributed smart meters. With AMI, the utilities send the DR-signal to households with smart meters in almost real time for ToU pricing information (Nagesh et al. 2010). The intelligent meter includes a network operator and an intelligent scheduler. Appliance requests for use of a designated power for a certain period of time are approved by the grid operator. In order to coordinate the planner's function and execute these electricity requests, it ensures that energy consumption is reduced at peak times and electricity costs minimised. This research classifies two types of domestic equipment: uncontrolled loads and adjustable loads, which will be discussed later in this section. First, people who use a set of equipment, represented by the L-BFGS-B algorithm, describes the mathematical model. Moreover, a self-employed schedule, namely SCL, was proposed to avoid manual involvement in DR programmes. The proposed SCL unit aims to integrate the energy management program into smart meters of all households. The main task of the unit is to co-ordinate energy costs. The SCL unit includes a grid operator, where equipment sends energy requests for a certain time, and a charging program that coordinates and performs such electricity requests. The flow chart for the proposed energy management system is shown in Figure 3.

As shown in the figure, the SCL monitors the patterns of household consumption to ensure collective demand does not exceed the fixed limit. The SCL device determines the beginning and end times for the subset intervals of each device and manages the energy consumption of every device. The devices react immediately after a schedule is established for the SCL device and must therefore immediately switch on or off. The planning system proposed should be able to manage the type of devices which are part of the optimization issue correctly. For example, electric loads which require power immediately after they are requested without delay must be allocated. If this type of device is allowed to be delayed with the energy allocation, the customer could decide to leave DR since their comfort is reduced. Appliances or electric loads are defined in the proposed model mathematically in the following paragraphs.

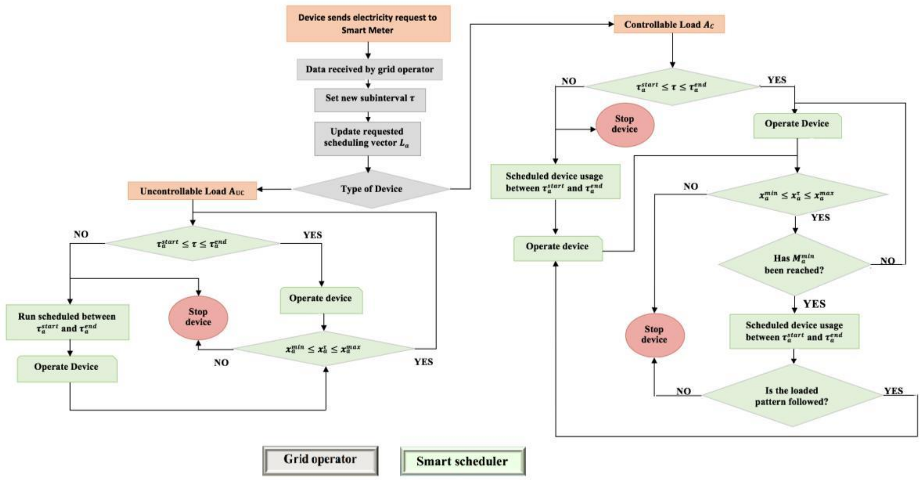


**Figure 1.2:** Proposed SCL model

# 4. IMPLEMENTATION AND RESULTS

## 4.1 SYSTEM MODEL

For one source of energy and N consumers, the power system is considered. Each consumer receives an SM which can monitor and monitor the operation of devices and storage devices in accordance with a specific timetable. In order to achieve an optimized energy plan. We split the H time slots for one day. Assume h = 24, for example, and every slot lasts 1 hour. We denote that consumer load n is I n^h at slot h. The total charge is therefore h at slot h

$$L_h = \sum_{n=1}^{N} I_n^h \tag{4.1}$$

A well-developed DLC charge system, available as a quadratic function $C = K_h L_h^2$, has been introduced in which Kh varies from time to time.

$A_n$ devices are deployed for each consumer. Equipments are composed of two categories: non -shifting equipment must work over a predetermined period of time. Shiftable devices can however be shifted to avoid maximum time within a certain range. Start and end times are described by beginning at n and ending at n and total daily use is desired at En, a. In addition, EMI, N and EMAX, N represent for one operating time the minimum and maximum energy consumption of devices. All of these parameters limit the programming of mobile devices. Consumers can choose storage devices in addition to residential appliances. Power can be stored and consumed in advance at peak times. The energy from the consumer's storage is described as $S_{in,n}^h$ $and$ $S_n^h = S_{in,n}^h - S_{out,n}^h$.

The ability of the consumer storage device is known as Smax and limits maximum energy consumption. The maximum load and discharge rate (smax, in, n, out and n) limits the maximum flow of energy to and from the consumer storage device over a certain time period.

## 4.2 ENERGY STORAGE PLANNING

In the next paragraph, we propose a hybrid approach to storage planning consisting of external GA-based optimization and an internal energy optimization algorithm. The GA shows the storage capacity of all storage devices for consumers. There are several base units to each power storage device. We call the base device BU, and KnBU has a non-negative integer capability as a consumer power device 1 / n/ N. A particular case is kn = 0, meaning that the consumer n does not use a Storage Device.

There are as many basic units for each consumer as possible, which we call Kmax. Some economic and technological conditions influence this maximum value. The GA is therefore restricted by the value Kmax, i.e. it ought to meet kn Kmax for each 1 n N. The fitness function shows the total cost of installation and daily energy consumption of the initial storage equipment. The energy schedule proposed will provide the consumers with optimal energy planning. After that, the fitness function will be computed to assess people and decide if the AG is to be stopped. The GA ends when the fitness function is minimum constant or reached throughout the assigned number of generations. Each user's energy storage device has the optimal output of GA.

## 4.3 DISCOUNTER ENERGY

In this sub-section, we use a theoretical approach to shape the energy management problem. Consumers are regarded as players that are concerned with reducing their own costs in the energy planning game proposed. For each consumer strategy, the limitations already described in the calendar and storage device are limited. The user shall therefore charge each user's costs

$$C_n = \sum_{h=1}^{H} K_h \left(\sum_{a=1}^{A_n} e_{n,a}^h + s_n^h\right)^2 \tag{4.2}$$

In the proposed energy planning game, there are several Nash balance sheets and the same cost. With the proximal discomposure algorithm and the best reaction algorithm [15] we can achieve an optimal schedule.

## 4.4 THE PROPERTIES MECHANISM IMPLEMENTATION

The mechanism for storage planning consists of external optimization and internal optimization. When an optimized solution is solved based on the current situation, the load and other information can be simultaneously processed for each customer.

Populations are constantly updated in external optimization. In order to assess the population with their optimized time schedules and costs, internal optimization must be defined by the consumer when new populations are generated. Fitness function is calculated. The energy programming mechanism has a nesting loop for internal optimization and can be further divided into two phases: initialization and runtime. The central unit broadcasts on {K} to (h h=1)^H in the first initialization phase of the external loop.

In the meantime, all consumers are chosen at random for their initial strategies. The first strategies are launched at random to regularize the play of all consumers and their corresponding loads are announced when the process is initialised. Then the inner loop runtime phase starts. Each user is solved separately for their optimization problem, and their new timetable is communicated to others. Users will constantly have updated optimization problems fixed once new loads are received before no new updates are reported. The regularized game was resolved at this point and the answer is the next strategy. The process begins until a solution for energy planning converges with the strategy. Following the planning process, the total grid costs are compared to non-storage costs. In the case of storage planning, storage equipment will at the beginning cost relatively highly. Then the daily cost is lower and in both cases the difference between the total costs is gradually diminished. The total cost for storage planning after 169 days is reduced compared to the other case. If we consider a 10 year lifespan, a total of $ 24.497 would be saved with storage planning compared to the case without the use of storage.

The energy schedule contributes significantly to flattening the maximum grid load for each single day. The load is displayed in the figure at every slot during the day. According to the wishes of the consumer, the case with the proposed mechanism of energy programming and energy use pattern of origin can be compared. The energy planning scheme reduces the peak load while the peak load increases off-peaks and the peak-to-average (PAR) ratio (pop-to-average) drop from 4.66 to 4.34. This leads directly to the previously shown daily savings.

# 5. CONCLUSION

These researchers assumed that customers would not need an independent planning system to optimize domestic energy consumption and reduce electricity costs, as well as the high energy expense problem in peak times. The research examined the approaches of literary candidates and found that a new DR program based on toU pricing and optimizing the scheduling of devices will not only address these questions, but also improve computer complexity and low-cost solutions.

In this work, the features of Smart Grid Big Data was discussed and a Smart Grid Analytics Big Data architecture was proposed. Then the wireless communication hierarchy for the smart grid was proposed, which includes large data knowledge and technology. We took into consideration residential storage planing on smart grids as a Fall study of the proposed architecture, and we recommended the hybrid approach of external GA optimisation and an internal energy planning optimisation algorithm. We considered wireless communication technologies. Finally, the results of the simulation are shown in the proposed storage scheme. The overall cost of consumers is significantly reduced in the long term by the storage planning scheme.

Customers in its assigned clusters and their respective ToU price categories reduced energy costs after using the proposed load planning system. The simulation results showed that customers saved 32.93 percent in electricity per days thanks to the proposed home energy management system based on ToU. Better results than in Ma et al, (2016), a charging scheduling model with maximum savings of 11.60 percent per day, were produced by the proposed Smems. The findings show that the system proposed is an efficient solution to the challenge for the domestic energy management, as the analysed data set optimized the energy allocation and minimized energy costs for all customers.

## 5.1 SUGGESTIONS

The following possibilities should be considered to extend the research work presented in this dissertation:

1. The proposed macroscopic smart load programming system could be considered in future studies. Therefore, in the context of engineering systems economic models, installation costs and other financial advantages are studied.
2. Given that in the next few years the number of electrical cars will increase between households, the effect of this type of load on the proposed load scheduling system is important to study.
3. Being aware of the intermittent energy resources that solar and wind are generating, the proposed approach should consider extending to a more robust optimization model, which would take into account the energy storage system capacity and effects of the model.
4. For inclusion in the optimization model additional criteria and requirements should be taken into account, such as household satisfaction and customer response to energy prices.

Load predictions should be considered to complement the proposed optimization model in order to improve scheduling system accuracy.

# REFERENCES

[1] IBM Corp. Software Group, “IBM Big Data Overview for Energy and Utilities”; http://www-01.ibm.com/software/tivoli/solution/industry/energy-utilities, 2012.

[2] R. Yu et al., “Hybrid Spectrum Access in Cognitive-Radio- Based Smart-Grid Communications Systems,” IEEE Sys. J., vol. 8, no. 2, 2014, pp. 577–87.

[3] G. Carpinelli et al., “Optimal Integration of Distributed Energy Storage Devices in Smart Grids,” IEEE Trans. Smart Grid, vol. 4, no. 2, 2013, pp. 985–95.

[4] H. Jiang et al., “Energy Big Data: A Survey,” IEEE Access, vol. 4, no. 2, 2016, pp. 3844–61.

[5] J. Hu and A. Vasilakos, “Energy Big Data Analytics and Security: Challenges and Opportunities,” IEEE Trans. Smart Grid, vol. 7, no. 5, 2016, pp. 2423–36.

[6] M. Bhide and K. Ramamritham, “Category-Based Infidelity Bounded Queries over Unstructured Data Streams,” IEEE Trans. Knowl. Data Eng., vol.25, no. 11, 2013, pp. 2448–62.

[7] K. Wang et al., “LDPA: A Local Data Processing Architecture in Ambient Assisted Living Communications,” IEEE Commun. Mag., vol. 53, no. 1, Jan. 2015, pp. 56–63.

[8] K. Wang et al., Mobile Big Data Fault-Tolerant Processing for eHealth Networks,” IEEE Network, vol. 30, no. 1, Jan. 2016, pp. 1–7.

[9] K. Wang et al., “Real-Time Load Reduction in Multimedia Big Data for Mobile Internet,” ACM Trans. Multimedia Computing, Commun. and Applications, vol. 12, no. 5s, Article 76, 2016.

[10] S. Bi et al., Wireless Communications in the Era of Big Data,” IEEE Commun. Mag., vol. 53, no. 10, Oct. 2016, pp. 190–99.

[11] K. Wang et al., A Game Theory Based Energy Management System using Price Elasticity for Smart Grids,” IEEE Trans. Ind. Info., vol. 11, no. 6, 2015, pp. 1607–16.

[12] Y. Kong, M. Zhang, and D. Ye, “A Belief Propagation-Based Method for Task Allocation in Open and Dynamic Cloud Environments,” Knowledge-Based Sys., vol. 115, 2016, pp. 123–32.

[13] Z. Fu et al., “Towards Efficient Content-Aware Search over Encrypted Outsourced Data in Cloud,” Proc. IEEE INFOCOM, San Francisco, CA, 2016.

[14] K. Wang et al., “Towards Trustworthy Crowdsourcing in Social Internet of Things,” IEEE Wireless Commun., vol. 30, no. 5, Oct. 2016, pp. 30–36.

[15] R. Johansson and A. Rantzer, “Distributed Decision-Making and Control,” Lecture Notes in Control and Information Sciences Series, Springer-Verlag, 2011.