

A Probabilistic Minimax Approach for Machine Learning-Based Optimization of Hybrid Energy Storage Systems for Electric Vehicle Charging

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Abstract

The increasing adoption of electric vehicles calls for effective and reliable energy management system that enhance performance, prolong battery lifespan and boost overall system efficiency. This research article represents an innovative control method for a hybrid energy storage system that integrates a battery with a supercapacitor, employing a Proportional Integral controller alongside a Bayesian classifier for smart energy allocation.

In dynamic scenario, the PI controller maintains system stability by controlling the DC bus voltage. Using real time vehicle and load data, a Bayesian classifier is utilized to classify operational states. This classification makes it possible to share power appropriately, which lower battery stress and boosts energy efficiency.

By efficiently managing power demand scenario the proposed control approach improves transient response, lowers voltage fluctuations, and prolongs batter life. According to the simulation results a Bayesian classifier perform better than conventional control methods in terms of system reliability, response time and energy economy. This research article shows how combining probabilistic machine learning technique with traditional control approaches can enhance energy management in electric vehicles, offering scalable and intelligent solution for electric vehicle systems of the future.

Keywords: Bayesian Classifier, Feature vector, Prior Probability, Likelihood, Posterior Probability.

1. Introduction

A Bayesian classifier approach offers a clever and probabilistic method for improving a hybrid energy storage system in electric vehicle charging systems.[1] Using ideas from Baye's theorem, a Bayesian classifier predicts an ideal operating mode of hybrid energy storage system under a range of conditions, including as load demand, state of charge, charging patterns and grid availability.[2] It classifies system situations, such as high demand low demand and peak load and assigns probability to determine how energy should be distributed among energy resources and storage components.[3] By providing a data driven, adaptable and reliable optimization technique for managing hybrid energy storage in electric vehicle charging infrastructure, a Bayesian classifier helps to create more intelligent and sustainable energy systems.[4]

2. Methodology

2.1. Control Architecture of Electric Vehicle Charging System

Figure 1 shows a Control Architecture for Electric Vehicle Charging System.[5]

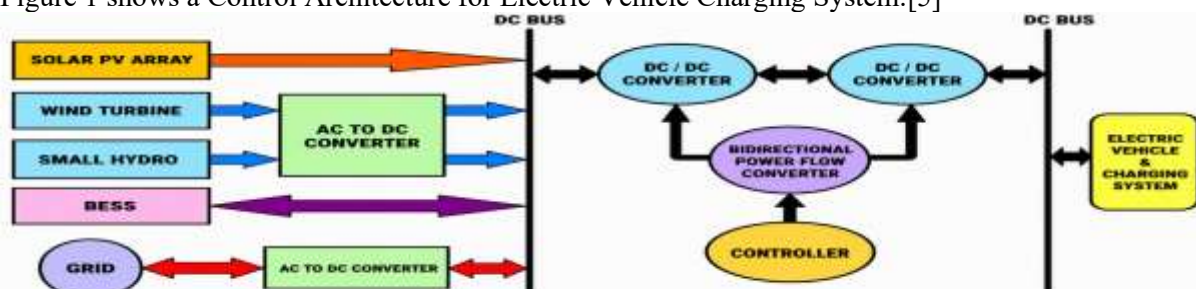


Figure - 1. Control Architecture for Electric Vehicle Charging System.

2.2. Basic Elements of Control Architecture

The following are the main elements of control architecture for Electric vehicle charging system.

- (1) Multiple renewable sources: Solar panel, Wind turbine, Small hydro.[6]
- (2) Battery Energy Storage System (BESS).
- (3) Grid connection.[7]
- (4) Converters (AC/DC, DC/DC, Bidirectional). Controller.[8]
- (5) EV charging system on the DC bus.[9]

2.3. Parameters evaluated on both the DC buses of Control Architecture

- (1) DC bus voltage (V_{dc} in Volts)[6]
- (2) DC bus current (I_{dc} in Amps)[4]
- (3) Power flow on DC bus (P_{dc} in Watts)[10]
- (4) EV (Electric Vehicle load demand
- (5) State of Charge (SoC) of BESS

2.4. Significance of Parameters evaluation on the both DC buses in control Architecture

- (1) Efficient energy management.[11]
- (2) Real time control by tuning the variables of controller.[11]
- (3) Ensuring reliable EV Charging.[11]
- (4) Maximizing renewable energy utilization.[11]
- (5) Maintaining system stability.[11]

2.5. A Bayesian Classifier

A Bayesian classifier is a statistical technique used in machine learning to categorise data based on probability. It is based on Bayes' Theorem, which defines how to update the probability of a hypothesis when new data becomes available.[10] At its core, a Bayesian classifier computes the likelihood that a given data point belongs to a specific class and then assigns it to the class with the highest probability. It makes decisions based on prior probability and likelihood.[5]

2.5.1. Purpose of a Bayesian Classifier

- (1) Evaluate the input conditions (i.e. resources status, load demand).[5]
- (2) Classify the system state or we can say that it provides optimal resource combinations.[5]
- (3) Inform the control system (controller) to allocate and schedule resources for efficient EV charging.[5]

Table 1: Shows the input quantities to a Bayesian classifier and its description.[8]

Sr. No.	Input Feature Vectors	Description
1	Solar Power Availability (P_{pv})	Measured solar PV array power output
2	Wind Power Availability (P_{wt})	Measured wind turbine power output
3	State of Charge of BESS (SoC_{BESS})	Charge level of Battery (%)
4	Grid Power Availability / Cost of Grid Power (P_{Grid})	Availability of Grid power and its price
5	DC bus voltage (V_{dc})	Stability indicator of the bus supplying to the EV charger
6	EV Charging demand (P_{EV})	Power demand by the EV charger
7	Time of day / Season	Temporal patterns of resource availability
8	Historical demand patterns	For probabilistic modelling of demand fluctuations

2.6. Formulation of a Bayesian Classifier

Equation of Baye's Theorem[12]

$$P(C_k/X) = [P(X/C_k) * P(C_k)] / P(X)$$

Where,

$P(C_k)$ = Prior Probability

$P(X/C_k)$ = Likelihood

$P(C_k/X)$ = Posterior Probability

2.6.1. Prior Probability $P(C_k)$ [13]

It is the Prior probability of class C_k = It is the initial probability of an event occurring before new data or evidences considered.

$$P(C_k) = \text{No. of Samples in } C_k / \text{Total No. of Samples}$$

2.6.2. Likelihood $P(X/C_k)$ [14]

It is the probability of evidence X for given event (C_k)

$$P(X/C_k) = \pi \text{ Gaussian } (X_j | \mu_{jk}, \sigma_{jk}^2)$$

μ_{jk} = Mean value of the j th feature in class C_k

σ_{jk}^2 = Variance of the j th feature in Class C_k

μ_{jk} and σ_{jk}^2 are the parameters which defines the Gaussian probability density function used to compute the likelihood in a Bayesian classification.

2.6.3. Posterior Probability $P(C_k/X)$ [15]

It is an Updated probability for event C_k after considering new evidences X .

$$P(C_k/X) = [P(X/C_k) * P(C_k)] / P(X)$$

Where $P(X)$ = Total probability of observing the data.

2.7. Training Algorithm for a Bayesian Classifier

Table 2: Shows Training algorithms for a Bayesian classifier.[13]

Sr. No.	Input of a Bayesian classifier	Steps to train a Bayesian classifier	Output of a Bayesian classifier
1	Training Data set	Compute Prior Probability $P(C_k)$ for each feature X_j	Prior and Likelihood parameters
2		Estimate mean μ_{jk} and variance σ_{jk}^2 for each class C_k	
3		Store $\{P(C_k), \mu_{jk}, \sigma_{jk}^2\}$	

2.8. Testing Algorithm for a Bayesian Classifier

Table 3: Shows Testing algorithms for a Bayesian classifier.[16]

Sr. No.	Input of a Bayesian classifier	Steps to train a Bayesian classifier	Output of a Bayesian classifier
1	Test Sample X	Compute likelihood $P(X/C_k)$ for each class C_k	Assign Class = $C^* = \text{argmax } P(C_k/X)$
2		Compute Posterior Probability $P(C_k/X)$ for each Class C_k $P(C_k/X) \propto P(X/C_k) X P(C_k)$	

2.9. Output of a Bayesian Classifier

Table 4: Shows Output or Class label of a Bayesian classifier.[17]

Sr. No.	Output Class (Label)	Interpretation
1	Class – 1: Use Only Renewable energy sources	Sufficient renewable energy generation, no grid power or battery discharge needed.
2	Class – 2: Use Renewable energy sources + BESS discharge	Renewable energy sources partially supply to load and battery support the load.
3	Class – 3: Use Renewable energy sources + Grid support	Renewable energy sources partially supply and grid support the shortage.
4	Class – 4: Use BESS + Grid power	No renewable power is available and battery and grid supply the EV charging load.
5	Class – 5: Prioritize Grid power (low tariff)	Grid is cheap and abundant so preferred to supply EV charging load.
6	Class – 6: Load shading / Throttling	Insufficient supply so throttle EV charging power.

2.10. Flowchart to implement a Bayesian classifier for the optimization of Hybrid Energy Storage System for Electric Vehicle charging system

Figure – 2 depicts a flowchart to implement a Bayesian classifier for the optimization of hybrid energy storage system for electric vehicle charging system.[18]

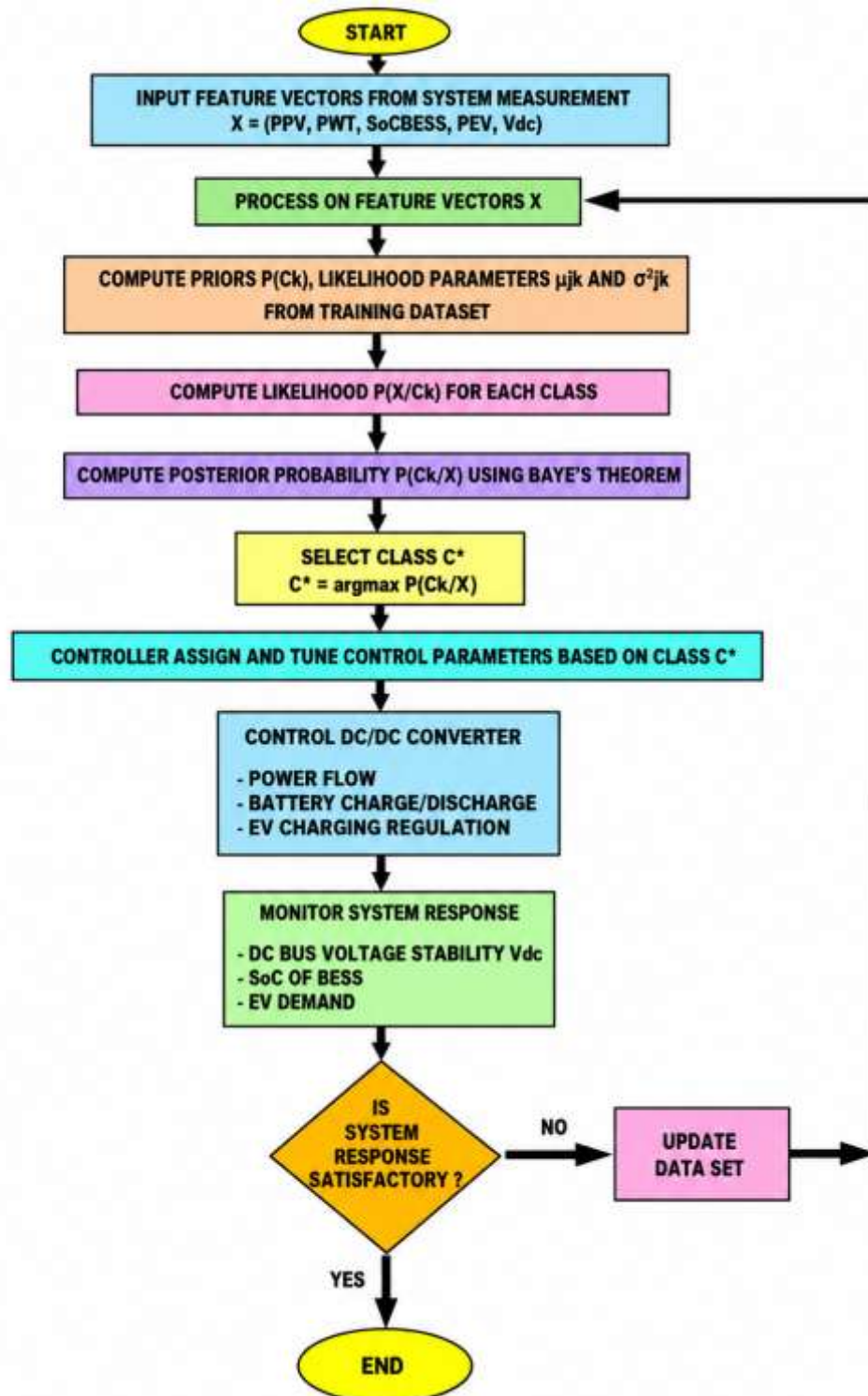


Figure - 2. Flowchart to implement a Bayesian classifier

3. Optimization

Optimization is the systematic process for making something as an effective, perfect or an efficient as possible by improving a design, system or process thorough analysis and strategic adjustment to achieve the best possible outcome. Table – 5 shows an optimization point which manage the bidirectional power flow.[19]

3.1. Computation to Implement a Bayesian Classifier

Table 5. shows Optimization points and its impact

Sr. No.	Optimization points	An impact of optimization
1	Power flow management	Balance energy from renewable energy sources and BESS to charge EV. Minimize power loss during the conversion. Maximize renewable energy sources usage.
2	Converter efficiency	Reduce switching losses. Optimize the control signals to the converters.
3	EV charging optimization	Optimize charging time and enhance the life span of the battery of electric vehicle.

3.1.1. Sample of Training Dataset

Table – 6 shows the training dataset to train a Bayesian classifier for the classification and these data are obtained from the system measurement.[20]

Sr. No.	Solar (PV array) Power (P_{PV} in kW)	Wind Turbine Power (P_{WT} in kW)	SoC of BESS (in %)	Charging power demand by EV (P_{EV} in kW)	DC Bus voltage (V_{dc} in Volts)	Class (C)
1	47	31	44	33	373	Low
2	192	31	65	20	395	Medium
3	211	119	76	16	388	High

3.1.2. Sample of Testing Dataset

Table – 7 shows the testing dataset to validate the class assigned by a Bayesian classifier.[21]

Sr. No.	Solar (PV array) Power (P_{PV} in kW)	Wind Turbine Power (P_{WT} in kW)	SoC of BESS (in %)	Charging power demand by EV (P_{EV} in kW)	DC Bus voltage (V_{dc} in Volts)	Class (C)
1	40	30	45	30	370	Low
2	50	28	65	20	395	Medium
3	215	125	75	20	385	High

Input Feature Vectors

$X = [PPV, PWT, SoCBESS, PEV, V_{dc}]$

Output of a Bayesian classifier =

Class label = $C \in \{\text{Low, Medium, High}\}$

These classes are representing the power flow management, charging priority and controller operating mode.

Step – 1: Compute the Prior Probability $P(C_k)$ from the training dataset.

$P(C_k) = \text{No. of Samples in class } C_k / \text{Total No. of Samples}$

Table – 8 shows the No. of samples taken in class C_k and the total no. of samples.[22]

Sr. No.	No. of Samples in Class (C_k)	Class (C_k)
1	30	Low

2	50	Medium
3	20	High
Total No. of Samples = 100		

Prior Probability for Low Class = $P(\text{Low}) = 30/100 = 0.30$

Prior Probability for Medium Class = $P(\text{Medium}) = 50/100 = 0.50$

Prior Probability for High Class = $P(\text{High}) = 20/100 = 0.20$

Step – 2: Compute Likelihood $P(X_j/C_k)$ for each class and for each feature

$$P(x_j | C_k) = [1 / \sqrt{(2\pi\sigma_{jk}^2)}] \times \exp\{ -[(x_j - \mu_{jk})^2 / (2\sigma_{jk}^2)] \}$$

Where,

μ_{jk} = Mean of j th feature in class k

σ_{jk}^2 = Variance of j th feature in class k

Table – 9 shows the value of mean of μ_{jk} (mean of j th feature in class k) and the value of σ_{jk}^2 variance of j th feature in class k .

Table – 9 shows mean of μ_{jk} and variance σ_{jk}^2 for j th feature.[23]

Sr. No.	Feature (j)	Mean of μ_{jk}	Variance σ_{jk}^2
1	P_{PV}	50 kW	25
2	P_{WT}	28 kW	16
3	SoC_{BESS}	60 %	36
4	P_{EV}	20 kW	09
5	V_{dc}	395 V	100

Input feature vectors = $X = [PPV = 50, PWT = 28, SoCBESS = 60, PEV = 20, Vdc = 395]$

Likelihood computation for PPV and for Class Medium = $P(X/C_k)$

$$P(50/\text{Medium}) = 1 / \sqrt{(2\pi \times 25)} \times \exp(-((50 - 45)^2 / (2 \times 25)))$$

Do this for all features j and multiply, so we will get

$$P(X | \text{Medium}) = \prod_{j=1}^n P(z_j | \text{Medium})$$

So, $P(50/\text{Medium}) = 9.5 \times 10^{-7}$

Repeat the above computation for Low and High Class also.

Step – 3: Compute Posterior Probability $P(C_k/X)$ by using Baye's Theorem

$$P(C_k/X) = [P(X/C_k) * P(C_k)] / P(X)$$

Since, $P(X)$ is common for all classes: $P(X) \propto P(X/C_k) P(C_k)$

So, $P(C_k/X) = P(\text{Medium}/50) = (9.5 \times 10^{-7} \times 0.50) / 1 = 9.5 \times 10^{-7}$ (By taking $P(X) = 1$)

Compute Posterior probability for all Low and High class and for all features and we will get the following data.

Table – 10 shows the posterior values after all the calculation.[24]

Sr. No.	Prior $P(C_k)$	Likelihood $P(X/C_k)$	Posterior Probability $P(C_k/X)$	Class (C)
1	0.30	1.2×10^{-8}	3.6×10^{-9}	Low
2	0.50	9.5×10^{-7}	4.75×10^{-7}	Medium
3	0.20	2.1×10^{-8}	4.2×10^{-9}	High

Step – 4: Class assignment

$C^* = \text{argmax } P(C_k/X) = 4.75 \times 10^{-7}$ (from the Table – 10)

Result: $C^* = \text{Medium}$

3.1.3. Interpretation of Class Assigned

Table – 11 shows the interpretation of class assigned by a Bayesian classifier after all computation.[25]

Sr. No.	Class assigned	Meaning of class assigned
1	Low	Low power generation from renewable energy source or low SoC of BESS resulting conservative EV charging.
2	Medium	Balance power from renewable energy sources and BESS resulting normal charging mode of EV.
3	High	High power generation from renewable energy sources and BESS resulting fast or aggressive charging of EV.

3.1.4. Validation of Testing Dataset

Table – 12 shows the correct prediction given by a Bayesian classifier against the total prediction done by a Bayesian classifier for the respective testing samples for each class assigned.[26]

Sr. No.	Correct Prediction (CP)	Total Prediction (TP)	Samples for Class assigned
1	10	12	Low
2	08	10	Medium
3	07	08	High

Accuracy = $[(\sum TP_i) / \text{Total Testing samples}] \times 100$

Accuracy = $[(10+08+07)/30] = [25/30] \times 100 = 83.33 \%$

The overall classification accuracy of a Bayesian classifier exceeds 80%, it represents the reliable operating mode decision making hybrid renewable energy system under varying generation, storage and EV charging conditions.[27]

3.1.5. Validation of True prediction done by a Bayesian classifier

For each test sample: Actual class is class given in test dataset and it is denoted by C_i^{actual} .

For each test sample: Bayesian predicted class is class assigned by Bayesian argmax rule and it is denoted by C_i^{Bayes}

Now Difference = $\Delta i = 0$, if $C_i^{\text{actual}} = C_i^{\text{Bayes}}$

$\Delta i = 1$, if $C_i^{\text{actual}} \neq C_i^{\text{Bayes}}$

Table – 13 shows the difference table by which we can know whether prediction is true or not done by a Bayesian classifier resulting we can find out the accuracy of a Bayesian classifier.[28]

Test sample	Actual predicted class	Bayesian predicted class	Difference
1	Low	Low	0
2	High	High	0
3	Low	Low	0
4	High	High	0
5	Medium	Medium	0
6	Medium	Medium	0
7	Medium	Medium	0
8	High	Low	1
9	High	High	0
10	Low	High	1

Meaning: 0 for True prediction by a Bayesian classifier

1 for Misclassification by a Bayesian classifier

N = Total no. of test samples = 10

N_{error} = No. of Mismatches = 02

Classification Error = $N_{\text{error}} / N = 02/10 = 0.2$

Accuracy = $(1 - \text{Classification Error}) \times 100 = (1 - 0.2) \times 100 = 80 \%$

4. Simulink model for power flow across DC/DC converter in the control architecture

Fig. – 3 depicts the Simulink model power the power flow across DC/DC converter for out control architecture.

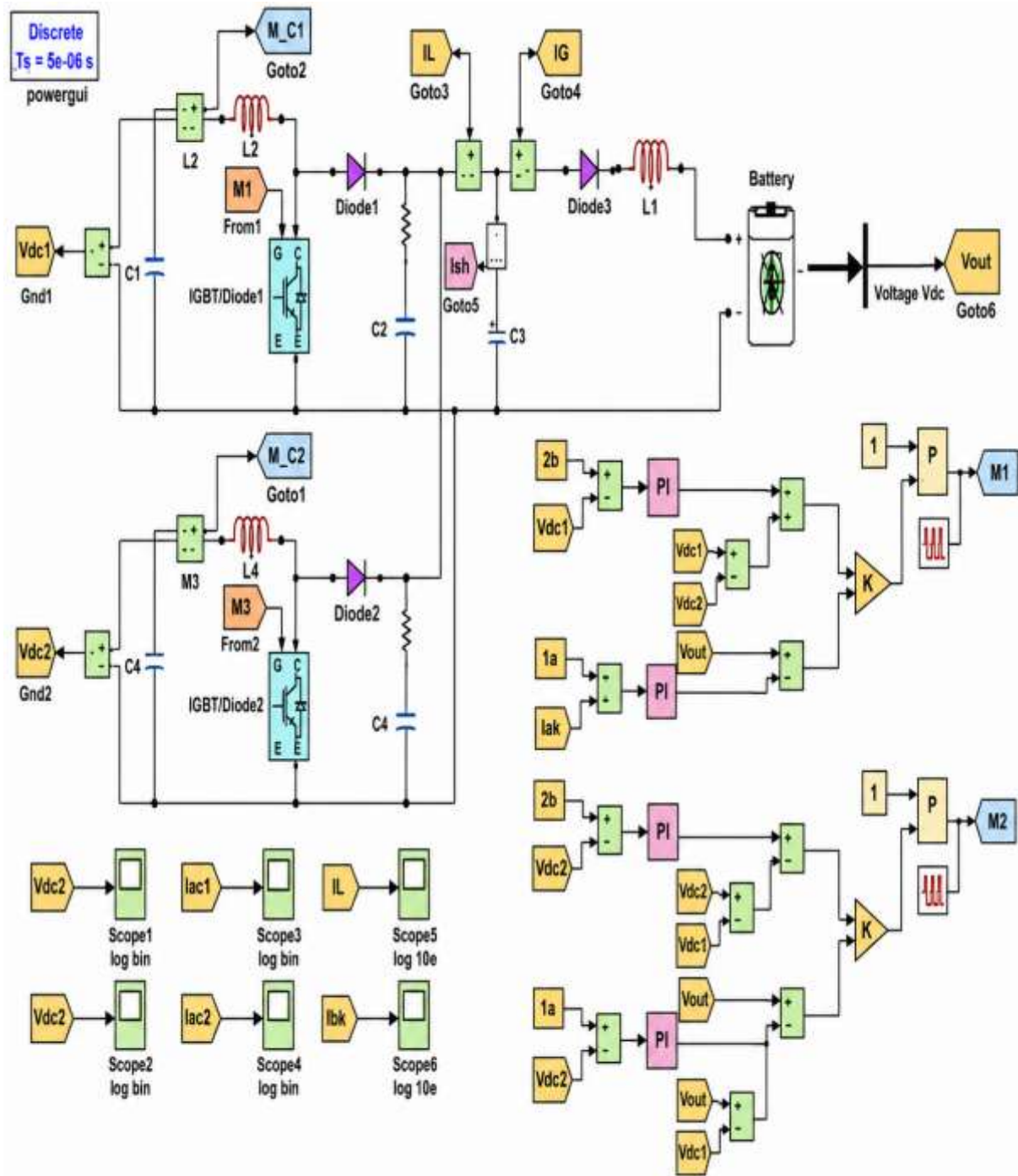


Figure - 3. Simulink model for power flow across DC/DC Converter

5. System Response (Result) Simulink model for power flow across DC/DC converter in the control architecture after actions taken by controller based on class assigned by a Bayesian Classifier

Fig. – 4 depicts the response of system in the form of waveforms of different parameters based on action taken by a controller with respect to class assigned by a Bayesian classifier.[29]

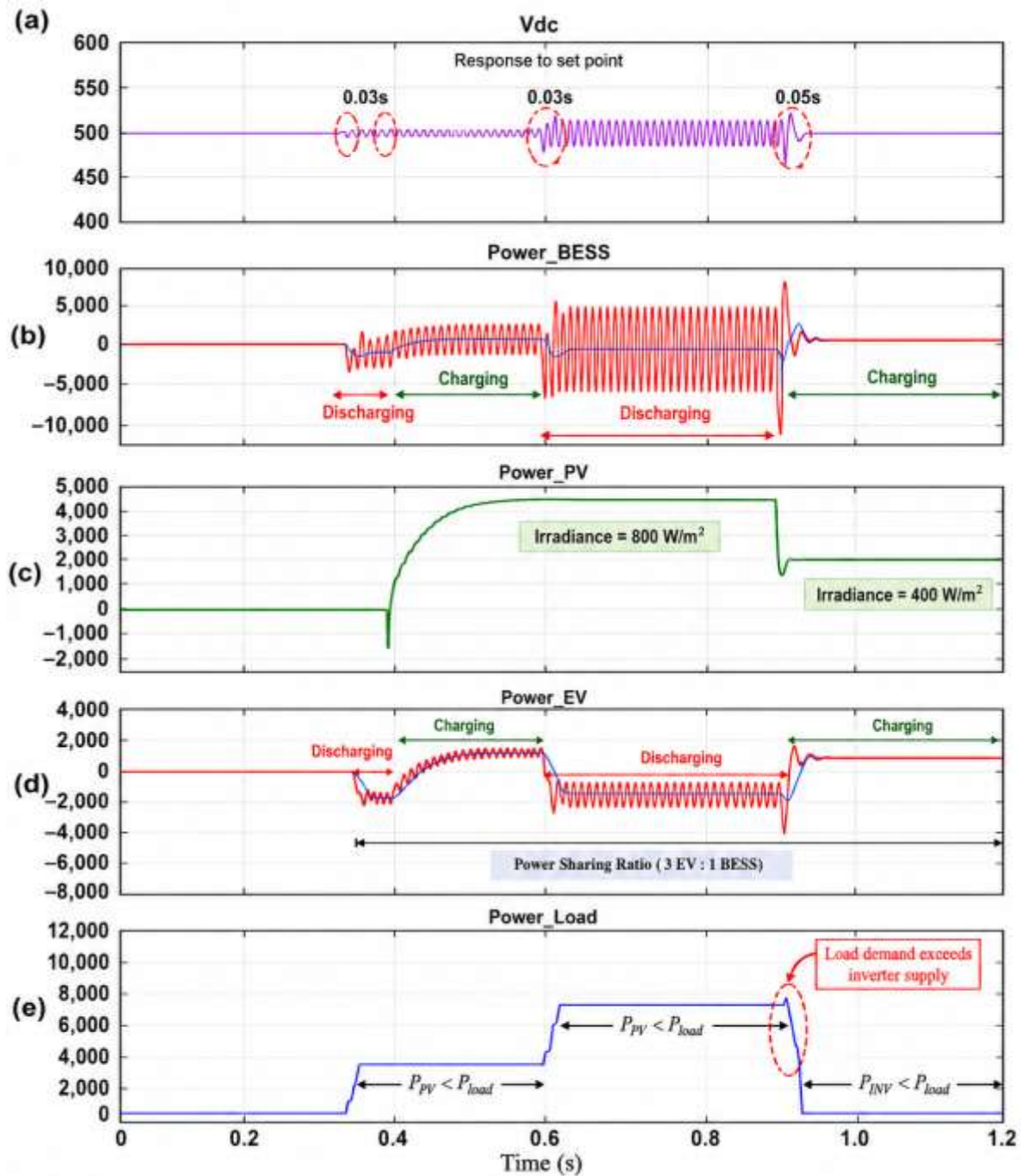


Figure 4. Result - System response after action of a controller based on class assigned by a Bayesian classifier

5.1. Interpretation of Result (System Response)

Table – 14 shows the interpretation of response of system shown in figure – 4 in the form of waveforms after actions taken by controller based on class assigned by a Bayesian classifier. [30]

Sr. No.	Waveform	Interpretation of system response (waveform)
1	(a)	DC bus voltage is regulated around 400 volts, small oscillations occur during power transient but it settles down within 0.03 seconds for moderate perturbation and 0.05 seconds for severe perturbation. Fast settling time indicates the controller maintain the voltage stability against the rapid change in PV generation, EV power and SoC of BESS.
2	(b)	Positive power indicates BESS is charging and negative power indicates BESS is discharging. BESS is discharging when PV power is insufficient to supply power demand by EV and BESS is charging when PV power generation exceeds the power demand by EV.

3	(c)	When Irradiance is 800 Watts/meter ² power generation by PV array rises up to 5 kW, and when Irradiance is becomes half i.e. 400 Watts/ meter ² power generation by PV array falls up to 2.5 kW. Smooth rises of power generation indicate MPPT operation and reduction in power generation by PV array must be handle by BESS.
4	(d)	Positive power indicates EV is charging and negative power indicates EV is discharging it is also known as V2G mode (Vehicle to Grid mode operation). Power sharing ratio is 3EV: 1 BESS. EV acts as controllable bidirectional resources.
5	(e)	When power generation of PV array is greater than power demand by EV indicates surplus power and during this condition BESS and EV is charging. When power generation of PV array is less than power demand by EV indicates deficit of power and during this situation BESS is discharging to support the charging of EV.

5.2. Advantages of a Bayesian Classifier

- (1) It is probabilistic method; no hidden layers or iterative update weights are required.[31]
- (2) A Bayesian classifier assigns the operating class in a single pass by using posterior probability maximization, enabling fast real time optimization of the controller.[32]
- (3) It has lower misclassification rate.[6]
- (4) Lowest expected error among all the classifier.[9]
- (5) Robust and often superior when the data are sparse or uncertain.[33]
- (6) It needs simple computation.[11]
- (7) It has high probabilistic and interpretable.[34]

Conclusion

In order to ensure that the controller meets both performance and efficiency goals, a Bayesian classifier is useful for scalable and sustainable energy management in electric vehicle charging system.

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