Agile Asset Criticality Assessment (ACA) Approach using Decision Making Grid (DMG)

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Abstract:

- Purpose: This paper proposes a framework for an agile ACA process using Decision-Making Grid (DMG) to accommodate the needs of this dynamic environment.
- Design/methodology/approach: The proposed approach has been validated through an industrial case study related to a Steam Generation System (SGS)
- Findings: The implementation of the proposed approach in a petroleum refinery to assess the criticality of Steam Generation System (SGS) has shown positive results in terms of time and effort optimization.
- Practical implications: The proposed new approach has delivered better results with more consistency when applied by different teams and achieved better distribution of assets over the criticality scale.
- Originality/value: This research contributes OM literature with respect to one of its core activities of maintenance, through an innovative systematic, and practical approach.

Keywords: Asset Criticality Assessment (ACA) – Decision-Making Grid (DMG) - Reliability – Maintenance

1. Introduction:

The business environment becomes more dynamic as a result of the accelerated move toward digital transformation and the internet of things. For companies to sustain their existence, it is vital to stay focus and set priorities for improvement in a more agile way. As maintenance and asset management cost represents a significant percentage of companies operating cost, then the optimization of maintenance and asset management efforts will definitely result in the overall optimization of companies' performance and increase in profit margin. Asset Criticality Assessment (ACA) represents the starting point of such optimization efforts as it helps teams to set their priorities properly when it comes to asset improvement or day-to-day activities management. Also, it enables the team to stay focus by creating a custom key performance indicator that monitors critical assets only. This paper proposes a framework for an agile ACA process using Decision-Making Grid (DMG) to accommodate the needs of this dynamic environment. The implementation of the proposed approach in a petroleum refinery to assess the criticality of Steam Generation System (SGS) has shown positive results in terms of time and effort optimization. In addition, it has delivered better results with more consistency when applied by different teams and, finally, better distribution of assets over the criticality scale.

2. Literature Review

The current rapid changes in today's business environment demand a more dynamic approach in criticality assessment. Adams et al. (2016) have addressed the need for a better understanding of the changes in asset criticality as a prerequisite for successful optimization of risk and operational cost throughout the entire asset life (Adams, et al., 2016, p. 107).

Maintenance management has been regarded as a strategic core activity that underpins excellence, servitization, in operations and production management (Velmurugan, and Dhingra, 2015; Baines and Lightfoot, 2014). This is also evidenced by the published work in providing a holistic approach to measure maintenance performance management (Jonsson and Lesshammar, 1999; Tsang, et al, 1999; Kutucuoglu et al, 2001), life cycle management to improve performance (Schuman and Brent, 2005), preventive maintenance and scheduling to improve manufacturing operations (Osborne and Taj, 1993; Paz, and Leigh, 1994), appropriate maintenance policy to improve production operations (Knezevic, 1994; Vineyard et al, 2000; McKone and Weiss, 1998), and the role of computerised maintenance management systems within production operations management (Raouf, and Duffuaa, 1993).

Evolution of subsequent generations of maintenance management approaches have been summarised comprising four generations in terms of their increasing value. The First Generation is characterised as being '*descriptive*' in nature and aims to answer the question of '*What happened?*'. The Second Generation is characterised as '*diagnostic*' and aims to answer the question of '*Why did it happen?*'. The Third Generation is characterised as '*prognostic*' and aims to answer the question of '*When will it happen?*'. Finally the Fourth Generation is characterised as '*prescriptive*' and aims to answer the question of '*What must be done?*' (Mobley, 2004). Hence the highest value in this classification is the prescriptive nature of models in order to strategically, and dynamically, inform the decision maker on what policies, strategies, or actions should be carried out.

The need for prescriptive requirements have been summarised by Labib et al, (1998), where it was observed that the '*vast majority of maintenance models are aimed at answering efficiency questions, that is questions of the form "how can this particular machine be operated more efficiently?"* [up till third generation mentioned above]*, and not at effectiveness questions, like "which machine should we improve and how?",* which is a more towards a prescriptive approach. They further explain that *'The latter question is often the one in which practitioners are interested. From this perspective it is not surprising that practitioners are often dissatisfied if a model is directly applied to an isolated problem….This is precisely why efficiency (do the thing right) should be preceded by effectiveness analysis (do the right thing)*' (Labib et al., 1998).

The basic idea of decision grids is that they aim to provide a visual representation of the performance of assets in order to subscribe appropriate maintenance actions based on the relative locations of different assets with respect to multiple criteria, and therefore directly address the prescriptive requirement. Examples of such grids in the maintenance field are the Decision Making Grid (DMG) (Labib, 2004) and Jack-Knife Diagram (JKD) (Knights, 2001).

As originally proposed by (Labib, 1996), and further extended in (Labib, 1998), the DMG is a map that depicts the relative performance of worst performing machines/assets according to multiple criteria; mainly downtime and frequency of failures, and accordingly informs the decision maker on the most appropriate maintenance strategy for each machine/asset based on its relative location within the model. In doing so, the DMG helps in machines performance tracking and creates proper recommendations. Moreover, it helps in preventive maintenance (PM) optimizations and reduces the number of breakdowns (Labib, 1998, p. 68). In addition, the DMG enables the decision maker to determine when to apply Total Productive Maintenance (TPM), or Reliability Cantered Maintenance (RCM) based approaches.

The common ACA approaches consider safety and probability of occurrence as a key input to the assessment process. These two inputs have been recognized by Labib (2014), and further extended by Stephen and Labib (2018), where they developed a DMG with increasing safety consequences on the horizontal axis and increasing likelihood on the vertical axis. They have considered only three levels, which was enough for the selected application. On the other side, ACA uses more levels to have a better distribution of assets over the criticality scale (Stephen & Labib, 2018, p. 219).

Hartini and Subekti (2019) have used failure frequency and downtime as two dimensions for DMG. In the ACA process, the effect of failure frequency is accommodated by Mean Time Between Failures (MTBF) or failure rate. Also, downtime is regarded as one of the key dimensions represented by availability or production loss in few ACA implementations (Hartini & Subekti, 2019, p. 3).

As stated in the ACA standard (Z-008, 2011, p. 24), “The results from the consequence classification are useful when defining criteria for prioritizing work orders both preventive and corrective work”. This statement is aligned with the work carried out by Aslam-Zainudeen and Labib (2011) to prioritize rolling stock systems for maintenance based on consequences through the implementation of DMG (Aslam-Zainudeen & Labib, 2011)[1].

“Some argue that the DMG is insufficient as the consideration of only two criteria does not necessarily result in a wise decision” (Seecharan, et al., 2017, p. 64)[2]. The same limitation did not allow Shahin et al. (2019) to consider the cost analysis as a third criterion beside MTBF and Mean Time To Repair (MTTR). To overcome this limitation,

[1] Received the 2012 "Highly Commended Award" from the Emerald Literati Network.
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this paper proposes the use of a nested (multi-stage) DMG to accommodate more than two criteria, as explained in the following section.

3. ACA Framework Using DMG

The ACA DMG consists of three stages of DMGs to accommodate the different ACA aspects where the three DMGs are integrated as depicted in Figure 1.

The first DMG represents the inherent asset criticality, and it helps to distribute the assets between four clusters (i, ii, iii, and iv) based on asset configuration and utilization settings.

Then, the second DMG evaluates the achieved criticality by considering MTBF value besides the asset inherent criticality value (i, ii, iii, or iv). Consequently, the achieved criticality DMG categories the assets using four clusters (I, II, III, and IV), which were used as an input to the last DMG.

In the end, the third DMG assesses the operational criticality by considering the Health Safety Environmental (HSE) consequences in addition to the achieved criticality value (I, II, III, or IV).

The following section provides a more detailed explanation of each DMG.

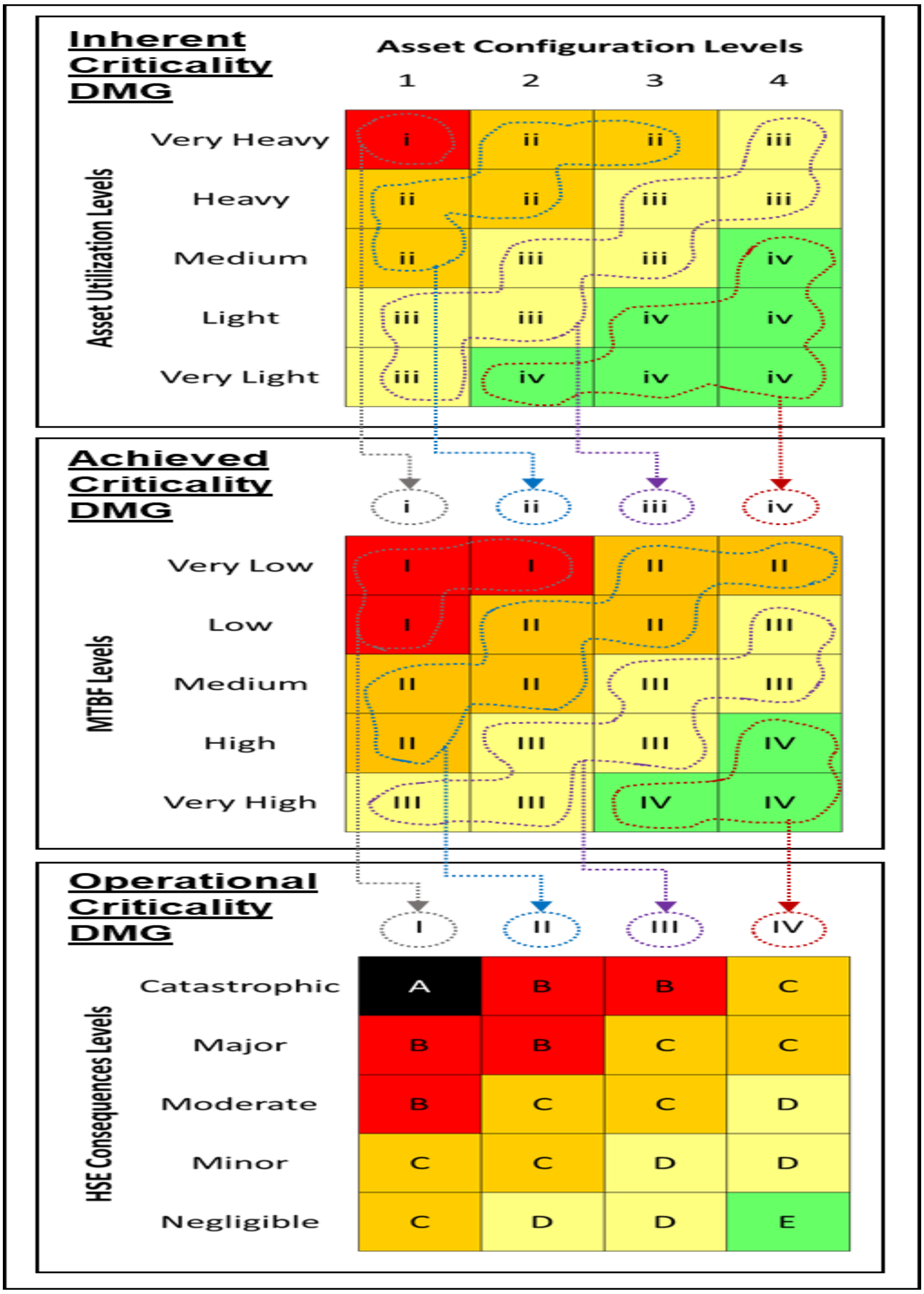


Figure 1: ACA Nested DMG's

3.1 Inherent Criticality DMG

The inherent criticality DMG has two dimensions: asset configuration and utilization.

The first dimension (asset configuration) considers the availability of redundancy and buffer. As the redundancy level and buffer capacity increase, the criticality of the asset decreases. Asset configuration has four levels (1, 2, 3, and 4). Level 1 represents the most critical situation where the asset has no redundancy and no downstream buffer. Level 2 presents the case where the asset has downstream buffer only while level 3 is for the asset with redundancy only. Finally, level 4 represents the scenario where the asset has redundancy and downstream buffer or more than one redundancy level, which is the least critical scenario.

The second dimension (asset utilization) reflects the ratio between the used and designed asset capacity. As this ratio increases, the criticality of the asset increases. The dimension has five levels of asset utilization, which are very heavy, heavy, medium, light and very light. Very heavy represents a high level of utilization scenario in which there is a low possibility to be able to compensate for any production losses, while very light shows a low utilization case in which the operator has enough capacity to correct any production drops. The inherent criticality is illustrated in Figure 2.

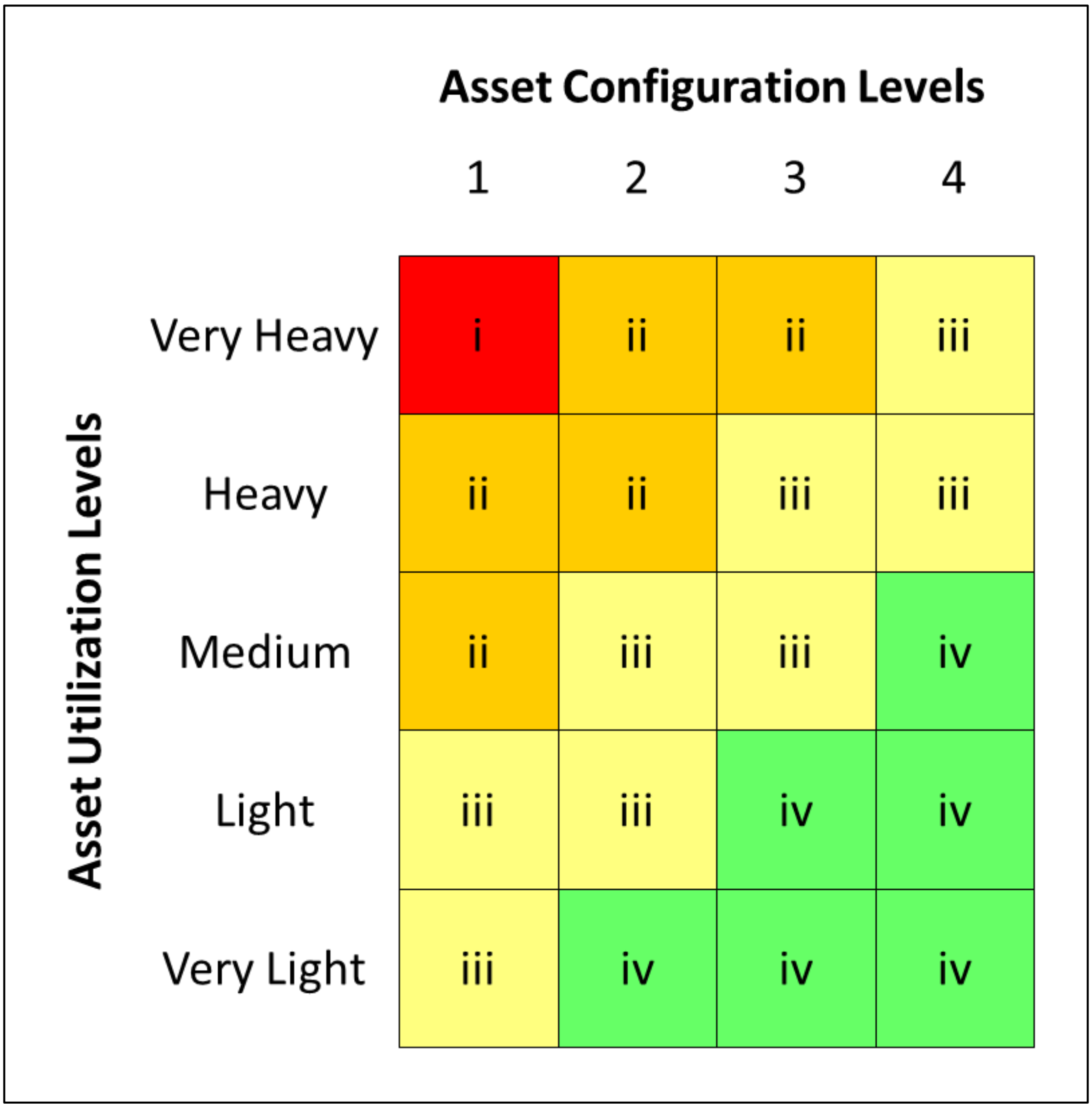


Figure 1: Inherent Criticality DMG

For instance, assume the pump designed capacity is 10 m^3/h while the process needs 6 m^3/h only, then the utilization of this pump is only 60% which is equivalent to the "Medium" asset utilization level. Table 1 provides more examples:

Table 1: Utilization level identification.

No.	Designed Capacity	Used Capacity	Utilization %	Utilization Level
1	10 m^3/h	1.5 m^3/h	15%	Very Light
2	10 m^3/h	3 m^3/h	30%	Light
3	10 m^3/h	7 m^3/h	70%	Heavy
4	10 m^3/h	9 m^3/h	90%	Very Heavy

It is worth to mention here that the exact values (numbers) for utilization levels may differ from one plant to another. In other words, the value considered as a high utilization threshold in a plant may be considered as a medium or a low utilization threshold in another plant.

As a result, asset Configuration and Utilization DMG distribute assets among four clusters (I, ii, iii, and iv) where (i) is the most critical and (iv) is the less critical. This grouping is used as an input to the achieved criticality DMG. As depicted in Figure 1, if the inherent asset criticality falls in any square within-cluster (ii), then ii will be used as an input level to the achieved criticality DMG.

3.2 Achieved Criticality DMG

The achieved criticality DMG has two dimensions: Mean Time Between Failures (MTBF) and Inherent Criticality DMG outcomes.

The MTBF dimension has been added to consider asset's reliability performance aspect, and as the MTBF reduces, asset criticality increases. The MTBF has been introduced in five levels, which are: very low, low, medium, high, and very high, as shown in Figure 3.

MTBF Levels	Inherent Criticality DMG Outcomes: i	ii	iii	iv
Very Low	I	I	II	II
Low	I	II	II	III
Medium	II	II	III	III
High	II	III	III	IV
Very High	III	III	IV	IV

Figure 2: Achieved Criticality DMG

The exact values (numbers) applied to these levels may differ between plant to another. Also, different values may be used for various equipment classes within the same plant.

The Inherent Criticality DMG outcomes dimension consists of four levels to match the four clusters introduced by the same DMG.

In the end, the achieved criticality DMG will group the assets into four clusters, which are I, II, III, and IV. These clusters to be used as an input to the operational criticality DMG as depicted in Figure 1.

3.3 Operational Criticality DMG

The operational Criticality DMG has two dimensions as shown in Figure 4:

HSE consequences and achieved criticality DMG outcomes. As the HSE consequences increase, the criticality of asset increases.

The HSE consequences dimension has five levels as proposed here: catastrophic, major, moderate, minor, and negligible. The detailed description of each level may vary from one plant to another.

The operational criticality DMG delivers the final asset criticality classification, which comes in five categories. Assets with “A” criticality considered as the most critical assets while assets with “E” criticality considered as the less critical assets.

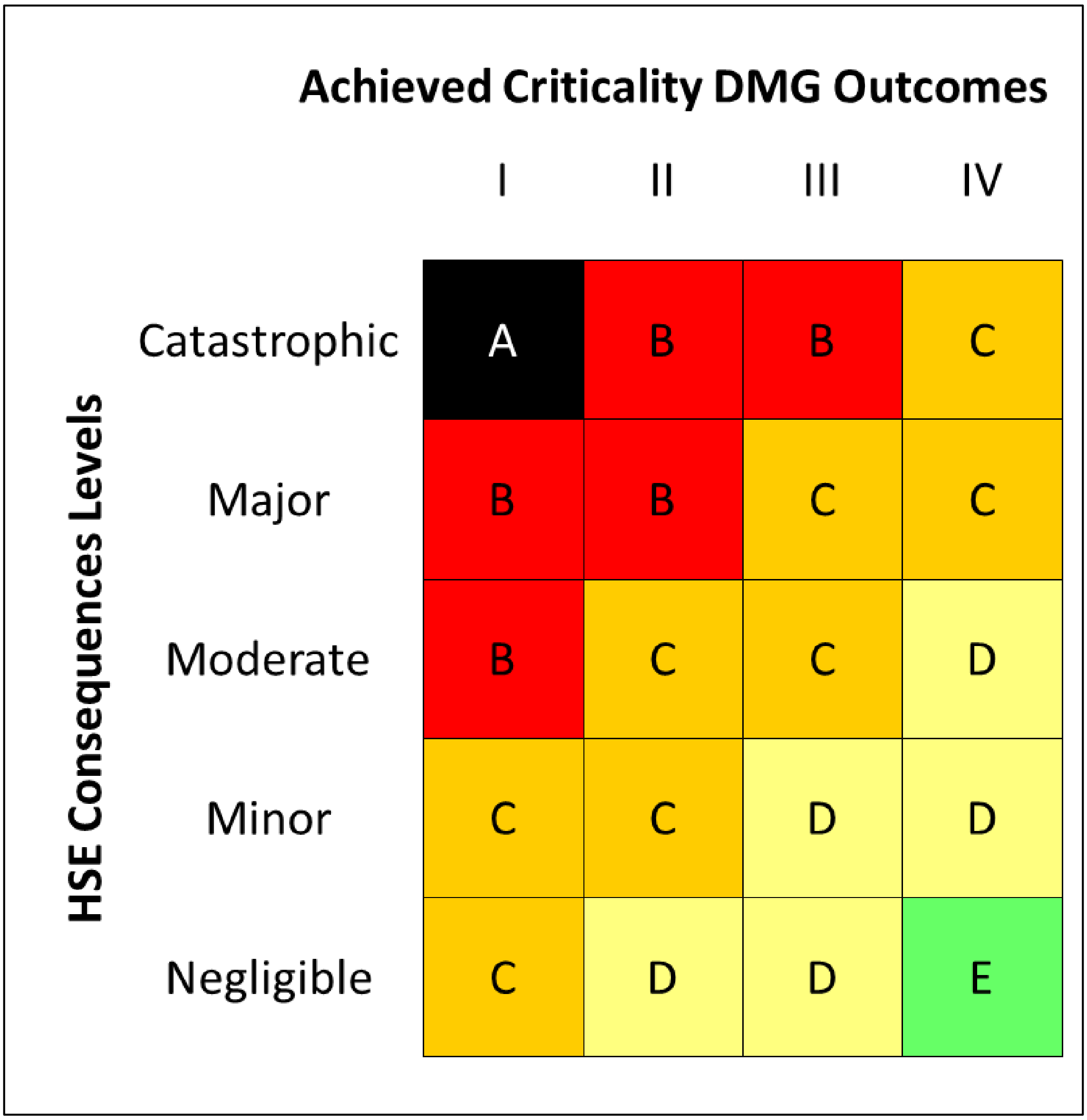


Figure 3: Operational Criticality DMG

4. Case Study (Steam Generation System ACA)

4.1 System Identification and Boundary Description

A steam generation system (SGS) within a petroleum refinery has been selected to validate the proposed ACA-DMG approach through the assessment of SGS assets' criticality.

The main purpose of the steam generation system (SGS) is to supply the refinery with the high, medium and low-pressure steam needed for process operation. Also, SGS plays a vital role in the case of plant total power failure, as it sustains the functionality of instrumentation on the essential power supply and key turbine-driven pumps.

The boundary of the SGS includes boiler feed water (BFW) system, boiler system, auxiliary systems, steam let-down stations, and desuperheaters.

Figure 5 depicts the SGS deaerators and boiler feed water pumps.

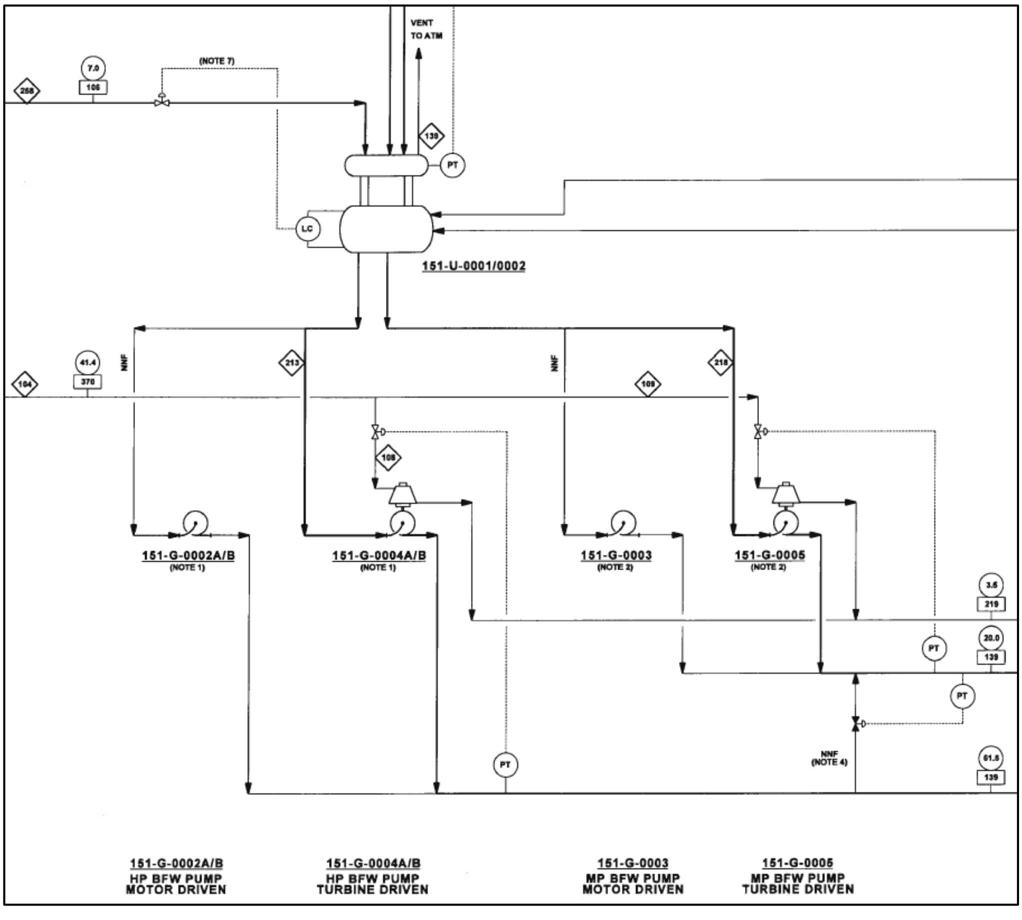


Figure 4: Steam generation system configuration

4.2 ACA DMG Level Descriptions

The DMG levels have to be clearly identified with a detailed description of each level before starting the ACA process. These descriptions facilitate the ACA teamwork and standardize the assessment process. The following table provides a detailed description of the DMG levels used in this case study.

Table 2: Case study DMG levels description

No.	DMG Stage	Dimension	Level	Description
1	Inherent Criticality	Asset Configuration	1	No redundancy nor downstream buffer
2			2	Downstream buffer only
3			3	Redundancy only
4			4	Redundancy and downstream buffer
5		Asset Utilization	Very Heavy	>90%
6			Heavy	>80%
7			Medium	>70%
8			Light	>60%
9			Very Light	=< 60%
10	Achieved Criticality	MTBF	Very Low	<6 months
11			Low	<1 year
12			Medium	<2 years
13			High	<3 years
14			Very High	>=3 years
15	Operational Criticality	HSE Consequences	Catastrophic	Multiple fatalities
16			Major	Single fatality / high pollution
17			Moderate	Permanent partial disability / emissions over the limit
18			Minor	Restricted work injuries/contamination
19			Negligible	First aid / local damage

4.3 ACA Team

To assess the criticality of SGS, a cross-functional team has been formed from different disciplines relevant to the DMG dimensions. The SGS ACA team formation was as follows:

- **a) Process Engineer**: to provide inputs regarding system/assets configuration.
- **b) Production Engineer**: to share system/assets utilization results and plans.
- **c) Reliability Engineer**: to assess the asset's MTBF value.
- **d) HSE Specialist**: to predict the probable HSE consequences as a result of asset failure.
- **e) ACA facilitator**: to facilitate the discussion and assure deliverables quality.

4.4 ACA process

As shown in the SGS configuration Figure 5, there are four high-pressure boiler feedwater pumps. Two are turbine-driven work as a duty pump while the other two serve as standby and driven by motors. The 151-G-0004A&B turbine-driven pumps are always in duty. In case of failure of turbine-driven pumps, the motor-driven pumps 151-G-0002A&B will take over. Hence, from asset configuration aspect level 3 is applied for the two duty pumps. The 151-G-0004A/B are utilized 95% of the time as per the production data history. As a result, the inherent criticality assessment of 151-G-0004A can be represented by an exclamation mark in square (ii) as depicted in Figure 6.

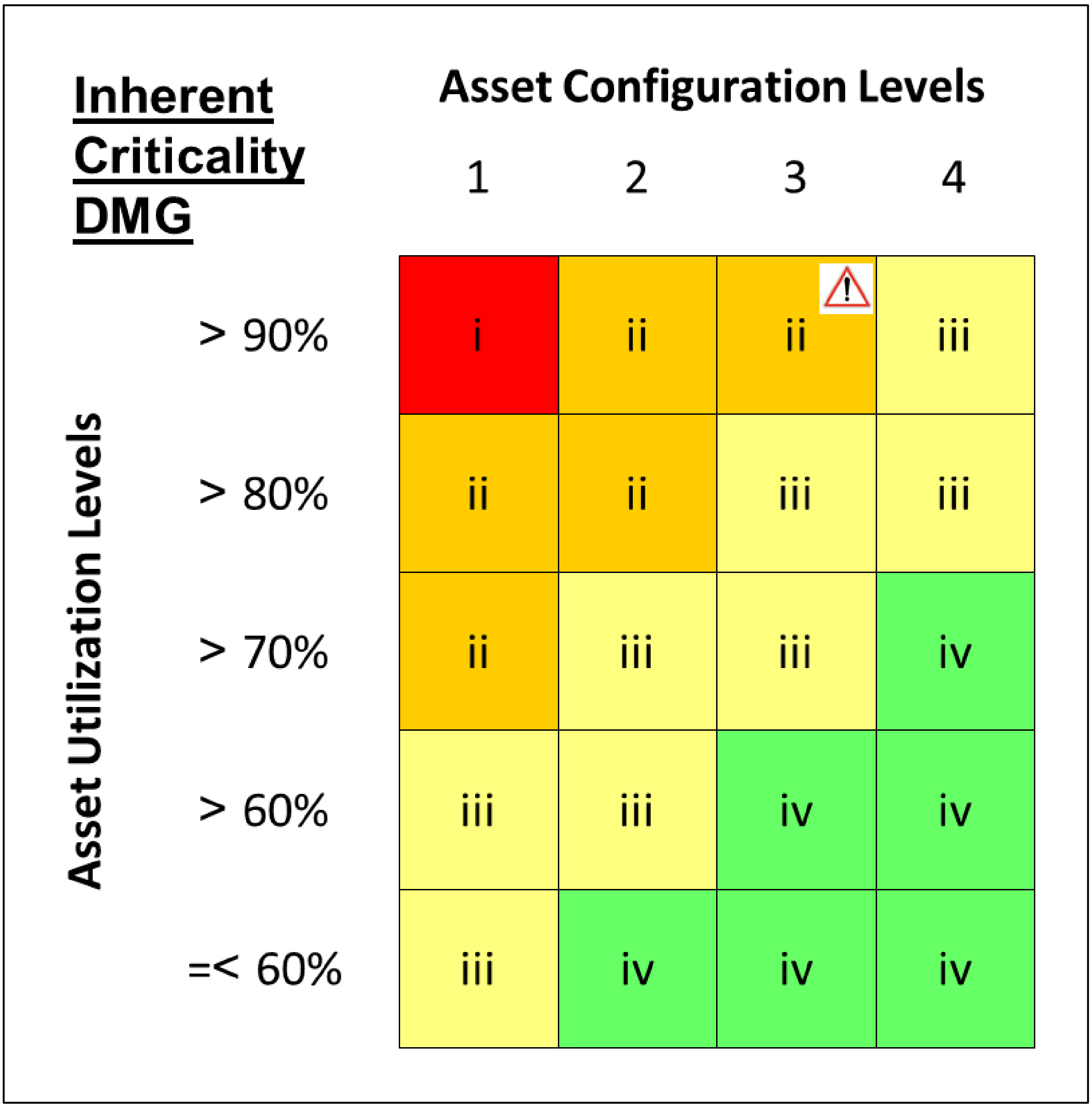


Figure 5: Pump inherent criticality Assessment

The outcome of the inherent criticality DMG, which is (ii) has been used as an input to the achieved criticality DMG. The second dimension (MTBF) level has been selected based on the MTBF calculations for asset 151-G-0004A using its failure history as per CMMS. The calculated MTBF value was 11 months which is higher than six months but less than one year.

This will result in an achieved criticality assessment as per Figure 7. Asset 151-G-0004A achieved criticality is (II). This value (II) is used as an input to the operational criticality DMG beside the HSE consequences dimension.

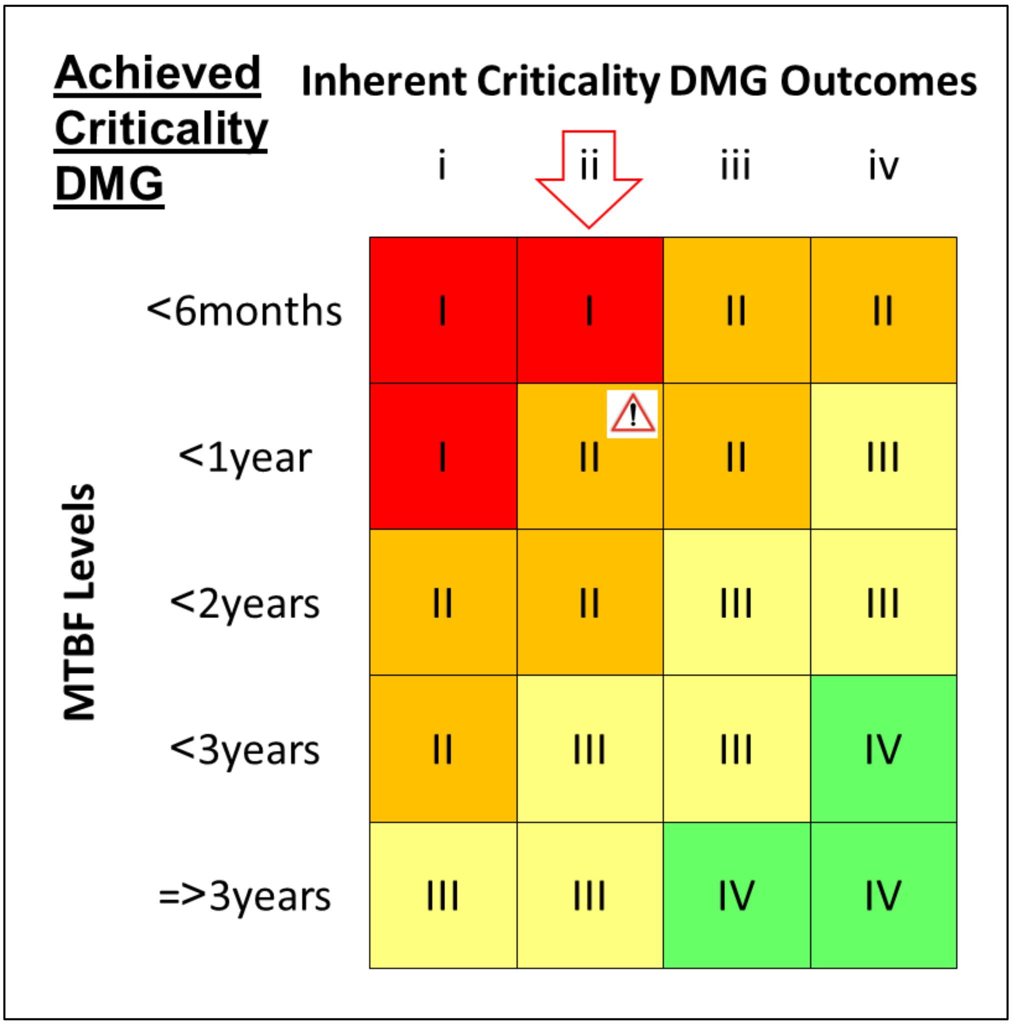


Figure 6: Pump achieved criticality assessment

Asset 151-G-0004A failure scenario considered by the ACA team is expected to lead to permanent partial disability to the unit operator. Hence, the HSE selected consequences level is "Moderate". As a result, the asset operational criticality value has been identified to be a "**C**" critical asset as shown in Figure 7.

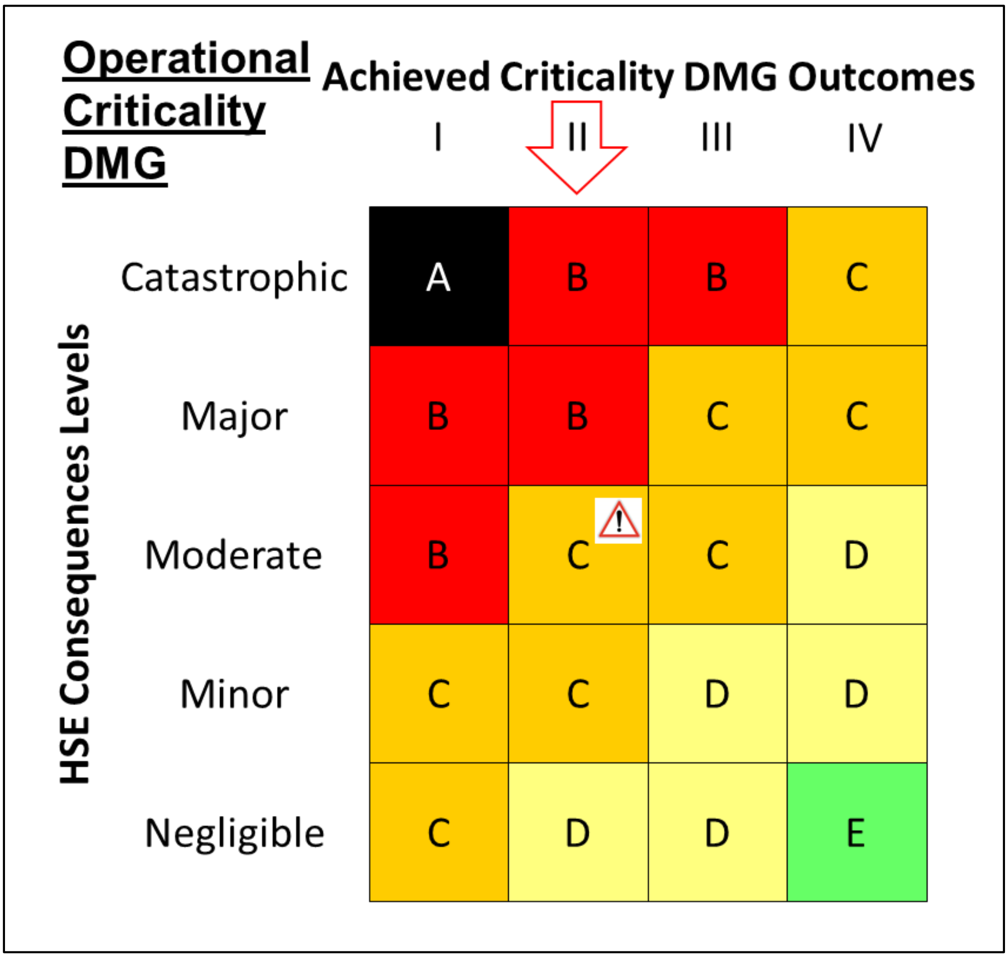


Figure 7: Pump operational criticality assessment

Then, the same approach has been followed by the ACA team to assess the criticality of the remain SGS assets. Table 3 indicates ACA DMG outcomes:

Table 3: SGS ACA Results

No.	Assed ID	Asset Description	Inherent Criticality	Achieved Criticality	Operational Criticality
1	151-G-0004A	HP boiler feed water duty pump	ii	II	C
2	151-G-0004B	HP boiler feed water duty pump	ii	II	C
3	151-G-0002A	HP boiler feed water stand-by pump	i	II	C

4	151-G-0002B	HP boiler feed water stand-by pump	i	II	C
5	151-U-001	Deaerator (duty)	ii	II	C
6	151-U-002	Deaerator (duty)	i	III	D
7	151-LIT-0475	Level transmitter of deaerator storage vessel	i	I	B
8	151-GT-0004A	Turbine, HP BFW pump	ii	III	C
9	151-GT-0004B	Turbine, HP BFW pump	ii	III	C
10	151-SCV-2004	Control valve of FD fan turbine	i	I	B
11	151-D-0205	Lube oil filter of HP BFWP	i	I	C
12	151-D-0001	Blowdown flash drum	iii	IV	D
13	151-D-0005	Scale inhibitor dosing tank	iv	IV	E
14	151-E-0302	Package boiler FD fan lube oil system - oil heater	ii	II	D
15	151-GM-0402	Lube pump motor	i	III	D

5. Discussion

The implementation of ACA using DMG has led to a more streamlined process where decision making is much easier and less debatable. On the other side, some areas need to be considered in order to avoid any drawbacks.

5.1 ACA DMG Strengths

a) **Time Optimization**: as the DMG dimensions and levels clearly described, as the time needed to complete the process becomes less.

b) **Standardization:** the use of DMG has reduced the variations when using different teams to assess assets' criticality at different locations.

c) **Easy Decision Making:** it was straightforward for the team to select the proper value in each DMG with very high confidence in the outcomes.

d) **Agility:** by applying simple software tools or even the advanced artificial intelligence tools, the ACA DMG process can be fully automated to adjust the criticality as a result of any changes in DMG dimensions.

5.2 ACA DMG Limitations

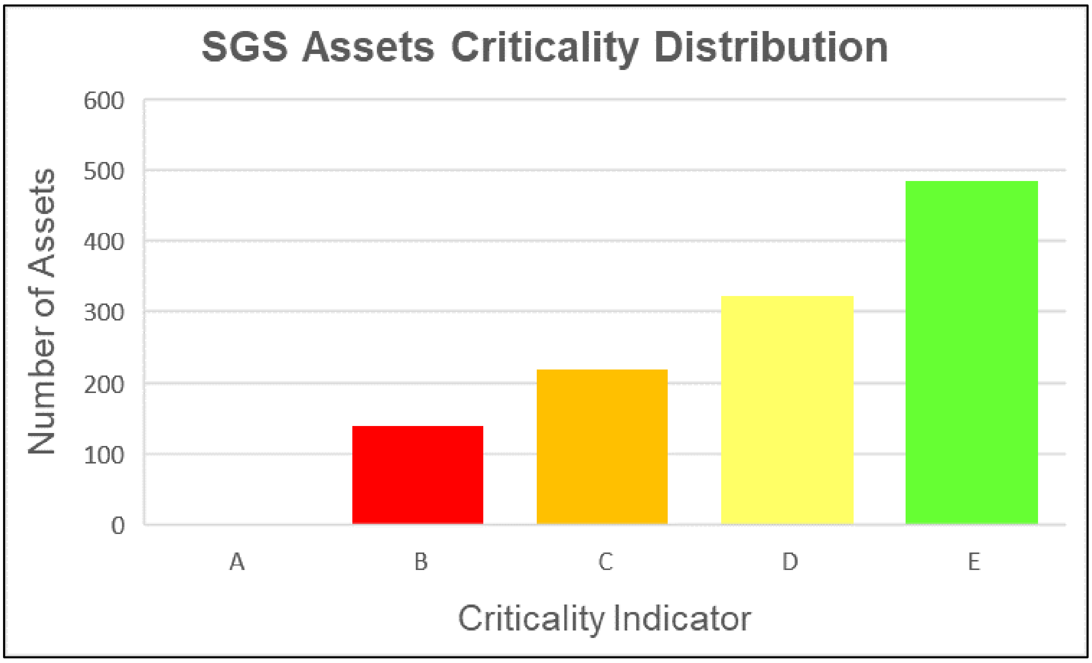
a) **MTBF calculations:** the proposed ACA DMG assumes the availability of a rigid CMMS in place with a high-quality data that make the MTBF calculations as good as it should be, which is not the case in many industrial plants.

b) **Thresholds identification**: DMG thresholds in all stages have to be adequately identified based on pilot implementation and try/error so the final stage DMG can distribute the assets rationally at different criticality levels. Future research can incorporate methods for setting the thresholds in DMG as an extension to) in terms of either approaches; fixed and equal boundaries versus clustering based on sensitivity of the data as proposed by the work of Yunusa-kaltungo and Labib (2020).

6. Conclusion

6.1 Summary of results

The proposed ACA DMG has been used to assess the criticality of (1,170) SGS assets. The implementation has resulted in a rational assets criticality distribution as per Figure 9.



.**Figure 8: SGS assets criticality distribution**

As depicted in the figure, out of the (1,170) assets, there are (780) instrument tags with multiple layers of redundancy. As a result, 42% of the assets were assessed as (E) critical. On the other side, the ACA team had not assessed any asset as critical (A) which is supports the common understanding of SGS criticality as a non-critical system. The remain 58% are distributed as 12%, 19% and 27% for (B), (C) and (D) critical in sequence.

In the end, the resulted distribution considered practical and helpful by plant teams as they believe this distribution will facilitate priorities setting for daily activities and long-term improvement plans.

6.2 Future research

In order to maintain consistency in risk and consequences assessment throughout the asset life, developing a framework for the implementation of DMG as a tool to assess failure modes consequences in Reliability Centred Maintenance (RCM) and Failure Mode Effect Analysis (FMEA) processes would be an exciting topic for a future research. Moreover, linking these processes (ACA, RCM, FMEA) using data analytics and artificial intelligence would be an additional point for interesting research.

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