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# MULTI-AGENT BASED HETEROGENEOUS POWER MANAGEMENT SYSTEM

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Abstract. *A heterogeneous energy source, comprising more than one type of energy sources, can function as a reliable source of power. The constituent energy sources may have characteristics with varying degree of preferences. In this paper, a multi-agent based system is used in a heterogeneous power system to maximize the use of energy sources with preferred characteristics while limiting the use of the least preferable sources. The problem is modeled as a bounded knapsack problem and each agent makes decision based on instantaneous local information, i.e., the value of the power it is drawing from the source it is connected to. Using this multi-agent system, a higher utilization of power produced by preferred source is achieved.*

**Keywords:** Multi-agent system, Bounded knapsack problem, Divide and conquer approach

## 1. **Introduction.**

Critical systems such as telecom equipment, data centers and medical devices need continuous and reliable electric energy for their proper and satisfactory operation. It is often the case that the requirements are fulfilled by using multiple sources of electric energy such as solar cells, wind turbines, diesel generating sets, rechargeable battery and grid electricity. Thus a heterogeneous power source is formed. The sources in such a system have varying characteristics and one is more preferable than others. For illustration, the solar cells and wind turbines provide greener energy locally but they, due to direct dependency on environmental factors, produce intermittent power. On the other hand, diesel generating sets are environmentally unfriendly but can provide continuous power output. The goal of the user of such a system is to use the preferable source the most over other sources.

This work considers a heterogeneous power system with 3 power sources namely solar cells, a small wind turbine and grid electricity which are simply connected in parallel as shown in Figure 1. Because of the fixed parallel connection, solar cells, the most preferable energy source is not fully used.

In order to maximize the utilization of the preferred power source, an algorithm is presented in this paper. Based on a homogeneous multi-agent system, the algorithm selectively draws energy from the pool of sources in the heterogeneous power system. The contributions of the algorithm presented in this work are as follows.

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- Fault tolerant system: the homogeneity of the agents allows the failure of an agent to be covered up by another agent.
- Non-existent communication infrastructure: the agents react to the change in the power flow in the bus and act without the need to directly communicate with each other.
- Less computational burden: The agents act on simple rules without the need to use huge computing power.
- Minimal input data: The decisions made by the agents are based on the amount of the power they are drawing from the sources.

This paper is organized into five sections. The current section (Introduction) introduces the problem context and highlights the contribution of the work. The Literature Review discusses the related theory and work that has been carried out on the subject. The Methodology section describes the way the research work is conducted in topics such as problem analysis, formulation, multi-agent based solution approach, the agent algorithm, modeling and simulation. The results of the simulation and the observations are discussed in the Results and Discussion section. Finally, Conclusion and Recommendation section summarizes the work and also highlights the limitations of the work.

2. **Literature Review.** The use of renewable energy sources (RES) such as solar cells is increasing in residential households and commercial buildings. However, the output power of such sources are intermittent [1] and the situation forces the users to integrate these RES with public grid and back-up with energy storage systems such as battery banks. In most of these installations, the sources are simply connected in parallel resulting in inefficient use of the RES. Thus, such a power system needs to be managed by a smart management system with one or more of following goals:

- Balance demand and supply;
- Minimize cost;
- Emphasize use of greener technology.

Numerous works have been carried out with different kinds of power sources in the heterogeneous system and specific to the application in hand. As discussed in [2], the members of a heterogeneous power system have unequal performances and the work proposes a hierarchical combination of conventional battery, fuel cell and capacitors for fulfilling the demand. The method implemented by [1] minimizes cost of electric energy bought from grid by using energy stored in batteries that are charged preferentially by RES. Microcontroller equipped with FPGA [3] and fuzzy logic controller [4] are used to manage and control hybrid power system with Proton Exchange Membrane Fuel Cell (PEMFC), battery, RES and grid power. The focus in these schemes is to control the start and shut down frequencies of PEMFC and maintaining battery SOC while delivering power. [5] presents a rule based and grey wolf optimization techniques in power system of electric ferries consisting of Diesel Generators (DG) integrated with battery backup with a goal to reduce fuel consumption of the DG. Similarly, [6] uses a deterministic dynamic programming to optimize an objective function incorporating variables representing fuel cell electroplate degradation, capacity decay and drive cycles to minimize the fuel consumption and maximize the lifetime of the fuel cell and the battery in electric bus. [7] achieves increased usage of PV energy, improvement in maintaining of battery SOC and reduction in fuel consumption of fuel cell by using fuzzy inference system and prediction of power generation and consumption. In [8], the uncertainties in power generation by renewable sources and the load are predicted in advance by using probability density functions along with lightning search algorithm and Particle Swarm

Optimization (PSO) methods are used to solve the objective function consisting of the uncertainties and relevant constraints. A specific algorithm is used to check the states of the power sources and the load and take appropriate control actions based on rules to satisfy the load in [9]. [10] performs review and comparison of several strategies to control and manage the power flow in heterogeneous power systems employed in electric vehicles. As pointed out in [10], some methods, such as dynamic programming, genetic algorithm, are computationally intensive. On the contrary, rule based systems are simple but may not find the globally optimal solutions and fuzzy logic systems require to devise a proper membership functions which in turn may need complex algorithms. Also discussed in [10] is robust control approach which can handle uncertainties and is adaptable but has computational complexity. In addition, forecasting systems need additional input data. Moreover, systems controlled centrally or realized in single central controller do not have the feature of resiliency.

So, to achieve robustness and resiliency, [11] recommends using multi-agent based systems to manage the micro-grids consisting of multiple power sources and thus having distributed nature. Multi-Agent System (MAS) based systems are implemented in [12-14]. The goals of the methods are to maximize RES usage, optimally maintain battery SOC and minimize operation cost. MAS based systems are also used to identify faults [15]. Similarly, an MAS based power management system (PMS) is used in [16] to reduce system operation cost and ensure user needs and comfort. The MAS is heterogeneous with a central coordinator agent to control and manage other 4 types of agents. This system involves a significant communication for the agents to achieve their goals. A discussion of MAS based optimization and a comparative analysis of those techniques is presented in [11]. An MAS represents a distributed architecture that is resilient and robust. According to the paper, homogeneous agents are simple to implement over heterogeneous ones. It concludes that PSO and its modified forms have better performance over other optimization algorithms, such as Genetic Algorithm (GA), on the basis of convergence time and memory usage. Also discussed in the paper is Ant Colony Optimization (ACO) which is a heuristic based nature inspired algorithm that can be used to manage hybrid power systems. The authors in [17] present ACO meta-heuristics, a generalized method of problem solving imitating the ants in the nature which can be adapted to different problem scenarios with problem specific modifications. The algorithm is implemented by using relatively very simple objects called agents or artificial ants that solve the problem acting on local information and indirect communication (stigmergy). The result is emergence of a collective behavior. They exist in quite a large number with little effect due to failure of some individuals which gives the property of system robustness.

To sum up, centralized management systems have single point of failure and hence lack robustness. On the other hand, MAS based techniques possess the feature of resiliency. However, the distributed nature of heterogeneous MAS cannot completely eradicate the single point of failure. Furthermore, the communication among agents introduce latency in the system as well as introduce additional mechanism that may be prone to failures. On top of all of these, many systems work on the basis of additional input data such as weather forecast, history of production and consumption. So, the algorithm presented in this work is developed considering those constraints. Firstly, it is based on homogeneous MAS concept to simplify implementation. Secondly, without any direct message exchange taking place among the agents, it avoids the communication overhead. Next, the agents work on simple rules formulated by studying the problem and significantly reduce computational complexities. Lastly, the agents make decisions based on the power they are drawing from the sources without any need of external data.

## 3. Methodology.

### 3.1. Problem context.

The current delivered by an electric energy source operating in fixed parallel connection of outputs with other energy sources depends upon the voltages and resistances formed as combination of internal and conversion stage resistances of all the sources. The resistances can be manipulated in order to control the delivered current. In the discussion that follows, the output voltages of the power sources are assumed to be equal so that computations and algorithm steps can be carried on using only the value of the current that flows.

The conceptual diagram of the problem scenario is shown in Figure 1. It shows a heterogeneous power system with 3 sources whose outputs are permanently tied together. Three power sources are named as S0, S1 and S2, S0 being the source with the most preference and S2, with capacity to supply maximum load, being the source with the least preference. In the fixed parallel connection based multi power source system, depicted in Figure 1, the current contributed by $n$th source out of $j$ power sources is given by Equation (1).

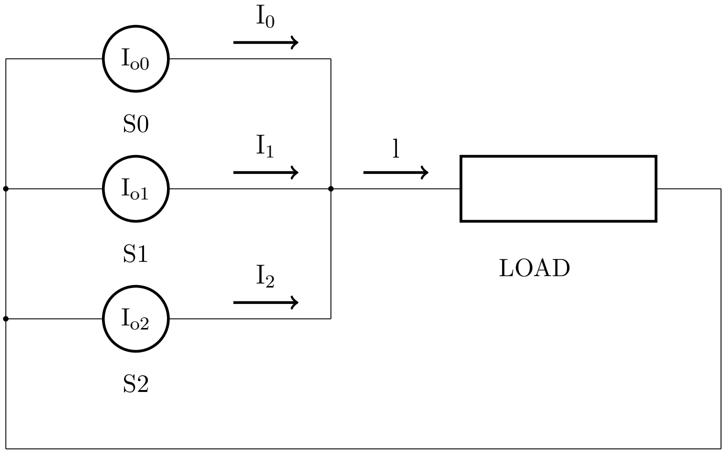
$$I_n = \frac{I_{on}}{I_{o0} + I_{o1} + \cdots + I_{oj-1}} \times l \tag{1}$$

where,

$I_{on}$: total current/power capacity of $n$th power source;

$l$: total instantaneous load current/power.

Equation (1) shows that the total power delivered to the load is composed of currents proportional to the capacities of the participating sources. Though source S0 in Figure 1 can deliver $I_{o0}$, it supplies only a fraction given by the relation shown in the figure.



$$\mathrm{I_n} = \frac{\mathrm{I_{on}}}{\mathrm{I_{o0}+I_{o1}+I_{o2}}} \times \mathrm{l}$$

FIGURE 1. Parallel connection of three power sources

### 3.2. Problem formulation.

The problem can be modeled as a bounded knapsack problem. The bounded knapsack problem has a knapsack of some capacity and is to be filled with different types of available items. Each type of item carries a profit value, has a weight and exists in some fixed quantity called the bound. Multiple items of a particular type can be used to fill the knapsack as long as the quantity is under the bound. The objective is to fill the knapsack such that the total profit or benefit due to the items in the knapsack has maximum value. Mathematically, the power problem can be represented as bounded knapsack problem in the following way:

$w_j$: amount of power from source $j$ that can be taken at a time;
$c_j$: cost and impact of an unit of power from source $j$;
$b_j$: bound or available amount of power in source $j$;
$l$: total load demand to be fulfilled, the size of the knapsack;
$N_s$: the number of types of power sources.

Now we need to select
$x_j$: number representing the quantity of power taken/drawn from source $j$. Power is drawn in unit quantity of value $w_j$.

Total power taken/drawn is expressed as $x_j w_j$ so as to minimize the cost and impact which is given by Equation (2).

$$\text{total cost} = \sum_{j=0}^{N_s-1} c_j x_j w_j \tag{2}$$

with the constraint as mentioned in Equations (3) and (4).

$$\sum_{j=0}^{N_s-1} w_j x_j \leq l \tag{3}$$

$$0 \leq x_j \leq b_j, \ \ j \in [0, N_s] \tag{4}$$

The load demand should be exactly met and the constraint is given by Equation (5).

$$\sum_{j=0}^{N_s-1} w_j x_j = l \tag{5}$$

3.3. **Solution approach.** The approach of divide and conquer algorithm is used to solve the problem. So the knapsack, $l$ in our case, is divided into smaller knapsacks. Each smaller knapsack is filled with the power from the most preferable source as far as possible. Any smaller knapsack can be filled with power from any source. So, to avoid size mismatches in our solution, the sizes of all the portions are made equal, and let the size be $w$.

$$w_0 = w_1 = w_2 = w_{N_s-1} = w \tag{6}$$

This equalization of the amount of power as in Equation (6) can be drawn from the sources that bring in the homogeneity and simplicity in implementation.

If variable load is considered, $l$ keeps changing. So, we can specify $w$ at maximum load, $l_m$. Let $w$ at maximum load be $w_m$. Since all the portions of $l_m$ are equal in size and are exactly fulfilled by using amount of power equal to $w_m$, it can be calculated as in Equation (7).

$$w_m N_A = l_m \tag{7}$$

where $N_A$ is the number of smaller portions of $l_m$. Equation (8) gives relation for $N_A$.

$$N_A = \frac{l_m}{w_m} \tag{8}$$

$N_A$ is fixed for an implementation instance and does not change with varying load, so $w$ changes. Equation (9) gives $w$ at any given load demand $l$.

$$w = \frac{l}{N_A} \tag{9}$$

The availability of power in preferable sources keeps changing. For an arbitrary value of $w$, it is likely that the available power may not be in exact multiple of $w$. In order to use most of the available power, the value of $w$ must be chosen carefully. Two conditions may occur

1) after taking power of quantity $(x_j w)$ from source $j$, there may be a surplus amount;
2) the available power may be less than $(x_j w)$ and $((x_j - 1)w)$ may have to be taken leaving some surplus amount.

If $b_j$ is the present available power, in the above described cases, there is unused power which can be calculated as Equation (10).

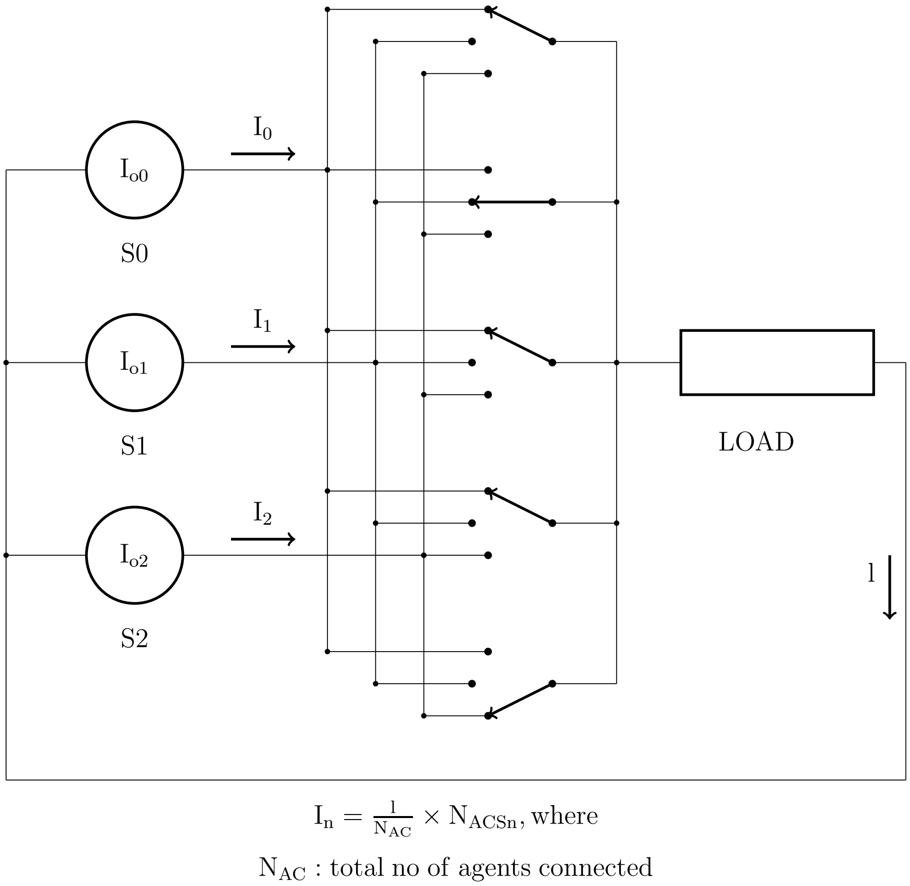
$$\text{unused power} = b_j - x_j w \tag{10}$$

The maximum unused power cannot be greater than $w$, because as soon as the unused power equals $w$, it will be used to fill a smaller knapsack, and the total power taken from that source will be $((x_j + 1)w)$.

So, it can be inferred that the unused power can be reduced by reducing the value of $w$ or increasing the number of smaller portions.

3.4. **Algorithm development.** The first step is to determine the maximum load, $l_m$, the system is required to fulfill and the acceptable error of unused power, $w_m$. And compute the number of smaller knapsacks $N_A$.

Each smaller portion of $l_m$, or $l$ in case of varying load, is to be filled with power from the most preferable source, if that is not available, then the next preferred source and so on. An agent is employed to make this decision. Each agent can choose to connect to any available power source. Figure 2 illustrates the concept of the solution. The connection is now dynamic.



$\mathrm{I_n} = \frac{\mathrm{l}}{\mathrm{N_{AC}}} \times \mathrm{N_{ACSn}}$, where

$\mathrm{N_{AC}}$ : total no of agents connected

$\mathrm{N_{ACSn}}$ : no of agents connected to Sn

FIGURE 2. Multi-agent based solution concept

- Initially, each agent is connected to the least preferable source.
- Because of the nature of the physical circuit, all the connected agents draw equal power from the source, the sum of which is equal to the load demand $l$.
- Each agent checks the available power sources in descending order of preference starting at the most preferred one. When it makes a new connection, it compares the power it can draw from this new connection to the power it was drawing previously.
- If the new value of power is greater than or equal to the previous value, it keeps the new connection.
- Else, if the new value is smaller than the previous value, it leaves the connection and goes on to try other remaining sources.
- If no source can satisfy the condition, the least preferable source will, because it is designed with enough capacity that can suffice the maximum load.
- At any time, the load is fulfilled by combining the power each agent is drawing from the sources.

### 3.5. **Algorithm.**

Parameters of the algorithm

| | |
|---|---|
| $l_m$: | Maximum load; |
| $w_m$: | Maximum acceptable utilization error. It represents the amount of power that may not be used; |
| $N_A$: | Total number of agents; |
| $N_S$: | Total number of power sources; |
| ics: | Index of the power source that an agent is connected to, and it may represent the position of physical switch; |
| pbd1: | Present value of power being drawn by an agent; |
| pbd2: | Next value of power being drawn by an agent. It is used to hold the value of power that an agent reads after a new connection. |

First the number of agents is calculated using Equation (8). Each agent starts with connection to the least preferable source as it can deliver the full load. So, each agent is initialized as

```
INITIALIZATION for each agent ics = $N_S - 1$

TASK performed by each agent
    read pbd1
    if (pbd1 $\neq$ 0){
        for(power source index s_count = 0 to ($N_S - 1$){
        ics = s_count
        read pbd2
        if (pbd2 $\geq$ pbd1){
            pbd1 = pbd2
            break loop
            }
        }
    }
```

The total load delivered by the system is given by Equation (11).

$$l = \sum_{n=0}^{n=N_A-1} \mathrm{pbd1}_n \tag{11}$$

3.6. **Experimentation.** A program was developed to implement the two systems, simple fixed parallel connection and the agent based system and the utilization of the sources in both the cases was computed.

For fixed parallel connection based system, the utilization of available power from source $j$ is computed by Equation (12).

$$ut_{Sj\_p} = \frac{\text{power drawn by load from source } S_j}{\text{total power available in source } S_j} \tag{12}$$

In the agent based system, $w$ is chosen and the number of agents is computed by Equation (8). Each agent makes contribution of $w$ power. The utilization of available power for a source $j$ is computed by Equation (13).

$$ut_{Sj\_a} = \frac{\text{power drawn by connected agents from source } S_j}{\text{total power available in source } S_j} \tag{13}$$

For both cases, the available power was simulated using various wave-forms that closely match the real world scenario. Two types of load profiles were fed into the simulation. One is typical load profile of telecom site during 12 hours in daytime and the other is a constant load demand profile that is much like a pure repeater station.

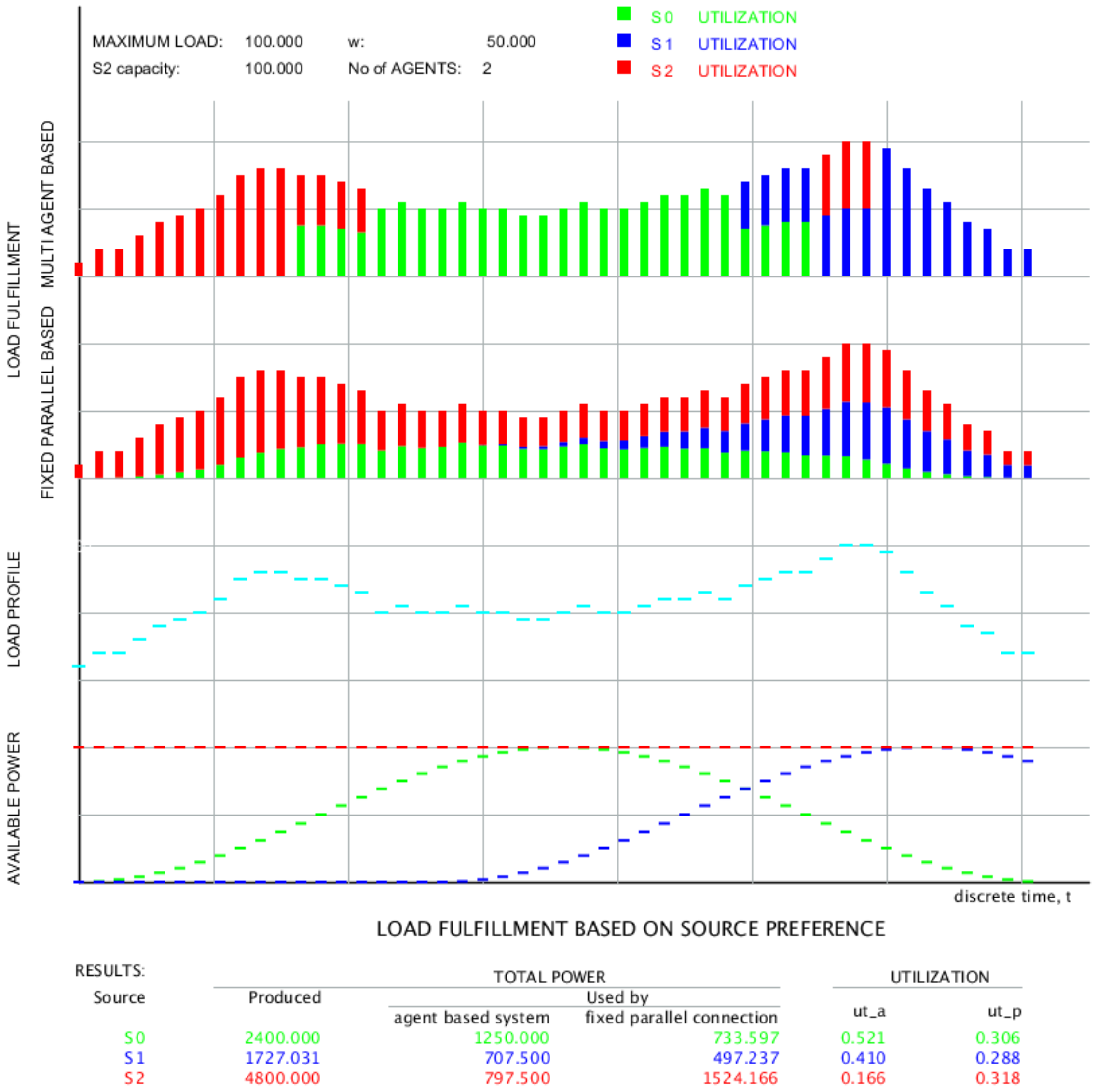
## 4. **Results and Discussion.**

4.1. **Results.** Three sources were considered, S0, S1 and S2, with S0 being the most preferred source. The simulation was run for various values of number of agents $N_A$. Figures 3 through 6 are comparative graphs that show time sampling of available power, load profile, and utilization of power sources based upon fixed parallel connection and multi-agent system for $N_A = 2$ and 100. The results for varying load profile are shown in Figures 3 and 4. Similarly, the cases of maximum constant load are illustrated in Figures 5 and 6 for the same values of $N_A$.

As seen in Figures 3 through 6, the main advantage of this research is the optimum utilization of preferred source S0. It can be seen the green colored source S0 is fully utilized when multi-agent based source utilization scheme is used. The utilization of 3 sources, as generated by the simulations for various values of $w$ and $N_A$ are tabulated in Table 1 (varying load profile) and in Table 2 (constant load profile). Both of these tables show the better utilization of preferred source with MAS system.

Table 1. Comparison between utilization achieved by multi-agent based system and simple fixed parallel connection for varying load profile

| | | | $ut_{S0}$ | | $ut_{S1}$ | | $ut_{S2}$ | |
|---|---|---|---|---|---|---|---|---|
| SN | $w$ | $N_A$ | $\_a$ | $\_p$ | $\_a$ | $\_p$ | $\_a$ | $\_p$ |
| 1 | 100 | 1 | 0.398 | 0.306 | 0.373 | 0.288 | 0.241 | 0.318 |
| 2 | 50 | 2 | 0.521 | 0.306 | 0.410 | 0.288 | 0.166 | 0.318 |
| 3 | 20 | 5 | 0.653 | 0.306 | 0.387 | 0.288 | 0.108 | 0.318 |
| 4 | 15 | 6 | 0.663 | 0.306 | 0.379 | 0.288 | 0.106 | 0.318 |
| 5 | 10 | 10 | 0.691 | 0.306 | 0.360 | 0.288 | 0.099 | 0.318 |
| 6 | 8 | 12 | 0.696 | 0.306 | 0.356 | 0.288 | 0.098 | 0.318 |
| 7 | 5 | 20 | 0.711 | 0.306 | 0.346 | 0.288 | 0.094 | 0.318 |
| 8 | 3 | 33 | 0.718 | 0.306 | 0.340 | 0.288 | 0.093 | 0.318 |
| 9 | 2 | 50 | 0.723 | 0.306 | 0.336 | 0.288 | 0.091 | 0.318 |
| 10 | 1 | 100 | 0.725 | 0.306 | 0.335 | 0.288 | 0.091 | 0.318 |



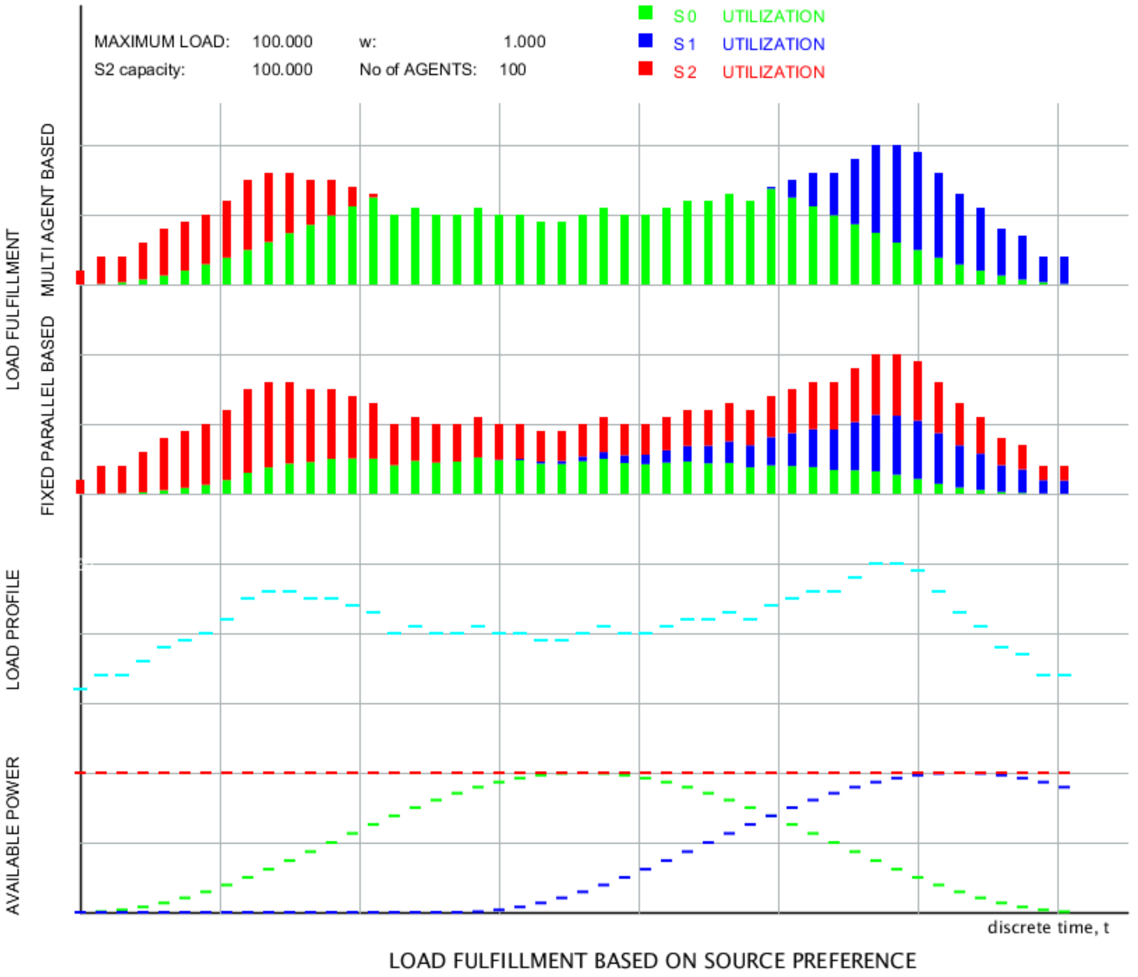
RESULTS:

| Source | TOTAL POWER<br>Produced | Used by<br>agent based system | <br>fixed parallel connection | UTILIZATION<br>ut_a | <br>ut_p |
|---|---|---|---|---|---|
| S0 | 2400.000 | 1250.000 | 733.597 | 0.521 | 0.306 |
| S1 | 1727.031 | 707.500 | 497.237 | 0.410 | 0.288 |
| S2 | 4800.000 | 797.500 | 1524.166 | 0.166 | 0.318 |

FIGURE 3. Source utilization for $w_m = 50/N_A = 2$ with variable load profile

TABLE 2. Comparison between utilization achieved by multi-agent based system and simple fixed parallel connection for constant load profile

| | | | $ut_{S0}$ | | $ut_{S1}$ | | $ut_{S2}$ | |
|---|---|---|---|---|---|---|---|---|
| SN | $w$ | $N_A$ | _$a$ | _$p$ | _$a$ | _$p$ | _$a$ | _$p$ |
| 1 | 100 | 1 | 0.042 | 0.508 | 0.058 | 0.454 | 0.958 | 0.583 |
| 2 | 50 | 2 | 0.500 | 0.508 | 0.521 | 0.454 | 0.562 | 0.583 |
| 3 | 20 | 5 | 0.808 | 0.508 | 0.718 | 0.454 | 0.338 | 0.583 |
| 4 | 15 | 6 | 0.847 | 0.508 | 0.724 | 0.454 | 0.316 | 0.583 |
| 5 | 10 | 10 | 0.900 | 0.508 | 0.712 | 0.454 | 0.294 | 0.583 |
| 6 | 8 | 12 | 0.931 | 0.508 | 0.695 | 0.454 | 0.285 | 0.583 |
| 7 | 5 | 20 | 0.954 | 0.508 | 0.686 | 0.454 | 0.276 | 0.583 |
| 8 | 3 | 33 | 0.971 | 0.508 | 0.677 | 0.454 | 0.271 | 0.583 |
| 9 | 2 | 50 | 0.980 | 0.508 | 0.671 | 0.454 | 0.269 | 0.583 |
| 10 | 1 | 100 | 0.991 | 0.508 | 0.666 | 0.454 | 0.265 | 0.583 |



RESULTS:

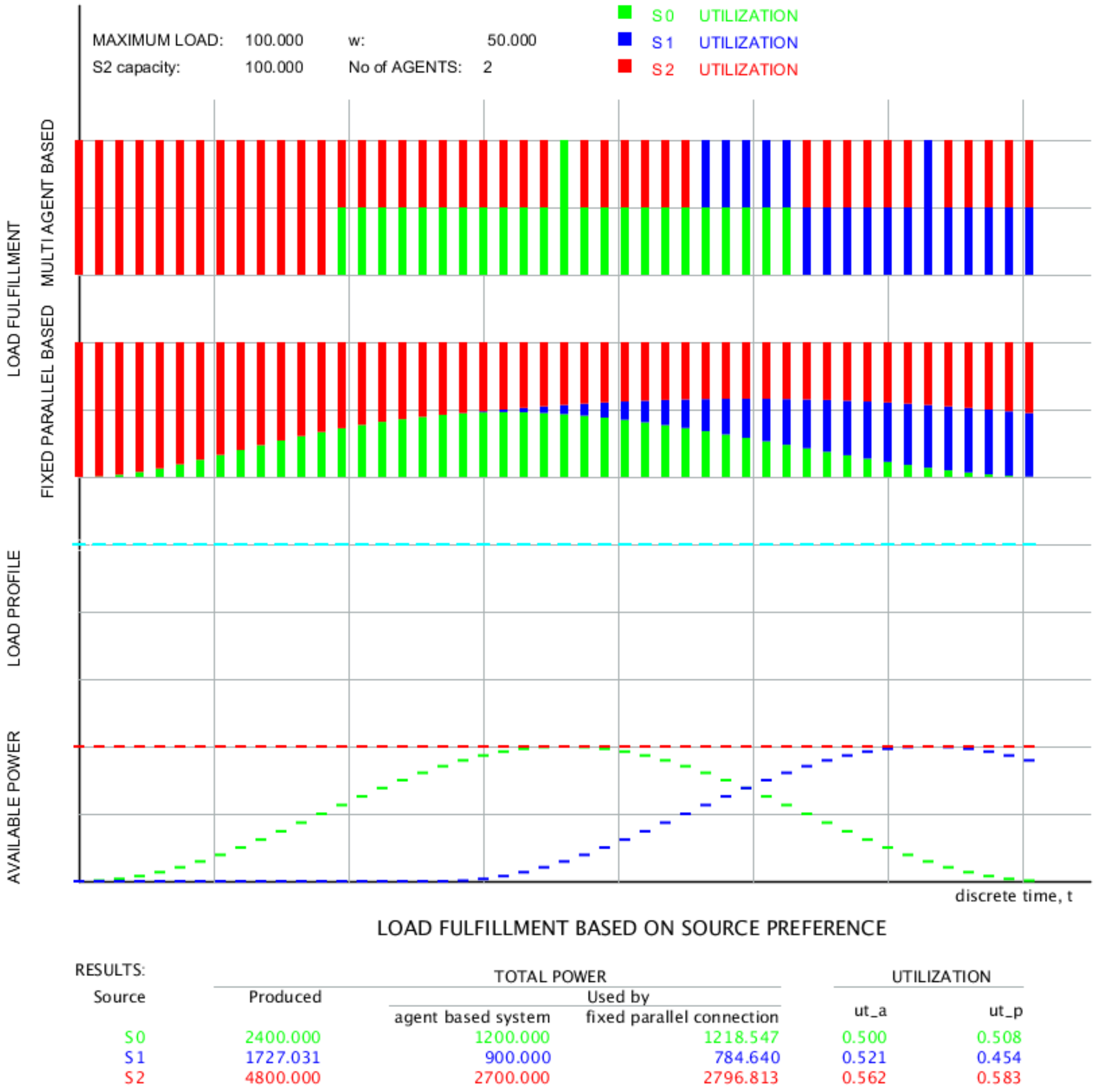
| Source | TOTAL POWER | | | UTILIZATION | |
|---|---|---|---|---|---|
| | Produced | Used by | | | |
| | | agent based system | fixed parallel connection | ut_a | ut_p |
| S0 | 2400.000 | 1739.850 | 733.597 | 0.725 | 0.306 |
| S1 | 1727.031 | 578.350 | 497.237 | 0.335 | 0.288 |
| S2 | 4800.000 | 436.800 | 1524.166 | 0.091 | 0.318 |

FIGURE 4. Source utilization for $w_m = 1/N_A = 100$ with variable load profile

4.2. **Discussion.** The following conclusions can be made from the observations:

1) In almost all the cases (except for $w_m = 100$ and 50 in maximum constant load profile), the utilization achieved by the agent based system is higher, 72% in case of varying load profile and 99% in case of maximum constant load profile, than that obtained without any control mechanism which is simple fixed parallel based connection, 30% in case of varying load profile and 50% in case of maximum constant load profile.
2) Utilization of the most desired system increases as the value of $w_m$ decreases or $N_A$ increases.
3) The utilization is higher when the power availability matches the load demand and is integer multiple of $w$. This is evident in Figures 3 through 6. The utilization for $N_A = 2$ in case of variable load is higher than that in constant maximum load while for $N_A = 100$, it is lower in case of variable load than in constant load.

The agent based system tries to closely follow the energy production and uses it as much as possible.



RESULTS:

| Source | Produced | TOTAL POWER Used by agent based system | TOTAL POWER Used by fixed parallel connection | UTILIZATION ut_a | UTILIZATION ut_p |
|---|---|---|---|---|---|
| S0 | 2400.000 | 1200.000 | 1218.547 | 0.500 | 0.508 |
| S1 | 1727.031 | 900.000 | 784.640 | 0.521 | 0.454 |
| S2 | 4800.000 | 2700.000 | 2796.813 | 0.562 | 0.583 |

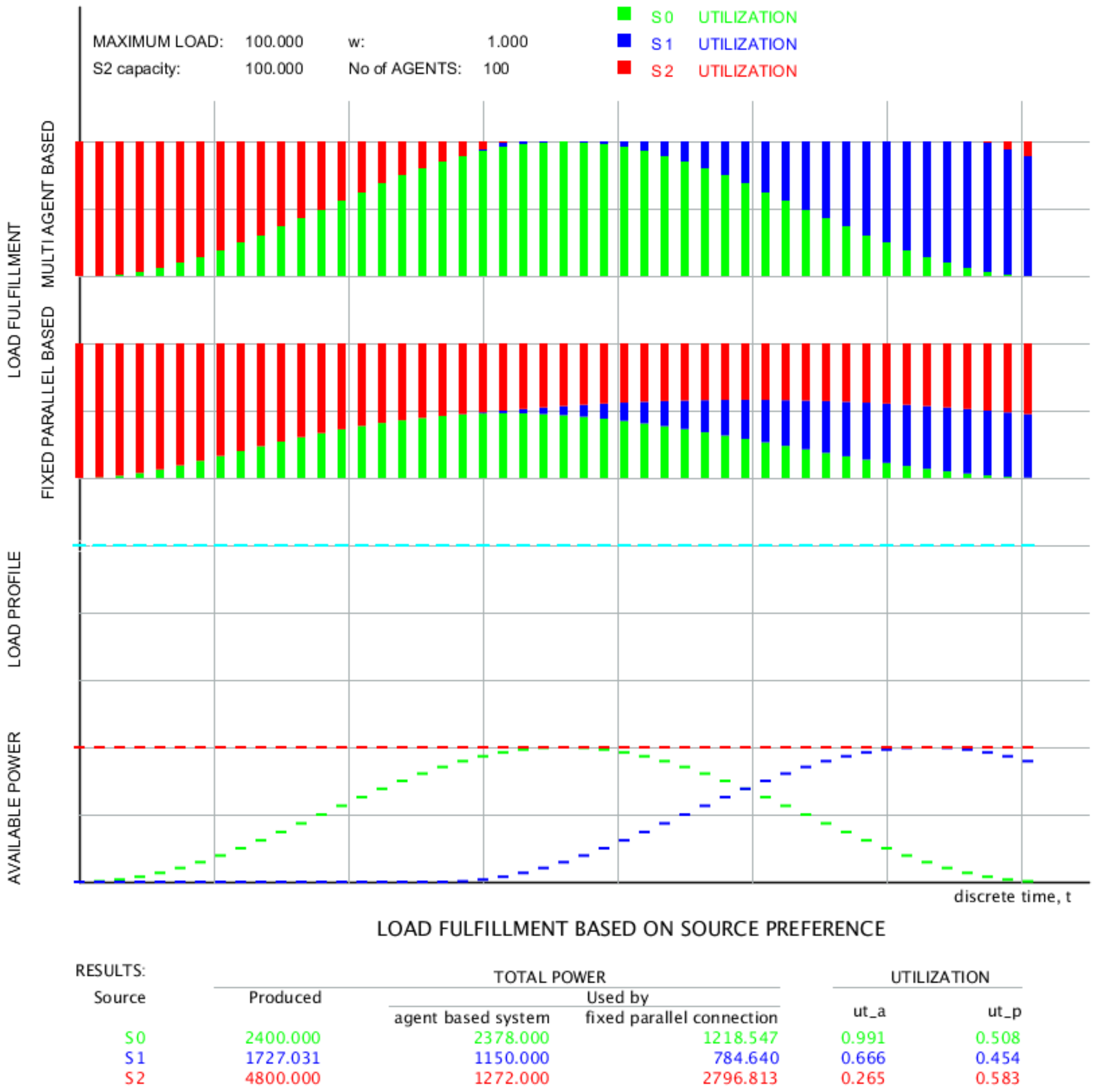
Figure 5. Source utilization for $w_m = 50/N_A = 2$ with constant maximum load profile

Compared to the works discussed in the literature review, the developed algorithm has the following advantages:

1) The algorithm requires no external data such weather predictions and estimations are required and depend upon local information only.
2) No single agent is a central component. They are homogeneous in nature and breaking down of one does not bring down the system.
3) A separate communication infrastructure is not required; agents decide upon a connection based upon the value of current they are drawing.

## 5. Conclusion and Recommendation.

**5.1. Conclusion.** In this work, the fulfillment of load demand using multiple power sources with differing properties is discussed. The goal is to use desired source the most to optimize factors such as cost and environmental impact. The case is treated as combinatorial optimization problem and solved by using bounded knapsack problem model



RESULTS:

| Source | TOTAL POWER |  |  | UTILIZATION |  |
|---|---|---|---|---|---|
|  | Produced | Used by |  |  |  |
|  |  | agent based system | fixed parallel connection | ut_a | ut_p |
| S0 | 2400.000 | 2378.000 | 1218.547 | 0.991 | 0.508 |
| S1 | 1727.031 | 1150.000 | 784.640 | 0.666 | 0.454 |
| S2 | 4800.000 | 1272.000 | 2796.813 | 0.265 | 0.583 |

FIGURE 6. Source utilization for $w_m = 1/N_A = 100$ with constant maximum load profile

which is tackled by divide and conquer approach. Each sub problem is solved by an agent making this a multi-agent system. The agent based system fulfills the main objective of maximum utilization of the preferred source. Using the multi-agent system, with $N_A = 100$, $w_m = 1$ utilization of 99% is achieved while with no control mechanism in fixed parallel connection, the utilization is 50.8%. The choice of the parameter $w_m$ can affect the performance of the system. For $w = 100$, that is $N_A$ =1, the utilization is only 4%. While smaller value of $w_m$ improves the utilization performance, the number of agents also increases which means increase in cost. Another aspect is that the utilization of the most preferred is dependent upon the load profile. The utilization is higher when the load profile and the power production matches and the value of produced power is integer multiple of $w$. For $N_A = 100$, in varying load profile the utilization of most preferable source is only 72.5% while in maximum constant load profile in which the load exceeds the production, the utilization achieved is 99.1%.

5.2. **Recommendation.** The power management systems in the papers discussed in literature review also had some form of energy storage systems. These units are required to compensate the intermittency of the renewable energy source and balance the load demand. As we can see in the case of varying load profile, the demand and the production by the most preferred source do not match. This decreases the utilization of the preferred source and the main objective is not fully accomplished. So, as an improvement in the present work, the agent structure and behavior can be modified to incorporate the energy storage systems. This would store the energy produced by the most preferred source during low load and use it during high demand and low energy production by the most preferred source.

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