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Labour Productivity Analysis in the Manufacturing Industries Using Fuzzy Logic Algorithm

M. Tech. Scholar Ramesh Kanase, Asst. Prof. Vivek singh, HOD. Rajesh Rathore
Department of Mechanical Engineering,
Vikrant institute of Technology & Management,
Indore (India)

Abstract- Manufacturing decisions inherently face uncertainties and imprecision. Fuzzy logic, and tools based on fuzzy logic, allow for the inclusion of uncertainties and imperfect information in decision making models, making them well suited for manufacturing decisions. In this study, we first review the progression in the use of fuzzy tools in tackling different manufacturing issues during the past two decades. We then apply fuzzy linear programming to a less emphasized, but important issue in manufacturing, namely that of product mix prioritization. The proposed algorithm, based on linear programming with fuzzy constraints and integer variables, provides several advantages to existing algorithm as it carries increased ease in understanding, in use, and provides flexibility in its application.

Keywords- artificial intelligence, fuzzy logic, expert system, decision support system, tool selection; production; Industry 4.0

I. INTRODUCTION

As we know whenever we planned the manufacturing system we consider the design criteria such as the system efficiency , the system will be efficient in all the way in production. All such criteria cannot be achieved until the design production, planning scheduling and controlling steps work well. A FMS can be defined as production system consisting of identical multipurpose numerically controlled machine (work stations). FMS is manufacturing system in which there is some amount of flexibility that allows the system to react in the case of changes. FMS works for automated material and tools handling system load and unload stations, inspection stations, storage areas and a hierarchical control system.

Generally when time is being planned, the objective is to design a system which will be efficient in the production of the entire range of parts. A FMS provides the efficiency of automated high-volume mass production. Scheduling in an FM environment is more complex and difficult than in conventional manufacturing environment. Scheduling of FMS determine an optimal schedule and controlling an FMS is considered as difficult task. Fuzzy set theory was introduced in 1965 by zadeh. Fuzzy logic approaches easily deal with uncertain and incomplete information and human experts, knowledge can be easily coded into fuzzy logic approaches for scheduling FMS is consider due to its ability to deal uncertain and incomplete information and with multi objective problem.

II. RESEARCH MOTIVATION

Smart Manufacturing System (SMS) is a vast field to be explored in the domain of Industry 4.0, even as it presents several advantages compared to conventional manufacturing systems. Thus, it is progressively being adopted by manufacturing industry players as a strategic method to enhance their performance, even when SMS is an expensive approach compared to the conventional system [**1**]. Many studies have been done in the past to explore the technical aspects in the development of a new SMS [**1**,**2**,**3**,**4**,**5**,**6**,**7**,**8**,**9**,**10**,**11**,**12**,**13**]. However, very limited studies have been conducted on investigating the configuration challenges when establishing new SMS [**7**,**14**,**15**,**16**] that requires pre-implementation planning and assessment. Specifying a correct SMS configuration prior to the costly implementation could assist industry players in planning and establishing a new SMS that minimizes the operational cost and time and improves efficient machine utilization.

In Industry 4.0, SMS is moving towards human-machine collaboration, and autonomous response is moving towards robot deployment to replace human intervention in smart manufacturing systems [**11**]. Extensive research was conducted in terms of having proper test methods for this smart manufacturing. This sheds light on the importance of evolving smart manufacturing systems involving adequate intelligent aspects to operate autonomously without human intervention [**11**]. The smart manufacturing environment can be envisioned as an environment that allows communication between humans and machines, and the system's success lies in the way the configuration is adopted.

Due to the increasing demand by consumers for continuously innovative and higher quality products and for affordable prices and product immediacy, market players constantly come under pressure to make well-informed decisions while establishing a new SMS that requires pre-implementation planning and assessment.

This proper pre-implementation planning aspect has been given little attention, despite it being the core of the manufacturing success as former research works such as a hybrid simulation-based assessment and agent-based modeling framework for smart manufacturing systems (SMS) focused mainly on assisting decision-makers in designing better configurations based on the establishment of appropriate information messaging protocols between system components using hybrid simulation modeling [7]. This assessment should be based on measured values using systematic approaches to stay ahead in the industry with high sustainability constantly. Clear and concise evaluation factors play key roles in any Smart Manufacturing System's configurations as each contributes to the level of success of the manufacturing products. Therefore, identifying evaluation factors to develop a coherent evaluation framework aids decision-makers in selecting the correct configuration.

III. LITERATURE REVIEW

Mirko Mazzoleni et al.[1] Since the introduction of the industry 4.0 paradigm, manufacturing companies are investing in the development of algorithmic diagnostic solutions for their industrial equipment, relying on measured data and process models. However, process and fault models are not usually available for complex productions plants and production data are usually unlabeled. Thus, to classify machine status, unsupervised approaches such as anomaly detection and signal processing strategies have to be employed. Due to the unsupervised nature of the problem, it is meaningful to apply several diagnostic algorithms to cover most of the process anomalous behaviors.

Additionally, in some contexts, the experience of process operators in grasping the correct functioning of machines as well as their ability in understanding early signs of deterioration is relevant for the diagnosis of incoming failures. However, seldom this information can be included in failure diagnosis algorithms. In this paper, we propose a diagnostic scheme for condition monitoring of mechanical components. The proposed scheme combines anomaly detection algorithms, envelope analysis of vibration data, and eventually additional qualitative information on machine functioning. The combination of all the fault indicators is obtained leveraging on a fuzzy inference system. The proposed scheme is experimentally validated on a steel making plant with real process data, making use of heuristic information such monitoring reports of machine health status.

Anita Susilawati et al.[2] Lean manufacturing is gaining popularity as an approach that can achieve significant performance improvement in the industry. However, the application of lean manufacturing is not an easy process. To reach the level of full implementation of lean manufacturing takes a long time and during that time the continuous improvement must be made. In the process of continuous improvement, lean manufacturing assessment is required. One form of assessment is to measure the degree of lean implementation. However, it is the complexity involved in the measure of degree of leanness.

This complexity arises due to (a) the inherent multi-dimensional concept of leanness (b) unavailability manufacturing practice database that can be used as a benchmark in assessing the degree of leanness and (c) the necessity for the application of subjective human judgement on lean practices which involve vagueness and bias due to variation of evaluator's knowledge and experience. In this paper a method to deal with the multi-dimensional concept, unavailability benchmark and uncertainty, which arises from the subjective and vague human judgement for the measurement of degree of leanness, is proposed. The multi-dimensional concept involving a variety of components of lean practices is measured in order to arrive at a measure for the lean activity of a given organization.

It is constructed from primary and secondary data involving a comprehensive literature review and validated with interviews with a set of sample organizations representing the entire spectrum of the industry. The vagueness of subjective human judgement on degree of application of lean practices is modelled by fuzzy number in conjunction with an additional consideration related to the length of lean practice implementation and the use of multi-evaluators. Value stream mapping is used in scoring the degree of implementation of lean so the use of benchmark is not necessary. Some results from an initial survey from a sample of respondents from the manufacturing industry in Indonesia are presented to illustrate the applicability and potential strength of the proposed method.

Ifeyinwa Juliet Orji et al.[3] Globally, supply chains compete in a complex and rapidly changing environment. Hence, sustainable supplier selection has become a decisive variable in the firm's financial success. This requires reliable tools and techniques to select the best sustainable supplier and enhance understanding about how supplier behavior evolves with time. System dynamics (SD) is an approach to investigate the dynamic behavior in which the system status alterations correspond to the system variable changes. Fuzzy logic usually solves the challenges of imprecise data and ambiguous human judgment. Thus, this work presents a novel modeling approach of integrating information on supplier behavior in fuzzy environment with system dynamics simulation modeling technique which results in a more reliable and responsible decision support system. Supplier behavior with respect to relevant sustainability criteria in the past, current and future time horizons were sourced through expert interviews and simulated in Vensim to select the best possible sustainable supplier. Simulation results show that an increase in the rate of investment in sustainability by the different suppliers causes an exponential increase in total sustainability performance of the suppliers. Also, the growth rate of the total performance of suppliers outruns their rate of investment in sustainability after about 12 months. A dynamic multi-criteria decision making model was presented to compare results from the systems dynamics model.

Taha Al-Saadi et al.[4] Since the development of the Fuzzy Logic theory by Zadah (1965), motivated by the human-level understanding of systems for the development of computational and mathematical frameworks, it has become an active research field for a broad spectrum of research in academia and the industry, from systems modelling to systems monitoring and control. In this research, the authors intend to highlight the use of Fuzzy Logic theory in metal additive manufacturing processes. The modelling of such processes has a lot of uncertainties due to the large underlying physics during the operation, which makes the Fuzzy Logic Controller a promising tool to deal with such a process. This work will provide a survey of the previous efforts and a case study to illustrate the approach's effectiveness in such a complex manufacturing technique.

Nedra Abbes et al.[5] The implementation of the Lean Six Sigma (LSS) in the textile and clothing industries is a successful strategy to reduce the defects produced along the production line in these industries. Lean Six Sigma readiness knowledge is a pre-requisite for a successful LSS implementation. Yet, the literature on Lean Six Sigma implementation and the readiness evaluation model in small and medium-sized textile and clothing are very limited. The purpose of this study is to develop a model of LSS readiness assessment for the clothing industries (LSRACI) using fuzzy logic. The present model is based largely on both the critical success factors (CSFs) of LSS and the LSS factors (enablers, criteria, and attributes) derived from the literature. The CSFs are identified using a questionnaire distributed to 85 small-medium clothing industries, and integration with the evaluation model. The outcome of this process is the identification of 5 enablers, 6 criteria, and 46 attributes which are finally ready to be used.

The use of CSFs from the clothing industries gives a specification to our evaluation model and makes the LSRACI model original and specified to clothing SMEs. This model is developed for assessing the readiness level of the clothing and textile industries and it helps as well as to improve the readiness level for successful implementation of LSS. The present study aims to contribute to the knowledge of readiness for the LSS implementation in clothing industries. The readiness level of this company is average ready with (3.28; 4.9; 6.7). Using a fuzzy performance importance index (FPII), 20 from 46 attributes were identified as weaker attributes and therefore necessary corrective actions were recommended to improve the readiness level. The proposed model helps managers and practitioners to find out the potential of the clothing and textile industries by evaluating the company readiness before implementation in order to overcome problems and achieve a successful LSS implementation.

IV. PROPOSED METHODOLOGY

Fuzzy logic is a form of many-valued logic in which the truth value of variables may be any real number between 0 and 1. It is employed to handle the concept of partial truth, where the truth value may range between completely true and completely false.[1] By contrast, in Boolean logic, the truth values of variables may only be the integer values 0 or 1.

The term fuzzy logic was introduced with the 1965 proposal of fuzzy set theory by Iranian Azerbaijani mathematician Lotfi Zadeh.[2][3] Fuzzy logic had, however, been studied since the 1920s, as infinite-valued logic—notably by Łukasiewicz and Tarski.[4]

Fuzzy logic is based on the observation that people make decisions based on imprecise and non-numerical information. Fuzzy models or fuzzy sets are mathematical means of representing vagueness and imprecise information (hence the term fuzzy). These models have the capability of recognising, representing, manipulating, interpreting, and using data and information that are vague and lack certainty.[5][6]

Fuzzy logic has been applied to many fields, from control theory to artificial intelligence. Classical logic only permits conclusions that are either true or false. However, there are also propositions with variable answers, such as one might find when asking a group of people to identify a color. In such instances, the truth appears as the result of reasoning from inexact or partial knowledge in which the sampled answers are mapped on a spectrum.[7]

Both degrees of truth and probabilities range between 0 and 1 and hence may seem similar at first, but fuzzy logic uses degrees of truth as a mathematical model of vagueness, while probability is a mathematical model of ignorance.[8]

1. Applying truth values:

A basic application might characterize various sub-ranges of a continuous variable. For instance, a temperature measurement for anti-lock brakes might have several separate membership functions defining particular temperature ranges needed to control the brakes properly. Each function maps the same temperature value to a truth value in the 0 to 1 range. These truth values can then be used to determine how the brakes should be controlled.[9] Fuzzy set theory provides a means for representing uncertainty.

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2. Linguistic variables:

In fuzzy logic applications, non-numeric values are often used to facilitate the expression of rules and facts.[10]

A linguistic variable such as age may accept values such as young and its antonym old. Because natural languages do not always contain enough value terms to express a fuzzy value scale, it is common practice to modify linguistic values with adjectives or adverbs. For example, we can use the hedges rather and somewhat to construct the additional values rather old or somewhat young.[11]

Fuzzification is the process of assigning the numerical input of a system to fuzzy sets with some degree of membership. This degree of membership may be anywhere within the interval [0,1]. If it is 0 then the value does not belong to the given fuzzy set, and if it is 1 then the value completely belongs within the fuzzy set. Any value between 0 and 1 represents the degree of uncertainty that the value belongs in the set. These fuzzy sets are typically described by words, and so by assigning the system input to fuzzy sets, we can reason with it in a linguistically natural manner.

For example, in the image below the meanings of the expressions cold, warm, and hot are represented by functions mapping a temperature scale. A point on that scale has three "truth values"—one for each of the three functions. The vertical line in the image represents a particular temperature that the three arrows (truth values) gauge. Since the red arrow points to zero, this temperature may be interpreted as "not hot"; i.e. this temperature has zero membership in the fuzzy set "hot". The orange arrow (pointing at 0.2) may describe it as "slightly warm" and the blue arrow (pointing at 0.8) "fairly cold". Therefore, this temperature has 0.2 membership in the fuzzy set "warm" and 0.8 membership in the fuzzy set "cold". The degree of membership assigned for each fuzzy set is the result of fuzzification.

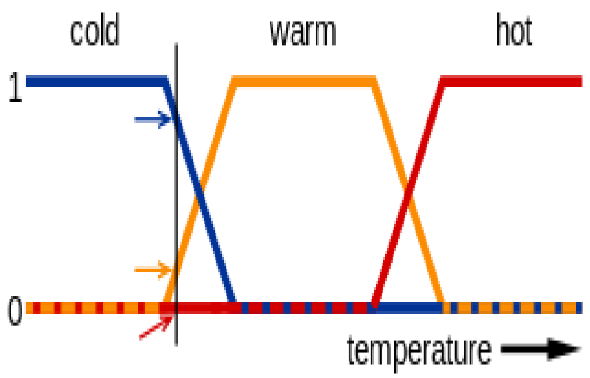

Fig 1. Fuzzy logic temperature

Fuzzy sets are often defined as triangle or trapezoid-shaped curves, as each value will have a slope where the value is increasing, a peak where the value is equal to 1 (which can have a length of 0 or greater) and a slope where the value is decreasing.[13]

V. RESULT AND SIMULATION

1. Data Collected From the Survey:

In successfully achieving main objective of the study, one of the most important phase is collection of accurate data. Data collection is a procedure of collecting crucial data records for a certain sample or population of observations.

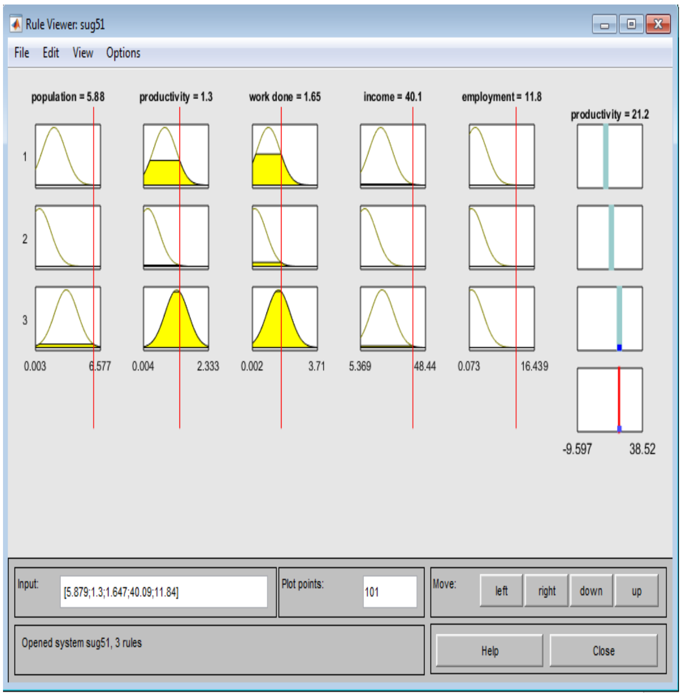

Fig 2. Range variation relationship range.

VI. CONCLUSION

In summary, our work here provides two contributions to the analysis. First, despite the increasing application of fuzzy logic to manufacturing challenges during the past two decades, a review of the uses of fuzzy logic suggests that the depth and breadth of applications of fuzzy logic can be enhanced.

Second, we demonstrate the strength of fuzzy logic in tackling specialized problems in manufacturing by developing an easy to use and flexible algorithm for product mix issues, an area of lesser focus in applying fuzzy logic.

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