SENSORS AND NEURAL NETWORKS TO SUPERVISE INTEGRATED RENEWABLE ENERGY SYSTEMS (IRES)

By

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SENSORS AND NEURAL NETWORKS TO SUPERVISE INTEGRATED RENWABLE ENRGY SYSTEMS (IRES)

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N1	Energy need with highest priority (cooking)
N2	Need with second highest priority (domestic water pumping)
N3	Need with next highest priority (lighting and educational)
N4	Need with least priority (irrigation water pumping)
R1	Volume of biogas available from biomass (m^3)
R2	Solar energy from PV panel 1 (kWh)
R3	Wind energy (kWh)
R4	Solar energy from PV panel 2 (kWh)
R5	Battery charge (kWh)
A1	Assumed percentage (100%) of N1 to be met
A2	Assumed percentage (80%) of N2 to be met
A3	Assumed percentage (50%) of N3 to be met
A4	Assumed percentage (25%) of N4 to be met

NOTATION USED IN NEURAL NETWORK ARCHITECTURE

D	Tapped delay
$\mathbf{P^l(t)}$	l^{th} input vector to the network at time ‘t’
$\mathbf{R^l}$	Number of elements in the input vector ‘l’
$\mathbf{IW^{11}}$	Input weight between input layer and layer 1
$\mathbf{b^1}$	Bias vector for layer 1
$\mathbf{s^1}$	Number of neurons in layer 1
LW^{11}	Layer weight of self-recurrent neurons of layer 1
$\mathbf{n^1(t)}$	Net input of layer 1
$\mathbf{f^1}$	Transfer function of layer 1
$\mathbf{a^1(t)}$	Output vector of layer 1
$\mathbf{LW}^{21}$	Layer weight between layer 1 and layer 2
$\mathbf{s^2}$	Number of neurons in layer 2
$\mathbf{b^2}$	Bias vector for layer 2
$\mathbf{n^2(t)}$	Net input of layer 2
$\mathbf{f^2}$	Transfer function of layer 2
$\mathbf{a^2(t)}$	Output vector of layer 2

CHAPTER I

INTRODUCTION

1.1 Background

Continued rapid increases in global demand for fossil fuels, environmental concerns, declining production levels and the ensuing steep increases in cost have contributed to a surge of interest in harnessing renewable energy resources. Nowhere is the situation more adverse than in remote rural areas of developing countries in Asia, Africa, and Latin America. The unabated growth rate of human population in these countries has placed considerable pressure on the available depletable energy resources to meet their demands. Constantly degrading standards of living in rural areas of developing countries are leading to large scale migration to urban areas. The result is the emergence of slums around many big cities [1,2]. Besides, environmental concerns such as acid rain, water pollution, global warming, green house gas emissions and forest depletion, among others, have highlighted the indispensable role of renewable energy resources. Radioactive emissions, disposal of spent fuel and potential environmental impacts have made nuclear fuels unpopular. All these factors have collectively contributed to a revived need for an effective alternative. The energy made available from locally available renewable energy resources such as biomass, wind, solar and hydroelectric power can be used to meet the energy and other needs of rural areas.

1.2 Energy Crisis

With steep increases in population and mass migration to urban areas, developing countries are facing difficulties to provide the basic amenities to their people such as food, clean drinking water and homes for even a reasonably healthy lifestyle. This problem is more pronounced in rural areas. With growing population, the delicate balance that exists in nature among energy consumption, growth and development is disturbed [3]. This leads to a vicious situation of the "survival of the fittest". People in urban areas with a constant source of income can afford a better standard of living compared to those in rural areas. Lack of energy supplies to rural areas leads to further deterioration in the quality of life in rural areas. Therefore, necessary steps need to be taken to develop economical and reliable sources of energy supply, especially in remote rural areas.

1.3 Role of Renewable Energy in Developing Countries

The two main dilemmas faced by all developing nations of the world are the exponential growth of human population and rapid urbanization. The governments face serious issues in supplying this population with the basic amenities for a reasonable standard of living. More than a third of these countries are primarily rural with no access to any commercial forms of energy such as coal, oil or natural gas. Most of these areas are not connected to national grids and therefore supplying electricity to these areas is highly uneconomic. Furthermore, migration of people from rural areas to urban areas results in an overall increase in the per-capita energy consumption. This places a considerable strain on the economies of these countries [4]. The development of techniques to harness renewable energy resources will have its greatest impact in densely populated developing countries [5]. Rural electrification has been considered a solution to the energy crisis faced by such nations. But supplying electric power to remote loads through national grids is prohibitively expensive and can take a heavy toll on the economies of such countries. Moreover, the light and sparse load demands in such areas will also make the process more difficult. One possible solution can be harnessing locally available renewable energy resources. These resources, however, have seasonal variations and are highly stochastic in nature. They are site-specific as well. But renewable energy resources have the advantage of being eco-friendly and pollution free. In order to take advantage of the temporal and seasonal variations in the availabilities of such resources, Ramakumar, et. al. [6] proposed an integrated approach for harnessing all the locally available renewable energy resources to power remote loads requiring a mixture of energy needs of various grades. Integrated Renewable Energy Systems (IRES) utilize several renewable energy resources with different and varying characteristics to supply various forms of energy and other needs in an economical manner with the goal of integrating benefits at the user end.

1.4 “Electrification” versus “Energization”

Renewable energy resources are dilute, abundant and are fairly evenly distributed around the world. The most important and useful forms of renewable energy resources are insolation, wind energy, biomass and hydro. Energy from these resources can be harnessed in a number of ways. Hybrid systems typically convert all the available resources to one form of energy, usually electricity, and supply all the loads with this form. The load demands of a rural area will be of different grades. For instance, cooking needs can be satisfied by low grade heat available from biomass. Meeting demands with a form of energy higher than needed may prove to be both expensive and wasteful. Using a number of resources in tandem and a variety of conversion technologies to achieve the benefits at the user end in an integrated fashion is the core idea behind IRES .

As mentioned earlier, extension of power grid to remote rural areas may be very expensive and inefficient due to low load demands. Physical connection to a grid is not the solution for supplying the energy needs of rural areas. Moreover, physical connection does not guarantee the availability of energy. What needs to be done is “energization” rather than “electrification” [7].

“Energization involves the harnessing of locally available renewable energy resources and the employment of several energy forms of differing quality and characteristics to satisfy a variety of energy and other needs in an integrated fashion”. The key here is to match a set of needs with a set of available resources (of variable characteristics) in an optimum way. For instance, converting biogas into electricity for meeting cooking needs is very inefficient, especially in a rural setting.

1.5 Objective of the Study

The essence of IRES is to utilize several renewable energy resources to supply various forms of energy and other needs in an economical manner. The key is to match the resources and needs *a-priori* and make decisions based on a prioritized set of needs. This work proposes an approach to assess the information provided by a set of sensors strategically located in the IRES and help generate control signals in discrete events of time to actuate a set of controllers to best meet the needs of a small rural area using wind, insolation, biomass and hydro. Suitable neural networks are proposed to accomplish this task. Approaches to train neural networks for performing the prioritization task and generating control signals are discussed.

1.6 Organization of the Thesis

This section provides a brief overview of the various topics discussed in the chapters that follow.

Chapter II: Review of Literature: evaluates the various renewable energy resources as alternatives to the depletable resources used extensively in today's world. It then moves on to discuss the pros and cons of renewable energy.

Chapter III: Integrated Renewable Energy Systems: introduces the reader to integrated renewable energy systems, which forms the core of the material covered in this work. It also discusses the need for such systems, the challenges faced during their design, and their operation. This section also summarizes previous work on such systems.

Chapter IV: Sensors and Controllers for IRES: identifies the various sensors and controllers proposed for the system. It presents the basic operation of the system and the scenarios that have been assumed to develop the overall system.

Chapter V: System Design: explains the prioritization algorithm, based on which the resources and needs are matched. This section discusses the possibilities of training a neural network to perform the task of prioritization. It also covers the decision making procedure adopted by the controller block in generating the control signals.

Chapter VI: Discussion of Results: discusses the simulation results and *Chapter VII: Conclusions and Scope for Further Work:* documents the concluding remarks and scope for further work.

CHAPTER II

REVIEW OF LITERATURE

2.1 Evaluating Renewable Energy Resources

The energy dilemma coupled with rapid urbanization in developing countries has led to an increase in poverty, unemployment, crime and starvation. Nearly a third (about two billion people) of the world's population lives in rural areas of developing countries with no access to commercial energy resources. This has left renewable energy as the only alternative to combat the energy crisis in these countries. Making energy resources available and accessible to everybody helps contribute to the socio-economic development of rural communities [8]. One of the greatest challenges facing the engineering community is global development in a sustainable manner. Sustainable development involves paving the path for meeting the present needs without compromising the ability of meeting the needs of the future. This implies that future generations should not be deprived of their opportunities to lead a life of quality as good as or better than that of the current generation. Sustainable development therefore necessitates the careful and planned utilization of locally available renewable resources. Sustainability can also be achieved by conservation of depletable resources and management of local resources by rural communities, among others. With renewables, there is a diversity of choices and a shift towards sustainable development will provide a far cleaner environment for all the inhabitants of planet earth. By using energy efficiently and by expanding the use of renewable energy, the world can have adequate supplies of energy well into the future [9, pp. 9].

The commercialization of renewable energy resources raises the question of how much they are worth as compared to conventional alternatives. This is a difficult question to answer. The determination of value is not straightforward in many cases. The value of electricity generated from renewable energy resources will vary depending on the technology, application, location and available alternatives. An overview of the various renewable energy resources is given below.

2.1.1 Hydroelectric Power

Energy harnessed from running/falling water is hydro energy. Hydroelectric power is a source of comparatively low cost electricity. It contributes to nearly 20 percent of the world's electricity [see Ref 9, pp. 17]. The abundance of water on the earth's surface is a boon. But due to a lack of capital investment in developing countries, only a small portion of the available energy is harnessed. A large amount of electricity can be generated using mini and micro hydro systems coupled with the installation of suitable infrastructure.

Energy can be generated from moving water in a variety of ways. Small-scale hydropower facilities almost invariably use run-of-river plants. A major disadvantage of such facilities is that they lack reservoir capacity to store water. A part of water from a river is channeled to flow into a pipeline at the other end of which is a turbine coupled to a generator to generate electricity [10]. These are mostly used in rural areas as they do not require large reservoirs. Small-scale hydropower units have been used extensively in

China. Currently, these units account for nearly a third of China's hydroelectric power generation.

Hydro power units are classified mainly based on their power output as large, medium, small, mini and micro hydro. Of these, mini and micro are used in rural areas.

2.1.2 Biomass

Biomass collectively refers to all organic matter on earth. It accounts for nearly 15 percent of the world's energy use and 38 percent of energy use in developing countries [11]. Biomass is extensively used in rural areas of developing countries mainly for heating and cooking purposes. But most of it is used very inefficiently. Biomass can be converted into gaseous (biogas) and liquid (ethanol) fuels and its use can be modernized. These energy carriers can be produced at competitive costs. As biomass is the most commonly available resource in rural areas, large scale utilization of biomass for energy can provide a good start for socio-economic development of such communities and can also help curb urban migration.

Biomass has been held in low esteem as an energy source and the role of biomass in global economy is not appreciable. But detailed surveys show that biomass accounts for about 27 percent of total energy in Egypt, 10 percent in Austria and 9 percent in Sweden [12]. Harvesting of forests for biomass fuel has been a growing concern. Over the next few decades, industries will surge into energy plantations, the greatest potential source for biomass. Degraded lands in developing countries and excess croplands in industrialized countries can be used as sites for energy plantations.

Most of the rural areas use firewood for cooking. Such firewood stoves are inefficient and generate considerable air pollution, causing health problems. In addition, gathering firewood leads to deforestation. But if biomass is specifically grown for fuel and used sustainably, no excessive release of carbon dioxide in the atmosphere results since all the carbon dioxide released during combustion will be extracted by plants via photosynthesis, completing the carbon cycle.

Ultimately, biomass could be a major source of energy, almost on par with natural gas. Biomass can be considered useful for the following reasons:

a. Biomass is more widely available than fossil fuels.
b. It is renewable.
c. They do not add to the carbon dioxide burden of the atmosphere.
d. If produced sustainably, biomass could become a major contributor to the world's commercial energy economy.

2.1.3 Wind Energy

Among all renewable energy resources, wind energy is gaining noticeable popularity. This is mainly attributed to its ease in distributed generation [13]. During the past two decades, commendable progress has been made in the technology used to convert wind energy to electrical energy. Utilities now routinely operate wind turbines in conjunction with conventional generators such as hydroelectric, coal, oil and gas fired plants and nuclear stations. Wind turbine manufacturing techniques have seen a remarkable growth. In areas with good wind resources, wind-generated electricity now costs only about U.S. $0.053 per kWh. This may decline to U.S. $0.029 per kWh with advances in wind turbine technology, power electronics and control strategies [14]. More than 15,000 wind turbines operate in California and nearly 2,800 in Denmark. It is estimated that about 1670 trillion kWh of energy is available annually from the winds sweeping the earth's surface [15]. Figure 2.1 shows the U.S. wind power capacity in MW, both annually and cumulatively.

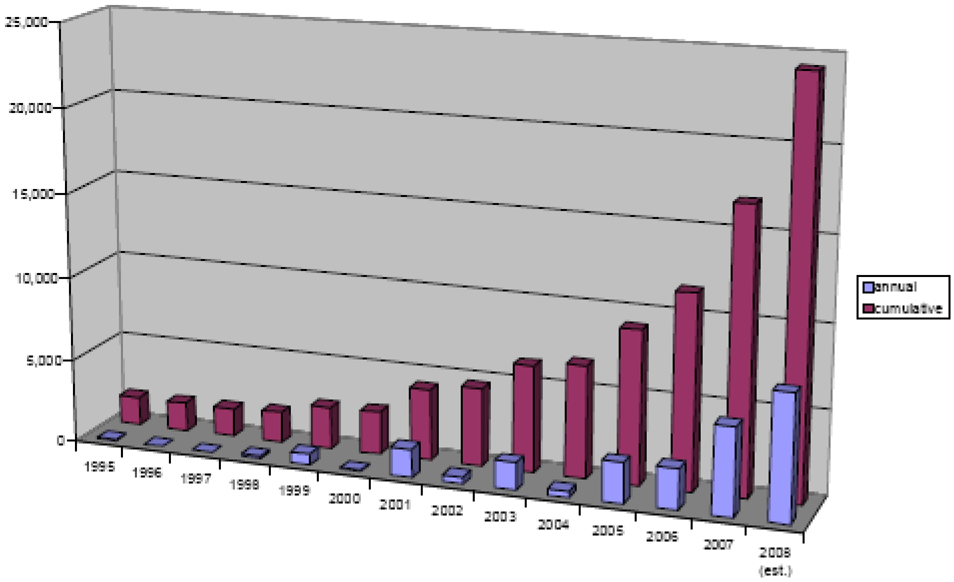


Figure 2.1: U. S. Wind power capacity, annual and cumulative (MW) [16]

Research is now being conducted on developing offshore wind energy, since wind speeds are higher and steadier offshore than onshore. Although wind energy conversion is relatively simple, designing large wind turbines is complex and requires a high capital investment as well. The basic limitation with wind is its intermittent nature. This problem can be overcome with better control, aggregated operation and use of suitable energy storage and reconversion systems.

Rural areas typically do not require large wind turbines with high power outputs. Small units with a few kWh energy output would suffice for meeting the energy needs of a variety of activities in such areas. Figure 2.2 shows the installed utility-scale wind power as recorded on September 30, 2008.

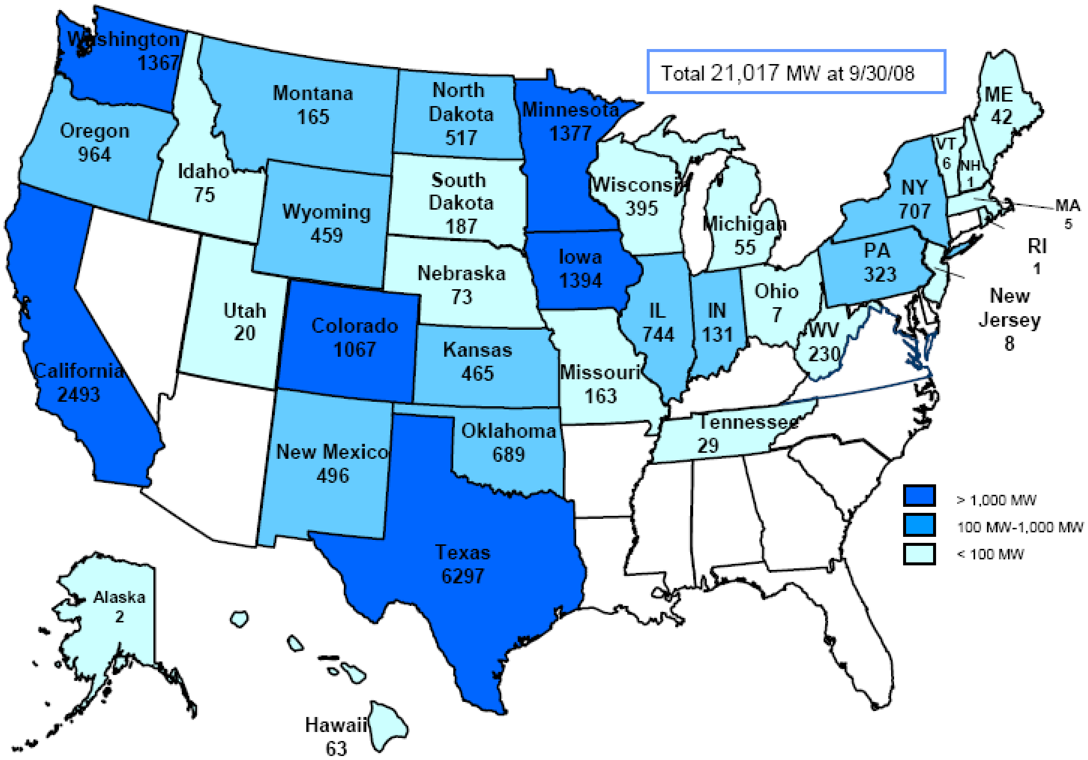


Figure 2.2: Installed utility-scale wind power as of September 30, 2008 [see Ref. 16]

2.1.4 Insolation

The incident solar radiation or insolation has been the major and only source of energy for all life forms since time immemorial. All of the world's energy needs can be met by utilizing just a small fraction of the energy available from the Sun. Although the rate of energy radiated by the Sun is $3.77*10^{26}$ W, only a small fraction (roughly to the tune of $1kW/m^2$) of this reaches the earth's surface after passage through the atmosphere [17,18]. It is, however, true that the conversion techniques are expensive and inefficient. But even with low conversion efficiencies, a variety of needs can be met from solar energy.

A photovoltaic (PV) cell is a large area p-n junction semiconductor diode. Outputs of individual cells are only about 1 or 2 watts at 0.5-0.6 V. In order to generate practical outputs, several such cells need to be connected in a series-parallel configuration [19]. PV modules and arrays can be used to provide energy for individual homes or commercial equipment. Capital costs for PV devices have decreased from \$50/Wp to below \$5/Wp over the past few decades [20]. However it is still expensive compared to wind energy systems. Developments in the technology of semiconductor materials used in such devices may lead to further reduction in cost and enhance the performance of such devices.

Some of the advantages of PV systems are:

a. They require relatively lower operation and maintenance costs as compared to other alternatives.
b. PV systems exhibit simplicity in operation with few moving parts.
c. PV systems can be installed rapidly.

Some of the limitations of PV systems are:

a. High capital cost
b. Large collection areas
c. Diurnal and seasonal variations in the availability of sunlight.

With low cost PV modules, a wide range of energy and other needs of developing countries can be met with the available solar energy, as most of the countries lie in the sunny equatorial regions of the world.

Thermophotovoltaics is a recent development and it can enable generation of electricity even during nights or during heavy cloud cover. This can eliminate the need for storage devices [21]. Solar-thermal-electric conversion is a group of technologies that harness solar energy for heat [see Reference 11]. It uses solar heat as the input for a conventional thermal cycle with a working fluid. The two broad categories available are:

a. Distributed collector with central or distributed generation
b. Central collector with a central generation system

The distributed collector can be either a flat-plate type or a parabolic trough or dish. Low temperature outputs are obtained using flat-plate collectors which makes them unsuitable for electric power generation. The parabolic trough type of collector results in a line-focus system, which enables an array of collectors to be employed to collect and transport thermal energy to a central location for use in a thermodynamic system.

In central collectors, insolation is concentrated on a central receiver. This energy can then be transferred to a working fluid or to a molten salt for storage.

2.2 Storage of Energy

As renewable energy resources are dilute and stochastic in nature, it is imperative that appropriate storage and reconversion systems be employed. Storage batteries are widely used as energy backup. Lead acid batteries are the most economic ones and are widely used in rural areas. Potential energy of stored water, biogas and biomass are additional storage options. Other options include flywheels, super-capacitors, and compressed air.

2.3 Pros and Cons of Renewable energy resources

Some of the advantages and limitations of renewable energy resources are listed below.

Advantages:

a. Abundant
b. Democratic in that they can be used by anybody.
c. Evenly distributed around the world.
d. Eco-friendly.

e. Absence of recurring fuel costs.

f. Suitable for rural areas, typically not connected to the grid.

g. Inputs are free or inexpensive.

h. Helps conserve fossil fuels.

i. Reduces the need for importation of fossil fuels.

Limitations:

a. Energy systems are highly capital intensive.

b. Highly stochastic in nature.

c. Requires large collection areas.

CHAPTER III

INTEGRATED RENEWABLE ENERGY SYSTEMS (IRES)

3.1 Introduction

Systems that utilize two or more forms of renewable energy resources in tandem to supply various grades of energy and other needs in the most efficient and economic manner possible, with the goal of integrating benefits at the user end are termed IRES. Such systems can operate equally well in both stand-alone mode and in conjunction with conventional energy systems. IRES provide an effective and economical approach to "energize" remote rural areas instead of the "electrification" approach promoted by hybrid systems [22,23]. IRES provide energy by harnessing locally available resources and thereby do not increase any of the environmental burdens. The renewable energy resources that are generally considered are:

a. insolation,
b. wind,
c. hydro, and
d. biomass.

The benefits of such a system are best realized in remote rural areas not connected to the grid.

3.2 Need for IRES

Renewable energy resources are highly site-specific and stochastic in nature. Their seasonal occurrences tend to complement each other. Some of the resources are available in excess whereas some are scarce; some resources are available during summer while others during winter. In order to best use such resources we need to utilize the strength of one resource to overcome the weakness of the other [24]. Integrated use of different resources helps minimize the amount of energy storage to a considerable extent. This is particularly applicable to rural areas as some of the resources such as biomass and insolation are available in abundance while others are sparsely distributed depending upon the location and the nature of the terrain. IRES have the potential to serve to "energize" such rural areas. Ultimately, it leads to a socio-economic upgrade of rural communities.

3.3 Design Considerations

Any design procedure aims at determining the sizes and ratings of the energy conversion and storage devices needed to supply the needs. IRES are highly capital intensive even though the inputs are virtually free of cost or inexpensive. Designing the system for minimal capital cost is a good first step in order to achieve low annual cost of operation.

The major challenges faced in the design of IRES are the intermittent nature of the resources and variations in loads. This calls for several compromises in the design. The designers are faced with the fundamental problem of meeting highly variable loads with highly stochastic resources. The design procedure therefore should emphasize the identification of the goals and benefits and the matching of resources and needs.

3.4 Operation of IRES

3.4.1 Hybrid versus Integrated Systems

In order to harness locally available resources, two approaches are primarily considered, namely hybrid and integrated. In hybrid systems, all available energy forms are converted into one form, namely electricity. This approach is expensive, inefficient and not economical for rural development. Moreover, meeting demands with a form of energy of higher quality than necessary will prove to be expensive and inefficient. On the other hand, IRES promote the concept of "energizing" rural areas by matching the available resources and the needs *a priori*. The goal is to integrate the benefits at the user end.

3.4.2 Components of IRES

One of the many possible configurations of IRES is shown in Figure 3.1. IRES mainly comprise of wind-electric conversion systems, anaerobic digesters, engine-driven generator, photovoltaic arrays, energy storage devices, water storage tanks, micro hydro and water pumps. These devices can be used in different combinations to meet the energy and other needs of the area under consideration. It is necessary that the designer survey the locality to gather both qualitative and quantitative information on the resources and needs in the particular locale under consideration.

3.4.3 Related Work

Previous work on IRES include a knowledge-based design approach [see Reference 6], operation based on a proposed priority for meeting demands [see Reference 14], and a probabilistic approach to study IRES operation using Markov models [25].

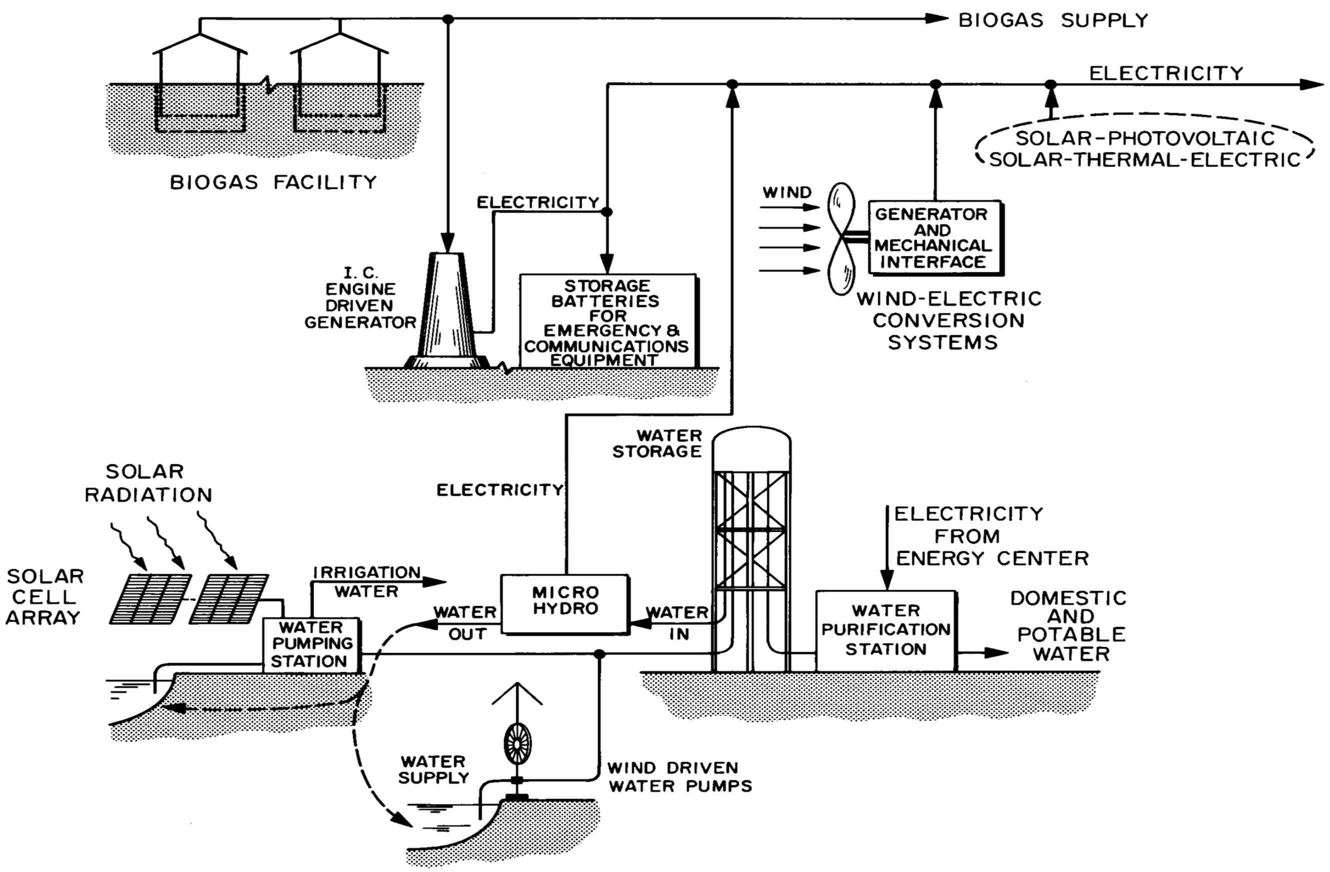


Fig 3.1: Schematic representation of IRES [31]

In the knowledge-based design approach, the year is divided into a number of seasons such that the variations of the loads and resources within each season are reasonably similar on a daily basis. The ratings of the various energy conversion and energy storage devices needed to satisfy the needs at a preset level of reliability are determined using the procedure for each of the seasons for corresponding sets of resource availabilities. The final design is obtained by prioritizing the various seasonal designs. Provisions are made for storage of excess energy in order to make the design cost effective. This task was facilitated by introducing a search algorithm and a knowledge base to the approach presented in [26]. Other design approaches such as chronological simulation [27], linear programming [28], [29], and goal programming [30] have been discussed in the literature.

CHAPTER IV

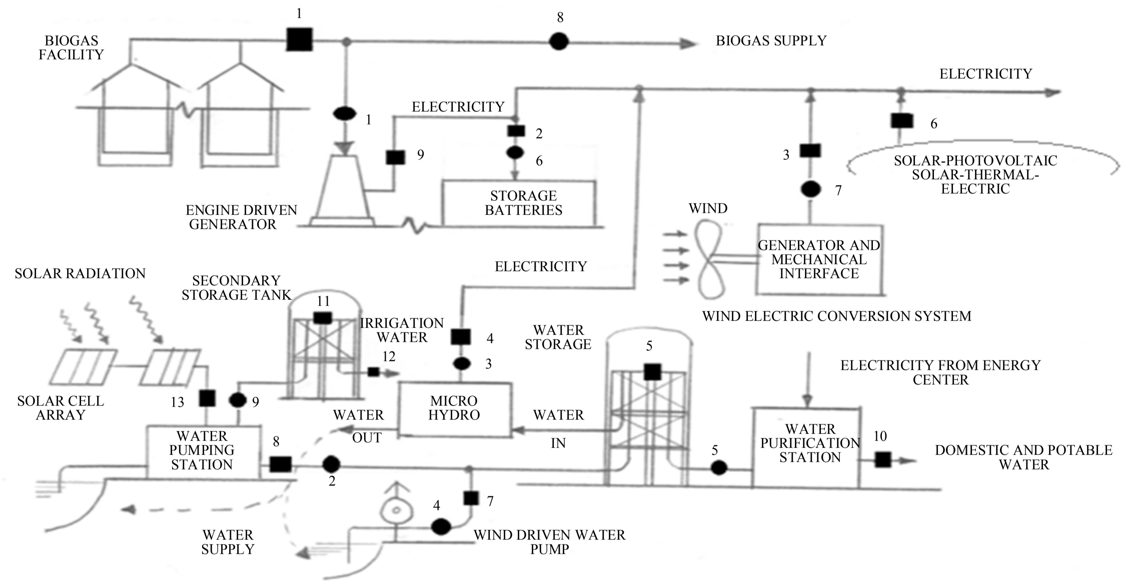
SENSORS AND CONTROLLERS FOR IRES

4.1 Introduction

An integrated renewable energy system typically operates in stand-alone mode, though it can perform equally well when connected to conventional energy systems. The unpredictable nature of the resources imposes some constraints on the system design, as described in the previous chapter. The stochastic nature of the renewable energy resources demands that the availability of these resources be monitored continuously. That will require sensors located at appropriate and strategic locations in the IRES. This work has identified 13 sensors in the design [32], as listed in Table 4.1. The number of sensors can be varied as the situation demands. Based on the outputs from the sensors and needs, control signals are generated and transmitted to controllers to turn devices ON/OFF as appropriate. A schematic representation of one such configuration of with sensors and controllers is shown in Fig 4.1.

4.2 Sensors

The sensors employed are categorized into two groups: **resource sensors** and **status sensors**. Resource sensors continuously monitor the variations in the availability of biomass, insolation values at the locations of the two photovoltaic (PV) panels, wind and the state of battery charge. The reading of the sensor that monitors the amount of



■ SENSORS FOR MONITORING

1 – AMOUNT OF BIOMASS (kg)
2 – CHARGE LEVEL IN BATTERY (kWh)
3 – WIND SPEED (m/s)
4 – MICRO HYDRO OUTPUT (kW)
5 – WATER LEVEL OF DOMESTIC WATER TANK (m)
6 – INSOLATION VALUE AT PANEL 1(kW/m^2)
7 – VOLUME OF WATER PUMPED BY WIND DRIVEN PUMP (m^3)
8 – VOLUME OF WATER PUMPED BY SOLAR WATER PUMP (m^3)
9 –OUTPUT OF ENGINE-DRIVEN GENERATOR (kW)
10 – VOLUME OF WATER DRWAN FOR DOMESTIC SUPPLY (m^3)
11 – WATER LEVEL OF SECONDARY STORAGE TANK (m)
12 – VOLUME OF WATER SUPPLIED FOR IRRIGATION (m^3)
13 – INSOLATION VALUE AT PANEL 2 (kW/m^2)

● MECHANICAL CONTROLLERS FOR TURNING ON/OFF

1 – ENGINE DRIVEN GENERATOR
2 – SOLAR WATER PUMP
3 – MICRO HYDRO
4 – WIND DRIVEN WATER PUMP
5 – SUPPLY TO WATER PURIFICATION STATION
6 – CHARGING OF STORAGE BATTERIES
7 – WIND ELECTRIC CONVERSION SYSTEM
8 – BIOGAS SUPPLY FOR COOKING
9 – SOLAR PUMP FOR IRRIGATION SUPPLY

Figure 4.1: IRES with sensors and controllers

insolation, for example, directly translates it to the amount of solar energy available per unit of incident area during that particular time step. Similar conversions are performed with all the sensors. As there are 5 sources of energy supply, 5 resource sensors are employed. The resource sensors are listed in Table 4.2 [see Reference 32]. The status sensors are the ones that contribute indirectly to generating control signals. For example, the sensor that monitors the water level in the storage tank helps in deciding whether or

Table 4.1: List of sensors used in IRES [see Ref. 32]

Sensor #	Monitors
1	Amount of biomass (kg)
2	Charge level in battery (kWh)
3	Wind Speed (m/s)
4	Micro hydro output (kW)
5	Water level of domestic water tank (m)
6	Insolation value at panel 1 (kW/m^2)
7	Volume of water pumped by wind driven pump (m^3)
8	Volume of water pumped by solar pump (m^3)
9	Output of engine-driven generator (kW)
10	Volume of water drawn for domestic use (m^3)
11	Water level of secondary storage tank (m)
12	Volume of water supplied for irrigation (m^3)
13	Insolation value at panel 2 (kW/m^2)

Table 4.2: Resource Sensors [see Ref. 32]

Sensor #	Monitors
1	Amount of biomass (kg)
2	Charge level in battery (kWh)
3	Wind Speed (m/s)
6	Insolation value at panel 1 (kW/m^2)
13	Insolation value at panel 2 (kW/m^2)

not the water pump needs to be turned ON or OFF, depending upon the level of water in the tank. This work has identified 8 status sensors, as tabulated in Table 4.3 [see Reference 32]. Figure 4.1 shows the various sensors located in the integrated renewable energy system.

Table 4.3: Status sensors [see Ref. 32]

Sensor #	Monitors
4	Micro hydro output (kW)
5	Water level of domestic water tank (feet)
7	Volume of water pumped by wind driven pump (m^3)
8	Volume of water pumped by solar pump (m^3)
9	Output of engine-driven generator (kW)
10	Volume of water drawn for domestic use (m^3)
11	Water level of secondary storage tank (feet)
12	Volume of water supplied for irrigation (m^3)

4.3 Controllers

Based on the outputs of the sensors and preset/forecasted needs, control signals are generated to turn ON/OFF the corresponding devices. This function is taken care of by a controller block. Nine controllers have been identified and their functions are tabulated in Table 4.4 [see Reference 32].

4.4 Basic Block Diagram of the Control System

The resource sensor readings are meaningfully assessed by a trained neural network to generate the percentages of various needs that can be met with the available resources during a particular time step, based on a priority classification of a given set of

Table 4.4: List of controllers [see Ref. 32]

Controller #	Turns on/off
1	Engine-driven generator
2	Solar water pump
3	Micro hydro
4	Wind driven water pump
5	Supply to water purification station
6	Charging of storage batteries
7	Wind electric conversion system
8	Biogas supply for cooking
9	Solar pump for irrigation supply

needs. The control logic then takes the values of the percentages of needs and the present readings of status sensors as inputs and generates the appropriate control signals at every time step. A time step of 1 minute is chosen for the study. A schematic representation of the system is shown in Fig 4.2.

4.5 Scenarios for IRES Operation

As long as all the resources are available at their maximum design values, all the needs can be met fully according to the pre-set priorities. The difficulty of having to utilize a variety of renewable energy resources in tandem for a particular end-use arises when some of the resources are not available to the full extent. Such scenarios have to be considered in the design of the neural network and controller block [33,34]. During every time step, the available resources need to be used in an optimal way as much as

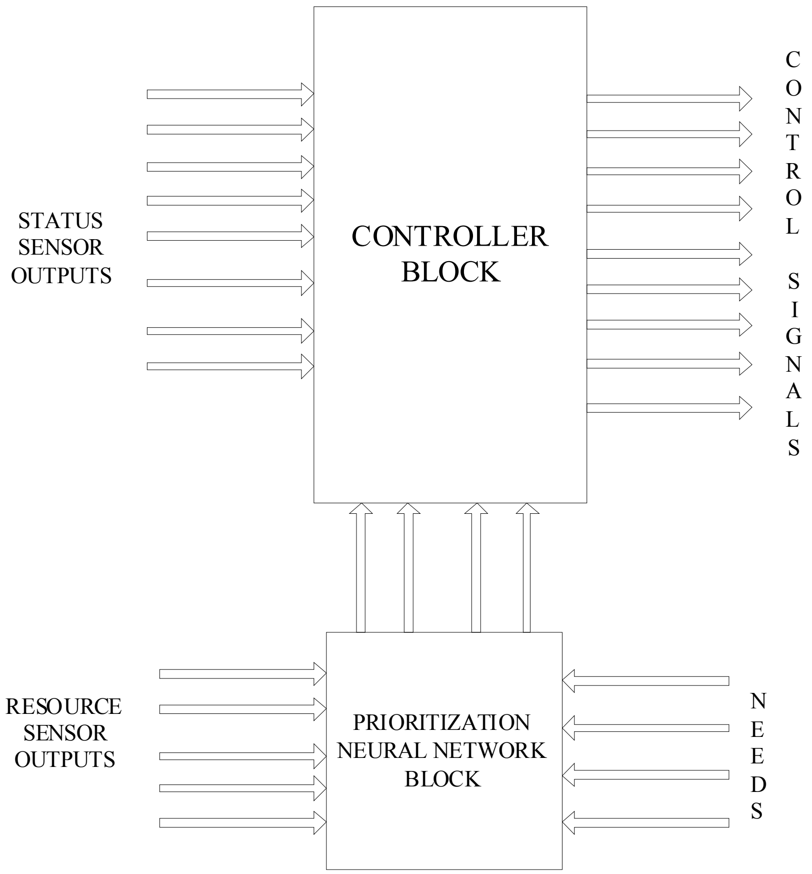


Fig. 4.2: Schematic representation of the control system

possible. This implies that excess energy, if available, needs to be stored in some form to be retrieved later. In the system under study, any excess energy available is converted into electricity and is used to charge a battery bank and/or pump water into an overhead storage tank for potential energy storage. Excess biogas, if any, can be stored as biogas for future use. Therefore, when the system faces a deficit, this stored energy is used to meet as much of the needs as possible. This makes the operation of the system economic and efficient.

Four possible scenarios are considered in this work. They are listed below:

i. All the resources are available at their maximum levels. In this scenario, all the needs can be met from the available resources as envisaged. Excess energy, if available, can be stored in the storage battery for energy backup or is used to pump water into an overhead storage tank.

ii. Low biomass levels are assumed for a given day. All other resources are assumed available as in scenario i. This is a more practical scenario that is often expected to occur. In this case, the cooking needs have to be met from other resources such as wind and solar energy. Care needs to be taken to make sure that other needs, which depend on the availability of wind and insolation are satisfied as well based on an established priority. The objective here is to meet as much of the needs as possible from all the available and stored energy sources. Any unmet need is met using battery charge, if available as the last resort.

iii. A poor wind regime is assumed for the day. In this case, wind electric conversion system and wind driven mechanical pump are not active. Domestic water needs now have to rely on insolation.

iv. In this scenario, a heavy cloud cover is assumed for the day resulting in low solar energy from PV modules. As a result, the irrigation water needs and part of domestic water needs have to be satisfied from other resources and stored energy. Detailed simulation results are presented for all these scenarios in Chapter VI.

It is evident from the discussion of the various possible scenarios that resource-need matching and establishment of a clear and unambiguous priority list and agenda are critical for successful operation of IRES.

CHAPTER V

SYSTEM DESIGN

5.1 Priority-Based Approach

The design of a sensor-neural-network-based control system aims at meeting a set of needs with the available resources during each time step. The top four basic energy needs for a rural area are listed below:

a. Cooking needs
b. Domestic water needs
c. Lighting and educational activity needs
d. Irrigation water needs

The highest priority is given to cooking needs, followed by domestic water needs, lighting and educational needs and irrigation needs in that order. This is a general priority based on the fact that cooking needs are the most important for any household in a rural area. Not meeting this need will lead to deforestation and highly inefficient use of animal wastes and agricultural wastes.

The following example helps to understand the prioritization used in the design. Cooking needs are best met by biogas. Therefore the system should first check for the volume of biogas available to meet this need. In case sufficient biogas is not available, the system should try meeting the need with other available resources. In case none of the other resources are able to meet the cooking needs, electricity is obtained from an external source to satisfy the unmet part of the demand as the last resort. Similarly, for pumping water for domestic needs, wind power and solar energy from PV panel 1 are considered first. In the event these resources fail to meet the demand, other resources are considered. If all the sources fail to supply this need, electricity from an external source will be the only choice. The notation used in this thesis is listed in Table 5.1.

Table 5.1: Notation employed in the prioritization algorithm [see Ref. 32]

Notation	Represents
N1	Need with highest priority (Cooking)
N2	Need with second highest priority (Domestic water)
N3	Need with next highest priority (Lighting and educational)
N4	Need with least priority (Irrigation water)
R1	Volume of biogas available from biomass (m^3)
R2	Solar energy from PV panel 1 (kWh)
R3	Wind energy (kWh)
R4	Battery charge (kWh)
R5	Solar energy from PV panel 2 (kWh)
A1	Assumed percentage (100%) of N1 to be met
A2	Assumed percentage (80%) of N2 to be met
A3	Assumed percentage (50%) of N3 to be met
A4	Assumed percentage (25%) of N4 to be met

These assumptions are applicable only for the energy supplied from IRES. The overarching objective is to assure that a minimum amount of every demand is first met with the available resources and only the energy available in excess after meeting this goal is used to satisfy the remaining unmet requirements. This approach provides for an even distribution and use of available resources rather than concentrating on just one or two needs.

5.2. Prioritization Neural Network

The main function of the prioritization neural network is to match the available resources during any given time step with the demands. For the purpose of simulation studies, resource sensor readings during a given time step are randomly generated over a reasonable range. Their equivalent energy outputs are obtained using a conversion block or perhaps a look-up table. These energy values are then given as inputs to the prioritization neural network, along with the needs.

The prioritization neural network will consist of 4 individual networks, one for each need.

5.2.1 Prioritization Algorithm

As an example, a typical rural village in India with a human population of 400, cattle population of 200, and other livestock population of 100 is chosen. Each neural network takes in all the 5 inputs as mentioned earlier (volume of biogas, solar energy from PV panel 1, wind power, solar energy from PV panel 2 and battery charge). Based on these data and the current needs, the neural network outputs the percentage of individual needs that can be met from the available resources, based on a prioritization algorithm, which is discussed next with the help of Fig. 5.1.

a. Since the cooking need N1 has the highest priority, the algorithm checks to see if the available biogas R1 is sufficient to meet this need.

b. If the cooking need N1 is greater than the energy available from biogas R1 the unmet cooking need has to be met from other resources. For this, the algorithm checks to see if the assumed minimum domestic water pumping needs A2*N2, where A2 is assumed to be 0.8, can be met using solar energy from PV panel 1, R2, and wind energy, R3.

c. If (R2+R3)>A2*N2, the excess energy, [(R2+R3)-A2*N2] can be used for cooking. In case there is excess energy despite meeting cooking needs, it is stored in the storage battery for later retrieval. If this is not the case, the next resource, battery charge, R4, is considered.
d. If R4>A3*N3 then the excess that is available is used to meet cooking needs. In a similar fashion, if the cooking need is not yet satisfied, we consider the next resource on the priority list and follow the same steps. If all the resources fail to supply cooking or any other need, then electricity from an external source will be the only choice.

As resource availabilities vary continuously, making a resource-need matching decision involves many complex computations. To automate this process, a trained neural network can be of assistance.

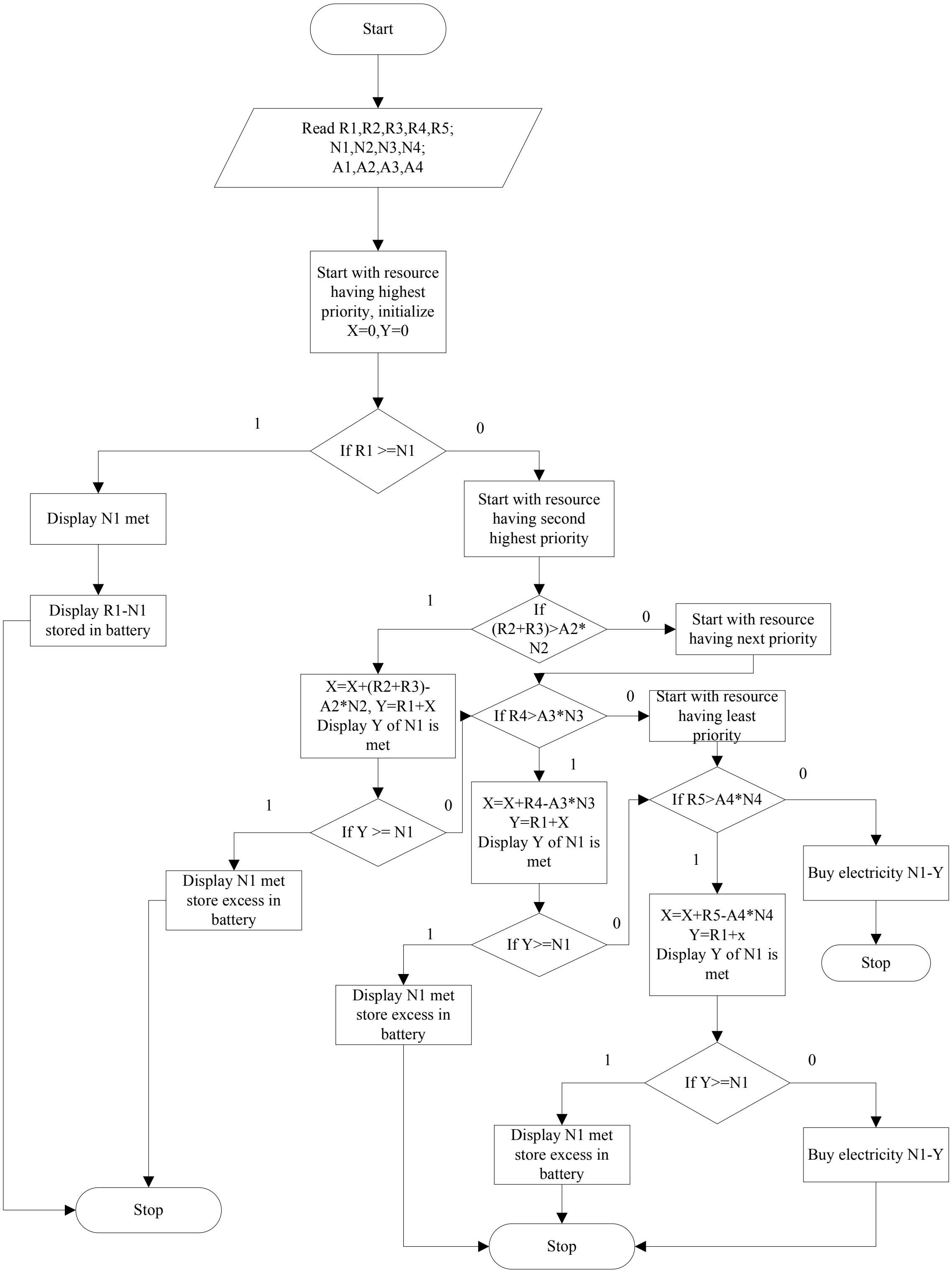


Figure 5.1: Prioritization algorithm [see Ref. 32]

5.2.2 Architecture

A number of neural network architectures and learning algorithms are available. Suitable combinations can be chosen based on the application. The network chosen for this study is discussed next.

For dynamic problems, feedforward neural network architectures with tapped delays are often employed. This network provides a static mapping and so needs many neurons in the hidden layer. They are not suitable for handling dynamic problems. Recurrent neural networks could be used instead. In these networks, however, the neurons in all the layers are interconnected among themselves. But the training and convergence of these networks take a very long time. The layered recurrent neural network (LRNN), shown in Figure 5.2, is more reliable in dealing with dynamic problems [36].

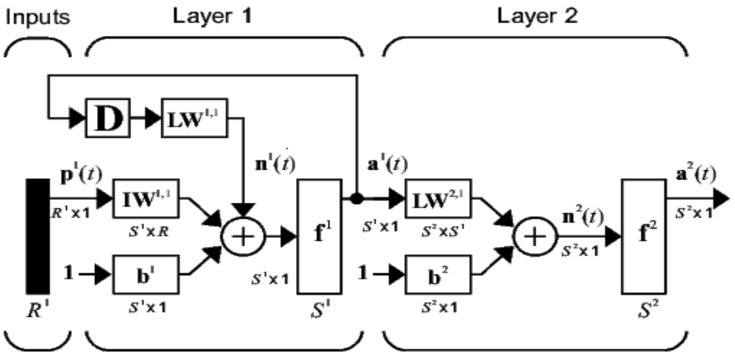


Fig. 5.2: Network architecture of layered recurrent neural network [35]

In this network, the neurons in the hidden layer are self-recurrent [37]. In other words, there are *no interlinks among neurons*. This reduces the number of weights considerably and makes it easy to train the network. Multilayer networks are very good function approximators. The *sigmoid* transfer function is used in the hidden layer and the *linear* transfer function in the output layer could be used to approximate almost any function, provided we have sufficient hidden layer neurons in the network. The flexibility of this architecture in function approximation is well described in [38].

The components of the layered recurrent neural network architecture are listed in Table 5.2.

Table 5.2: Elements of LRNN

Notation	Represents
D	Tapped delay
$\mathbf{P^{l}(t)}$	l^{th} input vector to the network at time ‘t’
$\mathbf{R^{l}}$	Number of elements in the input vector ‘l’
$\mathbf{IW^{11}}$	Input weight between input layer and layer 1
$\mathbf{b^{1}}$	Bias vector for layer 1
$\mathbf{s^{1}}$	Number of neurons in layer 1
$\mathbf{LW^{11}}$	Layer weight of self-recurrent neurons of layer 1
$\mathbf{n^{1}(t)}$	Net input of layer 1
$\mathbf{f^{1}}$	Transfer function of layer 1
$\mathbf{a^{1}(t)}$	Output vector of layer 1
$\mathbf{LW}^{21}$	Layer weight between layer 1 and layer 2
$\mathbf{s^{2}}$	Number of neurons in layer 2
$\mathbf{b^{2}}$	Bias vector for layer 2
$\mathbf{n^{2}(t)}$	Net input of layer 2
$\mathbf{f^{2}}$	Transfer function of layer 2
$\mathbf{a^{2}(t)}$	Output vector of layer 2

5.2.3 Training

The training data for the neural network is assembled by generating random power inputs and the percentage of needs to be met as targets. A number of training algorithms can be employed to train the neural networks in this system. The backpropagation algorithm has been chosen for training the networks in this case, as it calculates the sensitivities of the hidden layers accurately [see Ref 38]. *Once the neural network is trained for a sufficient number of data points, it can be used to replace the function of the prioritization block. This eliminates the complexity of resource need matching at every time step. It just monitors power inputs and the present needs and outputs the percentage of each need that can be met.* Four neural networks are necessary, one for each need. The neural network is trained for 300 epochs with 25 hidden layer neurons.

5.3 Controller Block

The controller block takes the outputs of the prioritization neural networks and also the present status of sensor outputs and generates the appropriate control signals to carry out the required operations. There are 8 status sensors as mentioned earlier. Each sensor output is compared with a preset threshold value and based on the percentage of each need met the controller block generates the control signals. As an example, if the prioritization neural network output indicates that the domestic water supply needs can be met from the available resources, the controller block first checks the water level of the storage tank, which is the input from sensor 5. It compares this value with its threshold and in case it is above the threshold it generates control signals to turn off the wind driven and the solar water pumps. The threshold values for various status sensor inputs are tabulated below in Table 5.3.

Table 5.3: Threshold values for status sensor readings [see Ref. 32]

Sensor #	Function	Threshold value
4	Micro hydro output	0.02 kW
5	Domestic water tank level	Upper level=49 m; Lower level=2 m
7	Volume of water pumped by wind driven water pump	0.25 m^3
8	Volume of water pumped by solar water pump	0.30 m^3
9	Engine driven generator output	0.20 kWh
10	Volume of water drawn for domestic use	0.20 m^3
11	Irrigation water tank level	Upper level=19 m
12	Volume of water drawn for irrigation	0.10 m^3

The simulation results are discussed in the chapter that follows.

CHAPTER VI

DISCUSSION OF RESULTS

6.1 Simulation Methodology

All the simulations are performed using MATLAB software. A layered recurrent neural network is trained to perform the prioritization function. Four different layered recurrent neural networks are trained individually – one for each need, namely, cooking need, domestic water pumping need, lighting and educational needs and irrigation water pumping needs. The training data are generated as follows.

i. Inputs: Resource sensor outputs are randomly generated over a reasonable range for simulation purposes. The energy equivalents of these available resources are obtained with the help of a lookup table. The resource availabilities and the power ratings of the various system components used in the simulations are listed in Tables 6.2 to 6.4. These energy values during each time step (1 minute) along with the initial battery charge and the individual needs are given as inputs to every neural network. For example, the energy equivalent of available biomass, insolation and wind, along with the initial battery charge and cooking need are given as inputs to the LRNN to be trained to determine the percentage of cooking need that can be met with these available resources. Similarly, inputs are given to the other three neural networks.

i. Targets: The energy inputs and the needs are given as inputs to the prioritization algorithm, the functionality of which the prioritization neural network needs to be trained to replace. The outputs of the prioritization algorithm, which are the percentages of the individual needs that can be met from the available resources are used as targets to train the neural network.

ii. Training: The neural networks are trained using the data generated. The command 'newlrn' from the Neural Network Toolbox of Matlab is used to create a layered recurrent neural network. It takes many arguments such as the input vector p with R elements, the number of neurons s^i in the ith layer and TF^i , the transfer function of the ith layer and returns an LRNN. The neural networks are trained using the backpropagation training function '*trainlm*'. These networks are trained with 25 neurons in the hidden layer, which is the layer in between the input and output layers (in this case, layer 1) for 300 epochs, where one epoch is one run through all the data in the training set [see Reference 36]. Once trained for a sufficient number of data points, the neural network can be used to replace the prioritization block, eliminating the need for complex computations.

iii. Controller Block: The controller block takes the output of the neural networks and the status sensor outputs as its inputs. The status sensor outputs are also randomly generated within an assumed range. During every time step, the controller logic processes these inputs and generates the appropriate control signals required for the operation of IRES. The controller block compares the status sensor outputs with a preset threshold value for each sensor. Based on a set of conditions, the controller block generates control signals. For example, consider the control signal to be generated to turn ON/OFF the solar driven water pump. In this case, the controller block checks to see what part of the domestic water needs can be satisfied from the available solar energy. In case there is sufficient solar energy to satisfy all the domestic water needs, then the solar water pump can be turned ON to pump water into the storage tank. But before generating this signal, the controller block compares the water level of the storage tank (monitored by status sensor 5) with that of the threshold value for sensor 5 to ensure that the tank is not full. If full, the controller generates an OFF signal. If not, a control signal to turn ON the solar water pump is generated. Similarly, the remaining 8 control signals are generated by the controller block.

6.2 Simulation Results

For simulation purposes a small village in rural India with a human population of 400, cattle population of 200, other livestock population of 100 is chosen. The energy needs of this village on a typical day are listed in Table 6.1.

Table 6.1: Energy needs of rural area under consideration

Cooking need	360 kWh/day
Domestic water pumping needs	80 kWh/day
Lighting and educational needs	70 kWh/day
Irrigation water pumping needs	60 kWh/day

The neural networks are trained for 4 practical scenarios**.** Resource sensor outputs are randomly generated over a reasonable range. The ranges of resource sensor values for the various scenarios are tabulated in Table 6.2.

Table 6.2: Resource sensor readings for the 4 scenarios

Scenario	Biomass (kg/day)		Output of PV1 (kWh)		Wind speed (m/s)		Output of PV2 (kWh)	
	Low	High	Low	High	Low	High	Low	High
I	500	700	0.6	1.2	3	10	1.0	1.8
II	150	250	0.6	1.2	3	10	1.0	1.8
III	500	700	0.6	1.2	1.5	3	1.0	1.8
IV	500	700	0.2	0.5	3	10	0.3	0.6

The power ratings of the various wind energy system components used for simulation purposes are listed in Table 6.3.

Table 6.3: Power ratings of wind energy system components

Component	Rating
Wind turbine for electricity generation	20 kW @ 6.6 m/s, 110 V
Wind turbine height	18 m to 37 m
Wind-driven water pumping unit	1.5 kW @ 6 m/s
Max. design wind speed	55 m/s

The power ratings of the PV system components used in the simulation are listed in Table 6.4. PV 1 is a 2 kW array of photovoltaic modules and PV 2 is a 1.5 kW array of modules. The arrays consist of BP350U solar panels and are made of silicon nitride multicrystalline type. Each panel has a maximum output of 50 W [see Ref. 14].

Table 6.4: Power rating of solar panel

Rated power (P_{max})	50 W
Voltage at P_{max}	17.34 V
Current at P_{max}	2.89 A

6.2.1 **Scenario I**:

All resources are at their maximum design values. Fig. 6.1 shows the equivalent energy outputs for the randomly generated resource sensor readings, as shown in Table 6.2. These energy outputs are obtained from a lookup table structure. Resource 1 is biomass, resource 2 refers to insolation from PV1, resource 3 and 4 are wind speed and insolation from PV2, respectively. Figure 6.2 gives the output of the prioritization neural network, that is the percentage of cooking, domestic water, lighting and irrigation needs that can be met from the available resources at every time step.

It can be seen that during time step 1 to 2 about 60% of the cooking need is met. At the same time, 80% of domestic water need and 25% of lighting needs are met. Since irrigation has the least preference, only a very small part of this need is met. During time step 0 to 1, since 100% of cooking need is met and the required amount of domestic water and about 25% of lighting needs are met, we are able to satisfy about 50% of irrigation water needs.

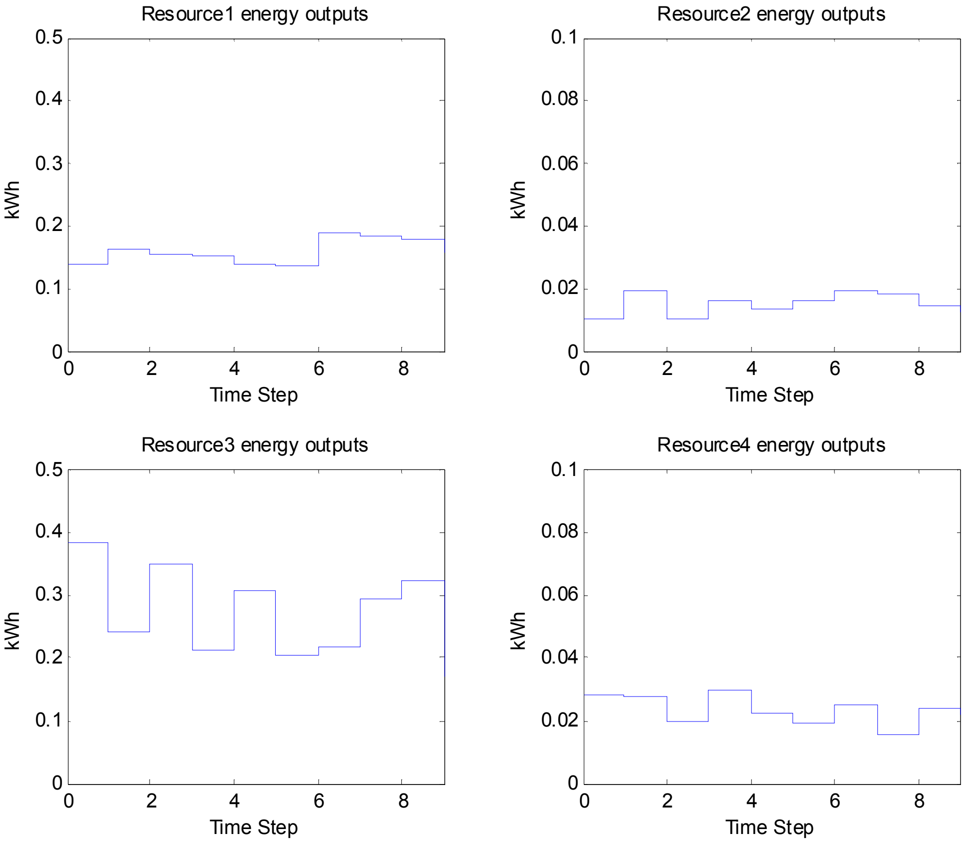


Figure 6.1: Equivalent energy values of resource sensor outputs for scenario I

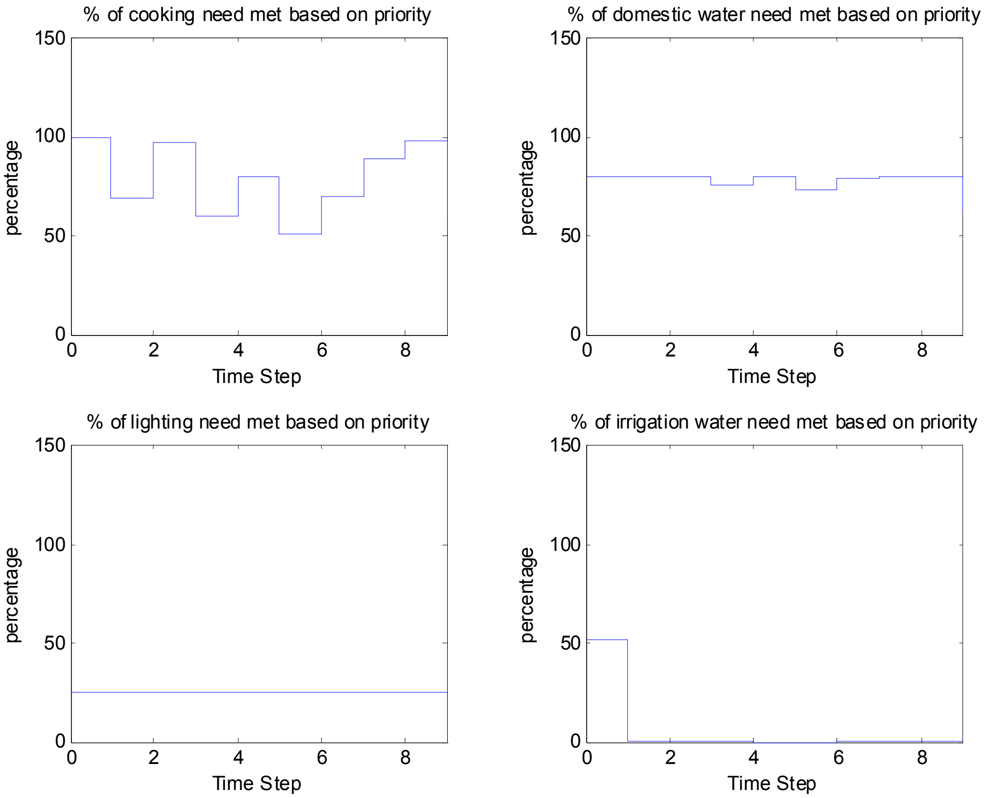


Figure 6.2: Output of prioritization neural network for scenario I

The control signals that are generated are shown in Figs. 6.4, 6.5 and 6.6. The controller block takes into account the neural network outputs and status sensor inputs to generate these control signals. Consider control signal 4 generated for controlling the wind-driven water pump. It is turned OFF during time step 6 to 7. This is because there is a drop in available wind energy as can be seen from Fig 6.1.

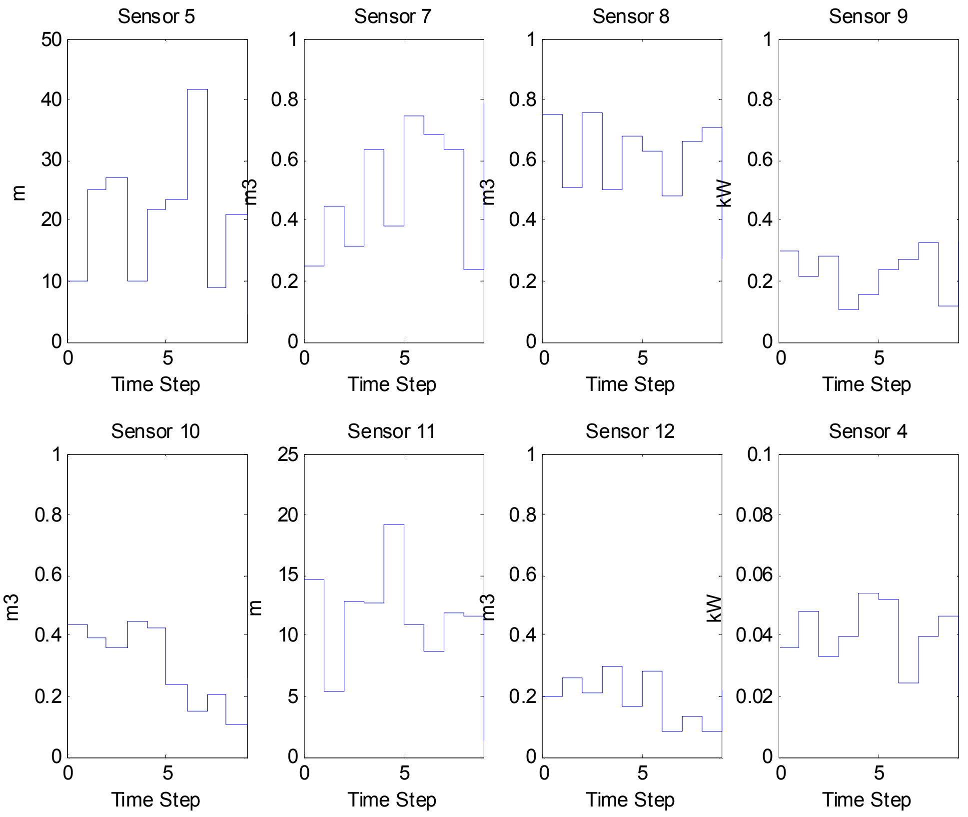


Figure 6.3: Status sensor outputs for scenario I

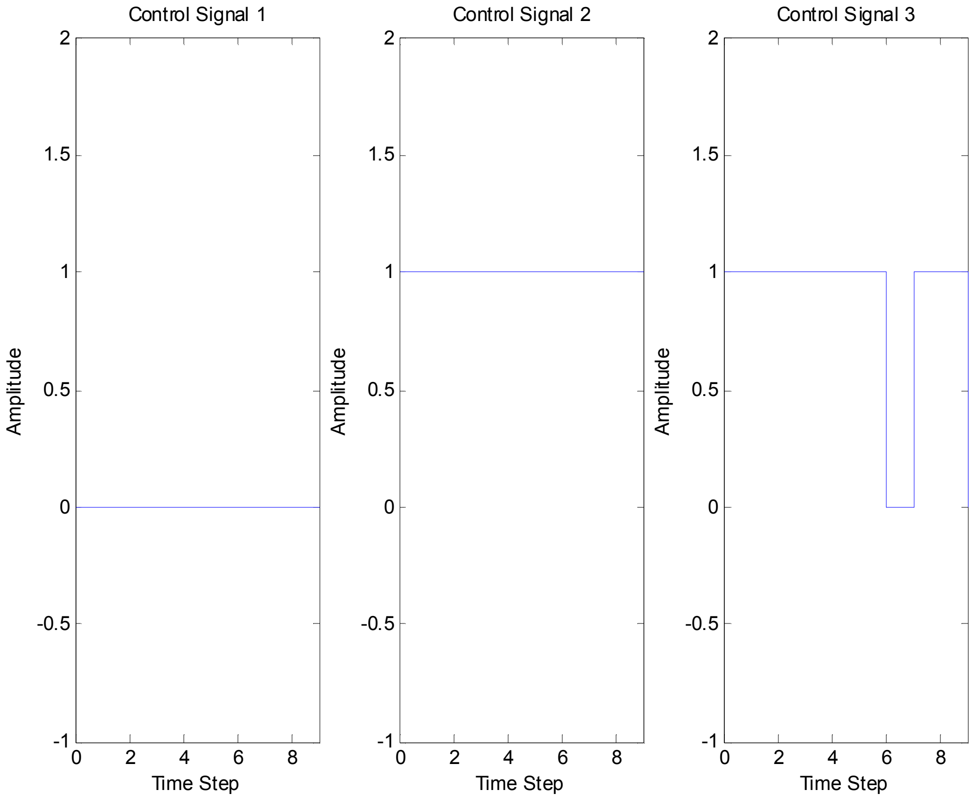


Figure 6.4: Control signals for scenario I

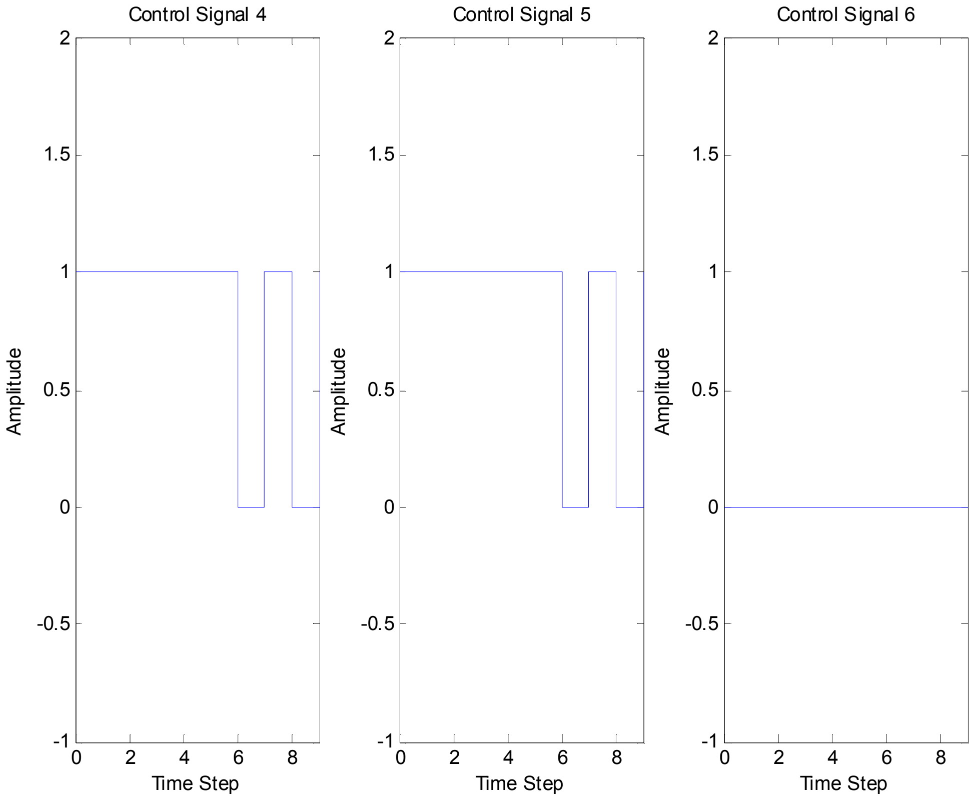


Figure 6.5: Control signals for scenario I

Similarly, control signal 9 turns OFF the solar water pump for irrigation during time step 4 to 5, even though solar energy is available. This is because the irrigation water tank level goes beyond the upper threshold value of the tank, which is pre-set to 19 feet. This can be seen from Figs 6.3 and 6.6. Similarly, other control signals are also generated based on status sensor readings and neural network outputs.

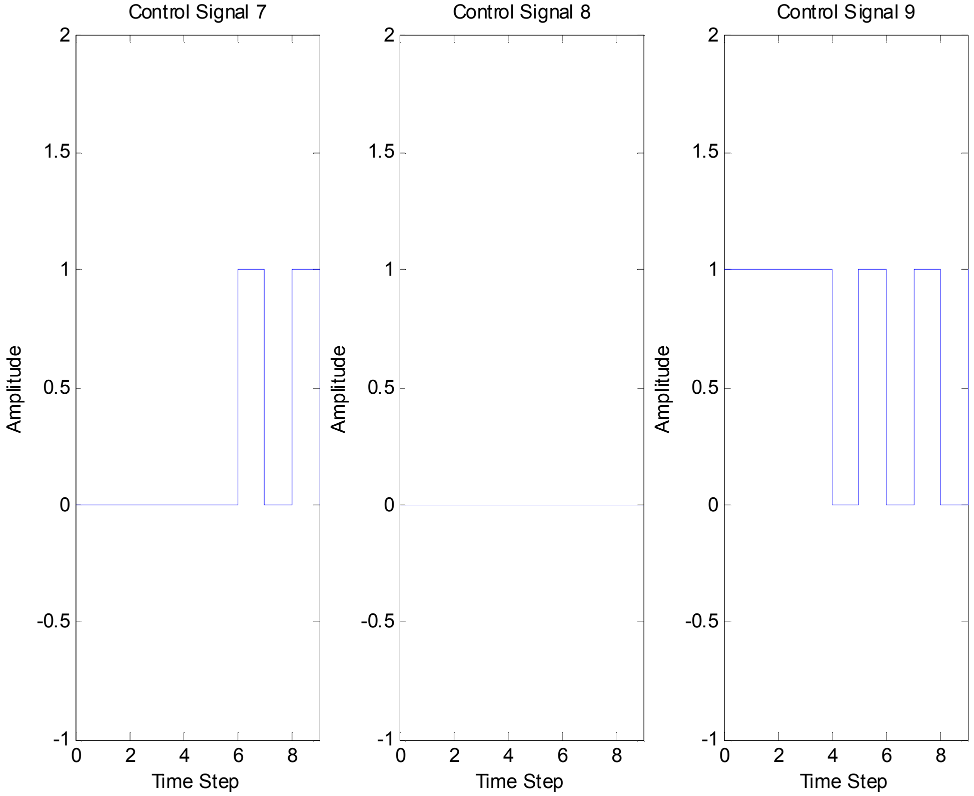


Figure 6.6: Control signals for scenario I

6.2.2 Scenario II:

Low biomass levels are assumed for a given day. All other resources are assumed available as in scenario I. This is a more practical scenario that is often expected to occur. In this case, the cooking needs have to be met from the other resources such as wind and solar energy. Care needs to be taken to make sure that other needs, which depend on the availability of wind and insolation have to be satisfied as well based on an established priority. A similar discussion holds good for this scenario as well. The sensor outputs, the neural networks outputs and control signals for this scenario are shown in figures 6.7 through 6.11.

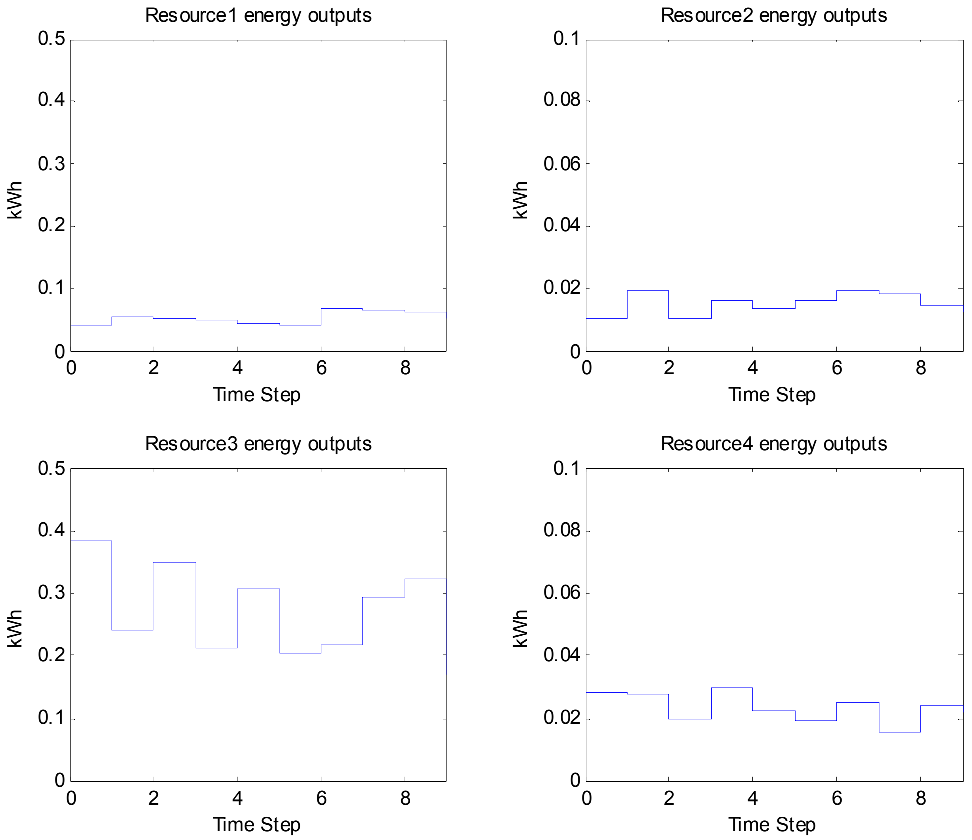


Figure 6.7: Equivalent energy values of resource sensor outputs for scenario II

The low biomass levels are evident from Figure 6.7. It can be seen from Figure 6.7 that during time step 5 to 6, very little biogas is available from biomass. As a direct consequence, the neural network determines the percentage of cooking needs that can be satisfied from biogas as less than 25%. Control signal 1 (generated to turn ON/OFF the engine-driven generator) is turned ON only when excess biogas is available. In this scenario, we can see from Figure 6.10 that control signal 1 is always ‘0’ indicating that the generator is always turned OFF, as no excess biogas is available.

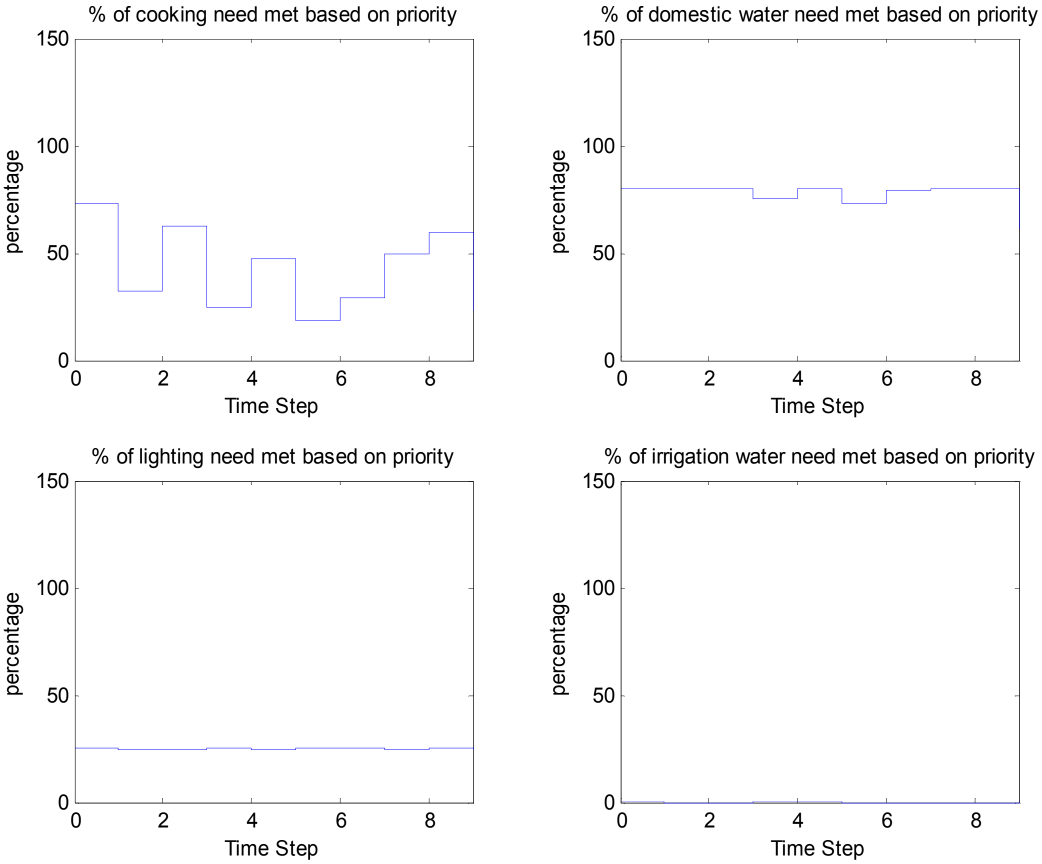


Figure 6.8: Output of prioritization neural network for scenario II

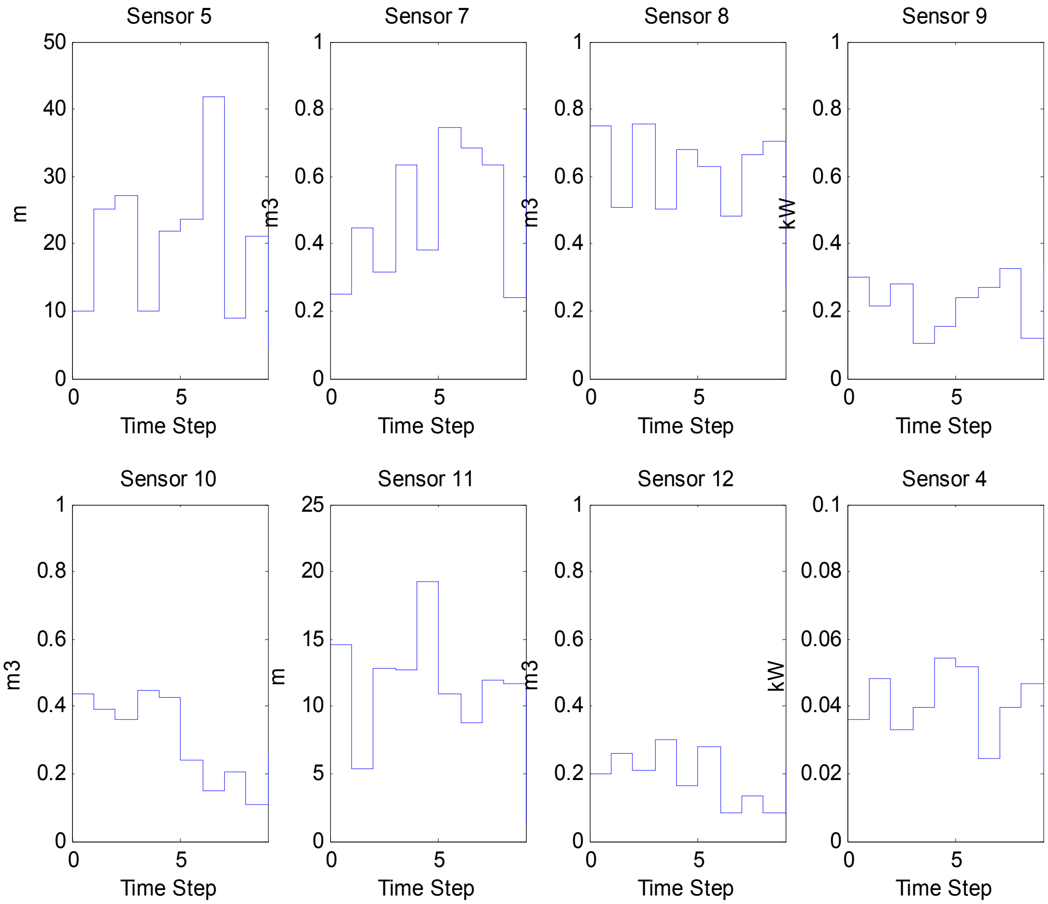


Figure 6.9: Status sensor outputs for scenario II

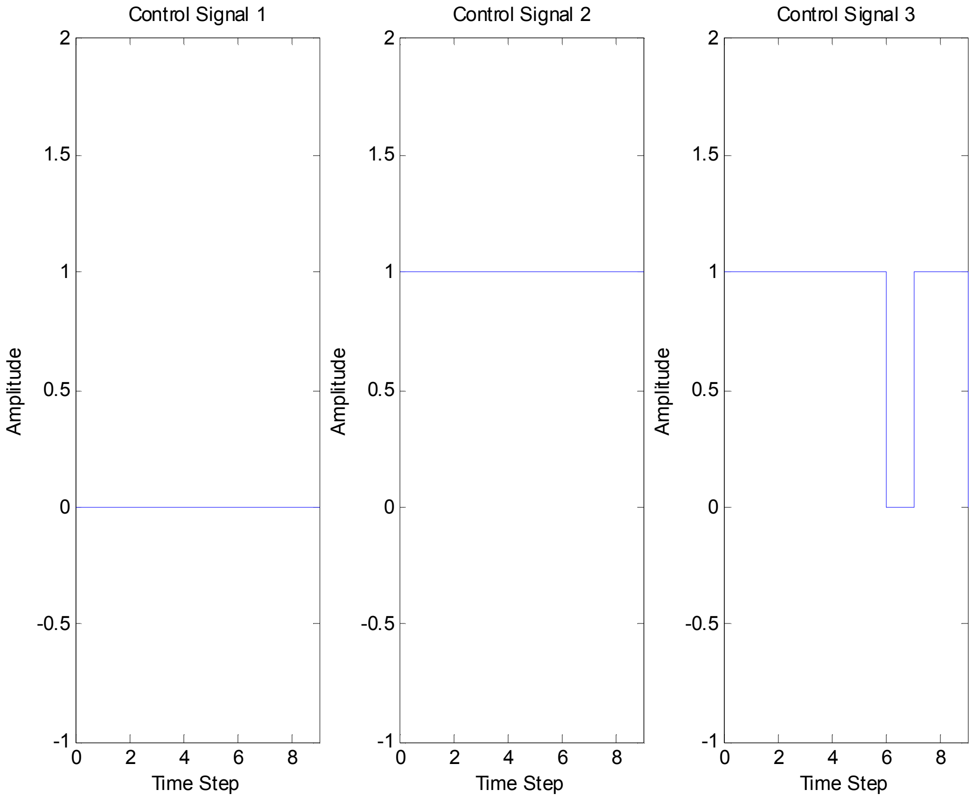


Figure 6.10: Control signals for scenario II

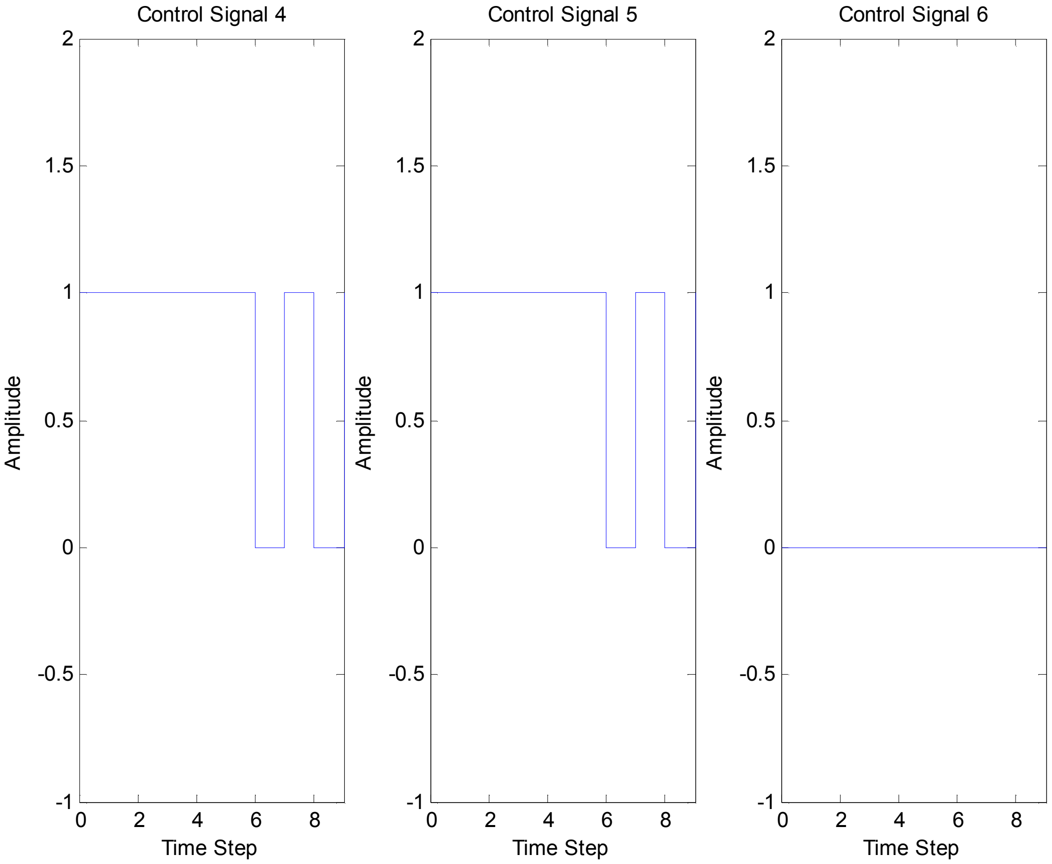


Figure 6.11: Control signals for scenario II

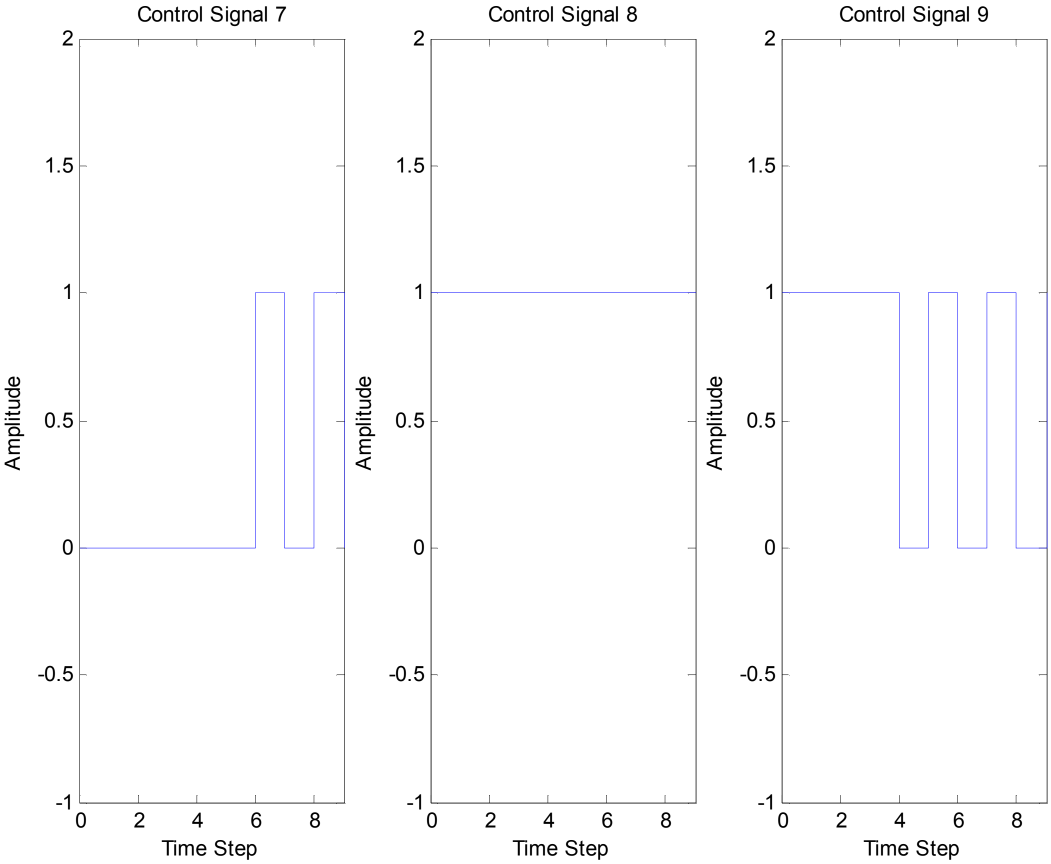


Figure 6.12: Control signals for scenario II

6.2.3 Scenario III:

In this scenario, we assume a poor wind regime. The domestic water needs now have to be satisfied from the available solar energy and other resources. The simulation results are shown in Figures 6.13 through 6.18. Figure 6.13 indicates the low wind energy levels. Very low wind energy is available during time step 5 to 6. As a result, control signal 4 (for controlling the wind-driven water pump) is turned OFF during this time step. From Figure 6.14 it can be seen that only about 50% of the domestic water pumping needs can be satisfied from the available wind energy combined with solar energy from PV 1.

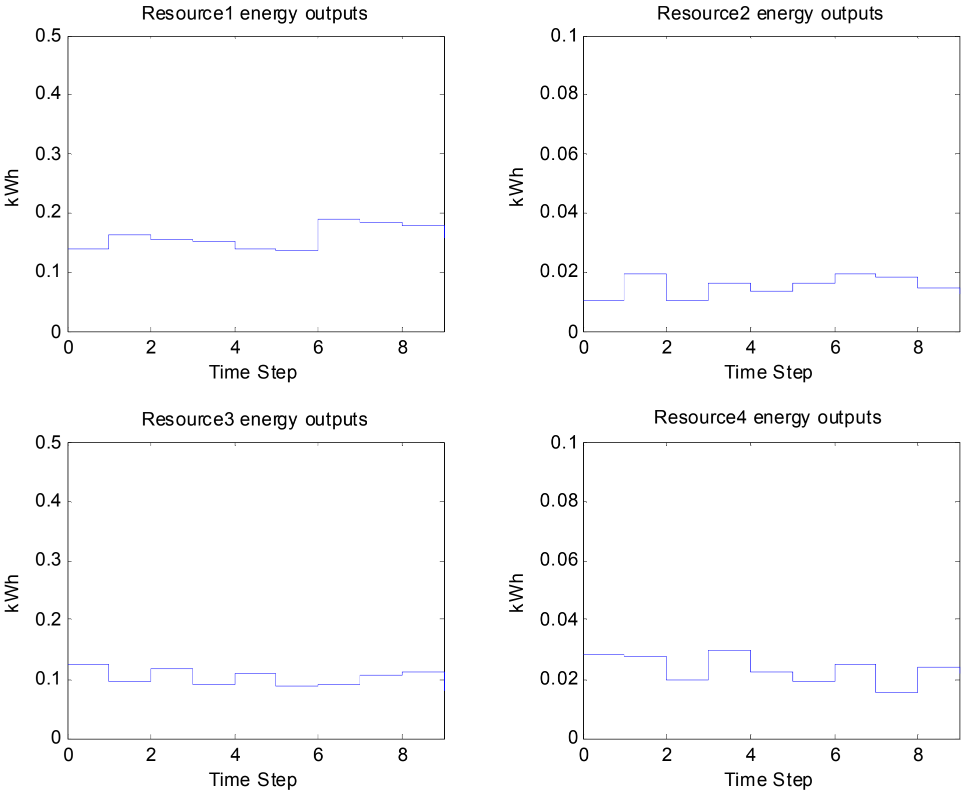


Figure 6.13: Equivalent energy values of resource sensor outputs for scenario III

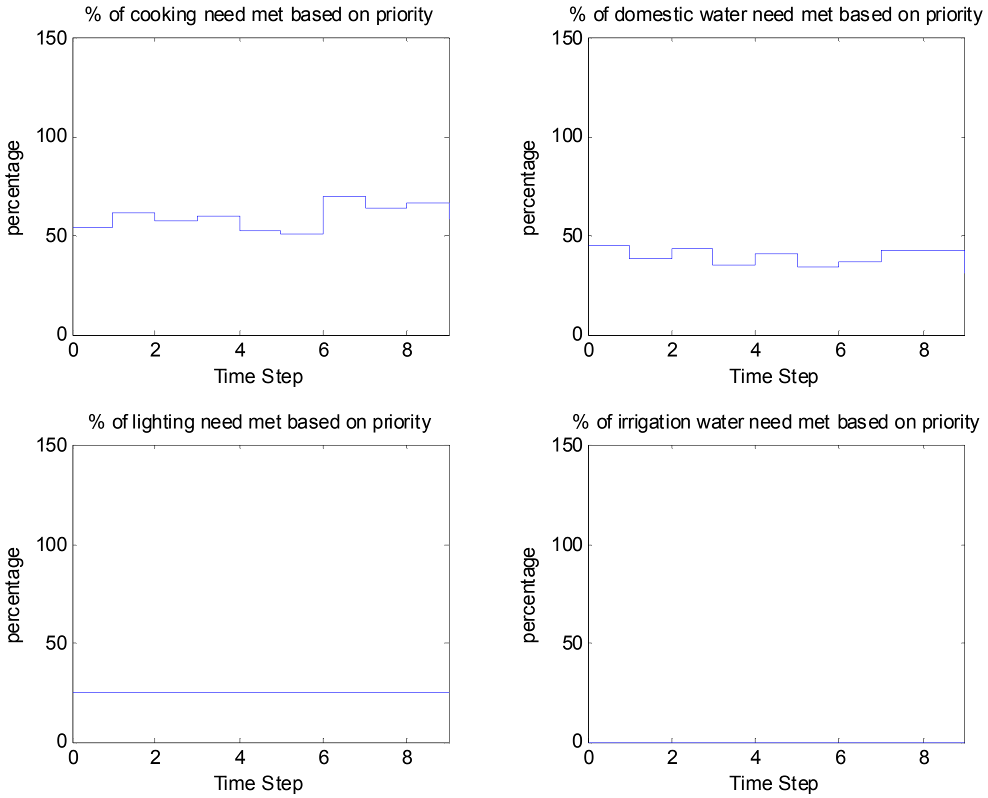


Figure 6.14: Output of prioritization neural networks for scenario III

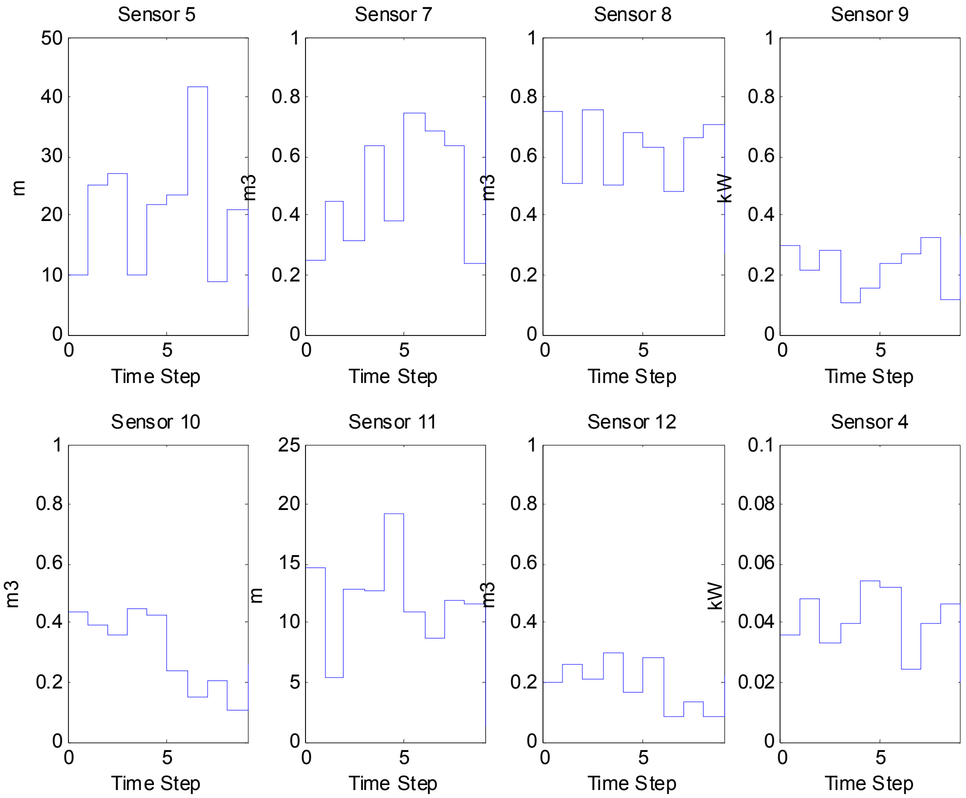


Figure 15: Status sensor outputs for scenario III

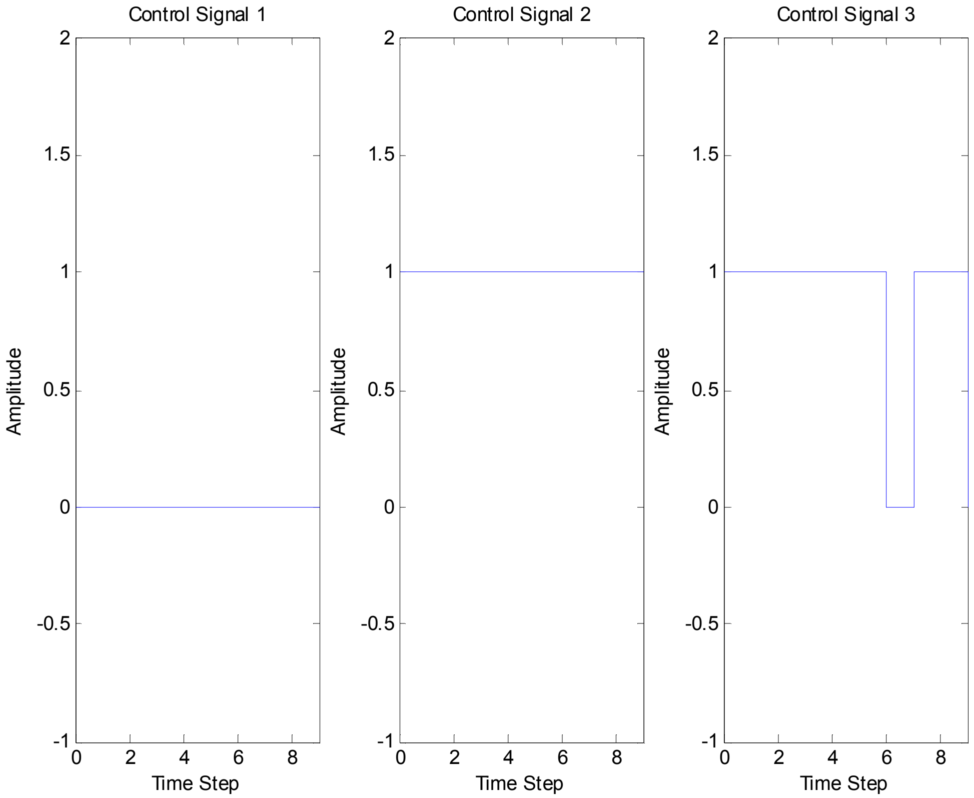


Figure 6.16: Control signals for scenario III

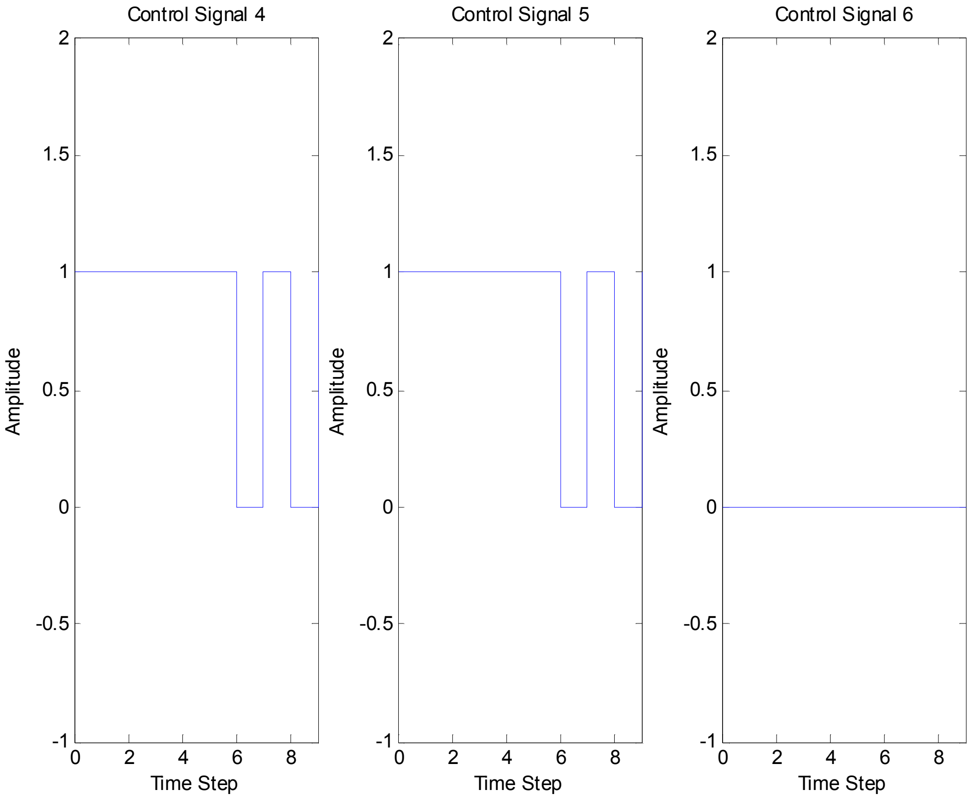


Figure 6.17: Control signals for scenario III

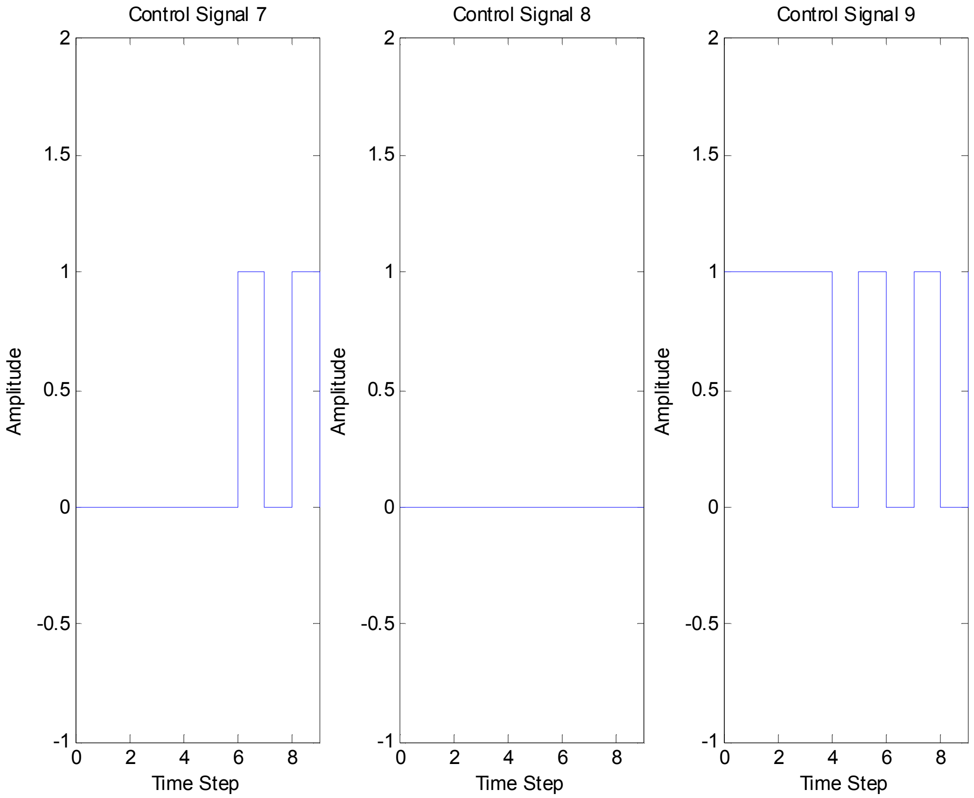


Figure 6.18: Control signals for scenario III

6.2.4 Sceanrio IV:

In this scenario, a heavy cloud cover is assumed for the day resulting in low solar energy from PV modules. As a result, the irrigation water needs and part of domestic water needs have to be satisfied from other resources and stored energy. Simulation results are shown in Figures 6.19 through 6.24. Figure 6.19 shows that the outputs of both the PV arrays are very low. Figure 6.20 shows that only a very small part of the irrigation water pimping needs can be met from the solar energy available from PV 2. Since domestic water pumping needs can be satisfied from both PV 1 and wind energy, about 80% of this need is satisfied, partly from PV 1 and mostly from wind energy.

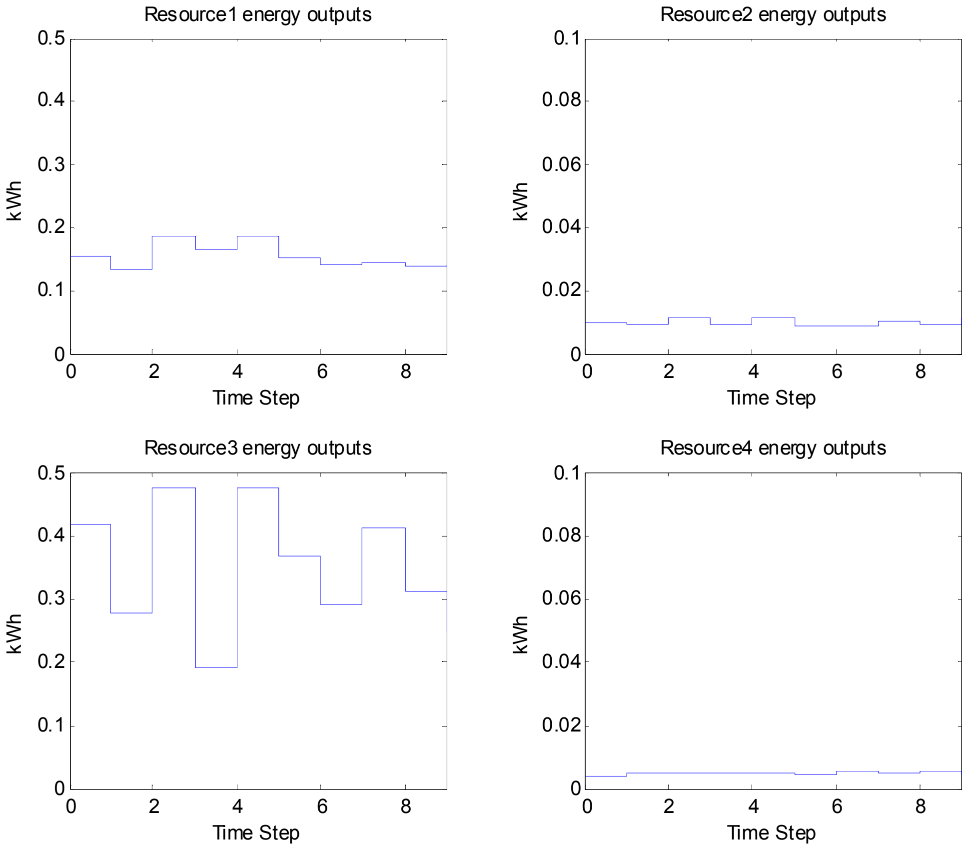


Figure 6.19: Equivalent energy values for resource sensor outputs for scenario IV

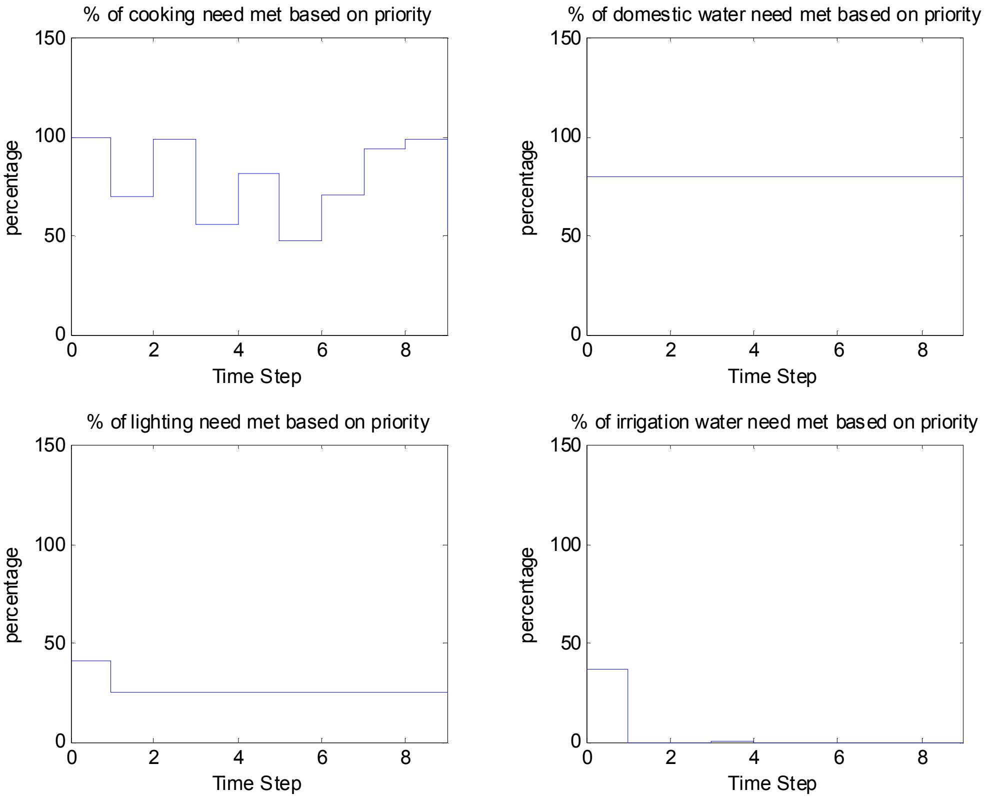


Figure 6.20: Output of prioritization neural network for scenario IV

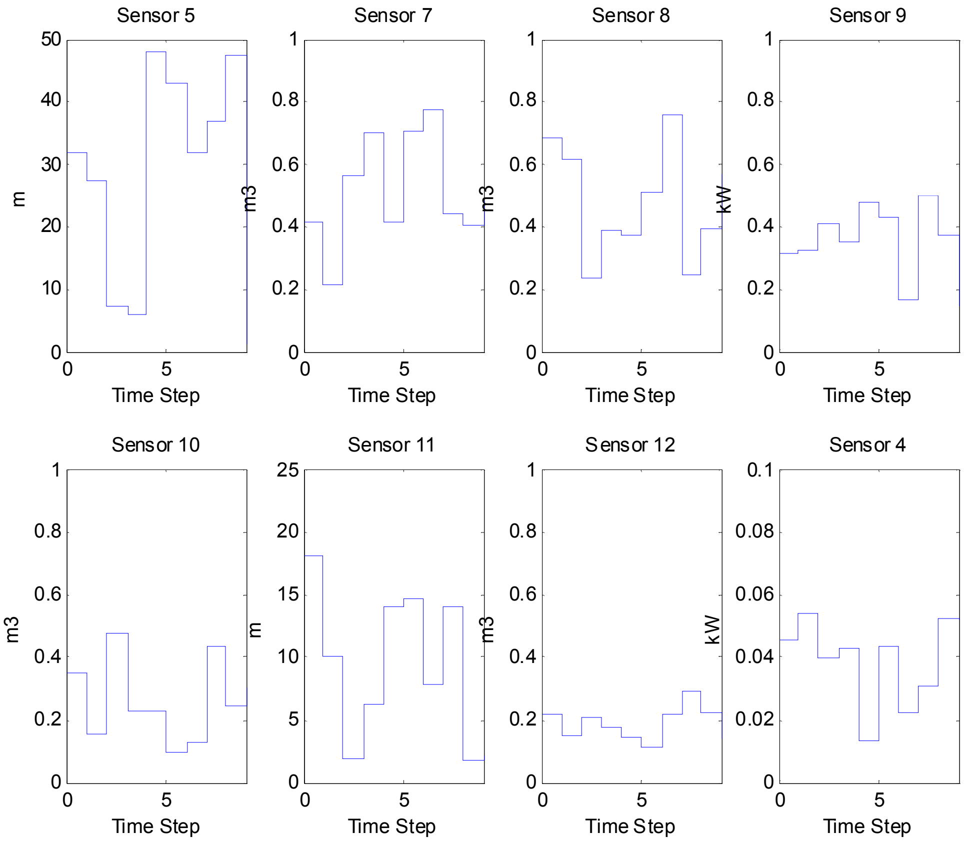


Figure 6.21: Status sensor outputs for scenario IV

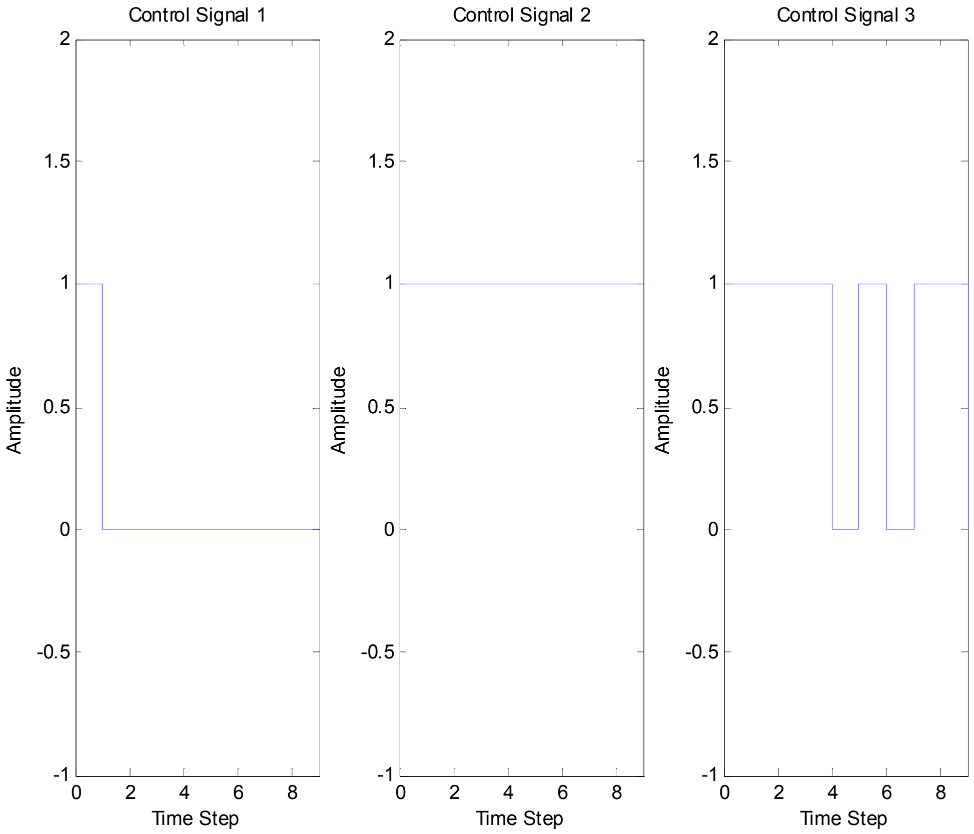


Figure 6.22: Control signals for scenario IV

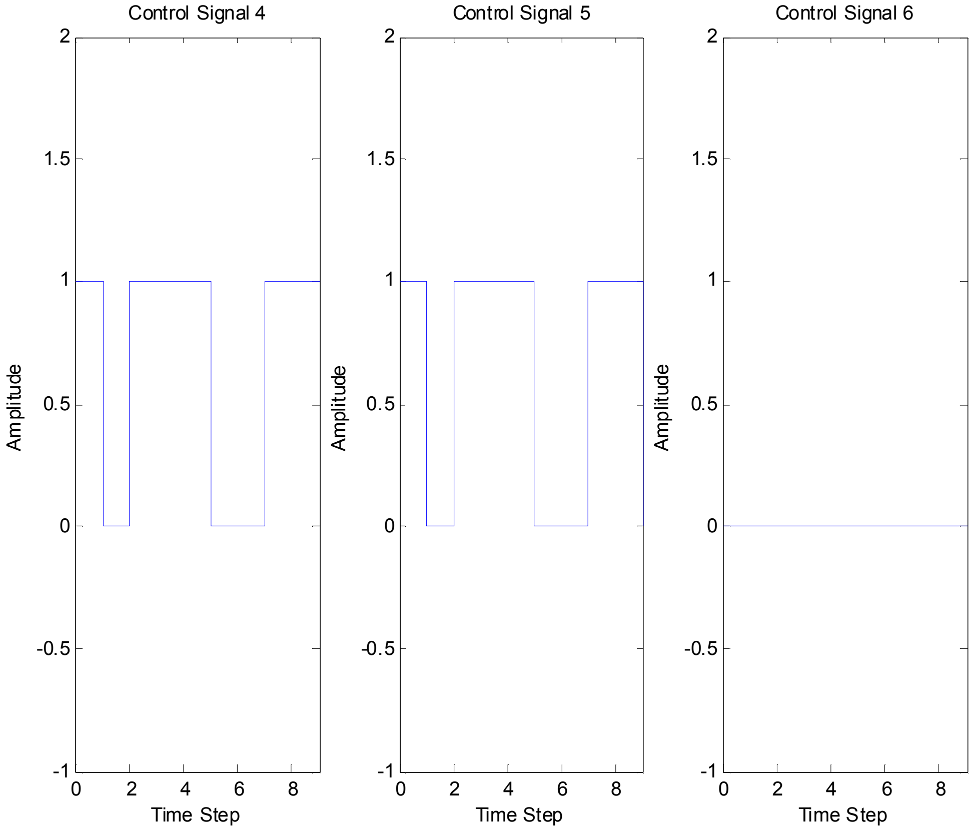


Figure 6.23: Control signals for scenario IV

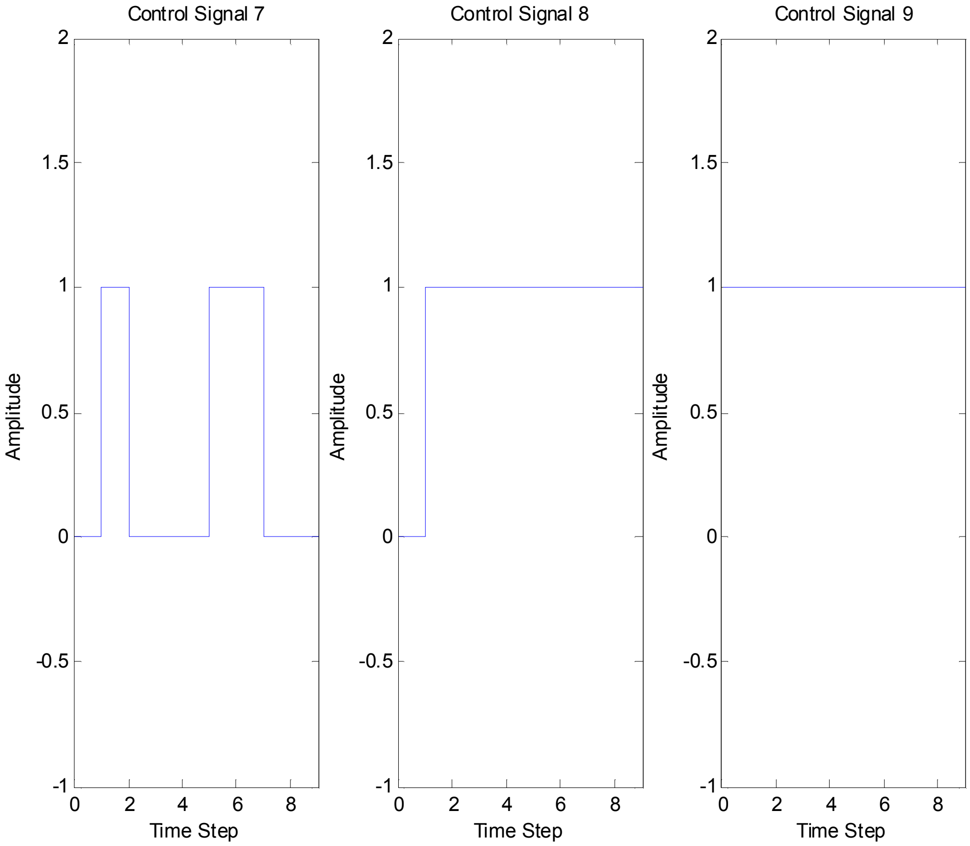


Figure 6.24: Control signals for scenario IV

CHAPTER VII

CONCLUSIONS AND SCOPE FOR FURTHER WORK

IRES can be effectively employed to energize remote rural areas by harnessing locally available renewable energy resources. To realize this, a well thought out set of sensors and controllers should be incorporated and used intelligently. This thesis has laid the groundwork for this enterprise.

The key is to match the available renewable energy resources and the needs *a-priori* and generate appropriate control signals. The primary needs of the rural area are cooking needs, domestic water pumping needs, lighting and educational needs and irrigation water pumping needs. Biomass, insolation, wind and hydro are the available resources. This work considers the possibility of using neural networks as a basic tool for the supervision and control of IRES.

The various sensors, controllers and control signals needed to supervise the operation of IRES are identified. A prioritization neural network is suggested to effectively process the sensor outputs and to help generate control signals. Four layered recurrent neural networks, one for each of the needs, are trained to assess the percentage of the individual needs that can be satisfied from the available resources. With these outputs and status sensor outputs as its inputs, the controller block generates the appropriate control signal for each time step, assumed to be 1 minute in this study.

The neural networks are trained for four practical scenarios that are encountered most often. These scenarios are:

a. All resources are at their maximum values.
b. Low biomass levels are assumed.
c. Low wind regime is assumed.
d. Heavy cloud cover and low insolation is assumed.

Simulation results show that for every scenario, the system accomplishes a good resource-need matching. Models such as Supervisory Control and Data Acquisition (SCADA) perform a similar function for automating industrial processes, but need complex infrastructure. This model is ideal for employing IRES at remote rural locations with minimal investment to best utilize all the available resources efficiently and energize such areas.

Additional detailed simulations need to be performed before any hardware implementation of the ideas suggested. The suitability of one minute time step should be examined in detail. Future work can also be directed towards more elaborate optimization techniques. The sensor readings can be generated over a reasonable range. A full system simulation under various energy level scenarios should be performed, with the control signals as its inputs and a performance function, say, profit as its output. A constrained optimization using the simulation results can be performed to determine the optimal control signals that maximize the profit while meeting the demands. Possible optimization techniques include the optimization toolbox of MATLAB and genetic algorithms. Multiple-input multiple-output neural networks may also be used instead of four multiple-input single-output neural networks. A neural network can also be trained to perform the function of the controller block.

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Scope and Method of Study: The purpose of the study was to consider a sensor-neural-network control system as a means to supervise integrated renewable energy systems (IRES) and to automate their operation. This work suggests an approach to assess the information provided by a set of sensors strategically located in the IRES and help generate control signals in discrete events of time to actuate controllers to best meet the energy and other needs of a small rural area, using the locally available renewable resources such as biomass, insolation, wind, and hydro. The key is to match the resources and the needs *a-priori* and make decisions based on a prioritized set of needs. Neural networks process the sensor outputs to perform this function of prioritization and generate appropriate control signals. This work uses layered recurrent neural network architecture and is trained using backpropagation.

Findings and Conclusions: All simulations are performed using MATLAB software. For simulation purposes, a small rural area is considered. Neural networks are trained for four practical scenarios of resource availabilities. The main advantage of using neural networks is that it eliminates the need for complex computations involved in resource need-matching. Results show that in each scenario, appropriate control signals are generated using neural networks. This model is ideal for employing IRES at remote rural locations with minimal investment to best utilize all the available resources efficiently and energize such areas.

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