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Suitable Decision using Decision Support System for Energy Saving

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Suitable Decision using Decision Support System for Energy Saving

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Abstract:
Decision Support System (DSS) is a system that facilitates the process of decision making by breaking down a complex problem into simple components. Main points that can be taken into consideration when examining various Decision making system literature related to E&E are the selection of appropriate method, selection of criteria to be used and the widely distributed application areas. The motivation behind this study is designing such a Decision Support System (DSS) that enables experts and end user to take proper decision in any field for energy saving. The decision support system established in this study integrates potential evaluations, cost analyses, legal incentives, and analysis of returns on investments with the construction of Data Warehouse and Data Mart. Various soft computing techniques: Artificial Neural Network, Fuzzy Logic, and Evolutionary Algorithm etc. can be used to make the system Intelligent.

Keywords: Data-driven modeling, Data mining, Hydrology, Artificial Neural Network, Artificial Intelligence, Energy

1. INTRODUCTION

The DSS is Information and Communication Technology (ICT) based tool and will provide need based information on technical, social, financial and environmental aspects related to hydrological system.
A Decision Support System (DSS) plays very important role to take decisions quickly and without much paper work. It is tough to see lots of data and many files with vast domain knowledge while taking decision so this reduces the workload and time consumption.
DSS helps managers react quickly to their changing needs. The Decision Support System enables users to gain access to vast amounts of information, which can assist them in meeting their overall business objectives.
Thus, DSS provides better understanding of the organization's functions from a historical perspective to improve tracking and responding to business trends, facilitating forecasting and planning efforts, and making strategic business decisions.
A Decision support system is a computer-based system that enables management to interrogate the computer system on an ad hoc basis for various kinds of information in the organization and to predict the effect of potential decisions beforehand. Drawing on various definitions that have been suggested [2], 20, 32] a DSS system can be described as a computer-based interactive human computer decision-making system that:

- Supports decision makers rather than replace them
- Utilizes data and models
- Solves problems with varying degrees of structure
  - a) Non-structured (unstructured or ill-structured)
  - b) Semi-structured
  - c) Semi-structured and unstructured
- focuses on effectiveness rather than efficiency in decision Processes (facilitating decision processes).

DSS support technological and managerial decision making by assisting in the organisation of knowledge about ill-structured, semi-structured, or unstructured issues. A structured issue has a framework comprising elements and relations between them are known and understood [15]. Emphasis in the use of a decision support system is upon provision of support to decision makers in terms of increasing the effectiveness of the decision-making effort [10]. This support involves the systems engineering steps of formulation of alternatives, the analysis of their impacts, and interpretation and selection of appropriate options for implementations [9].

Traditional legacy and on line transaction processing (OLTP) systems are not adequate for decision support. So we will have to see the components and other required things to take right decision.

Components of DSS

Social: The social component is evaluated through the *'Social Assessment'* questionnaire which takes input from the end user of the society. Water uses, power uses, number of persons any standard of the living etc. are collected using this sheet.

Technical: Evaluation of the technical component is through the *'Resource Assessment'* and *'Demand Estimation' questionnaire*. Resource assessment considers infrastructure, machines, input parameters, gauzing tools and techniques, historical data with experts of the area for designing the system. Demand Estimation helps us assess the current and future demand of the resource. The technical component provides the technical details mainly the input parameters, architecture and suitable technique to develop the system.

Financial: The financial component is inbuilt in the *'Resource Assessment'* and *'Demand Estimation'* sheets and it gives an estimate of the total capital cost of the plant, the costs to be incurred after plant commissioning for financial year our project tenure (includes operation & maintenance costs, personnel costs, equipment & infrastructure costs and raw material costs) and a fund gap analysis.

Environmental: The environmental component is also in built in the *'Resource Assessment'* and *'Demand Estimation'* sheets and gives the requirement of the various constituents, whether, power demand, waste management, energy dissipation and energy utilization.

Target Group

1. Communities (PRI members, Farmers etc)
2. Entrepreneurs
3. NGOs
4. Funding agencies
5. Local distributor
6. Policy makers

Study Area

Result or proposed output will be based upon the location or the area. Environmental condition and other conditions are taken into the consideration for taking decisions.

Research Scope

Primary Focus - A decision maker wants to estimate the quantity of energy saved from various processes involved in a system (including waste reuse or management).

Secondary Focus

A utility decision-maker wants to reduce energy consumption for but is not sure where to start or what sorts of tools or approaches are available

A utility decision-maker wants to understand benefits or impacts of decisions involving energy but is not sure what methodologies exists

Advent of Multimedia and Internet technologies has entirely changed the way of computing and made it accessible to common man. Latest Multimedia and Internet technologies had changed the process of knowledge acquisition and presentation (Ahmed Rafea et al., 1995), (Lim Kyoung Jae et. Al., 2003), (Shaalan Khaled et al., 2004). DSS which are based upon simple mathematical calculation are not very fruitful. Web based DSS can provide its accessibility from any place data and knowledge can be imparted from any part. Distributed nature of the DSS enables remote knowledge acquisition from domain expert as well as at local level. Maintenance and knowledge including data can be part of the system from any remote locations also.

The emergence of the ANNs, on the positive side, has provided many promising results in the field of hydrology and water resources engineering (ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000a, 2000b; Maier and Dandy, 2000), leading to the creation of a new chapter in hydrology that has been termed "neurohydrology." However, on the darker side, until recently, ANNs were not readily accepted as a modeling tool by the wider hydrological community and decision makers, based on the perception that the ANNs are pure black-box models and they do not consider the underlying physics. Nevertheless, recent studies by Jain et al. (2004), and Sudheer and Jain (2004) have demonstrated that the ANNs are not pure black-box models and it is possible to extract some of the physics involved. Hence lately, more research has been directed to identifying the mechanism by which ANNs learn the hydrological patterns embedded in the input-output data.

Although several studies indicate that the data-driven models have proven to be potentially useful tools in hydrological modeling, two of the main issues that needs to be further explored before these models gain wider acceptability by researchers and practitioners are: (i) bringing transparency (insights), even if only partially, on the basic process by which these data-driven models arrive at a decision, and thereby extending their usefulness beyond forecast applications as a tool for scientific investigations; and (ii) identifying the effective ways for performing uncertainty analysis in the data-driven models, which in-turn contributes to improving the reliability of such models. Therefore this research, driven by the motivation of improving the credibility of the data-driven models among researchers and practitioners, is carried out to identify some of the possible solutions to the above mentioned issues.

The present work is part of a large research program that aims at developing a DSS to help various agencies which prepare plans for societies. Data driven approach is taken to develop system as we know it is still impossible to know all factors which influence any hydrological system. Various environmental factors are taken to calculate or predict any environmental events.

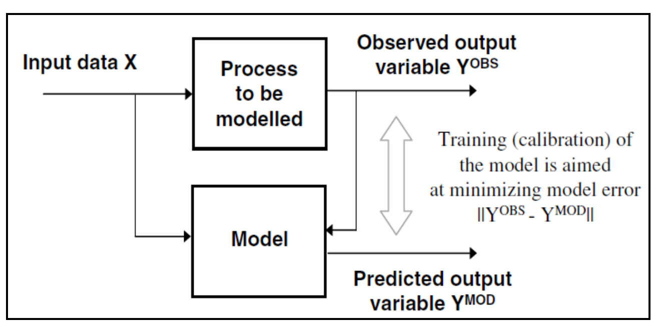

Figure 1.1: Training of the proposed model

2. DIFFERENT MODELS OF INTELLIGENT SYSTEM

Any physical world models can be characterized as physical, mathematical (including lumped conceptual and distributed physically based models) and empirical. Different techniques give different models to simulate different complex problems. Many fields are overlapped and are given below.

• Artificial intelligence (AI): This is the overarching study of how human intelligence can be incorporated into computers.

• Computational intelligence (CI): which includes neural networks, fuzzy systems and evolutionary computing as well as other areas within AI and machine learning.

• Soft computing (SC), which is close to CI, but with special emphasis on fuzzy rule-based systems induced from data.

• Machine learning (ML), which was once a sub-area of AI that concentrates on the theoretical foundations used by CI and SC.

• Data mining (DM) and knowledge discovery in databases (KDD) are focused often at very large databases and are associated with applications in banking, financial services and customer resources management. DM is seen as a part of a wider KDD. Methods used are mainly from statistics and ML.

• Intelligent data analysis (IDA), which tends to focus on data analysis in medicine and research and incorporates methods from statistics and ML.

Data-driven modeling is therefore focused on CI and ML methods that can be used to build models for complementing or replacing physically based models. A machine-learning algorithm is used to determine the relationship between a system's inputs and outputs using a training data set that is representative of all the behavior found in the system.

Once the model is trained, it can be tested using an independent data set to determine how well it can generalize to unseen data.

3. METHODOLOGY

Criteria in Decision Support for Energy Efficiency and Energy Management

Energy is in embodied in every facet of utility operations, management, and planning (1). Climate changes associated with greenhouse gas emissions have a substantial impact on the need of the energy and energy resource. Weather or climate change also fluctuates the energy requirement and resultant pollution.

Utilities currently have major challenges identifying the "most appropriate" strategic and operational decisions regarding energy management choice

The criteria for energy efficiency and energy management in a new establishment or in a existing system can be either quantitative or qualitative. Following are some points to consider for DSS

1. Heating and cooling load for conditioned buildings(for purification and supply purpose (D'Cruz and Radford, 1987; Bouchlaghem, 2000);
2. Normalized annual energy consumption and energy use for heating in kWh/m2 (Rey, 2004; Zhu, 2006);
3. Annual electricity use in kWh/m2 (Rey, 2004);
4. Embodied energy (Chen et al, 2006);
5. Energy and time consumption index (ETI) (Chen et al, 2006);
6. Energy savings by retrofitting expressed by **:-**

   (1- $\frac{Energy}{Energybaseline}$ **) % (Gholap and Khan, 2007).**

Energy Management

In any kind of hydrological system, energy issue is the key one. Electricity consumption rises as the demand rise. For energy saving proper responsibility and actions are needed. Following are the criteria for improving the system.

Responsibility:	Responsibility for these activities can involve a number of organizations in a variety of combinations
Performance:	System performance dependent on regional characteristics, water balance and types of technologies.
Actions	Energy actions can affect marginal or whole system, which action is correct

Model Performance Measures

There are many statistical parameters used to evaluate the performances of various models suggested to develop in this study. Following are statistical ways used for measuring performance:

Sum Square error (SSE)

Sum square error is a standard statistic that is used to find the 'best fit' to a set of data. In ANN model development also, SSE is normally employed as the objective function to be minimized. Mathematically, it is expressed as follows:

$$\textbf{SSE=} \sum_{i-1}^{N} (Q\,obs - Q\,cal)^2 \qquad \textbf{(Eq. 3.1)}$$

Where N= Total number of data points

Q_{cal} = Calculated Value

Q_{obs} = Calculated Value

Lower SSE implies good model performance, and vice-versa

Average Absolute Relative Error (AARE)

AARE is the absolute value of the relative error in predicting a number of data points. To find the value of AARE, we have to first find relative error in predicting a data point. Relative error is a measure of the error in forecasting a particular variable relative to its exact value. Mathematically, it can be represented by the following equation:

AARE = $$\frac{1}{N}\sum\left|\frac{Q\,cal - Qobs}{Qobs}\right| \times 100$$ **(Eq. 3.2)**

Where N= Total number of data points

Q_{cal} = Calculated Value

Q_{obs} = Calculated Value

Lower AARE implies good model performance, and vice-versa.

Correlation Coefficient (R)

The coefficient of correlation is a measure of the linear independence of two variables. It can be used as a measure of the performance of the model. Higher the value of R, better is the performance and vice versa. Mathematically, it can be expressed by the following equation:

R= $$\frac{\sum(Q\,obs - \overline{Q}obs) \quad X \;(Q\,cal - \overline{Q}\,cal)}{\sum(Q\,obs - \overline{Q}obs)^2 \;\sum(Q\,cal - \overline{Q}\,cal)^2}$$ **Eq. 3.3)**

Where $\overline{Q}obs$ is the mean of the observed values.

$\overline{Q}cal$ is the mean of the computed values, and other notation are same as above. The value of R ranges from -1 to +1.

R= -1 indicating perfect negative correlation.

R= +1 indicates perfect positive correlation.

R= 0.0 indicates absence of correlation.

Normalized Root Mean Square error (NRMSE)

The root mean square error (RMSE) statistic is an absolute measure of the residual variance from the developed model. Its magnitude relative to the observed, called NRMSE is employed to have an unbiased statistic. Mathematically, it is represented as follows

NRMSE = $$\frac{\sqrt{\frac{1}{N}\sum (Q\,obs - Qcal)^2}}{\frac{1}{N}\sum Q\,obs}$$ **(Eq. 3.4)**

Where the notations have same meaning as defined earlier.

Nash-Sutcliffe Efficiency (E)

The coefficient of efficiency (E) was proposed by Nash and Sutcliffe (1870). It is one of the widely employed to measure the strength of a model developed. Mathematically, it can be represented by the following equation.

E = 1 - $$\frac{\sum(Q\,cal - Q\,obs)^2}{\sum(Q\,obs - \overline{Q}\,obs)^2}$$ **(Eq. 3.5)**

A value of E=1.0 represents a perfect model while a model with E=0.0 is no more accurate than predicting the mean observed value. The negative value of E indicates that the model performs worse than mean and indicates very poor performance evaluation using E.

Table 3.1: Measurement of Goodness of Fit

S.N	Efficiency	Goodness of Fit
1.	< 0.2	Insufficient
2.	0.2-0.4	Satisfactory
3.	0.4-0.6	Good
4.	0.6-0.8	Very Good
5.	>0.8	Excellent

Points to Consider while Taking Optimal Decisions

1. Energy recovery vs. energy consumption
   – How can utility make decisions to be more energy independent?
2. Green House Emissions(GHG)
   – How do energy decisions affect GHG emissions?
3. Infrastructure
   – How can infrastructure be designed and operated to to minimize energy use, GHG emissions, and associated costs (e.g. through forecasting energy needs, use of off-peak power etc)?
4. Cycle of the Constituents
   – The components or the constituents used in the system are cyclic or nor, regeneration is possible or not.
   – What is the balance between energy usage and service delivery (i.e. quality vs. energy)?

DSS supports these decisions

1. What process best supports sustainable energy management decisions for decision makers?
2. What decision process might a utility consider when deciding what option would be best for a utility in ensuring its next water source (e.g. desalination, reuse) is carbon- neutral?
3. What tools, approaches, or knowledge best informs the decision-making method?
4. At what stage in the process, and to what level of detail?

Development of a Decision Support

In any support system three things are mostly required: Data, Analytical Tools and Decision making. Basically data is historical data on which Analytical Tool works and optimal solutions are taken by the decision makers or executer of the system.

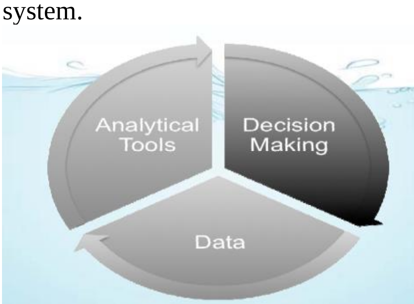

Fig 3.1: Component of Support System

Need of Data Warehouse and Data Mart

Data Warehouse integrates the organization's operational data, historical data, and external data into a single Data system. It stores the data from many databases of different formats and schema manages and molds the data into a subject-oriented format that is optimized for end users to access and analyze.
The Data Warehouse consolidates all the diversified information subsystems in the organization: legacy Databases, on-line transaction processing (OLTP) systems, external data sources, and decision-support applications: which in most organizations have been impossible to compile, correlate and contrast.
More precisely a Data Warehouse can be defined as "Subject-oriented, integrated, Time-variant, and Non-Volatile collection of data in support of management's decision-making process," (definition by W H Inmon)

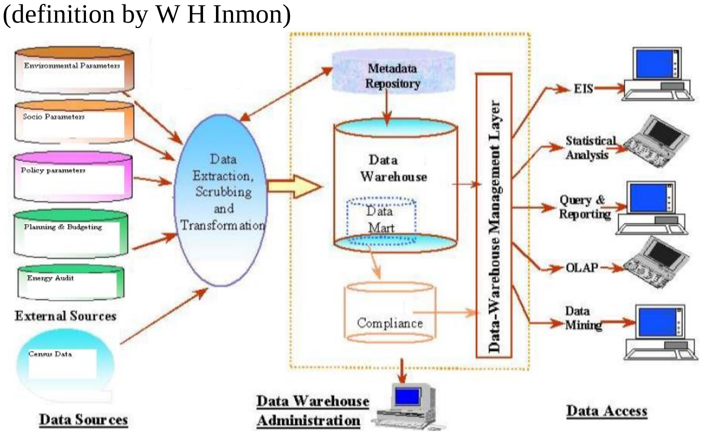

Fig 3.2: Architecture of Data Warehouse & Information mechanism

The Data Warehouse consolidates all the diversified information subsystems in the organization: legacy Databases, on-line transaction processing (OLTP) systems, external data sources, and decision-support applications: which in most organizations have been impossible to compile, correlate and contrast.
More precisely a Data Warehouse can be defined as "Subject-oriented, integrated, Time-variant, and Non-Volatile collection of data in support of management's decision-making process," (definition by W H Inmon)
Data used in the system is not accurate always so some treatment is required. Data cleaning, data integration, data transformation etc. are performed for better results.
Some other steps are required to make data ready for applying intelligent techniques: some are given;

- **Data reduction:** Obtains reduced representation in volume but produces the same or similar analytical results
- **Data discretization:** Part of data reduction but with particular importance, especially for numerical data preprocess the data
- **Data Normalization:** Formula for normalization is $X_i' = X_i - X_{i\,min} / X_{i\,max} - X_{i\,min}$
  Where Xi is one group of meteorological data collected (like temperature, humidity etc.). Xi min Xi max is the minimum and maximum of this group of data respectively. Xi' is output data

After data has been transformed it can be loaded into the data warehouse in a recognized and required format.

Analysis and Reporting Tools

Analysis tools: An analysis tool is basically an instrument that applies business rules or other logic to data in order to derive meaning. This includes time series analysis, cost allocations, data mining, and other user-driven manipulation and investigation. Analysis tools are available in many software applications, including spreadsheets, databases, and other stand-alone programs [25]. In a DSS environment, however, analysis tools are particularly powerful because they rely on On-Line Analytical Processing (OLAP) technologies. OLAP tools are applications that permit users to browse, query, analyze, and summarize large amounts of data in an efficient, interactive, and dynamic way [3]. The ability to manipulate data in multiple dimensions improves data analysis and reporting capabilities, making OLAP cubes invaluable for data mining, data management, and trend analysis and powerful analytical components of DSSs [3].

Reporting tools: Robust reporting tools are a major element of any DSS. Presenting information in multiple formats (as a blend of text, tables, and graphics) and in multiple dimensions, changing an axis to present information more clearly, sometimes further clarifies the meaning of the data. Unlike a date warehouse or database, which both focuses on data storage, a DSS often includes reporting tools that permit a user too easily:

● Place headings, titles, and explanatory information within charts, tables, and other derived figures;

● Add borders and shading to clarify and highlight important information and groupings;

● Modify font size and style to emphasize points;

● Move, edit, or delete data, text, and graphics in final reports;

● Produce a wide range of figures, including bar graphs, pie charts, bar and line graph combinations, multiple axis graphics, and scatter plots;

● Export data in various formats (such as, ASCII, Excel);

● Generate reports in various formats (such as, html, PDF, e-mail, paper); and

● Include legends, citations,explanations, and other information.

A DSS`s reporting functions must serve a wide range of users including novices and users with expert analytical capabilities. To accommodate this, most systems offer two primary classes of reporting tools: (1) predefined (static) reports that require little system expertise and are ideal for users with typical information needs; and (2) dynamic (ad-hoc) report-generating capabilities that require greater understanding of both the data and the querying technology, but allow users to investigate more complex questions [2].

Balanced Decision Making

Proper coordination and contribution is required for taking decision using DSS. Though the proposed model is based upon Artificial Neural Network which is based upon data but requires parameters which influences the system can be known using the scientific information. Intelligent system cannot give 100% accurate system even at the pure balances system

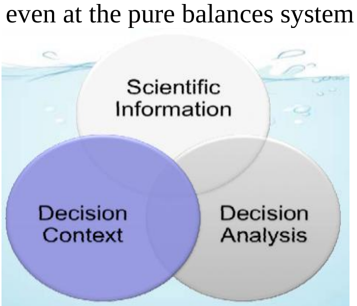

Fig 3.3: Balanced system

Decision Context

1. Decision makers do not always know the implications of their decisions
2. Decision support systems must interpret decision makers':
   – Goals
   – Objectives
   – Organizational Capabilities

Uncertainty Management

1. Uncertainties
   – Future energy pricing
   – Reliability of energy supplies
   – Water supply forecasts
   – Customer use
   – Population growth
   – Climate change
   – GHG regulations
   – Management directions
   – Workforce sustainability
   – Energy Audit
   – Heat Audit
   – Future technologies

Decision Modeling

It is a multistep development. Following are steps for modeling and DSS.

Formulation: Formulation is the first and often most challenging stage in using formal decision methods (and in decision analysis in particular). The objective of the formulation stage is to develop a formal model of the given decision.

Evaluation: Evaluation is the second and most algorithmic stage in using formal decision methods. The objective of the evaluation stage is to produce a formal recommendation (and its associated sensitivities) from a formal model of the decision situation.

Appraisal: Appraisal is the third and most insightful stage in using formal decision methods. The objective of the appraisal stage is for the decision maker to develop insight into the decision and determine a clear course of action. Much of the insight developed in this stage results from exploring the implications of the formal decision model developed during the formulation stage (i.e., from mining the model). Central to these implications is the formal recommendation for action calculated during the evaluation stage. Other implications include various forms of Sensitivity of the recommendation to various components of the decision model. Insight may also result from discussion of the key aspects of the reasoning that led to the formal decision model (i.e., by justifying the model). Possible actions following the appraisal stage include implementing the recommended course of action, revising the formal model and Reevaluating it, or abandoning the analysis and doing something else.

Justifying a decision model entails exploring and explaining the reasoning that led to the formulation of particular aspects of the decision model.
Mining a decision model entails extracting information (e.g., sensitivity, value of prediction, and value of revelation) from a given decision model.

Refinement: Refinement is the fourth and most critical stage in using formal decision methods. The refinement stage responds to the insights obtained during the Appraisal stage. Effective refinement activities include opportunities to test possible decision model changes to see their implications and suggest better ways to modify the decision model.

Scope of decision support tools

Fig 3.3: Parts of Decision making

Decision Support Tools

Operationally-oriented tools to minimize pumping costs
End-use models address the use of water and issues such as water heating "Water to Air" models to understand to capture total emissions for a system scenario

4. System Development and Result Analysis

A Design of DSS for any system is given which can calculate demand, management, planning and forecasting. This DSS integrates a data warehouse with the system. The system provides resource planners with the facilities for managing domestic - demand for any region and time period weather short term or long term. The system is generic and can be used for any region as the information used gives the user several options based on the existing socio or environmental conditions. It allows for computing many parameters required for forecasting.

The system is developed using Artificial Neural Network using back propagation algorithm.
In general, the system is composed of the following elements:
- Database management system,
- Expert system,
- Decision Task Analysis,
- User Needs Analysis,
- Knowledge based system,
- Multi-decision component,
- Prediction models,
- User-interface, and
- Hypertext files.

Architecture of Proposed Decision Support System

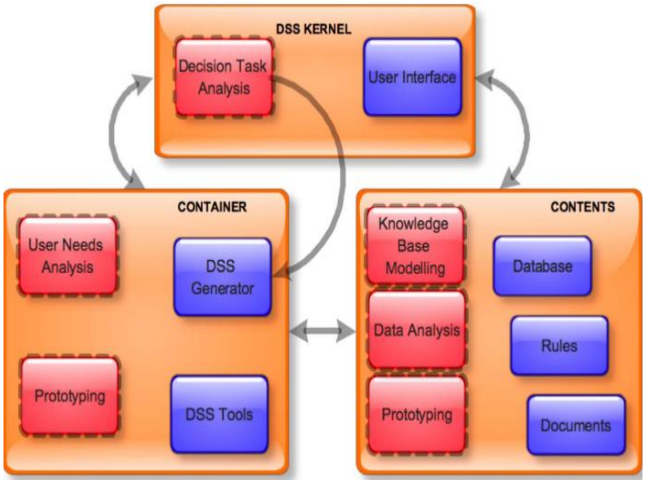

Fig 4.1: Proposed Decision Support System

DSS Architecture

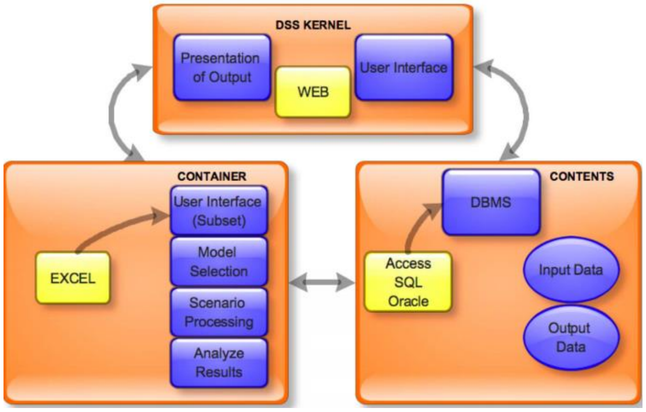

Fig 4.2: Architecture of DSS with Kernel

DSS comprises three parts: Kernel, Container and Contents Kernel is for view reason, Container acts as Controller and Content part holds DBMS, Input data, output data, data integration and other data related tasks.

Intermodal Versus Road: TOTAL COSTS (Patras - Gothenburg)

Cost Category	Intermodal Cost (Euro/LU)	Intermodal % Total	All Road Cost (Euro/LU)	All Road % Total	
Depreciation	854,25	22,09	804,31	23,41	Internal Costs
Maintenance costs	390,99	10,11	609,29	17,73	
Insurances	19,32	0,5	111,63	3,25	
Energy consumption	438,62	11,34	569,44	16,57	
Personnel	717,99	18,56	992,03	28,87	
Third party services	67	1,73	67	1,95	
Overhead costs	1.379,76	35,67	282,09	8,21	
Total Internal/Direct Cost	3.867,93	100	3.435,79	100	
Taxes	68,42	1,54	761,53	15,88	
Charges	503,96	11,35	618,86	12,91	
Subsidies	0	0	-21,91	-0,46	
Total Taxes, charges, subsidies	572,38	12,89	1.358,48	28,34	
Total Internal Cost	4.440,31	100	4.794,27	100	
External Cost - Air Pollution	47,89	6,16	139,03	14,28	External Costs
External Cost - Global Warming	42,67	5,49	119,55	12,28	
External Cost - Accidents	135,28	17,41	392,82	40,35	
External Cost - Up & Down Stream	14,96	1,92	84,95	8,73	
External Cost - Noise	134,27	17,28	87,49	8,99	
External Cost - Infrastructure	402,17	51,74	149,73	15,38	
Total External Cost	777,24	100	973,57	100	

Fig4.3: Total cost generated by DSS-RECORDIT (Patras Gothenburg) isis-it.com

The above table shows the energy consumption. So output of DSS can be in tabular form. Similarly graphs are very informatory which can also be used to show output.

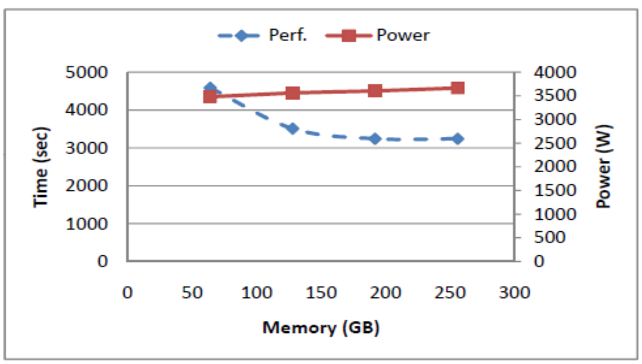

Fig 4.4: Graph of power verses Memory

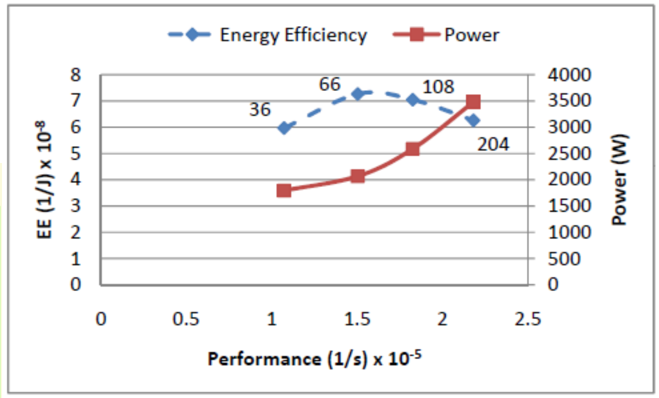

Figure 4.5: Graph of Power verses performance

Using DSS a survey is carried out and areas are chosen from desired location. The data generated is given in Figure (4.3). Graphs are generated by the intelligent system is given in fig (4.4).

Energy requirement, consumption and performance etc can be calculated using DSS.

5. Conclusions

A DSS clearly holds great potential for productivity, optimization of resources, planning, budgeting, threats and future scopes in almost all the field without wasting much paper and time. Many small label decisions are also possible without having vast technical knowledge of domain. It also helps to formulate policies, services and service rule for the benefit for business as well as different government agencies using different soft computing techniques. There are various statistical methods to check the performance of DSS.

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